Property Insurance and Disaster Risk: New Evidence from Mortgage Escrow Data*

Benjamin J. Keys[1] and Philip Mulder[2]

[1]The Wharton School, University of Pennsylvania and NBER
[2]University of Wisconsin-Madison

July 2025

Abstract

We develop a new dataset to study homeowners insurance. Our data on over 84 million observations of households' property insurance expenditures from 2014–2024 are inferred from mortgage escrow payments. First, we find a 25% real increase in average premiums from 2018 to 2024 that is highly uneven across geographies. This growth is associated with a stronger relationship between premiums and local disaster risk: A one standard-deviation increase in disaster risk is associated with $610 higher premiums in 2024, up from $250 in 2018. Second, using the rapid rise in reinsurance prices as a natural experiment, we show that the increase in the risk-to-premium gradient was largely caused by higher costs of insuring correlated catastrophic risks. Third, we find that this reinsurance shock capitalized into home values, reducing home price growth by over $22,000 in zipcodes exposed to severe hurricanes and wildfires between 2020 and 2024. The insurance and home price effects of the reinsurance shock are larger in areas exposed to increasing climate risk. Our results highlight how prices in global reinsurance markets determine the pricing of climate risk and pass through to household budgets.

*We thank Dani Bauer, Juliane Begenau, Sid Biswas, Ben Collier, Ty Leverty, Dan Sacks, Joan Schmit, Ana-Maria Tenekedjieva, and Varun Sharma for their helpful comments. We thank seminar and conference participants at the Treasury OCC, Fannie Mae, Federal Reserve Bank of Chicago, Federal Reserve Bank of Richmond, Freddie Mac, HUD, St. John's University, BYU, the FHFA Fall Economic Summit, SIPA-FRBNY Environmental Economics and Policy Conference, Stanford, the Urban Institute, Wharton, and the Wisconsin School of Business for their thoughtful suggestions. Fabio Cardoso Schanaider, Octavio Elias de Lima, Declan Mirabella, and Joshua Boyd provided outstanding research assistance. We thank Jeremy Porter and the First Street Foundation for data provision and guidance. Keys thanks the Wharton ESG Initiative's Research Fund, ESG Initiative Climate Center, and the Research Sponsors of the Zell/Lurie Real Estate Center for support. Any remaining errors are our own. Contact: benkeys@wharton.upenn.edu, philip.mulder@wisc.edu

1 Introduction

Finding ways to mitigate escalating climate-related risks is particularly challenging for the real estate sector, given its inherent durability and immobility. Property insurance serves as a crucial safeguard for homeowners, protecting the value of their assets against disaster risk. As these risks intensify, however, the availability and affordability of homeowners insurance cannot be assumed. With widespread rate increases since 2020 and forecasts of heightened climate risk, the impact of rising insurance premiums has become a pivotal issue for households, financial institutions, researchers, and policymakers.[1] Unfortunately, existing data on premiums are coarse and inadequate, preventing a clear understanding of the extent and underlying causes of these increases.

In this paper, we use data from mortgage escrow payments to develop a new approach to measuring homeowners insurance premiums. Most mortgage borrowers make a single monthly payment into an escrow account that disburses funds toward mortgage principal, interest, local property taxes, and insurance (a.k.a. PITI). Our loan-level mortgage servicing data allow us to decompose the escrow payment into these four distinct elements and thereby construct a new dataset of insurance premium expenditures. The dataset yields over 84 million observations from 2014 to 2024. We create a zipcode-level insurance premium expenditure index (IPI) in the style of a home price "repeat sales index" following changing premiums on the same loan over time, thereby holding time-invariant characteristics of the home and policyholder fixed.

To examine the robustness of our methodology to infer insurance premiums, we benchmark our expenditure estimates to the limited available public data. These data come from state-level insurer filings, Census surveys, carrier price quotes, and a new data collection from the Federal Insurance Office. We find that our indices yield strongly correlated insurance pricing by locations, but that our estimated expenditures are consistently somewhat larger than other sources, reflecting that average home values are 10-15% larger in our sample of mortgaged single-family homes than in the general population.[2]

With this new dataset in hand, we analyze the causes and consequences of recent insurance market trends in three parts. First, we characterize the state of insurance premiums in the United States to a more precise degree than any previous research. We find that average nominal annual premiums increased $1,000 from $1,800 in 2018 to $2,800 in 2024, a 25% inflation-adjusted increase. We use the geographic granularity of our data to provide the first estimates of the relationships between premiums, disaster risk, demographics, and housing costs at the ZIP code level. We find

[1] See, e.g., Treasury Secretary Yellen's remarks to the Federal Advisory Committee on Insurance Meeting, March 2023, `https://home.treasury.gov/news/press-releases/jy1375`.

[2] See Appendix Section 10.2 for the detailed comparison between these sources.

that housing structure values and disaster risk explain most of the variation in insurance premiums, but we also document large heterogeneity in premiums across incomes and socioeconomic status. For instance, lower income areas see much higher premiums as a share of income, and zipcodes with larger nonwhite population shares pay higher premiums after conditioning on disaster risk and income.

Second, we examine the role of building costs, disaster risk, and reinsurance costs in driving recent insurance market dynamics. While we find that the increase in construction costs can explain 40% of the rise in homeowners insurance premiums after 2018, we also show that the largest increases were concentrated among zipcodes with the highest disaster risk. These effects cannot be explained by differences in construction cost inflation or state-specific factors. Rather, our estimates show that the association between a one standard deviation increase in disaster risk and premiums rose from $225 in 2018 to $610 by 2024. This increase in the cost of risk explains nearly 25% of the increase in premiums between 2018 and 2024.

The dynamic relationship between disaster risk and premiums is an important, previously undocumented driver of the impact of climate change on homeowners' insurance costs. The ultimate change in insurance costs for homeowners will be a function of both the change in their risk and any change in the price of insuring that risk. Our analysis shows that the relationship between premiums and risk increased by 170% in just six years. Thus, projecting the impact of climate risk on real estate markets is clouded by uncertainty in both future disaster risk and the price of risk.

Why did the risk-to-premium gradient increase so sharply in recent years? Importantly, this increase coincides with a doubling of U.S. property catastrophe reinsurance prices between 2018 and 2024 (Guy Carpenter). Reinsurance refers to secondary insurance contracts with global insurers used by U.S. insurers to hedge severe correlated risks, such as hurricanes and wildfires. Thus, reinsurance prices provide an important window into the cost of insuring the risks that are expected to increase the most dramatically with climate change. The 100% increase in reinsurance prices over just five years is potentially due to a number of factors, including construction cost inflation, a "climate epiphany" as reinsurers reassess climate exposure, increasingly concentrated disaster exposure as Americans move into harm's way, and the end of a low interest rate environment that led to a capital crunch.[3] Thus, reinsurers are responding to real cost increases driven by many of the same factors increasing homeowners insurance premiums in other markets where risk is less concentrated.

We use our data to isolate the extent to which rising reinsurance prices signal a real increase in the relative costs of insuring correlated hurricanes and wildfires. To proxy for a market's exposure

[3]See Gallagher Re (2024); Swiss Re (2024).

to reinsurance market fluctuations, our empirical specification uses variation in the county-level correlation of historical losses within states. Correlated losses drive reinsurance demand as geographically concentrated insurance companies seek to spread their risks across global capital markets. Thus, we compare the change in premiums in areas with similar expected losses but different degrees of correlated risk. Our most stringent specification includes state-by-risk controls to absorb the effects of state-level factors such as regulations or recent natural disasters that might affect general premium trends, as well as structure value controls to account for housing cost inflation.

We find that premiums increased disproportionately where risk is more correlated. Thus, the rise in reinsurance prices reflects higher costs of insuring correlated catastrophic risks above and beyond the pricing of expected losses. Among zipcodes exposed to catastrophic hurricane and wildfire risks ("cat-exposed"), this reinsurance shock increased annual premiums by $230 in 2024. We conclude from this exercise that insurers' pass through costs of reinsurance to homeowners. Their reliance on reinsurance markets makes the cost of insuring catastrophic risk sensitive to the cost of hedging those risks in global capital markets.

In the third and final step of our analysis, we estimate the capitalization of the reinsurance shock into home prices. While it may seem natural that higher insurance costs would result in lower home values, historical periods of tightening in reinsurance markets have often been followed by falling reinsurance prices as additional capital enters the market. If this pattern holds and housing market participants expect the reinsurance shock to be temporary, we should expect to see little effect on home values.

In contrast to this theory, we find that the reinsurance shock reduced 2024 home values by an average of approximately $22,000 among cat-exposed zipcodes. This implies a $95 reduction in home values for every $1 increase in premiums, well within the range of full capitalization. Thus, our findings suggest that homeowners do not view the reinsurance shock as transitory and expect to continue paying higher costs to insure correlated risks. We find heterogeneous results by growing climate exposure, with areas that are projected to see growing risk experiencing both larger premium increases and home price declines due to the reinsurance shock. The fact that reinsurance costs are rising faster in the areas exposed to greater future risk suggests that reinsurers are already starting to reprice risk in these markets based on recent loss trends. Furthermore, the reinsurance shock has resulted in a major repricing of climate-exposed housing assets. In total, our findings emphasize the critical role played by global insurance and capital markets in the dynamic repricing of climate risk.

Taken together, our approach delivers unprecedented insight into the state of homeowners insurance markets, describes a new methodology for observing and analyzing these markets, provides a

new causal estimate on the degree of pass-through from secondary reinsurance markets to primary homeowners insurance premiums and ultimately into house prices, and benchmarks the potential effects of climate change on homeowners' premium costs. We produce the first estimate of a central determinant of the cost of climate risk: the relationship between expected disaster losses and homeowners insurance premiums. This key parameter shows significant volatility over time and sensitivity to the cost of reinsurance, suggesting that the costs of climate change will crucially depend on the ability of global capital markets to absorb catastrophic risk.

By providing new estimates of how much individuals are paying for growing climate risks, our paper extends the climate finance literature around housing, mortgage, and insurance markets. A growing literature has established connections between asset values and climate risk in the housing market, with important heterogeneity around realized declines and climate beliefs.[4] We show that rising insurance premiums are being capitalized into house prices, and may further reduce demand for at-risk properties (Poterba, 1984).[5] Recent research, focusing on publicly provided flood insurance, shows that the availability, cost, and stability of disaster insurance has first-order effects on the availability of mortgage credit and loan performance (Sastry, 2021; Sastry et al., 2023; Blickle and Santos, 2022; Kousky et al., 2020).

Our analysis expands connections between financial markets and the costs of climate change. Previous studies have shown how mortgage markets can act as climate risk sharing tools, but can also create adverse selection and moral hazard given unpriced climate risk (Kahn et al., 2024; Panjwani, 2022; Issler et al., 2020).[6] Another strand of research finds that various frictions in the flood insurance market generate large welfare losses (Wagner, 2022; Weill, 2022; Ostriker and Russo, 2022), and that the mispricing of flood risk substantially increases long-run climate costs (Mulder, 2023). We provide the first estimates of U.S. homeowners' potential premium increases due to increasing disaster risk based on the dynamic relationship between risk and premiums. Furthermore, we show that this key parameter is sensitive to the cost of accessing global reinsurance markets to diversify catastrophic risk. Thus, our estimates provide novel counterfactuals of the costs of climate change depending on the long-run costs of reinsurance.

Our findings provide new insights into private insurance market pricing and its relationship with the cost of capital in secondary markets. A literature in asset pricing and macro-finance has emphasized the importance of capital frictions and liquidity on firm price-setting in financial markets

[4]See, for instance, Bernstein et al. (2019); Bakkensen and Barrage (2021); Baldauf et al. (2020); Murfin and Spiegel (2020); Keys and Mulder (2020). For a recent survey of this literature, see Contat et al. (2024).

[5]Nyce et al. (2015), Georgic and Klaiber (2022), and Ge et al. (2022) estimate the capitalization of flood insurance premiums on house prices.

[6]See also relevant work by Lewis (2023) on the value of water markets as climate hedges.

(Brunnermeier et al., 2021).[7] In life insurance markets, where price data for standardized policies is readily available, researchers have found that frictional costs from firms' liquidity constraints or regulatory requirements pass-through to premiums with meaningful effects on consumer welfare (Koijen and Yogo, 2015, 2016; Bauer et al., 2021; Ge, 2022). Eastman and Kim (2023) estimate the pass-through of capital requirements to homeowners insurance premiums using household survey data on insurance expenditures. Most relevant to the reinsurance shock we study, many researchers have examined the forces that drive "underwriting cycles" of increasing and decreasing premiums.[8] Using our granular premium data, we provide a novel estimate of the pass-through of reinsurance prices to homeowners insurance premiums. Our evidence shows that capital market dynamics will be an important determinant of premiums in high-risk states.

Finally, our paper sheds light on understanding the price signals reaching climate-exposed homeowners. One line of research has found large markups for catastrophic reinsurance above expected losses (Froot, 2001; Zanjani, 2002; Froot and O'Connell, 2008) and noted the particular challenges of insuring correlated risks (Jaffee and Russell, 1997; Cummins and Weiss, 2009; Ibragimov et al., 2009; Kousky and Cooke, 2009; Marcoux and Wagner, 2023).[9] We extend these findings by showing how reinsurance price shocks not only affect premiums today, but could also affect the costs of increasing disaster risk under different climate change scenarios. Oh et al. (2022) find that insurers face substantial rate-setting frictions due to state regulation, and pass on climate-risk-induced losses to safer areas in less regulated states, leading to spatial cross-subsidization. Boomhower et al. (2024) use rate filing data to show that insurers price wildfire risk in California depending on the sophistication of their risk models, which can induce cream skimming effects. Sastry et al. (2025) show that rising insurance premiums drive down coverage limit take-up, especially for credit-constrained households. We find that capital cost frictions can also distort the pricing of climate risk within and across states. Ultimately, the price signal from property insurance premiums will prompt adaptation, mitigation, and relocation, but will require a competitive and well-capitalized insurance market to set an accurate price signal.

[7] See Bauer et al. (2023) for a more comprehensive review and discussion of capital frictions and pricing in insurance markets.

[8] See e.g. Gron (1994); Gron and Lucas (1995); Froot and O'Connell (1999); Harrington (2004); Born and Viscusi (2006); Boyer et al. (2012).

[9] On more general uses of reinsurance in P&C markets, see, for example, Anand et al. (2021) who show that insurers contract with reinsurers to access specialized knowledge about new markets.

2 The Residential Homeowners Insurance Market

Property and casualty (P&C) insurance protects homeowners from physical and liability damages. In the United States, insurers collected $133 billion in gross premiums for homeowners insurance products in 2022 (Insurance Information Institute, 2024). Data from the American Housing Survey suggest that 94% of all homeowners have homeowners insurance (Jeziorski and Ramnath, 2021). The McCarran-Ferguson Act of 1945 codified the regulatory framework for insurers, which leaves regulatory oversight as a responsibility of individual states. In 2010, as part of the Dodd-Frank Act, a Federal Insurance Office (FIO) was created within the U.S. Treasury Department, but the regulatory purview of this office is thus far limited.

Obtaining property insurance is generally a prerequisite to qualify for a mortgage. Most owner-occupied residential homeowners insurance policies are "HO-3," which covers the structure, contents, legal expenses in the event of a lawsuit, and living expenses during the time to make the home habitable if the home is damaged. These policies generally have clauses that specifically exclude certain perils, such as floods, earthquakes, or, in some cases, high winds or wildfires.[10] Other types of policies cover these perils, and the market provides a variety of other policies that cover either more or less than the standard HO-3 policy (NAIC, 2022). In some cases, homeowners turn to state-sponsored "insurers of last resort," such as Citizens Property Insurance in Florida or the California FAIR plan, to provide coverage if they cannot find a willing private insurer.

Insurers manage their risk through a variety of tools and subject to state-level regulations (Froot, 2007). Primarily, insurers hold capital to meet claims and diversify their losses across multiple lines of business. Insurers facing more concentrated risks often purchase reinsurance from large, global reinsurers (Froot et al., 1995). Reinsurance contracts specify some coverage of the insurer's losses by the reinsurer. Reinsurance contracts detail deductibles, coinsurance, limits, and other terms. For the purposes of covering catastrophic disaster risk, "excess of loss" reinsurance that covers an insurer's losses above a set amount is most common. Insurers purchase reinsurance in order to limit their downside risk in the event of a catastrophic disaster, and to smooth the path of cash flows (Cummins et al., 2021). In 2022, P&C insurers ceded roughly $19 billion in premiums to reinsurers (Insurance Information Institute, 2024). Most large insurance companies work with brokers to place many reinsurance contracts with many reinsurers; Guy Carpenter is one such broker that publishes data on the cost of reinsurance, which we use in our analysis below.

For monitoring purposes, mortgage lenders typically require that insurance payments are made through an escrow account. An escrow account is created for the purposes of collecting funds from

[10] Although the private market for flood insurance is growing, most flood insurance is still provided by the federally-run National Flood Insurance Program (NFIP) (Kousky et al., 2018).

the homeowner along with their monthly mortgage payments and distributing these funds to the local taxing authority and their insurance provider. Each month, the mortgage servicer takes a portion of the total monthly payment and holds it in the escrow account until tax or insurance payments are due.

The advantages of the escrow account are that the lender can monitor whether the homeowner is current on their tax and insurance payments, which protects their collateral. By including tax and insurance costs in the total payment, homeowners do not have to save to make (or remember to make) annual or bi-annual lump-sum payments, but instead smooth the costs across their twelve monthly payments. The manager of the escrow account, usually the mortgage servicer, ensures that tax and insurance payments are made on time.

Escrow accounts are usually required to hold a buffer amount above the prior year's tax and insurance payments to account for potential changes. A change in escrow payments may reflect not only a change in the insurance premium, but also an additional amount needed to rebuild an escrow buffer after a drawdown. The Biggert-Waters Act of 2012 required the escrow of flood insurance policies issued by the National Flood Insurance Program starting in 2016, and other peril-specific policies can also be similarly escrowed. However, flood insurance is largely purchased by homes located inside the floodplain even though flood risk itself is much more widespread (Weill, 2022). Furthermore, the actual enforcement of the escrow requirement remains uncertain (Government Accountability Office, 2021). Finally, escrow accounts are infrequently used to cover HOA fees or other home- or community-specific expenses.

3 Data

3.1 Loan-Level Data

Our data on mortgage escrow accounts come from CoreLogic, a leading property information and analytics provider. CoreLogic's Loan-Level Mortgage Analytics (LLMA) dataset follows residential loans from origination to termination using data provided by loan servicers. The data contains information at the time of origination, as well as continuing information on repayment and loan performance. Combined with the Supplemental Loan Analytics (SLA) file (with a unique loan ID), the data provides information on the total payment made by the borrower, the amount of principal and interest, and the current property taxes paid on the property.[11] The data includes the zipcode of the property, as well as loan type (e.g. purchase vs. refinance) and property and borrower

[11] Note that these fields represent the scheduled payments or amounts due, making it straightforward to consistently infer premiums. If we instead observed actual payments, we would need to adjust for some borrowers falling behind and others repaying faster than the amortization schedule to reduce their outstanding principal balance.

characteristics.

3.2 Disaster Risk, Climate Risk, and Socioeconomic Data

Our primary measure of climate risk comes from a combination of the National Risk Index (NRI) and the First Street Foundation (FSF). The NRI was designed by FEMA to communicate the extent of risk from 18 different climate-related hazards.[12] The FSF is a private climate risk provider that creates highly localized risk models for wildfire, wind, flood, and heat risk (First Street Foundation, 2020).

To measure zipcode disaster risk in 2023, we combine the expected annual loss (EAL) rates per dollar of building value across different hazards typically covered by HO-3 homeowners policies (i.e. excluding earthquake and flood). We use FSF's zipcode-level models to measure EAL rates for wildfire and hurricane hazards. We add in EAL rates for cold waves, hail, heat waves, ice storms, lightning, strong winds, tornadoes, volcanic activity, and winter weather from the NRI.[13] We winsorize each hazard's EAL rate at the 1st and 99th percentile across all zipcodes, and divide the overall EAL rate by its standard deviation to form the 2023 disaster risk measure.

We measure 2053 climate risk as the expected increase in disaster risk between 2023 and 2053. We construct our measure of expected disaster risk in 2053 by replacing the FSF hurricane and wildfire 2023 EAL rates with their projected 2053 EAL rates, still normalizing by the 2023 EAL rate standard deviation. This measure of climate risk assumes that the other hazards in the NRI will remain constant. Given that wildfires and hurricanes – along with flooding which is covered under separate policies – account for the primary physical loss risks expected to increase with climate change, we believe this is a reasonable initial benchmark for climate risk.

In addition to creating separate measures of disaster and climate risk, there are several other benefits to using the FSF hurricane and wildfire models. First, because the NRI is largely based on historical losses, it is an intentionally "backward-looking" measure of current risk.[14] In contrast, the FSF 2023 models account for recent changes in climate and land use that are particularly important to accurately assess current wildfire and hurricane risks. Second, the NRI hurricane measure does not distinguish wind-related damages, which are typically covered by HO-3 policies, and flood-related damages that would be covered by separate policies. The FSF hurricane model, on the other hand, only includes wind-related damages.

We also use county-level historical loss data from the Spatial Hazard Events and Losses Database

[12] See Appendix Figure 16, `https://hazards.fema.gov/nri/learn-more`.

[13] The NRI EAL rates are measured at the census tract level.(FEMA, 2023) We aggregate these to the zipcode weighting by the share of housing units using "geocorr" (Missouri Census Data Center, 2014).

[14] See `https://cemhs.asu.edu/sheldus` for more information on the SHELDUS historical disaster database.

(SHELDUS). The database aggregates reports from a diverse array of sources to estimate injuries, fatalities, and economic damages from natural disasters. We use monthly per-capita losses by state and county between 2000 and 2013 to measure the historical correlation of losses predating our analysis period within states. We show that these within-state correlations are an important driver of reinsurance demand. We subset the data to perils typically covered by homeowners insurance policies.

We further supplement this climate and disaster data with zipcode-level covariates from US Census ACS data, such as median household income, population share of renters, share of white/nonwhite residents, and share living below the poverty line. We also account for home price trends with Zillow's home value estimates at the zipcode level.

Of particular importance to our study are zipcode-level panel estimates of annual land and structure values of single family housing from the Federal Housing Finance Administration (FHFA). In an updated methodology from Davis et al. (2021), the dataset uses appraisal data between 2012–2022 to build a panel dataset of the share of home values attributable to land.[15] We apply these land shares to Zillow home prices to construct an annual zipcode-level measure of average structure values.[16] While these structure values represent depreciated replacement values, the dataset directly uses construction cost indices to update its structure values over time so that they grow proportionately with replacement values across geographies.

3.3 Insurance Data

We use insurer regulatory filings collected by the National Association of Insurance Commissioners (NAIC) to create state-level measures of reinsurance exposure. In particular, we use the total direct homeowners premiums written by each insurer in each state as well as the total share of each insurer's direct homeowners premiums that they ceded to unaffiliated reinsurers.

To illustrate the dynamics of reinsurance market tightness, we turn to the Guy Carpenter Rate-On-Line Index for the U.S. property catastrophe market. The Guy Carpenter index tracks the cost of reinsurance over time for constant amounts of coverage, i.e. holding coverage limits and thresholds fixed. This index is commonly cited in reinsurance market analyses (see, e.g. Gron, 1999; Araullo, 2024), and reflects contracts written on a brokered basis between insurers and reinsurers.

[15] The dataset is publicly available and described in more detail at `https://www.fhfa.gov/blog/statistics/land-price-appreciation-during-the-covid-19-pandemic`

[16] Due to data limitations, we apply the 2022 land share (the most recent year calculated by the FHFA) to 2023 and 2024 home prices.

4 Measuring Insurance Expenditures

To measure insurance premium expenditures, we rely on mortgage servicer data on the borrower's payments to their escrow account. For the large majority of borrowers who pay their taxes and insurance through an escrow account, their total scheduled loan payment each month is defined as Prinicipal + Interest + Property Taxes + Insurance. For loans without mortgage insurance (MI), the decomposition is a simple one:

$$Insurance = TotalPayment - Principal - Interest - Taxes \tag{1a}$$

However, loans backed by the FHA or the GSEs with high loan-to-value ratios (typically above 80%) are required to take on a mortgage insurance policy. For loans with MI from either the FHA or the private mortgage insurance (PMI) market, we impute payments using a method from Bhutta and Keys (2022) that relies on using VA loans, which have no mortgage insurance, as a high-LTV counterfactual for loans paying MI. We regress total insurance premiums on an MI indicator interacted with FICO-by-LTV bin indicators, county-by-house price decile indicators, and county-by-time fixed effects to account for other sources of heterogeneity, then recover fitted values as the best estimate of MI premiums. For this sample, we then subtract the imputed monthly MI premium payment to recover property insurance expenditure:

$$Insurance = TotalPayment - Principal - Interest - Taxes - MI \tag{1b}$$

All of our analyses annualize these monthly payments. Our approach assumes that the residual component of the total escrow payment is entirely attributable to property insurance. We note, however, that there may be errors of both omission and commission present. Some homeowners may have insurance policies, especially supplemental peril-specific policies like flood or wind insurance, that are not included in escrow. On the other hand, some lenders offer the option to include HOA fees in escrow payments. It is also possible that borrowers may make extra payments to eliminate escrow shortfalls.

Table 1 describes the process by which we reach our analysis sample from the raw data. Our data come from nearly 20 million purchase and refinance fixed-rate loans for single-family homes that were originated between 2014 and 2023. We restrict the sample to loan-level records where total payments, principal+interest, and property tax data are all populated. We then focus on observations where the total payment changes (usually once per year). Next, we modestly restrict our sample by removing outliers and winsorizing premium values at the 1st and 99th percentiles by state-year. Finally, we impute MI premiums and remove a subset of loans with insufficient

	Mortgage Payments	Loans
All	1,241,482,608	40,822,952
Non-Missing LTVs	1,235,541,064	40,579,829
TP, P&I, Tax > 0	924,521,128	32,336,954
Drop repeated tot. pay rows	144,865,162	32,336,954
Owner Occupied	134,620,760	29,934,170
TP $\neq$ P&I	130,725,864	27,417,850
Premium > 0	124,270,299	25,534,564
Relative Premium < 5	119,597,877	25,367,966
Winsorized Premium > 10	118,982,593	25,283,319
Collapse to year & quarter	113,349,634	25,283,319
PMI Adjustments	84,010,753	19,888,374

Table 1: This table describes how the sample size progresses from the full data to the sample of loans and observations used to estimate premiums. "TP" is total payment, "P&I" is principal and interest, and "Tax" is annual property taxes from escrow. Relative premium is defined as the annual premium divided by the inferred price of the home, expressed as a percentage.

information to impute MI, or implausible values of imputed MI payments. Collapsing our data to year and quarter yields 47 million observations building off of over 12 million mortgagor escrow accounts.

Zip Code	**Date**	**Total Payment**	**Principal + Interest**	**Taxes**	**Insurance**
34239	2015Q2	9200.88	6422.88	1301.22	1476.78
34239	2016Q1	9092.04	6422.88	1307.96	1361.20
34239	2017Q1	9194.64	6422.88	1291.32	1480.44
34239	2018Q1	9069.12	6422.88	1305.74	1580.50
34239	2019Q1	9408.36	6422.88	1327.67	1657.81
34239	2020Q1	9647.28	6422.88	1357.61	1866.79
34239	2021Q1	9680.16	6422.88	1403.95	1853.33
34239	2022Q1	10095.84	6422.88	1397.79	2275.17
34239	2023Q1	11133.36	6422.88	1402.01	3308.47
34239	2024Q1	12914.64	6422.88	1481.6	5010.16

Table 2: Example of one loan's total payment decomposition. All values are annualized from monthly payments.

Table 2 shows the decomposition exercise for one loan's total payment and how we infer insurance premiums in the case where LTV$<$80% so there is no mortgage insurance payment. The loan is located in zipcode 34239 in Sarasota, FL. The inferred insurance payment is the remainder from subtracting principal, interest, and taxes from the total escrow payment. The annual insurance payment adjusts each time the total payment adjusts, with the tax amount sometimes changing

Statistic	Mean	St. Dev.	10th Pct.	90th Pct.
Premium Expenditure	2,770.23	2,257.89	8,61.92	5,319.48
Purchase Price	360,091.9	894,902.6	135,009	645,161.3
Premium as % of Price	.98	.79	.25	2.02
Premium as Pctg. of P&I	21.32754	17.87	05.46	43.52
FICO Score	730.34	61.86	646	801

Table 3: Summary statistics from the cross-section of premium estimates in 20.

(by small amounts) over time.

With our premium data in hand, we build an annual insurance premium index (IPI) at the zipcode level. The goal of the IPI is to compare insurance premiums across markets and over time adjusting for potential differences in the housing stock or composition of borrowers. We use a repeat-loan specification:

$$Premium_{izt} = \alpha_{zt} + \lambda_i + \epsilon_{izt}. \tag{2}$$

where *Premium* is the inferred premium of loan i in zipcode z in year t. In the spirit of a home price repeat-sale index, the repeat-loan index in Equation 2 includes loan fixed effects λ_i and only identifies changes in the IPI from changes in premiums for the same loan observed across multiple periods. Thus, this index holds fixed all time-invariant characteristics of the underlying property, borrower, and location. The coefficient of interest is α_{zt}, or the zipcode-by-time fixed effects. The estimated coefficients $\widehat{\alpha_{zt}}$ are recovered to construct the IPI.

5 Homeowners Premiums Across Time and Geography

Table 3 presents summary statistics from our sample of premiums paid in 2023. The mean homeowner in our sample pays $2,650 per year, with a wide amount of variation: The 90th percentile premium is nearly $5,000, and the 10th percentile less than $800. Homeowners pay premiums that are on average 21% of their principal and interest payments, but that share rises to over 40% at the 90th percentile, suggesting the insurance expenditures are in some cases a large portion of the monthly outlays towards housing services.

Figure 1 presents a U.S. map of county-level annual average insurance premiums in 2024. The map shows a clear gradient in insurance costs, with higher insurance burdens in the riskiest coastal areas along the Gulf of Mexico and the East Coast, as well as high premiums (over $3,000 or more)

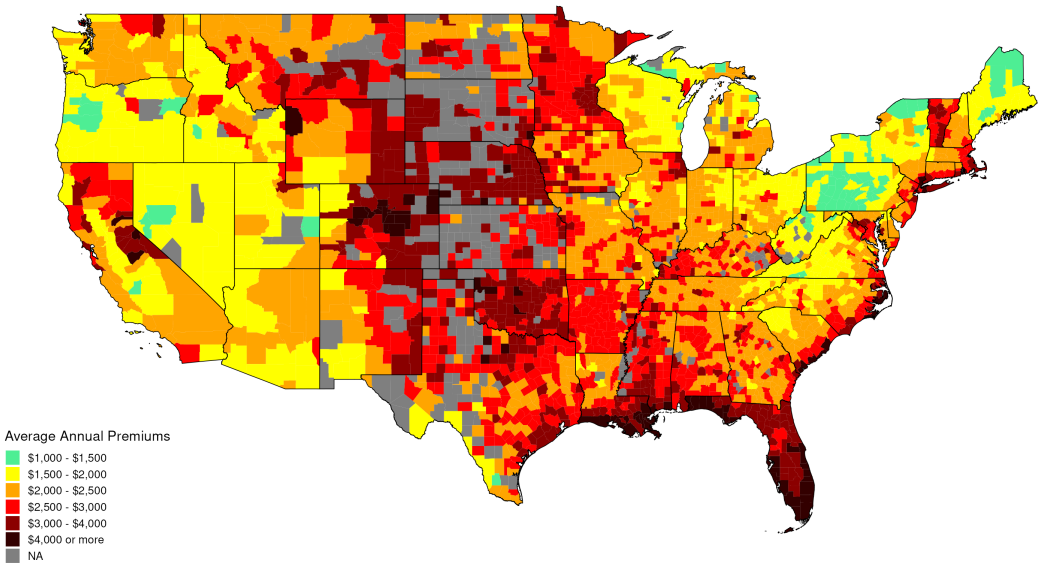


Figure 1: This figure maps average annual insurance premiums in 2024 by county. Counties with fewer than 20 premium observations are excluded.

through tornado and hail-exposed regions of the Great Plains, eastern Colorado, Oklahoma, and North Texas.

Figure 2 shows the granular richness of the escrow data by contrasting county-level (left panel) and zipcode-level (right panel) premiums in Southern California. Although the geography of premiums appears smooth at the county level, there are clear pockets of high premium zipcodes when viewed with more granularity.[17]

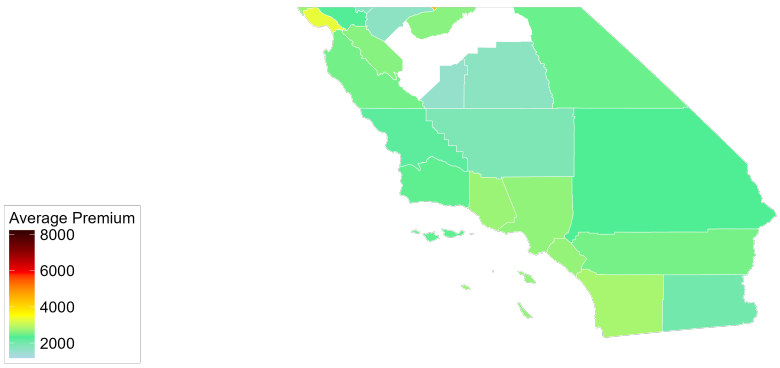
Our data show two main drivers of higher insurance expenditures across places: the structure value of homes and disaster risk. Figure 3 plots the average 2023 zipcode premium by quantiles of FHFA structure values (left) and standardized disaster risk (right). Both show a strong, linearly increasing relationship with premiums, but have different implications for homeowners' insurance burdens. The ability of our insurance expenditure index to condition on structure values is key to disentangling the effects of insured values and disaster risk towards driving premiums.

The granularity of our data demonstrate that premium levels do not give a complete picture of the relative economic burden of homeowners insurance across places. Our loan-level data can

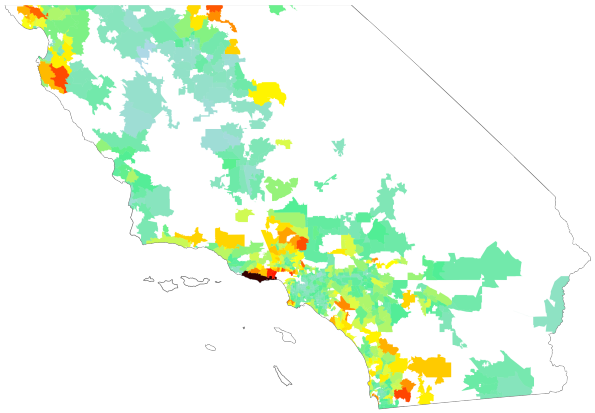
[17] Appendix Figure 17 shows significant heterogeneity in premiums within Miami-Dade County, with much higher costs along the coast relative to inland.

separate between markets with high absolute premiums versus where premiums are placing the largest economic burden on homeowners relative to their resources. The left panel of Figure 4 plots average insurance premiums by zipcode income ventile. The figure shows an increasing relationship between premiums and income, consistent with the increasing relationship between premiums and home prices in Figure 3. In the right panel of Figure 4, we instead plot average premiums as a share of income on the y-axis. In contrast to the left panel, this figure shows a decreasing relationship between homeowners insurance burden and income. Moving from a zipcode with a median income of $50,000 to a median income of $100,000 is associated with a decrease in premiums as a share of income from 3% to 2%.

In addition to its cross-sectional richness, our data track 11 years of premium dynamics. Figure 5 presents the time series of average nominal homeowners insurance premiums in the United States from 2014 to 2024. Premiums rose relatively steadily but gradually between 2014 and 2021. Since 2021, average premiums have risen sharply, with the average premium increasing by over $900 in three years. Appendix Figure 18 shows a similarly sharp increase in inflation-adjusted dollars.



(a) Premiums by county, 2024



(b) Premiums by zip code

Figure 2: This figure maps average annual insurance premiums for Southern California in 2024 by county (top panel) and by zipcode (bottom panel).

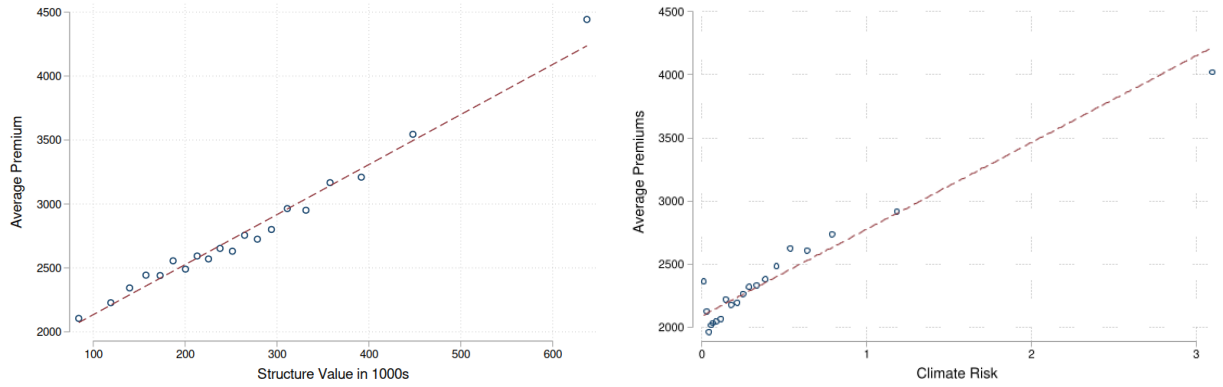


Figure 3: This figure shows the relationship between average premiums in 2023H1 by 20 ventiles of structure values (left panel) and the disaster risk index (right panel).

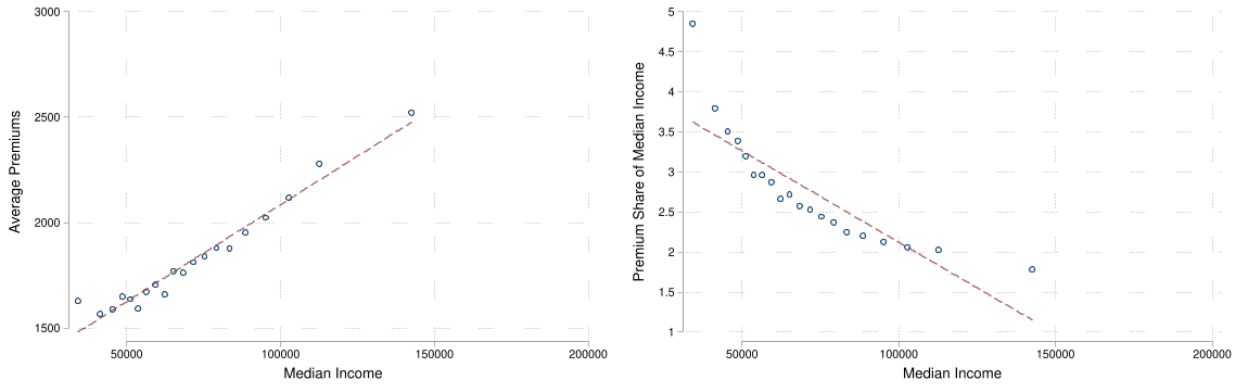


Figure 4: Figures show average premiums (left panel) and average premiums as a share of income (right panel) by twenty ventiles of zipcode median income. Income is median income of owner-occupied households from the 2014–2018 American Community Survey measured in 2018 dollars. Average premiums are taken over 2014–2018 and measured in 2018 dollars.

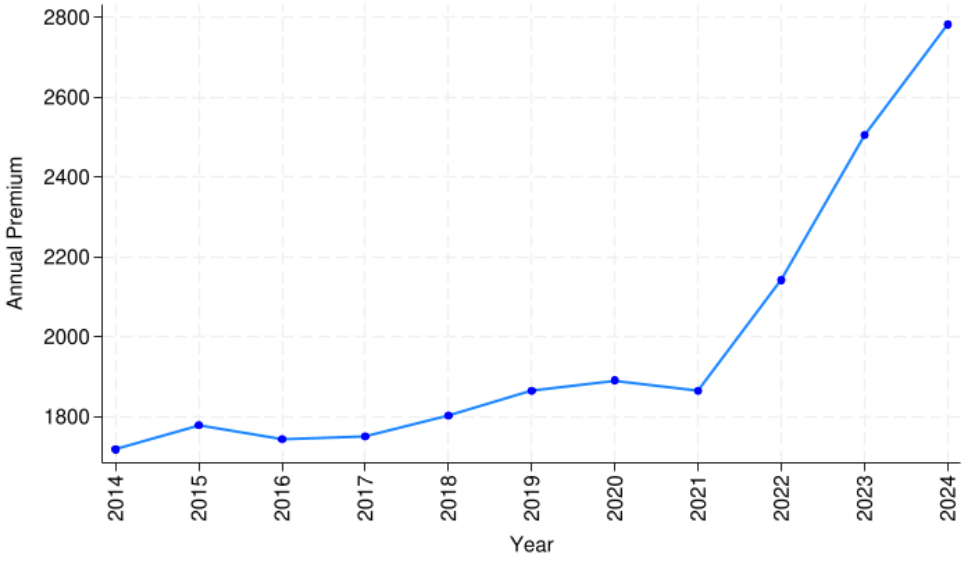


Figure 5: Time series of nominal average annual homeowners insurance premiums.

6 Insurance Expenditure Correlates and Dynamics

Having established some of the key correlates and dynamics of insurance premiums, this section examines the relative influences of risk, structure value, and demographics on premium differences across space and over time. First, we examine the conditional relationships between average premiums from our data, structure values, disaster risk, and zipcode demographics. Next, we look at how the relationship between risk and premiums has evolved over time. Finally, we consider the implications of our findings for the potential impacts of climate change on homeowners insurance premiums over the next thirty years.

6.1 Insurance Expenditure Correlates

While existing research has established that insurers tend to charge higher premiums for properties with greater disaster risk (Oh et al., 2022), there is little existing analysis linking the premiums homeowners actually pay with their risk.[18] The relationship between risk and premiums may be more complicated than what is suggested by rate filings because of adverse selection across insurers with different pricing strategies (Boomhower et al., 2024), the effect of credit score on premiums (Blonz et al., 2024), and heterogeneous intensive margin insurance demand or shopping behavior (Sastry et al., 2025; Armantier et al., 2023; Gropper and Kuhnen, 2021; Cookson et al., 2025).

We use our geographically granular premiums data to provide novel evidence on the risk-to-premiums gradient by estimating the following equation:

$$P_{zt} = \alpha_t + \beta_0 X_z + \beta_1 S_{z,t-1} + \beta_2 Risk_z + \epsilon_{zt}, \tag{3}$$

where P_{zt} are the average premiums observed in year t for zipcode z in our estimation sample, α_t are year fixed effects, X_z are ZIP characteristics from the 2014–2018 ACS (population share white, median income), $S_{z,t-1}$ is the one year lagged structure value from the FHFA data, and $Risk_z$ is our standardized disaster risk measure constructed from the National Risk Index and First Street Foundation data.

Table 4 shows the results of our regression analyses following Equation 3. In the first column, we omit the zipcode characteristics and only study the basic relationship between premiums, disaster risk, and lagged structure values with time fixed effects. Zipcodes where structures are more expensive tend to have higher premiums, likely reflecting higher replacement costs and coverage limits on policies. There is also a positive relationship between expected losses and premiums, with

[18] A recent, notable exception is Blonz et al. (2024) who study the relationship between property-level expected loss measures and premiums in a cross-section of policies.

a one-standard deviation increase in expected disaster losses associated with a $390 increase in average premiums.

Column (2) adds zipcode-level covariates for the population share white and median household income in thousands of dollars. Although they show a statistically significant relationship with premiums, these covariates do little to change the estimated disaster risk coefficient. The positive relationship between incomes and insurance expenditures may reflect higher income households buying more generous coverage, consistent with evidence that wealthier households demand more insurance (Gropper and Kuhnen, 2021; Armantier et al., 2023). Column (2) also shows that zipcodes with higher nonwhite population shares see higher premiums, with a 10 percentage point decrease in the white population share associated with approximately $37 higher annual premiums. While this relationship is conditional on home price controls and credit score controls in the IPI, disaster risk, and income, we note that it does not hold fixed other factors that may affect insurers' costs or differences in insurance demand.[19]

In column (3), we add state-by-time fixed effects to absorb time-varying factors at the state level, such as insurance market regulations or natural disasters, that might affect premiums. Here, we see that the disaster risk coefficient attenuates to a $334 premium increase with a one standard deviation increase in disaster risk. This analysis suggests that state-level factors and differences in structure values partially, but not completely, drive the aggregate relationship between premiums and disaster risk. Thus, our zipcode-level measures are critical for estimating the appropriate pass-through of risk to premiums.

It is important to note that the disaster risk coefficients in Table 4 measure the effect of disaster risk on insurance spending, i.e. premiums, and not rates, or the cost per unit of coverage. This approach is a consequence of our data, where we only observe total premiums and not the exact coverage purchased relative to our structure value measure. We note that Sastry et al. (2025) find that policyholders in higher-risk areas tend to purchase *less* coverage relative to their replacement cost, which would suggest that our estimates understate the true coverage-adjusted relationship between risk and premiums.

6.2 Insurance Expenditure Dynamics

Table 4 assumes that the relationship between disaster risk and premiums is constant over the sample period. However, the dramatic increase in premiums documented in Figure 5 raises the question of whether insurers are changing how they price risk. To investigate premium dynamics

[19]Klein and Grace (2001) study zipcode-level insurance premiums in Texas and find that differences in premiums by socioeconomic status can be explained by insurance demand and expected losses.

	(1)	(2)	(3)
	Average Premium		
Disaster Risk	390.899***	407.009***	334.252***
	(10.957)	(10.925)	(12.768)
Structure Value ($1000s)	3.645***	2.704***	4.330***
	(0.099)	(0.130)	(0.192)
Pop. Share White		-371.041***	-394.349***
		(30.236)	(28.952)
Median income ($1000s)		5.966***	1.806***
		(0.425)	(0.546)
N	140602	140602	140602
R^2	.49	.51	.67
Demographic Controls	No	Yes	Yes
Year FE	Yes	Yes	Yes
Year # State FE	No	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Table 4: Regression analysis of the determinants of insurance premiums. Dependent variable is average premium. Observations are weighted by ACS 2010–2014 5-year estimates of owner-occupied property counts in each zipcode, and subset to a balanced panel of zipcodes with at least 20 observations in each period.

by risk, Figure 6 shows the time series of real average insurance premium expenditures by disaster risk quintile. As reflected in Table 4, disaster risk was a strong predictor of average premiums at the start of our time series in 2014, with the riskiest quintile paying approximately 35% higher premiums than the safest quintile. The differences across quintiles were stable until 2021, when premiums in the riskiest quintile began to increase sharply. Thereafter, premiums have risen across all climate risk quintiles, but the gap between risky and safe areas has substantially widened. As of 2024, average premiums in the riskiest quintile were now more than 60% higher than those in the safest quintile.

Figure 6 shows that recent premium increases have been concentrated in the highest risk areas. However, it is not clear what factors are driving this widening gap. A number of general factors – such as inflation, interest rates, supply chain, and labor shortages – contributed to rising replacement costs for homes that likely increased both coverage purchased and premiums. In addition, rising premiums in specific states have been attributed by industry participants to idiosyncratic factors, such as fraudulent claims in Florida (Johnson et al., 2023).

To investigate the extent to which higher premiums are being driven by disaster risk exposure as opposed to some other correlated factor, we estimate the dynamic relationship between premiums

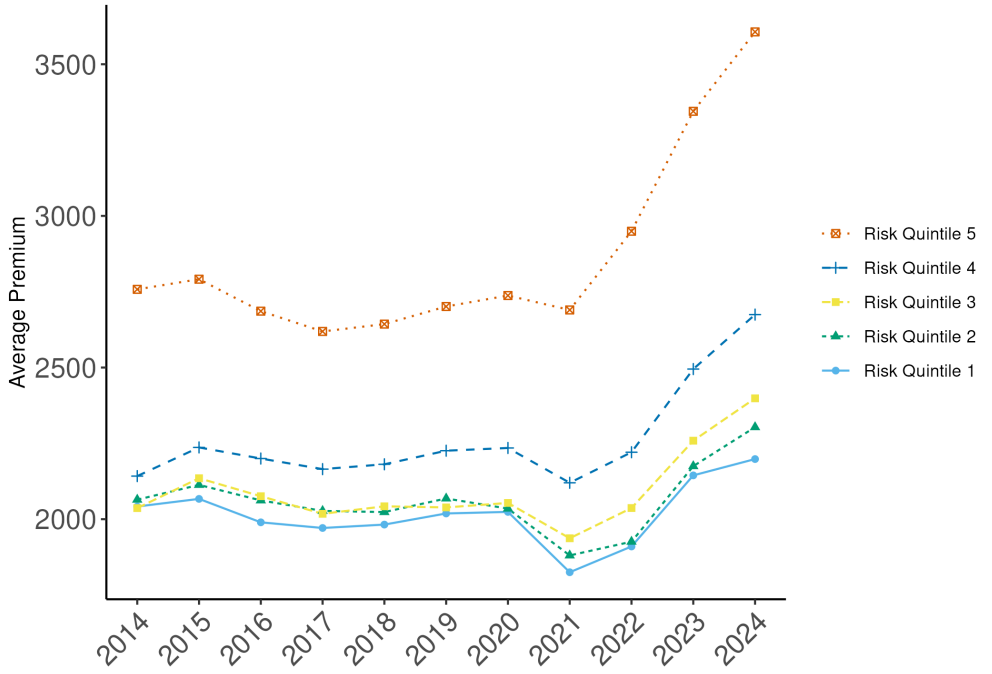


Figure 6: Average premiums plotted by quintile of disaster risk exposure. Premiums are in real 2024 dollars.

and risk with additional covariates to control for other factors that may drive dynamic and cross-sectional differences in premiums:

$$P_{zt} = State_z + \alpha_t + \lambda_1 ShareWhite_z + \lambda_2 Income_z + \lambda_3 S_{z,t-1} + \sum_{t=2014}^{2024} \beta^t Risk_z + \epsilon_{zst}. \quad (4)$$

The specification in 4 includes state and time fixed effects, zipcode socioeconomic characteristics, and lagged structure values as controls. The key parameters of interest are the annual β^t on $Risk_z$, which give the changing effect of a one-standard deviation increase in disaster risk on premiums over time. Insofar as the widening gap between high- and low-risk zipcodes is attributable to other factors, we would expect to find a constant β^t over time.

Figure 7 presents the time-varying coefficient of climate risk on premiums from Equation 4. While the relationship between climate risk and premiums was trending downwards until 2017, it starts to increase in 2018 and substantially increases through 2024, consistent with the raw data in Figure 6. The coefficient on risk more than doubles from $225 per index unit in 2018 to $610 in 2024. For a zipcode at the 90th percentile of disaster risk, our estimated change in the risk-to-premiums gradient increased annual premiums by $590 between 2018 and 2024.

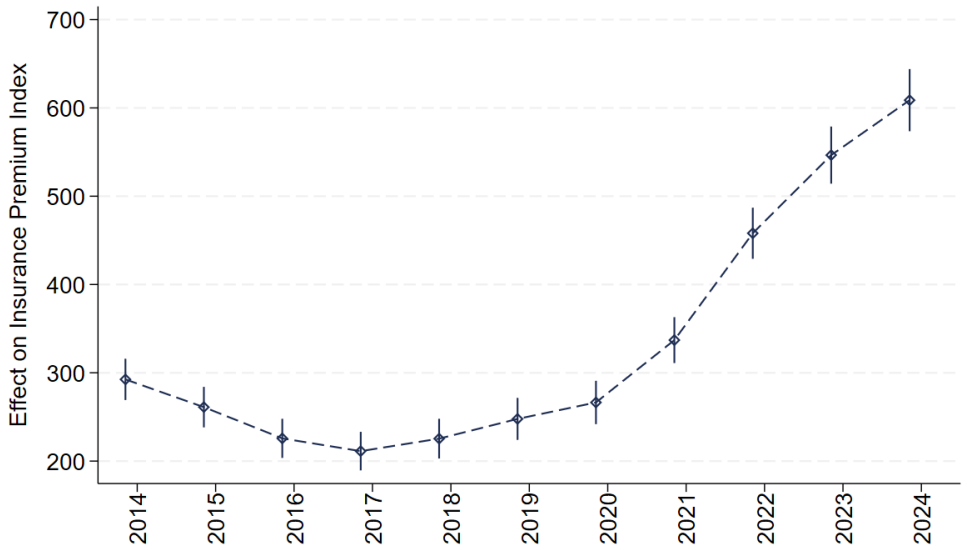


Figure 7: Plots the time-varying estimated effect of disaster risk on premiums. Vertical lines indicate 95% confidence intervals. See Equation 4 for more details.

We can also use the estimated results of Equation 4 to unpack the drivers of the recent spike in homeowners insurance premiums. Average premiums increased by approximately $1,000 between 2018 and 2024. Our estimated structure values coefficient implies that the increase in rebuilding costs can explain $400, or about 40%, of this increase. Thus, while construction costs also outpaced the general pace of inflation, they cannot explain the full rise in homeowners insurance premiums.[20] The increase in the coefficient on disaster risk explains another $220 of the increase. Thus, these two factors alone account for approximately $\frac{2}{3}$ of the increase in premiums in our data over this period.

To examine the robustness of our results, we re-estimate the dynamics of the risk coefficient with our repeat-loan IPI as the dependent variable with zipcode fixed effects. Because it identifies changes in premiums by following the same loan over time, it is more robust to potential biases caused by changes in the composition of homeowners over time. The results, shown in Appendix Figure 19, show a similar increase in the risk coefficient of approximately $400 between 2018 and 2024 as in our baseline estimates. As an additional robustness check, we control for the time-varying effects of flood risk to account for potential contamination from changing NFIP premiums in Appendix Figure 20, and again find minimal differences in the premium-to-risk gradient dynamics.

[20]This finding is consistent with results from Sastry et al. (2025), who find that homeowners have failed to increase their coverage limits to keep up with rising replacement costs over this period.

6.3 Forward-looking Implications of the Changing Price of Risk

Our estimates document a dramatic increase in the relationship between risk and premiums over the last decade. This pattern suggests that the ultimate effects of increasing disaster risk on homeowners insurance markets will depend on a changing risk-to-premium gradient. To explore the forward-looking implications of the dynamics documented above, we project the potential increases in homeowners insurance premiums between 2023 and 2053 using our forward-looking measure of hurricane and wildfire expected loss rates and time-varying estimates of the relationship between risk and premiums.

This exercise fixes a vast array of other factors that will also influence future disaster damages.[21] Furthermore, rather than a complete accounting of the welfare costs of rising disaster risk, our projections only consider household premium payments and do not account for insurer profits, state subsidies, or uninsured losses. Thus, we view this exercise as an informative baseline that suggests how insurance market dynamics may drive the costs of insuring climate risk higher or lower.

Noting these caveats, we measure the expected increase in annual premiums due to climate change with the formula:

$$\Delta_{2023}^{2053} IPI_{z,t} = \widehat{\beta}_t^{Risk} * (Risk_{z,2053} - Risk_{z,2023}), \tag{5}$$

where $\Delta_{2023}^{2053} IPI_{z,t}$ is the change in annual homeowners insurance premiums for zipcode z in 2053 relative to 2023 given the estimated $\widehat{\beta}_t^{Risk}$ of the conditional relationship between premiums and a one standard deviation increase in risk as of year t from Figure 7. $Risk_{z,2053}$ and $Risk_{z,2023}$ are the disaster risk values in zipcode z in 2023 and 2053, respectively.

Figure 8 plots the distribution of $\Delta_{2023}^{2053} IPI_{z,t}$ across zipcodes at values of β_t^{Risk} setting $t = 2024$ (red) and $t = 2018$ (blue) by 20 ventiles of climate exposure. Moving from $\widehat{\beta}_{2018}^{Risk}$ to $\widehat{\beta}_{2024}^{Risk}$ more than doubles the projected annual premium increases among homeowners in the top 5% of climate change exposure from an average of $300 to over $800 by 2053.

To illustrate the geographic dispersion of potential climate-driven increases in homeowners insurance premiums, Figure 9 plots the county-level averages of $\Delta_{2023}^{2053} IPI_{z,2024}$ for climate-exposed zipcodes. The figure shows that increasing wildfire risk in the west drives most of the expected

[21] For example, adaptation may reduce premium increases relative to our projections as building standards make homes more resilient and spatial resorting moves population out of harm's way (Bunten and Kahn, 2017; Baylis and Boomhower, 2022; Cruz and Rossi-Hansberg, 2024; Kahn et al., 2024). Conversely, continued cross-subsidization of risk from premium regulations and subsidized insurers-of-last-resort could blunt the incentives to adapt and increase building in disaster-prone areas (Medders and Nicholson, 2018; Oh et al., 2022).

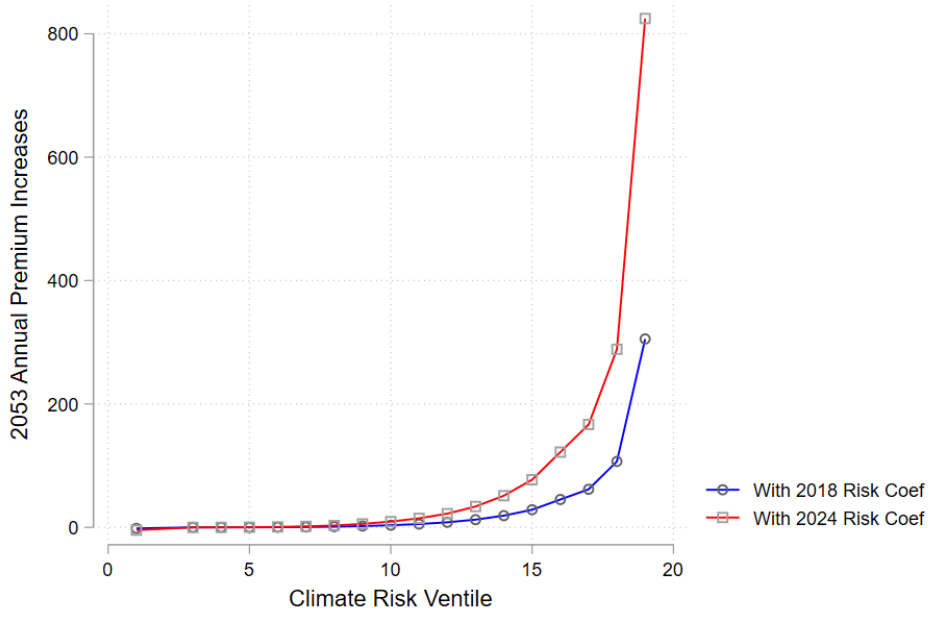


Figure 8: Predicted increase in annual insurance premiums in 2053 due to climate change under the estimated risk coefficient in 2018 (blue) versus 2024 (red) by twenty ventiles of climate exposure. The 2018 and 2024 risk coefficients are taken from the estimates shown in Figure 7.

increase in homeowners insurance premiums by 2053.[22] Extrapolating our estimates to the approximately 80 million single-family homes in the U.S. implies that climate change will increase aggregate annual premiums by $6.4 billion by 2053, holding current estimates fixed and considering only impacts from the increased frequency and severity of wildfires and hurricanes.

7 Reinsurance and the Cost of Disaster Risk

The previous section established that the real cost of homeowners insurance has grown between 2018 and 2024, especially in areas exposed to more climate risk. Furthermore, we have shown that the widening premium gap between high and low risk areas cannot be explained by statewide factors or relative structure value trends. In this section, we motivate and test one mechanism that partly drove the increasing risk-premium gradient: Increasing prices in the reinsurance market.

As homeowners' premiums increased between 2021 and 2024, the price of reinsurance for catastrophic risk rose even as reinsurers reduced the amount of coverage they were willing to write

[22]The First Street Foundation has further detail on their wildfire model (`https://firststreet.org/research-library/fueling-the-flames` and hurricane model (`https://firststreet.org/research-library/worsening-winds`) projections. Climate change is expected to move hurricane landfalls further north along the Mid-Atlantic. In fact, Miami-Dade county sees a modest *decrease* in expected hurricane losses by 2053, although it still faces substantial increased risk due to sea level rise and flooding that may increase flood insurance premiums under the National Flood Insurance Program or in the emerging private market.

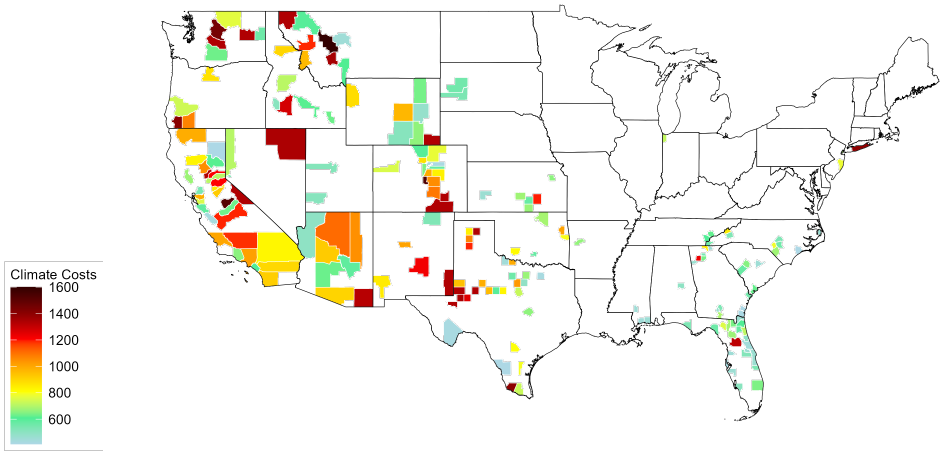


Figure 9: This figure shows the county average expected increase in annual homeowners insurance premiums by 2053 among zipcodes in the top 5% of the expected increase in disaster risk. Costs are calculated using the 2024 coefficient on disaster risk from Figure 7.

(Eaglesham, 2024; Corbineau et al., 2023). Insurers rely on reinsurance, often called "insurance for insurers," to diversify their own geographically concentrated risks through global capital markets. Between 2017 and 2024, reinsurance prices for U.S. Property Catastrophic coverage more than doubled according to the Guy Carpenter Rate-on-Line Index, as shown in Figure 10.

Understanding the role of reinsurance in driving premium dynamics is important for two reasons. First, climate change is expected to exacerbate the wildfire and hurricane risks that form much of the underlying risk in reinsurance contracts (First Street Foundation, 2020). Second, the effect of reinsurance prices on premiums shows how the cost of global risk intermediation affects what homeowners pay to insure catastrophic risk. It is plausible that rising reinsurance rates may partially drive the rising risk-premium gradient. Such a hypothesis is consistent with a long literature showing that the cost of reinsurance is greater than the expected claims payments, and that reinsurance markets go through tightening cycles when capital is scarce (Li, 2025; Froot and O'Connell, 1999; Zanjani, 2002; Born and Viscusi, 2006; Boyer et al., 2012). An alternative hypothesis is that rather than reflecting rising markups, reinsurance prices are increasing due to the same forces of rising replacement costs and sensitivity to disaster risk that are causing primary insurers to increase their rates.

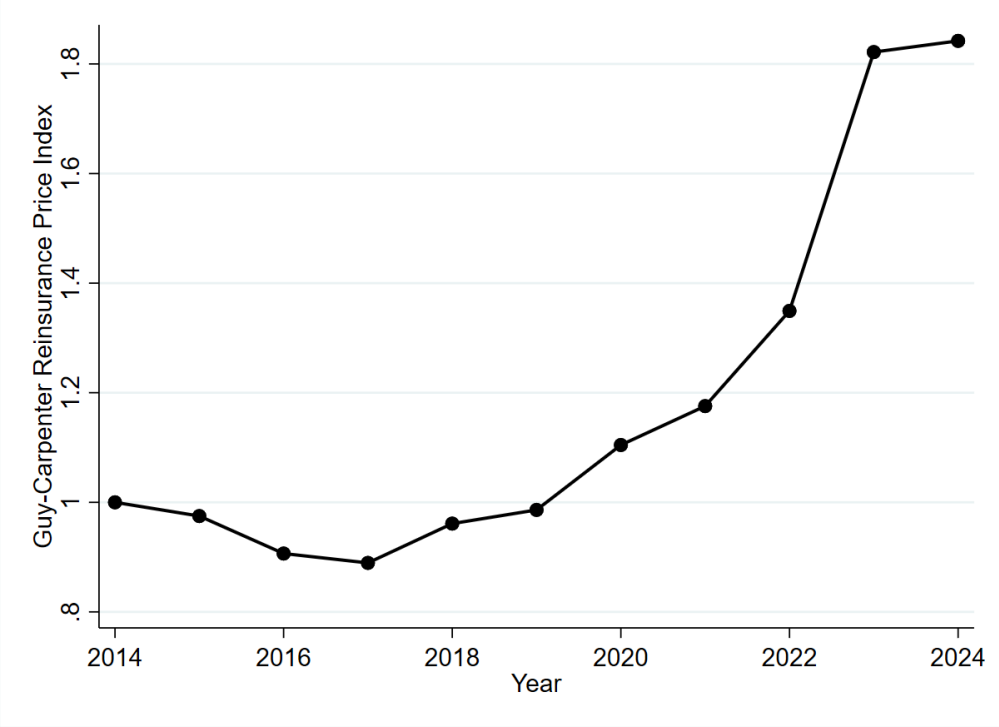


Figure 10: Time series of the Guy-Carpenter U.S. Property Catastrophe Rate-on-Line Index. See `https://www.artemis.bm/us-property-cat-rate-on-line-index/` for more information.

7.1 Theoretical Framework

We introduce a theoretical framework below to illustrate how multiple factors can simultaneously drive the cost of reinsurance and premiums, and to motivate our identification strategy for separately identifying time-varying reinsurance markups.

Consider the actuarially fair homeowners insurance premium charged by insurer j on a home i at time t, $\overline{P}_{ijt}$, for a contract that pays replacement cost coverage C_{it} on total losses $L_{it} \in \{0, 1\}$ where $E[L_{it}] = p_{it}$. Assume that insurer j holds some capital, and denote the event that j's aggregate losses exceed its capital by $R_{jt} \in \{0, 1\}$ where $E[R_{jt}] = r_j$.[23] The insurer also has a reinsurance contract that pays all losses exceeding its capital that is priced according to the insurer's expected reinsurance claims times a markup $(1 + \alpha_t)$.[24] The actuarially fair average premium for household i is given by the expected loss borne by the insurer plus the effect of insuring i on the cost of

[23]Technically, this assumption requires the insurer to increase their capital holdings when writing new policies i to keep r_j constant. This requirement would impose a cost of capital term similar to the pricing formula of Koijen and Yogo (2015) that would be part of the price of correlated risk that we derive below. We omit the cost of capital for expositional clarity to focus on the pricing effects of reinsurance. We discuss later how a time-varying cost of capital might influence the interpretation of our results.

[24]The markup term α_t represents anything that causes the price of the reinsurance contract to differ from the insurer's subjective expectation of their reinsurance claims. This could include the loading fees, cost of capital, different subjective beliefs over the distribution of losses, pricing under asymmetric information, or market rents from imperfectly competitive markets.

reinsurance:[25]

$$P_{ijt} = C_{it} * (E[L_{it}|R_{jt} = 0] + (1 + \alpha_t) * f_{ij}). \tag{6}$$

In Equation 6, $E[L_{it}|R_{jt} = 0]$ is the probability that i will have a loss conditional on j's aggregate losses being below its capital and not triggering reinsurance. The term f_{ij} is the effect of adding household i to j's book of business on its reinsurance costs. Because the reinsurer prices its contract at expected claims times the markup, $f_{ij} = E[L_{it}|R_{jt} = 1]$. Substituting $E[L_{it}|R_{jt} = 1] = p_{it} * r_j + Cov(R_{jt}, L_{it})$ and $E[L_{it}|R_{jt} = 0] = p_{it} * (1 - r_j) - Cov(1 - R_{jt}, L_{it})$ and taking logs, Equation 6 simplifies to:

$$ln(P_{ijt}) = \underbrace{ln(C_{it})}_{\text{Exposure}} + \underbrace{ln(p_{it})}_{\text{Frequency}} + \underbrace{ln(\alpha_t * (r_j + \frac{Cov(R_{jt}, L_{it})}{p_{it}}) + 1)}_{\text{Price of Correlated Risk}}. \tag{7}$$

Equation 7 illustrates how property insurance premiums generally scale with three terms: The frequency of loss, exposure conditional on a loss, and a third term that we call the "price of correlated risk." While the first two terms are clear, it is worth noting two facts about the price of correlated risk. First, it is a function of the markup that insurers pay to cover their tail risks; if $\alpha_t = 0$ then the third term disappears. Second, the sensitivity of premiums to α_t is increasing with the correlation between the individual risk and aggregate tail loss events that trigger reinsurance claims.

7.2 Identification

Our theoretical framework, summarized by Equation 7, suggests correlated risks are more exposed to changing reinsurance prices. Following this insight, we leverage the granularity of our data along with geographic variation in the correlation of catastrophic risks to identify the relative contributions of exposure, frequency, and the price of correlated risk in driving homeowners insurance premium trends.[26] With our zipcode panel of premiums, we can estimate the time-varying effects of disaster risk, capturing the impacts of any changed modeling of the frequency or severity of disaster trends, while controlling for the evolution of structure values with the FHFA price index, capturing the effect of changes in the exposure base across markets.[27]

[25] In practice, reinsurance contracts for catastrophic risk have more complicated structures than a simple coinsurance rate. Furthermore, property & casualty insurers also manage catastrophic risk by holding more capital or investing in financial instruments like cat bonds in addition to accessing reinsurance markets. Thus, Equation 6 is a simplified pricing formula capturing that insurers typically pay markups in financial markets to manage correlated risks.

[26] If we generalize Equation 7 to non-binary losses, we could call the second term "frequency and severity."

[27] We make two caveats on our interpretation of the exposure and frequency terms in our empirical estimation relative to the more abstract Equation 7. First, we do not expect premiums to scale 1:1 with replacement values.

First, we measure the correlation of monthly inflation-adjusted per-capita losses using SHELDUS data from 2000 to 2013 between each county and the total losses in its state. We adopt this within-state measure of correlated risk for several reasons. First, because insurance companies are regulated at the state level and often operate with a relatively high degree of geographic concentration, within-state correlated losses are a primary driver of earnings volatility and regulatory capital requirements. In 2014, the premium-weighted average insurer obtained 74 percent of its gross homeowners premiums from its single largest state market.[28] Although insurance companies do write some of their business across multiple states and have other mechanisms for spreading losses across business lines or within their insurance group, those activities are likely endogenous to the concentration of risk and cost of reinsurance. Thus, another reason we favor the within-state correlation measure is that it is more plausibly exogenous to market conditions.[29] Next, we classify "cat-exposed" zip codes as those in the top quartile of hurricane wind plus wildfire expected loss ratios. Figure 11 maps the loss correlation of each county with at least one high cat-exposed zipcode.

To validate our correlated risk proxy, we test its ability to predict reinsurance usage as measured by insurer spending on reinsurance from 2014 NAIC filings. To do so, we use 2014 NAIC filings data to create state-level measures of the share of premiums insurers operating in each state cede to unaffiliated reinsurers.[30] Ideally, we would observe the details of each insurer's reinsurance contracts along with a geographically granular description of their book of business. Instead, we only observe the total amount each insurer i pays for reinsurance ("premiums ceded") across their entire portfolio and the amount of premiums they write in each state. Given these limitations, we approximate state-level reinsurance usage, Re_s, as the market-share weighted average of the percent of premiums ceded by each insurer:

$$Re_s = \frac{\sum_{i \in I} d_{is} c_i}{\sum_{i \in I} d_{is}},$$

where d_{is} are the dollar value of insurer i's direct premiums written in state s, and c_i is the share of i's premiums that they cede to unaffiliated reinsures (i.e. excluding affiliated reinsurance purchased from other companies in the same insurance group).

Due to loading fees, doubling coverage generally less than doubles premiums. In addition, research from Sastry et al. (2025) shows that homeowners did not increase their coverage to keep up with rising replacement costs over this period. Second, we do not necessarily interpret changes in the premium loading on disaster risk as indicating that the actual frequency or severity of disasters increased. Rather, insurers may have reevaluated the trend from their backward looking models.

[28] The top state share of premiums at the insurer group level is 57 percent.

[29] Our results remain substantially similar when we use a correlation measure derived from premium weighted losses across states rather than within-state.

[30] We thank Ty Leverty for his help using this data and advice defining the exposure measures.

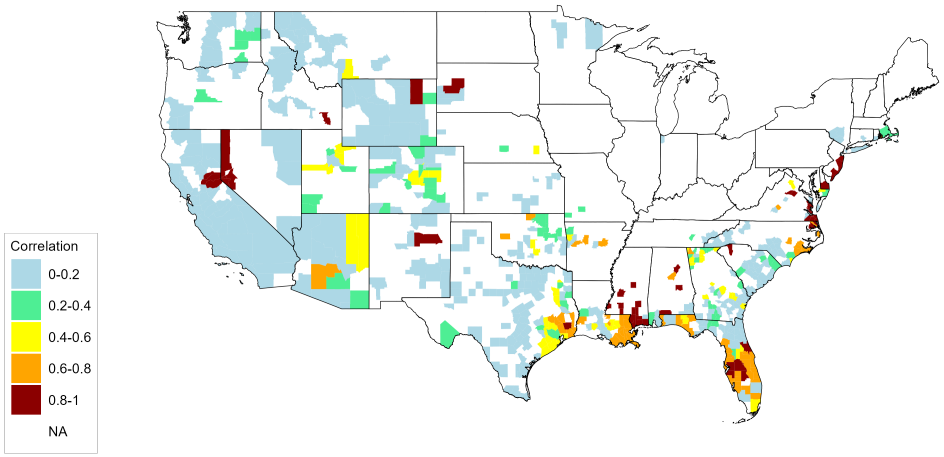


Figure 11: Shows county-level loss correlations for counties with a zipcode in the top quartile of cat risk exposure.

To test whether our correlated risk proxy predicts reinsurance usage, we estimate the cross-sectional model:

$$Re_s = \alpha_0 + \beta_1 \overline{HighCat}_s + \beta_2 \overline{HighCat}_s \times \overline{Corr}_s + \epsilon_s,$$

where $\overline{HighCat}_s$ and $\overline{Corr}_s$ are the state-level ashare of zipcodes with high cat exposure and average historical loss correlation among cat-exposed zipcodes weighted by zipcode number of owner-occupied housing units. The results of this equation are shown in Table 5. In column (1) where we omit the loss correlation terms, we find a positive and statistically significant relationship between a state's share of cat-exposed zipcodes and average reinsurance usage. However, when we estimate the full model in column (2), the coefficient on the cat-exposed share attenuates and becomes statistically insignificant whereas the coefficient on the interaction with loss correlations

	State Reinsurance Usage	
	(1)	(2)
High Cat	0.191**	-0.0166
	(2.42)	(-0.50)
High Cat × Correlation		0.484***
		(4.37)
Observations	51	51
R^2	0.536	0.769

* p<0.10, ** p<0.05, *** p<0.01

Table 5: Results from state-level regressions of reinsurance usage on average disaster risk, share of zipcodes exposed to high cat risk, and the average within-state loss correlation of cat-exposed zipcodes. State variable averages and regression observations are weighted by the total number of owner-occupied housing units in the 2010–2014 ACS data in the estimation sample zipcodes. Robust standard errors in parentheses.

is positive and statistically significant. These findings show that it is *correlated* cat risks, and not cat risk per se, that drives reinsurance usage. Notably, the two terms in column (2) explain over 75% of the variation in reinsurance usage across states. These findings support the hypothesis that the correlation of cat risks within states drives reinsurance usage.

7.3 Estimating the Changing Price of Correlated Risk

Motivated by our stylized pricing model from Equation 7, we specify our primary estimating equation:

$$ln(\overline{IPI}_{zct}) = \alpha_z + \alpha_t + \beta_1 ln(S_{z,t-1}) + \sum_{t=2014}^{2024} (\beta_2^t Risk_z + \beta_3^t HighCat_z) + \beta_4 ln(Z_{t-1}) \times HighCat_z \times Corr_c + \epsilon_{zt}, \tag{8}$$

where the dependent variable $ln(\overline{IPI}_{zct})$ is the log repeat-loan insurance premium index of zipcode z in county c in year t. The terms α_z and α_t are zipcode and year fixed effects, respectively.

The β_4 coefficient represents the price of correlated risk from Equation 7. We use lagged log reinsurance prices $ln(Z_{t-1})$ from the Guy Carpenter reinsurance rate-on-line price index as our proxy for the α_t markup term.[31] The challenge in estimating the price of correlated risk, however, is that reinsurance prices rose for many of the same reasons that primary insurance prices rose: an

[31] As noted earlier, the α_t terms do not necessarily represent changes in reinsurers' pure economic profit. They could, for example, reflect differences in the modeling of risk between insurers and reinsurers or changes in the cost of capital. In addition, the rise in reinsurance prices coincided with a decline in reinsurance availability, which could further increase costs for insurers to cover their own correlated risks at a higher cost of capital.

increase in the exposure to and perceived frequency or severity of disaster losses over this period.

Thus, the first key to our identification strategy is the inclusion of the lagged log FHFA structure value terms $ln(S_{z,t-1})$ and the time-varying coefficients on the $Risk_z$ measure, which capture changes in "exposure" and "frequency" terms from Equation 7, respectively. In addition, we include the high cat risk exposure term $HighCat_z$ with a time-varying coefficient β_3^t to capture changes in the pricing of cat risks in particular.[32] Under the null hypothesis that changes in reinsurance prices are entirely driven by the same forces driving changes in primary insurance prices, we should expect the β_4 coefficient to be zero once we condition on changing structure value and the time-varying pricing of disaster risk.

However, given that global reinsurance prices do not vary across our market, we need some variation in reinsurance exposure to identify β_4 separately from general time trends in insurance pricing. As motivated by Equation 7 and supported by evidence from Table 5, reinsurance take-up is driven by exposure to correlated catastrophic losses. Thus, we identify β_4 by comparing changes in premiums between zipcodes with similar risk but different historical correlation of losses as measured by the $HighCat_z \times Corr_c$ interaction term. If the underlying markup on reinsurance has changed with rising reinsurance prices, we should expect to see a positive β_4 coefficient.

We maintain a parallel trends assumption to identify the β_4 parameter in Equation 8. Specifically, conditional on risk and replacement costs, we assume that there is no unobserved driver of insurance costs that is correlated with reinsurance exposure and the time trend of reinsurance prices. To test this assumption, we estimate an event-study style version of Equation 8 that replaces the β_4 interaction term with time-varying coefficients estimated on the $HighCat_z \times Corr_c$ interaction term.

Supporting the parallel trends assumption, Figure 12 presents the time-varying reinsurance exposure coefficients for high cat-exposed zipcodes. These coefficients follow the same pattern as the lagged reinsurance price index from Figure 10. Notably, insurance premium trends in reinsurance-exposed zipcodes not only follow the rise in reinsurance prices after 2020, but also the earlier modest decline in the late 2010s.

We next turn to the results of Equation 8, shown in column (1) of Table 6. We find positive and statistically significant coefficients on the interaction term between correlated risk and log reinsurance prices for cat-exposed zipcodes. The coefficient implies that a 10% increase in reinsurance prices causes a 2.5% increase in cat-exposed annual premiums for perfectly correlated losses.[33]

[32] As documented in Eastman and Kim (2023), a change in NAIC capital requirements affected the pricing of catastrophic risks over this period.

[33] In general, the reinsurance price-elasticity of premiums is the interaction term coefficient scaled by the loss correlation.

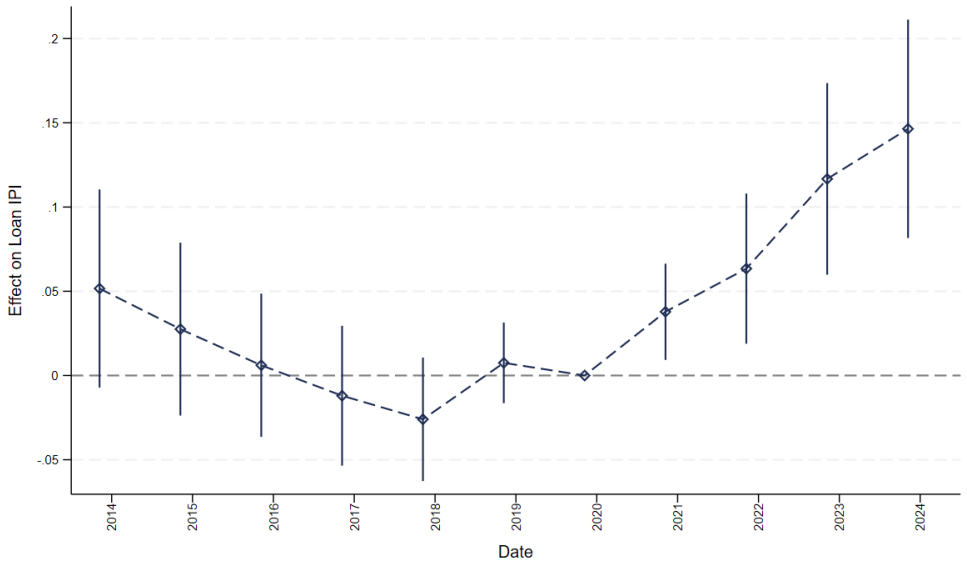


Figure 12: Time-Varying Relationship Between Correlated Catastrophic Risk and Premiums.Plots time-varying coefficients for the effects of the correlated catastrophic risks on homeowners insurance premiums as measured by the log repeat-loan insurance premium expenditures index. Specification is weighted by the number of owner-occupied housing units in the 2010–2014 ACS, and includes zipcode and year FEs, lagged log structure values, and time-varying controls for disaster risk and catastrophic risk exposure. Standard errors are clustered by county.

Interpreting their economic significance, these estimates suggest that the rise in reinsurance costs between 2019 and 2024 raised annual homeowners insurance premiums by $230 in the average cat-exposed zip code and by $560 among those in the top decile of correlated risk exposure. These magnitudes suggest that the reinsurance shock can explain about 25% of the rising passthrough of disaster risk into premiums between 2018 and 2024 documented in Figure 7.

More generally, the results reject the hypothesis that the rise in reinsurance prices was driven by the same trends driving higher premiums elsewhere. Even after adjusting for changing pricing of expected disaster frequency and exposure, zipcodes exposed to more correlated risks saw higher premiums. Thus, these findings support the hypothesis that the price of correlated risk increased with rising reinsurance prices.

7.4 Robustness, Heterogeneity, and Extensions

We begin by exploring the robustness of these findings that reinsurance costs are driving the changing price of risk and rising premiums in a subset of risky areas in the remaining columns of Table 6. First, we consider whether our findings might be contaminated by changing flood insurance premiums. Starting in 2016, flood insurance reform legislation strengthened regulations

	Log Insurance Premium Expenditures Index			
	(1)	(2)	(3)	(4)
Log Reinsurance × Cat Correlation	0.247***	0.251***	0.203***	0.194***
	(4.02)	(4.13)	(3.52)	(3.16)
R^2	0.917	0.917	0.901	0.924
N	140602	140602	131967	140602
Time-Varying Flood Controls	N	Y	Y	Y
Drop Florida	N	N	Y	N
State-by-Time Risk Controls	N	N	N	Y

* p<0.10, ** p<0.05, *** p<0.01

Table 6: This table estimates the passthrough of reinsurance price shocks to homeowners insurance premiums. The dependent variable is the log repeat-loan insurance premium expenditures index. Shown coefficients are for the triple interactions between lagged log reinsurance rates, the county loss correlation, and indicators for low and high cat-risk exposure. All specifications are weighted by the number of owner-occupied housing units in the 2010-2014 ACS, and include zipcode and year-semester fixed effects and log structure values. T-statistics from standard errors clustered by county in parentheses.

requiring homeowners with mandatory flood insurance policies to escrow their premiums (Kousky et al., 2020). To account for this factor, we add the expected loss rate due to flood risk from the First Street Foundation Flood Model with time-varying coefficients into Equation 8. The results, shown in column (2), are little changed.

Another concern is that our results might be driven entirely by Florida, which has highly correlated risk exposure and has experienced a number of idiosyncratic market issues contributing to rising premiums (Johnson et al., 2023; Sastry et al., 2023). We exclude Florida observations from our specification and report the results in column (3) of Table 6, still finding similar results.

Beyond Florida, every state has an idiosyncratic insurance market subject to its own regulations and shocks that might dynamically affect the pricing of catastrophic risk on a state-by-state basis (Oh et al., 2022). To account for this heterogeneity, we modify Equation 8 to flexibly include state-by-year wildfire plus hurricane wind loss rate coefficients, so that every state can have a unique catastrophic risk coefficient in every year. The results in column (4) continue to show positive and statistically significant coefficients on the reinsurance price interaction terms.[34]

Next, to investigate heterogeneity, we assess whether the effects of the reinsurance shock depend on state-level regulatory environments. In particular, we use the "high," "medium," and "low" classification of state regulatory frictions from Oh et al. (2022). We study heterogeneity by

[34]We map the average reinsurance shock among cat-exposed zipcode by county in Appendix Figure 13. The impact of the reinsurance shock is particularly acute in areas exposed to hurricanes, such as Florida and Louisiana, although many wildfire-exposed zipcodes also see substantial premium increases.

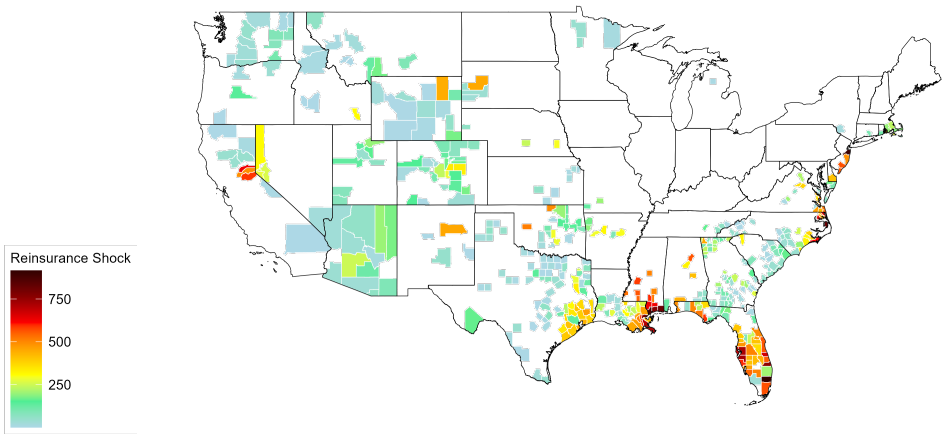


Figure 13: This figure plots the estimated average effect of the rise in reinsurance prices between 2018 and 2024 on annual homeowners insurance premiums for cat-exposed zipcodes by county.

regulatory frictions by altering Equation 8 to include an additional interaction term between log reinsurance prices, correlated cat risk, and an indicator variable if the state is designated as high friction. We also include year-by-high friction fixed effects. The results of this specification are shown in Appendix Table 10. We find little evidence of pass-through of higher reinsurance prices into premiums in high friction states.

Finally, we explore the extensive margin of insurance availability. While pricing regulation may prevent primary insurers from incorporating the reinsurance shock into their premiums, reinsurers face no such restrictions on their pricing. This raises the question of how insurers in high friction states responded to higher reinsurance costs. One possibility is that they rationed coverage. To test this hypothesis, we use data released by the Senate Budget Committee from an insurer data call describing the number of policies written and nonrenewed by insurers in each county between 2018

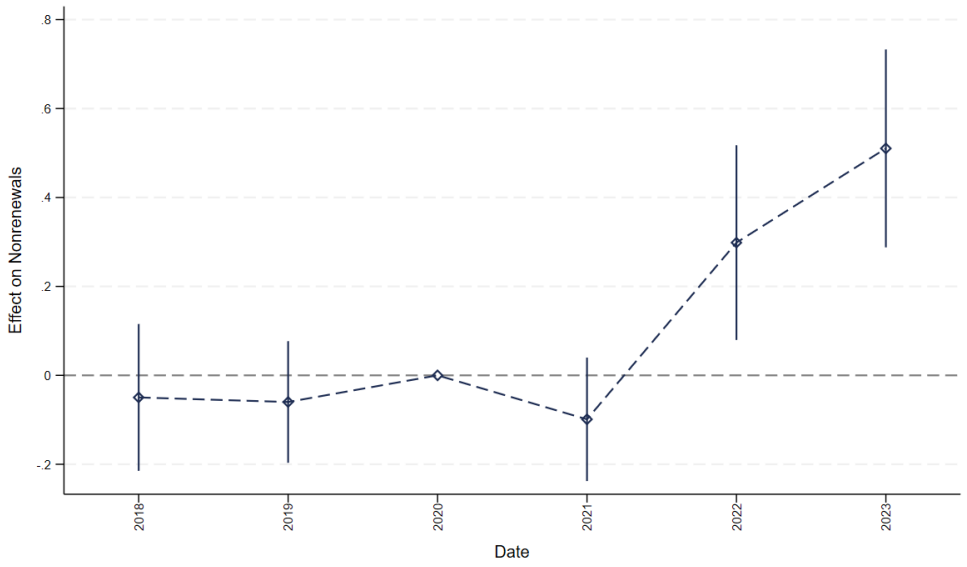


Figure 14: Dynamic effects of correlated cat risk on log insurer-initiated home insurance nonrenewals. Data comes from a balanced panel of 3,065 counties with at least 50 policies written in each year. Specification includes log policies written at the start of the year and time-varying risk controls. Standard errors are clustered at the county level.

and 2023. Our estimation dataset documents over 1.9 million policy nonrenewals across approximately 25 million homeowners insurance policies written between 2018 and 2023. We aggregate our disaster risk measures up to the county level and designate the top quartile of counties in terms of wildfire plus hurricane wind risk as cat-exposed. Our estimating equation is given by:

$$Ln(NR_{ct}) = Ln(Pol_{ct}) + \sum_{t=2018}^{2023} \beta_0^t Risk_c + \beta_1^t Cat_c + \beta_2^t Cat_c \times Corr_c + \epsilon_{ct}, \tag{9}$$

where NR_{ct} and Pol_{ct} are the number of nonrenewed and written policies in county c in year t, respectively. We include time-varying coefficients on our disaster risk measure aggregated to the county level ($Risk$), an indicator variable for counties in the top quartile of wildfire plus hurricane wind expected loss rates (Cat_c), and the correlated cat exposure interaction term ($Cat_c \times Corr_c$).

Figure 14 plots the annual coefficients on the correlated cat exposure term from estimating the effect of the reinsurance shock on policy nonrenewal (instead of log premiums). As with premiums, we see that counties exposed to correlated cat-risks see much higher policy nonrenewals in 2022 and 2023 relative to 2020. The reinsurance shock increased policy nonrenewals by approximately 30% among counties in the top decile of correlated risk exposure. We note that our findings are consistent with those in Solomon (2024), who finds that public cyclone reinsurance in Australia increased availability.

To study whether this is driven by rate suppression in states with high pricing frictions, we separately estimate Equation 9 for high friction states versus those with medium and low frictions. The results, shown in Appendix Figure 21, shows little difference in the relationship between nonrenewals and correlated cat risk. While beyond the scope of this paper to fully trace out the effects of the reinsurance shock in the presence of pricing frictions, we note several plausible channels for why we find significant heterogeneity in pricing but not supply according to state regulations. First, as found with post-disaster price adjustments in Oh et al. (2022), it is possible that insurers in high friction states are cross-subsidizing the reinsurance shock from low friction states. We also note that our data do not necessarily capture the full effects of insurers that stop writing new policies even if they continue renewing existing ones. Furthermore, insurers of last resort may have already picked up uninsurable policies in high friction states, leaving less scope for private insurer nonrenewal. In sum, our findings provide novel empirical evidence on how the rising price of correlated risk can contribute to unraveling in private homeowners insurance markets, even independent of pricing frictions.

8 House Price Effects and Implications of Reinsurance Shocks

8.1 House Price Effects

The results above suggest that the rising cost of reinsurance between 2019 and 2024 reflects not only higher structure values and a repricing of general disaster risk, but also a rising cost of insuring correlated risk. Next, we turn to the broader implications of the rising costs of correlated risks for home prices.

Higher homeowners insurance premiums increase housing user costs, and a growing literature finds that rising disaster insurance premiums can depress home prices (Ge et al., 2022; Eastman et al., 2024). However, the effect of the reinsurance shock on home prices is ambiguous. Historically, reinsurance prices have risen through periods of market "hardening," but then fallen as capital flows back into the market. Indeed, hit by record losses starting in 2017, reinsurers saw low returns on capital and struggled to attract enough capital to meet primary insurers' demand. Following the most recent price increases in 2024, reinsurers have enjoyed higher returns and capital inflows. If home buyers and sellers expect the reinsurance shock to fade as in past cycles, then we should expect to find minimal home price effects.

To test whether the reinsurance shock has been capitalized into home prices, we replace the dependent variable in Equation 8 with average home prices (at the zipcode level from Zillow). We first show the event study version of our estimates, plotting the annual coefficients on the correlated

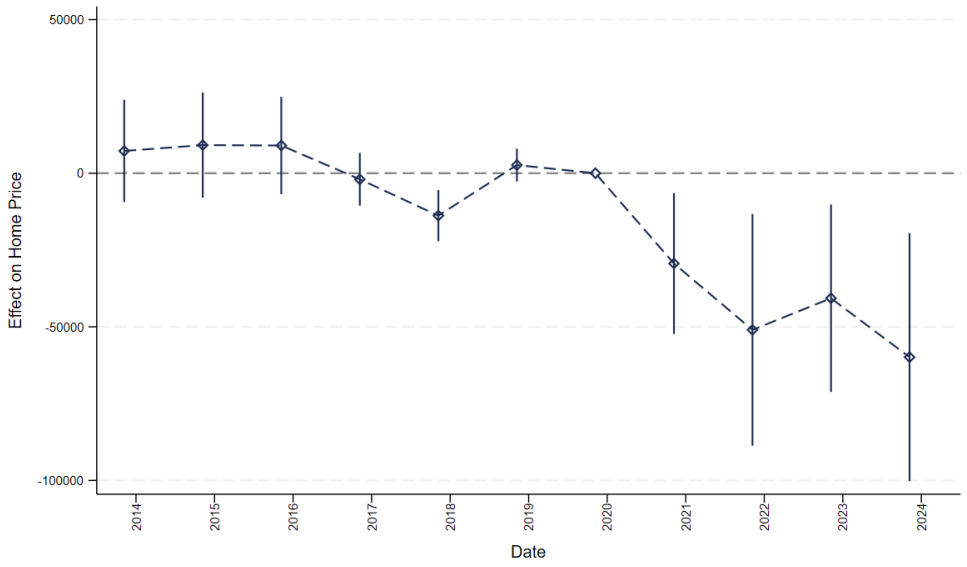


Figure 15: Effect of correlated cat risk on home prices by year.

cat risk term in Figure 15. The results show generally stable relative home price trends in areas with differential correlated risk between 2014 and 2020. Then, as reinsurance costs, we see a steady decline in relative home values in areas exposed to more correlated risk.

Table 7 shows the estimation results of Equation 8, mirroring the specifications from Table 6. Our baseline specification in column (1) shows that higher reinsurance prices led to lower home values in zipcodes exposed to more correlated risk. The magnitudes and statistical significance of this effect remain consistent across our robustness tests in columns (2)-(4) as we include time-varying flood controls, exclude Florida, and add state-by-year disaster risk controls, respectively.

Our estimates imply that the rise in reinsurance prices between 2018 and 2024 reduced relative home values in cat-exposed zips by an average of $22,000. As with the effect of the reinsurance shocks on premiums, this average masks substantial heterogeneity, as cat-exposed zipcodes in the top decile of correlated risk exposure saw relative prices decline by an average of $47,000. Although average home prices in cat-exposed zipcodes nonetheless increased by over $185,000 over this same period, our results establish that the rise in homeowners insurance premiums slowed their growth.

Taking the average premium reinsurance shock estimates from Table 6, the home price effect described above implies a capitalization rate of approximately $95 in lower home prices for every $1 increase in premiums. While this figure suggests a very low discount rate of around 1%, we note that the ratio of our home price and premium shock estimates is noisy and that we cannot reject higher discount rates. We can, however, reject the null hypothesis of low or null capitalization, which implies that housing market participants are treating the premium increases resulting from

	Home prices ($1000s)			
	(1)	(2)	(3)	(4)
Log Reinsurance × Cat Correlation	-90.59**	-91.36***	-115.6**	-92.99***
	(-2.56)	(-2.60)	(-2.58)	(-3.29)
R^2	0.977	0.977	0.977	0.979
N	140602	140602	131967	140602
Time-Varying Flood Controls	N	Y	Y	Y
Drop Florida	N	N	Y	N
State-by-Time Risk Controls	N	N	N	Y

* p<0.10, ** p<0.05, *** p<0.01

Table 7: This table estimates the capitalization of reinsurance price shocks into home prices. The dependent variable is home prices in thousands of dollars. Shown coefficients are for the triple interaction between lagged log reinsurance rates, the county loss correlation, and an indicator for cat risk exposure. All specifications include zipcode and year-semester fixed effects and structure values. T-statistics from standard errors clustered by county in parentheses.

the reinsurance shock as non-transitory. Thus, it would seem that there is some belief among buyers and sellers that, rather than a temporary spike, the higher costs of correlated cat risks will be the new normal.

8.2 The Reinsurance Shock and the Repricing of Climate Risk

The capitalization of the reinsurance shock into home prices raises the question of why some market participants are expecting elevated insurance costs to persist. In addition to the short-term challenges of high losses and rising costs of capital, industry analysis also indicate that reinsurers are grappling with the longer-term challenges of increasing disaster risk. As discussed in Section 6, the First Street Foundation models project increasing wildfire and hurricane risks between 2023 and 2053, indicating a worsening of the catastrophic risks that contribute to correlated loss exposure. Although insurance and reinsurance contracts are typically written on a short-term basis, climate uncertainty has led insurers to reevaluate their old models that assumed the frequency and severity of wildfires and hurricanes followed a stationary trend.

We might expect reinsurers to reevaluate their catastrophic risk models and adapt to emerging loss trends faster than primary insurers for two reasons. First, reinsurers cover a disproportionate share of hurricane and wildfire risk, the two perils most exposed to climate change, and thus should be more sensitive than primary insurers to changes in loss trends. Second, reinsurers are generally larger firms with access to more sophisticated pricing models than primary insurers (Anand et al., 2021).

To examine whether a repricing of risk in climate-exposed areas is driving part of the rising price

of correlated risk, we first test whether premiums are more responsive to the reinsurance shock in areas exposed to greater future risk. We expand Equation 8 to include an additional interaction term between log reinsurance prices, correlated cat risk, and the expected change in disaster risk between 2023 and 2053, which we denote $\Delta Risk$. We also include additional controls for $\Delta Risk$ with time-varying coefficients to control for any baseline repricing of climate risk.

We show the results of this test in column (1) of Table 8. The statistically significant coefficient on the triple interaction term with $\Delta Risk$ shows that the effects of the reinsurance shock were stronger in more climate-exposed zipcodes, even conditional on their exposure to current correlated risk. The first column of Table 9 shows the average estimated premium reinsurance shock by the tercile of $\Delta Risk$ among zipcodes in the top decile of correlated risk exposure. Zipcodes in the top tercile of climate exposure saw an average reinsurance shock of \$200 in the bottom tercile of of $\Delta Risk$, \$430 in the middle tercile, and \$635 in the top tercile. In other words, holding today's exposure fixed, places expected to grow in risk saw larger premium increases.

Next, we similarly adjust our home price estimating equation to study heterogeneity in the reinsurance shock's effects of home prices by exposure to future risk. The results, shown in column (2) of Table 8, indicate that home prices fell by a greater amount in markets exposed to more future risk. Among zipcodes in the top decile of correlated risk exposure, holding today's exposure fixed, places expected to grow in risk saw larger house price declines. The reinsurance shock lowered relative average home values by \$23,560 in the bottom tercile of $\Delta Risk$, \$38,890 in the middle tercile, \$61,200 in the top tercile (Table 9).

Given that homeowners insurance contracts are written on an annual basis, it is perhaps surprising that insurers are responding to expectations of future risk with higher premiums today. As one plausible explanation, climate research already points to the nonlinear effect of warming temperatures on the severity of wildfires over the past half century (Jones et al., 2022; Williams et al., 2019). Thus, the recent large wildfire losses may have led insurers and reinsurers to realize that their historical models of cat risk in areas with increasing risks are mispecified, leading to larger recent price increases. In fact, before insurers began to rapidly increase their prices in 2022 and 2023, they had experienced consecutive years of low returns on equity driven by severe wildfire losses (Aon, 2024).

Taken together, these results suggest that the reinsurance shock presents a major repricing of both current and future climate risk. Applying our estimates in Table 9 to 2024 average home values, the reinsurance shock reduced home values by 11% among zipcodes in the top tercile of increasing risk. This effect is substantially larger than the approximately 5% price discount found for homes exposed to sea level rise (Bernstein et al., 2019; Keys and Mulder, 2020). The reinsurance

Outcome:	Log IPI	Home Price ($1000s)
	(1)	(2)
Log Reinsurance × Cat Correlation	0.104	-51.75
	(1.21)	(-1.44)
Log Reinsurance × Cat Correlation × $\Delta Risk$	0.350***	-91.54***
	(3.41)	(-2.96)
R^2	0.918	0.977
N	140602	140602

* p<0.10, ** p<0.05, *** p<0.01

Table 8: This table estimates the passthrough of reinsurance price shocks to homeowners insurance premiums (column 1) and home prices (column 2) allowing for heterogeneity by the expected change in disaster risk between 2023 and 2053. All specifications are weighted by the number of owner-occupied housing units in the 2010-2014 ACS, and include zipcode and year fixed effects, lagged log structure values, and time-varying controls on disaster risk and catastrophic risk exposure. Standard errors clustered by county with t-statistics in parentheses.

$\Delta Risk$ Tercile	Premiums Effect	Home Price Effect
Bottom	+$200	-$23,560
Middle	+$430	-$38,890
Top	+$635	-$61,200

Table 9: This table shows the estimated effect of the reinsurance shock on premiums (first column) and home prices (second column) among zipcodes in the top decile of correlated catastrophic risk exposure. The estimates are shown separately for zipcodes in the bottom, middle, and top tercile of their expected increase in disaster risk between 2023 and 2053.

shock suggests that insurance markets are already repricing disaster risk and affecting home values in areas where risk is expected to continue increasing.

9 Conclusion

Property insurance serves as the front line of defense against climate risk for homeowners, lenders, and real estate investors. The cost of this insurance is a critical input into decisions to adapt or relocate. To date, however, data limitations have hampered investigations of the geography of homeowners insurance, the relationship between disaster risk and the price of insurance, and the role of reinsurance markets in insurance pricing.

In this paper, we bring a new data source to bear on these critical questions. Using data from mortgage escrow payments, we infer insurance expenditures and show that this method produces expenditure estimates that are consistent with other publicly available sources. While the approach

has limitations, the sample size and level of detail allow for unprecedented insight into homeowners insurance markets.

We find that premiums have risen sharply since 2021, that this growth has been concentrated in disaster-prone zipcodes, and that elevated reinsurance costs are an important driver of the rising price of risk. We provide new estimates of the risk-to-premiums gradient, and show that the pass-through of risk to premiums more than doubled between 2018 and 2024.

We also provide a new estimate of the pass-through of reinsurance costs to insurance premiums in markets exposed to correlated catastrophic disasters, finding that the increase in reinsurance prices contributed to the increasing relationship between premiums and risk. The reinsurance shock added $430 to the 2024 annual homeowners insurance premiums of households in the top decile of exposure to correlated hurricanes and wildfires. These premium increases capitalized into home values, reducing prices by an average of $22,000 in cat-exposed zipcodes. These findings indicate that housing market participants do not expect the reinsurance shock to be temporary as in past market cycles.

The effects of the reinsurance shock on both insurance premiums and home values are larger in zipcodes that are exposed to increasing risk, suggesting that reinsurers have already started to reprice risk in climate-exposed markets. Thus, the reinsurance shock caused a major repricing of climate risk in the housing market. These findings highlight that the impacts of climate change on U.S. insurance markets and household budgets will depend on the costs of insuring correlated catastrophic risks through global reinsurance markets.

We intend for our novel data effort to provide transparent measures of insurance expenditures that are valuable to researchers, policymakers, and households that must navigate an increasingly challenging property insurance landscape.

References

Anand, V., J. Tyler Leverty, and K. Wunder (2021). Paying for expertise: The effect of experience on insurance demand. *Journal of Risk and Insurance 88*(3), 727–756.

Aon (2024, September). Reinsurance market dynamics: September 2024. `https://assets.aon.com/-/media/files/aon/reports/2024/reinsurance-market-dynamics-sept-2024-report.pdf`.

Araullo, K. (2024). January 1 renewals reflect a responsive reinsurance market – guy carpenter. *Insurance Business Magazine*.

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

Bakkensen, L. A. and L. Barrage (2021, 11). Going Underwater? Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics. *The Review of Financial Studies*. hhab122.

Baldauf, M., L. Garlappi, and C. Yannelis (2020). Does climate change affect real estate prices? only if you believe in it. *The Review of Financial Studies 33*(3), 1256–1295.

Bauer, D., R. Phillips, and G. Zanjani (2023). Pricing insurance risk: reconciling theory and practice. *Handbook of Insurance*.

Bauer, D., L. Powell, B. Su, and G. H. Zanjani (2021). Life insurance and annuity pricing during the financial crisis, revisited. *Revisited (March 6, 2021)*.

Baylis, P. W. and J. Boomhower (2022). Mandated vs. voluntary adaptation to natural disasters: The case of us wildfires. Technical report, National Bureau of Economic Research.

Bernstein, A., M. T. Gustafson, and R. Lewis (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of financial economics 134*(2), 253–272.

Bhutta, N. and B. J. Keys (2022). Moral hazard during the housing boom: Evidence from private mortgage insurance. *The Review of Financial Studies 35*(2), 771–813.

Blickle, K. and J. A. Santos (2022). Unintended consequences of. *FRB of New York Staff Report* (1012).

Blonz, J. A., M. Hossain, and J. Weill (2024). Pricing protection: Credit scores, disaster risk, and home insurance affordability. *Disaster Risk, and Home Insurance Affordability*.

Boomhower, J., M. Fowlie, J. Gellman, and A. J. Plantinga (2024). How are insurance markets adapting to climate change? risk selection and regulation in the market for homeowners insurance.

Born, P. and W. K. Viscusi (2006). The catastrophic effects of natural disasters on insurance markets. *Journal of risk and Uncertainty 33*, 55–72.

Boyer, M. M., E. Jacquier, and S. Van Norden (2012). Are underwriting cycles real and forecastable? *Journal of Risk and Insurance 79*(4), 995–1015.

Brunnermeier, M., E. Farhi, R. S. Koijen, A. Krishnamurthy, S. C. Ludvigson, H. Lustig, S. Nagel, and M. Piazzesi (2021). Perspectives on the future of asset pricing. *The review of financial studies 34*(4), 2126–2160.

Bunten, D. and M. E. Kahn (2017). Optimal real estate capital durability and localized climate change disaster risk. *Journal of Housing Economics 36*, 1–7.

Contat, J., C. Hopkins, L. Mejia, and M. Suandi (2024). When climate meets real estate: A survey of the literature. *Real Estate Economics*.

Cookson, J. A., E. Gallagher, and P. Mulder (2025). Coverage neglect in homeowner's insurance.

Corbineau, G., E. Fayad, D. Grunebaum, T. Lindeman, D. Reed, S. Hibler, and J. DeMarkey (2023). Reinsurers defend against rising tide of natural catastrophe losses, for now. *Moody's*.

Cruz, J.-L. and E. Rossi-Hansberg (2024). The economic geography of global warming. *Review of Economic Studies 91*(2), 899–939.

Cummins, J. D., G. Dionne, R. Gagné, and A. Nouira (2021). The costs and benefits of reinsurance. *The Geneva Papers on Risk and Insurance-Issues and Practice 46*, 177–199.

Cummins, J. D. and M. A. Weiss (2009). Convergence of insurance and financial markets: Hybrid and securitized risk-transfer solutions. *Journal of Risk and Insurance 76*(3), 493–545.

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

Eaglesham, J. (2024). The hidden driver of soaring home insurance costs. *Wall Street Journal*.

Eastman, E. and K. Kim (2023). Regulatory capital and catastrophe risk. *Available at SSRN 4468543*.

Eastman, E., K. Kim, and T. Zhou (2024). Homeowners insurance and housing prices. *Available at SSRN 4852702*.

FEMA (2023). National risk index. `https://hazards.fema.gov/nri/learn-more`.

First Street Foundation (2020). `https://firststreet.org`.

Froot, K. A. (2001). The market for catastrophe risk: a clinical examination. *Journal of Financial Economics 60*(2-3), 529–571.

Froot, K. A. (2007). Risk management, capital budgeting, and capital structure policy for insurers and reinsurers. *Journal of risk and Insurance 74*(2), 273–299.

Froot, K. A., B. Murphy, A. Stern, S. Usher, et al. (1995). The emerging asset class: insurance risk. *A Special Report From Guy Carpenter & Company, Inc.*

Froot, K. A. and P. G. O'Connell (1999). The pricing of us catastrophe reinsurance. In *The financing of catastrophe risk*, pp. 195–232. University of Chicago Press.

Froot, K. A. and P. G. O'Connell (2008). On the pricing of intermediated risks: Theory and application to catastrophe reinsurance. *Journal of Banking & Finance 32*(1), 69–85.

Gallagher Re (2024). First view. Technical report.

Ge, S. (2022). How do financial constraints affect product pricing? evidence from weather and life insurance premiums. *The Journal of Finance 77*(1), 449–503.

Ge, S., A. Lam, and R. Lewis (2022). The costs of hedging disaster risk and home prices: Evidence from flood insurance. *Available at SSRN*.

Georgic, W. and H. A. Klaiber (2022). Stocks, flows, and flood insurance: A nationwide analysis of the capitalized impact of annual premium discounts on housing values. *Journal of Environmental Economics and Management 111*, 102567.

Government Accountability Office (2021). National flood insurance program: Congress should consider updating the mandatory purchase requirement. Technical report.

Gron, A. (1994). Capacity constraints and cycles in property-casualty insurance markets. *The RAND Journal of Economics*, 110–127.

Gron, A. (1999). Insurer demand for catastrophe reinsurance. In *The financing of catastrophe risk*, pp. 23–50. University of Chicago Press.

Gron, A. and D. J. Lucas (1995). External financing and insurance cycles.

Gropper, M. J. and C. M. Kuhnen (2021). Wealth and insurance choices: Evidence from us households. Technical report, National Bureau of Economic Research.

Harrington, S. E. (2004). Tort liability, insurance rates, and the insurance cycle. *Brookings-Wharton Papers on Financial Services 2004*(1), 97–138.

Ibragimov, R., D. Jaffee, and J. Walden (2009). Nondiversification traps in catastrophe insurance markets. *The Review of Financial Studies 22*(3), 959–993.

Insurance Information Institute (2024). Facts + statistics: Homeowners and renters insurance.

Issler, P., R. Stanton, C. Vergara-Alert, and N. Wallace (2020). Mortgage markets with climate-change risk: Evidence from wildfires in california. *Available at SSRN 3511843*.

Jaffee, D. M. and T. Russell (1997). Catastrophe insurance, capital markets, and uninsurable risks. *Journal of Risk and Insurance*, 205–230.

Jeziorski, W. and S. Ramnath (2021). Homeowners insurance and climate change. *Chicago Fed Letter* (460), 1–6.

Johnson, E., A. Nowak, L. Powell, and A. Ross (2023). Asymmetric information in the florida homeowners insurance market.

Jones, M. W., J. T. Abatzoglou, S. Veraverbeke, N. Andela, G. Lasslop, M. Forkel, A. J. Smith, C. Burton, R. A. Betts, G. R. van der Werf, et al. (2022). Global and regional trends and drivers of fire under climate change. *Reviews of Geophysics 60*(3), e2020RG000726.

Kahn, M. E., A. Ouazad, and E. Yönder (2024). Adaptation using financial markets: Climate risk diversification through securitization. Technical report, National Bureau of Economic Research.

Keys, B. J. and P. Mulder (2020). Neglected no more: Housing markets, mortgage lending, and sea level rise. Technical report, National Bureau of Economic Research.

Klein, R. W. and M. F. Grace (2001). Urban homeowners insurance markets in texas: A search for redlining. *Journal of Risk and Insurance*, 581–613.

Koijen, R. S. and M. Yogo (2015). The cost of financial frictions for life insurers. *American Economic Review 105*(1), 445–475.

Koijen, R. S. and M. Yogo (2016). Shadow insurance. *Econometrica 84*(3), 1265–1287.

Kousky, C. and R. M. Cooke (2009). The unholy trinity: fat tails, tail dependence, and micro-correlations. *Resources for the Future Discussion Paper*, 09–36.

Kousky, C., H. Kunreuther, B. Lingle, and L. Shabman (2018). The emerging private residential flood insurance market in the united states. *Wharton Risk Management and Decision Processes Center*.

Kousky, C., M. Palim, and Y. Pan (2020). Flood damage and mortgage credit risk: A case study of hurricane harvey. *Journal of Housing Research 29*(sup1), S86–S120.

Lewis, R. (2023). The value of climate hedge assets: Evidence from australian water markets.

Li, P. H. K. A. (2025). Reinsurance, financial frictions, and subsidy efficiency: Evidence from health insurance.

Marcoux, K. and K. R. H. Wagner (2023). Fifty years of us natural disaster insurance policy.

Medders, L. A. and J. E. Nicholson (2018). Evaluating the public financing for florida's wind risk. *Risk Management and Insurance Review 21*(1), 117–139.

Missouri Census Data Center (2014). Mable geographic database. `http://mcdc.missouri.edu/applications/geocorr.html`.

Mulder, P. (2023). Mismeasuring risk: The welfare effects of flood risk information. Technical report, Working Paper.

Murfin, J. and M. Spiegel (2020). Is the risk of sea level rise capitalized in residential real estate? *The Review of Financial Studies 33*(3), 1217–1255.

NAIC (2022). A consumer's guide to home insurance.

Nyce, C., R. E. Dumm, G. S. Sirmans, and G. Smersh (2015). The capitalization of insurance premiums in house prices. *Journal of Risk and Insurance 82*(4), 891–919.

Oh, S., I. Sen, and A.-M. Tenekedjieva (2022). Pricing of climate risk insurance: Regulation and cross-subsidies. *Available at SSRN 3762235*.

Ostriker, A. and A. Russo (2022). The effects of floodplain regulation on housing markets. *URL https://ostriker. github. io/papers/Ostriker-Russo_floodplain-regulations. pdf*.

Panjwani, A. (2022). Underwater: The effect of federal policies on households' exposure to climate change risk. Technical report, Working paper.

Poterba, J. M. (1984). Tax subsidies to owner-occupied housing: an asset-market approach. *The quarterly journal of economics 99*(4), 729–752.

Sastry, P. (2021). Who bears flood risk? evidence from mortgage markets in florida.

Sastry, P., I. Sen, and A.-M. Tenekedjieva (2023). When insurers exit: Climate losses, fragile insurers, and mortgage markets. *Fragile Insurers, and Mortgage Markets (December 23, 2023)*.

Sastry, P. P., T. Scharlemann, I. Sen, and A.-M. Tenekedjieva (2025). Climate risk and the us insurance gap: Measurement, drivers and implications.

Solomon, A. (2024). Insuring correlated climate risk: Evidence from public reinsurance. *Available at SSRN 4881751*.

Swiss Re (2024). Sigma 01/2024. Technical report.

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

Weill, J. (2022). Perilous flood risk assessments. *Available at SSRN 4143914*.

Williams, A. P., J. T. Abatzoglou, A. Gershunov, J. Guzman-Morales, D. A. Bishop, J. K. Balch, and D. P. Lettenmaier (2019). Observed impacts of anthropogenic climate change on wildfire in california. *Earth's Future 7*(8), 892–910.

Zanjani, G. (2002). Pricing and capital allocation in catastrophe insurance. *Journal of financial economics 65*(2), 283–305.

10 Appendix

10.1 Appendix Figures and Tables

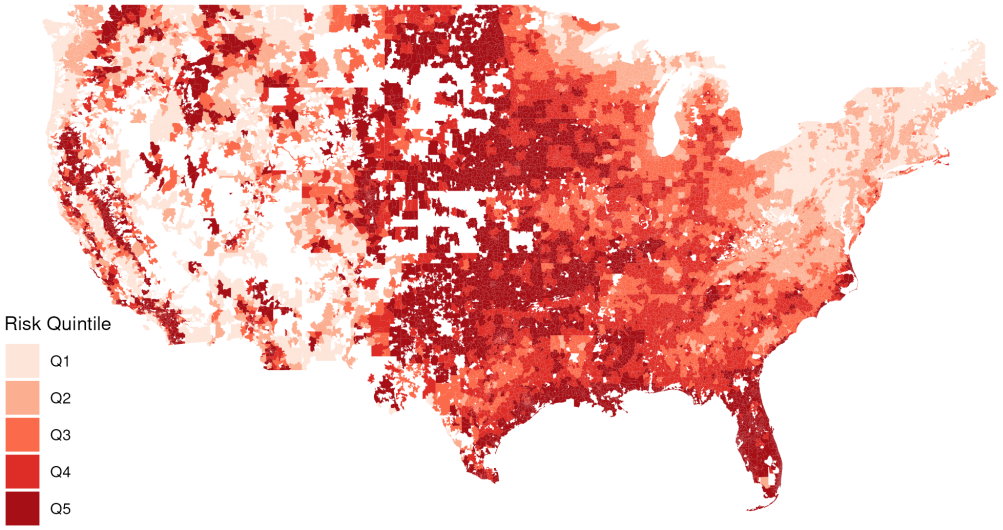


Figure 16: Map of US zipcodes by risk measure quintile

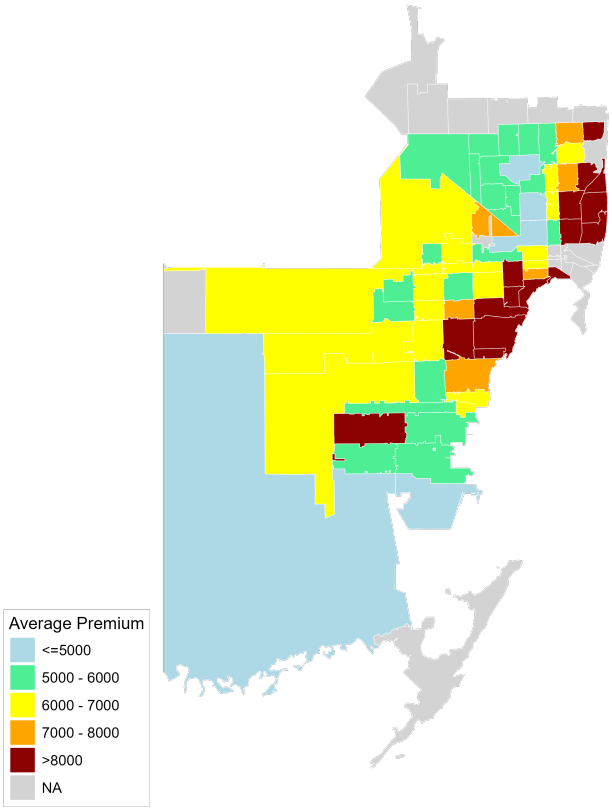


Figure 17: Shows average annual homeowners insurance premiums by zipcode in Miami-Dade County in 2024.

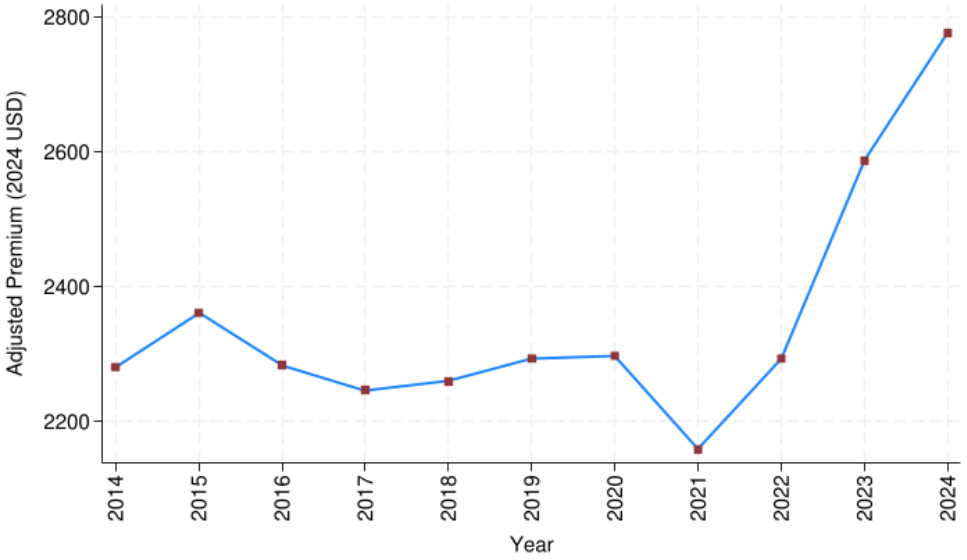


Figure 18: Time series of average annual homeowners insurance premiums. Values are inflated to constant 2024 dollars.

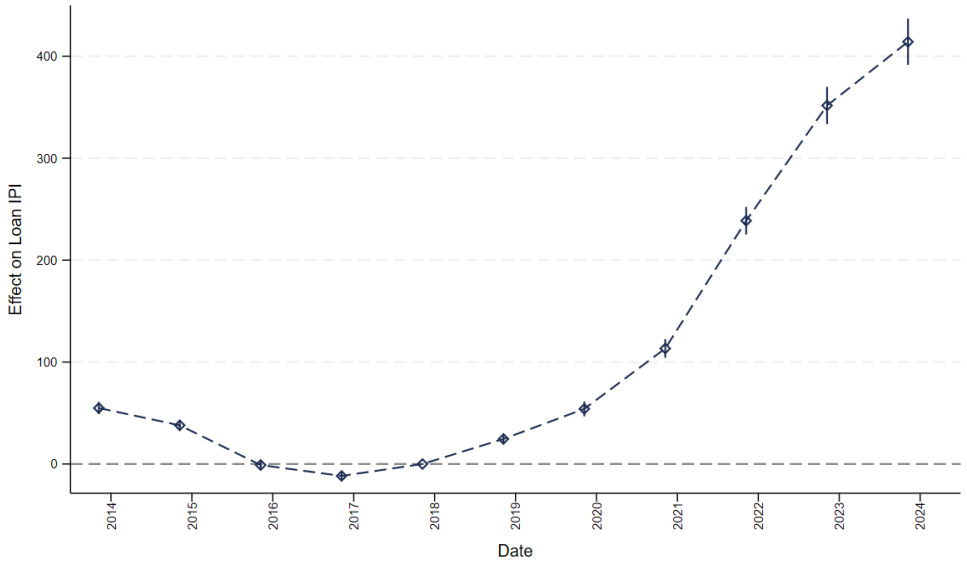


Figure 19: Plots the time-varying estimated effect of disaster risk on premiums. Dependent variable is the repeat-loan insurance premium expenditures index.

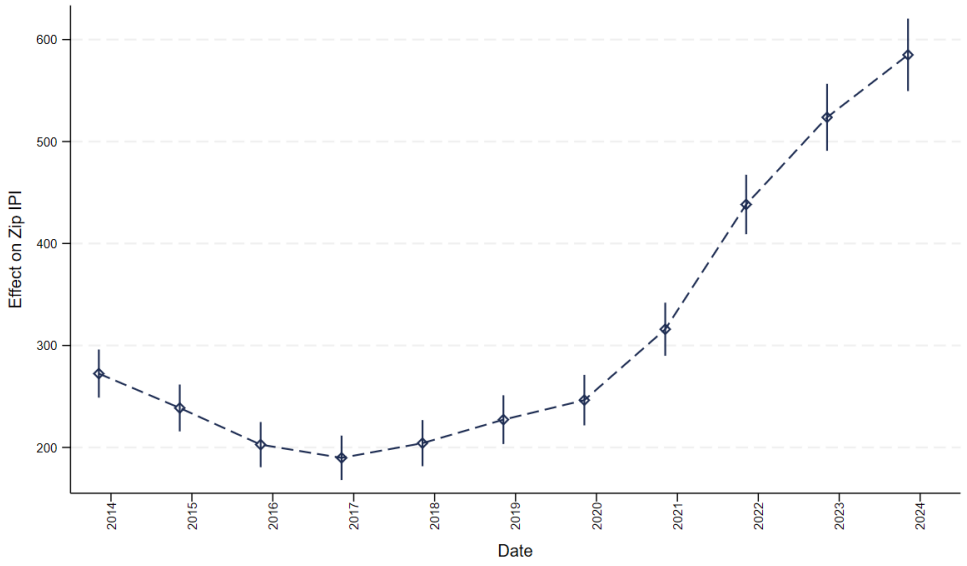


Figure 20: Plots the time-varying estimated effect of disaster risk on premiums. Controls for time-varying flood risk coefficients.

	Log Insurance Premium Expenditures Index			
	(1)	(2)	(3)	(4)
Log Reinsurance × Cat Correlation	0.337***	0.340***	0.362***	0.247***
	(5.10)	(5.23)	(5.84)	(3.29)
Log Reinsurance × Cat Correlation × High Friction	-0.469***	-0.467***	-0.410***	-0.234*
	(-3.93)	(-3.11)	(-3.70)	(-1.96)
R^2	0.918	0.919	0.902	0.925
N	140602	140602	131967	140602
Time-Varying Flood Controls	N	Y	Y	Y
Drop Florida	N	N	Y	N
State-by-Time Risk Controls	N	N	N	Y

* p<0.10, ** p<0.05, *** p<0.01

Table 10: This table estimates the passthrough of reinsurance price shocks to homeowners insurance premiums allowing for heterogeneity among "high friction" states in the top third of pricing regulation (Oh et al., 2022). The dependent variable is the log repeat-loan insurance premium expenditures index. Shown coefficients are for the interaction between correlated risk exposure and log reinsurance prices, and the triple interaction term with an indicator for high friction states. All specifications are weighted by the number of owner-occupied housing units in the 2010-2014 ACS, and include zipcode and year fixed effects and log lagged structure values. Standard errors clustered by county with t-statistics in parentheses.

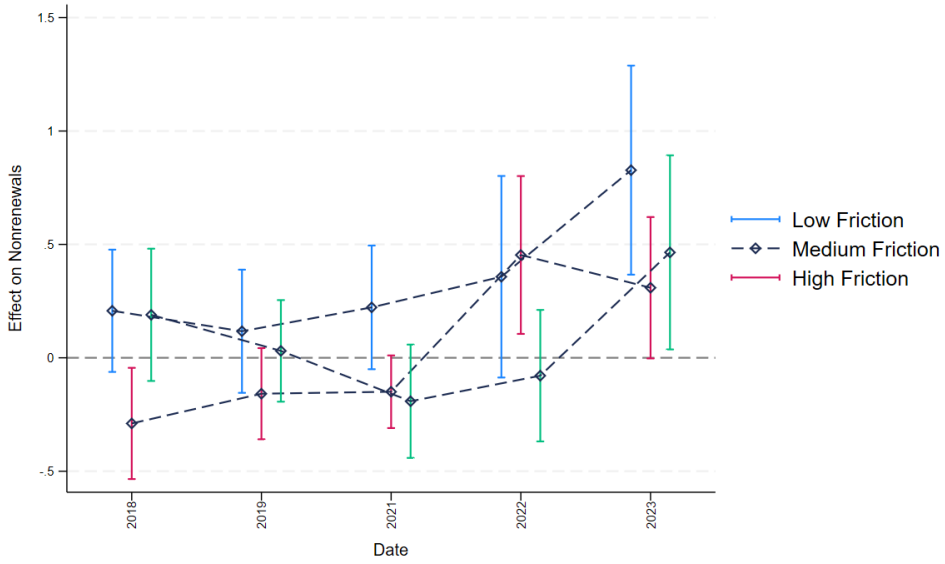


Figure 21: Effect of correlated cat risk on home insurance nonrenewals by state financial frictions.

10.2 Comparison to III, Census, Quadrant, and Treasury Data

Figure 22 compares the average nominal premiums calculated using our escrow approach with three alternative measures, from Insurance Information Institute at the state level (III), the Census American Community Survey (ACS) at the county-level, and from Quadrant Information Services at the zipcode level.

Looking at the comparison with III, we see a strong and approximately one-to-one relationship between the escrow premium estimates and the III premium estimates.[35] However, the escrow estimates are consistently about $500 more expensive than their corresponding III figures. We consider several potential explanations for this. First, our estimates consider whatever premiums homeowners pay out of escrow, including flood insurance policies, policies outside the standard HO-3 coverage, or supplemental wind-only or fire-only coverage. The III numbers, on the other hand focus on standard HO-3 policies. Second, the property values of our sample of mortgaged homeowners are about 15% higher than the corresponding Zillow home value estimates.

We see a similarly strong linear relationship between the escrow premium estimates and surveyed homeowners insurance premiums for the ACS and a similar upward level shift in the escrow estimates. However, the gap between escrow and ACS premiums is larger at the top-end of the premium distribution. We believe this gap can be explained by the fact that reported disaster insurance premiums in the ACS are top-coded at $10,000.

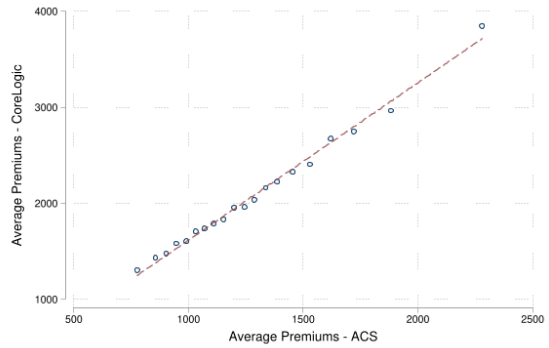
Finally, we compare our premiums against price quotes from Quadrant in Florida, Louisiana, Texas, and California.[36] Quadrant's data is unique in that it matches the zipcode granularity of the the escrow estimates. However, it comes from estimated insurer prices based on their state rate filings for standardized amounts of coverage rather than reflecting the actual premiums paid for purchased coverage. There is a weaker positive relationship between escrow premium estimates and the Quadrant price quotes relative to the III and ACS estimates. In particular, among zipcodes with the highest average Quadrant quotes, the escrow premium estimates are substantially lower.

We believe this pattern plausibly reflects the shopping behavior of households, their downward sloping demand for insurance, and unobserved coverage denials by insurers. Where Quadrant sees some insurers setting the highest premiums, homeowners are most likely to shop and find the lowest premium available to them. In addition, the insurers setting the highest premiums may also be the most likely to deny coverage. It is also relevant that, whereas the Quadrant data compare prices across a fixed contract, homeowners may choose higher deductibles or buy less coverage when facing higher rates. Although Quadrant data provides valuable insight into the rates set by insurers, it does not show the premiums actually paid by homeowners as in the escrow estimates.

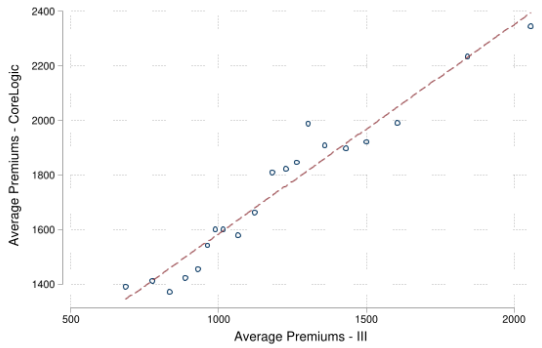
In sum, the escrow premium estimates have a strong and positive relationship with coarser existing datasets on homeowners insurance premiums. The escrow premiums are a level shift higher than other sources, a fact that can be primarily explained by the more valuable homes in our sample and that escrow payments likely cover a broader range of policies.

[35] III premium tables are provided here: `https://www.iii.org/table-archive/21407`.

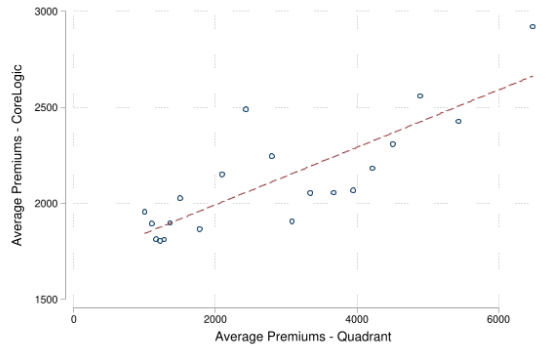
[36] Quadrant data is representative of publicly-sourced data and should not be interpreted as bindable quotes.



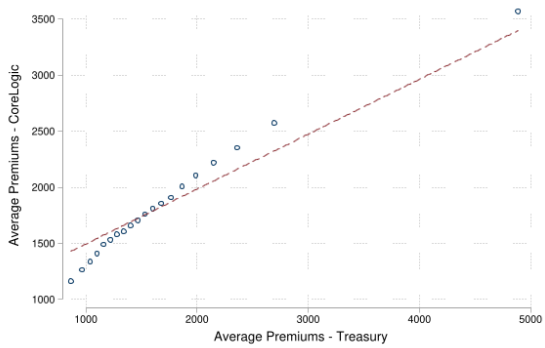
(a) ACS



(b) III



(c) Quadrant



(d) Treasury

Figure 22: Escrow Premium Estimates versus other sources. Each figure compares the average premiums from the escrow estimates against different sources in the form of a binscatter. Panel (a) compares state-by-year premium estimates between 2014 and 2020 from the Insurance Information Institute. Panel (b) compares county-by-year premium estimates between 2014 and 2022 from the American Community Survey. Panel (c) compares zipcode-by-year insurer cost quotes between 2014 and 2021 from Quadrant Information Services in Florida, Louisiana, California, and Texas. Cost quotes are averaged within each zipcode by insurer, level of coverage (250K or 500K), credit score (excellent, good, fair, or poor where applicable) and home age (new, 10 years old, 25 years old). Quadrant rates are representative of publicly sourced data and should not be interpreted as bindable quotes. Panel (d) compares zipcode-level premium estimates between 2018 and 2022 collected by the Federal Insurance Office.