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

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Abstract

We develop a new dataset to study homeowners insurance. Our data on over 47 million observations of households' property insurance expenditures from 2014–2023 are inferred from mortgage escrow payments. First, we find a sharp 33% increase in average premiums from 2020 to 2023 (13% in real terms) 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 $425 higher premiums in 2023, 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 $8,000 in zipcodes exposed to severe hurricanes and wildfires between 2020 and 2023. Our results highlight that prices in global reinsurance markets pass through to household budgets, and will ultimately drive the cost of rising climate risk.

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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 is coarse and inadequate, preventing a clear understanding of the extent and underlying causes of these increases.

In this paper, we use information on mortgage escrow payments to develop a new approach to measuring homeowners insurance premiums. Most mortgage borrowers make a single monthly payment toward 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 allows 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 47 million observations from 2014 to 2023. We create zipcode-level insurance premium expenditure indices (IPI) using both loan-level controls and in the style of a home price "repeat sales index," that follows premiums on the same loan over time.

To examine the robustness of our methodology to infer insurance premiums, we benchmark our expenditure estimates to publicly available but more geographically coarse data from the National Association of Insurance Commissioners (NAIC), homeowner surveys (American Community Survey, ACS), and carrier price quotes (Quadrant Information Services).[2] We find that our indices yield extremely similar rank-ordering of insurance pricing by locations, but that our estimated expenditures are consistently somewhat larger than other sources, reflecting that average home values are 15% larger in our sample of mortgaged single-family homes than in the general population.[3]

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 premiums increased by 33% from $1,902 in 2020 to $2,530 in 2023, a 13% real increase. With the granularity of our data, we provide the first estimate of the relationship between disaster risk and premiums using within-state variation in expected disaster losses. We estimate that a one standard deviation

[1] See, e.g., Treasury Secretary Yellen's remarks to the Federal Advisory Committee on Insurance Meeting, March 23, 2023, `https://home.treasury.gov/news/press-releases/jy1375`.

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

[3] See Appendix Section 9.2 for the detailed comparison between these sources.

increase in disaster risk is associated with an average annual premium increase of $335.

We are able to provide new measures of the level of insurance premium expenditure and the extent of "insurance burden" relative to incomes and home prices for thousands of zipcodes across the United States. Housing structure values and disaster risk explain most of the variation in insurance premiums, but we also observe 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 recent insurance market dynamics and the role of reinsurance costs in driving premiums higher. While we find that the increase in construction costs can explain a little over half 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 effect of a one standard deviation increase in disaster risk on premiums rose from $250 to $425 by 2023. This increase in the premium cost of risk explains nearly 20% of the real increase in premiums between 2018 and 2023. If this higher pass-through of risk into premiums continues, we estimate that homeowners in the top ventile of exposure to increasing disaster risk will pay $600 per year in higher homeowners insurance premiums by 2053.

This increase in the risk-to-premium gradient coincides with a doubling of U.S. property catastrophe reinsurance prices between 2018 and 2023.[4] 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.[5] Thus, reinsurers are responding to real increases in the costs of insuring correlated risks and to many of the same factors increasing homeowners insurance premiums in other markets where risk is less concentrated. It is therefore an open question whether the relative costs of insuring correlated catastrophic risks are increasing.

We use our data to study the effects of this "reinsurance shock," and isolate the extent to which rising reinsurance prices signal a real increase in the relative costs of insuring correlated hurricanes and wildfires. Our empirical specification uses variation in the county-level correlation of historical

[4]See `https://www.artemis.bm/us-property-cat-rate-on-line-index/`.
[5]See Gallagher Re (2024); Swiss Re (2024).

losses within states. Because insurance markets are organized and regulated by state, within-state correlation of losses drives greater reinsurance demand as state-level insurance companies seek to spread their concentrated risks across global reinsurance markets. Thus, we are able to compare the change in premiums as reinsurance rates rise for zipcodes exposed to similar expected losses but with different exposure to reinsurance because of the differential correlation of their risk. Our most stringent specification includes state-by-risk controls to absorb the effects of state-level factors such as regulations or natural disasters that might affect general premium trends, as well as structure value controls to account for housing cost inflation.

Our study of the reinsurance shock shows that premiums in cat-exposed zipcodes primarily increased in areas exposed to correlated risks, while increases were more modest where losses were less correlated. Thus, the rise in reinsurance prices reflects higher costs of insuring correlated catastrophic risks above and beyond the pricing of expected losses. Among the most heavily cat-exposed zipcodes, this reinsurance shock increased annual premiums by nearly $300 in 2023. We conclude from this exercise that insurers' 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 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 2023 home values by an average of approximately $8,400. This implies a capitalization rate of a $50 reduction in home values for every $1 increase in premiums, consistent with a 2% discount rate and well within the range of full capitalization. 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. Furthermore, the capitalization rate of premiums into home prices is larger in these areas with growing risk. Thus, our findings suggest that homeowners do not view the most recent reinsurance shock as transitory and expect the higher costs of correlated risk to remain, especially in more climate-exposed markets.

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 to 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.[6] The rising insurance premiums we document are being capitalized into house prices, and may further reduce demand for at-risk properties (Poterba, 1984).[7] 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 (Ouazad and Kahn, 2021; Kahn et al., 2024; Panjwani, 2022; Issler et al., 2020).[8] 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. 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 (Brunnermeier et al., 2021).[9] In life insurance markets, where price data for standardized policies is readily available, researchers have found that frictional costs from firms' liquidity constraints or

[6] 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).

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

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

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

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.[10] 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 is relevant to 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).[11] 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) uses 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) shows 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.

Section 2 describes the context of the residential homeowners insurance market, Section 3 presents the data used in our analysis, and Section 4 provides our methodology for measuring insurance expenditures. Section 5 shows homeowners insurance premiums across time and geography, while Section 6 examines the dynamics and correlates of insurance expenditures. Section 7 explores the role of reinsurance and estimates the extent of pass-through from the secondary reinsurance market to primary homeowner insurance premiums. Section 8 uses forward-looking measures of climate risk to project the potential costs of climate change on insurance premiums, and Section 9

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

[11] 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.

concludes with directions for future research using this new data.

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). Survey data from the American Housing Survey suggests 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.[12]. 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.

[12] 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).

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 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 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 escrowing of flood insurance policies issued by the National Flood Insurance Program starting in 2016, and other peril-specific policies may 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 comes 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.[13] The data includes the zipcode of the property, as well as loan type (e.g. purchase vs. refinance) and property and borrower 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.[14] FSF is a non-profit that seeks to provide risk data to homeowners, policymakers, and academics with highly localized risk models for wildfire, wind, flood, and heat risk (First Street Foundation, 2020) (FEMA, 2023).[15]

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. 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.[16] 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.

Besides 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.[17] In contrast, the FSF 2023 models account for recent changes in climate and land use that are particularly important for accurately measuring current wildfire and hurricane risks. Second, the NRI hurricane measure does

[13] 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.

[14] See Appendix Figure 13, `https://hazards.fema.gov/nri/learn-more`.

[15] See `https://firststreet.org` for details.

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

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

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 (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. 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.[18] We apply these land shares to our Zillow home prices to construct an annual measure of structure values.[19] 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;

[18]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`

[19]Due to data limitations, we apply the 2022 land share to 2023 prices.

Araullo, 2024), and reflects contracts written on a brokered basis between insurers and reinsurers.

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

	Rows	Loans
All	544,233,838	19,865,300
TP, P&I, Tax > 0	417,638,088	17,127,580
Drop repeated tot. pay rows	65,287,361	17,127,580
Owner Occupied	60,969,155	15,963,449
TP = P&I	59,112,086	14,758,689
Premium > 0	56,802,215	14,006,693
Relative Premium < 5	56,126,679	13,997,243
Winsorized Premium > 10	55,950,617	13,970,825
Collapse to year & quarter	53,421,021	13,970,825
PMI Adjustments	47,462,795	12,412,223

Table 1: This table describes how our sample size progresses from the full loan-level 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.

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 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	2020Q3	9725.64	6422.88	1357.61	1945.15
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

Table 2: Example of one loan's annualized 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 (by small amounts) over time.

With our premium data in hand, we build two insurance premium indices (IPIs) at the zipcode level at a half-year frequency. 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 first estimate a *controls IPI*:

$$Premium_{izt} = \alpha_{zt} + Orig_i + Price_i + FICO_i + \epsilon_{izt}, \tag{2}$$

where $Premium$ is the inferred premium of loan i in zipcode z in half-year t. As controls, we include loan origination date year-quarter fixed effects $Orig_i$, the sales price of the home $Price_i$, and the borrower's FICO score $FICO_i$. The coefficient of interest is α_{zt}, or the zipcode-by-time fixed effects. The estimated coefficients $\widehat{\alpha_{zt}}$ become the "controls IPI."

As a second IPI, we use a repeat-loan specification:

$$Premium_{izt} = \alpha_{zt} + \lambda_i + \epsilon_{izt}. \tag{3}$$

In the spirit of a home price repeat-sale index, the "repeat-loan index" in Equation 3 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 more restrictively holds fixed all time-invariant characteristics of the underlying property, borrower, and location.

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 2023. 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) through tornado- and flood-exposed regions of the Great Plains, eastern Colorado, Oklahoma, and

Statistic	Mean	St. Dev.	10th Pct.	90th Pct.
Premium Expenditure	$2,530.22	$2,220.16	$753.34	$4,906.98
Purchase Price	$356,671.80	$469,230.80	$129,996.90	$640,000.00
Premium as % of Price	0.94%	0.77%	0.22%	1.97%
Premium as Pctg. of P&I	21.17%	17.71%	5.49%	42.91%
FICO Score	736.86	56.77	655	802

Table 3: Summary statistics from the cross-section of premium estimates in the first half of 2023.

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. Whereas the geography of premiums appears smooth at the county-level, there are clear pockets of high premium zipcodes when viewed with more granularity. Appendix Figure 14 shows significant heterogeneity in premiums within Miami-Dade County, with much higher costs along the coast relative to inland.

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 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 10 years of premium dynamics from 2014 to 2023. Figure 5 presents the time series of average nominal homeowners insurance premiums in the United States from 2014 to 2023. Premiums were steady in nominal terms from 2014 through

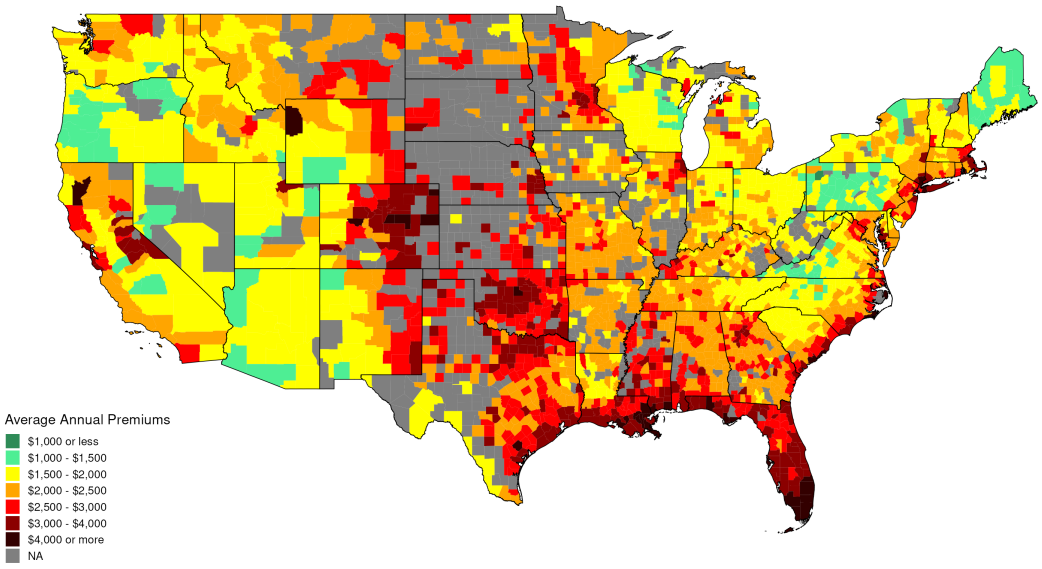
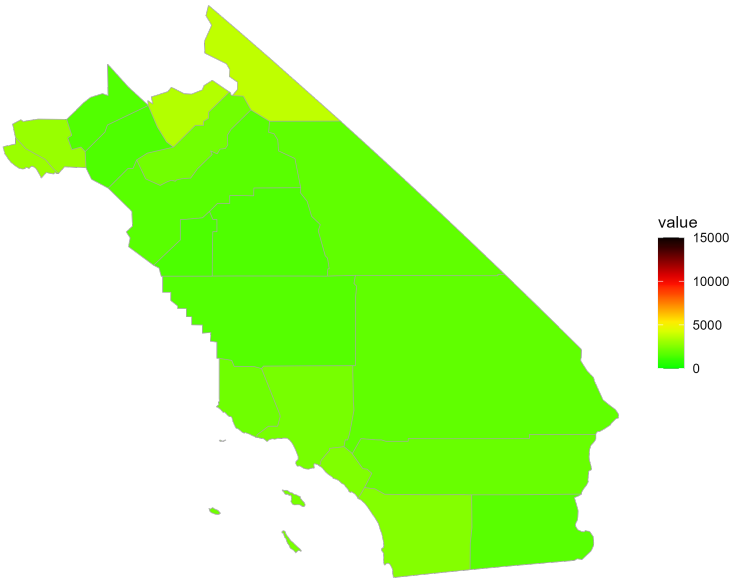
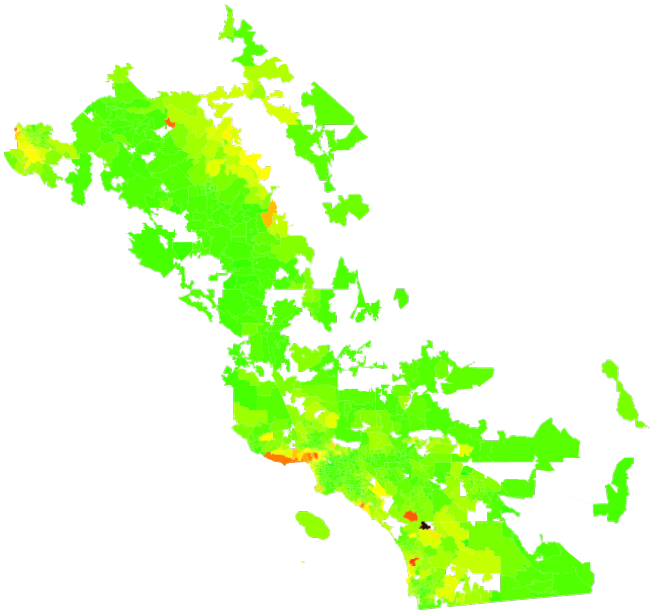


Figure 1: This figure maps average annual insurance premiums in the first half of 2023 by county. Counties with fewer than 20 premium observations are excluded.

2017, then rose between 2017 and 2019. Beginning in 2019, premiums leveled out until 2021. Since 2021, average premiums have risen sharply, with the average premium increasing by over $500 in three years. To investigate whether insurance costs rose faster than inflation over this period, Appendix Figure 15 shows a similarly sharp increase in inflation-adjusted dollars.



(a) Premiums by county, 2023H1



(b) Premiums by zip code

Figure 2: This figure maps average annual insurance premiums for Southern California in the first half of 2023 by county (top panel) and by zipcode (bottom panel).

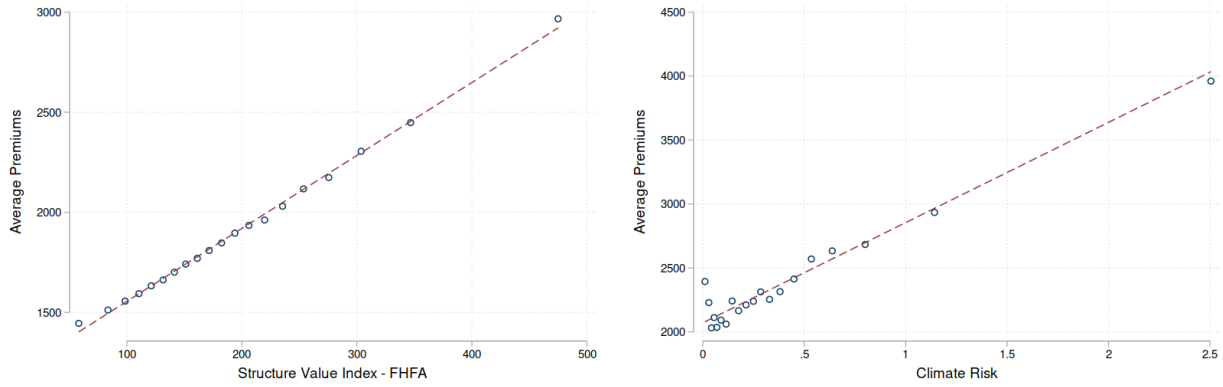


Figure 3: This figure shows the relationship between average premiums in 2023H1 by 20 ventiles of structure values (left panel) and the disaster risk index (right panel).

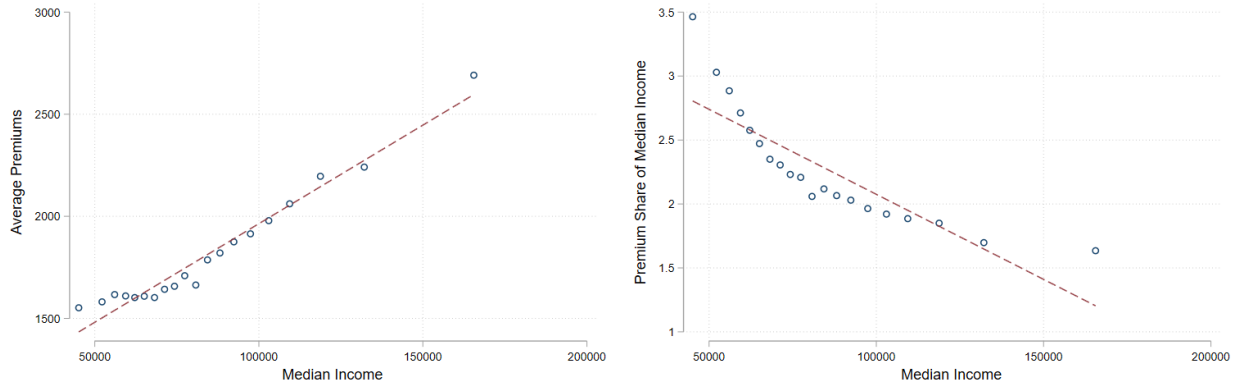


Figure 4: Figures show average premiums (left panel) and average premiums as a share of income (right panel) by twenty ventiles of zipcode median income. Income is median income of owner-occupied households from the 2014–2018 American Community Survey measured in 2018 dollars. Average premiums are taken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

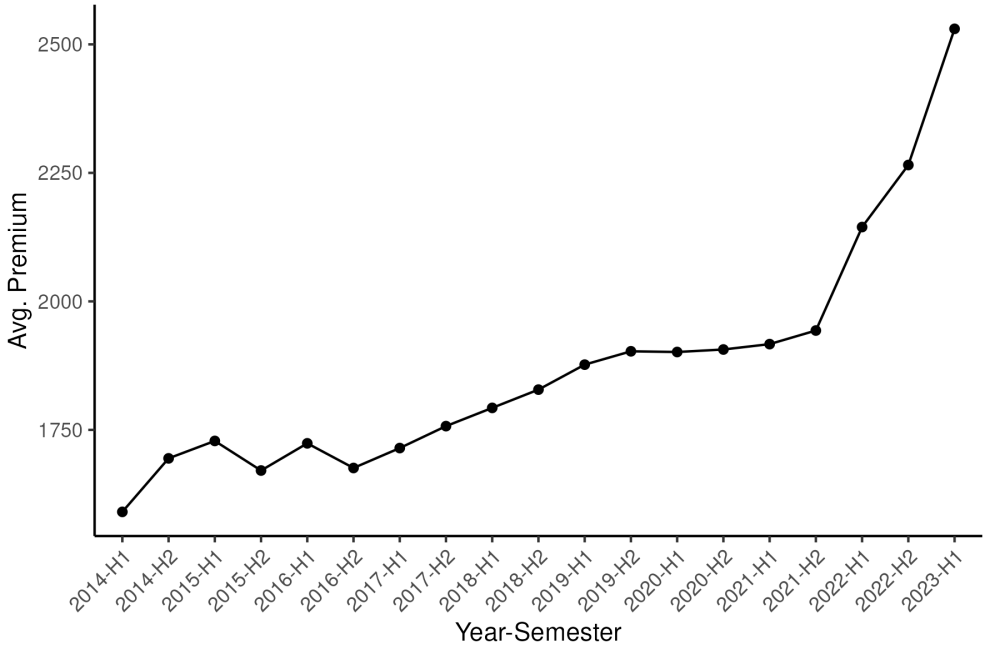


Figure 5: Time series of nominal average annual homeowners insurance premiums.

6 Insurance Expenditure 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. Table 4 examines these characteristics in a regression analysis. The first column takes the IPI constructed with loan-level controls as the dependent variable and regresses it on FHFA structure values and our standardized disaster risk measure 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 a one-standard deviation increase in expected disaster losses associated with a $340 increase in average premiums.

Column (2) adds zipcode-level covariates for the population share white and median household income in thousands of dollars. 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 $32 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.[20]

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 $300 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 IPIs are critical for estimating the appropriate pass-through of risk to premiums.

It is important to note that column (3) of Table 4 measures 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. However, the effect of risk on total insurance spending is a relevant measure of the costs of disaster risk for households. If living in a risk-prone area leads homeowners to choose a lower

[20]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)
	Insurance Premium Expenditures Index		
Disaster Risk	338.54***	358.48***	298.38***
	(9.804)	(9.848)	(11.754)
Structure Value ($1000s)	3.23***	1.96***	3.95***
	(0.105)	(0.130)	(0.167)
Pop. Share White		-314.74***	-315.82***
		(31.789)	(33.986)
Median Income ($1000s)		7.29***	1.96***
		(0.390)	(0.456)
N	176994	176994	176994
R^2	0.419	0.444	0.625
Demographic Controls	No	Yes	Yes
Year#Semester FE	Yes	Yes	Yes
Year#Semester#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 the controls insurance premium expenditure index. 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.

deductible or buy more coverage, then paying for that lower deductible is as much a cost of risk as facing a higher rate for coverage.[21]

A caveat to this interpretation is that differences in coverage choices driven by risk preference heterogeneity correlated with risk do not reflect the cost of risk. While it is impossible to perfectly control for such preference heterogeneity, this concern motivates the inclusion of loan-level and zipcode-level controls as well as state-by-time fixed effects. Conversely, if higher rates lead homeowners to buy less coverage, then our measures will understate the true costs of risk and climate change. Indeed, this is precisely the phenomenon documented in Sastry et al. (2025), who find that rising insurance premiums reduce the coverage limit choices of credit-constrained homebuyers.

Table 4 assumes that the relationship between disaster risk and premiums is constant over the sample period. To interrogate this assumption, 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 nearly double the premiums of the safest quintile. The differences across quintiles were stable until 2020, when premiums in the riskiest quintile began to increase sharply. Thereafter,

[21]Leverty et al. (2023) finds a positive effect of climate risk perceptions on homeowner's insurance demand.

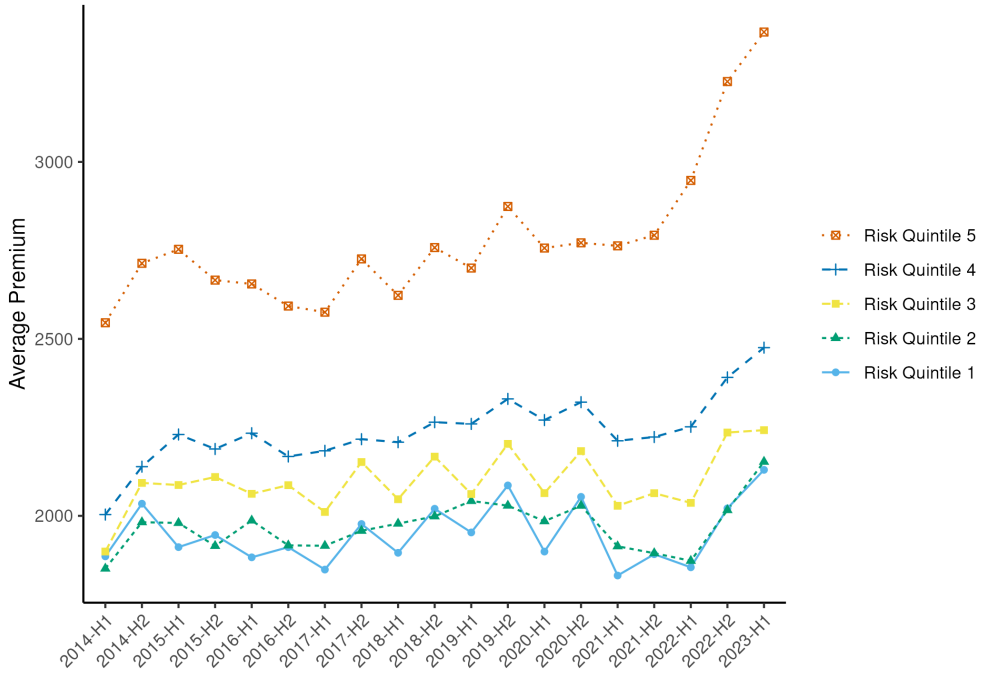


Figure 6: Average premiums plotted by quintile of disaster risk exposure. Premiums are in real 2023 dollars.

premiums have risen across all climate risk quintiles, but the gap between risky and safe areas has substantially widened.

The larger increases in premiums among the riskiest zipcodes relative to the safest ones show 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 replacement costs and premiums. In addition, rising premiums in specific states have been attributed by industry participants to idiosyncratic factors, such as fraudulent claims in Florida.

To investigate the extent to which higher premiums are being driven by disaster risk exposure versus some correlated factor, we estimate the following specification:

$$IPI_{zst} = \alpha_{st} + \beta_1 ShareWhite_z + \beta_2 Income_z + \lambda StructureValue_{zt} + \sum_{t=2014H2}^{2023H1} \beta^t Risk_z + \epsilon_{zst}, \quad (4)$$

IPI_{zst}, the controls insurance premium index, is the dependent variable. α_{st} are state-by-time fixed effects to capture state-specific factors that cause general changes in premiums over time. We

also control for population share white and median income as in column (2) of Table 4, and for trends in the structure values of homes with the FHFA estimates ($StructureValue_{zt}$) as our key proxy for time-varying structure values. The key parameters of interest are the period-by-period β^t on $Risk_z$, which give the effect of a one-standard deviation increase in disaster risk on premiums. Insofar as the widening gap between high and low risk zipcodes in our data is attributable to state-specific factors or rising replacement costs, we would expect to find a constant β^t over time given our structure value controls and state-by-time fixed effects.

Figure 7 presents the time-varying coefficient of climate risk on premiums from Equation 4. While the relationship between climate risk and premiums was stable – or even decreasing – through 2019, starting in 2020 we estimate a substantially stronger relationship between premiums and climate risk, consistent with the raw data in Figure 6. The coefficient on risk increases over 50% from \$275 per index unit through 2018 to approximately \$425 in 2023. This increase implies a \$260 increase in annual premiums for zipcodes in the top decile of disaster risk all else equal.

We can also use the estimated results of Equation 4 to unpack the drivers of the recent spike in homeowners insurance premiums. Our insurance premium expenditures index increased by \$560 between the second half of 2018 and the start of 2023. Our estimated structure values coefficient implies that the increase in rebuilding costs can explain \$320, or a little over half, of this increase. Thus, while construction costs also outpaced the general pace of inflation, they cannot explain the full rise in homeowners insurance premiums. 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. The increase in the coefficient on disaster risk can explain approximately \$105 of the increase. These two factors alone account for approximately $\frac{3}{4}$ of the increase in premiums over this period.

To examine the robustness of our results, we re-estimate the dynamics of the risk coefficient with our repeat-loan IPI adjusted for inflation as the dependent variable. 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 16, show a similar increase in the risk coefficient from the base period as in the controls IPI. We control for the time-varying effects of flood risk to account for contamination from changing NFIP premiums in Appendix Figure 17.

To explore the forward-looking implications of this rise in the pass-through of disaster risk to premiums, 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. We measure the expected increase in annual premiums due to climate change with the formula:

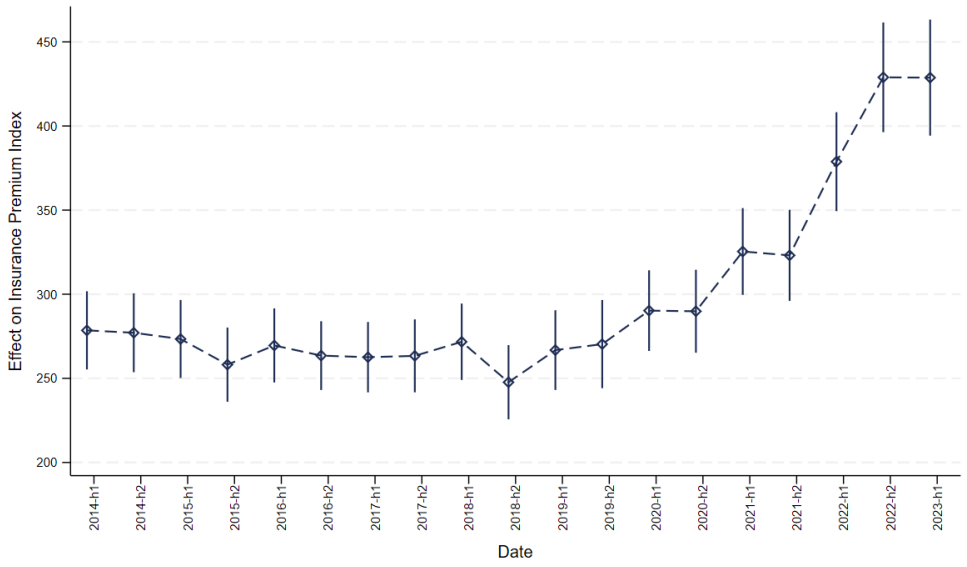


Figure 7: Plots the time-varying estimated effect of disaster risk on premiums. Vertical lines indicate 95% confidence intervals. See Equation 4 for more details.

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

where $\Delta_{2023}^{2053} IPI_{z,t}$ is the change in annual homeowners insurance premiums for zipcode z in 2053 relative to 2023, $\widehat{\beta}_t^{Risk}$ is the estimated coefficient for the effect of a one standard deviation increase in disaster risk on premiums in period t, and $Risk_{z,2053}$ and $Risk_{z,2023}$ are the disaster risk values in zipcode z in 2023 and 2053, respectively.

As shown in Figure 7, the estimated value of $\widehat{\beta}_t^{Risk}$ changes significantly over time. To illustrate the importance of this variation, Figure 8 plots the distribution of $\Delta_{2023}^{2053} IPI_{z,t}$ across zipcodes at values of β_t^{Risk} setting $t = 2023H1$ (red) and $t = 2018H2$ (blue) by 20 ventiles of climate exposure. Moving from $\widehat{\beta}_{2018H2}^{Risk}$ to $\widehat{\beta}_{2023H1}^{Risk}$ magnifies annual premium increases among climate-exposed homeowners – those in the top 5% of expected disaster risk increases – more than 75% from an average of $345 to nearly $600 by 2053.

To illustrate the geographic dispersion of potential climate-driven increases in homeowners insurance premiums, Figure 9 plots the county-level averages of $\Delta_{2023}^{2053} IPI_z$ for climate-exposed zipcodes using $\widehat{\beta}_{2023H1}^{Risk}$. The figure shows that increasing wildfire risk in the west drives most of the expected increase in homeowners insurance premiums by 2053.[22] Extrapolating our estimates to

[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

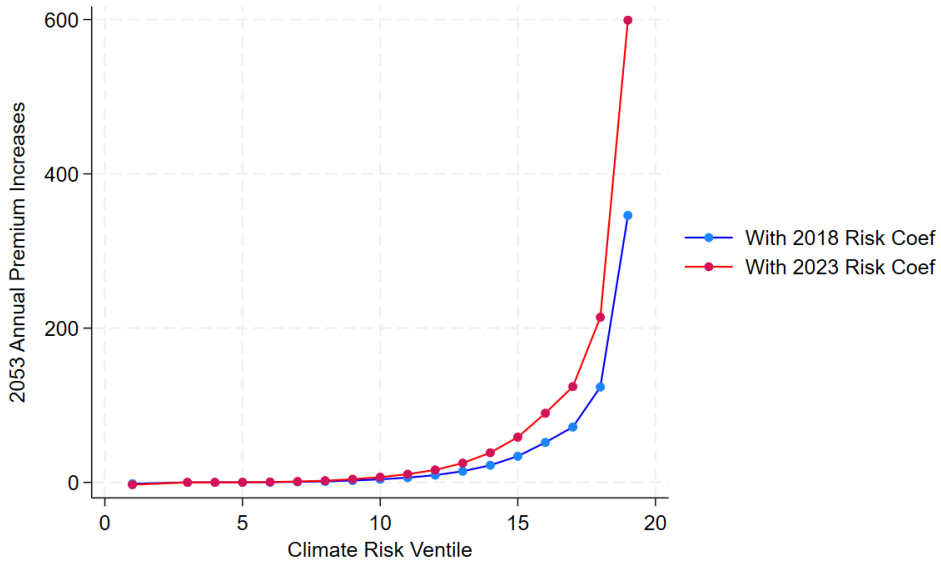


Figure 8: Predicted increase in annual insurance premiums in 2053 due to climate change under 2018 insurance costs (blue) and 2023 insurance costs (red) by twenty ventiles of climate exposure as implied by the time-varying coefficients on disaster risk shown in Figure 7.

the approximately 80 million single-family homes in the U.S. implies additional annual premiums of approximately $5 billion by 2053.

The preceding analysis is subject to several caveats. First, these climate projections hold fixed a vast array of other factors between 2023 and 2053 that will also influence disaster damages. Second, these projections only consider climate costs from the perspective of household premium payments and do not account for insurer profits or state subsidies. Third, these costs do not account for the economic costs households face from uninsured losses. Finally, these costs reflect insurance spending and not premium rates. If households reduce their coverage in response to higher rates, premium costs will further understate climate costs.

Thus, we view these estimates as an informative baseline that suggests potential economic responses to a changing climate as well as what factors may drive climate costs higher or lower. Adaptation may reduce premium increases relative to our projections as building standards make homes more resilient and spatial resorting moves population out of harms way (Bunten and Kahn, 2017; Baylis and Boomhower, 2022; Cruz and Rossi-Hansberg, 2024; Kahn et al., 2024). Continuing cross-subsidization of risk from premium regulations and subsidized insurers-of-last-resort could, however, blunt the incentives to adapt and increase building in disaster-prone areas (Medders and Nicholson, 2018; Oh et al., 2022).

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.

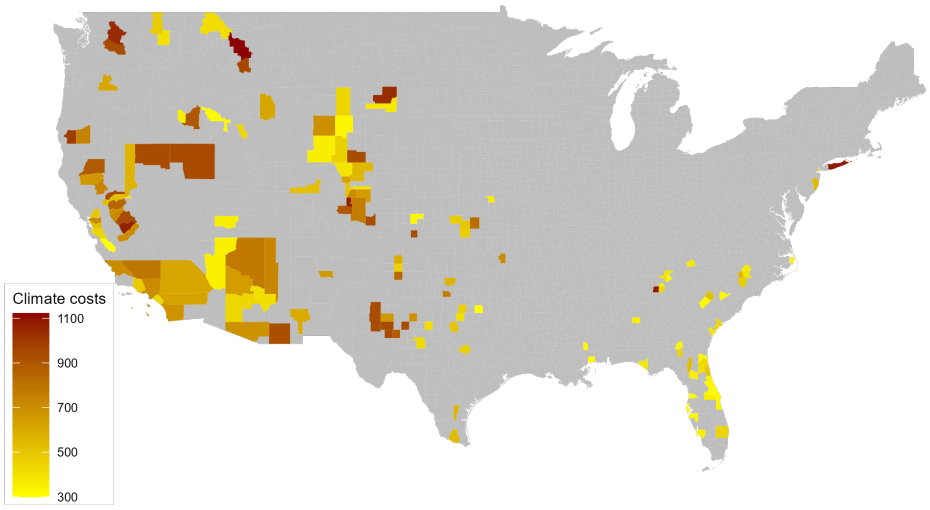


Figure 9: This figure shows the county average expected increase in annual homeowners insurance premiums by 2053 among zipcodes in the top 5% of the expected increase in disaster risk between 2023 and 2053. Costs are calculated using the 2023 coefficient on disaster risk from Figure 7.

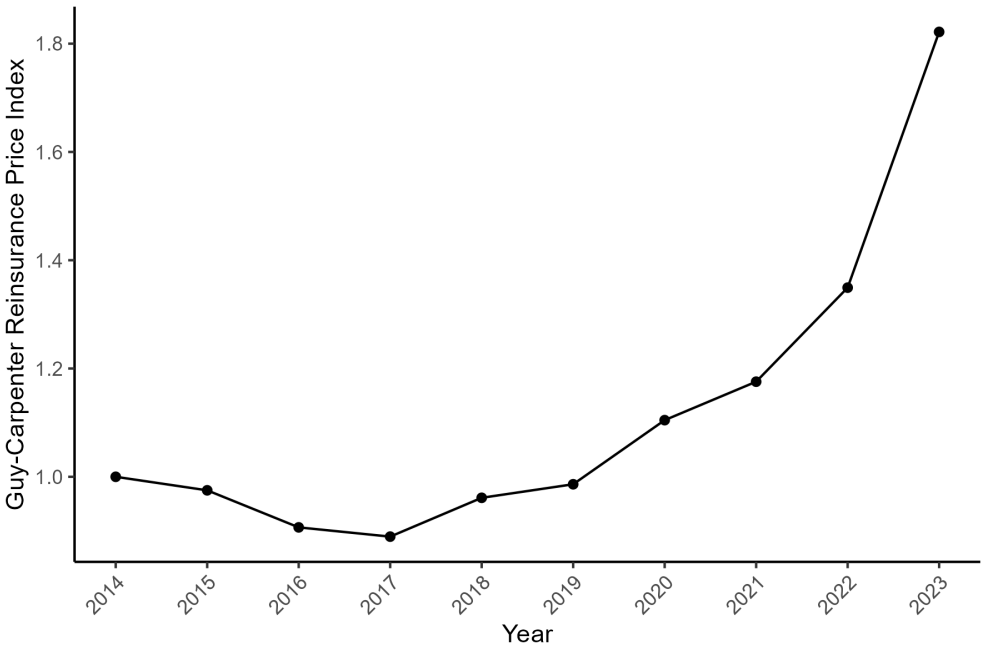


Figure 10: Time series of the Guy-Carpenter U.S. Property Catastrophe Rate-on-Line Index. See `https://www.artemis.bm/us-property-cat-rate-on-line-index/` for more information.

7 Reinsurance and the Cost of Disaster Risk

The previous section established that the real cost of homeowners insurance has grown between 2018 and 2023, especially in areas exposed to more climate risk. Furthermore, we show that the widening premium gap between high and low risk areas cannot be explained by statewide factors or relative structure value trends. Over this same period, catastrophe reinsurance markets hardened substantially, raising the possibility that some of this spending increase reflects insurers passing through reinsurance costs to homeowners (Eaglesham, 2024). Between 2019 and 2023 – the same period as the risk-to-premium pass-through rose – the price of reinsurance in the U.S. Property Catastrophe market increased by over 85% according to the Guy Carpenter Rate-On-Line Index, as shown in left panel of Figure 10. Even as their prices rose, reports indicate that reinsurers also restricted the quantity of coverage they were willing to write (Corbineau et al., 2023).

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. Second, the effect of reinsurance prices on premiums shows how the cost of global risk intermediation affects what homeowners pay to insure catastrophic risk. The hypothesis that rising reinsurance rates may be an important driver of the rising price of disaster risk is consistent with a long literature showing high mark-ups above expected losses for

reinsurance contracts and that reinsurance markets go through tightening cycles when capital is scarce. However, isolating the passthrough of rising reinsurance costs faces significant identification challenges.

To illustrate the different factors potentially driving insurance premium dynamics, consider the average actuarially fair homeowners insurance premium, $\overline{P}$, that would be observed in zipcode z at time t for contracts that pay replacement cost coverage C_{zt} on total losses that occur with probability p_{zt}. Insurers cede share R_t of their expected losses at a price $Z(R) = (1 + \alpha_t) * C * p$, where $\alpha_t > 0$ is a markup term, while bearing the other $(1 - R_t)$ share directly. We can write the reduced form formula for $\overline{P}_{zt}$:

$$\overline{P}_{zt} = R_{zt} * Z(R_t) + (1 - R_t)C_{zt} * p_{zt} = C_{zt} * p_{zt}(1 + \alpha_t * R_t) \tag{6}$$

$$\rightarrow ln(\overline{P}_{zt}) = ln(p_{zt}) + ln(C_{zt}) + ln(1 + \alpha_t * R_t). \tag{7}$$

Equation 7 shows that log premiums are a linear function of the probability of losses, replacement costs, and the markup paid by insurers to reinsure their risk. Although stylized, Equation 7 illustrates the challenges in disentangling the various factors driving homeowners insurance premium dynamics.[23] First, replacement values C_{zt} will change with housing market conditions and construction costs. Second, perceived loss probabilities p_{zt} may change as insurer modeling evolves. Finally, replacement costs and loss probabilities will also affect reinsurance prices $Z(R_t)$, making it difficult to disentangle changing reinsurance markups from changes in expected losses. In short, the reinsurance price trends in Figure 10 may be driven by the same factors driving higher premiums in general, rather than an increase in the markup on reinsurance.

We leverage the granularity of our data along with geographic variation in reinsurance exposure to identify the relative contributions of replacement costs, risk perceptions, and reinsurance markups in driving homeowners insurance premium trends. With our zipcode panel of premiums, we can estimate the time-varying effects of disaster risk while controlling for the evolution of structure values with the FHFA price index, much as in Equation 4. Nonetheless, given the simultaneity of risk, replacement costs, and reinsurance prices, we need plausibly exogenous variation in reinsurance exposure to identify changing reinsurance markups. To motivate our identification strategy, we note that reinsurance take-up in the P&C insurance industry is driven by demand for hedging correlated tail risks from catastrophic loss events such as hurricanes or wildfires. Furthermore,

[23] 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 7 is a simplified pricing formula capturing that insurers typically pay markups in financial markets to manage correlated risks.

because insurance companies are regulated at the state level, *within-state* correlated losses are the primary driver of earnings volatility and regulatory capital requirements. Motivated by these institutional features of the homeowners insurance market, we proxy for zipcode-level reinsurance exposure based on the within-state correlation of their historical catastrophic disaster losses.

To create our reinsurance exposure proxy, we classify zipcodes as "high", "low," or "minimally" cat-exposed according to their expected loss rates due to wildfires and hurricanes. Next, we measure how correlated their historical losses have been with overall losses in the same state. Although it is impossible to quantify the geographic correlation matrix of insured losses, we create a proxy for zipcode-level correlated risk using historical county-level disaster loss data from SHELDUS. For each county, we measure the correlation between its monthly per-capita disaster losses from 2000 to 2013 and the annual monthly per-capita losses in its state over the same period. Figure 11 maps the within-state loss correlation of each county with at least one high cat-exposed zipcode. These cat-exposed loss correlations, denoted $\widetilde{R}_z$, serve as our proxy for reinsurance exposure from Equation 7.

7.1 Predictors of Reinsurance Usage

We first test the ability of our reinsurance exposure proxy to predict reinsurance usage. To do so, we use NAIC filings data to create state-level measures of the share of premiums insurers operating in each state cede to unaffiliated reinsurers.[24] While premiums ceded are not strictly defined by geography in the NAIC data or in practice, we observe the dollar value of every insurer i's direct premiums written in each state s (d_{is}) and the share of their overall premiums ceded to unaffiliated reinsurers (c_i), i.e. reinsurance contracts purchased from other insurance companies that are not part of the same insurance group. We define each state's reinsurance take-up as:

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

or the market-share weighted average of the share of premiums ceded by each insurer in the state. We measure Re_s using the 2014 NAIC filings data.

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

$$Re_s = \beta_0 \overline{Risk}_s + \beta_1 \overline{HighCat}_s + \beta_2 \overline{HighCat}_s \times \overline{Corr}_s + \epsilon_s,$$

where $\overline{Risk}_s$, $\overline{HighCat}_s$, and $\overline{Corr}_s$ are the state-level average disaster risk, share of zipcodes with

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

	State Reinsurance Usage		
	(1)	(2)	(3)
Disaster Risk	0.083***	0.019	0.001
	(0.010)	(0.037)	(0.022)
High Cat		0.265*	-0.129*
		(0.151)	(0.073)
High Cat × Correlation			0.832***
			(0.148)
Observations	51	51	51
R^2	0.826	0.843	0.894

* 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. All variable averages and the regression specifications are weighted by the number of owner-occupied housing units in the 2010-2014 ACS data as measured across the estimation sample zipcodes. Robust standard errors in parenthesis.

high cat exposure, and average historical loss correlation among cat-exposed zipcodes. The results of this equation are shown in Table 5. In column (1), we only include the disaster risk variable, finding a positive and statistically significant relationship between average risk and reinsurance usage across states. In column (2), when we add the share of zipcodes with high cat risk exposure, the coefficient on disaster risk attenuates and becomes statistically insignificant while cat risk exposure, and not expected loss rates per se, predict reinsurance take-up. Finally, we include the full specification in column (3) where we find that reinsurance usage loads entirely on *correlated* cat risks, and not on cat risk or general disaster risk exposure. These findings support the hypothesis that the correlation of cat risks within states drive reliance on the reinsurance market.

7.2 Pass-through of Reinsurance costs to Insurance Premiums

With our proxies for disaster risk, replacement values, and reinsurance exposure, we specify our primary estimating equation:

$$ln(\overline{P}_{zt}) = \alpha_z + \alpha_t + \beta_0 ln(Structure_{zt}) + \beta_1^t Risk_z + \beta_2 ln(Z_{t-1}) * \widetilde{R}_z + \epsilon_{zt}, \tag{8}$$

where the dependent variable $ln(\overline{P}_{zt})$ is the log repeat-loan insurance premium index, and α_z and α_t are zipcode and half-year fixed effects, respectively, while $ln(Structure_{zt})$ are log structure values and $Risk_z$ are expected disaster risk loss rates with time-varying coefficients β_1^t. $ln(Z_{t-1})$ is the one year lagged log Guy Carpenter reinsurance rate-on-line price index, and $\widetilde{R}_z$ is our correlation

measure for cat-exposed zipcodes.

Mirroring the motivation from Equation 7, the estimates from Equation 8 empirically estimate the contributions of structure values, loss rates, and reinsurance prices to changing premiums. If changes in reinsurance prices were entirely driven by rising structure values and perceptions of disaster risk, then we would expect the coefficient on β_2 to be zero as the $ln(Structure_{zt})$ term and time-varying β_1^t coefficients on $Risk_z$ should be able to explain the premium variation across zipcodes regardless of reinsurance exposure. In contrast, if reinsurance markups increased, then we would expect a positive β_2 coefficient as premiums should rise more in reinsurance-exposed zipcodes relative to otherwise similar, less exposed zipcodes.

We maintain a parallel trends assumption to identify the β_2 parameter in Equation 8, specifically that, conditional on risk and replacement costs, premiums would have evolved similarly in more and less reinsurance exposed zipcodes absent changing reinsurance prices.[25] To test this assumption, we estimate an event-study style version of Equation 8, replacing the log reinsurance price interaction term on reinsurance exposure with time-varying coefficients. Supporting the parallel trends assumption, we see that the time-varying reinsurance exposure coefficients for high cat-exposed zipcodes, shown in Figure 11, follow the same pattern as the reinsurance price index from Figure 10. Notably, insurance premium trends in reinsurance-exposed zipcodes not only follow the rise in reinsurance prices after 2017, but also the decline between 2014 and 2017.

We next turn to the results of Equation 8, shown in column (1) of Table 6. We see positive and statistically significant coefficients on the interaction terms between correlated risks and log reinsurance prices for cat-exposed zipcodes. The coefficients imply that a 10% increase in reinsurance prices cause 4% and 2.5% premium increases in high cat-exposed and low cat-exposed zipcodes, respectively, for perfectly correlated losses.[26] Interpreting their economic significance, these estimates suggest that the rise in reinsurance costs between 2018 and 2023 contributed to $75 and $300 higher annual homeowners insurance premiums, on average, in low and high cat-exposed zipcodes, respectively. 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 loss rates and structure values, zipcodes exposed to more correlated risks saw higher premiums. Thus, these findings support the hypothesis that insurance markets started differentially charging a higher risk premium on correlated catastrophic losses.

[25] Notably, our assumption is not that the actual total costs of insuring risks remained similar across cat-exposed zipcodes with different loss correlations. Rather, reinsurers likely raised their prices precisely because they saw their historical rates as inadequate and faced growing pressure to attract capital. Supposing reinsurance prices remained flat is a partial equilibrium counterfactual, and if reinsurance prices had been exogenously fixed, it likely would have led to an even sharper decline in reinsurance capacity.

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

	Log Insurance Premium Expenditures Index			
	(1)	(2)	(3)	(4)
Log Reinsurance × Low Cat Correlation	0.252**	0.254***	0.140**	0.301***
	(0.098)	(0.098)	(0.068)	(0.089)
Log Reinsurance × High Cat Correlation	0.396***	0.427***	0.579***	0.244**
	(0.114)	(0.117)	(0.169)	(0.101)
R^2	0.877	0.879	0.857	0.894
N	176991	176991	164570	176991
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. Standard errors clustered by county in parenthesis.

We further explore the robustness of our findings across the rest of Table 6. First, we consider whether our findings might be contaminated by changing flood insurance premiums. Starting in 2017, flood insurance reform legislation strengthened regulations requiring homeowners with mandatory flood insurance policies to escrow their premiums. 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 is a market that has very large correlated risk exposure and has experienced a number of idiosyncratic market issues contributing to rising premiums. 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 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-period expected loss rate coefficients, so that every state can have a unique disaster risk coefficient in every half-year period. The results in column (4) continue to show positive and statistically significant coefficients on the reinsurance price interaction terms.

The average effect of the rise in reinsurance prices on premiums masks substantial heterogeneity. The more correlated a cat-exposed zipcode's losses are with its state-level losses, the larger the

implied "reinsurance shock" from our estimates. We map the average reinsurance shock among cat-exposed zipcode by county in Figure 12. 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.

7.3 House Price Capitalization of Reinsurance Shocks

The results above suggest that reinsurers demanded larger risk premiums to accept correlated cat risks between 2018 and 2023. The costs of this reinsurance shock were concentrated and can explain much of the rising passthrough of disaster risk into premiums that we document in Figure **??**. 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 into the market. If home buyers and sellers expect the reinsurance shock to fade, then we should expect to find minimal home price effects.

To test the home price capitalization of the reinsurance shock, we replace the dependent variable in Equation 8 with Zillow zipcode home prices and pooling the low and high cat-exposed zipcodes into a single interaction term. Table 7 shows these results, mirroring the specifications from Table 6. Our baseline specification in column (1) shows that a 10% increase in reinsurance prices reduces home prices by approximately $5,680 for a cat-exposed zipcode with perfectly correlated losses. The magnitudes and statistical significance of this effect remain consistent across our robustness tests in columns (2)-(4).

Our estimates imply that the rise in reinsurance prices between 2018 and 2023 reduced relative home values in cat-exposed zips by an average of $8,430. 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 prices decline by more than $21,000. Although average home prices in cat-exposed zipcodes nonetheless increased by over $150,000 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 implies a capitalization rate of approximately $50 in lower home prices for every $1 increase in premiums. This capitalization rate, consistent with a discount rate of about 2% on permanent cash flow, implies that housing market participants are treating the premium increases resulting from the reinsurance shock as relatively permanent. Thus, it would seem that there is some belief among

	Home prices ($1000s)			
	(1)	(2)	(3)	(4)
Log Reinsurance × Cat Correlation	-56.8**	-57.0**	-58.4**	-49.7***
	(23.011)	(22.841)	(28.165)	(17.574)
R^2	0.981	0.981	0.981	0.984
N	176994	176994	164573	176994
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. Standard errors clustered by county in parenthesis.

buyers and sellers that, rather than a temporary spike, the higher costs of correlated cat risks will be the new normal.

7.4 Reinsurance Shock Heterogeneity by Climate Change Exposure

Next, we turn to heterogeneity in the effects of the reinsurance shock focusing on exposure to increasing climate risks. 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. To investigate how insurers and homeowners may respond differently to the reinsurance shock in areas where risk is expected to grow in the coming decade, we expand Equation 8 to include an additional triple interaction term between log reinsurance prices, an indicator for low or high cat-risk exposure, 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 general premium changes in climate-exposed areas over this period.

First, we test heterogeneity in the effect of the reinsurance shock on premiums, shown in Table 8. Mirroring the four specifications from Table 6, the base interaction term between log reinsurance prices is generally positive and statistically significant, indicating that the reinsurance shock raises premiums even where expected risk increases are relatively modest. However, the triple interaction term shows that the largest premium increases are observed where risk is expected to increase the most. Taking the coefficients in column (1), moving from the bottom to top quartile of $\Delta Risk$ in the average cat-exposed zipcode increases premiums by an additional 10 percentage points.

	Log Insurance Price Index			
	(1)	(2)	(3)	(4)
Log Re × Cat Risk Corr	0.172*	0.180**	0.0343	0.222**
	(0.092)	(0.092)	(0.075)	(0.088)
Log Re × Cat Risk Corr × $\Delta Risk$	0.301***	0.291***	0.295***	0.111
	(0.093)	(0.093)	(0.088)	(0.098)
Time-Varying Flood Controls	N	Y	Y	Y
Drop Florida	N	N	Y	N
State-by-Time Risk Controls	N	N	N	Y
R^2	0.877	0.877	0.854	0.894
N	176991	176991	164570	176991

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

Table 8: Climate Heterogeneity, Insurance Premium Effects.

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). We also note that when we control for state-specific risk trends in column (4) of Table 8, the triple interaction coefficient on $\Delta Risk$ is attenuated and no longer statistically significant, although still positive. Thus, this climate heterogeneity may reflect at least in part a broader repricing of risk in climate-exposed states.

Next, we turn to the heterogeneity of home price capitalization with respect to expected climate change. The results in Table 9 demonstrate that the reduction in home values from the reinsurance shock is concentrated where disaster risk is expected to increase. Comparing the magnitude of the increases in premiums implied by our estimates in column (1) of Table 8 with the home price changes in column (1) of Table 9, a one dollar increase in premiums causes a $29 reduction in home prices among cat-exposed zipcodes in the bottom quartile of $\Delta Risk$ versus a $107 decrease in home prices for those in the top quartile of $\Delta Risk$. Thus, our climate heterogeneity results suggest that exposure to increasing climate risk is also associated with a stronger capitalization of insurance premiums into home prices.

Notably, our results are consistent with findings in Ge et al. (2022), who find that the capital-

	Home Prices ($1000s)			
	(1)	(2)	(3)	(4)
Log Reinsurance × Corr	-10.27	-10.84	1.411	-22.06
	(17.959)	(17.800)	(16.791)	(20.143)
Log Reinsurance × Corr × $\Delta Risk$	-113.5***	-112.8***	-138.1***	-47.99
	(32.320)	(32.586)	(32.821)	(38.530)
Time-Varying Flood Controls	N	Y	Y	Y
Drop Florida	N	N	Y	N
State-by-Time Risk Controls	N	N	N	Y
R^2	0.981	0.981	0.982	0.984
N	176994	176994	164573	176994

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

Table 9: Climate Heterogeneity, Home Price Effects.

ization of flood insurance premiums into home prices is stronger in areas exposed to future sea level rise risk. The reinsurance shock may play a similar information role in this setting, making homeowners more aware of the possibility that their risk and premiums will continue to rise. We further note that, as in Table 8, the inclusion of state-by-time risk controls attenuates the triple interaction term so that it is no longer statistically significant. Thus, the home price effect heterogeneity we find may again be part of a broader repricing in states where risk is increasing.

8 Conclusion and Directions for Future Research

Property insurance serves as the front line of defense against climate risk for homeowners 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.

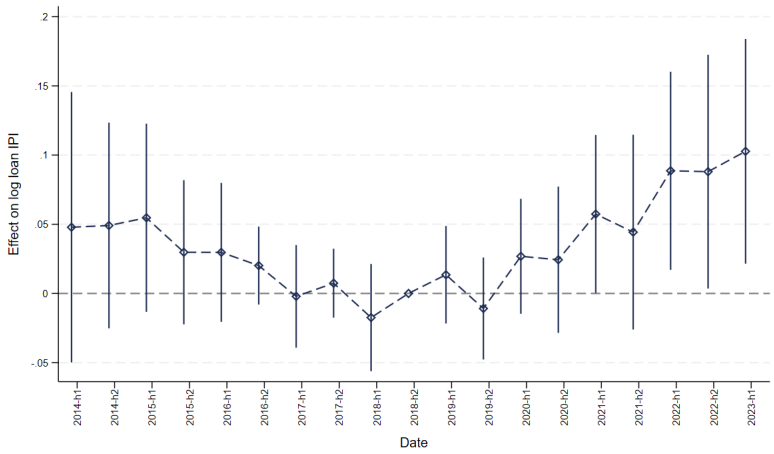
In this paper, we bring a new data source to bear on these critical questions. Using data from mortgage escrow payments, we infer insurance expenditures and show that this method produces expenditure estimates that are consistent with other publicly available sources. While the approach has limitations, the sample size and level of detail allow for unprecedented insight into homeowners insurance markets.

We find that premiums have risen sharply since 2020, that this growth has been concentrated in disaster-prone zipcodes, and that elevated reinsurance costs are a critical driver of the increase. We provide new estimates of the elasticity of premiums with respect to climate risk, and show that

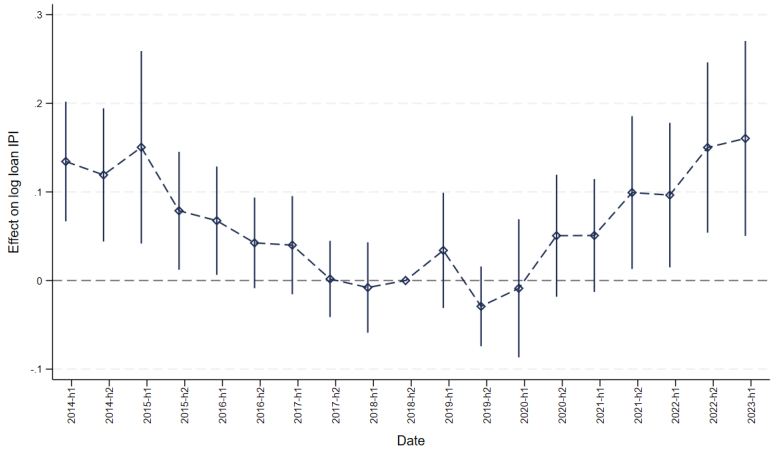
the pass-through of risk to premiums increased more than 60% between 2018 and 2023. Our results also benchmark potential increases in premiums that climate-exposed homeowners will face due to increasing risk. By 2053, we estimate that climate-exposed homeowners will be paying $600 higher annual premiums on average due to increasing wildfire and hurricane risk.

We also provide a new estimate of the pass-through of reinsurance costs to insurance premiums in markets exposed to catastrophic disasters, finding that the increase in reinsurance prices can explain much of the increase in the relationship between premiums and risk. The reinsurance shock added $300 to the 2023 annual homeowners insurance premiums of households in the top decile of exposure to hurricanes and wildfires. These premium increases capitalized into home values, reducing prices by an average of $8,430 in cat-exposed zipcodes. The effects of the reinsurance shock on both insurance premiums and home values are larger in zipcodes that are exposed to increasing risk. These findings highlight that the impacts of climate change on insurance markets and household budgets will depend on the costs of insuring correlated catastrophic risks.

Finally, we establish that the increased insurance costs stemming from the reinsurance shock are capitalized into house prices. These real asset valuation consequences of insurance markets will ultimately affect mobility and housing tenure choice, as well as heightened risk of mortgage default in the face of asset value declines. 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.



(a) Low Cat-Risk Exposure



(b) High Cat-Risk Exposure

Figure 11: Plots time-varying coefficients for the effects of the interaction between loss correlation and indicators for low cat-risk exposure (top panel) and high cat-risk exposure (bottom panel) 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-semester FEs and log structure values with standard errors clustered by county.

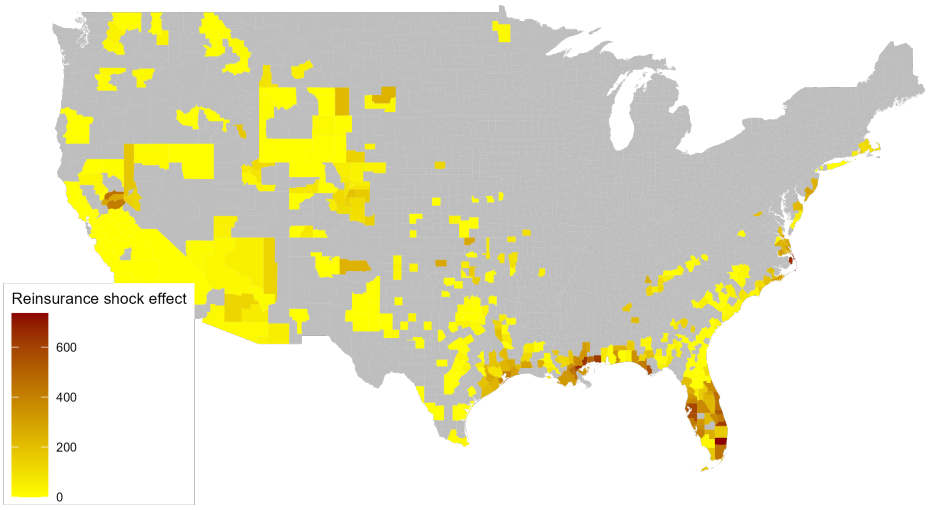


Figure 12: This figure plots the estimated average effect of the rise in reinsurance prices between 2018 and 2023 on annual homeowners insurance premiums for cat-exposed zipcodes by county.

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9 Appendix

9.1 Appendix Figures and Tables

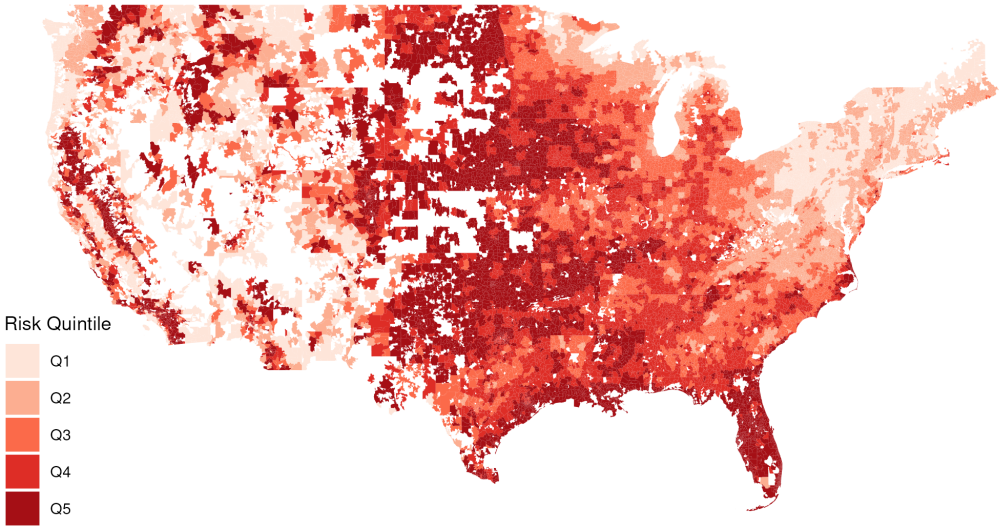


Figure 13: Map of US zipcodes by risk measure quintile

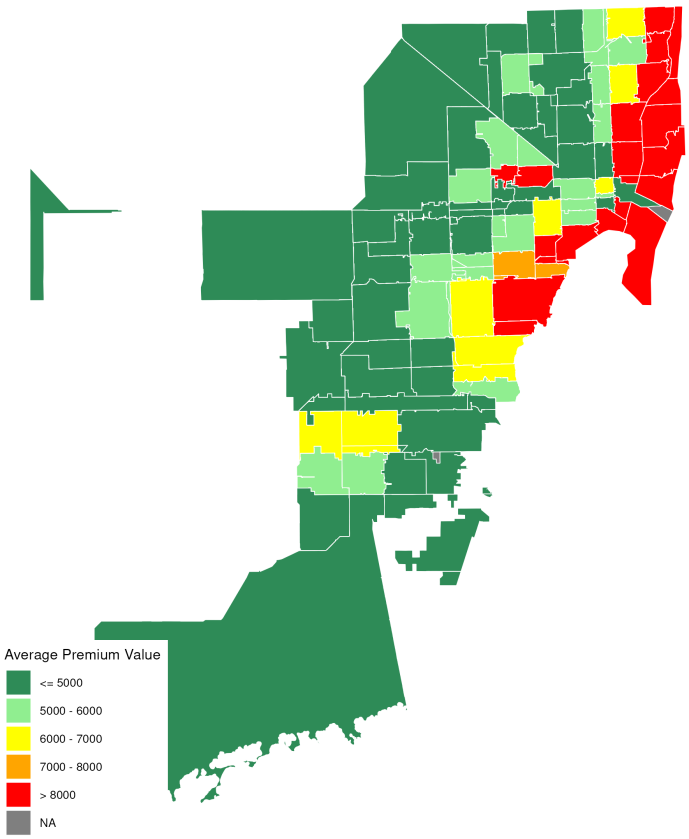


Figure 14: Shows average annual homeowners insurance premiums by zipcode in Miami-Dade County in the first half of 2023.

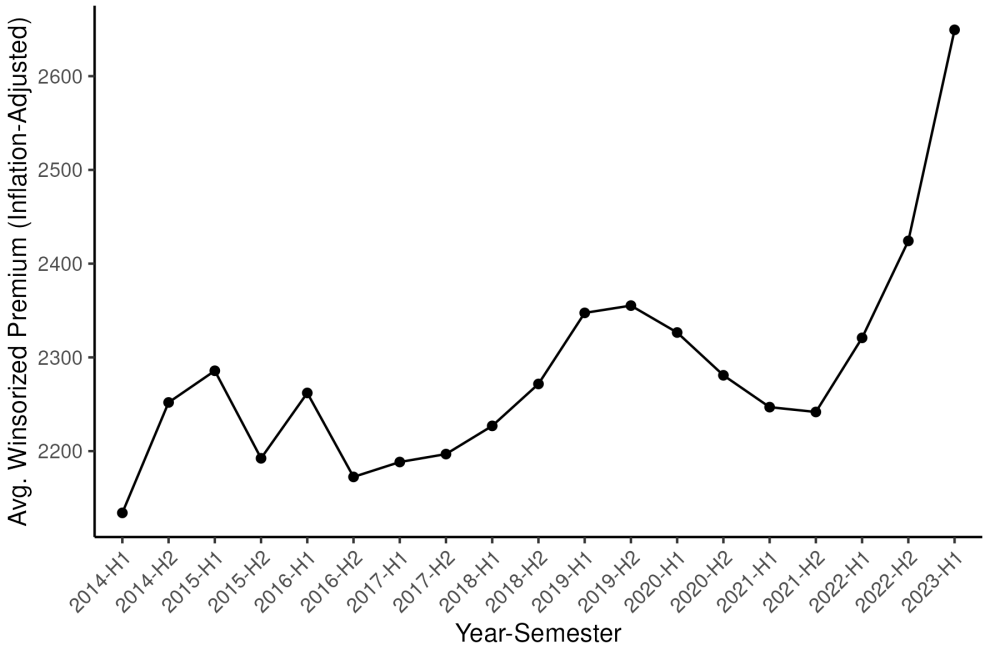


Figure 15: Time series of average annual homeowners insurance premiums. Values are inflated to constant 2023 dollars.

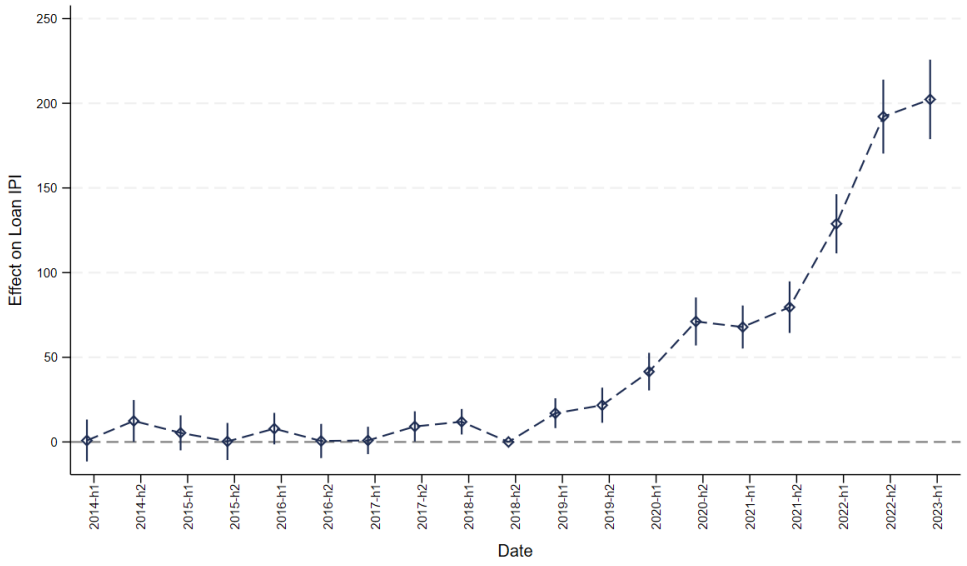


Figure 16: Plots the time-varying estimated effect of disaster risk on premiums. Dependent variable is the repeat-loan insurance premium expenditures index.

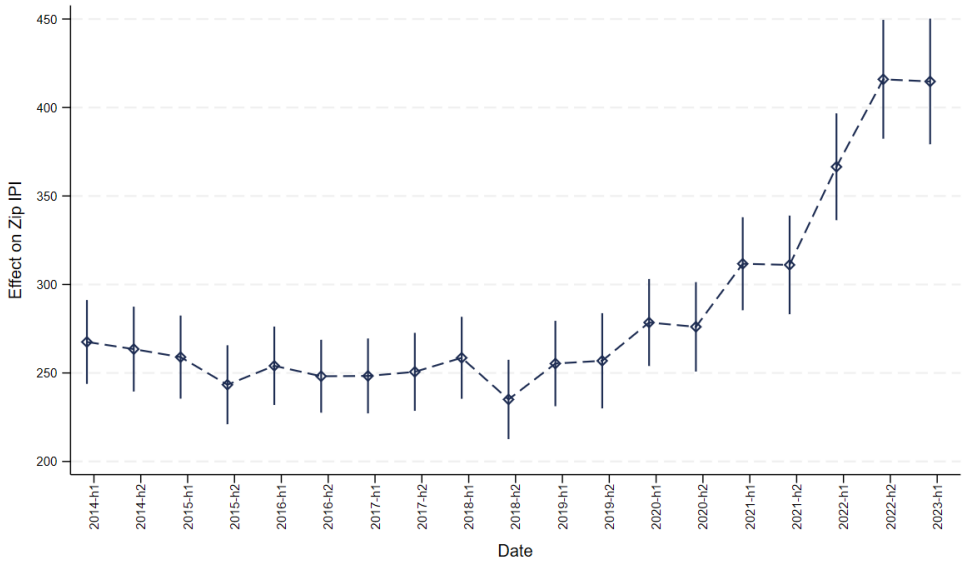


Figure 17: Plots the time-varying estimated effect of disaster risk on premiums. Controls for time-varying flood risk coefficients.

9.2 Comparison to III, Census, and Quadrant

Figure 18 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.[27] 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.

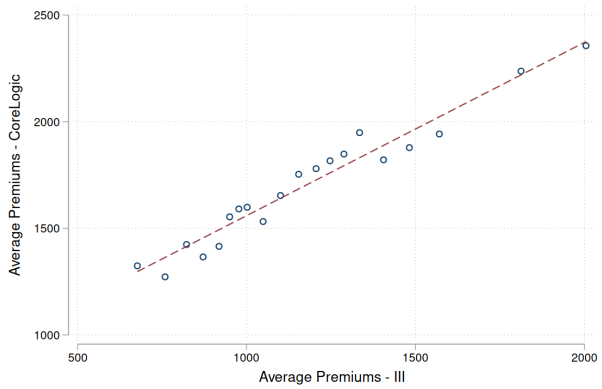
We see a similarly strong linear relationship between the escrow premium estimates and surveyed homeowners insurance premiums for the ACS and a similar upward level shift in the escrow estimates. However, the gap between escrow and ACS premiums is larger at the top-end of the premium distribution. We 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. 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.

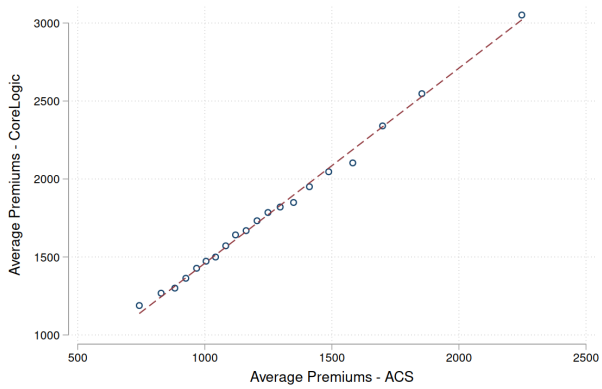
We believe this pattern plausibly reflects the shopping behavior of households, their downward sloping demand for insurance, and unobserved coverage denials by insurers. Where Quadrant sees some insurers setting the highest premiums, homeowners are most likely to shop and find the lowest premium available 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.

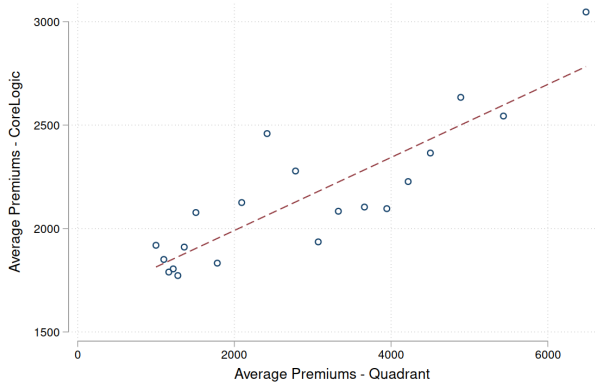
[27] III premium tables are provided here: `https://www.iii.org/table-archive/21407`.



(a) III



(b) ACS



(c) Quadrant

Figure 18: 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.