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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 using over 74 million premiums from 2014–2024 inferred from mortgage escrow payments. We document rapidly rising premiums and a doubling of the pass-through from disaster risk into premiums. Using variation in correlated wildfire and hurricane exposure, we show that the increase in the risk-to-premium gradient was accelerated by a repricing of catastrophic risk in global capital markets. Premium increases are capitalized into home values, reducing home price growth by over $40,000 in the most exposed zipcodes. The premium and home price effects are larger in areas facing rising climate risk.

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1 Introduction

The impact of changing disaster risk on real estate markets depends on the prices set by insurance markets. Lenders universally require homeowners insurance policies with mortgage loans, and homeowners rely on property insurance payouts in the wake of disasters. For buyers, sellers, and lenders, homeowners insurance premiums are a leading price signal of changing climate-related physical risks.

Despite the importance of homeowners insurance, existing public data on premiums are coarse and out-of-date. As a result, it has been difficult to understand the causes and consequences of ongoing premium increases, even as policymakers point to rising insurance market distress as a pivotal issue for households and financial institutions.[1] Industry reports have variously attributed the recent rise in premiums to cost inflation, reluctance by global investors to enter wildfire and hurricane exposed markets, and a repricing of disaster risk by insurers in response to growing loss trends (Eaglesham, 2024; Pande, 2023; Insurance Information Institute, 2024b). Disentangling the contributions of these various factors to premiums is crucial for understanding how climate risk is reflected in insurance pricing, and how premiums impact housing markets more broadly.

In this paper, we introduce a new measure of homeowners insurance premiums based on mortgage escrow data and provide evidence on the factors underlying their recent growth. Most mortgage borrowers make a single monthly payment into an escrow account that disburses funds toward mortgage principal, interest, local property taxes, and insurance (a.k.a. PITI). Loan-level mortgage servicing data allow us to decompose the escrow payment into these four distinct elements to construct a new dataset of insurance premiums. The dataset yields over 74 million observations from 2014 to 2024. We create a zipcode-level insurance premium expenditure index (IPI) in the style of a home price "repeat sales index" following changing premiums on the same loan over time, holding time-invariant characteristics of the home and policyholder fixed. These data provide geographically granular information on homeowners insurance premiums that can be recreated using datasets that are already regularly used in research on housing and mortgage markets. Our premium estimates are strongly correlated with comparable public data on zipcode premiums released by the U.S. Treasury's Federal Insurance Office and show similar estimates of mean premiums (Appendix Section A.2.

With this new dataset in hand, we analyze the causes and consequences of recent insurance market trends in three parts. First, we characterize the cost of homeowners insurance. We find that average nominal annual premiums increased from $1,690 in 2017 to $2,750 in 2024, a 28%

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

inflation-adjusted increase. We use our geographic granularity to provide the first estimates of the relationships between premiums, disaster risk, demographics, and structure costs at the zipcode level. We find that housing structure values and disaster risk explain most of the variation in insurance premiums, but we also document large heterogeneity in premiums across incomes and socioeconomic status.

Second, we examine the role of building costs, disaster risk, and reinsurance costs in driving recent insurance market dynamics. While we find that the increase in construction costs can explain 35% of the rise in homeowners insurance premiums after 2017, we further show that the largest increases were concentrated among zipcodes with the highest disaster risk. These effects cannot be explained by differences in construction cost inflation or state-specific factors. Rather, our estimates show that the association between a one standard deviation increase in disaster risk and premiums rose from \$220 in 2017 to \$615 by 2024. This increase in the cost of disaster risk explains 20% of the growth in premiums between 2017 and 2024.

Why did the risk-to-premium gradient increase so sharply in recent years? Primary insurers' cost of covering disaster risk depends on the prices of reinsurance contracts and catastrophe bonds ("cat bonds") in secondary markets. Reinsurance refers to secondary contracts through which U.S. insurers transfer portions of severe correlated risks, such as hurricanes and wildfires. In the closely related cat bond market, insurance-linked securities pay out based on disaster loss triggers.

Rising homeowners insurance premiums coincided with a doubling of U.S. property catastrophe reinsurance prices and catastrophe bond rates between 2018 and 2024 (Guy Carpenter, 2024; Artemis, 2025). On the one hand, the rise in reinsurance prices is potentially caused by many of the same forces pushing up homeowners insurance premiums, such as rising construction costs and a sequence of severe disaster losses. On the other hand, the price of catastrophic risk is uniquely relevant for understanding how insurance markets are repricing the most climate-exposed perils. The global investors who invest in reinsurers and catastrophe bonds have the deepest expertise in catastrophe and climate modeling across the insurance sector and should be especially sensitive to changing loss trends (Gallagher Re, 2024; Swiss Re, 2024).

We use our data to test whether rising reinsurance prices reflect higher costs of covering catastrophic hurricane and wildfire risks. To capture a market's exposure to capital market shocks, we create a zipcode level measure of "catastrophe exposure" based on the intensity of hurricane and wildfire exposure plus the correlation of historical losses. When extreme losses are highly correlated, insurers demand more capital to spread catastrophe risk globally. Our specifications include controls for zipcode-level disaster risk with time-varying coefficients to reflect the changing pricing of disaster risk and structure values to absorb the effects of increasing construction costs. We estimate the reinsurance price elasticity of premiums as the coefficient on the interaction between catastrophe exposure and annual reinsurance prices.

Our identification strategy compares changes in premiums across areas with similar expected losses but different levels of catastrophe exposure. In an event-study style estimation, we show that the dynamic premium markup on catastrophic risk closely follows the time series of reinsurance and catastrophe bond prices. Furthermore, our findings are robust to adding controls for flood risk to absorb any escrowed flood insurance premiums, allowing the coefficients on zipcode disaster risk to vary by state to reflect different regulatory environments and recent disasters, excluding Florida from our analysis, using an alternative portfolio-weighted measure of correlated losses, and replacing reinsurance prices with cat bond markups as a price proxy.

We find that premiums increased disproportionately in the zipcodes with the most catastrophe exposure, suggesting that the rise in reinsurance prices reflects higher costs of insuring catastrophic risk above and beyond the pricing of expected losses. This "reinsurance shock" increased 2024 annual premiums by $425 and explains 45% of the increase in the pass-through of disaster risk among zipcodes in the top decile of catastrophe exposure. We find that the reinsurance shock affected not only the cost of insurance, but also its availability, as it led insurers to cancel policies in the most catastrophe-exposed counties. This exercise shows that the cost of homeowners insurance in the United States is sensitive to the cost of hedging catastrophic risk in global capital markets.

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

To study home price impacts, we adopt a similar specification to that for premiums, controlling for changing amenity values that are correlated with disaster risk and construction cost shocks. We find that the premium increases induced by the reinsurance shock reduced 2024 home values by an average of nearly $44,000 among zipcodes in the top decile of catastrophe exposure. Relative to the increase in premiums, our estimated home price effects imply a relatively low discount rate of 1%, and well within the range of full capitalization. Our findings suggest that homeowners expect to continue paying higher costs to insure catastrophic risk.

In the fourth and final step of our analysis, we test whether the rising price of catastrophic risk is driven by changing beliefs about the frequency and severity of hurricanes and wildfires. We modify our reinsurance shock estimating equation to include a triple interaction term between reinsurance prices, catastrophe exposure, and each zipcode's expected change in wildfire and hurricane risk between 2023 and 2053 according to the First Street Foundation models. Given that insurance and reinsurance contracts are written on a short term basis, expectations of future risk should not necessarily affect premiums today. However, the string of severe wildfires and hurricanes over the past two decades has raised considerable uncertainty about the extent to which catastrophic risk is already increasing.

We find that premiums are most sensitive to rising reinsurance prices in zipcodes where catastrophic risk is expected to increase, suggesting that global investors are already starting to reprice disaster risk. We find that the home price effects of the reinsurance shock also scale with future risk, consistent with homeowners viewing rising premiums as a signal of future disaster risk. Our estimates show that rising premiums have resulted in a major repricing of climate-exposed housing assets, causing a relative home price decline of 11% among zipcodes that are highly exposed to increasing risk and in the top decile of catastrophe exposure.

Taken together, our approach delivers novel insights 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 capital markets to primary homeowners insurance premiums and ultimately into house prices, and shows how insurance markets more broadly are driving the repricing of disaster risk into home values and homeowners' premiums.

Our findings yield new insights into private insurance market pricing and its relationship with the cost of capital in secondary reinsurance markets and among insurance-linked securities. 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; Bauer et al., 2023). In life insurance markets, researchers have found that frictional costs from firms' liquidity constraints or regulatory requirements pass-through to premiums with meaningful effects on consumer welfare (Koijen and Yogo, 2015, 2016; Bauer et al., 2021; Ge, 2022). Eastman and Kim (2023) estimate the pass-through of capital requirements to homeowners insurance premiums, while Damast et al. (2025) show how capital market frictions in property and casualty markets interact with monetary policy. We establish that financial frictions transmitted through the reinsurance market have a substantial impact on homeowners insurance costs. Most relevant to the reinsurance shock we study, many researchers have examined the forces that drive "underwriting cycles" of increasing and decreasing premiums.[2] Our evidence of home price capitalization indicates that, unlike in previous reinsurance cycles, buyers and sellers appear to be pricing in continuing premium increases.

Our analysis expands connections between climate finance and insurance. Studying the public

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

National Flood Insurance Program, one 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). Several recent papers use closely related, newly available data on escrowed homeowners insurance policies. Blonz et al. (2024) show that a policyholder's credit history can be as important as their disaster risk in setting insurance premiums, Ge et al. (2025) estimate the effect of rising insurance costs on mortgage performance, and Sastry et al. (2025) show that rising insurance premiums drive down coverage limit take-up, especially for credit-constrained households. Our research expands the data available to researchers to study homeowners insurance and advances our understanding of how and why prices are changing in this market.

By providing new estimates of how much homeowners are paying for insurance, our paper extends climate finance research around housing and mortgage markets. Previous studies have shown how mortgage markets can act as risk-sharing tools, while also creating adverse selection and moral hazard given unpriced climate risk (Hurst et al., 2016; Panjwani, 2022; Issler et al., 2024).[3] 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 (Sastry, 2021; Sastry et al., 2023; Blickle and Santos, 2022; Kousky et al., 2020). A growing literature has established connections between asset values and climate risk in the housing market, with important heterogeneity around realized declines and climate beliefs.[4] We show that rising insurance premiums, driven by changing reinsurance prices that reflect increasing catastrophic risk, are being capitalized into house prices, and may further reduce demand for properties exposed to increasing disaster risk (Poterba, 1984).[5]

Finally, our paper sheds new light on the price signals reaching climate-exposed homeowners through insurance markets. 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).[6] Focusing more specifically on pricing by primary insurers, Oh et al. (2022) find that insurers face substantial

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

[4]See, for instance, Bernstein et al. (2019); Bakkensen and Barrage (2021); Baldauf et al. (2020); Murfin and Spiegel (2020); Keys and Mulder (2020); Gourevitch et al. (2023). For a recent survey of this literature, see Contat et al. (2024).

[5]Nyce et al. (2015) and Eastman et al. (2024) study premiums and home prices in Florida, Kim et al. (2025) studies the effects of premiums on commercial property rents, and Georgic and Klaiber (2022) and Ge et al. (2022) estimate the capitalization of flood insurance premiums on house prices both directly and as signals of increasing climate risk.

[6]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.

rate-setting frictions due to state regulation, leading to spatial cross-subsidization. Boomhower et al. (2024) use rate filing data to show that insurers price wildfire risk in California depending on the sophistication of their risk models, which can induce cream skimming effects. Our findings illustrate the important interactions between primary and secondary markets that influence how insurers price risk.

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 $173 billion in gross premiums for homeowners insurance products in 2024 (A.M. Best, 2025). Data from the American Housing Survey suggest that 94% of all homeowners have homeowners insurance (Jeziorski and Ramnath, 2021). The McCarran-Ferguson Act of 1945 codified the regulatory framework for insurers, which leaves regulatory oversight as a responsibility of individual states. In 2010, as part of the Dodd-Frank Act, a Federal Insurance Office (FIO) was created within the U.S. Treasury Department, but the regulatory purview of this office is thus far limited.

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. 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 to limit their downside risk and smooth the path of cash flows (Froot et al., 1995; Cummins et al., 2021). 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. Increasingly, insurance-linked securities like catastrophe bonds ("cat bonds") play an important role in spreading disaster risks in global capital markets (Braun, 2016). In 2022, P&C insurers ceded roughly $19 billion in premiums to reinsurers (Insurance Information Institute, 2024a).

Obtaining property insurance is generally a prerequisite to qualify for a mortgage. Fannie Mae and Freddie Mac require homeowners insurance to cover the lesser of the property's replacement cost or the unpaid loan balance, provided the policy covers at least 80% of replacement cost. For monitoring purposes, mortgage servicers 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 (or remember to make) annual or bi-annual lump-sum payments, but instead smooth the costs across their twelve monthly payments. The manager of the escrow account, usually the mortgage servicer, ensures that tax and insurance payments are made on time.

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

3 Data

3.1 Loan-Level Data

Our data on mortgage escrow accounts come from CoreLogic, a leading property information and analytics provider. CoreLogic's Loan-Level Mortgage Analytics (LLMA) dataset follows residential loans from origination to termination using data provided by loan servicers. The data contain 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.[7] The data include the zipcode of the property, as well as loan type (e.g. purchase vs. refinance) and property and borrower characteristics.

3.2 Disaster Risk Data

Our primary measure of disaster risk comes from a combination of the National Risk Index (NRI) and the First Street Foundation (FSF), both measured as of their 2023 estimates. The NRI was designed by FEMA to communicate the extent of risk from 18 different physical hazards.[8] The FSF is a private climate risk provider that creates highly localized risk models for wildfire, wind, flood, and heat risk (First Street Foundation, 2020).

To measure zipcode disaster risk, we combine the expected annual loss (EAL) rates per dollar of building value across different hazards typically covered by HO-3 homeowners policies (i.e. excluding earthquake and flood). We use FSF's zipcode-level models to measure EAL rates for wildfire and hurricane hazards. We add in EAL rates for cold waves, hail, heat waves, ice storms, lightning, strong winds, tornadoes, volcanic activity, and winter weather from the NRI.[9] 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 disaster risk measure.

In the main specifications we use constant 2023 risk measures, while in additional analyses around expectations of future risk, we use forecasts of risk in 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. This measure of climate risk assumes that the other hazards in the NRI will remain constant. Although 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, other hazards such as severe convective storms may also see climate impacts. Thus, our projections of future risk are likely conservative.

In addition to creating separate measures of disaster and climate risk, there are several other benefits to using the FSF hurricane and wildfire models. First, because the NRI is largely based on

[7] Note that these fields represent the scheduled amounts due rather than actual payments made, making it straightforward to consistently infer premiums even when borrowers fall behind or make advance payments.

[8] See Appendix Figure A2, `https://hazards.fema.gov/nri/learn-more`.

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

historical losses, it is an intentionally "backward-looking" measure of current risk.[10] In contrast, the FSF 2023 models account for recent changes in climate and land use that are particularly important to accurately assess current wildfire and hurricane risks. Second, the NRI hurricane measure does not distinguish wind-related damages, which are typically covered by HO-3 policies, and flood-related damages that would be covered by separate policies. The FSF hurricane model, on the other hand, only includes wind-related damages.

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

3.3 Housing, Insurance Coverage, and Socioeconomic Data

Given that we cannot directly observe coverage limits in our loan-level data, we turn to two complimentary data sources that track changing structure values and insurance coverage limits over time. As our primary measure, we use zipcode-level panel estimates of annual land and structure values of single family housing from the Federal Housing Finance Administration (FHFA). In an updated methodology from Davis et al. (2021), the dataset uses appraisal data between 2012–2022 to build a panel dataset of the share of home values attributable to land.[11] We apply these land shares to Zillow home prices to construct an annual zipcode-level measure of average structure values with a one-year lag to represent the delay between changing housing costs and when homeowners update their coverage limits at policy renewal.[12] 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.

As homeowners with mortgages are subject to minimum coverage requirements and that most homeowners insurance policies automatically adjust coverage limits for building cost inflation at renewal, we should expect changes in replacement costs to closely track changes in coverage limits. However, one may be concerned that these structure value measures are noisy proxies for actual coverage limits, and thus understate the role of cost inflation in driving recent premium increases.

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

[11] 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`.

[12] We apply the 2022 land share (the most recent year calculated by the FHFA) to 2023 house prices to calculate lagged structure values for 2024.

To address these concerns, we supplement our FHFA data with the quoted "coverage A" limits (i.e., primary structure coverage) from over 180 million homeowners insurance policy quotes requested from an online insurance broker between January 2019 and September 2024. Each quote shows the insurer's suggested coverage limit based on their estimate of the quoted home's replacement cost. These quoted coverage limits are based on local measures of construction cost inflation, so they should closely track replacement costs over this period. We measure annual average quoted coverage limits for zipcodes where we observe at least 20 requests in each year, yielding a balanced panel of 8,574 zipcodes with average coverage limit data between 2019 and 2024, or 73% of the estimation sample over that period weighted by housing units.

We use the coverage quotes data to validate our use of the FHFA structure value for our replacement cost proxy across the full sample. First, we show that our lagged structure value measures are strong predictors of average quoted coverage limits. The two measures have a correlation coefficient of 0.81 and display a strong linear relationship (Appendix Figure A1). Second, as discussed in more detail below, we replicate all of our main results substituting the structure value controls for quoted coverage A limit controls where available. These findings show that the publicly available FHFA structure value data is an accurate replacement cost proxy for researchers working with premium data but without coverage details.

We further supplement this housing and coverage 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 measure home price trends with Zillow's single-family Home Value Index estimates at the zipcode level.

3.4 Insurance and Reinsurance Data

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

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

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 Principal + Interest + Property Taxes + Insurance. For loans without mortgage insurance (MI), the decomposition is a simple one:

$$Insurance = TotalPayment - Principal - Interest - Taxes$$

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:

$$Insurance = TotalPayment - Principal - Interest - Taxes - MI$$

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.

Table 1 describes the process by which we reach our analysis sample from the raw data. Our data come from over 40 million purchase and refinance fixed-rate loans for single-family homes that were active between 2014 and 2024. We restrict the sample to loan-level records where total payments, principal+interest, and property tax data are all populated. We then focus on observations where the total payment changes (usually once per year). Next, we modestly restrict our sample by removing outliers and winsorizing premium values at the 1st and 99th percentiles by state-year. Finally, we impute MI premiums and remove a subset of loans with insufficient information to impute MI, or implausible values of imputed MI payments. Collapsing our data to year yields 76

	Mortgage Payments	Loans
All	1,228,319,520	40,775,634
Non-Missing LTVs	1,222,327,612	40,532,558
TP, P&I, Tax > 0	914,433,328	32,295,539
Drop repeated tot. pay rows	143,659,124	32,295,539
Owner Occupied	133,496,010	29,895,521
TP ≠ P&I	129,609,168	27,379,263
Premium > 0	123,187,088	25,494,590
Relative Premium < 5	118,536,880	25,330,444
Winsorized Premium > 10	117,986,480	25,255,804
Collapse to year	91,552,624	25,255,804
PMI Adjustments	76,326,070	21,433,354

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

million observations building off of over 21 million mortgagor escrow accounts.

Appendix Table A1 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.

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

$$Premium_{izt} = \alpha_{zt} + \lambda_i + \epsilon_{izt}. \tag{1}$$

where $Premium$ is the inferred premium of loan i in zipcode z in year t. In the spirit of a home price repeat-sale index, the repeat-loan index in Equation 1 includes loan fixed effects λ_i and only identifies changes in the IPI from changes in premiums for the same loan observed across multiple periods. Thus, this index holds fixed all time-invariant characteristics of the underlying property, borrower, and location. The coefficient of interest is α_{zt}, or the zipcode-by-time fixed effects. The estimated coefficients $\widehat{\alpha_{zt}}$ are recovered to construct the IPI.

Our estimation sample is constructed as the balanced panel of zipcodes where we observe at least 20 insurance premiums in each year between 2014–2024. This criteria results in a sample of

Statistic	Mean	St. Dev.	10th Pct.	90th Pct.
Premium Expenditure	2,712.98	2,213.90	862.79	5,131.79
Purchase Price	355,181	251,305	133,861	640,023
Premium as % of Price	0.96	0.76	0.25	1.98
Premium as Pctg. of P&I	21.08	17.36	05.56	42.59
FICO Score	732	62	647	801

Table 2: Summary statistics from the cross-section of 6,783,322 premium estimates in 2024. Home prices are winsorized at $5 million.

16,072 zipcodes representing over 74 million premium observations.[13]

5 Homeowners Premiums Across Time and Geography

Table 2 presents summary statistics from our sample of premiums paid in 2024. The mean homeowner in our sample pays $2,710 per year, with a wide amount of variation: The 90th percentile premium is over $5,000, and the 10th percentile less than $900. 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 insurance expenditures are in some cases a large portion of the monthly outlays towards housing services.

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

Figure 2 shows the granular richness of the escrow data by contrasting county-level (left panel) and zipcode-level (right panel) premiums in Southern California. Although the geography of premiums appears smooth at the county level, there are clear pockets of high premium zipcodes when viewed with more granularity.[14]

In the appendix, we offer further descriptive evidence of the two main drivers of higher insurance expenditures across places: the structure value of homes and disaster risk. Appendix Figure A4 plots the average 2023 zipcode premium by quantiles of FHFA structure values and standardized disaster risk. Both show a strong, linearly increasing relationship with premiums, but have different

[13]See Appendix Section A.2, which validates our premium estimates against public zipcode premiums data released by the U.S. Treasury Federal Insurance Office.

[14]Appendix Figure A3 shows significant heterogeneity in premiums within Miami-Dade County, with much higher costs along the coast relative to inland.

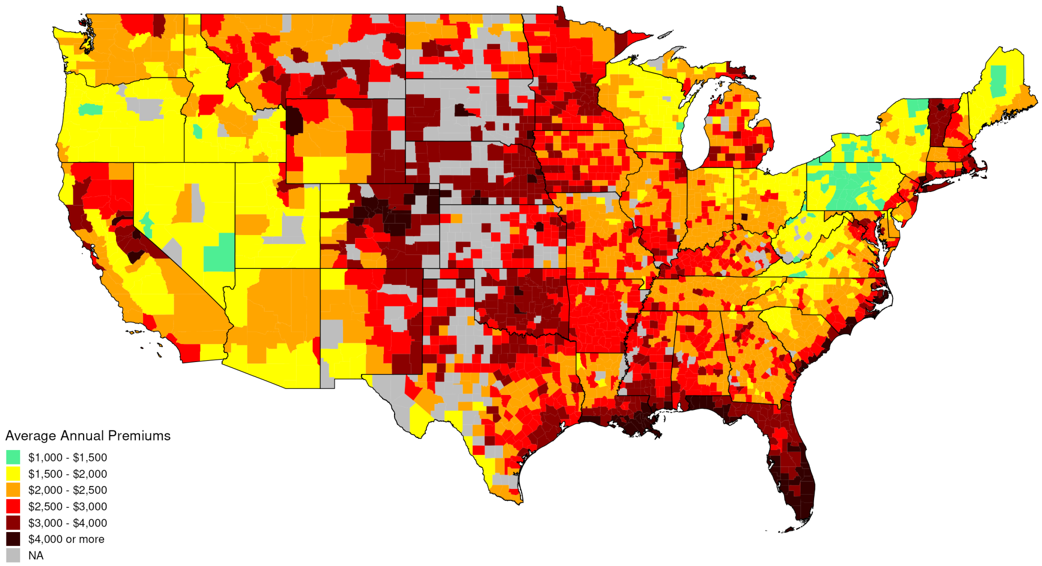
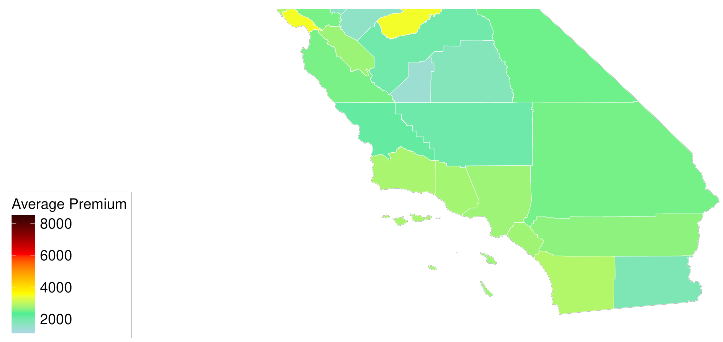


Figure 1: This figure maps average annual insurance premiums in 2024 by county. Counties with fewer than 20 premium observations are excluded.

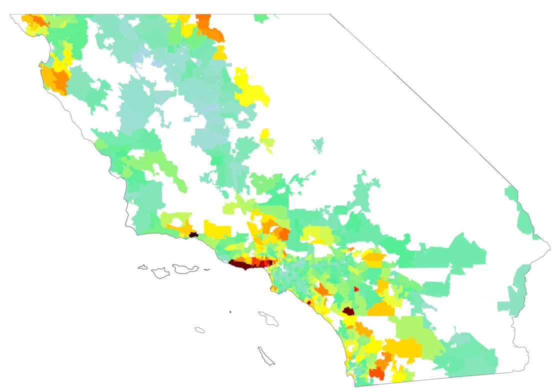
implications for homeowners' insurance burdens. The ability of our insurance expenditure index to condition on structure values is key to disentangling the effects of insured values and disaster risk towards driving premiums.[15]

Finally, Figure 3 presents the average nominal homeowners insurance premiums in the United States from 2014 to 2024, highlighting the time series dimension of our data. Premiums rose relatively steadily but gradually between 2014 and 2021. Since 2021, average premiums have risen sharply, with the average premium increasing by over $900 in three years. Appendix Figure A6 shows a similarly sharp increase in inflation-adjusted dollars.

[15] Appendix Figure A5 shows an increasing relationship between premiums and income, consistent with the increasing relationship between premiums and home prices in Appendix Figure A4. We further find a decreasing relationship between homeowners insurance burden (premiums as a share of income) and income.



(a) Premiums by county, 2024



(b) Premiums by zipcode, 2024

Figure 2: This figure maps average annual insurance premiums for Southern California in 2024 by county (top panel) and by zipcode (bottom panel). Zipcodes with fewer than 20 premium observations are omitted.

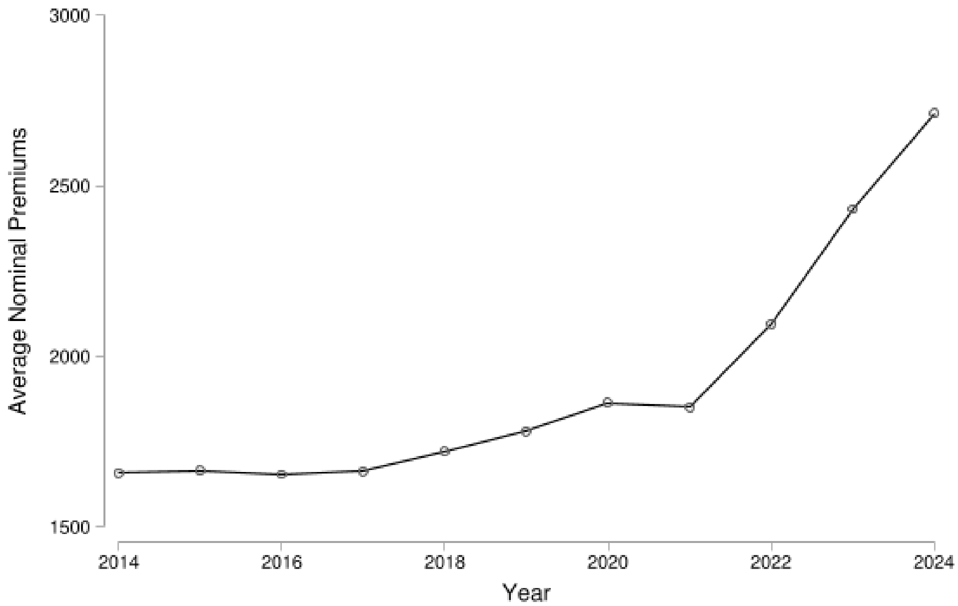


Figure 3: Time series of nominal average annual homeowners insurance premiums, 2014–2024.

6 Insurance Expenditure Correlates and Dynamics

Having established some of the basic correlates and dynamics of insurance premiums, this section examines the relative influences of expected disaster losses, structure value, and demographics on premium differences across space and over time. First, we examine the conditional relationships between average premiums from our data, structure values, disaster risk, and zipcode demographics. Next, we look at how the relationship between disaster risk and premiums has evolved over time.

6.1 Insurance Expenditure Correlates

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

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

$$P_{zt} = \alpha_t + \beta_0 X_z + \beta_1 S_{z,t-1} + \beta_2 Risk_z + \epsilon_{zt}, \tag{2}$$

where P_{zt} are the average premiums observed in year t for zipcode z in our estimation sample, α_t are year fixed effects, X_z are zipcode characteristics from the 2010–2014 ACS (population share white, median income), $S_{z,t-1}$ is the one year lagged structure value from the FHFA data, and $Risk_z$ is our standardized disaster risk measure constructed from the National Risk Index and First Street Foundation data.

In the first column of Table 3, we find that zipcodes where structures are more expensive tend to have higher premiums, as well as a positive relationship between expected losses and premiums. A one-standard deviation increase in expected disaster losses is associated with a \$395 increase in average premiums. In column (2), we show that zipcode-level covariates do little to change the estimated disaster risk coefficient. The positive relationship between incomes and insurance expenditures is consistent with evidence that wealthier households demand more insurance (Gropper and Kuhnen, 2021; Armantier et al., 2023), although we also find that zipcodes with higher nonwhite population shares see higher premiums. 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,

	(1)	(2)	(3)
	Average Premium		
Disaster Risk	393.42***	409.31***	337.88***
	(11.359)	(11.429)	(13.262)
Structure Value ($1000s)	3.46***	2.62***	3.81***
	(0.154)	(0.193)	(0.376)
Pop. Share White		-336.59***	-354.12***
		(29.630)	(27.546)
Median income ($1000s)		6.043***	3.27***
		(0.635)	(1.106)
N	176792	176792	176792
R^2	0.488	0.503	0.650
Demographic Controls	No	Yes	Yes
Year FE	Yes	Yes	Yes
Year # State FE	No	No	Yes

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

Table 3: Regression analysis of the determinants of insurance premiums at the zipcode level. Dependent variable is average premium. Observations are weighted by ACS 2010–2014 5-year estimates of owner-occupied property counts in each zipcode, and subset to a balanced panel of zipcodes with at least 20 observations in each period.

which might affect premiums. These fixed effects only modestly attenuate the disaster risk coefficient. This analysis highlights the value of our granular data in teasing apart the relationships between premiums and disaster risk, structure values, and other state-level factors.

6.2 Insurance Expenditure Dynamics

Table 3 assumes that the relationship between disaster risk and premiums is constant over time. However, the dramatic increase in premiums documented in Figure 3 raises the question of whether insurers are changing how they price risk. To investigate premium dynamics by risk, Figure 4 shows the time series of real average insurance premiums by disaster risk quintile. At the start of our time series in 2014, the riskiest quintile paid approximately 30% higher premiums than the safest quintile. Starting in 2021, real premiums started to increase sharply everywhere, but most dramatically in the riskiest quintile. As of 2024, average premiums in the riskiest quintile were now more than 55% higher than those in the safest quintile.

Figure 4 shows that recent premium increases have been concentrated in the highest risk areas. However, it is not clear what factors are driving this widening gap. A number of general factors — such as inflation, interest rates, supply chain disruptions, and labor shortages — contributed to

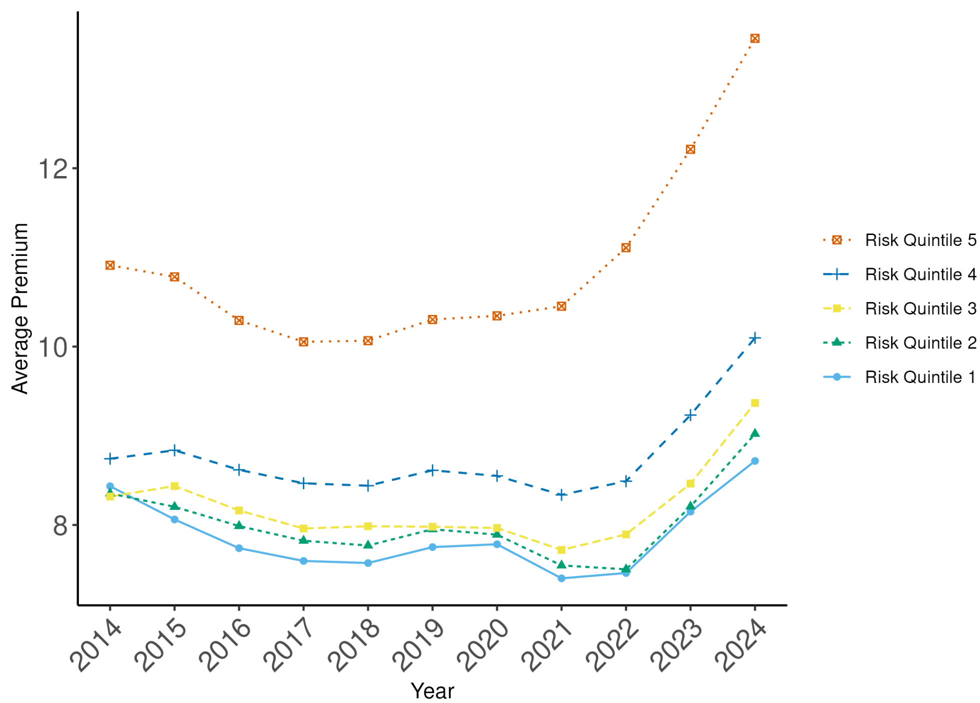


Figure 4: Average annual premiums plotted by quintile of zipcode disaster risk exposure. Premiums are in real 2024 dollars.

rising replacement costs for homes that likely increased both coverage purchased and premiums. In addition, rising premiums in specific states have been attributed by industry participants to idiosyncratic factors, such as fraudulent claims in Florida (Johnson et al., 2023).

To investigate the extent to which higher premiums are being driven by disaster risk exposure as opposed to some other correlated factor, we estimate the dynamic relationship between premiums and risk with additional covariates to control for other factors that may drive dynamic and cross-sectional differences in premiums:

$$P_{zt} = State_z + \alpha_t + \lambda_1 ShareWhite_z + \lambda_2 Income_z + \lambda_3 S_{z,t-1} + \sum_{t=2014}^{2024} \beta^t Risk_z + \epsilon_{zst}. \tag{3}$$

The specification in Equation 3 includes state and time fixed effects, zipcode socioeconomic characteristics, and lagged structure values as controls. The key parameters of interest are the annual β^t coefficients on $Risk_z$, which give the changing effect of a one-standard deviation increase in disaster risk on premiums over time. Insofar as the widening gap between high- and low-risk zipcodes is attributable to other factors, we would expect to find a constant β^t over time.

Figure 5 presents the time-varying coefficient of climate risk on premiums from Equation 3.

While the relationship between climate risk and premiums was trending downwards until 2017, it began to increase in 2018 and accelerated through 2024, consistent with the raw data in Figure 4. The coefficient on risk more than doubles from $220 per standard deviation in 2017 to $615 in 2024. For a zipcode at the 90th percentile of disaster risk, our estimated change in the risk-to-premium gradient increased annual premiums by $580 between 2017 and 2024.

We can also use the estimated results of Equation 3 to unpack the drivers of the recent spike in homeowners insurance premiums more broadly. Average nominal premiums increased by approximately $1,065 between 2017 and 2024. Our estimated structure values coefficient implies that the increase in rebuilding costs can explain $385, or about 35%, of this increase. Thus, while construction costs also outpaced the general pace of inflation, they cannot explain the full rise in homeowners insurance premiums.[16] The increase in the coefficient on disaster risk explains another $225 of the increase. These two factors alone account for over half of the increase in premiums in our data over this period.

To examine the robustness of our results, we re-estimate the dynamics of the risk coefficient with our repeat-loan IPI as the dependent variable with zipcode fixed effects. Because it identifies changes in premiums by following the same loan over time, the repeat-loan index is more robust to potential biases caused by changes in the composition of homeowners over time. The results, shown in Appendix Figure A7, show a similar increase in the risk coefficient of approximately $400 between 2018 and 2024 as in our baseline estimates.

As an additional robustness check, we control for the time-varying effects of flood risk to account for potential contamination from flood insurance premiums. Starting in 2016, flood insurance reform legislation strengthened regulations requiring homeowners with mandatory flood insurance policies to escrow their premiums (Kousky et al., 2020). To account for this factor, we add the expected loss rate due to flood risk from the First Street Foundation Flood Model with time-varying coefficients into Equation 3. The results, shown in Appendix Figure A8, continue to show a similar increase in the premium-to-risk gradient and a small, stable relationship between escrowed premiums and flood risk.

Finally, one may be concerned that our structure value controls do not adequately control for rising replacement costs over this period. To evaluate the robustness of our replacement cost proxy, in Appendix Figure A9 we re-estimate Equation 3 over the 2019–2024 panel of zipcodes with structure value controls, and then substituting the structure value controls for the average quoted coverage A limits from the insurer broker data. Both figures show similar coefficients, suggesting that our structure value controls closely track replacement costs.

[16] This finding is consistent with results from Sastry et al. (2025), who find that homeowners have failed to increase

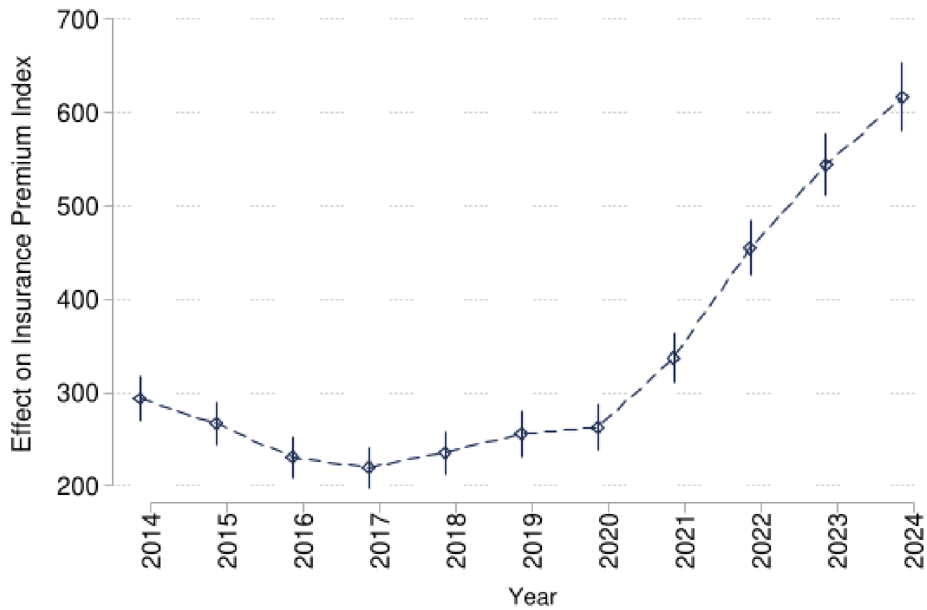


Figure 5: Plots the estimated annual coefficients estimating the effect of disaster risk on premiums from Equation 3. The specification includes controls for zipcode population share white and median household income, lagged average zipcode structure values, and state and time fixed effects. Observations are weighted by the number of housing units in the 2014–2018 American Community Survey. Vertical lines indicate 95% confidence intervals.

Looking ahead, our estimates suggest that the cost of increasing disaster risk with climate change for households will depend on a potentially volatile relationship between disaster risk and premiums. As an illustrative exercise, we project the potential increases in homeowners insurance premiums between 2023 and 2053 due to rising disaster risk under different estimates of β_t^{Risk}. Appendix Figure A10 plots the distribution of predicted premium changes in 2053 across zipcodes by 20 ventiles of the predicted change in wildfire and hurricane expected loss rates under the First Street Foundation models. Moving from $\widehat{\beta}_{2017}^{Risk}$ to $\widehat{\beta}_{2024}^{Risk}$ more than doubles the projected annual premium increases in 2053 due to climate change among homeowners in the top 5% of climate change exposure.

7 Capital Markets and the Cost of Disaster Risk

The previous section established that the real cost of homeowners insurance has grown substantially between 2018 and 2024, especially in areas exposed to more disaster risk. Furthermore, we have shown that the widening premium gap between high and low risk areas cannot be explained by

their coverage limits to keep up with rising replacement costs over this period.

statewide factors or relative structure value trends. In this section, we motivate and test one mechanism that partly drove the increasing risk-premium gradient: increasing prices in the reinsurance market.

Insurers rely on reinsurance, often called "insurance for insurers," to diversify their own geographically concentrated risks through global capital markets. As homeowners' premiums increased over our sample, the price of reinsurance for catastrophic risk rose even as reinsurers reduced the amount of coverage they were willing to write (Eaglesham, 2024; Corbineau et al., 2023). Between 2017 and 2024, reinsurance prices for U.S. Property Catastrophic coverage more than doubled according to the Guy Carpenter Rate-on-Line Index (Figure 6).

The reinsurance market is closely related to other capital markets that share global disaster risk. Insurance-linked securities (ILS), most notably catastrophe bonds ("cat bonds"), pay a coupon rate to investors and pay out the principal to issuers under disaster event triggers. Mirroring rising reinsurance rates, the coupon spread relative to modeled expected losses for cat bonds also approximately doubled between 2017 and 2024 (Appendix Figure A13). In addition, rising interest rates over the same period have tightened primary insurers' balance sheets and contributed to a higher cost of capital (Damast et al., 2025).

Understanding the role of capital markets in driving premium dynamics is important for three reasons. First, climate change is expected to exacerbate the wildfire and hurricane risks that form much of the underlying risk in reinsurance and cat bond contracts (First Street Foundation, 2020). Second, the effect of capital market prices on premiums shows how the cost of financial frictions affects what homeowners pay to insure catastrophic risk (Koijen and Yogo, 2015). It is plausible that rising reinsurance rates may partially drive the rising risk-premium gradient. Such a hypothesis is consistent with a long literature showing that the costs of reinsurance and cat bonds are greater than the expected claims payments, and that reinsurance markets go through tightening cycles when capital is scarce (Froot and O'Connell, 1999; Zanjani, 2002; Born and Viscusi, 2006; Boyer et al., 2012; Tomunen, 2025; Li, 2025). Third, reinsurers have the best access to risk models and loss trends data, and so might be the first mover to reprice dynamic disaster risk. However, an alternative hypothesis is that reinsurance prices rose due to the same inflationary pressures that have caused primary insurers to increase their rates.

7.1 Theoretical Framework

We introduce a conceptual framework below to illustrate how multiple factors can simultaneously drive the cost of capital and premiums, and to motivate our identification strategy for separately identifying time-varying markups on correlated catastrophic risks.

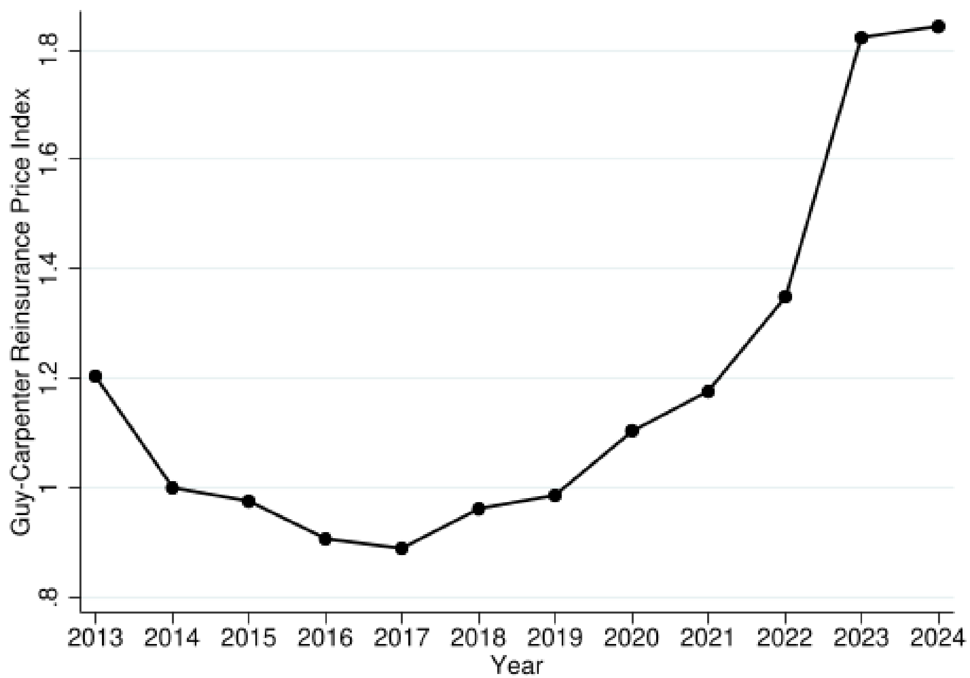


Figure 6: Time series of the Guy-Carpenter U.S. Property Catastrophe Rate-on-Line Index. Index values reflect changes in the "rate-on-line," or the premium as a percentage of the coverage limit, on renewing reinsurance policies for US property catastrophe policies. See `https://www.artemis.bm/us-property-cat-rate-on-line-index/` for more information.

Consider the actuarially fair homeowners insurance premium charged on home i by insurer j at time t, $\overline{P}_{ijt}$, for a contract that pays replacement cost coverage C_{it} on total losses $L_{it} \in \{0,1\}$ where $E[L_{it}] = p_{it}$. Assume that insurer j holds some capital, and denote the event that j's aggregate losses exceed its capital by $R_{jt} \in \{0,1\}$ where $E[R_{jt}] = r_j$. The insurer also has a reinsurance contract that pays all losses exceeding its capital, which is priced according to the insurer's expected reinsurance claims times a markup $(1+\alpha_t)$.[17] The actuarially fair average premium for household i is given by the expected loss borne by the insurer plus the effect of insuring i on the cost of reinsurance:

$$P_{ijt} = C_{it} * (E[L_{it}|R_{jt} = 0] + (1+\alpha_t) * f_{ij}). \tag{4}$$

In Equation 4, $E[L_{it}|R_{jt} = 0]$ is the probability that home i will have a loss conditional on insurer j's aggregate losses being below its capital and not triggering reinsurance. The term f_{ij}

[17]The markup term α_t represents anything that causes the price of the reinsurance contract to differ from the insurer's subjective expectation of their reinsurance claims. This could include the loading fees, cost of capital, different subjective beliefs over the distribution of losses, pricing under asymmetric information, or market rents from imperfectly competitive markets. In practice, reinsurance contracts for catastrophic risk have more complicated structures than a simple coinsurance rate.

is the effect of adding household i to j's book of business on its reinsurance costs. Because the reinsurer prices its contract at expected claims times the markup, $f_{ij} = E[L_{it}|R_{jt} = 1]$. Substituting $E[L_{it}|R_{jt} = 1] = p_{it} * r_j + Cov(R_{jt}, L_{it})$ and $E[L_{it}|R_{jt} = 0] = p_{it} * (1 - r_j) - Cov(1 - R_{jt}, L_{it})$ and taking logs, Equation 4 simplifies to:

$$ln(P_{ijt}) = \underbrace{ln(C_{it})}_{\text{Exposure}} + \underbrace{ln(p_{it})}_{\text{Frequency}} + \underbrace{ln(\alpha_t * (r_j + \frac{Cov(R_{jt}, L_{it})}{p_{it}}) + 1)}_{\text{Price of Catastrophic Risk}}. \quad (5)$$

Equation 5 illustrates how property insurance premiums generally scale with three terms: The frequency of loss, exposure conditional on a loss, and a third term that we call the "price of catastrophic risk." While the first two terms are clear, it is worth noting two facts about the price of catastrophic risk.[18] First, it is a function of the markup that insurers pay to cover their tail risks; if $\alpha_t = 0$, then the third term disappears. Second, the sensitivity of premiums to α_t is increasing with the correlation between the individual risk and aggregate tail loss events that trigger reinsurance claims.

In practice, insurers adjust their capital along multiple dimensions rather than relying solely on reinsurance. From this perspective, α_t is the lowest marginal cost of capital available to the insurer, whether through reinsurance, cat bonds, or its own balance sheet. Thus, Equation 5 can be seen as a specific case of the more general formula for insurance pricing with financial frictions from Koijen and Yogo (2015). Our own simplified pricing formula illustrates how property insurers pay time-varying markups to insure correlated catastrophes.

7.2 Identification

This framework, summarized by Equation 5, suggests catastrophic risks are more exposed to changing capital market prices. Following this insight, we leverage the granularity of our data along with geographic variation in the correlation of catastrophic risks to identify the relative contributions of exposure, frequency, and the price of catastrophic risk 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 changes in the exposure base (structure values) across markets.[19]

[18] The Society of Actuaries defines catastrophic risk for P&C insurers as, "...infrequent events that cause severe loss, injury or property damage to a large population of exposures [share of the portfolio]" (American Academy of Actuaries, 2001).

[19] We make two caveats on our interpretation of the exposure and frequency terms in our empirical estimation relative to the more abstract Equation 5. First, we do not expect premiums to scale 1:1 with replacement values. Due to loading fees, doubling coverage generally less than doubles premiums. In addition, research from Sastry et al. (2025) shows that homeowners did not increase their coverage to keep up with rising replacement costs over this period. Second, we do not necessarily interpret changes in the premium loading on disaster risk as indicating that the actual frequency or severity of disasters increased. Rather, insurers may have re-evaluated the trend from their

To create our measure of catastrophe exposure, we first identify catastrophe-exposed areas that would likely experience losses during the most extreme disaster events, which we designate as zipcodes in the top quartile of hurricane plus wildfire expected loss ratios nationally. For this subset of exposed zipcodes, we measure the correlation of monthly inflation-adjusted per-capita losses using SHELDUS data from 2000 to 2013 between each zipcode's county (the most granular geography available) and the total losses in its state. Our catastrophe exposure variable is equal to the county loss correlation for catastrophe-exposed zipcodes, and normalized to zero for zipcodes outside this top quartile. Figure 7 maps the catastrophe exposure in each county with at least one catastrophe-exposed zipcode.

This within-state measure of catastrophe exposure has several advantages as a proxy for reinsurance demand. First, because insurance companies are regulated at the state level and often operate with a relatively high degree of geographic concentration, within-state correlated losses are a primary driver of earnings volatility and regulatory capital requirements. In 2014, the premium-weighted average insurer obtained 74 percent of its gross homeowners premiums concentrated in a single state.[20] Although insurance companies do write some of their business across multiple states and have other mechanisms for spreading losses across business lines or within their insurance group, those activities are likely endogenous to the concentration of catastrophic risk and cost of reinsurance.[21]

To validate our catastrophe exposure measure, we test its ability to predict reinsurance usage as measured by insurer spending on reinsurance. To do so, we use 2014 NAIC filings data to create state-level measures of the share of premiums insurers operating in each state cede to unaffiliated reinsurers.[22] We approximate state-level reinsurance usage, Re_s, as the market-share weighted average of the percent of premiums ceded by each insurer:

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

where d_{is} are the dollar value of insurer i's direct premiums written in state s, and c_i is the share of i's premiums that they cede to unaffiliated reinsures (i.e. excluding affiliated reinsurance purchased from other companies in the same insurance group). Appendix Figure A11 plots the reinsurance share across states.

backward-looking models.

[20] At the insurer group level, the share is 57 percent.

[21] We replicate our main results using a correlation measure derived from premium weighted losses across states rather than within-state (see Appendix Table A4).

[22] These NAIC filings are the most granular information available on reinsurance contracts and do not distinguish prices or coverage characteristics. We thank Ty Leverty for his help using this data and advice defining the exposure measures.

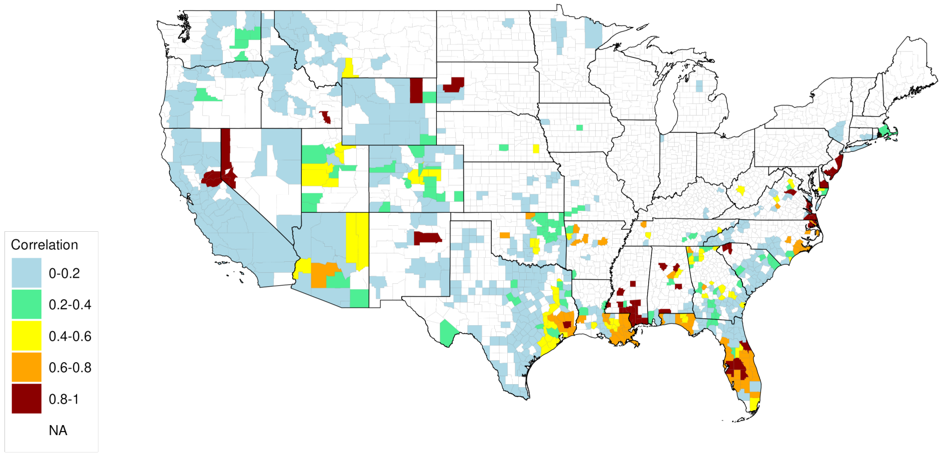


Figure 7: Shows county-level loss correlations for counties with a zipcode in the top quartile of hurricane wind plus wildfire expected loss rates.

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

$$Re_s = \alpha_0 + \beta_1 \overline{HighRisk}_s + \beta_2 \overline{CatExposure} + \epsilon_s,$$

where $\overline{HighRisk}_s$ is the state-level share of catastrophe-exposed zipcodes, and $\overline{CatExposure}_s$ is the state-level average zipcode catastrophic exposure measured from the within-state correlation of historical losses. The results of this equation are shown in Table 4. In column (1) where we omit catastrophe exposure, we find a positive and statistically significant relationship between a state's share of catastrophe-exposed zipcodes and average reinsurance usage. However, when we estimate the full model in column (2), the coefficient on the high risk share attenuates and becomes statistically insignificant, whereas the coefficient on catastrophe exposure is positive and statistically significant. These findings show that it is *correlated* catastrophic risk, and not high expected losses *per se*, that drives reinsurance usage. Notably, the two variables in column (2) explain over 75% of the variation in reinsurance usage across states. These findings support the hypothesis that the correlation of cat risks within states drives reinsurance usage.

7.3 Estimating the Changing Price of Catastrophic Risk

Motivated by our stylized pricing formula in Equation 5, we specify our primary estimating equation:

	State Reinsurance Usage	
	(1)	(2)
High Risk	0.19**	-0.02
	(0.079)	(0.033)
		0.48***
		(0.112)
Observations	51	51
R^2	0.53	0.77

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

Table 4: Results from state-level regressions of reinsurance usage on the average share of catastrophe-exposed zipcodes with and the average zipcode catastrophe exposure. Catastrophe-exposed zipcodes are those in the top quartile of hurricane wind plus wildfire expected loss rates nationally, and catastrophe exposure is the historical within-state loss correlation measured from SHELDUS data. State variable averages and regression observations are weighted by the total number of owner-occupied housing units in the 2010–2014 ACS data. Robust standard errors in parentheses.

$$\begin{aligned} ln(IPI_{zct}) = \alpha_z + \alpha_t + \beta_1 ln(S_{z,t-1}) + \sum_{t=2014}^{2024} (\beta_2^t Risk_z + \beta_3^t HighRisk_z) \\ + \beta_4 ln(Z_{t-1}) \times CatExposure_{zc} + \epsilon_{zt}, \end{aligned} \tag{6}$$

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

The β_4 coefficient represents the price of catastrophe exposure from Equation 5. We use lagged log reinsurance prices $ln(Z_{t-1})$ from the Guy Carpenter reinsurance rate-on-line price index as our proxy for the α_t markup term. The challenge in estimating the price of catastrophe risk, however, is that reinsurance prices rose for many of the same reasons that primary insurance prices rose: an increase in the exposure to and perceived frequency or severity of disaster losses over this period.

Thus, the first key to our identification strategy is the inclusion of the lagged log FHFA structure value terms $ln(S_{z,t-1})$ and time-varying coefficients β_2^t and β_3^t on continuous disaster risk $Risk_z$ measure and the indicator variable $HighRisk_z$ indicator of non-zero catastrophe exposure to capture changes in "exposure" and "frequency" terms from Equation 5. Under the null hypothesis that changes in reinsurance prices are entirely driven by the same forces driving changes in primary insurance prices, we should expect the β_4 coefficient to be zero once we condition on changing structure value and the time-varying pricing of expected disaster losses.

Given that our measure of global reinsurance prices does not vary by geography, we use variation in our catastrophe exposure variable, $CatExposure_{zc}$, to identify β_4 separately from general time trends in insurance pricing. As motivated by Equation 5 — and supported by evidence from Table 4 — reinsurance take-up is driven by exposure to catastrophic risk. If the underlying markup on insuring catastrophic risks has changed with rising capital market prices, we should expect to see a positive β_4 coefficient.

We maintain a parallel trends assumption to identify the β_4 parameter in Equation 6. Specifically, conditional on risk and replacement costs, we assume that premiums in areas with more and less catastrophe exposure would have evolved similarly absent changing capital market prices. To test this assumption, we estimate an event-study style version of Equation 6 that replaces the β_4 interaction term between reinsurance prices and catastrophe exposure with time-varying coefficients estimated on $CatExposure_{zc}$.

Supporting the parallel trends assumption, Figure 8 shows that the time-varying $CatExposure$ coefficients follow the same pattern as the lagged reinsurance price index from Figure 6. Notably, insurance premium trends in catastrophe exposed zipcodes not only follow the rise in reinsurance prices after 2020, but also the earlier modest decline in the late 2010s.

We next turn to the results of Equation 6, shown in column (1) of Table 5. We find positive and statistically significant coefficients on the interaction term between catastrophe exposure and log reinsurance prices. The coefficient implies that a 10% increase in reinsurance prices causes a 2.6% increase in premiums for perfectly correlated catastrophes.[23] Interpreting their economic significance, these estimates suggest that the rise in reinsurance costs between 2017 and 2024 raised annual homeowners insurance premiums by $195 in the top quartile of catastrophe exposure and by $425 among those in the top decile of catastrophe exposure.[24] These magnitudes suggest that the reinsurance shock can explain about 45% of the rising pass-through of disaster risk into premiums between 2017 and 2024 documented in Figure 5 among zipcodes in the top decile of catastrophe exposure.

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

[23] In general, the reinsurance price-elasticity of premiums is the interaction term coefficient scaled by the catastrophe exposure.

[24] We map the average reinsurance shock among catastrophe-exposed zipcodes by county in Appendix Figure A12.

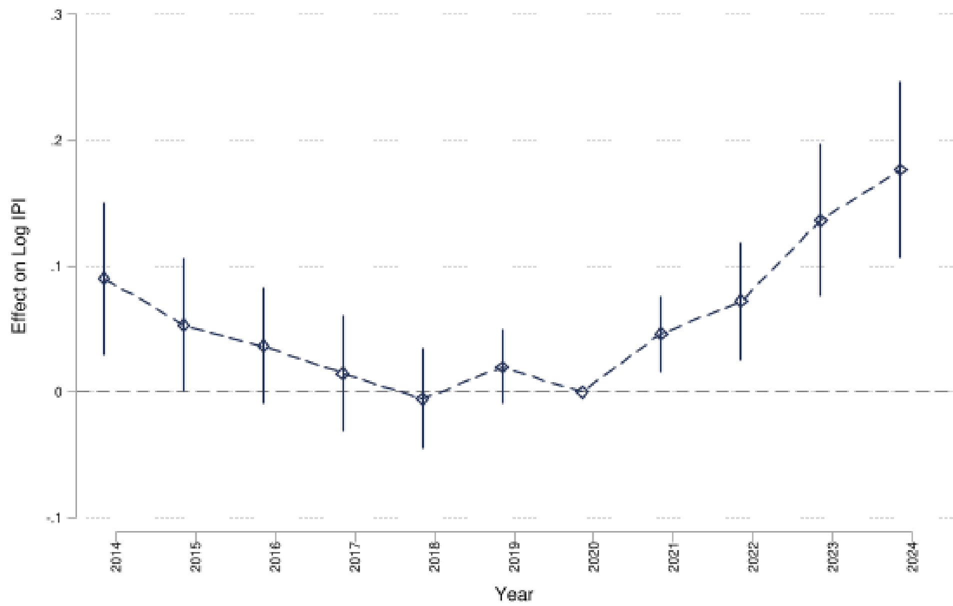


Figure 8: Time-varying coefficients for the effects of catastrophe exposure on homeowners insurance premiums. Dependent variable is log repeat-loan insurance premium expenditures index. Specification is weighted by the number of owner-occupied housing units in the 2010–2014 American Community Survey, and includes zipcode and year FEs, lagged log structure values, and time-varying controls for disaster risk and an indicator variable for non-zero catastrophe exposure. Standard errors are clustered by county.

7.4 Robustness, Heterogeneity, and Extensions

We explore the robustness of these findings that the price of catastrophic risk is rising in the remaining columns of Table 5. First, we show in column (2) that adding time-varying flood risk controls does not change the premium elasticity. Every state has an idiosyncratic insurance market subject to its own regulations and shocks that might dynamically affect the pricing of catastrophic risk on a state-by-state basis (Oh et al., 2022). To account for this heterogeneity, we modify Equation 6 to flexibly include state-by-year wildfire plus hurricane wind loss rate coefficients, so that every state can have a unique catastrophic risk coefficient in every year. The results in column (3) continue to show positive and statistically significant coefficients on the reinsurance price interaction terms. Another concern is that our results might be driven entirely by Florida, which has highly correlated catastrophe exposure and has experienced a number of idiosyncratic market issues contributing to rising premiums separately from rising costs in the reinsurance market (Johnson et al., 2023; Sastry et al., 2023). We exclude Florida observations from our specification and report the results in column (4), still finding similar results. Finally, in Appendix Table A3, we show that our findings remain similar when we substitute our structure value controls for average

	Log Insurance Premium Expenditures Index			
	(1)	(2)	(3)	(4)
Log Reinsurance × Cat Correlation	0.26***	0.27***	0.20***	0.17***
	(0.067)	(0.066)	(0.067)	(0.054)
R^2	0.903	0.903	0.911	0.891
N	176792	176792	176792	167596
Zip and Year FEs	Y	Y	Y	Y
Log Structure Value	Y	Y	Y	Y
Time-Varying Risk Coefficients	Y	Y	N	N
Time-Varying Flood Coefficients	N	Y	Y	Y
State-by-Time Risk Coefficients	N	N	Y	Y
Drop Florida	N	N	N	Y

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

Table 5: Pass-through 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 interaction between lagged log reinsurance rates and catastrophe exposure. All specifications are weighted by the number of owner-occupied housing units in the 2010-2014 ACS, and include zipcode fixed effects, year fixed effects, and log structure value controls as well as controls indicated in the table. Standard errors clustered by county in parentheses.

insurer quoted coverage A limits from the insurance broker data.[25]

While our within-state catastrophe exposure measure is a strong predictor of reinsurance usage and not biased by endogenous insurer portfolio responses, one may be concerned that it does not capture the fact that large insurers tend to write business across multiple states. In Appendix Table A4, we address this concern by re-running the specifications from Table 5 using a historical loss correlation measure that accounts for insurers' average portfolio weights across states, and find similar results.

As we discuss in Section 7.1, the reinsurance market is only one of the global capital markets used by insurers to manage their catastrophe exposure. To test whether our findings are robust to other proxies for global capital market prices, we replace the Z_{t-1} term with the relative markup over expected loss in the cat bond market (Appendix Figure A13). In Appendix A.1, we find similar premium elasticities with respect to cat bond prices as with reinsurance prices.

Next, to investigate heterogeneity, we assess whether the effects of the reinsurance shock depend on state-level regulatory environments. In particular, we use the "high," "medium," and "low" classification of state regulatory frictions from Oh et al. (2022). We study heterogeneity by regulatory frictions, altering Equation 6 to include an additional interaction term between log

[25] It is still possible that policyholders reduced their coverage limits below the insurer quotes that we use as controls (Sastry et al., 2025). In that case, our estimates would be conservative and understate the size of the coverage-adjusted reinsurance shock.

reinsurance prices, catastrophe exposure, and an indicator variable if the state is designated as high friction. We also include year-by-high friction fixed effects. The results of this specification are shown in Appendix Table A5. We find little evidence of pass-through of higher reinsurance prices into premiums in high friction states.

Finally, we explore the extensive margin of insurance availability. It is an open question how insurers in high friction states respond to higher reinsurance costs that they may be prevented from passing through to consumers. One possibility is that they ration coverage. To test this hypothesis, we use data released by the U.S. Senate Budget Committee from an insurer data call describing the number of policies written and non-renewed by insurers in each county between 2018 and 2023 (U.S. Senate Committee on the Budget, Majority Staff, 2024). The dataset documents over 1.9 million policy non-renewals across approximately 270 million homeowners insurance policies written between 2018 and 2023. We aggregate our disaster risk measures up to the county level and designate the top quartile of counties in terms of wildfire plus hurricane wind risk as cat-exposed. Our estimating equation is given by:

$$Ln(NR_{ct}) = Ln(Pol_{ct}) + \sum_{t=2018}^{2023} \beta_0^t Risk_c + \beta_1^t HighRisk_c + \beta_2^t CatExposure_c + \epsilon_{ct}, \tag{7}$$

where NR_{ct} and Pol_{ct} are the number of non-renewed and written policies in county c in year t, respectively. We include time-varying coefficients on our disaster risk measure aggregated to the county level ($Risk$), an indicator variable for counties in the top quartile of wildfire plus hurricane wind expected loss rates ($HighRisk_c$), and catastrophe exposure ($CatExposure_c$).

Figure 9 plots the annual coefficients on the catastrophe exposure term from estimating the effect of the reinsurance shock on policy non-renewal. As with premiums, we see that counties exposed to catastrophic risk see much higher policy non-renewals in 2022 and 2023 relative to 2020. The reinsurance shock increased policy non-renewals by approximately 30% among counties in the top decile of catastrophe exposure.[26]

However, when we separately estimate Equation 7 for high friction states versus those with medium and low frictions, we find little difference in the estimated non-renewal effects (Appendix Figure A14). While it is beyond the scope of this paper to fully model insurance supply in the face of catastrophic risk, we note several plausible channels for why we find significant heterogeneity in pricing but not supply according to state regulations. As found with post-disaster price adjustments in Oh et al. (2022), it is possible that insurers in high friction states are cross-subsidizing the reinsurance shock from low friction states. We also note that our data do not necessarily capture

[26]These findings are consistent with those in Solomon (2024), who finds that public cyclone reinsurance in Australia increased insurance availability.

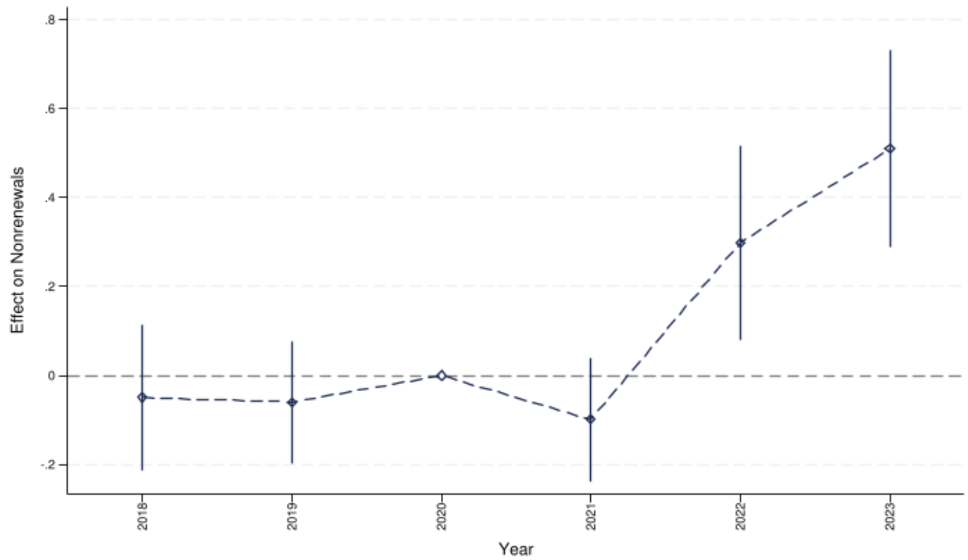


Figure 9: Dynamic effects of catastrophic risk on log insurer-initiated home insurance non-renewals. Data comes from U.S. Senate Budget Committee data on nonrenewals, subset to a balanced panel of 3,065 counties with at least 50 policies written in each year. Specification includes log policies written at the start of the year and time-varying risk controls. Standard errors are clustered at the county level.

the full effects of insurers that stop writing new policies even if they continue renewing existing ones. Furthermore, insurers of last resort may have already picked up uninsurable policies in high friction states, leaving less additional scope for private insurer non-renewal.

8 House Price Effects and Implications of The Rising Price of Catastrophic Risk

The results so far suggest that rising premiums through 2024 reflect not only inflation, but also a rising cost of insuring catastrophic risk. Next, we turn to the broader implications of these rising costs for housing markets.

8.1 House Price Effects

Higher homeowners insurance premiums increase housing user costs, and a growing literature finds that rising disaster insurance premiums can depress home prices (Ge et al., 2022; Eastman et al., 2024). However, the effect of the reinsurance shock on home prices is ambiguous. Historically, reinsurance prices have risen through periods of market “hardening,” but then fallen as capital flows back into the market (Gron, 1994). Indeed, hit by record losses starting in 2017, reinsurers

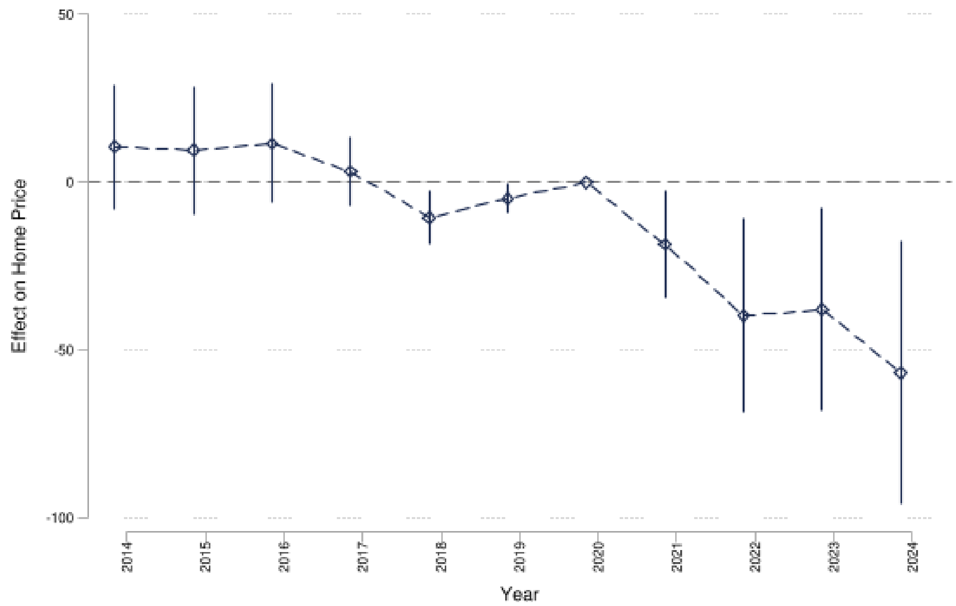


Figure 10: Time-varying coefficients for the effects of catastrophe exposure on house prices. Specification is weighted by the number of owner-occupied housing units in the 2010–2014 American Community Survey, and includes zipcode and year FEs, lagged structure values, and time-varying controls for disaster risk and catastrophe-exposed indicators. Standard errors are clustered by county.

saw low returns on capital and struggled to attract enough capital to meet primary insurers' demand (Pande, 2023). Following the most recent price increases in 2024, reinsurers have enjoyed higher returns and capital inflows. If home buyers and sellers expect the reinsurance shock to fade as in past cycles, then we should expect to find minimal home price effects.

To test whether the reinsurance shock has been capitalized into home prices, we replace the dependent variable in Equation 6 with average home prices (at the zipcode level from Zillow). We first show the event study version of our estimates, plotting the annual coefficients on the catastrophe exposure term in Figure 10. The results show generally stable relative home price trends in areas with differential catastrophe exposure between 2014 and 2020. Then, as reinsurance costs rise, we see a steady decline in relative home values in areas exposed to more catastrophic risk through 2024.

Table 6 shows the estimation results of Equation 6, mirroring the specifications from Table 5. Our baseline specification in column (1) shows that higher reinsurance prices led to lower home values in zipcodes exposed to more catastrophic risk. The magnitudes and statistical significance of this effect remain consistent across our robustness tests in columns (2)-(4) as we include time-varying flood controls, add state-by-year risk controls, and exclude Florida.

	Home prices ($1000s)			
	(1)	(2)	(3)	(4)
Log Reinsurance × Cat Correlation	-85.73**	-86.32**	-90.39***	-91.83***
	(34.639)	(34.400)	(27.376)	(31.029)
R^2	0.978	0.978	0.979	0.980
N	176792	176792	176792	167596
Zip and Year FEs	Y	Y	Y	Y
Structure Value	Y	Y	Y	Y
Time-Varying Risk Coefficients	Y	Y	N	N
Time-Varying Flood Controls	N	Y	Y	Y
State-by-Time Risk Controls	N	N	Y	Y
Drop Florida	N	N	N	Y

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

Table 6: 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 interaction between lagged log reinsurance rates and catastrophe exposure. All specifications include zipcode and year fixed effects, structure values, and time-varying risk controls in addition to the controls specified in the table. Standard errors clustered by county in parentheses.

Our estimates imply that the rise in reinsurance prices between 2018 and 2024 reduced relative home values among zipcodes in the top quartile of catastrophe exposure by an average of $20,500. As with the effect of the reinsurance shocks on premiums, this average masks substantial heterogeneity, as zipcodes in the top decile saw relative prices decline by an average of $43,900. Although average home prices among catastrophe-exposed zipcodes nonetheless increased by over $185,000 over this same period, our results establish that the rise in homeowners insurance premiums meaningfully slowed their growth.

Taking the average premium reinsurance shock estimates from Table 5, the home price effects described above implies a relatively low discount rate of around 1%. We note, however, that the ratio of our home price and premium shock estimates is noisy and that we cannot reject higher discount rates. We can, however, reject the null hypothesis of low or null capitalization, which implies that housing market participants are treating the premium increases resulting from the reinsurance shock as non-transitory. Similar to the growing awareness of sea level rise risks in housing markets (Bernstein et al., 2019; Keys and Mulder, 2020), our results suggest that climate-exposed buyers and sellers expect that higher premiums will be the new normal.

8.2 The Reinsurance Shock and the Repricing of Climate Risk

The capitalization of the reinsurance shock into home prices raises the question of why some market participants are expecting elevated insurance costs to persist. In addition to the short-term challenges of high losses and rising costs of capital, industry analysis also indicate that reinsurers are grappling with the longer-term challenges of increasing disaster risk (Pande, 2023). As discussed in Section 6, the First Street Foundation models project increasing wildfire and hurricane risks, indicating a worsening of catastrophic risk. Although insurance and reinsurance contracts are typically written on a short-term basis, climate uncertainty has led insurers to reevaluate their old models that assumed the frequency and severity of wildfires and hurricanes followed a stationary trend (Kunreuther and Michel-Kerjan, 2011).

We might expect reinsurers to reevaluate their catastrophic risk models and adapt to emerging loss trends faster than primary insurers for two reasons. First, reinsurers and global capital market actors like cat bond investors cover a disproportionate share of hurricane and wildfire risk, and thus should be more sensitive than primary insurers to changes in loss trends. Second, such investors and reinsurers are generally larger firms with access to more sophisticated pricing models than primary insurers (Anand et al., 2021).

To examine whether a repricing of risk in climate-exposed areas is driving part of the rising price of catastrophic risk, we first test whether premiums are more responsive to the reinsurance shock in areas exposed to greater future risk. We expand Equation 6 to include an additional interaction term between log reinsurance prices, catastrophe 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 baseline repricing of changing risk.

We show the results of this test in column (1) of Table 7. The statistically significant coefficient on the triple interaction term with $\Delta Risk$ shows that the effects of the reinsurance shock are stronger in more climate-exposed zipcodes, even conditional on their catastrophe exposure. Based on our estimates across zipcodes in the top decile of catastrophe exposure, the bottom tercile of $\Delta Risk$ saw an average reinsurance shock of \$205, whereas those in the top terciles saw a \$515 premium increase.

Next, we adjust our home price estimating equation to study heterogeneity in the reinsurance shock's effects of home prices by exposure to future risk. The results, shown in column (2) of Table 7, indicate that home prices fell by a greater amount in markets exposed to more future risk. The estimates imply home price declines of \$26,700 in the bottom tercile of $\Delta Risk$ and \$59,200 in the top tercile across zipcodes in the top 10% of catastrophe exposure. In other words, holding today's exposure fixed, places where disaster risk is expected to grow saw larger premium increases and home price declines.

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.

Outcome:	Log IPI	Home Price ($1000s)
	(1)	(2)
Log Reinsurance × Cat Exposure	0.13	-49.16
	(0.097)	(34.434)
Log Reinsurance × Cat Exposure × $\Delta Risk$	0.34***	-90.67***
	(0.106)	(32.141)
R^2	0.904	0.978
N	176792	176792
Zip and Year FEs	Y	Y
Structure Value	Y	Y
Time-Varying Risk Coefficients	Y	Y
Time-Varying Δ Risk Coefficients	Y	Y

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

Table 7: This table estimates the pass-through of reinsurance price shocks to homeowners insurance premiums (column 1) and home prices (column 2) allowing for heterogeneity by the expected change in disaster risk between 2023 and 2053 ($\Delta Risk$). Shown estimates are for the coefficient on the interaction between lagged log reinsurance prices and catastrophe exposure, and the triple interaction term adding $\Delta Risk$. All specifications are weighted by the number of owner-occupied housing units in the 2010-2014 ACS, and include zipcode and year fixed effects, lagged structure values, and time-varying controls on disaster risk, $\Delta Risk$, and non-zero catastrophe exposure. Standard errors clustered by county in parentheses.

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, recent large wildfire losses may have led the most sophisticated reinsurers and investors to realize that their historical models of catastrophic risk in areas with increasing hurricane and wildfire losses are mis-specified, leading to larger recent price increases. In fact, before insurers began to rapidly increase their prices in 2022 and 2023, they had experienced consecutive years of low returns on equity driven by severe wildfire losses (Aon, 2024).

Taken together, these results suggest that the reinsurance shock presents a major repricing of both current and future disaster risk. Among zipcodes that are both in the top decile of catastrophe exposure and top tercile of $\Delta Risk$, the reinsurance shock reduced relative home prices in 2024 by 11%. This effect is substantially larger than the approximately 5% price discount found for homes exposed to sea level rise (Bernstein et al., 2019; Keys and Mulder, 2020). The reinsurance shock suggests that insurance markets are already repricing premiums and affecting home values in areas where catastrophic risk is expected to continue increasing.

9 Conclusion

Property insurance serves as the front line of defense against natural disasters for homeowners, lenders, and real estate investors. The cost of this insurance is a critical input into decisions to adapt or relocate. To date, however, data limitations have hampered investigations of the geography of homeowners insurance, the relationship between disaster risk and the price of insurance, and the role of reinsurance and global capital 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. 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. Our escrow imputation method can be replicated from datasets already commonly used in real estate research, and we show that publicly available structure values are reliable proxies for replacement costs.

We find that premiums have risen sharply since 2021, and that this growth has been concentrated in disaster-prone zipcodes. We provide new estimates of the relationship between disaster risk and premiums, and show that the pass-through of risk to premiums more than doubled between 2018 and 2024. Using the granularity of our data, we decompose the recent rise in premiums attributable to a steepening risk-to-premiums gradient versus rising replacement costs and coverage.

We also provide a new estimate of the pass-through of global capital prices to insurance premiums in markets exposed to correlated catastrophic disasters. Using variation in catastrophe exposure paired with changes in reinsurance and cat bond prices, we find that global capital prices are an important driver of the price of catastrophic risk. The "reinsurance shock" added $425 to the average 2024 annual homeowners insurance premium and reduced relative home prices by an average of $43,900 among zipcodes in the top decile of catastrophe exposure. These findings indicate that housing market participants do not expect the reinsurance shock to be temporary as in past market cycles.

The effects of the reinsurance shock on both insurance premiums and home values are larger in zipcodes that are exposed to increasing risk, suggesting that reinsurers have already started to reprice premiums in climate-exposed markets. The reinsurance shock caused a major repricing of climate risk in the housing market, reducing relative 2024 home prices by 11% in the most catastrophe exposed zipcodes where disaster risk is expected to continue increasing. These findings highlight that the impacts of climate change on insurance markets, household budgets, and real estate will depend on how global capital markets price changing catastrophic risk.

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A Appendix

A.1 Appendix Figures and Tables

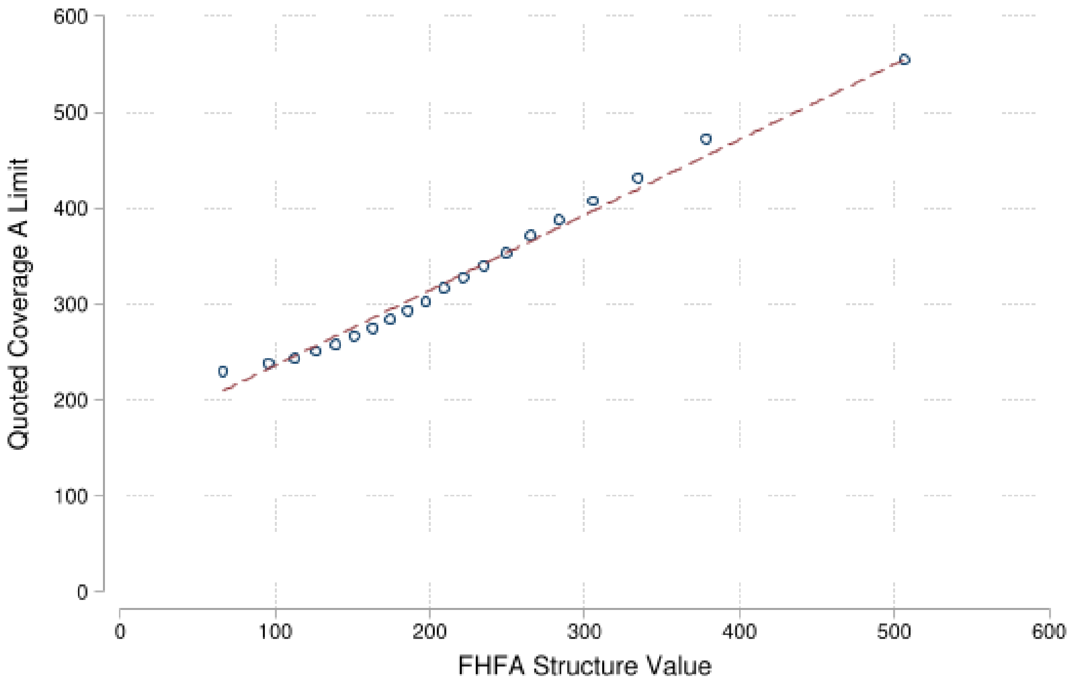


Figure A1: Binscatter relationship between zipcode average quoted coverage A limits (y-axis) and FHFA structure values (x-axis).

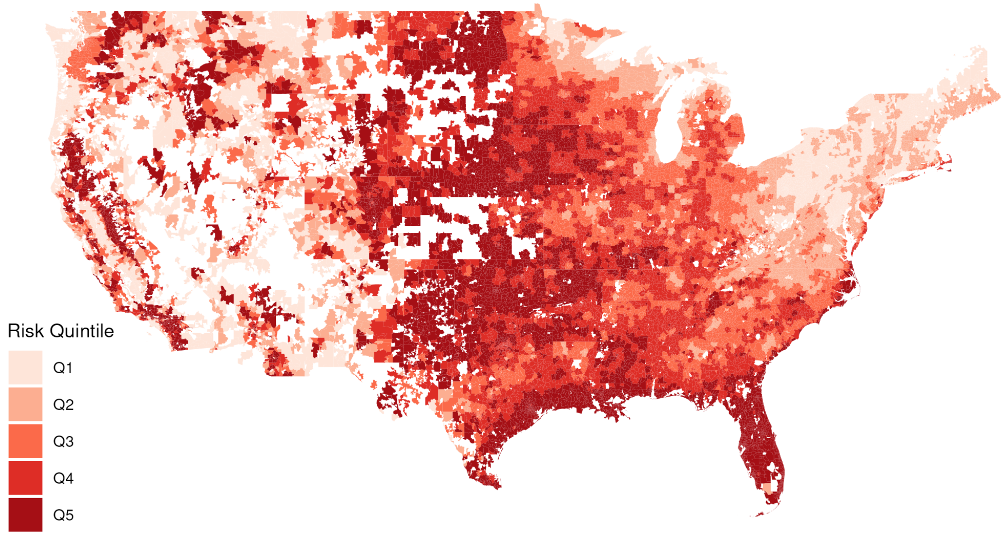


Figure A2: Map of US zipcodes by disaster risk quintile. Disaster risk is measured as the expected loss to a dollar of property value from all physical perils excluding flood and earthquake as measured by the National Risk Index and supplemented by the First Street Foundation wildfire and hurricane wind risk models.

Loan Zip Code	Date	Total Payment	Principal + Interest	Taxes	Insurance
34239	2015	9200.88	6422.88	1301.22	1476.78
34239	2016	9092.04	6422.88	1307.96	1361.20
34239	2017	9194.64	6422.88	1291.32	1480.44
34239	2018	9309.12	6422.88	1305.74	1580.50
34239	2019	9408.36	6422.88	1327.67	1657.81
34239	2020	9686.46	6422.88	1357.61	1905.97
34239	2021	9680.16	6422.88	1403.95	1853.33
34239	2022	10095.84	6422.88	1397.79	2275.17
34239	2023	11079.84	6422.88	1402.01	3254.95
34239	2024	12914.64	6422.88	1481.60	5010.16

Table A1: Example of one loan's total payment decomposition from Sarasota, FL (zip 34239). All values are annualized from monthly payments.

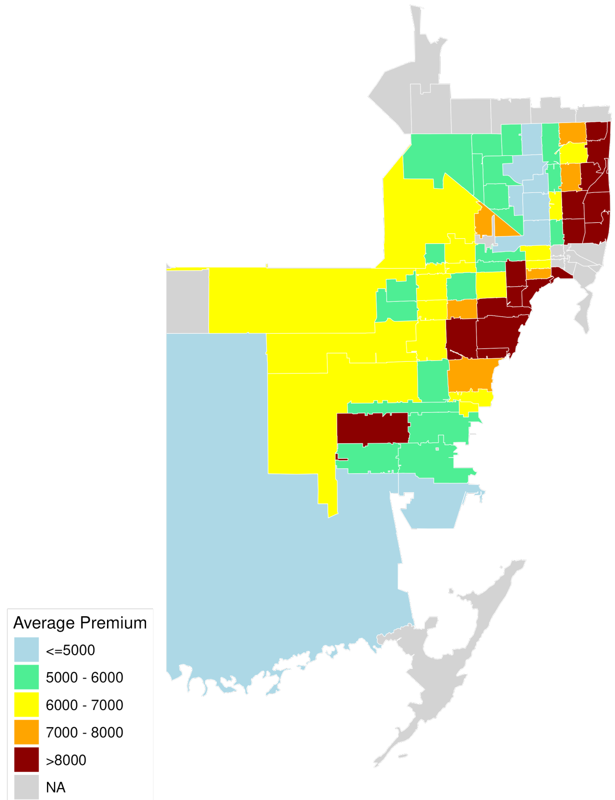


Figure A3: Average annual homeowners insurance premiums by zipcode in Miami-Dade County in 2024.

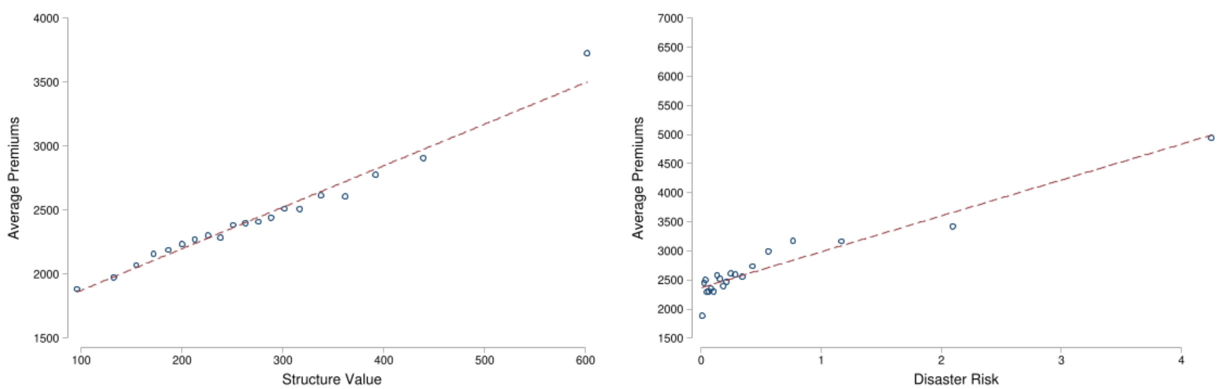


Figure A4: Relationship between average premiums in 2024 by 20 ventiles of structure values (left panel) and disaster risk (right panel).

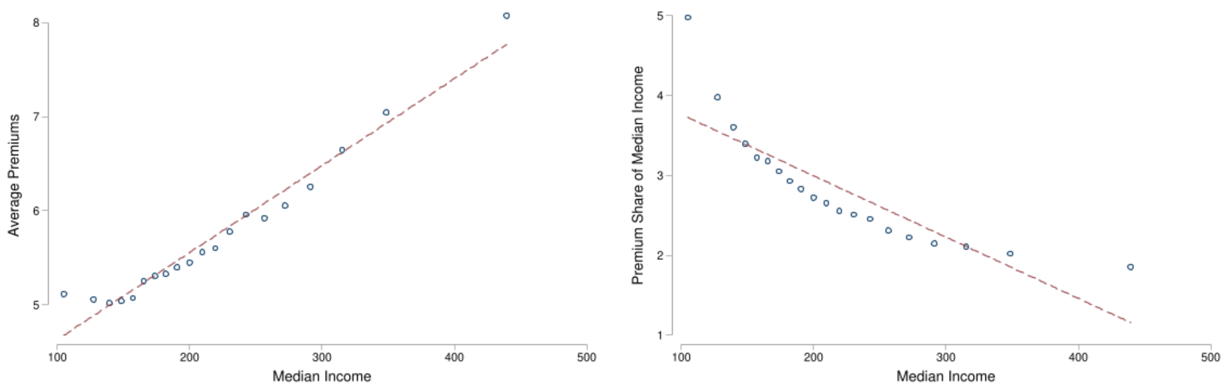


Figure A5: Average premiums (left panel) and average premiums as a share of income (right panel) by twenty ventiles of zipcode median income. Income is median income of owner-occupied households from the 2014–2018 American Community Survey. Average premiums are taken over 2014–2018 and measured in 2018 dollars.

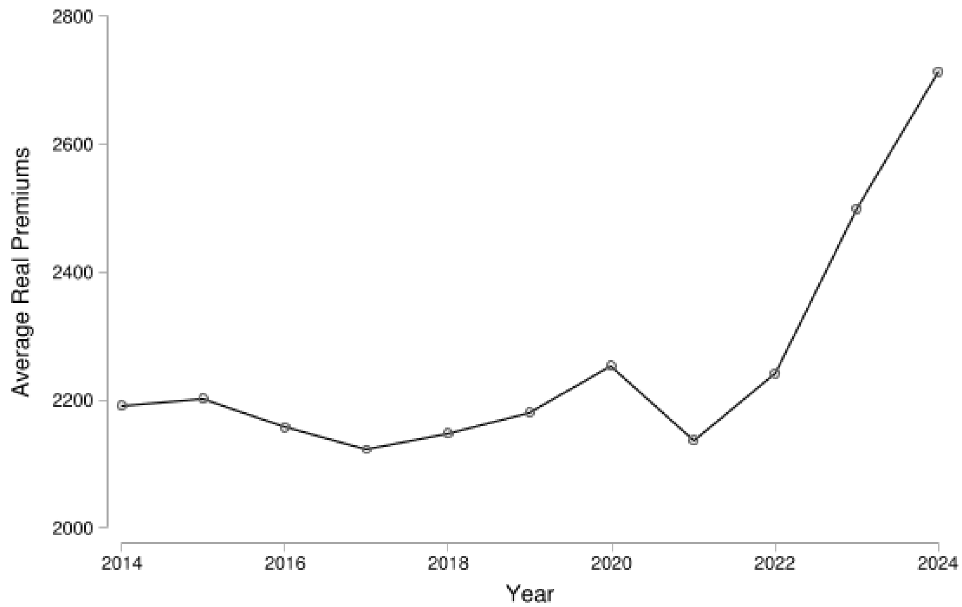


Figure A6: Time series of average annual homeowners insurance premiums. Values are inflated to constant 2024 dollars.

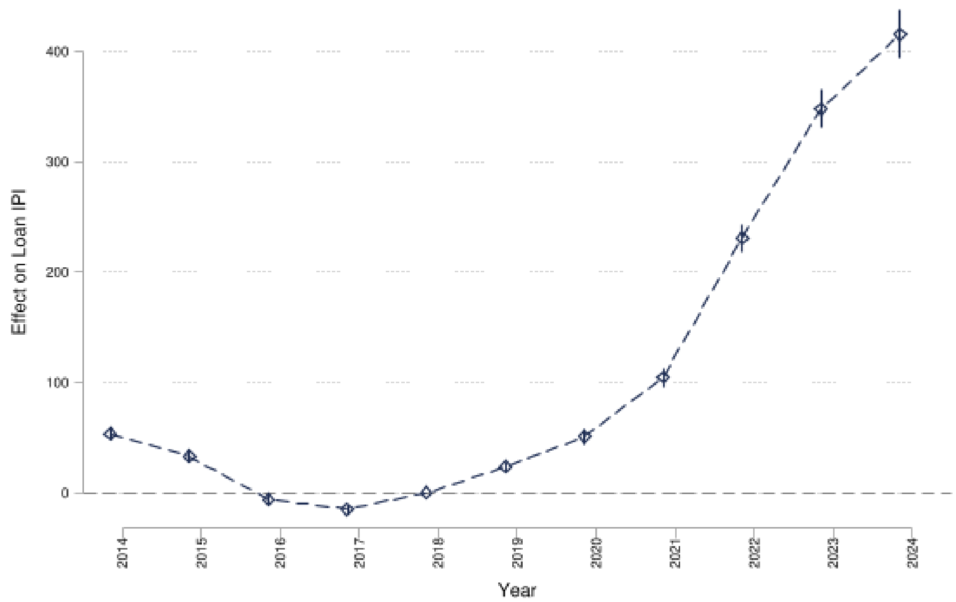


Figure A7: Plots the time-varying estimated effect of disaster risk on premiums. Dependent variable is the repeat-loan insurance premium expenditures index. The specification includes zipcode fixed effects, lagged average zipcode structure values, and year fixed effects. Observations are weighted by the number of housing units in the 2014–2018 American Community Survey. Vertical lines indicate 95% confidence intervals.

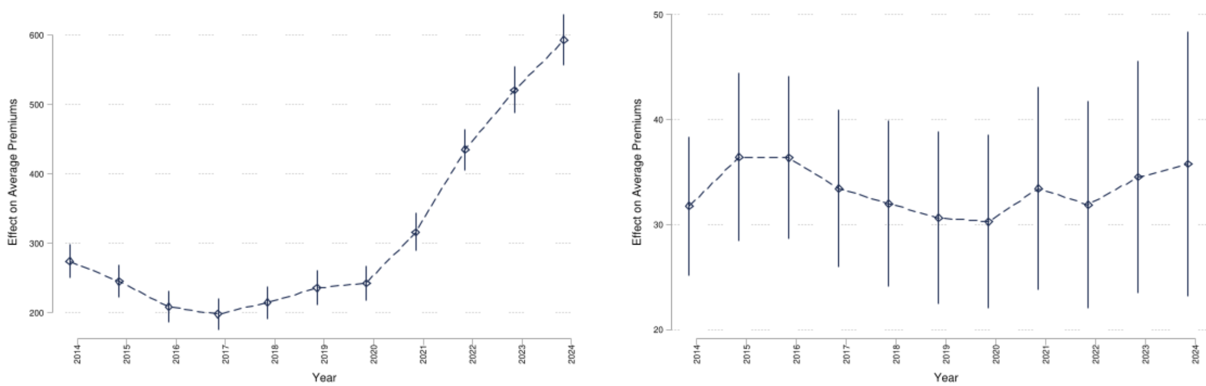
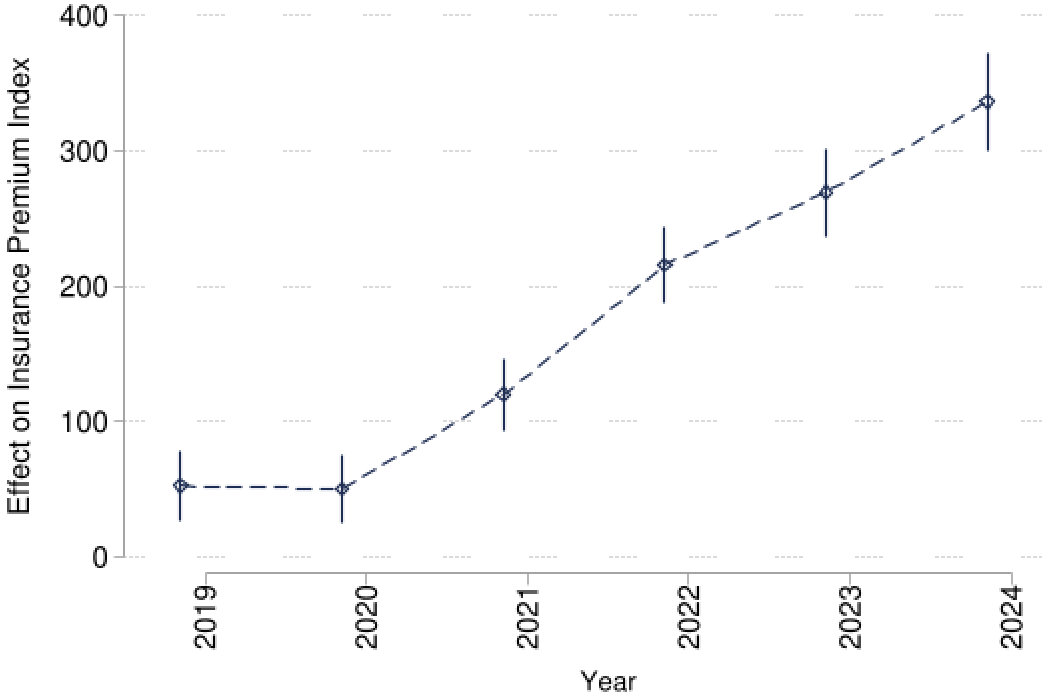
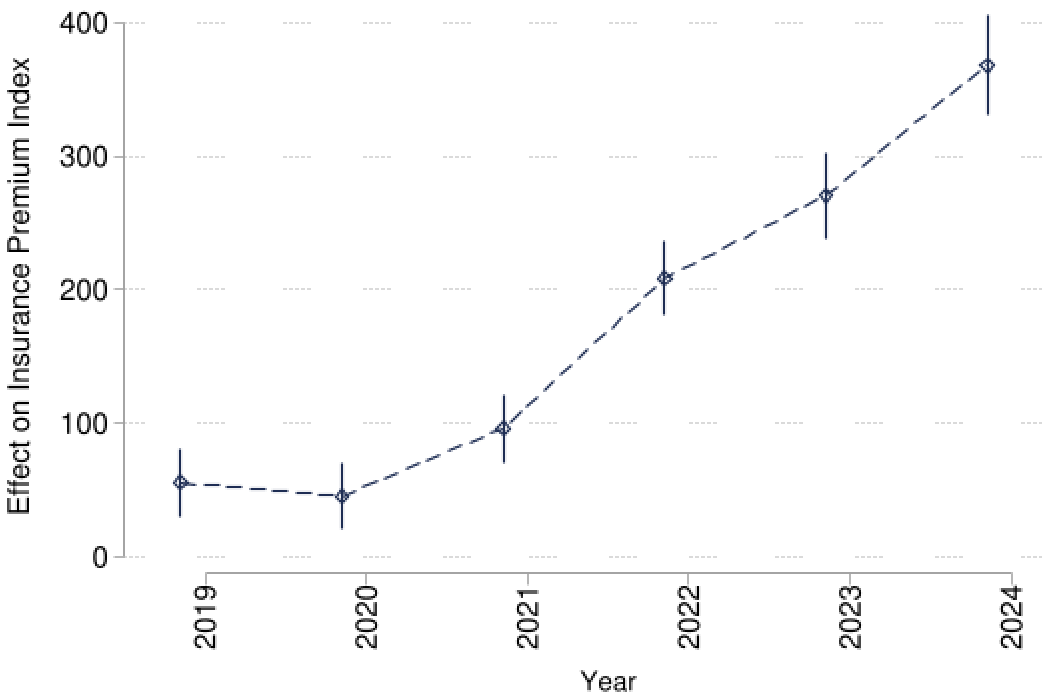


Figure A8: Time-varying estimated effect of disaster risk on premiums with controls for time-varying flood risk coefficients (left panel) and the coefficients on the time-varying flood risk controls (right panel). The specification includes controls for zipcode population share white and median household income, lagged average zipcode structure values, and state and time fixed effects. Observations are weighted by the number of housing units in the 2014–2018 American Community Survey. Vertical lines indicate 95% confidence intervals.



(a) Coverage limit quotes subsample with structure value controls



(b) Coverage limit quotes subsample with coverage limit controls

Figure A9: Plots the estimated annual coefficients estimating the effect of disaster risk on premiums from Equation 3 on the balanced panel of zipcodes between 2019 and 2024 with average quoted coverage A limits using structure value controls (top panel) and coverage limit controls (bottom panel). Both specifications include controls for zipcode population share white and median household income, and state and time fixed effects. Observations are weighted by the number of housing units in the 2014–2018 American Community Survey. Vertical lines indicate 95% confidence intervals.

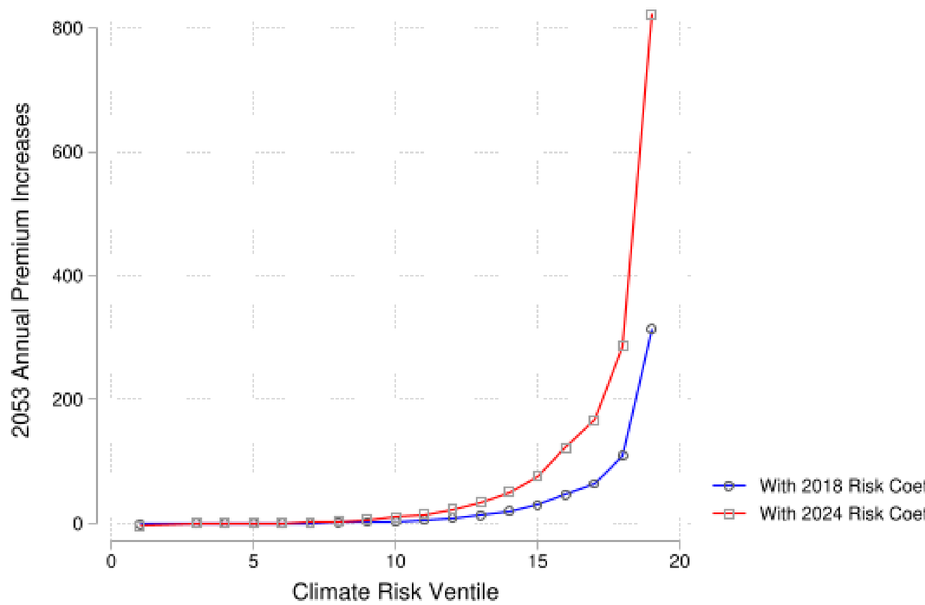


Figure A10: Predicted increase in annual insurance premiums in 2053 due to climate change under the estimated risk coefficient in 2018 (blue) versus 2024 (red) by twenty ventiles of climate exposure. Predicted premium increases in zipcode z are calculated as $\Delta Prem_z = \widehat{\beta}_t^{Risk} * \Delta Risk_z$. $\widehat{\beta}_t^{Risk}$ are the estimated premium coefficients on disaster risk at taken from Figure 5 at $t = 2018, 2024$. $\Delta Risk_z = Risk_{z,2053} - Risk_{z,2023}$, where $Risk_{z,2023}$ is the current risk measure and $Risk_{z,2053}$ is the projected disaster risk in 2053 based on the First Street Foundation hurricane wind and wildfire models.

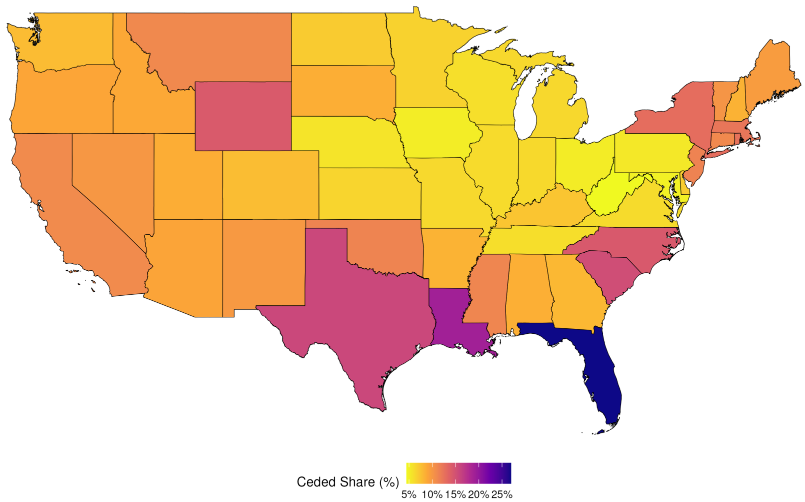


Figure A11: Premium-weighted average share of homeowners insurance premiums ceded to unaffiliated reinsurers across insurers by state in 2014.

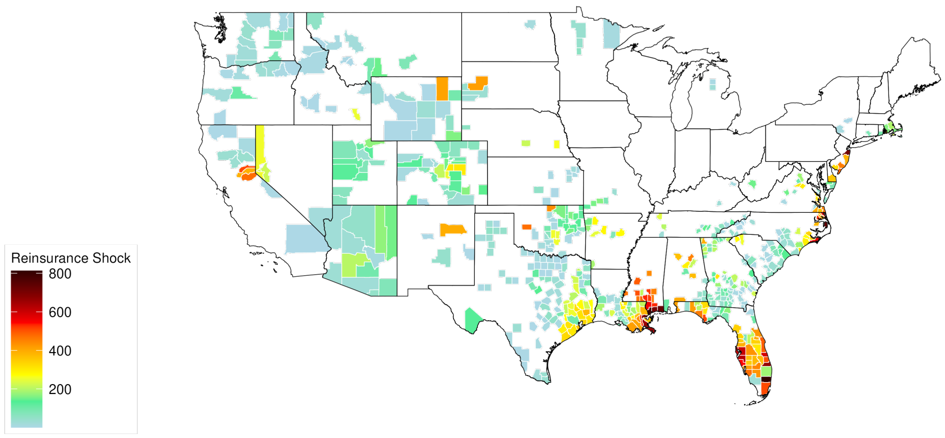


Figure A12: Estimated average effect of the rise in reinsurance prices between 2017 and 2024 on annual homeowners insurance premiums for catastrophe exposed zipcodes, aggregated by county.

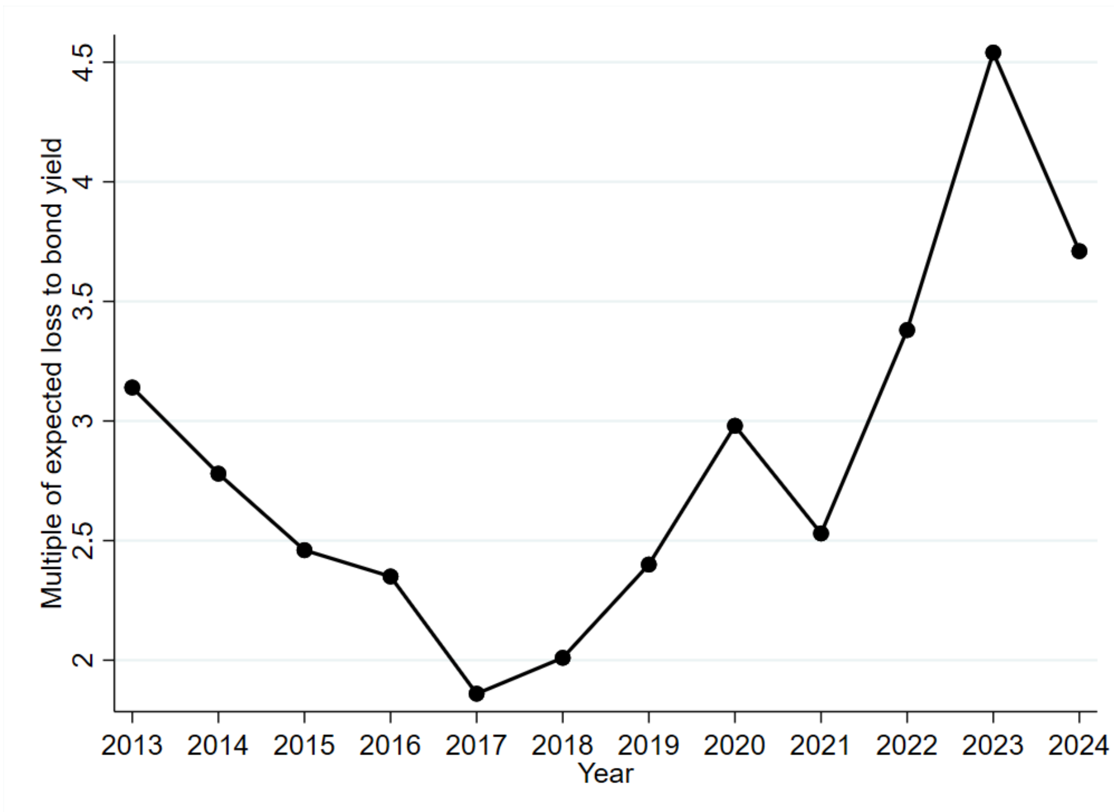


Figure A13: Time series of the ratio of average catastrophe bond yield to expected loss rates from the Artemis Catastrophe Bond and Insurance-Linked Securities Deal Directory. Y-axis values are the average spread of catastrophe bond yields above the reported expected loss rate divided by the expected loss rate across bonds issued in that year. See `https://www.artemis.bm/dashboard/cat_bonds_ils_average_multiple/` for more information.

	(1) Log IPI	(2) Log IPI	(3) Log IPI	(4) Log IPI
Log Cat Bond Price × Catastrophe Exposure	0.21***	0.21***	0.17***	0.15***
	(0.046)	(0.046)	(0.047)	(0.035)
R^2	0.903	0.903	0.911	0.891
N	176792	176792	176792	167596
Time-Varying Flood Controls	N	Y	Y	Y
Drop Florida	N	N	N	Y
State-by-Time Risk Controls	N	N	Y	Y

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

Table A2: Pass-through of catastrophe bond price shocks to homeowners insurance premiums. This specification uses lagged values of the average annual ratio of catastrophe bond yields divided by their expected loss rates instead of the reinsurance rate-on-line index as the proxy for the price of correlated risk. The dependent variable is the log repeat-loan insurance premium expenditures index. Shown coefficients are for the interaction between lagged log cat bond prices and catastrophe exposure. All specifications are weighted by the number of owner-occupied housing units in the 2010–2014 ACS, and include lagged log structure value controls, zipcode fixed effects, and year fixed effects. Standard errors clustered by county in parentheses.

	(1) Log IPI	(2) Log IPI	(3) Log IPI	(4) Log IPI
Log Reinsurance × Cat Exposure	0.29***	0.29***	0.17***	0.18***
	(0.057)	(0.057)	(0.052)	(0.064)
R^2	0.909	0.910	0.914	0.910
N	51444	51444	51444	50202
Zip and Year FEs	Y	Y	Y	Y
Log Coverage Limit	Y	Y	Y	Y
Time-Varying Risk Coefficients	Y	Y	N	N
Time-Varying Flood Coefficients	N	Y	Y	Y
State-by-Time Risk Coefficients	N	N	Y	Y
Drop Florida	N	N	N	Y

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

Table A3: Pass-through of reinsurance price shocks to homeowners insurance premiums with quoted coverage limit controls. The dependent variable is the log repeat-loan insurance premium expenditures index. Shown coefficients are for the interaction between lagged log reinsurance rates and catastrophe exposure. Instead of controlling for lagged structure value, the specification controls for the log average quoted coverage limit from the insurance broker data over the balanced panel of zipcodes with available data between 2019–2024. All specifications are weighted by the number of owner-occupied housing units in the 2010-2014 ACS, and include zipcode fixed effects and year fixed effects. Standard errors clustered by county in parentheses.

	Log Insurance Premium Expenditures Index			
	(1)	(2)	(3)	(4)
Log Reinsurance × Cat Exposure	0.34***	0.35***	0.27***	0.22**
	(0.091)	(0.089)	(0.086)	(0.086)
R^2	0.903	0.903	0.911	0.891
N	176792	176792	176792	167596
Zip and Year FEs	Y	Y	Y	Y
Lagged Structure Value	Y	Y	Y	Y
Time-Varying Risk Coefficients	Y	Y	N	N
Time-Varying Flood Coefficients	N	Y	Y	Y
State-by-Time Risk Coefficients	N	N	Y	Y
Drop Florida	N	N	N	Y

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

Table A4: Pass-through of reinsurance price shocks to homeowners insurance premiums with a portfolio-weighted disaster correlation measure. To construct the portfolio-weighted catastrophe exposure measure, we first measure the "portfolio losses" (PL) of insurers operating in state s. Let d_{is} be the share of state s's total gross homeowners premiums written by insurer i in 2014, q_{is} be the share of i's total gross homeowners insurance premiums written in state s, and L_{st} the SHELDUS losses in year t. We measure the portfolio losses of state v: $PL_v = \sum_i d_{iv} * \sum_s q_{is} * L_{st}$. We define the alternative portfolio-weighted catastrophe exposure measure as the correlation between historical losses in each county and portfolio losses in its state, rather than the within-state losses. The dependent variable is the log repeat-loan insurance premium expenditures index. Shown coefficients are for the interaction between catastrophe exposure and log reinsurance prices. All specifications are weighted by the number of owner-occupied housing units in the 2010-2014 ACS, and include zipcode and year fixed effects and log lagged structure values. Standard errors clustered by county in parentheses.

	Log Insurance Premium Expenditures Index			
	(1)	(2)	(3)	(4)
Log Reinsurance × Cat Exposure	0.39***	0.40***	0.28***	0.31***
	(0.077)	(0.076)	(0.086)	(0.060)
Log Reinsurance × Cat Exposure × High Friction	-0.61***	-0.61***	-0.33**	-0.26**
	(0.143)	(0.143)	(0.134)	(0.111)
R^2	0.904	0.905	0.911	0.891
N	176792	176792	176792	167596
Zip and Year FEs	Y	Y	Y	Y
Log Structure Value	Y	Y	Y	Y
Time-Varying Risk Coefficients	Y	Y	N	N
Time-Varying Flood Coefficients	N	Y	Y	Y
State-by-Time Risk Coefficients	N	N	Y	Y
Drop Florida	N	N	N	Y

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

Table A5: Pass-through of reinsurance price shocks to homeowners insurance premiums allowing for heterogeneity among "high friction" states in the top third of pricing regulation (Oh et al., 2022). The dependent variable is the log repeat-loan insurance premium expenditures index. Shown coefficients are for the interaction between correlated risk exposure and log reinsurance prices, and the triple interaction term with an indicator for high friction states. All specifications are weighted by the number of owner-occupied housing units in the 2010-2014 ACS, and include zipcode and year fixed effects and log lagged structure values. Standard errors clustered by county in parentheses.

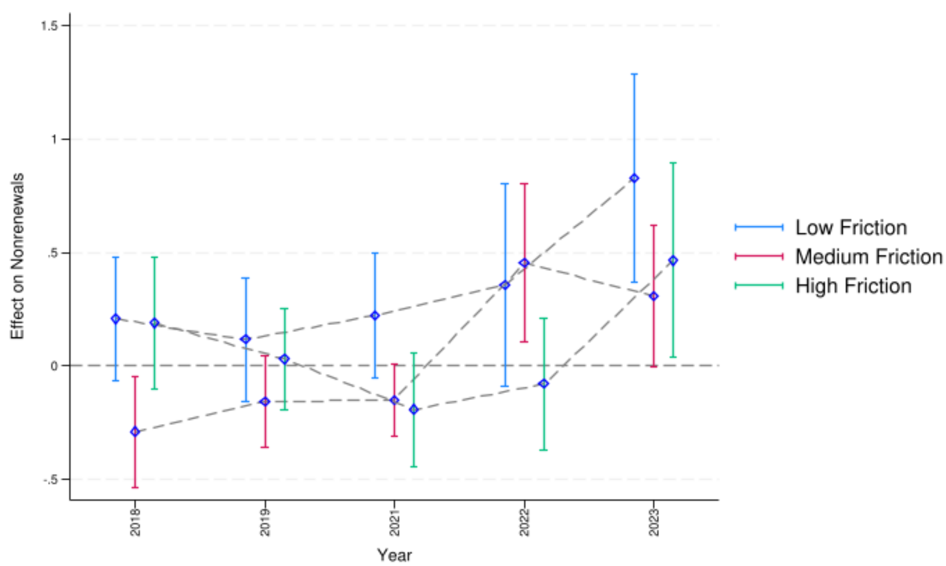
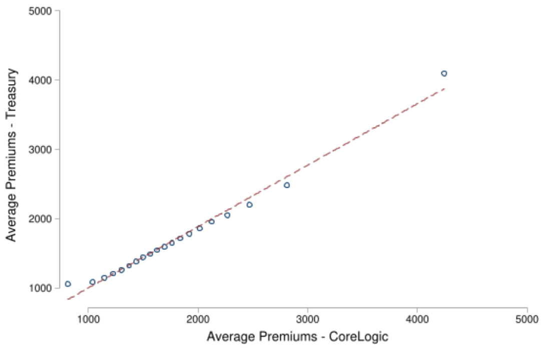
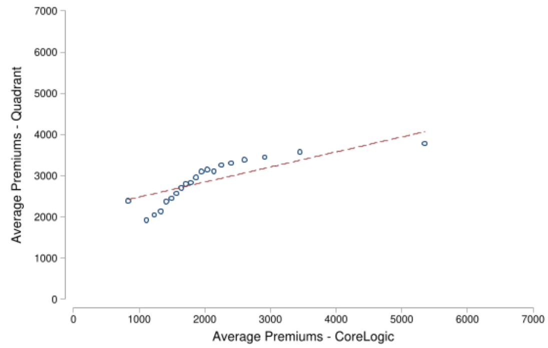


Figure A14: Effect of catastrophe exposure on log home insurance nonrenewals by state financial frictions. Plots annual coefficients on catastrophe exposure estimated separately by regulatory friction tercile (Oh et al., 2022). Specifications include county and year fixed effects and controls for log policies written at the start of the year. Lines indicate 95% standard errors clustered by county.

A.2 Comparison to Alternative Homeowners Insurance Premiums Data and Insurer Quotes



(a) Treasury



(b) Quadrant

Figure A15: Escrow Premium Estimates versus other sources. Each figure compares the average premiums from the escrow estimates against matched zipcode-by-year datapoints from other sources in the form of a binscatter. Panel (a) compares premium estimates between 2018 and 2022 collected by the U.S. Treasury Federal Insurance Office. Panel (b) compares average insurer cost quotes between 2014 and 2021 from Quadrant Information Services in Florida, Louisiana, California, and Texas. Quadrant rates are representative of publicly sourced data and should not be interpreted as bindable quotes.

Figure A15 compares the average nominal premiums calculated using our escrow approach with two alternative measures of zipcode homeowners insurance premiums: U.S. Treasury data collected from insurers on average premiums between 2018–2022 and sample homeowners insurance quotes collected from Quadrant Information Services between 2014–2022 in Florida, Louisiana, Texas, and California. To compare the datasources, we match corresponding zipcode-by-year observations and show binscatter relationships in Figure A15 between our premium estimates (x-axis) and the corresponding premiums in the other data (y-axis).

First, we compare our premiums against those measured in the U.S. Treasury Federal Insurance Office Property and Casualty Market Intelligence Data Call call on zipcode homeowners insurance premiums (panel a). The Treasury data, issued in cooperation with the National Association of Insurance Commissioners, collects annual information on average zipcode homeowners insurance premiums and claims collected form insurers. The data cover 80% of HO-3 and HO-5 homeowners policies nationally measured by direct premiums written (U.S. Department of the Treasury, 2025). Our escrow estimates are strongly correlated with the Treasury data, and the matched datasets have similar mean premiums of $1,808 (escrow) and $1,718 (Treasury).

Next, we compare our premiums against price quotes from Quadrant (panel b).[27] Quadrant's data come from estimated insurer prices based on their state rate filings for standardized amounts of coverage, so they reflect the cost of hypothetical policies averaged across the active insurers

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

in each state rather than reflecting the actual premiums paid for purchased policies. We average Quadrant's premium quotes within each zipcode across insurers, coverage A limit (250K and 500K), credit score (excellent, good, fair, or poor where applicable), and home age(new, 10 years old, 25 years old). There is a weaker, albeit still positive, relationship between escrow premium estimates and the Quadrant price quotes relative to the Treasury data.

In sum, the escrow premium estimates have a strong and positive relationship with the only other existing zipcode-level public data on homeowners insurance premiums, supporting the validity of our imputation method. In contrast, premium quotes, although providing valuable insight into the rates set by insurers, is a noisy proxy for the premiums actually paid by homeowners.