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PROPERTY INSURANCE AND DISASTER RISK:
NEW EVIDENCE FROM MORTGAGE ESCROW DATA

Benjamin J. Keys
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ABSTRACT

We develop a new dataset to study homeowners insurance. Our data on over 47 million observations of households' property insurance expenditures from 2014-2023 are inferred from mortgage escrow payments. First, we find a sharp 33% increase in average premiums from 2020 to 2023 (13% in real terms) that is highly uneven across geographies. This growth is associated with a stronger relationship between premiums and local disaster risk: A one standard-deviation increase in disaster risk is associated with $500 higher premiums in 2023, up from $300 in 2018. Second, using the rapid rise in reinsurance prices as a natural experiment, we show that the increase in the risk-to-premium gradient was largely caused by the pass-through of reinsurance costs. Third, we project that if the reinsurance shock persists, growing disaster risk will lead climate-exposed households to face $700 higher annual premiums by 2053. Our results highlight that prices in global reinsurance markets pass through to household budgets, and will ultimately drive the cost of rising climate risk.

Benjamin J. Keys
Department of Real Estate
The Wharton School
University of Pennsylvania
432 Vance Hall
3733 Spruce Street
Philadelphia, PA 19104
and NBER
benkeys@wharton.upenn.edu

Philip Mulder
Wisconsin School of Business
4263 Grainger Hall
975 University Avenue
Madison, WI 53715
Philip.Mulder@wisc.edu

1 Introduction

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

In this paper, we use information on mortgage escrow payments to develop a new approach to measuring homeowners insurance premiums. Most mortgage borrowers make a single monthly payment toward an escrow account that disburses funds toward mortgage principal, interest, local property taxes, and insurance (a.k.a. PITI). Our loan-level mortgage servicing data allows us to decompose the escrow payment into these four distinct elements and thereby construct a new dataset of insurance premium expenditures. The dataset yields over 47 million observations from 2014 to 2023. We create zipcode-level insurance premium expenditure indices (IPI) using both loan-level controls and in the style of a home price "repeat sales index," that follows premiums on the same loan over time.

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

With this new dataset in hand, we analyze the causes and consequences of recent insurance market trends in three parts. First, we characterize the state of insurance premiums in the United States to a more precise degree than any previous research. We find that average nominal premiums increased by 33% from $1,902 in 2020 to $2,530 in 2023, a 13% real increase. With the granularity of our data, we provide the first estimate of the relationship between disaster risk and premiums using within-state variation in expected disaster losses. We estimate that a one standard deviation

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

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

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

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

We are able to provide new measures of the level of insurance premium expenditure and the extent of "insurance burden" relative to incomes and home prices for thousands of zipcodes across the United States. Home prices and disaster risk explain most of the variation in insurance premiums, but we also observe large heterogeneity in premiums across incomes and socioeconomic status. For instance, lower income areas see much higher premiums as a share of income, and zipcodes with larger nonwhite population shares pay higher premiums after conditioning on disaster risk and income.

Second, we examine recent insurance market dynamics and the role of reinsurance costs in driving premiums higher. We find that the sharp increases in insurance premiums after 2018 were concentrated among zipcodes with the highest disaster risk. These effects cannot be explained by inflation, relative changes in home prices, or state-specific factors. Rather, our estimates show that the effect of a one standard deviation increase in disaster risk on premiums rose from $300 to nearly $500 by 2023. This increase in the premium cost of risk explains over 25% of the real increase in premiums between 2018 and 2023.

This increase in the risk-to-premium gradient coincides with a doubling of U.S. property catastrophe reinsurance prices between 2018 and 2023.[4] Reinsurance refers to secondary insurance contracts with global insurers used by U.S. insurers to hedge correlated or severe risks, such as hurricanes and wildfires. Thus, reinsurance prices provide an important window into the cost of insuring risks that are expected to increase with climate change. The 100% increase in reinsurance prices over just five years is potentially due to a number of factors, including inflation, a "climate epiphany" as reinsurers reassess climate exposure, increasingly concentrated disaster exposure as Americans move into harm's way, and the end of a low interest rate environment that led to a capital crunch.[5] It is therefore an open question whether reinsurers are raising prices in response to the same forces that are increasing premiums across the U.S., or if it is becoming especially costly to insure catastrophic risks.

We use our data to study the effects of this "reinsurance shock," and isolate the effects of reinsurance rates on homeowners insurance premiums. Our empirical specification uses variation across states in the reliance of insurers on reinsurance markets. However, a simple difference-in-difference strategy might violate the parallel trends assumption if state-level reinsurance exposure is correlated with other factors that also affect premium dynamics. To enhance the robustness of our results, we also use within-state disaster risk variation in a triple-difference design that interacts risk with reinsurance exposure. Thus, this design isolates the effect of tightening reinsurance markets

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

on the relationship between risk and premiums. Our most stringent specification includes state-by-time fixed effects to absorb the effects of state-level factors such as regulations or natural disasters that might affect general premium trends, as well as zipcode home price trends to adjust for housing cost inflation.

Our study of the reinsurance shock shows that premiums in disaster-prone zipcodes primarily increased in states exposed to reinsurance markets, while increases were more modest in less exposed states. Thus, the rise in reinsurance prices reflects higher costs of insuring catastrophic risks relative to less correlated risks in other states. We find that reinsurance exposure explains nearly $\frac{2}{3}$ of the increase in the pass-through of risk to premiums. Among zipcodes in the top decile of disaster risk, the reinsurance shock increased annual premiums by over \$375 in 2023. We conclude from this exercise that insurers' reliance on reinsurance markets makes the cost of insuring catastrophic risk sensitive to the cost of hedging those risks in global capital markets.

In the third and final step of our analysis, we use our estimates to benchmark potential increases in premiums due to climate change. Using the First Street Foundation's hurricane and wildfire models, we observe projected changes in disaster risk between 2023 and 2053. We then use our estimates of the risk-to-premiums gradient to translate changes in risk into changes in premiums, and compare projected increases pre- and post-reinsurance shock.

If the conditions for the reinsurance shock continue, we estimate that the top 5% of climate risk exposed homeowners would see increased premiums by 2053 of \$700 per policyholder under a conservative climate change estimate. This estimate should be considered a lower bound, as it assumes that reinsurance frictions do not get worse, that insurers continue to offer policies in risky areas, that regulations continue to cross-subsidize risks within and across states (Oh et al., 2022), and does not account for climate impacts on disaster risks besides hurricanes and wildfires. Our results show the sensitivity of premium increases under climate change to the resiliency of reinsurance markets. If instead reinsurance markets revert to their 2018 prices, we anticipate that climate change would increase the annual premiums of climate-exposed homeowners by only \$480. While these stylized projections hold fixed other factors that will undoubtedly change between 2023 and 2053, they demonstrate that the cost of climate change to households will depend on the capital costs of insuring catastrophic risk.

Taken together, our approach delivers unprecedented insight into the state of homeowners insurance markets, describes a new methodology for observing and analyzing these markets, provides a new causal estimate on the degree of pass-through from secondary reinsurance markets to primary homeowners insurance premiums, and benchmarks the potential effects of climate change on homeowners' premium costs. We produce the first estimate of a central determinant of the

cost of climate risk: the relationship between expected disaster losses and homeowners insurance premiums. This key parameter shows significant volatility over time and sensitivity to the cost of reinsurance, suggesting that the costs of climate change will crucially depend on the ability of global capital markets to absorb catastrophic risk.

By providing new estimates of how much individuals are paying for growing climate risks, our paper extends the climate finance literature around housing, mortgage, and insurance markets. A growing literature has established connections between asset values and climate risk in the housing market, with important heterogeneity around realized declines and climate beliefs.[6] The rising insurance premiums we document should eventually be capitalized into house prices (a pattern we are exploring in ongoing work), and may further reduce demand for at-risk properties (Poterba, 1984).[7] Recent research, focusing on publicly provided flood insurance, shows that the availability, cost, and stability of disaster insurance has first-order effects on the availability of mortgage credit and loan performance (Sastry, 2021; Sastry et al., 2023; Blickle and Santos, 2022; Kousky et al., 2020).

Our analysis expands connections between financial markets and the costs of climate change. Previous studies have shown how mortgage markets can act as climate risk sharing tools, but can also create adverse selection and moral hazard given unpriced climate risk (Ouazad and Kahn, 2021; Kahn et al., 2024; Panjwani, 2022; Issler et al., 2020).[8] Another strand of research finds that various frictions in the flood insurance market generate large welfare losses (Wagner, 2022; Weill, 2022; Ostriker and Russo, 2022), and that the mispricing of flood risk substantially increases long-run climate costs (Mulder, 2023). We provide the first estimates of U.S. homeowners' potential premium increases due to increasing disaster risk. Furthermore, we show that this key parameter is sensitive to the cost of accessing global reinsurance markets to diversify catastrophic risk. Thus, our estimates provide novel counterfactuals of the costs of climate change depending on the long-run costs of reinsurance.

Our findings provide new insights into private insurance market pricing and its relationship with the cost of capital in secondary markets. A literature in asset pricing and macro-finance has emphasized the importance of capital frictions and liquidity on firm price-setting in financial markets (Brunnermeier et al., 2021).[9] In life insurance markets, where price data for standardized policies is readily available, researchers have found that frictional costs from firms' liquidity constraints or

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

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

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

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

regulatory requirements pass-through to premiums with meaningful effects on consumer welfare (Koijen and Yogo, 2015, 2016; Bauer et al., 2021; Ge, 2022). Eastman and Kim (2023) estimate the pass-through of capital requirements to homeowners insurance premiums using household survey data on insurance expenditures. Most relevant to the reinsurance shock we study, many researchers have examined the forces that drive "underwriting cycles" of increasing and decreasing premiums.[10] Using our granular premium data, we provide a novel estimate of the pass-through of reinsurance prices to homeowners insurance premiums. Our evidence shows that capital market dynamics will be an important determinant of premiums in high-risk states.

Finally, this paper is relevant to understanding the price signals reaching climate-exposed homeowners. One line of research has found large markups for catastrophic reinsurance above expected losses (Froot, 2001; Zanjani, 2002; Froot and O'Connell, 2008) and noted the particular challenges of insuring correlated risks (Jaffee and Russell, 1997; Cummins and Weiss, 2009; Ibragimov et al., 2009; Kousky and Cooke, 2009; Marcoux and Wagner, 2023).[11] We extend these findings by showing how reinsurance price shocks not only affect premiums today, but could also affect the costs of increasing disaster risk under different climate change scenarios. Oh et al. (2022) find that insurers face substantial rate-setting frictions due to state regulation, and pass on climate-risk-induced losses to safer areas in less regulated states, leading to spatial cross-subsidization. Boomhower et al. (2024) uses rate filing data to show that insurers price wildfire risk in California depending on the sophistication of their risk models, which can induce cream skimming effects. We find that capital cost frictions can also distort the pricing of climate risk within and across states. Ultimately, the price signal from property insurance premiums will prompt adaptation, mitigation, and relocation, but will require a competitive and well-capitalized insurance market to set an accurate price signal.

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

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

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

2   The Residential Homeowners Insurance Market

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

Obtaining property insurance is generally a prerequisite to qualify for a mortgage. Most owner-occupied residential homeowners insurance policies are "HO-3," which covers the structure, contents, legal expenses in the event of a lawsuit, and living expenses during the time to make the home habitable if the home is damaged. These policies generally have clauses that specifically exclude certain perils, such as floods, earthquakes, or, in some cases, high winds or wildfires.[12]. Other types of policies cover these perils, and the market provides a variety of other policies that cover either more or less than the standard HO-3 policy (NAIC, 2022). In some cases, homeowners turn to state-sponsored "insurers of last resort," such as Citizens Property Insurance in Florida or the California FAIR plan, to provide coverage if they cannot find a willing private insurer.

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

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

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

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

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

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

3 Data

3.1 Loan-Level Data

Our data on mortgage escrow comes from CoreLogic, a leading property information and analytics provider. CoreLogic's Loan-Level Mortgage Analytics (LLMA) dataset follows residential loans from origination to termination using data provided by loan servicers. The data contains information at the time of origination, as well as continuing information on repayment and loan performance. Combined with the Supplemental Loan Analytics (SLA) file (with a unique loan ID), the data provides information on the total payment made by the borrower, the amount of principal and interest, and the current property taxes paid on the property.[13] The data includes the zipcode of the property, as well as loan type (e.g. purchase vs. refinance) and property and borrower

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

characteristics.

3.2 Disaster Risk, Climate Risk, and Socioeconomic Data

Our primary measure of climate risk comes from a combination of the National Risk Index (NRI) and the First Street Foundation (FSF). The NRI was designed by FEMA to communicate the extent of risk from 18 different climate-related hazards.[14] FSF is a non-profit that seeks to provide risk data to homeowners, policymakers, and academics with highly localized risk models for wildfire, wind, flood, and heat risk (First Street Foundation, 2020) (FEMA, 2023).[15]

To measure zipcode disaster risk in 2023, we combine the expected annual loss (EAL) rates per dollar of building value across different hazards typically covered by HO-3 homeowners policies. We use FSF's zipcode-level models to measure EAL rates for wildfire and hurricane hazards. We add in EAL rates for cold waves, hail, heat waves, ice storms, lightning, strong winds, tornadoes, volcanic activity, and winter weather from the NRI.[16] We winsorize each hazard's EAL rate at the 1st and 99th percentile across all zipcodes, and divide the overall EAL rate by its standard deviation to form the 2023 disaster risk measure.

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

Besides creating separate measures of disaster and climate risk, there are several other benefits to using the FSF hurricane and wildfire models. First, because the NRI is largely based on historical losses from SHELDUS, it is an intentionally "backward looking" measure of current risk.[17] In contrast, the FSF 2023 models account for recent changes in climate and land use that are particularly important for accurately measuring current wildfire and hurricane risks. Second, the NRI hurricane measure does 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.

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

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

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

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

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

3.3 Insurance Data

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

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

4   Measuring Insurance Expenditures

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

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

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

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

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

$$Insurance = TotalPayment - Principal - Interest - Taxes - MI \qquad (1b)$$

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

Table 1 describes the process by which we reach our analysis sample from the raw data. Our data come from nearly 20 million purchase and refinance fixed-rate loans for single-family homes that were originated between 2014 and 2023. We restrict the sample to loan-level records where total payments, principal+interest, and property tax data are all populated. We then focus on observations where the total payment changes (usually once per year). Next, we modestly restrict our sample by removing outliers and winsorizing premium values at the 1st and 99th percentiles by state-year. Finally, we impute MI premiums and remove a subset of loans with insufficient information to impute MI, or implausible values of imputed MI payments. Collapsing our data to year and quarter yields 47 million observations building off of over 12 million mortgagor escrow accounts.

Table 2 shows the straightforward decomposition exercise for one loan's total payment and

Zip Code	Date	Total Payment	Principal + Interest	Taxes	Insurance
34239	2015Q2	9200.88	6422.88	1301.22	1476.78
34239	2016Q1	9092.04	6422.88	1307.96	1361.20
34239	2017Q1	9194.64	6422.88	1291.32	1480.44
34239	2018Q1	9069.12	6422.88	1305.74	1580.50
34239	2019Q1	9408.36	6422.88	1327.67	1657.81
34239	2020Q1	9647.28	6422.88	1357.61	1866.79
34239	2020Q3	9725.64	6422.88	1357.61	1945.15
34239	2021Q1	9680.16	6422.88	1403.95	1853.33
34239	2022Q1	10095.84	6422.88	1397.79	2275.17
34239	2023Q1	11133.36	6422.88	1402.01	3308.47

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

how we infer insurance premiums in the case where LTV¡80% so there is no mortgage insurance payment. The loan is located in zipcode 34239 in Sarasota, FL. The inferred insurance payment is the remainder from subtracting principal, interest, and taxes from the total escrow payment. The annual insurance payment adjusts each time the total payment adjusts, with the tax amount sometimes changing (by small amounts) over time.

With our premium data in hand, we build two insurance premium indices (IPIs) at the zipcode level at a half-year frequency. The goal of the IPI is to compare insurance premiums across markets and over time adjusting for potential differences in the housing stock or composition of borrowers. We first estimate a *controls IPI*:

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

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

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

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

In the spirit of a home price repeat-sale index, the "repeat-loan index" in Equation 3 includes loan fixed effects λ_i and only identifies changes in the IPI from changes in premiums for the same loan observed across multiple periods. Thus, this index more restrictively holds fixed all time-invariant characteristics of the underlying property, borrower, and location.

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

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

5 Homeowners Premiums Across Time and Geography

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

Figure 1 presents a U.S. map of county-level annual average insurance premiums in 2023. The map shows a clear gradient in insurance costs, with higher insurance burdens in the riskiest coastal areas along the Gulf of Mexico and the East Coast, as well as high premiums (over $3,000 or more) through tornado- and flood-exposed regions of the Great Plains, eastern Colorado, Oklahoma, and North Texas.

Figure 2 shows the granular richness of the escrow data by contrasting county-level (left panel) and zipcode-level (right panel) premiums in Southern California. Whereas the geography of premiums appears smooth at the county-level, there are clear pockets of high premium zipcodes when viewed with more granularity. Appendix Figure 15 shows significant heterogeneity in premiums within Miami-Dade County, with much higher costs along the coast relative to inland.

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

The granularity of our data demonstrate that premium levels do not give a complete picture of the relative economic burden of homeowners insurance across places. Our loan-level data can
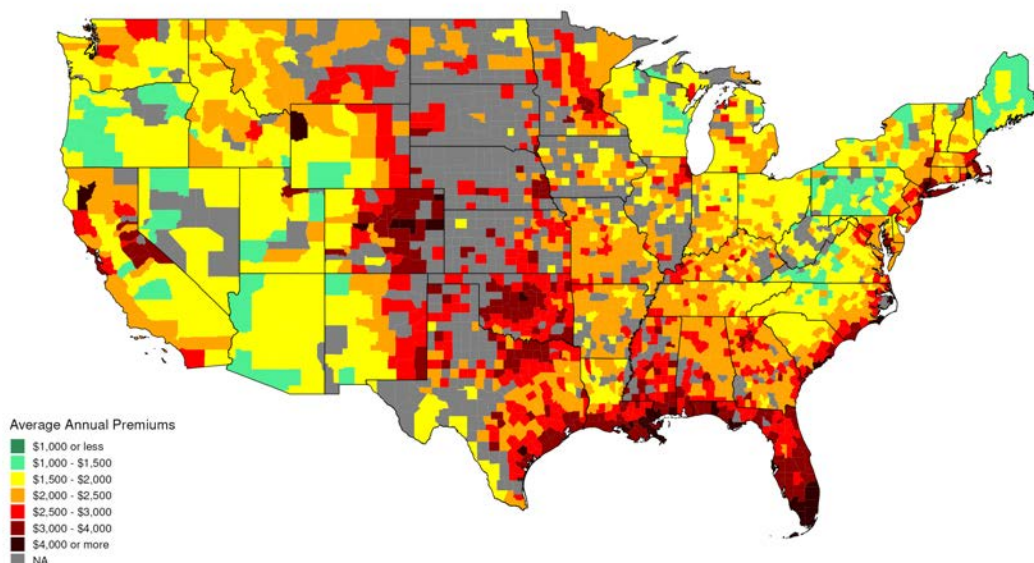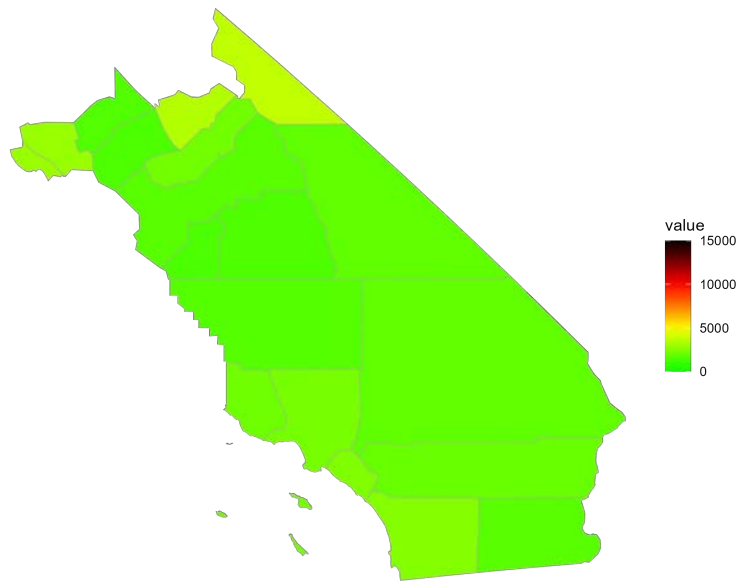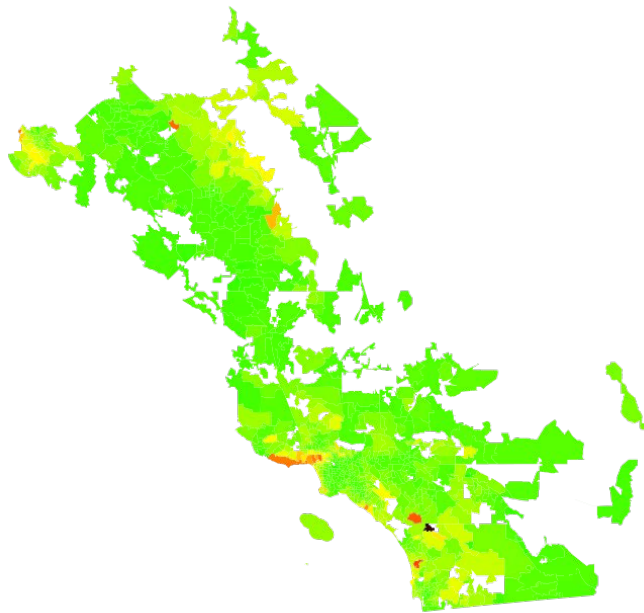
Figure 1: This figure maps average annual insurance premiums in the first half of 2023 by county. Counties with fewer than 20 premium observations are excluded.

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

In addition to its cross-sectional richness, our data track 10 years of premium dynamics from 2014 to 2023. Figure 5 presents the time series of average nominal homeowners insurance premiums in the United States from 2014 to 2023. Premiums were steady in nominal terms from 2014 through 2017, then rose between 2017 and 2019. Beginning in 2019, premiums leveled out until 2021. Since 2021, average premiums have risen sharply, with the average premium increasing by over $500 in three years. To investigate whether insurance costs rose faster than inflation over this period, Appendix Figure 16 shows a similarly sharp increase in inflation-adjusted dollars.

(a) Premiums by county, 2023H1

(b) Premiums by zip code

Figure 2: This figure maps average annual insurance premiums for Southern California in the first half of 2023 by county (top panel) and by zipcode (bottom panel).
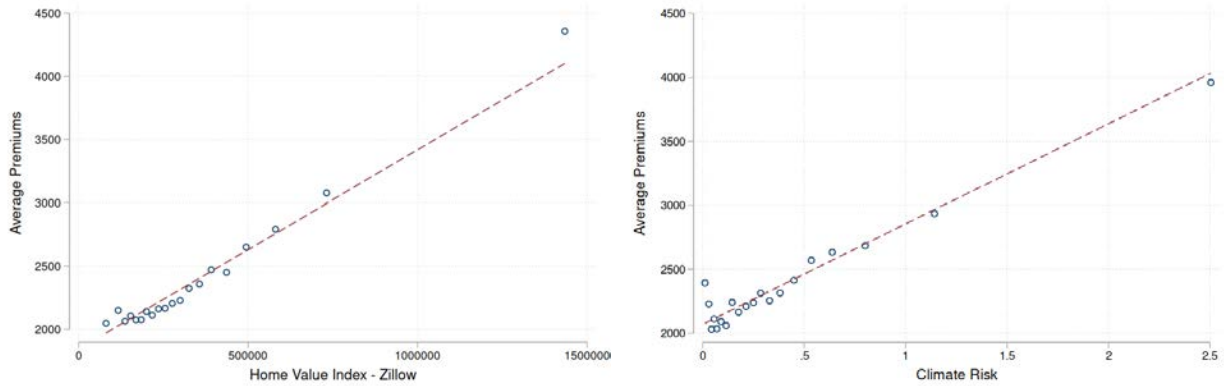
Figure 3: This figure shows the relationship between average premiums in 2023H1 by 20 ventiles of home values (left panel) and the disaster risk index (right panel).
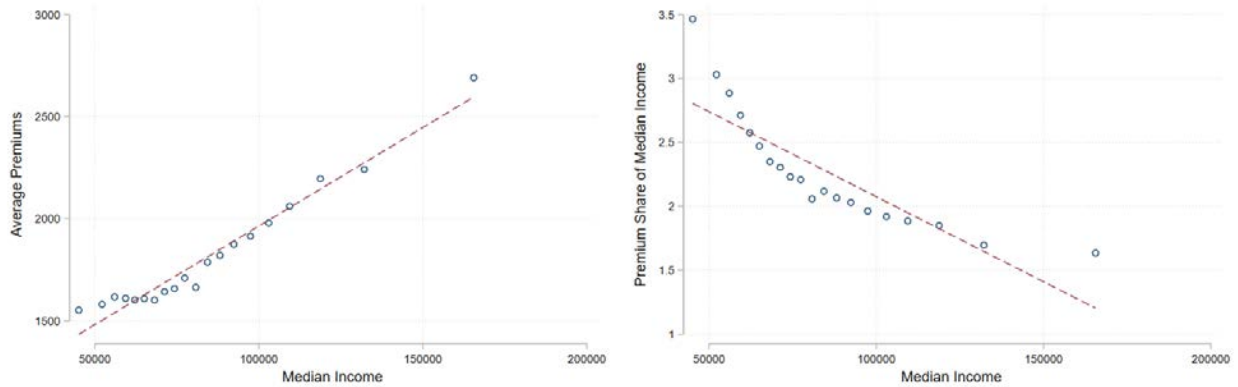

Figure 4: Figures show average premiums (left panel) and average premiums as a share of income (right panel) by twenty ventiles of zipcode median income. Income is median income of owner-occupied households from the 2014–2018 American Community Survey measured in 2018 dollars. Average premiums are taken over 2014–2018 and measured in 2018 dollars.
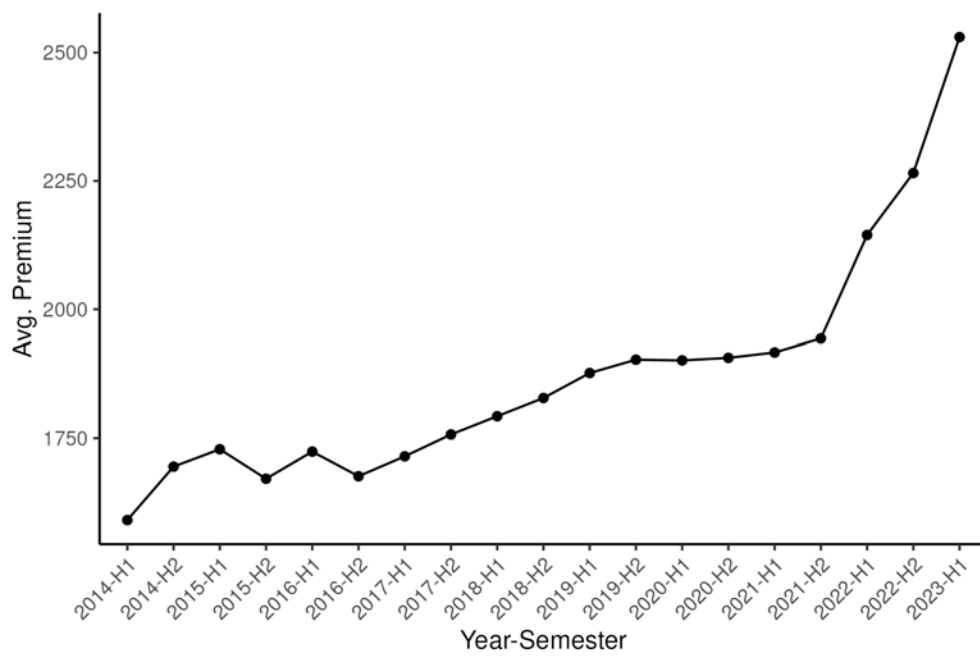
Figure 5: Time series of nominal average annual homeowners insurance premiums.

6   Insurance Expenditure Dynamics

Having established some of the key correlates and dynamics of insurance premiums, this section disentangles the relative influences of risk, home values, and demographics on premium differences across space and over time. Table 4 examines the effects of home values, risk, and zipcode characteristics in a regression analysis. The first column shows the bivariate relationship between real average premiums and the IPI constructed with loan-level controls, conditional on time fixed effects. A one-standard deviation increase in expected disaster losses is associated with a \$450 increase in average premiums.

Column (2) adds zipcode-level covariates for the population share white and median household income in thousands of dollars. These covariates do little to change the estimated disaster risk coefficient. The positive relationship between incomes and insurance expenditures in consistent with evidence that wealthier households demand more insurance (Gropper and Kuhnen, 2021; Armantier et al., 2023). Column (2) also shows that zipcodes with higher nonwhite population shares see higher premiums, with a 10 percentage point decrease in the white population share associated with approximately \$38 higher annual premiums. While this relationship is conditional on home price controls and credit score controls in the IPI, disaster risk, and income, we note that it does not hold fixed other factors that may affect insurers' costs or differences in insurance demand.[18]

In column (3), we add state-by-year fixed effects to absorb time-varying factors at the state level, such as insurance market regulations or natural disasters, that might affect premiums. Here, we see that the disaster risk coefficient attenuates to a \$330 premium increase with a one standard deviation increase in disaster risk. This analysis suggests that state-level factors and differences in home values partially, but not completely, drive the aggregate relationship between premiums and disaster risk. Thus, our zipcode-level IPIs are critical for estimating the appropriate pass-through of risk to premiums.

It is important to note that column (3) of Table 4 measures the effect of disaster risk on insurance spending, i.e. premiums, and not rates, or the cost per unit of coverage. This approach is a consequence of our data, where we only observe total premiums and not the exact coverage purchased. However, the effect of risk on total insurance spending is a relevant measure of the costs of disaster risk for households. If living in a risk-prone area leads homeowners to choose a lower deductible or buy more coverage, then paying for that lower deductible is as much a cost of risk as

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

	(1)	(2)	(3)
	Insurance Premium Expenditures Index		
Disaster Risk	447.822***	495.943***	333.540***
	(15.737)	(15.288)	(16.357)
Pop. Share White		-380.382***	-287.976***
		(32.872)	(35.363)
Median Income ($1000s)		12.584***	12.764***
		(0.357)	(0.329)
N	177,631	177,479	177,479
R2	0.254	0.391	0.545
Demographic Controls	No	Yes	Yes
Year#Semester FE	Yes	Yes	Yes
Year#Semester#State FE	No	No	Yes

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

Table 4: Regression analysis of the determinants of insurance premiums. 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.

facing a higher rate for coverage.[19]

A caveat to this interpretation is that differences in coverage choices driven by risk preference heterogeneity correlated with risk do not reflect the cost of risk. While it is impossible to perfectly control for such preference heterogeneity, this concern motivates the inclusion of loan-level and zipcode-level controls as well as state-by-time fixed effects. On the other hand, if higher rates lead homeowners to buy less coverage, then our measures will understate the true costs of risk and climate change.

Table 4 assumes that the relationship between disaster risk and premiums is constant over the sample period. To interrogate this assumption, Figure 6 shows the time series of average insurance premium expenditures by disaster risk quintile (as measured by NRI). As reflected in Table 4, disaster risk was a strong predictor of average premiums at the start of our time series in 2014, with the riskiest quintile paying nearly double the premiums of the safest quintile. The differences across quintiles were stable until 2020, when premiums in the riskiest quintile began to increase sharply. Thereafter, premiums have risen across all climate risk quintiles, but the gap between risky and safe areas has substantially widened.

This cross-sectional variation across disaster exposure in the rise of premiums suggests that general factors – such as inflation, interest rates, supply chain, or labor shortages – cannot fully explain the post-2020 rise in premiums. While the notable premium increases across all five quintiles

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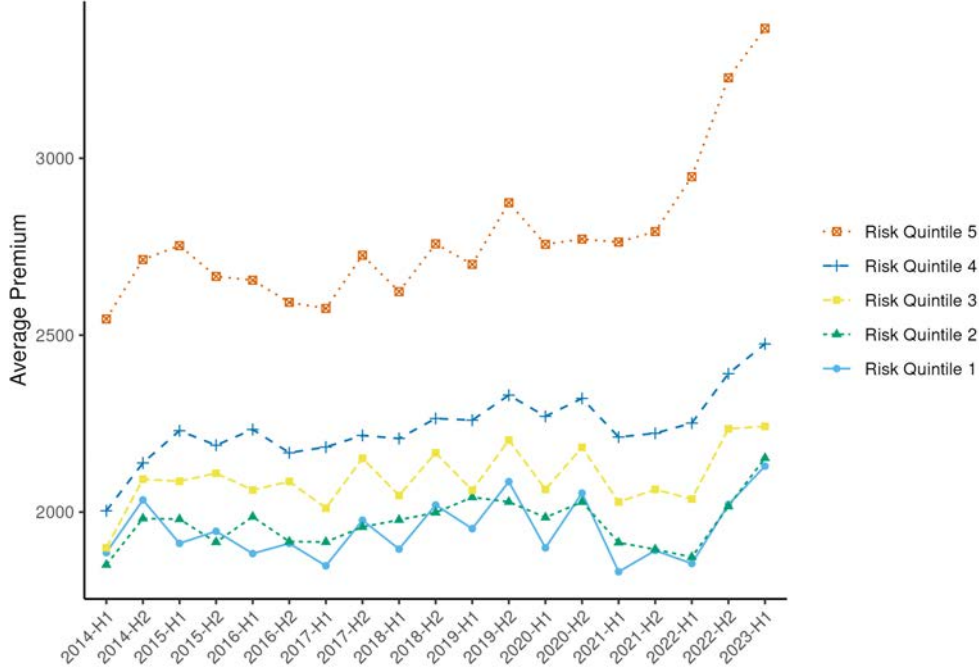[19]Leverty et al. (2023) finds a positive effect of climate risk perceptions on homeowner's insurance demand.

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

show that these factors likely played some role in higher premiums, the data also provide evidence that disaster risk became a more important determinant of premiums after 2019.

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

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

IPI_{zst} is the controls insurance premium index. α_z and α_{st} are zipcode and state-by-time fixed effects, respectively. We also control for population share white and median income as in column (2) of Table 4, and for home price trends with the Zillow home value estimates ($HomePrice_{zt}$). The key parameters of interest are the period-by-period β^t on $Risk_z$, which give the effect of a one-standard deviation increase in disaster risk on premiums. Critically, the β^t coefficients are estimated conditional on home price growth or other time-varying statewide factors that also affected premiums.

Figure 7 presents the time-varying coefficient of climate risk on premiums from Equation 4. While the relationship between climate risk and premiums was stable – or even decreasing – through
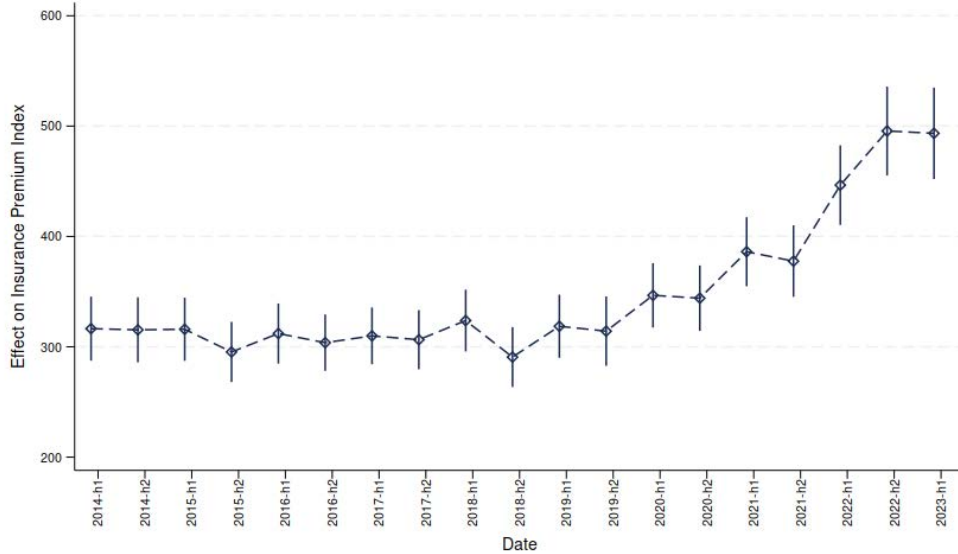
Figure 7: Plots the time-varying estimated effect of disaster risk on premiums. Vertical lines indicate 95% confidence intervals. See Equation 4 for more details.

2019, starting in 2020 we estimate a substantially stronger relationship between premiums and climate risk, consistent with the raw data in Figure 6. The coefficient on risk increases 66% from $300 per index unit through 2018 to nearly $500 in 2023. This increase implies a $260 increase in annual premiums for zipcodes in the top decile of disaster risk.

To examine the robustness of our results, we re-estimate the dynamics of the risk coefficient with our repeat-loan IPI adjusted for inflation as the dependent variable. Because it identifies changes in premiums by following the same loan over time, it is more robust to potential biases caused by changes in the composition of homeowners over time. The results, shown in Appendix Figure 17, show a similar increase in the risk coefficient from the base period as in the controls IPI.

7 Reinsurance and the Cost of Disaster Risk

The previous section established that the real cost of homeowners insurance has grown between 2018 and 2023, especially in areas exposed to more climate risk. Furthermore, we show that the widening premium gap between high and low risk areas cannot be explained by statewide factors or relative home price trends. Over this same period, catastrophe reinsurance markets hardened substantially, raising the possibility that some of this spending increase reflects insurers passing through reinsurance costs to homeowners (Eaglesham, 2024). Between 2019 and 2023 – the same period as the risk-to-premium pass-through rose – the price of reinsurance in the U.S. Property Catastrophe market increased by over 85% according to the Guy Carpenter Rate-On-Line Index,
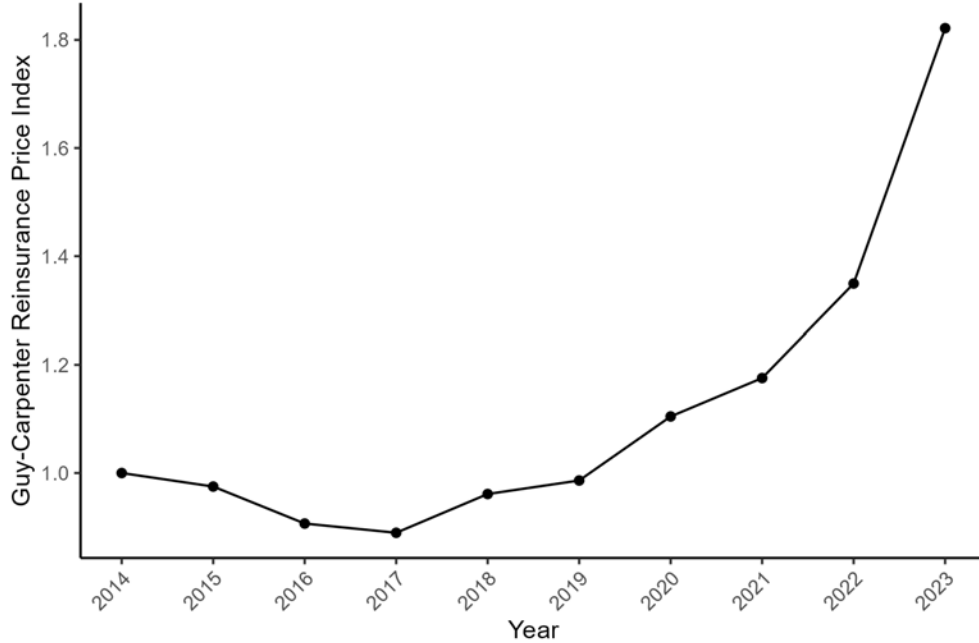
Figure 8: Time series of the Guy-Carpenter U.S. Property Catastrophe Rate-on-Line Index. See `https://www.artemis.bm/us-property-cat-rate-on-line-index/` for more information.

as shown in left panel of Figure 8. Even as their prices rose, reports indicate that reinsurers also restricted the quantity of coverage they were willing to write (Corbineau et al., 2023).

The role of reinsurance in driving premium dynamics is important for two reasons. First, climate change is expected to exacerbate the wildfire and hurricane risks that form much of the underlying risk in reinsurance contracts. Second, the effect of reinsurance prices on premiums shows how the cost of global risk intermediation affects what homeowners pay to insure catastrophic risk. However, it is an open question whether rising reinsurance prices reflect higher costs of homeowners insurance everywhere, or if the cost of insuring risk is rising faster in markets that rely on reinsurers for diversification.

To separate the pass-through of reinsurance prices from other potential causes of rising premiums in high-risk areas, we create a state-level measure of 2019 reinsurance exposure.[20] While premiums ceded are not defined by geography, we do know insurers' direct premiums written in each state. Let d_{is} be the direct premiums written by insurer i in state s, $D_i = \sum_{s \in S} d_{is}$ be the total direct premiums written by i across all states, c_i be the dollar value of premiums ceded by i to unaffiliated reinsurers, and $C_i = \frac{c_i}{D_i}$ be the share of i's premiums ceded to unaffiliated reinsurers. We define each state's reinsurance exposure:

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[20]We thank Ty Leverty for his help accessing this data and advice defining the exposure measures.
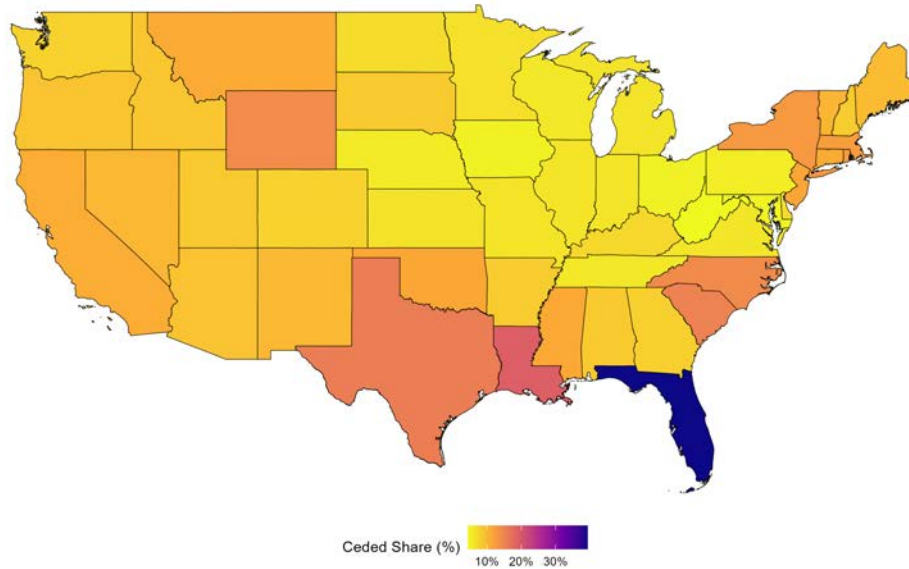
Figure 9: Map of state-level reinsurance exposure. Reinsurance exposure for each state is defined as the market-share weighted average of the share of premiums ceded by each insurer.

$$ReExposure_s = \frac{\sum_{i \in I} d_{is} C_i}{\sum_{i \in I} d_{is}}.$$

A state's exposure to reinsurance markets, $ReExposure_s$, is thus the market-share weighted average of the share of premiums ceded by each insurer. Figure 9 maps reinsurance exposure across states. The insurers that tend to write business in riskier states – especially hurricane-exposed states – also tend to transfer more of their risk to reinsurers, consistent with the purpose of reinsurance to manage catastrophic risk.

Before proceeding to our econometric analysis, we compare two adjacent states with different reinsurance exposure: Florida, with an exposure of nearly 40%, and Georgia with an exposure of less than 10%. Nearly all of Florida is hurricane-exposed and its property & casualty insurance market is dominated by specialty Florida insurers, whereas Georgia has more national carriers who rely less on reinsurance. Figure 10 plots the zipcode-level change in premiums between 2018 and 2023 along the northeast coast of Florida in St. Johns county across the border with Georgia into McIntosh county.

Although the stretch of zipcodes along either side of the state boundary are similarly disaster-exposed, the zipcodes in Florida saw higher premium increases between 2018 and 2023 than their
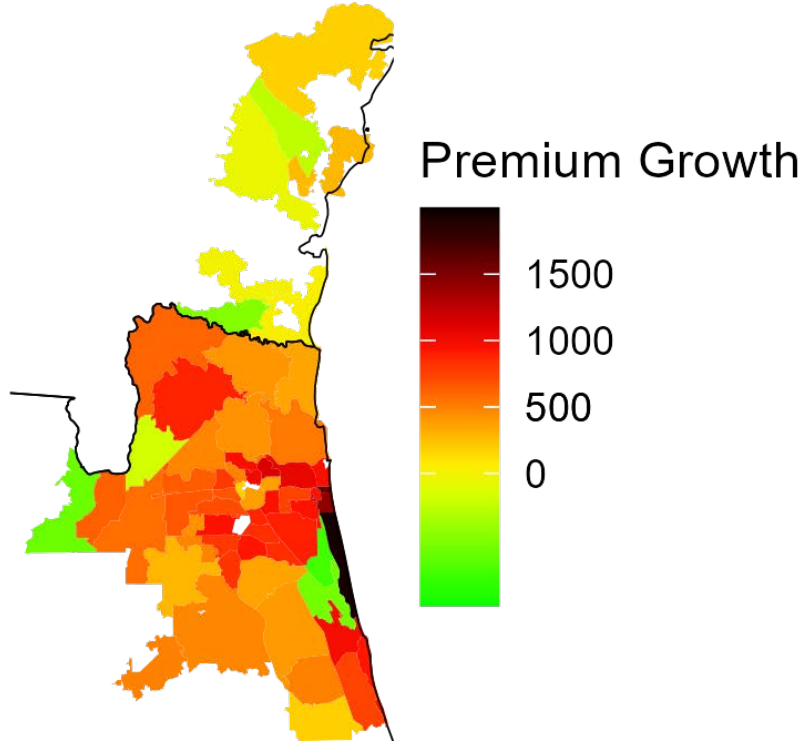
23

Figure 10: The real difference in annual insurance premiums between the second half of 2018 and the first half of 2023 for zipcodes in selected counties in Florida and Georgia. Zipcodes with fewer than 20 loan observations in 2018H2 or 2023H1 are omitted. Dark lines indicate state and coastal boundaries.

counterparts in Georgia.[21] Real premiums increased by approximately \$1,000 on the Florida side of the boundary but by less than \$500 on the Georgia side.

Moving from this case study to statistical analysis, we treat the sudden increase in reinsurance prices from 2019 to 2023 as a natural experiment. We use the following triple-difference specification to test the effect of reinsurance rates on the pricing of disaster risk:

$$\Delta_{2018H2}^{2023H1}IPI_{zs} = \beta_1\Delta_{2018H2}^{2023H1}HPI_z + \beta_2ReExposure_s + \beta_3Risk_z + \beta_4ReExposure_s \times Risk_z + \epsilon_{zs}, \quad (5)$$

where the dependent variable, $\Delta_{2018H2}^{2023H1}IPI_{zs}$, is the change in the Insurance Premium Index in inflation-adjusted 2023 dollars between the second half of 2018 and the first half of 2023 in zipcode z of state s. The independent variables are the change in zipcode z's home values in thousands of 2023 dollars over the same period, s's reinsurance exposure, zipcode z's disaster risk, and the

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[21]See Appendix Figure 14 for the associated zipcode risk measures.

	(1)	(2)	(3)	(4)
	2018–2023 Premium Change (2023 Dollars)			
	Dependent Variable Mean: 284.93			
Disaster Risk	260.445***	13.221	70.155***	87.797***
	(16.335)	(25.597)	(25.427)	(22.778)
ReExposure	1,644.371***	33.971		
	(120.237)	(151.466)		
Risk X ReExposure		1,232.308***	517.096***	456.530***
		(95.736)	(106.202)	(102.612)
Risk X Regulatory Friction				-245.379
				(197.647)
2018–2023 Home Price Change	0.843***	0.785***	1.312***	1.315***
	(0.194)	(0.188)	(0.207)	(0.207)
Constant	-89.474***	97.089***	110.316***	108.094***
	(14.167)	(18.111)	(15.834)	(15.657)
Observations	9,336	9,336	9,336	9,336
R-squared	0.259	0.283	0.438	0.438
State FE	N	N	Y	Y

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: This table shows estimates of the pass-through of reinsurance prices to premiums. The dependent variable is the change in the fixed effects insurance premium expenditures index between 2018H2 and 2023H1 by zipcode in 2023 dollars. Only zipcode observations with at least twenty loan observations in 2018H2 and 2023H1 are included. Observations are weighted by the number of owner-occupied housing units according to the 2010–2014 5-year American Community Survey. See Equation 5 for details.

interaction between reinsurance exposure and disaster risk. Specifications are estimated with robust standard errors.

The key assumption to identify β_4 is that the risk-to-premium relationship would have evolved similarly in more- and less-reinsurance exposed states absent changing reinsurance prices. To lend this assumption more credibility, we add state fixed effects to Equation 5 that absorb state-level factors driving premium changes that might be correlated with reinsurance exposure. Thus, we can identify β_4 from within-state variation in disaster risk.[22]

The results of estimating Equation 5 are shown in Table 5. In column (1), we include the reinsurance exposure and disaster risk terms without an interaction term. A $1,000 increase in

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[22]Notably, our assumption is not that the actual private cost of insuring risk remained similar across states with different reinsurance exposure. Rather, reinsurers likely raised their prices precisely because they perceived higher costs of insuring in states with concentrated catastrophic risk exposure. In addition, supposing reinsurance prices remained flat is a partial equilibrium counterfactual. If reinsurance prices had been exogenously fixed, it likely would have led to an even sharper decline in reinsurance capacity.

home values is associated with about \$0.84 more insurance spending, while a one-standard deviation increase in disaster risk is associated with \$260 higher premiums in 2023 relative to 2018. The coefficient on reinsurance exposure implies that moving from the 10th percentile to the 90th percentile of reinsurance exposure (e.g. from Pennsylvania where insurers cede an average of 5% of their premiums, to Texas where they cede 16% of their premiums) increases average premiums by approximately \$180.

In column (2) we add a risk-by-reinsurance exposure interaction term. Moving from column (1) to column (2), the disaster risk term attenuates from positive and statistically significant to approximately null. Much of the positive effect of reinsurance exposure on premiums from column (1) is now explained by the interaction between reinsurance exposure and risk. In short, premiums increased after 2019 for high-risk zipcodes relative to low-risk ones, but primarily in states exposed to reinsurance.

In column (3), we apply a more stringent identification standard to our baseline specification by adding state fixed effects. This specification absorbs any state factors – such as idiosyncrasies of the housing market not captured in prices, natural disasters, or insurance market regulations – that may be correlated with reinsurance exposure and explain some of the change in premiums around the reinsurance price shock. This specification shows a positive and statistically significant risk-by-reinsurance exposure term.[23]

To illustrate the economic significance of our estimates, Figure 11 maps the reinsurance premium shock by county from our estimates in column (3).[24] The pass-through of reinsurance costs is extremely concentrated in disaster-prone areas in states with more reinsurance exposure. While the median reinsurance shock across zipcodes was less than \$10, zipcodes in the top decile of disaster risk experienced average real increases of \$375 from rising reinsurance rates, or over $\frac{1}{3}$ of their total increase in premiums between 2018 and 2023. Seven counties in Florida, collectively containing over two million owner-occupied housing units, had reinsurance shocks of \$600.[25]

We learn several novel facts about homeowners insurance markets from the results above. While the previous literature has documented markups and fluctuations in reinsurance costs, we show the first evidence that those costs are largely passed through to homeowners. Second, we have shown that the pass-through of reinsurance costs changes not just the level of premiums but the relationship between premiums and disaster risk. Third, we show that reinsurance shocks are

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[23]In column (4) we add an interaction term between disaster risk and regulatory pricing frictions, as defined in Oh et al. (2022), reflecting state regulatory barriers to freely adjusting premiums. The inclusion of this regulatory stringency measure does little to change the risk and reinsurance interaction term.

[24]The reinsurance premium shock is defined at the zipcode level as $ReShock_{zs} = \widehat{\beta_4} * ReExposure_s * Risk_z$. We take the mean of $ReShock_{zs}$ at the county level weighted by the number of owner-occupied housing units according to the 2010–2014 5-year American Community Survey.

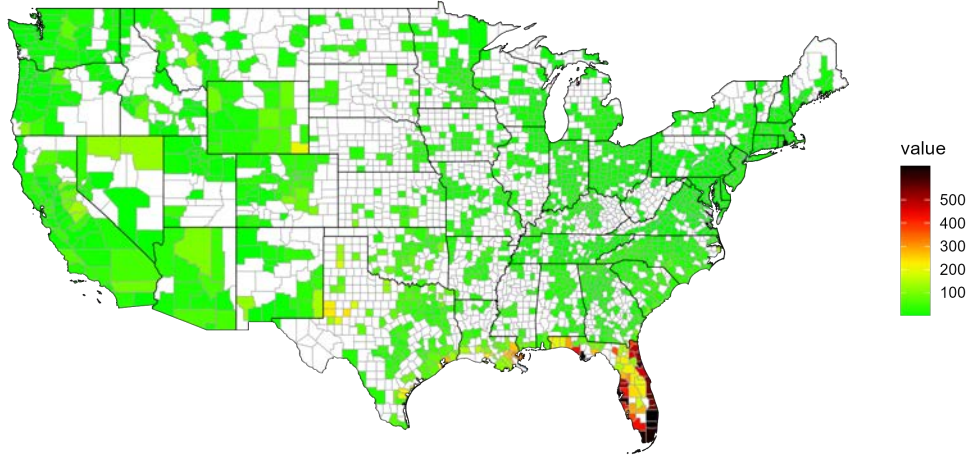[25]Number of owner-occupied housing units comes from July 2023 Census estimates.

Figure 11: Plots reinsurance shocks by county. Reinsurance shocks are calculated as the real dollar increase in premiums between 2018 and 2023 caused by rising reinsurance prices.

geographically concentrated, leading to large burdens in a relatively small number of markets rather than evenly spreading costs. In sum, insurers' reliance on reinsurance markets combined with an unexpected cost shock has made it more expensive to insure catastrophic risk.

8   Reinsurance and the Cost of Climate Change

The previous section detailed how recent insurance and reinsurance market dynamics have heterogeneously affected the premiums paid by U.S. homeowners, increasing the effect of disaster risk on premiums in some states more than others. In this section, we use our forward-looking measure of climate risk that accounts for expected changes in hurricane and wildfire losses to project how homeowner's insurance premiums will increase between 2023 and 2053.

First, we show projected premium increases due to climate change given the premium coefficients on disaster risk after the reinsurance shock. Specifically, we measure the expected increase in premiums due to climate change:

$$(\widehat{\beta}_{2018H2}^{Risk} + \widehat{\beta}_{ReShock}^{Risk} + ReExposure_s * \widehat{\beta}^{RiskXReExposure}) * (Risk_{2053} - Risk_{2023}), \qquad (6)$$

where $\widehat{\beta}_{ReShock}^{Risk}$ and $\widehat{\beta}^{RiskXReExposure}$ are the estimated risk and risk-by-reinsurance exposure interaction terms from column (3) of Table 5, and $\widehat{\beta}_{2018H2}^{Risk}$ is the baseline effect of disaster risk on premiums in 2018H2 as estimated in Figure 7.

The county-level averages of these potential climate premium costs for "climate-exposed" homeowners – those in the top 5% of expected disaster risk increase – are shown in Figure 12. On average, this group faces annual premium increases of over \$700 by 2053 due to higher disaster risk. Extrapolating our full-sample estimates to the approximately 80 million single-family homes in the U.S. implies additional annual premiums of \$5.1 billion by 2053.

This analysis assumes that the risk-to-premium relationship will resemble our estimates from 2023 after the reinsurance shock increased the risk-to-premium gradient. However, to benchmark premium changes if reinsurance prices fall, we can calculate the projected increase in premiums if the risk-to-premium relationship reverts to its 2018 levels. Effectively, we recalculate Equation 6 setting $\widehat{\beta}_{ReShock}^{Risk}$ and $\widehat{\beta}^{RiskXReExposure}$ to zero.
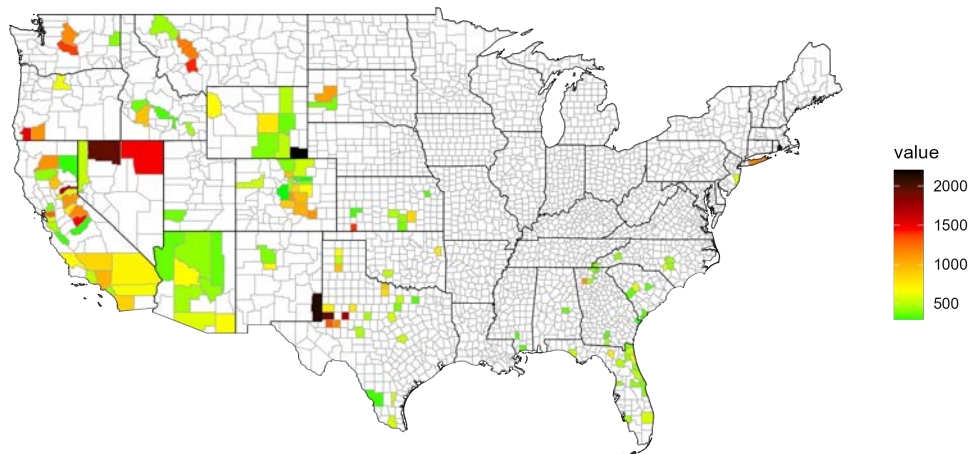

Figure 12: Climate Premium Shocks. This figure shows the expected increase in average annual homeowners insurance premiums by county among households in the top 5% of expected disaster risk increase under 2023 insurance costs.

To illustrate the influence of reinsurance costs on the premium costs of climate change, Figure 13 plots 2053 annual premium increases under 2023 (red) and 2018 (blue) insurance costs by 20

ventiles of climate exposure. Annual premium increases among climate-exposed homeowners are only \$480 under 2018 costs instead of \$700 under 2023 costs, and aggregate premium increases due to climate change are reduced by more than 30%. Premium increases are 90% higher in Florida and 50% higher in Texas under 2023 insurance costs relative to 2018 insurance costs. Thus, our reinsurance shock estimates show that the costs of intermediating catastrophic risk are an important determinant of the potential costs of climate change.

Another upshot of our findings is that premium increases due to climate change will depend on the correlation between where disaster risk is expected to increase and where insurers rely on reinsurance markets. While the FSF model projects expected wildfire losses to double by 2053, hurricane losses are only expected to increase by about 10%.[26] Reinsurance exposure today is concentrated among states exposed to hurricane rather than wildfire risks, attenuating the projected impact of the reinsurance shock on projected premium increases due to climate change.

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

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

Our results also show that climate costs are extremely sensitive to reinsurance markets. In projecting climate costs from 2023 insurance costs, we assume that reinsurance exposure will remain fixed. Given that reinsurance exposure is correlated with catastrophic risk, we might also expect to see this exposure increase with climate change. On the other hand, reinsurance costs have

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[26]The First Street Foundation has further detail on their wildfire model (https://firststreet.org/research-library/fueling-the-flames and hurricane model (https://firststreet.org/research-library/worsening-winds) projections. Climate change is expected to move hurricane landfalls further north along the Mid-Atlantic. In fact, Miami-Dade county sees a modest *decrease* in expected hurricane losses by 2053, although it still faces substantial increased risk due to sea level rise and flooding.

risen and declined before the most recent reinsurance shock (Boyer et al., 2012). Before 2023, reinsurance prices peaked in 2006 before declining nearly 50% to their trough in 2017 according to the Guy Carpenter Index (Guy Carpenter, 2024). As of writing, there are already some signs that the reinsurance market is softening in 2024 (Araullo, 2024; Howard, 2024). Even if reinsurance prices are lower in 2053 than 2023, our findings still show that volatility in reinsurance prices create volatility in premiums under climate change. Furthermore, it is unclear what effect the increasing frequency and severity of catastrophic risks will have on long-run reinsurance prices and capacity.

A final implication of our findings is that reducing the frictional capital costs of insuring catastrophic risks is a tool to reduce the costs of climate change. Although reinsurance contracts still represent the main conduit of global capital to U.S. insurers, growing markets in cat bonds and other insurance linked securities may hold promise to lower the cost of financing catastrophic risk (Cummins et al., 2004; Braun, 2016).
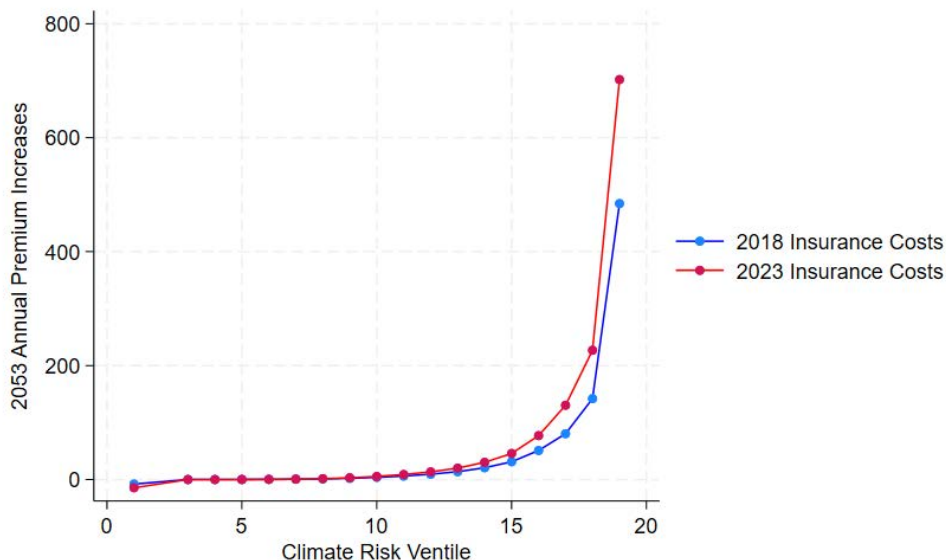

Figure 13: Predicted increase in annual insurance premiums in 2053 due to climate change under 2018 insurance costs (blue) and 2023 insurance costs (red) by twenty ventiles of climate exposure.

9 Conclusion and Directions for Future Research

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

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

We find that premiums have risen sharply since 2020, that this growth has been concentrated in disaster-prone zipcodes, and that elevated reinsurance costs are a critical driver of the increase. We provide new estimates of the elasticity of premiums with respect to climate risk, and show that the pass-through of risk to premiums increased more than 60% between 2018 and 2023. We also provide a new estimate of the pass-through of reinsurance costs to insurance premiums in markets exposed to catastrophic disasters, finding that the increase in reinsurance prices can explain over half of the increase in the relationship between premiums and risk. The reinsurance shock added $375 to the 2023 annual homeowners insurance premiums of households in the top decile of disaster risk.

Our results also benchmark potential increases in premiums that climate-exposed homeowners will face due to increasing risk. By 2053, we estimate that climate-exposed homeowners will be paying $700 higher annual premiums due to increasing wildfire and hurricane risk. However, these premium increases are highly sensitive to reinsurance prices. If insurance costs revert to their 2018 levels, then premium increases will be reduced by $\frac{1}{3}$. Thus, the costs of climate change depend on the cost of accessing reinsurance markets to diversify catastrophic risks.

In subsequent research, we intend to use this large panel dataset of insurance expenditures to examine whether insurance costs are capitalized into house prices; how rising user costs of homeownership affect mobility and housing tenure choice; the consequences of increased insurance burdens on mortgage default; and the impact of insurer exit and growing dependence on state-mandated FAIR plans on insurance spending. We anticipate that this data effort is only an initial foray into measuring homeowners insurance markets, and that additional data availability on policy coverage, deductibles, and claims will be valuable for researchers, policymakers, and households that must navigate an increasingly challenging property insurance landscape.

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10 Appendix
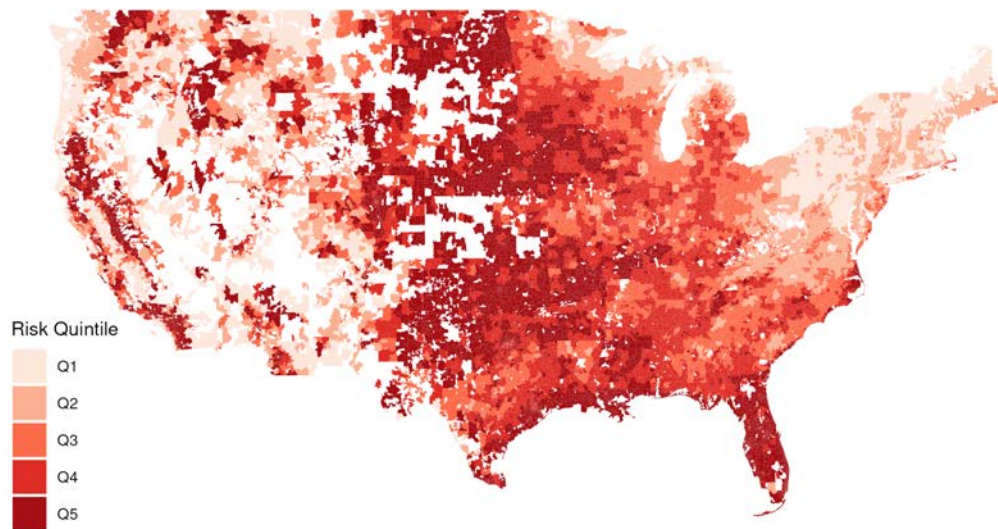
10.1 Appendix Figures and Tables
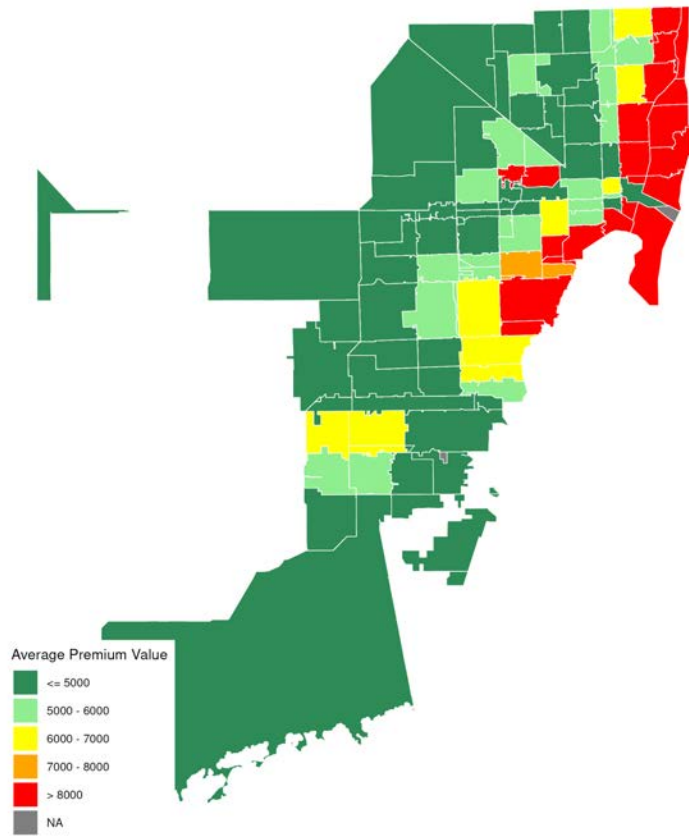

Figure 14: Map of US zipcodes by risk measure quintile

Figure 15: Shows average annual homeowners insurance premiums by zipcode in Miami-Dade County in the first half of 2023.
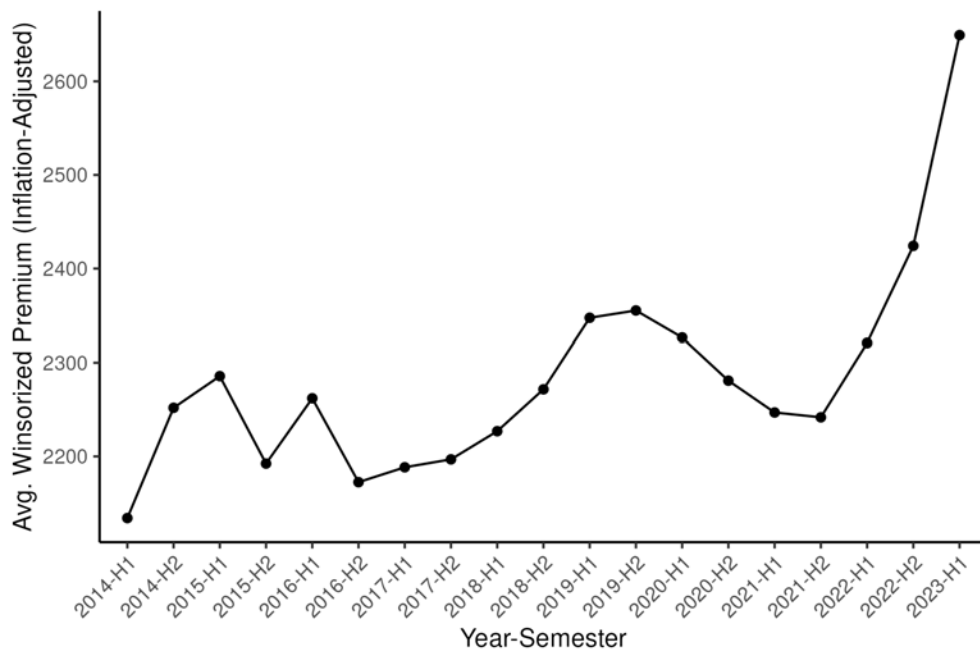
Figure 16: Time series of average annual homeowners insurance premiums. Values are inflated to constant 2023 dollars.
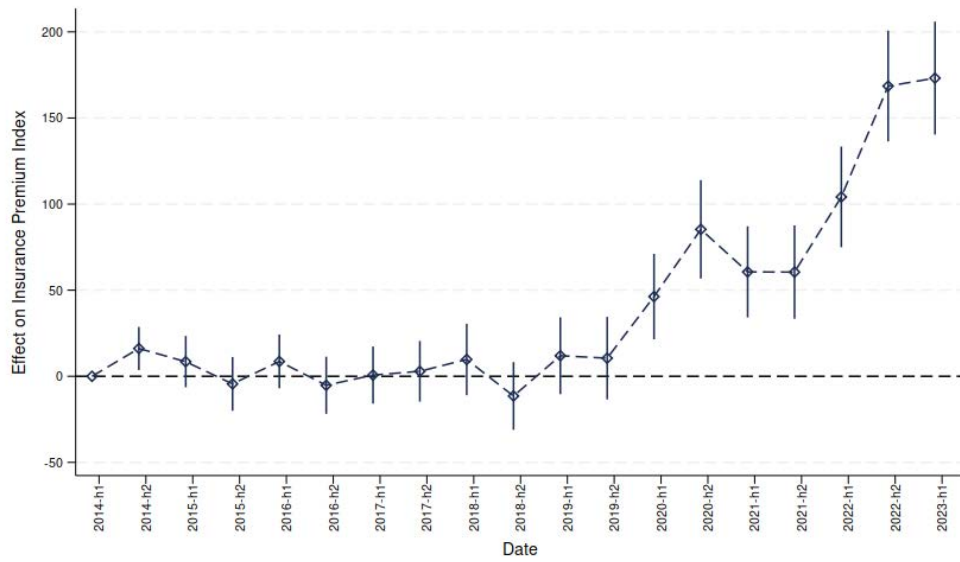
Figure 17: Plots the time-varying estimated effect of disaster risk on premiums. Dependent variable is the repeat-loan insurance premium expenditures index.

10.2 Comparison to III, Census, and Quadrant

Figure 18 compares the average nominal premiums calculated using our escrow approach with three alternative measures, from Insurance Information Institute at the state level (III), the Census American Community Survey (ACS) at the county-level, and from Quadrant Information Services at the zipcode level.

Looking at the comparison with III, we see a strong and approximately one-to-one relationship between the escrow premium estimates and the III premium estimates.[27] However, the escrow estimates are consistently about $500 more expensive than their corresponding III figures. We consider several potential explanations for this. First, our estimates consider whatever premiums homeowners pay out of escrow, including flood insurance policies, policies outside the standard HO-3 coverage, or supplemental wind-only or fire-only coverage. The III numbers, on the other hand focus on standard HO-3 policies. Second, the property values of our sample of mortgaged homeowners are about 15% higher than the corresponding Zillow home value estimates.

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

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

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

In sum, the escrow premium estimates have a strong and positive relationship with coarser existing datasets on homeowners insurance premiums. The escrow premiums are a level shift higher than other sources, a fact that can be primarily explained by the more valuable homes in our sample and that escrow payments likely cover a broader range of policies.
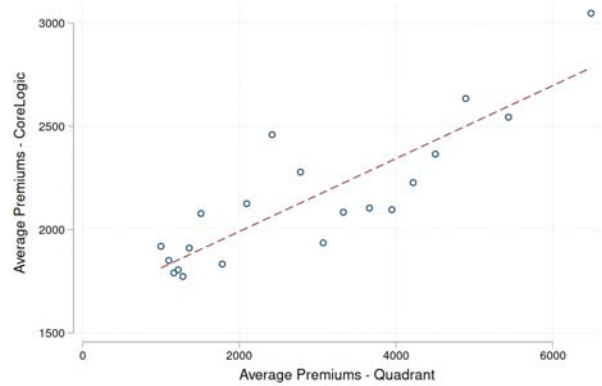
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[27]III premium tables are provided here: `https://www.iii.org/table-archive/21407`.
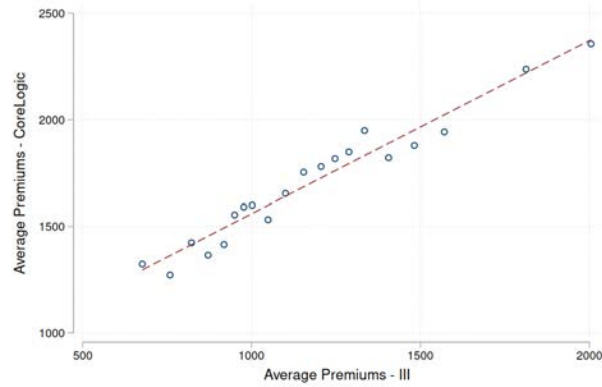
(a) III
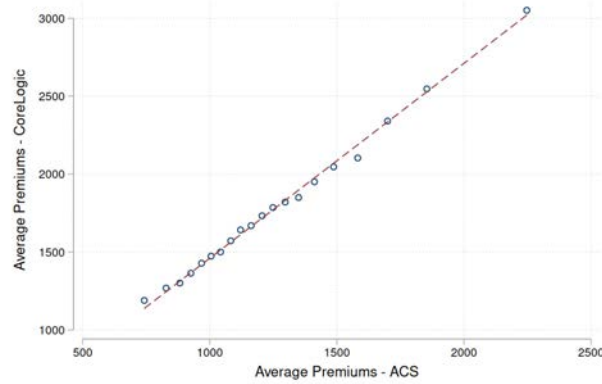
(b) ACS

(c) Quadrant

Figure 18: Escrow Premium Estimates versus other sources. Each figure compares the average premiums from the escrow estimates against different sources in the form of a binscatter. Panel (a) compares state-by-year premium estimates between 2014 and 2020 from the Insurance Information Institute. Panel (b) compares county-by-year premium estimates between 2014 and 2022 from the American Community Survey. Panel (c) compares zipcode-by-year insurer cost quotes between 2014 and 2021 from Quadrant Information Services in Florida, Louisiana, California, and Texas. Cost quotes are averaged within each zipcode by insurer, level of coverage (250K or 500K), credit score (excellent, good, fair, or poor where applicable) and home age (new, 10 years old, 25 years old). Quadrant rates are representative of publicly sourced data and should not be interpreted as bindable quotes.