The Rise in Insurance Costs for Commercial Properties: Causes, Effects on Rents, and the Role of Owners

Minjoo Kim, Prateek Mahajan, and Zirui Wang

McCombs School of Business, University of Texas at Austin

Introduction

- U.S. billion-dollar disasters increased from 3.3/year (1980–2000) → 23/year (2020–2024)
- Home insurance premium ↑ 33% (13% in real terms) from 2020–2023 (Keys and Mulder, 2024)
- Commercial property insurance cost has also steeply increased, but existing research relies on aggregate data and lacks property-level granularity, so it remains understudied

This Paper

1. Documents **time-series** and **cross-section** of insurance rise
2. Determines **causes** of property insurance rise
3. Determines **effects** on rent and profitability
4. Determines the role of **property owners** and **their portfolios**

Preview of Results

Rise in Insurance Cost:

- Insurance cost rose ≥15% each year since 2019, 30% in 2023
- 37% of CBSAs saw 2x+ increases, both coastal & interior area
- 95% of individuals where commercial ↑ > 2x homeowner ↑

Causes:

- Post 2018, higher **risk scores/past damage** ⇒ bigger cost ↑
- Higher **reinsurance** exposure ⇒ amplified cost ↑
- Insurer **losses out-of-state** ⇒ local cost ↑

Effects on Rents and Profitability:

- 67% passthrough to rent, but concave and ↓ over time

Role of Property Owners:

- **Property owner size** ↑ ⇒ insurance cost ↓, esp. in risky areas
- Owners with **property portfolios** with ↓ average risk ⇒ cost ↓
- High risk properties increasing owned by larger owners

Data

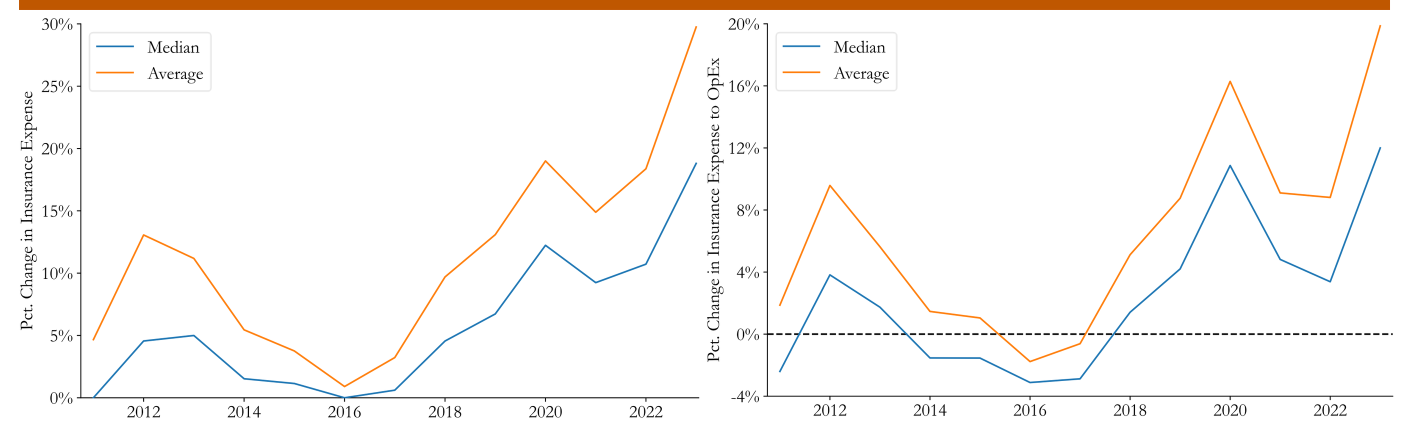
Agency CMBS:

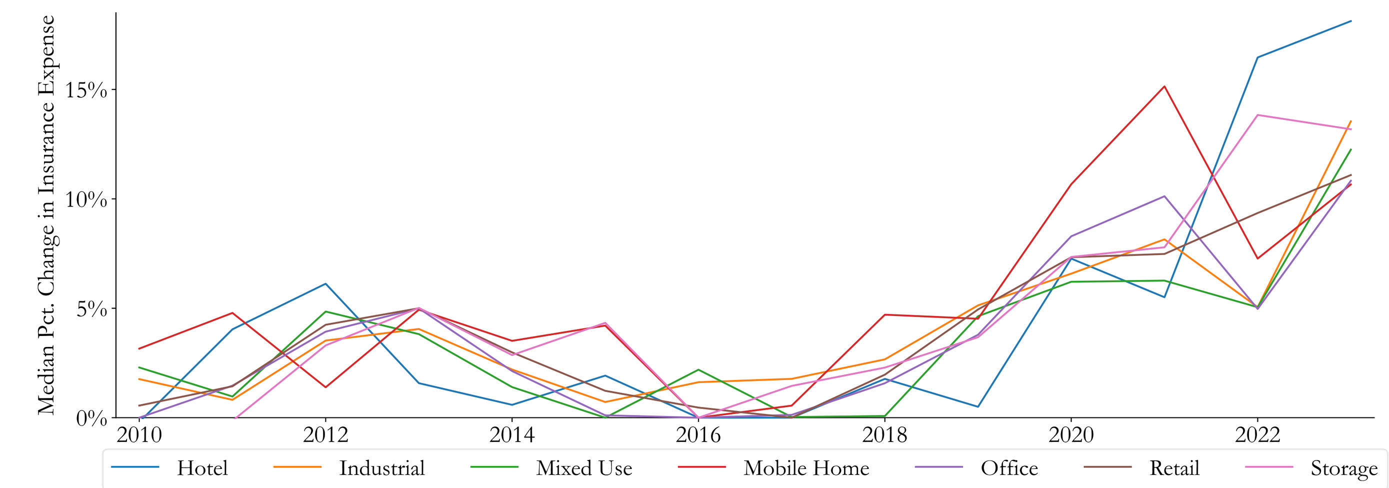
- Observe full operating statements
- **350k property-year** observations across **73k MF properties**

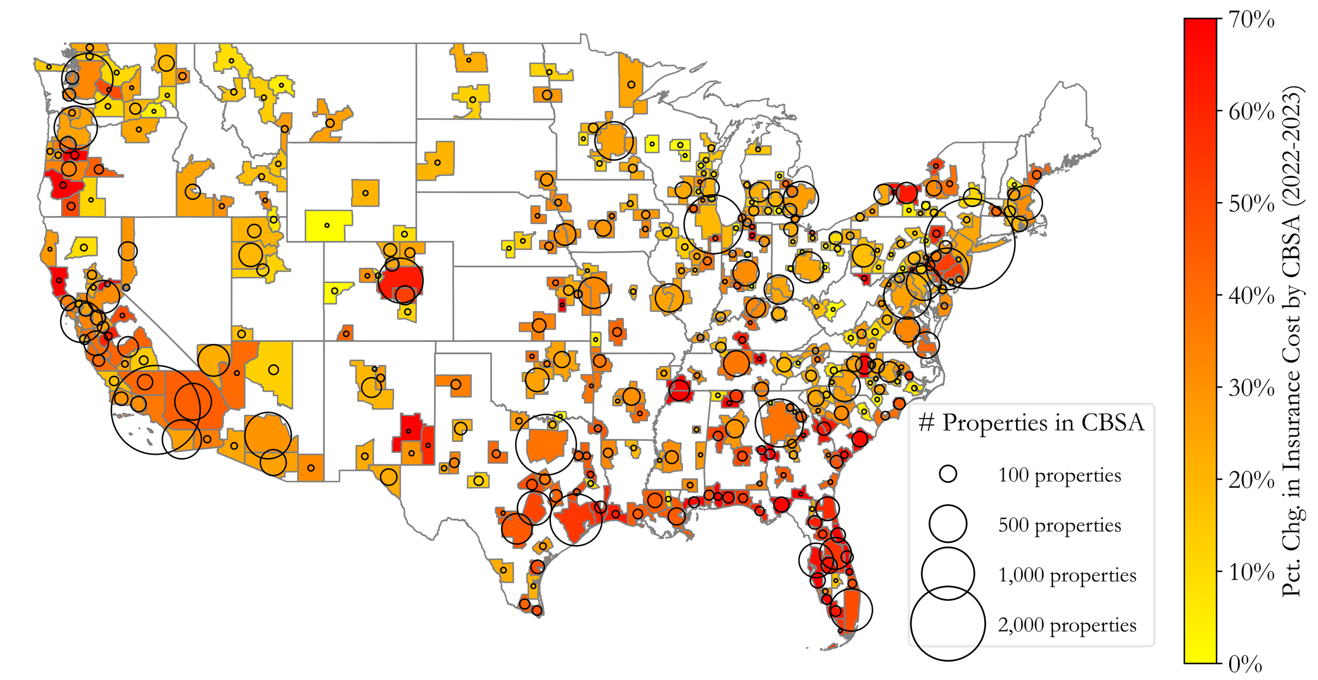
Other Datasets:

- **Bloomberg:** Non-agency MF and other property types
- **National Risk Index:** Tract-level risk scores & expected losses
- **SHELDUS:** County-year disaster losses
- **NAIC:** Insurance company-state-year-level losses, premium written, and reinsurance
- **FIO:** Zip-level homeowners insurance premiums
- **RCA:** Commercial property ownership and transactions

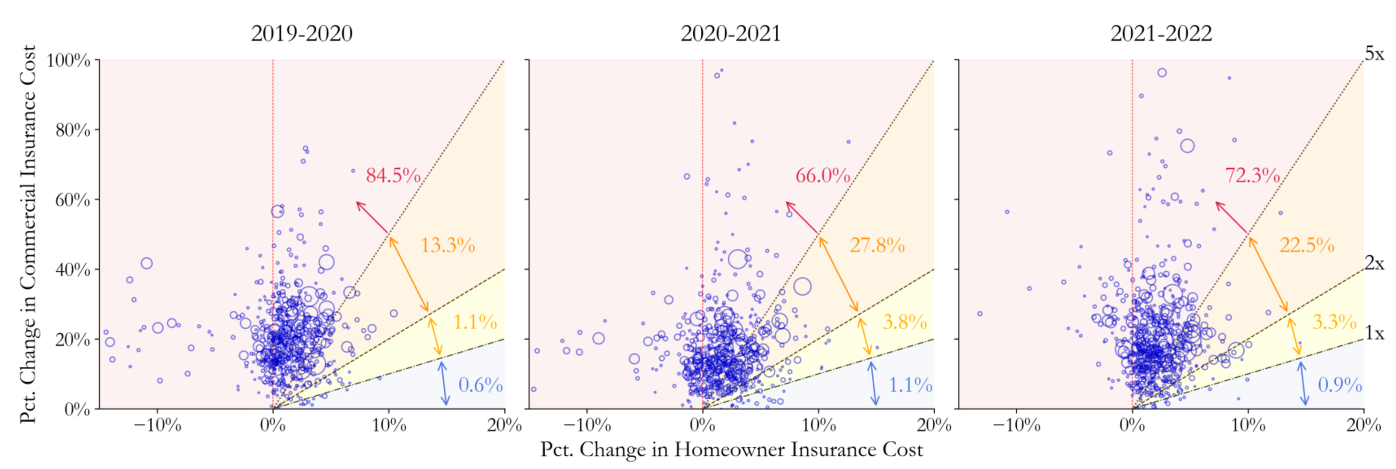
The Rise in Insurance Cost

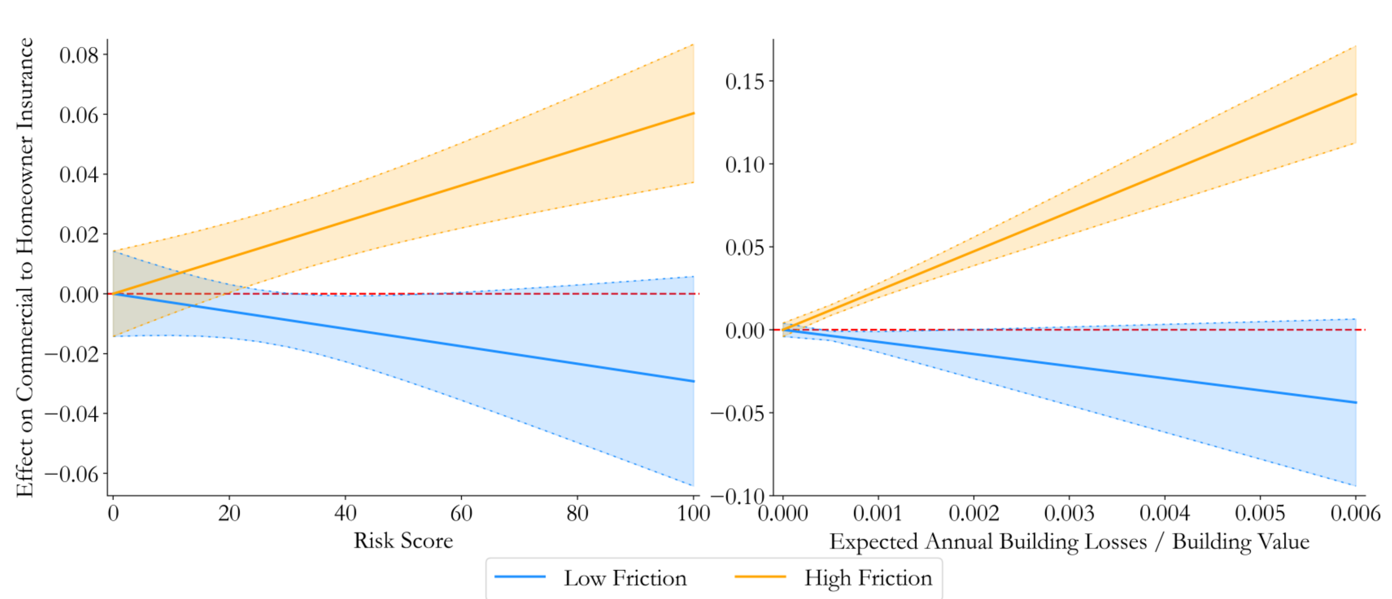






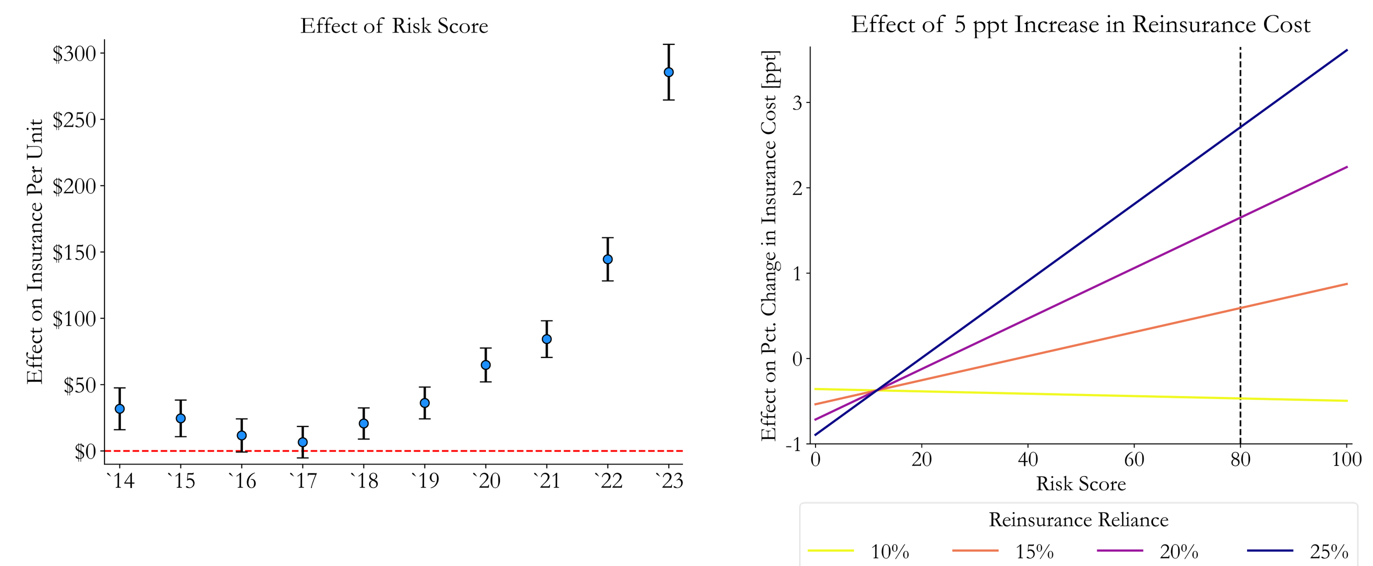
Commercial vs. Homeowners Insurance





Causes: Local Risk, Reinsurance Costs, Out-of-State Losses

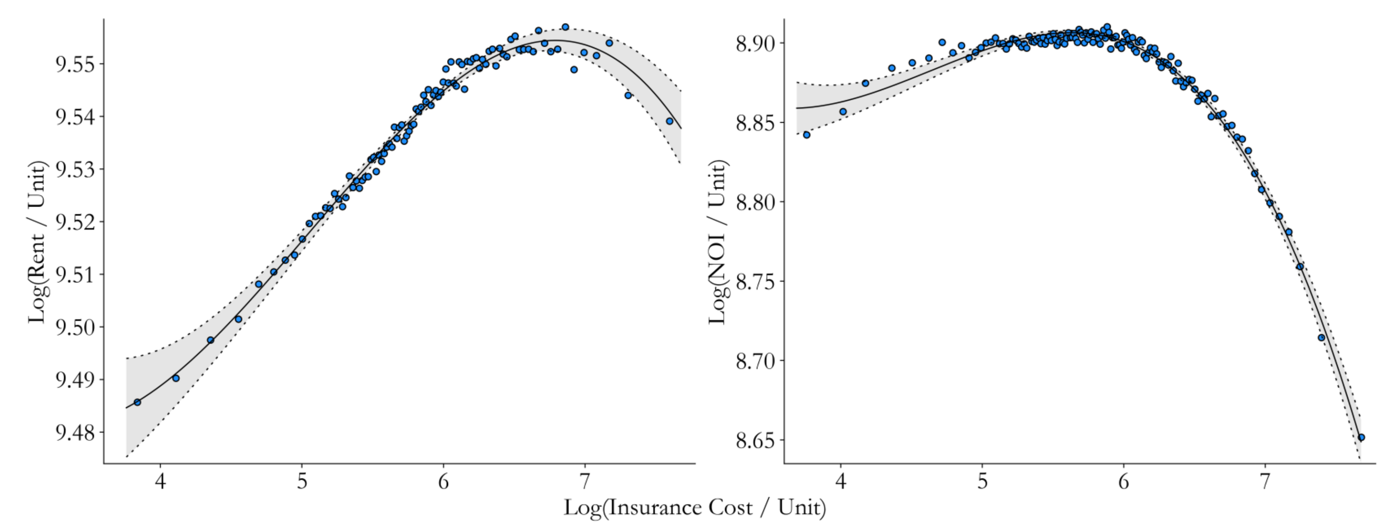
$$RR_s = \frac{\sum_{i\in I} DirectPremiumWritten_{i,s} \times PctCeded_i}{\sum_{i\in I} DirectPremiumWrittin_{i,s}}$$

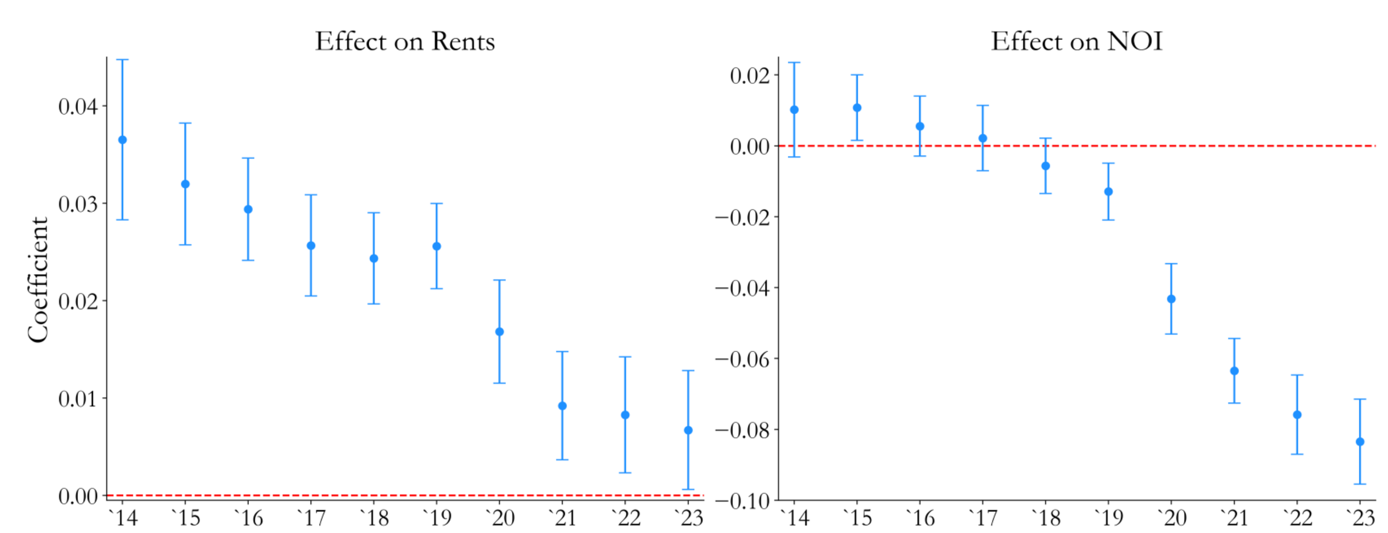


$$OOS_{s,t} = \frac{\sum_{i\in I} DirectPremiumWritten_{i,s,t} \times Losses_{i,-s,t}}{\sum_{i\in I} DirectPremiumWritten_{i,s,t}}$$

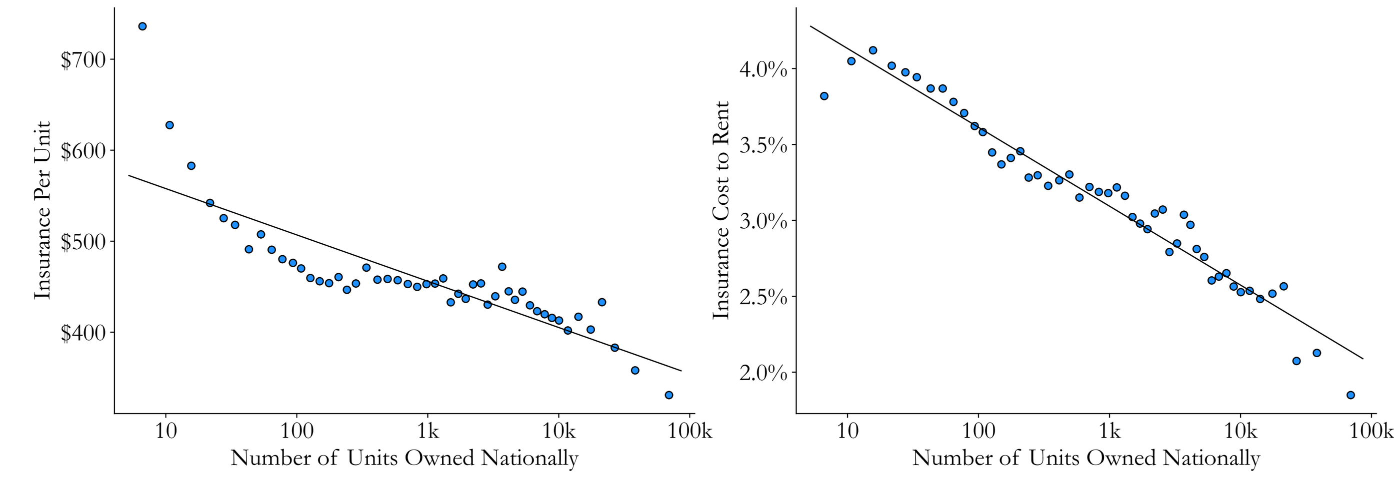
Dep. Variable:	Pct. Change in Insurance Cost			
	(1)	(2)	(3)	(4)
Log(OOS Losses) Std. × Risk Score		0.0304***	0.0351***	0.0567**
		(3.17)	(2.82)	(2.21)
Log(OOS Losses) Std.	0.0620**	0.0356	0.0306	-0.0228
	(2.36)	(1.66)	(1.42)	(-1.33)
Risk Score		0.00607	0.00139	
		(1.00)	(0.17)	
Year FE	✓	✓	✓	✓
State FE	✓	✓		
County FE			✓	
Property FE				✓
Observations	264,591	264,591	264,531	251,508
Adjusted R^2	0.0692	0.0696	0.0701	0.00528

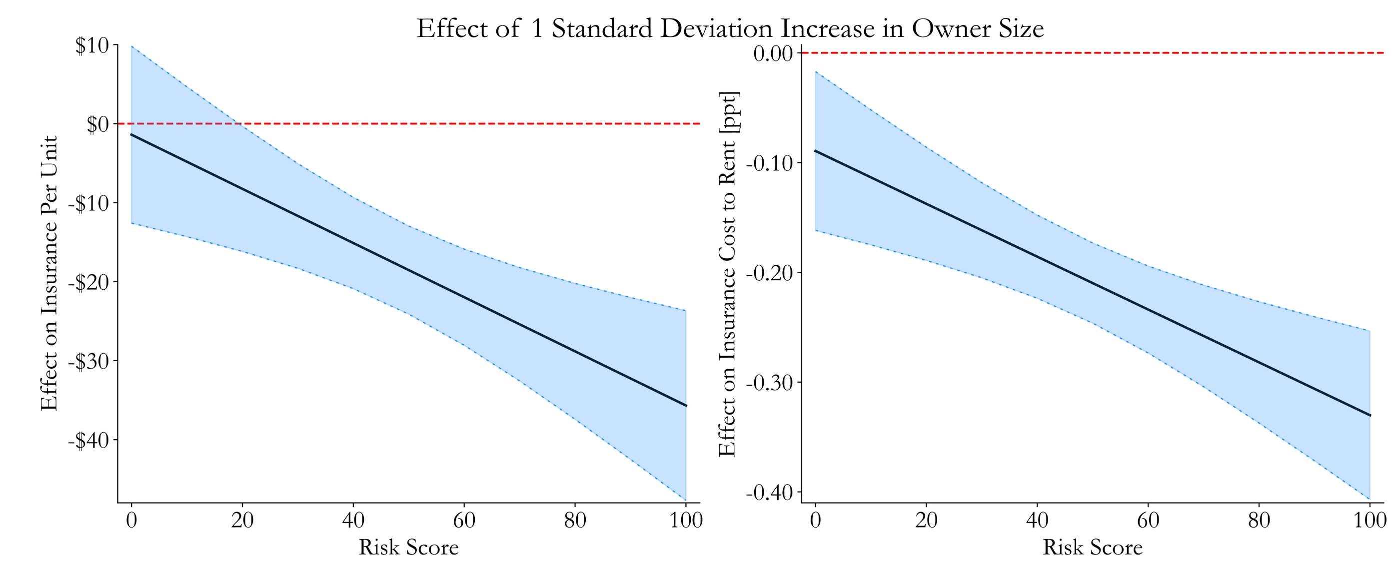
Effects on Rents and Profitability

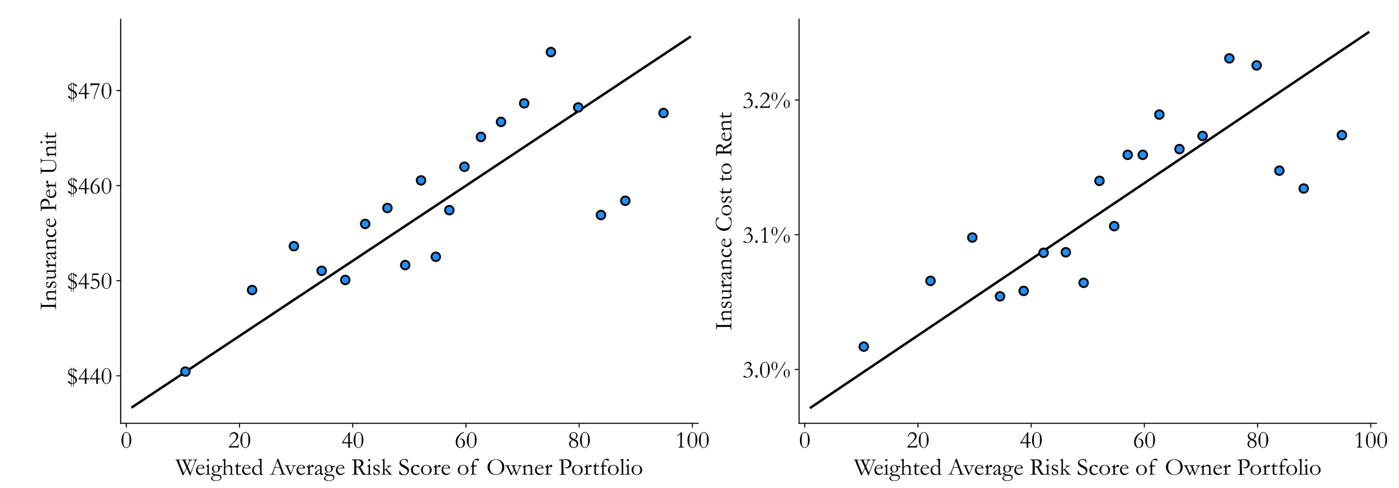


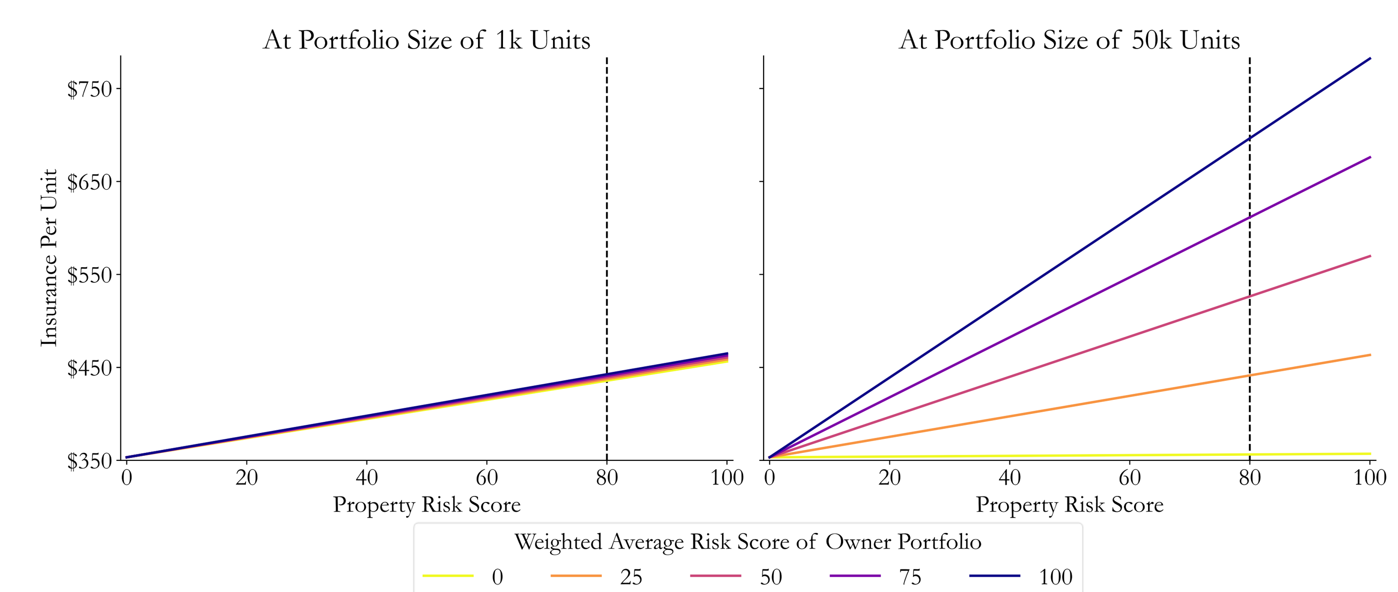


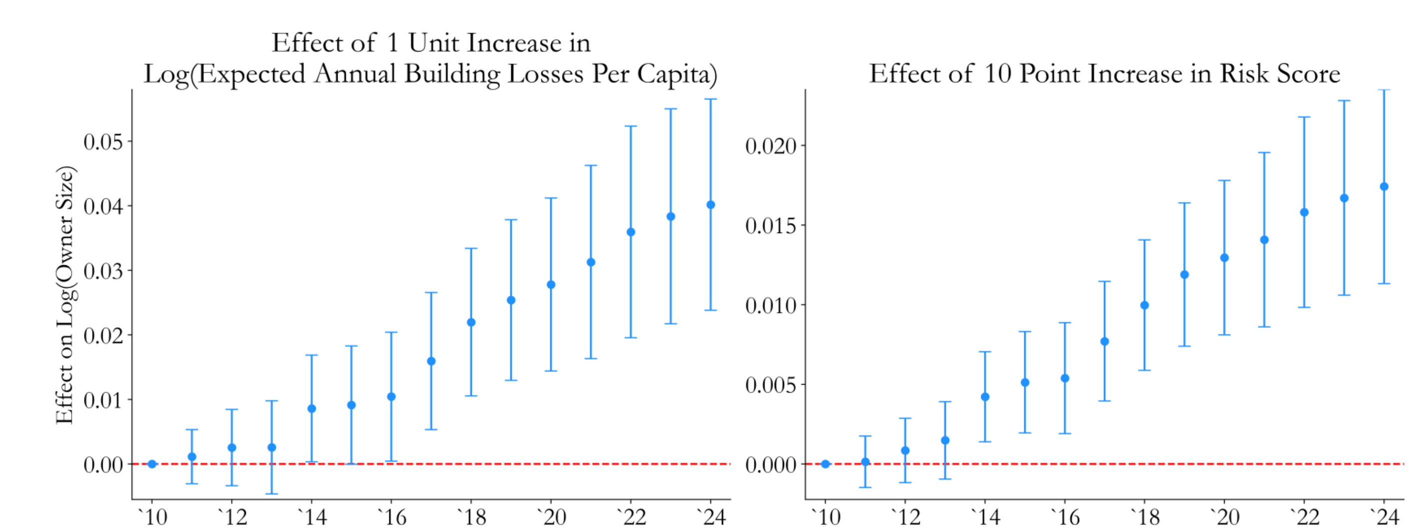
Role of Property Owners











The Rise in Insurance Costs for Commercial Properties: Causes, Effects on Rents, and the Role of Owners[*]

Minjoo Kim[†] Prateek Mahajan[‡] Zirui Wang[§]

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Abstract

Using a large and novel set of property-level operating statements for commercial properties, we analyze the causes behind the rise in insurance costs, its effects on rents and profits, and how property owners are managing it. First, we document a significant and persistent year-over-year increase in insurance costs across nearly all regions of the US over the last decade. 95% of individuals reside in counties where the increase in commercial insurance costs is at least double that of homeowner insurance costs, which is due in part to regulatory frictions in the homeowner insurance market. Second, we provide evidence of three primary drivers of rising insurance costs: heightened pricing of local risk, a substantial increase in reinsurance costs, and cross-subsidization across states. Third, we find that, on average, 67% of the rise in insurance costs is passed through to rents; however, the passthrough to rent is concave and decreasing over time. Finally, we examine the role of property owners and find that: 1) larger owners are able to maintain lower insurance costs, 2) the impact of owner size on insurance costs are more pronounced in high-risk areas, and 3) owners with a property portfolio that has lower average risk have lower insurance costs, even holding the risk of a given property fixed. The advantage of larger owners in managing insurance costs in risky areas has grown in recent years, resulting in properties in high-risk regions being increasingly owned by larger owners. Our findings suggest that commercial property insurance pricing is influenced by both localized risk factors and broader systematic risk exposure, with risks extending beyond individual properties through insurers and property owners' portfolios.

JEL classification: G22, G52, D10, Q54, R11, R31
keywords: Insurance Costs, Climate Risk, Rents, Commercial Real Estate

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[†]McCombs School of Business, University of Texas at Austin. Minjoo.Kim@mccombs.utexas.edu
[‡]McCombs School of Business, University of Texas at Austin. Prateek.Mahajan@mccombs.utexas.edu
[§]McCombs School of Business, University of Texas at Austin. Zirui.Wang@mccombs.utexas.edu

I. Introduction

In recent years, insurance costs have dramatically increased. However, due to limited granular data on insurance costs, there has been limited comprehensive examination of the factors causing this increase and its effects. In this paper, we collect and analyze a novel set of property-level operating statements from Commercial Mortgage-Backed Securities (CMBS). To the best of our knowledge, we are the first paper to use this data to provide a detailed view of how insurance costs have risen over time and across geographic areas. Using this data and a series of additional datasets, we examine the causes of the rise in insurance costs, the effects of the rise in insurance costs on rental prices and profitability, and the role that property owners play in managing the rise in insurance costs.

We start by showing the dramatic increase in insurance costs over time and across nearly all regions of the United States. The average percentage change in insurance costs that a property has faced has been 15% annually during each year since 2019 and was nearly 30% in 2023. Insurance costs increased by the largest amounts near the coasts, including in Florida, Texas, Louisiana, and California, but they also increased by substantial amounts in the core of the US, such as Oklahoma, Colorado, Tennessee, and Indiana.

In comparing commercial property insurance to homeowners insurance, which has been the focus of much of the existing literature, we find that commercial premiums have risen at substantially higher rates in nearly every county. Specifically, 95% of individuals live in counties where the increase in commercial insurance costs is at least double that of homeowners insurance. This widening gap is largely driven by state-level regulations in the homeowners market that constrain pricing of risk, preventing insurers from fully adjusting rates in response to local risk, whereas commercial insurance remains more flexible in reflecting risk-driven cost increases. This makes the commercial property sector an ideal setting to observe the unrestricted response of insurance costs to accelerating climate change and increasing disaster frequency and severity.

Next, we explore three main factors contributing to this increase: local risk, exposure on reinsurance, and out-of-state losses. First, insurance pricing reflects the underlying risk of a property's location, particularly its exposure to natural disasters. As climate risks intensify, insurers may place greater weight on regional risk measures when setting premiums. We hypothesize that properties in areas with higher risk scores or greater expected building losses per capita should experience larger insurance cost increases. Using census tract-level data from FEMA's National Risk Index, we find that properties in high-risk areas see significantly higher insurance cost increases, particularly after 2018. Before 2017, insurance costs were relatively insensitive to local risk measures, but after 2018, insurers appear to have adjusted their pricing models to incorporate risk exposure more directly. Our empirical design includes property fixed effects to account for time-invariant property characteristics and year fixed effects to control for macroeconomic shocks. The results show that within the same property, moving from a low-risk to a high-risk tract is associated with steeper insurance cost increases, highlighting the growing role of local risk in driving premium adjustments.

Second, primary insurers often transfer a portion of their risk to global reinsurers, and rising reinsurance costs can be passed through to policyholders. The extent of this passthrough should depend on how much insurers rely on reinsurance markets. To quantify this, we follow Keys and Mulder (2024) and construct a state-level measure of reinsurance exposure, capturing the share of direct premiums ceded to unaffiliated reinsurers. We find that states with higher reinsurance exposure, such as Florida, Louisiana, and Texas, experience significantly larger increases in insurance costs when reinsurance prices rise. The identification strategy benefits from sharp discontinuities in reinsurance exposure across state borders, where risk exposure is similar but insurers' exposure on reinsurance differs. Using a triple-interaction regression design and incorporating property fixed effects, we show that holding the same property fixed, when the national level of reinsurance cost rises by 5 percentage points, insurance costs increase by nearly 3 percentage points for properties in high-exposure states but remain largely unchanged in low-exposure states.

Third, insurers operate across multiple states and may respond to losses in one area by raising premiums in others. If an insurer experiences substantial out-of-state losses, regulatory constraints or market conditions may limit its ability to increase rates in the affected area, leading it to raise premiums elsewhere to maintain financial stability. We construct a measure of out-of-state losses, capturing the extent to which insurers in a given state face underwriting losses outside that state. We find that a one-standard-deviation increase in out-of-state losses is associated with a 6.2 percentage point increase in local insurance costs. This effect is most pronounced for high-risk properties—those with top-quartile risk scores see nearly twice the impact compared to low-risk properties. Our regression framework includes state and year fixed effects to account for time-invariant state characteristics and macroeconomic trends, ensuring that the observed relationship is not driven by broader industry dynamics. These findings suggest that insurance cost increases are not solely a function of local conditions but also reflect broader financial pressures faced by insurers across their underwriting portfolios.

In addition to these main factors, we also examine other potential drivers of insurance cost increases, including geographic characteristics, property features, and insurance market concentration. However, we find that these factors explain little of the observed variation in insurance cost increases.

Furthermore, we examine whether the rise in insurance costs is passed through to rents or absorbed as operating losses. Higher insurance expenses often lead to rent increases as property owners attempt to offset rising costs. On average, 67% of the increase in insurance costs is incorporated into rents, but this pass-through effect has diminished as costs have risen, suggesting that property owners face increasing constraints in adjusting rents to fully offset higher expenses. Our regression estimates show that while landlords initially compensate through rent increases, their ability to do so weakens over time, leading to a growing erosion of net operating income (NOI). Nonlinear estimates from binscatters plots reveal a concave relationship, where higher insurance costs are increasingly absorbed by property owners rather than tenants. Consistent with this pattern, the passthrough rate has declined significantly over the past decade, particularly since 2019, as insurance costs have continued to rise. A 10% increase in insurance costs, which previously led to a 0.35% rise in rents, now results in only a 0.05% increase, whereas the associated decline in NOI has grown to over 0.80%. These findings suggest that rising insurance costs are placing growing financial strain on property owners, as their ability to transfer costs to tenants becomes increasingly limited.

The impact of insurance pricing varies significantly across property owners, with ownership size and the owner's portfolio playing a critical role in determining insurance costs. Larger property owners benefit from economies of scale and greater bargaining power, allowing them to negotiate lower per-unit insurance costs compared to smaller owners. This advantage is particularly pronounced in high-risk areas, where insurers have more pricing discretion, and large owners can leverage their extensive holdings to secure more favorable terms.

Beyond scale, an owner's overall portfolio risk influences insurance pricing at the individual property level. Insurers assess not only the risk of a specific property but also the average risk level of the owner's entire portfolio. Owners with a lower portfolio risk score tend to receive lower insurance premiums, even after accounting for the risk of each property. This suggests that insurers price risk at a broader level, incorporating the overall composition of an owner's holdings when determining insurance rates. The relationship between owner portfolio risk and insurance pricing also varies by owner size. While small owners experience little to no cost advantage based on their portfolio's overall risk level, large owners with lower average portfolio risk enjoy significantly lower insurance costs. This suggests that insurers not only reward lower portfolio risk but also do so more favorably when the owner has a larger portfolio. Taken together, these findings highlight how ownership characteristics influence insurance pricing as insurers evaluate risk beyond individual properties, factoring in both the scale and composition of an owner's portfolio.

We find that rising insurance costs contributed to the reshaping of property ownership, steering high-risk properties toward larger owners with the scale and diversification to better manage mounting costs. Before 2020, the size advantage was relatively uniform across different risk categories, but after 2020 it began to narrow for low-risk properties while expanding significantly for riskier locations. Over time, this has prompted a shift in high-risk property ownership toward larger owners, who can more effectively negotiate and absorb insurance expenses. Overall, these patterns illustrate how bargaining power and portfolio composition work together to shape insurance outcomes, reinforcing the rising prominence of large owners in challenging, high-risk markets.

Our findings indicate that insurance pricing for multifamily properties is shaped not only by local risk factors but also by broader systematic risk exposure. Risks are distributed and priced beyond individual property characteristics through insurers and property owners' portfolios. Additionally, our results highlight the importance of understanding how these pricing dynamics affect housing costs. With a significant share of rising insurance expenses passed on to tenants, the financial burden extends beyond property owners, placing additional pressure on housing affordability in the multifamily market.

Related Literature Our paper contributes to four main strands of literature. First, our paper contributes to the literature on insurance market pricing, which has largely focused on homeowners' and climate risk insurance. Recent studies have provided valuable insights into the factors shaping insurance premiums and market behavior. Oh, Sen, and Tenekedjieva (2022) examine the pricing of climate risk insurance, emphasizing the roles of regulation and cross-subsidies in shaping market outcomes. Similarly, Boomhower, Fowlie, and Plantinga (2023) investigate the influence of information asymmetry on homeowners' insurance pricing, highlighting the challenges of aligning premiums with risk levels. Ge (2022) explores how financial constraints affect product pricing, using evidence from weather and life insurance markets to demonstrate how economic conditions influence pricing strategies. Moreover, Keys and Mulder (2024) analyze how reinsurers' exposure influences homeowners' insurance pricing, illustrating how reinsurance market conditions shape homeowners' insurance premiums. In contrast, the pricing of commercial real estate (CRE) insurance remains relatively underexplored, as most research has focused on homeowners' insurance. The CRE market offers a cleaner laboratory for studying insurance pricing because homeowners' insurance premiums are often distorted by strict regulatory constraints. Our study extends this literature by examining the drivers of rising insurance premiums in the commercial real estate sector and assessing their broader impact on households. In addition, we show how out-of-state losses can further increase local insurance premiums, underscoring the interconnectedness of insurance markets across geographic regions.

Second, our paper also contributes to the literature on the impact of climate risk. Prior studies have shown that climate risk influences a broad range of real estate and financial market outcomes (Bakkensen and Barrage, 2021; Bernstein, Gustafson, and Lewis, 2019; Murfin and Spiegel, 2020). Sastry (2025) shows how climate exposure affects mortgage origination decisions. Beyond housing markets, Seltzer, Starks, and Zhu (2022) illustrate the implications of climate risk for corporate bond pricing, while Sastry, Sen, Tenekedjieva, and Scharlemann (2024) demonstrate how climate vulnerability constrains the supply of insurance. We extend this literature by linking rising climate risk to higher insurance costs, which are ultimately passed on to tenants.

Third, our paper also extends the understanding of the effect of rising insurance premiums on household outcomes. Previous studies link premium hikes to house price declines (Hino and Burke, 2021; Ge, Lam, and Lewis, 2024) and heightened mortgage or credit card delinquency (Ge, Johnson, and Tzur-Ilan, 2024). While this existing work generally focuses on residential real estate, our research shows that higher insurance premiums correlate with elevated rents for households and reduced profitability for landlords.

Lastly, our paper contributes to the literature on the role of property owners in real estate markets. Previous studies have primarily examined the long-term rental market and demonstrated how large institutional owners influence rents (Austin, 2022; Coven, 2023; Gorback, Qian, and Zhu, 2024). We extend this line of research by showing that large property owners also benefit from lower insurance costs, particularly in high-risk areas. Moreover, even after controlling for individual property risk, owners with lower average portfolio risk enjoy reduced insurance costs. These findings underscore the significance of ownership structure in shaping insurance market outcomes and highlight how economies of scale and owner portfolios can affect commercial real estate insurance pricing.

II. Data

Our primary dataset focuses on multifamily properties with loans securitized through the Commercial Mortgage-Backed Securities (CMBS) of Freddie Mac and Fannie Mae. These two entities play critical roles in the U.S. residential and commercial mortgage market and, as of September 2023, owned or guaranteed roughly 40% of the $2.2 trillion in multifamily mortgage debt, according to estimates reported by the Wall Street Journal based on their latest annual filings (Heeb, 2024). Given their prominence, Freddie Mac and Fannie Mae have regulatory mandates to publicly disclose comprehensive loan performance data for properties underlying their CMBS offerings. This disclosed data encompasses various key metrics, including insurance costs, rent, and net operating income (NOI). The data also includes property-level details such as address, number of units, year built, and year last renovated. Our hand-collected dataset comprises property-year observations and 93,878 unique properties. We also collect similar property-level data for other property types, including hospitality, office, industrial, and retail, from Bloomberg.[1]

To understand the relationship between the rise in insurance costs and natural disaster risk, we use two datasets: the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and the National Risk Index (NRI) dataset. SHELDUS provides granular, county-level data on historical natural hazard events and associated losses, offering a robust view of past disaster impacts on properties. The NRI, on the other hand, offers a forward-looking assessment of expected losses and risk scores for each census tract across the United States. Additionally, to understand the role of geographic location in explaining the rise in insurance cost, we also geocode all of the property addresses using the US Census Geocoder and determine each property's distance to the nearest coast and elevation using topographic maps (from Natural Earth for coastline and National Elevation Dataset for elevation).

We obtain insurance company information from the NAIC Annual Statement's State Page (Exhibit of Premiums and Losses) and Schedule P for the period from 2010 through 2023. The State Page provides state-level premiums and losses by line of business, while Schedule P offers reinsurance information. We specifically focus on non-liability commercial lines, capturing annual observations of direct written premiums, direct earned premiums, incurred losses, and reinsurance transactions reported in Schedule P.

To accurately determine property ownership, we utilized Real Capital Analytics (RCA). A common challenge in this process arises from variations in how ownership names are recorded, often due to the use of subsidiaries, holding companies, and other non-standardized naming conventions. RCA addresses this issue by identifying the ultimate parent owner and standardizing ownership names across records, ensuring consistency and accuracy in ownership identification. Using this data, we determine the total number of multifamily units across the entire United States that each entity owns during

[1] We focus on multifamily properties for the majority of the analysis since it is the most common property type in CMBS deals.

each year and use this as a measure of each owner's size.

By building a comprehensive dataset from these sources, we offer a detailed examination of how market structure, risk exposure, and ownership dynamics interact to influence insurance pricing and its broader effects. Table IA.I provides summary statistics for the main variables used throughout the paper.

III. The Rise

We start by examining time-series and cross-sectional variation in the rise in insurance cost. Figure 1 examines the time-series variation, and Figure 2 examines the cross-section variation.

A. Time-Series Variation

The left subpanel of Figure 1 Panel A shows the median and average percentage change in insurance cost during each year from 2011 to 2023. The average percentage change in insurance cost has been at least 15% each year since 2019 and nearly 30% during 2023. The right subpanel of Figure 1, Panel A examines the percentage change in insurance costs to operating expenses (OpEx) to account for the general rise in operating costs. A similar time-series pattern remains with a rise in insurance cost to OpEx of at least 8% from 2019 onward and a rise of nearly 20% during 2023.

Panel B of Figure 1 replicates the left subpanel of Figure 1, Panel A for other property types besides multifamily using data from Bloomberg. A very similar time-series pattern emerges across all of the property types. For the remainder of the paper, we focus on multifamily properties since they are by far the largest property type and to have a comparison across properties and interpretation of the remaining results simpler.

B. Cross-Sectional Variation

Panel A of Figure 2 plots the median annual insurance cost per unit in 2022-23 versus 2010-17. Each bubble represents one Core-based Statistical Area (CBSA) and is sized based on the number of properties in each CBSA in our sample. Bubbles are colored based on the change in insurance cost between the two periods, and dashed lines representing a 1x, 2x, and 3x change are shown. The average property in our sample is in a CBSA that has faced a 1.94x times increase in median insurance costs per unit. 37% of CBSAs, which contain 34% of properties in our sample, have the median insurance cost at least double.

Panel B of Figure 2 focuses on the rise in insurance cost between 2022 and 2023 across CBSAs and shows a heatmap of the percentage change in insurance cost over this one year period. Insurance costs increased by the largest amounts near the coasts, including in Florida, Texas, Louisiana, and California, but they also increased by substantial amounts in the core of the US, such as Oklahoma, Colorado, Tennessee, and Indiana. Only 12% (29%) of CBSAs, which contain 1% (9%) of the properties in our sample, faced an increase of less than 10% (20%). Based on both panels of Figure 2, it is apparent that the rise in insurance costs has affected nearly all areas of the US.

C. Comparison to Homeowner Insurance

In this subsection, we compare the rise in commercial property insurance costs to the rise in homeowner insurance costs. This comparison is important because prior literature has documented substantial increases in homeowner insurance costs in recent years (Keys and Mulder, 2024). However, homeowner insurance cost increases are often limited by state-level regulatory constraints (Oh, Sen, and Tenekedjieva, 2022). In contrast, commercial property insurance costs are generally not subject to these regulatory constraints, providing a clearer perspective on the market-driven impacts of climate risk on insurance pricing. Given accelerating climate change and increasing disaster frequency and severity, the commercial property sector serves as a natural setting to observe the unrestricted response of insurance costs to these risks.

To conduct this comparison, we obtain homeowner insurance cost data from the U.S. Department of the Treasury (2025). The data is available at the ZIP-year level, capturing average homeowner insurance costs per policy for each ZIP code annually from 2018 to 2022. We aggregate this data to the county-year level to compute annual percentage changes. Similarly, using our commercial property insurance dataset, we calculate the annual average percentage change in insurance costs at the county-year level.

Panel A of Figure 3 presents scatterplots comparing the annual percentage change in commercial insurance costs to the percentage change in homeowner insurance costs for each county across three yearly intervals: 2019–2020, 2020–2021, and 2021–2022. Each bubble represents a county and is sized based on its population. Three dashed lines are drawn for reference: a 1x line indicating equal percentage changes between commercial and homeowner insurance costs (the 45-degree line), a 2x line indicating commercial insurance increases at twice the rate of homeowner insurance, and a 5x line indicating commercial insurance increases five times as large as homeowner insurance. We label the percentage of the population living in counties falling within specific regions defined by these reference lines in each scatterplot.

Specifically, from 2021 to 2022, 72.3% of the population lived in counties where commercial insurance costs increased by more than five times homeowner insurance costs or increased despite homeowner costs decreasing. Furthermore, 98.1% (94.8%) of the population lived in counties where commercial insurance costs increased at least (at least twice) as much as homeowner insurance costs. Only 0.9% of the population lived in counties where the commercial increase was smaller than the homeowner increase, and only 1.0% of the population resided in counties where commercial insurance costs decreased; these counties are omitted from the figure for clarity.

The plots show that commercial insurance costs consistently rise at higher rates than homeowner insurance costs across most counties, a pattern stable across the three yearly intervals. If there is any trend, there has been a widening gap in recent years, with commercial insurance cost increases accelerating, whereas homeowner insurance cost increases remain relatively consistent in magnitude.

As Oh, Sen, and Tenekedjieva (2022) show, the homeowner insurance market is subject to state-level regulation, which introduces differing levels market frictions to price increases across states. To examine whether these frictions help explain differences between commercial and homeowner insurance costs, we use the state-level friction measure proposed by Oh, Sen, and Tenekedjieva (2022). Specifically, we compute the ratio of each commercial property's insurance costs per unit to average homeowner insurance premiums in the same zip code as the property as follows:

$$CoHoRatio_{i,z,t} = \frac{\text{Commercial Insurance/Unit}_{i,t}}{\text{Average Homeowner Insurance Premiums}_{z,t}}$$

and estimate the following regression equation:

$$CoHoRatio_{i,z,t} = \beta \times LocalRisk_c \times \mathbb{1}(HighFriction)_s + StateYearFE_{s,t} + \varepsilon_{i,z,t}$$

where $LocalRisk_c$ denotes either the risk score or expected annual building losses scaled by building value of the census tract c that the commercial property i is in, and $\mathbb{1}(HighFriction)_s$ is a binary variable that equals one if state s is in the top tercile of the friction measure.[2] The regression includes state $\times$ year fixed effects, and standard errors are clustered at the state level. In the left subpanel of Panel B in Figure 3, we plot the predicted effects of risk score on the ratio of commercial to homeowner insurance costs separately for high-friction (orange line) and low-friction (blue) states. The results reveal that in high-friction states, the ratio of commercial to homeowner insurance costs is higher in riskier areas because commercial premiums are able to more closely reflect underlying local risk than homeowners insurance due to fewer regulatory constraints on insurance pricing. In contrast, in low-friction states, this ratio does not vary with geographic risk, presumably because homeowner premiums can also be adjusted for local risk factors and losses. We repeat this analysis using expected annual building losses scaled by building value in the right subpanel and find a similar pattern.

Building on this observation, we run the same regression equation, replacing local risk measures with the lagged loss ratio, to examine how past realized losses influence the relative pricing of commercial versus homeowner insurance. In addition to the state $\times$ year fixed effects included previously, we also include property fixed effects in order to examine changes in the wedge between commercial and homeowner insurance due to realized local losses. Table 1 shows the regression results. Column (1) shows that areas experiencing greater losses exhibit a higher ratio of commercial to homeowner insurance costs. While column (1) of Table 1 indicates a positive overall relationship between lagged losses and this ratio, the effect is primarily driven by high-friction states. In Column (2), only the interaction between the lagged loss ratio and high-friction states shows a substantial and statistically

[2] Both risk scores and expected annual losses are from FEMA's National Risk Index (NRI) dataset, which we explore further below.

significant increase in the ratio, whereas the interaction with low-friction states is small and statistically insignificant. This pattern reflects regulatory constraints that limit insurers' ability to raise homeowner insurance costs in high-friction states despite rising losses, while commercial insurance pricing remains more flexible. Moreover, as previously discussed, Figure 3, Panel B shows that the wedge between commercial and homeowner insurance markets in high-friction states increases with local risk. To examine this further, Columns (3) and (4) of Table 1 interact losses with risk scores, with Column (3) focusing on low-friction states and Column (4) on high-friction states. In high-friction states, the effect of losses is most pronounced in high-risk areas, indicating the difference in insurers' ability to respond to heightened loss between the commercial and the homeowner insurance markets is the largest in high-friction, high-risk areas. That is, the widening gap between commercial insurance and homeowner insurance is most pronounced in high-friction, high-risk areas, which is consistent with the mismatch between risk and homeowner insurance prices highlighted by Oh, Sen, and Tenekedjieva (2022).[3]

IV. Causes of Rise

In the previous section, we presented the time-series and cross-sectional variation in the rise of insurance costs. Now, we turn to examining the potential causes of this rise. We propose and investigate three main factors that may contribute to these increases, including local risk, exposure on reinsurance, and out-of-state losses.

A. Local Disaster Risk

We first assess how the local disaster risk of a property's location relates to rising insurance costs. To do so, we use two measures of local risk: (1) risk scores and expected annual losses from FEMA's National Risk Index, which reflect the assessed risk level of each census tract, and (2) past property damages from the SHELDUS dataset, which capture actual historical losses at the county-year level.

Risk Scores and Expected Annual Losses To begin with, we examine how risk scores and expected annual building losses relate to changes in insurance costs, presenting the results in Figure 4. We use

[3] Table IA.II finds similar results when the percentage of homeowner policies with claims is used instead of loss ratios.

data at the census tract level from the Federal Emergency Management Agency's National Risk Index dataset. Panel A presents binscatters showing the relationships over the entire sample period (2010 to 2023), while Panel B splits the analysis into early years (2017 and earlier) and later years (2018 and later). In both panels, we include year fixed effect to control for time-specific unobserved factors, and the lines shown represent the best linear fit based on the underlying data.

The left subpanel of Panel A plots the percentage change in insurance costs against area risk scores. We find a strong positive correlation, indicating that areas with higher risk scores tend to experience larger increases in insurance costs. Similarly, the right subpanel plots the percentage change in insurance costs against the logarithm of expected annual building losses per capita, revealing another positive correlation. These results suggest that insurers incorporate both risk scores and expected losses into their pricing decisions, with higher risk areas facing more substantial rate increases. In Panel B, we extend this analysis by splitting the results into early years (2017 and earlier) and later years (2018 and later). In the left subpanel, we find that risk scores had no significant effect on insurance cost changes before 2017, but the effect becomes significant after 2018. A similar pattern emerges in the right subpanel, where the impact of expected annual building losses on insurance costs is negligible in earlier years but becomes strongly positive in later years. Figure IA.5 shows the effect of risk score (left subpanel) and expected annual losses (right subpanel) over time. Panel A shows the effect on insurance costs per unit, while Panel B shows the effect on percentage change in insurance costs. Across all subpanels, we find the positive and statistically significant effect kicks in after 2018. These findings suggest that insurers have become more responsive to the riskiness of the regions over time.

Past Property Damages Next, we explore the relationship between past property damages and the percentage change in insurance costs and present our results in Figure 5. We use property damage data at the county level from Arizona State University's Spatial Hazard Events and Losses Database (SHELDUS). Panel A presents a binscatter plot of the percentage change in insurance costs against the inverse hyperbolic sine (asinh) transformation of average property damages per capita over the past five years. We include year fixed effects to control for time-specific unobserved factors and cluster standard errors at the county level. The line shown represents the best linear fit based on the underlying data.

We find a positive correlation, indicating that areas with greater historical property damages tend to experience higher increases in insurance costs. However, even in areas with the lowest average property damages per capita over the last 5 years, the insurance cost has increased more than 12%.

We build on Panel A and investigate the relationship between property damages and insurance cost increases over different time horizons in Panel B. The left subpanel presents regression coefficients capturing the effect of average property damages per capita over horizons ranging from one to five years. Notably, the slope of Panel A corresponds to the coefficient for the five-year horizon in Panel B, labeled "5." We find the effect is relatively stable, with damages over the last five years showing the strongest correlation. The right subpanel splits the results into early years (2017 and earlier) and later years (2018 and later). We find that before 2017, property damages had no significant effect on insurance cost increases, as evidenced by the insignificant coefficients. However, after 2018, the effect becomes significant, suggesting that insurers have started to respond more strongly to areas with high past damages in recent years. It is possible that this shift was due to the abnormally high amount of property losses during 2017 (see Figure IA.1, Panel A). It could also reflect an industry-wide reaction to growing losses in the face of more frequent or severe disasters, leading to sharper rate increases in areas with a history of high property damage.

B. Reinsurance Exposure

Reinsurance plays a fundamental role in the property insurance market by enabling primary insurers to manage catastrophic risks. It functions as a form of insurance for insurers, transferring portions of risk to global reinsurers who specialize in absorbing large-scale losses. This system allows primary insurers to maintain solvency in the face of extreme events such as hurricanes, wildfires, and other natural disasters. However, as reinsurance prices rise, insurers that rely heavily on reinsurance may pass these costs through to policyholders in the form of higher premiums.

In recent years, the cost of reinsurance has increased substantially. The Guy Carpenter Rate-On-Line Index, as shown in Panel A of Figure 6, a widely used benchmark for reinsurance pricing, shows a steady rise in reinsurance costs since 2018, with a particularly sharp increase from 2021 to 2023. This trend suggests that insurers operating in disaster-prone areas face higher reinsurance costs, which could contribute to the broader increase in property insurance premiums. As the reinsurance market hardens, primary insurers with significant exposure on reinsurance may be more sensitive to these pricing dynamics, amplifying insurance cost increases in regions where coverage is heavily exposed on reinsurance.

To quantify the role of reinsurance exposure in driving insurance cost increases, we follow Keys and Mulder (2024) and construct a state-level reinsurance exposure measure. This measure captures the extent to which insurers operating in a given state depend on reinsurance to manage their risk. We define reinsurance exposure as:

$$ReinsuranceExposure_s = \frac{\sum_{i \in I} DirectPremiumsWritten_{i,s} \times PctCeded_i}{\sum_{i \in I} DirectPremiumsWritten_{i,s}}$$

where $DirectPremiumsWritten_{i,s}$ represents the total direct insurance premiums written by insurer i in state s and $PctCeded_i$ is the percentage of insurer i's total direct premiums that are ceded to unaffiliated reinsurers.[4]

Using the constructed reinsurance exposure measure, we calculate state-level reinsurance exposure and plot it in Panel B of Figure 6. The color gradient represents the share of total direct premiums ceded to unaffiliated reinsurers, with darker shades indicating higher reinsurance exposure. States along the Gulf Coast and the southeastern United States, including Florida, Louisiana, and Texas, exhibit the highest reinsurance exposure, exceeding 20% in some cases. This pattern aligns with the fact that insurers in these states face elevated hurricane risk and rely more heavily on reinsurance markets to hedge catastrophic losses. In contrast, states in the Midwest and parts of the Northeast show relatively lower reinsurance exposure, with many falling below 10%.

To formally test whether reinsurance exposure amplifies insurance cost increases, we estimate the following triple-interaction regression model:

[4] We define reinsurance exposure based on data from 2017 since insurers may respond to rising reinsurance costs by reducing their usage of the reinsurance markets. However, we show in Figure IA.6 that the percentage of premiums ceded to reinsures at the company level and the exposure to reinsurance markets at the state-level are largely stable over time.

$$
\begin{aligned}
PctChangeInsurance_{i,s,t} = {} & \beta \times PctChangeReCost_t \times ReinsuranceExposure_s \times RiskScore_i \\
& + \gamma \times PctChangeReCost_t \times ReinsuranceExposure_s \\
& + \delta \times PctChangeReCost_t \times RiskScore_i \\
& + PropertyFE_i + YearFE_t + \varepsilon_{i,s,t}
\end{aligned}
$$

where $PctChangeInsurance_{i,s,t}$ represents the percentage change in insurance costs for property i in state s during year t, $PctChangeReCost_t$ is the percentage change in the Guy Carpenter Rate-On-Line Index, capturing changes in national reinsurance pricing, $ReinsuranceExposure_s$ measures the extent to which insurers in state s rely on reinsurance markets, and $RiskScore_i$ represents the tract-level disaster risk score of property i. We include property fixed effects to control for unobservable, time-invariant property characteristics and include year fixed effects to account for macroeconomic shocks or broader trends affecting insurance costs for all properties in that year. This specification allows us to assess whether states with higher reinsurance exposure experience larger insurance cost increases when reinsurance prices rise while holding the riskiness of the area fixed.

To further illustrate the exogenous variation in reinsurance exposure, we zoom in on two southeastern states, Florida and Georgia, as an example. Panel B of Figure 6 plots reinsurance exposure, while Figure IA.2 displays the corresponding risk scores on the county level. A key observation is the sharp discontinuity in reinsurance exposure at the Florida-Georgia border, despite the fact that risk scores vary smoothly across the region. This pattern aligns with intuition—natural disaster risks, such as hurricane exposure, do not abruptly change at state borders, but insurance companies operate under state-level regulations, which make it difficult for an insurer in Florida to simply move its business to Georgia in response to higher reinsurance costs. As a result, insurers in Florida exhibit significantly higher reinsurance exposure than those in Georgia, even for properties with identical risk profiles.

This stark contrast in reinsurance exposure across state lines, while holding geographic risk relatively constant, provides a useful source of identification. Given that our regression framework includes property fixed effects, we are not comparing different properties across state lines; rather, we compare the same property—holding all unobservable characteristics constant—assessing how its insurance cost increase would differ if it were located on the Florida side versus the Georgia side of the border, given the same change in reinsurance cost as captured by the Guy Carpenter Index. This setup allows us to isolate the role of reinsurance markets from underlying risk factors in driving insurance cost increases. While the Florida-Georgia border serves as an illustration of the variation in reinsurance exposure, our formal empirical test includes the full sample across the entire United States.

The results of estimating the regression equation specified above are shown in Figure 7. The left subpanel of Panel A presents the marginal effects of a 5 percentage point increase in reinsurance cost on the percentage change in insurance cost, holding different levels of risk score and reinsurance exposure fixed. Each line represents a different level of reinsurance exposure, ranging from 10% to 25%. To interpret the results, we focus on a risk score of 80, marked by the dotted vertical line for ease of interpretation. For a property located in a census tract with a risk score of 80 and reinsurance exposure of 10%, a 5 percentage point increase in reinsurance cost leads to no change in insurance cost. However, for the same property with a reinsurance exposure of 25% instead, the same increase in reinsurance cost leads to an almost 3 percentage point increase in insurance cost. If we replace the measure of risk score with log(expected building losses per capita), we observe a very similar pattern, as shown in the right subpanel. This pattern demonstrates that higher exposure on reinsurance amplifies the passthrough of changes in reinsurance cost into primary insurance premiums, with the effect increasing as disaster risk scores rise.

The left subpanel of Panel B of Figure 7 presents the marginal effects of a 10-point increase in risk score on the percentage change in insurance costs as a function of different levels of reinsurance exposure and reinsurance cost increases. It shows how a 10-point increase in risk score translates into changes in insurance costs for properties in states with different levels of reinsurance exposure, given a certain percentage change in reinsurance cost. To interpret the results, we focus on a reinsurance exposure level of 20%. At this level, when reinsurance costs increase by 10%, a 10-point increase in risk score leads to a 0.5 percentage point increase in insurance cost. Instead, when reinsurance costs increase by 25%, the same 10-point increase in risk score leads to a 1.5 percentage point increase in insurance cost. The right subpanel of Panel B replaces the risk score with log(expected building losses per capita) and finds a very similar pattern. This pattern demonstrates that the effect of local risk on the insurance cost is amplified when insurers face higher reinsurance costs, with a greater passthrough occurring in states where insurers rely more on reinsurance markets.

C. Out-of-State Losses

Insurance markets are geographically interconnected, with insurers operating across multiple states and pooling risks across regions. When an insurer experiences substantial losses in one state, regulatory constraints or market frictions may limit its ability to raise premiums in that affected area. As a result, the insurer may recoup these losses by increasing premiums across its broader portfolio, including in states that were not directly impacted by the original events (Oh, Sen, and Tenekedjieva, 2022). Consequently, out-of-state losses can significantly influence insurance pricing beyond the directly affected regions.

To quantify insurers' exposure to losses occurring outside the states where they underwrite policies, we construct a measure of *Out-of-State Losses* ($OOSLoss_{s,t}$). This measure reflects the extent to which insurers operating in state s are affected by losses in other states through their cross-state underwriting.

Formally, we define *Out-of-State Losses* as:

$$OOSLoss_{s,t} = \frac{\sum_{i \in I} \text{DirectPremiumsWritten}_{i,s,t} \times \text{Losses}_{i,-s,t}}{\sum_{i \in I} \text{DirectPremiumsWritten}_{i,s,t}},$$

where $\text{DirectPremiumsWritten}_{i,s,t}$ represents the direct premiums that insurer i writes in state s at time t, and $\text{Losses}_{i,-s,t}$ denotes the losses incurred by insurer i in all states other than s. Conceptually, for each insurer operating in state s, we calculate its total losses incurred outside s. We then aggregate these out-of-state losses across all insurers in state s, weighting each insurer's losses by its market share in that state (as measured by direct premiums written).

To illustrate the variation in out-of-state losses, Panel A of Figure 8 shows the distribution of $OOSLoss_{s,t}$ across different states in 2010. Lighter shades indicate lower levels of out-of-state exposure, while darker shades suggest higher levels. The figure reveals considerable geographic variation, indicating that insurers in some states face substantially more cross-state risk than others. Further, Panel B of Figure 8 shows the abnormal amount of out-of-state losses in a select number of states over time.[5] From this figure, we can see that there is a large degree of variation in out-of-state losses over time for each state.

To examine how out-of-state losses affect changes in insurance costs, we estimate the following equation:

$$PctChangeInsurance_{i,s,t} = \beta \times Log(OOSLoss)_{s,t-1} \times RiskScore_i + \gamma \times Log(OOSLoss)_{s,t-1} + \delta \times RiskScore_i + YearFE_t + StateFE_s + \varepsilon_{i,s,t}$$

where $\log(OOSLoss)_{s,t-1}$ is the (standardized) log of out-of-state losses for state s in the previous period $t-1$, and RiskScore_i (ranging from 0 to 100) captures the intrinsic risk level of property i. The key coefficient of interest is on the interaction term, $\log(OOSLoss)_{s,t-1} \times \text{RiskScore}_i$, which tests whether insurers increase premiums more aggressively for high-risk properties when they experience larger out-of-state losses. We include year fixed effects ($YearFE_t$) and state fixed effects ($StateFE_s$) to account for time-invariant and state-specific unobservable factors.

Table 2 presents the estimated relationship between out-of-state losses and changes in insurance costs. In Column (1), we begin by examining the direct effect of out-of-state losses on insurance costs. $\log(OOSLoss)$ is standardized for interpretative convenience. The coefficient estimate of 0.0620 is statistically significant at the 5% level, indicating that a one-standard-deviation increase in out-of-state losses leads to a 6.2 percentage point increase in insurance costs. This finding suggests that when insurers face larger out-of-state losses, they respond by raising premiums even in states not directly affected by those loss events. It underscores the role of inter-state risk pooling, whereby insurers price risk in light of their broader underwriting portfolio rather than focusing solely on local conditions.

Columns (2)–(4) explore how this relationship varies with property-level risk. We introduce the interaction term $\log(OOSLoss) \times$ RiskScore. The coefficient on this interaction term is consistently positive and statistically significant, indicating that higher-risk properties experience larger premium increases in response to insurer losses. By incorporating state, county, and property fixed effects,

[5] Abnormal losses are defined as the $\varepsilon_{s,t}$ from estimating $Log(OOSLosses)_{s,t} = StateFE_s + YearFE_t + \varepsilon_{s,t}$.

the estimates ensure that the observed variation in insurance costs is not driven by time-invariant regional characteristics or other confounding factors. In Column (4), the interaction coefficient is 0.0567, significant at the 5% level. Given that risk scores range from 0 to 100, this implies that for a high-risk property (risk score of 100), a one-standard-deviation increase in out-of-state losses leads to a 5.67 percentage point increase in insurance costs. For a medium-risk property (risk score of 50), the impact is 2.84 percentage points, while for a low-risk property (risk score of 10), the effect is only 0.57 percentage points. This pattern suggests that insurers pass on the financial burden of out-of-state losses more aggressively to high-risk properties.

Overall, these results demonstrate that out-of-state losses contribute to higher insurance costs, but the effect is concentrated among high-risk properties. This underscores the broader systemic consequences of geographically dispersed insurance losses, showing that premium adjustments are not only reactive to local conditions but also shaped by the financial health of insurers across state lines.

D. Other Potential Causes

We examine additional factors that could influence insurance cost changes, including geographic characteristics, property features, and insurance market concentration. Specifically, we analyze the relationship between insurance cost increases and distance to the coast and elevation, as shown in Figure IA.7. We also assess the impact of property-specific features, such as the number of units and building age, with results presented in Figure IA.8. Additionally, we investigate insurance market concentration at both the state level and the county level for California, measuring it using the Herfindahl-Hirschman Index (HHI). As illustrated in Figure IA.9, we document a decline in HHI over time, indicating increased competition in the commercial insurance market, which contrasts with trends observed in homeowner insurance markets. However, none of these factors meaningfully explain the variation in insurance cost increases.

V. Effects of Rise on Rents and Profits

In the previous sections, we have documented the time-series and cross-sectional rise in insurance costs and explored the potential causes of these increases. In this section, we now turn to the consequences of rising insurance costs, analyzing their impact on rents and property profitability.

A. Regression Analysis

To examine the effects of rising insurance costs on rents and net operating income (NOI) for multi-family properties, we first estimate a regression of the following form:

$$Log(y)_{imt} = \beta_0 + \beta_1 Log(Insurance\ per\ Unit)_{imt} + \gamma_i + \eta_{mt} + \epsilon_{imt}$$

where $Log(y)$ represents our outcome variable, which could be either *Log(Rents per Unit)* or *Log(NOI per Unit)* of property i in CBSA m in year t, and γ_i are property fixed effect, and η_{mt} are CBSA × year fixed effects. $Log(Insurance\ per\ Unit)_{imt}$ is our variable of interest, and β_1 captures the rate of passthrough to either rent or operating profits/losses. Note that given both the dependent and independent variables are in logs and we include a property fixed effect, the coefficients can be interpreted as elasticities or the effect of a percentage change in insurance cost on the percentage change in rent or NOI.[6]

Table 3 presents the results. Columns (1) and (2) present results on passthrough to rents and columns (3) and (4) to operating income. All columns include a property fixed effect. In columns (1) and (3), we include a year fixed effect, and in columns (2) and (4), we include a CBSA × year fixed effect to absorb any time-varying CBSA-level factors. Using more specification with a CBSA × year fixed effect, a 10% increase in insurance cost is associated with a 0.21% increase in rents and a 0.35% decrease in NOI. Both of these results are highly statistically significant with t-statistics of over 8 based on standard errors that are clustered at the CBSA-level.[7]

To qualify the portion of the insurance cost increase that is being passed through to rents, consider a 25% increase in insurance cost. Based on column (2) of Table 3, a 25% increase in insurance cost is associated with a 0.53 ppt increase in rents (25% × 0.0209). Since 3.1% of rent is spent on insurance on average, a 25% increase in insurance cost would be associated with a 0.78% if fully passed through to rent (3.1% × 25%). Thus, 67% of the rise in insurance cost is being passed through to rent (0.53 / 0.78).

[6] We normalize both the dependent and independent variable by the number of units in order for the CBSA × year fixed effect to capture the average rent or NOI in each CBSA across time more precisely.

[7] The specifications that include a year fixed effect instead of a CBSA × year fixed effect implies a higher passthrough to rent and lower passthrough to operating losses.

Note that the 67% passthrough figure holds regardless of the level of rise in rise in insurance costs, not just the 25% level considered in this example.

B. Non-linearity of Passthrough

Next, we graphically examine the passthrough of insurance cost to rents and NOI in order to examine any nonlinearities. In particular, Panel A of Figure 9 displays binscatter plots showing the relationship between the log insurance costs per unit and two outcomes: log rents per unit (left subpanel) and log NOI per unit (right subpanel). As in the above regressions, both plots include CBSA $\times$ year and property fixed effects and can be interpreted as elasticities. The black curves represent third-degree polynomial fits based on the underlying residualized data, with the gray region surrounding the curves representing 95% confidence intervals.

The binscatter in the left subpanel shows a positive relationship between insurance costs per unit and rents per unit, indicating that rising insurance costs are partially passed on to tenants through higher rents. However, the concave shape of the fitted polynomial suggests that this pass-through diminishes as insurance costs increase, implying that property owners face limitations in transferring higher costs to tenants and lower levels of profit. The binscatter in the right subpanel reveals a concave relationship, with NOI initially increasing as insurance costs rise but eventually declining at higher levels of insurance costs. This pattern suggests that while property owners may absorb some of the rising costs through operational adjustments or increased rents, their ability to maintain profitability weakens as insurance costs escalate. At higher insurance cost levels, the inability to fully pass through costs results in a reduction in NOI.

C. Passthrough Over Time

Panel B of Figure 9 examines how the passthrough of insurance cost increases to rents and operating profits has changed over time. We estimate the same regression as above but now include an interaction between an indicator variable for each year and the independent variable of interest (either log rents per unit or log NOI per unit). The left subpanel shows there has been a decline in the rate of passthrough to rents over time, with a particularly large decrease between 2019 to 2020. A 10%

increase in insurance cost resulted in a rent increase of approximately 0.35% in 2013, but a decade later, in 2023, it would result in an increase of only approximately 0.05%. On the other hand, the passthrough to operating losses has increased over time. Before 2018, an increase in insurance cost was both economically and statistically not associated with a change in NOI, but by 2023, a 10% increase in insurance cost was associated with an over 0.80% decrease in NOI. Note that the concavity shown in Panel A of Figure 9 and the decreasing (increasing) passthrough to rent (NOI) are driven by the same factor: as insurance costs have dramatically increased in recent years, property owners have not been able to increase rents or make operating adjustments to maintain the same level of profitability. It is left to be seen how property owners respond in the long-term, especially if insurance costs continue to rise at the same rates as they have in recent years.

VI. Role of Property Owners

Beyond geographic and market factors, property owners themselves play a role in shaping insurance costs. In this section, we examine how owner size and portfolio composition influence insurance pricing.

A. Owner Size

Ownership structure interacts significantly with rising insurance costs, with larger property owners demonstrating a notable advantage in maintaining lower per-unit insurance expenses. Panel A of Figure 10 illustrates the relationship between property owner size and insurance costs, highlighting how this interaction varies across regions with different risk levels and over time. Panel A shows that larger property owners typically incur lower insurance costs per unit and as a percentage of rent, underscoring the advantage of economies of scale. This trend reflects their stronger bargaining power with insurers, which enables them to secure more favorable rates.[8]

The bargaining power and economies of scale for large owners are likely to be the largest in high-risk areas since insurance companies have more discretion in pricing in such regions. To examine this,

[8] We include CBSA $\times$ year fixed effects in this figure to account for variation in insurance pricing across regions and time.

we estimate

$$Log(Insurance/Unit)_{i,o,c,t} = \beta \times RiskScore_i \times LogOwnerSize_{o,t} + \gamma \times LogOwnerSize_{o,t} + PropertyFE_i + CBSAYearFE_{c,t} + \varepsilon_{i,o,c,t}$$

where RiskScore_i is the risk score of census tract that property i is located in and $\text{LogOwnerSize}_{o,t}$ is the log of number of units owned by owner o in year t across the entire country. We also include property fixed effects (PropertyFE_i) and CBSA-by-year fixed effects ($\text{CBSAYearFE}_{c,t}$) to account for local market conditions over time. Note that the inclusion of property fixed effects implies that the results are entirely based on variation in the size of the owner of a given property over time.

Panel B of Figure 10 shows the marginal effect of increasing owner size by one standard deviation at varying levels of risk score. At relatively lower risk scores, the effect of owner size is economically small and statistically indistinguishable from zero. However, at high values of risk score, the effect of owner size is both economically sizable and highly statistically significant. In particular, for the riskiest properties (i.e., a risk score of 100), a one standard deviation increase in owner size is associated with a decrease in insurance cost per unit of over \$35, which is 7.8% of the average insurance cost per unit (\$458). It is worth noting again that this decrease in insurance costs is based on holding the same property fixed and only varying owner size. We also find similar results based on the ratio of insurance cost to rent in the right subpanel.

B. Owner Portfolio Risk

In this subsection, we examine whether an owner's overall (i.e., pooled) portfolio risk influences the insurance pricing of individual properties within that portfolio. Specifically, as a measure of the overall riskiness of each owner's portfolio, we define

$$PortfolioRiskScore_{o,t} = \frac{\sum_{i \in Portfolio_o} Units_i \times RiskScore_i}{\sum_{i \in Portfolio_o} Units_i}$$

To estimate the effect of an owner's portfolio risk, we begin by estimating the following equation:

$$Log(Insurance/Unit)_{i,o,c,t} = \beta \times PortfolioRiskScore_{o,t} + \gamma \times LogOwnerSize_{o,t}$$
$$+ PropertyFE_i + CBSAYearFE_{c,t} + \varepsilon_{i,o,c,t}$$

where PortfolioRiskScore$_{o,t}$ reflects the average riskiness of owner o's portfolio at time t. The specification also includes controls for the owner's overall size (LogOwnerSize$_{o,t}$), property fixed effects (PropertyFE$_i$), and CBSA-by-year fixed effects (CBSAYearFE$_{c,t}$) to account for local market conditions over time. Note that the inclusion of property fixed effects implies that the results are entirely based on variation in the property owner's portfolio risk over time, which could either be due changes the portfolio of an owner over time (while keeping the ownership of the focal property fixed) or a change in ownership of the focal property.

Panel A of Figure 11 shows that as an owner's average portfolio risk score declines, the insurance cost per unit given property also tends to decrease. This pattern indicates that insurers do not set premiums based solely on a property in isolation but also take into account the risk profile of the entire portfolio held by the owner.[9]

Next, we extend the analysis by allowing a property's *own* risk score to interact with the owner's *portfolio* risk score. Specifically, we estimate

$$Log(Insurance/Unit)_{i,o,c,t} = \beta \times PortfolioRiskScore_{o,t} \times RiskScore_i + \gamma \times RiskScore_i$$
$$+ OwnerYearFE_{o,t} + \varepsilon_{i,o,c,t}$$

where RiskScore$_i$ denotes the risk score of property i, and PortfolioRiskScore$_{o,t}$ is the weighted average risk of the owner's full portfolio. The interaction term (PortfolioRiskScore$_{o,t}$ $\times$ RiskScore$_i$) captures how the effect of a property's own risk score depends on the owner's overall portfolio risk, while OwnerYearFE$_{o,t}$ accounts for any unobserved time-varying factors unique to each owner.

Panel B of Figure 11 each colored line represents a different level of the owner's weighted average portfolio risk (e.g., 0, 25, 50, 75, and 100). We see that, for a high-risk property (e.g., risk score

[9]Note that the effect of an owners average portfolio risk is distinct from the owner size effect we discussed in the previous section; both effects are economically and statistically significant when considered together.

100), insurance costs are substantially lower if the overall portfolio risk score is shared with lower-risk properties. Specifically, consider an owner holding a portfolio of several properties, some of which are relatively high risk while others are moderate or low risk. If the owner sells one or two of the riskier properties in the portfolio and replaces them with safer ones, the owner's overall risk profile declines (i.e., the portfolio now has a lower average risk score). Even if the riskiness of a particular property remains unchanged, its insurance premium may fall simply because it is now pooled with relatively safer properties.

C. Combining Effects of Owner Size and Portfolio Risk

We now consider the combined role of owner size and the average risk of the owner portfolio. Specifically, we estimate the following equation:

$$\begin{aligned} Log(Insurance/Unit)_{i,o,c,t} = {} & \beta \times PortRiskScore_{o,t} \times RiskScore_i \times OwnerSize_{o,t} \\ & + \gamma \times PortRiskScore_{o,t} \times RiskScore_i \\ & + \delta \times RiskScore_i \times OwnerSize_{o,t} + \eta \times RiskScore_i \\ & + OwnerYearFE_{o,t} + \varepsilon_{i,o,c,t} \end{aligned}$$

where RiskScore_i denotes the risk score of property i, $\text{PortRiskScore}_{o,t}$ is the weighted average risk of the owner's full portfolio, and $\text{OwnerSize}_{o,t}$ is the log of number of units owned by owner o in year t across the entire country. $\text{OwnerYearFE}_{o,t}$ accounts for any unobserved time-varying factors unique to each owner. The triple interaction term ($\text{PortRiskScore}_{o,t} \times \text{RiskScore}_i \times \text{OwnerSize}_{o,t}$) captures the extent to which owner portfolio risk channels described the the previous subsection varys by owner size.

As in Panel B of Figure 11, each colored line in Panel A of Figure 12 represents a different level of the owner's weighted average portfolio risk (e.g., 0, 25, 50, 75, and 100). The left (right) subpanel shows the case when the property owner has 1,000 (50,000) units across the entire nation. We see that for small owners, regardless of their average portfolio risk, there is no difference in their insurance cost per unit. In contrast, for large owners, insurance costs are substantially lower if the overall portfolio risk score is shared with lower-risk properties. Panel B shows very similar results when the ratio of insurance cost to rent is used instead of insurance cost per unit. That is, the average portfolio risk channel interacts with the owner size channel and leads to large owners having significantly lower insurance costs.

D. Role of Property Owners Over Time

So far, we have shown that larger property owners enjoy a significant advantage in negotiating lower insurance costs due to economies of scale and greater bargaining power. Additionally, we demonstrate that insurers not only price individual properties based on their isolated risk but also consider the owner's overall portfolio risk, benefiting properties pooled with lower-risk assets. In this subsection, we revisit and further investigate how this advantage has changed over time, as well as how property owners strategically adjust to leverage it.

We first examine how the size advantage of large owners evolved over the past decade. Panel A of Figure 13 shows the annual effects of owner size on insurance costs to rent, separately for properties in low-, medium-, and high-risk areas. A negative effect indicates that larger owners pay lower insurance costs to rent, reflecting their size advantage. In the earlier years of the sample, the size advantage is similar across properties in all three risk categories. However, this pattern begins to shift in recent years. Specifically, the size advantage becomes smaller (less negative) in lower-risk areas but grows substantially larger (more negative) in high-risk areas. In other words, the advantage of larger owners is increasingly concentrated among properties located in riskier regions. Furthermore, we examine how the effect of owner portfolio risk varies over time. Panel B of Figure 13 illustrates the owner portfolio effect over time by property risk and owner size. It shows that in recent years, reducing owner portfolio risk substantially lowers insurance costs to rent, especially for large owners with properties in high-risk areas.

To investigate this shift further, we analyze how the riskiness of a property's location relates to the size of its owner over time. Panel A of Figure 14 shows two binscatter plots, separately for the years 2010 (left subpanel) and 2024 (right subpanel). Each plot illustrates the relationship between the log of expected annual building losses per capita (a measure of local risk) and the log of the owner size, measured as the number of units owned nationally by that owner. Both plots control for differences across CBSAs by including CBSA fixed effects. In 2010, we see almost no relationship between local risk and owner size—the fitted line is flat. By contrast, in 2024, the relationship is strongly positive. This indicates that, by 2024, properties in riskier areas are more likely to be owned by larger owners.

We further quantify this evolving relationship using a dynamic regression. Specifically, we estimate the following regression:

$$Log(OwnerSize)_{o,t} = \sum_{t \neq 2010} \beta_t \times \mathbb{1}(Year = t) \times RiskScore_i + PropertyFE_i + YearFE_t + \varepsilon_{i,o,t}$$

In this equation, the dependent variable is the log of the owner's size (number of units owned nationally), and the independent variable is the risk score of the property's location, interacted with a set of year indicators. We include property fixed effects, meaning the regression relies entirely on within-property variation over time. Conceptually, this approach allows us to compare ownership size changes for the same property if it were hypothetically located in areas with different risk levels. Year fixed effects are also included to account for general market trends that affect all properties similarly.

Panel B of Figure 14 plots the estimated coefficients (β_t) for each year. The left subpanel shows the effect of a one-unit increase in the log of expected annual building losses per capita, and the right subpanel shows the effect of a 10-point increase in the risk score. We observe that the effects become progressively stronger each year. These findings align closely with the results described above: as larger owners gain a growing insurance cost advantage in riskier locations, ownership of risky properties shifts increasingly toward larger owners.

VII. Conclusion

In this paper, we show that multifamily properties across nearly all regions of the United States have experienced a substantial rise in insurance costs over the past decade. Compared to the homeowners insurance market, 95% of individuals reside in counties where commercial property's insurance costs have risen at least twice as much as homeowners insurance costs—an outcome driven in part by regulatory constraints in the homeowners market. Our paper identifies three primary drivers of this increase: heightened pricing of local risk, a significant rise in reinsurance costs, and cross-subsidization across states.

The sharp rise in insurance costs has broader implications for the multifamily housing sector, particularly in terms of its economic pass-through to tenants. On average, we find that 67% of the increase in insurance costs is passed through to rents, though this pass-through effect follows a concave pattern and diminishes over time. As a result, many property owners are experiencing an erosion of net operating income, highlighting the financial strain imposed by rising insurance expenses.

The financial impact of insurance pricing, however, is not uniform across all property owners. Larger property owners benefit from economies of scale and stronger bargaining power, allowing them to secure lower per-unit insurance costs compared to smaller owners. This advantage is particularly pronounced in high-risk areas, where pricing flexibility enables them to negotiate more favorable terms with insurers. Beyond scale, we also find that owners with lower average portfolio risk benefit from reduced insurance costs, even after controlling for the risk level of individual properties. This underscores the role of portfolio composition in shaping insurance outcomes, as insurers assess risk not only at the property level but also across an owner's entire holdings.

Rising insurance costs have also reshaped ownership patterns in the multifamily sector, especially in high-risk areas. Since 2020, larger owners have increasingly acquired high-risk properties, leveraging their scale and diversification to manage costs more effectively. This shift shows growing role of large owners in riskier markets.

In conclusion, our findings show that insurance pricing for multifamily properties is influenced not only by local risk factors but also by broader systematic risk exposure. Through interconnected portfolios, risks are spread and priced beyond the characteristics of individual properties, both at the insurer level and through the property owners' portfolio. Moreover, our results highlight the importance of understanding how these pricing dynamics translate into higher housing costs for tenants. With a significant share of rising insurance expenses being passed through to rents, the financial burden ultimately extends beyond property owners, shaping affordability in the multifamily housing sector.

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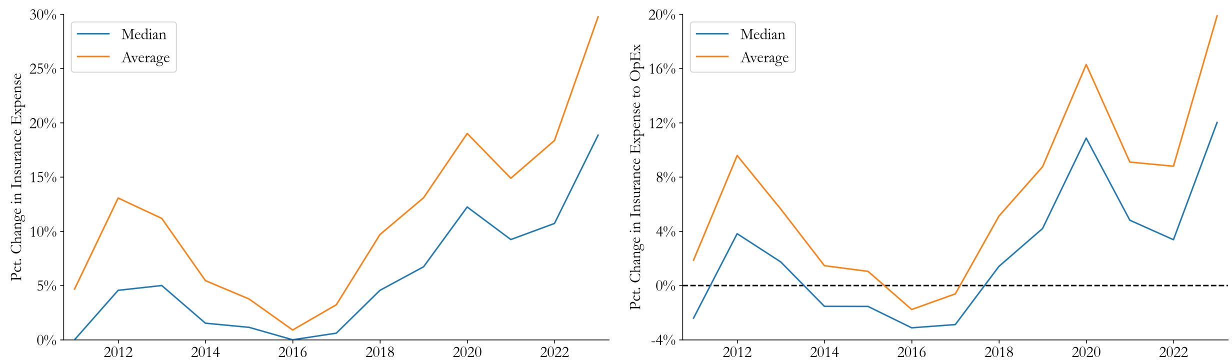
Figure 1: Time-Series Changes in Insurance Costs

This figure shows the average and median percentage changes in insurance costs for multifamily and other commercial properties in the US during each year from 2010 to 2023. Panel A focuses on multifamily properties, and Panel B shows other property types.

Panel A: Multifamily



Panel B: Other Property Types

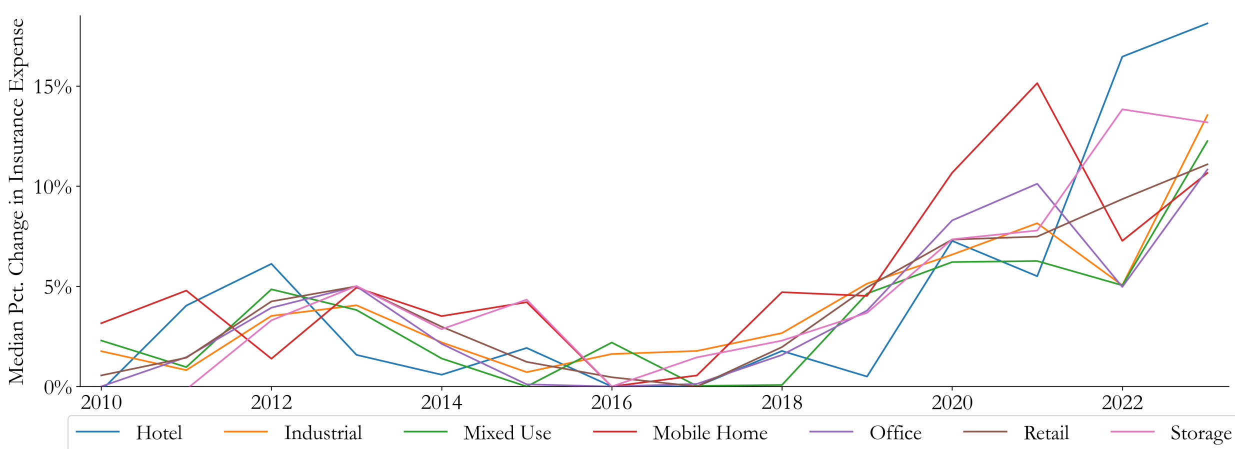
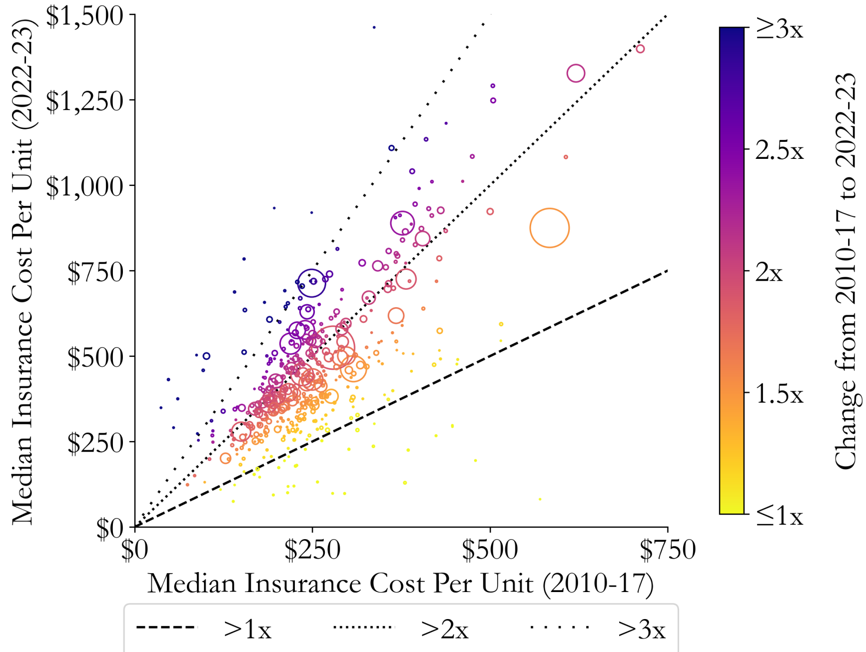


Figure 2: Cross-Sectional Differences in Insurance Cost Changes

This figure shows the cross-sectional differences in insurance cost changes for multifamily properties across Core-based Statistical Areas (CBSAs). Panel A shows a scatterplot of the median insurance cost per unit in 2010–2017 compared to 2022–2023 for each CBSA, where each circle represents a CBSA. Panel B provides a heat map of the percentage change in insurance costs between 2022 and 2023. For both panels, the color of each CBSA reflects the magnitude of the change, as shown in the respective color bars, and the size of the circles is scaled by the number of properties in each CBSA. In both panels, we restrict to CBSAs with at least five observations in both periods (2010-17 and 2022-23 in panel A, 2022 and 2023 in panel B).

Panel A: Insurance Cost Per Unit by CBSA, 2010-17 vs 2022-23



Panel B: CBSA-level Heatmap of Insurance Cost Increase Between 2022 and 2023

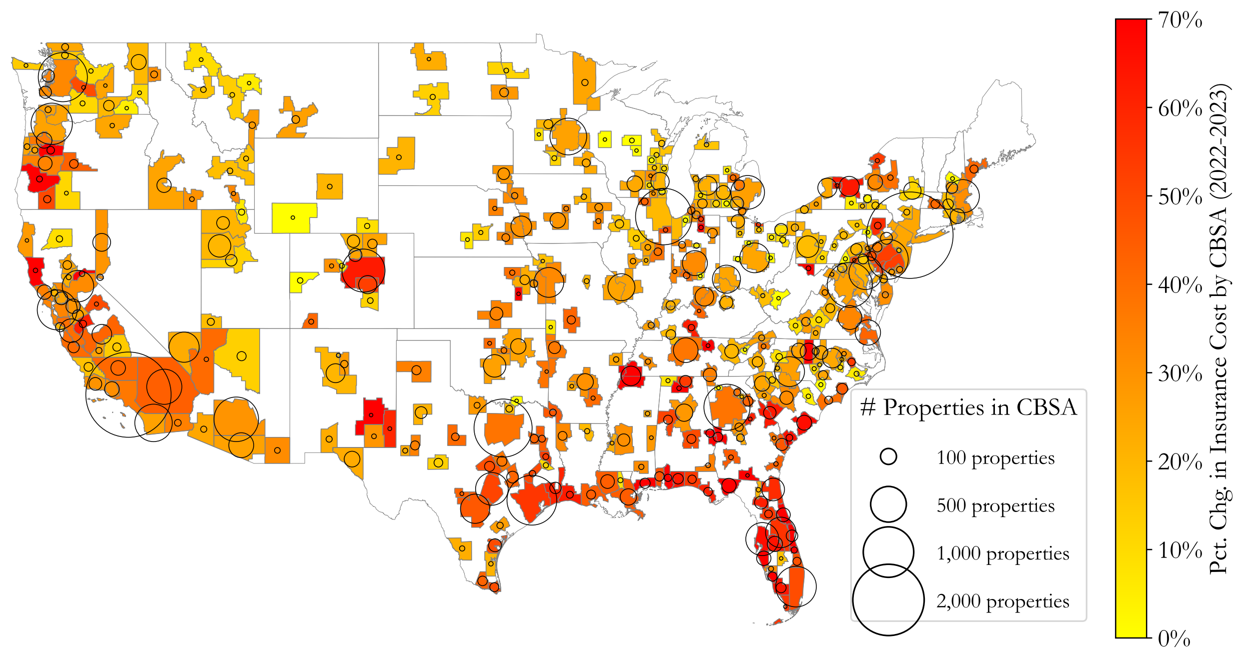
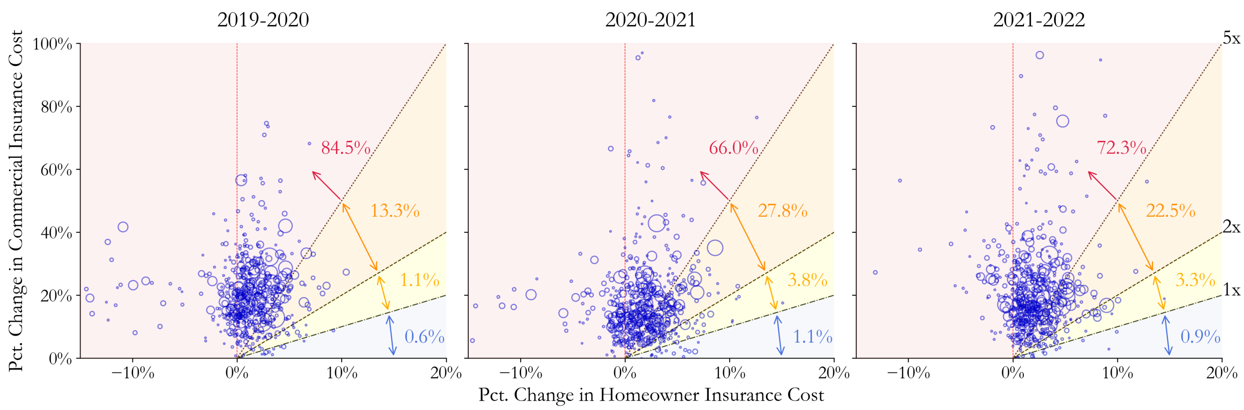


Figure 3: Commercial Versus Homeowner Insurance Costs

This figure compares commercial property insurance costs to homeowner insurance costs. Panel A presents scatterplots of the annual average percentage change in commercial insurance costs versus homeowner insurance costs for three consecutive yearly intervals: 2019–2020, 2020–2021, and 2021–2022. Each bubble represents a county, sized by the county's population. Three dashed reference lines are shown: a 1x line (45-degree line), a 2x line, and a 5x line. The percentages labeled within each region indicate the proportion of the U.S. population residing in counties experiencing these relative insurance cost changes. Homeowner insurance cost data is sourced from U.S. Department of the Treasury (2025). Panel B further explores the differential rise between commercial and homeowner insurance costs by examining how this wedge varies with local risk and state-level regulatory frictions. It includes state × year fixed effects, and standard errors are clustered at the state level. The state-level friction measure is from Oh, Sen, and Tenekedjieva (2022). The risk score and expected annual loss data are at the census tract level, sourced from FEMA's National Risk Index.

Panel A: Change in Commercial vs Homeowner Insurance, by Year



Panel B: Commercial vs Homeowner Insurance, by Riskiness and Frictions

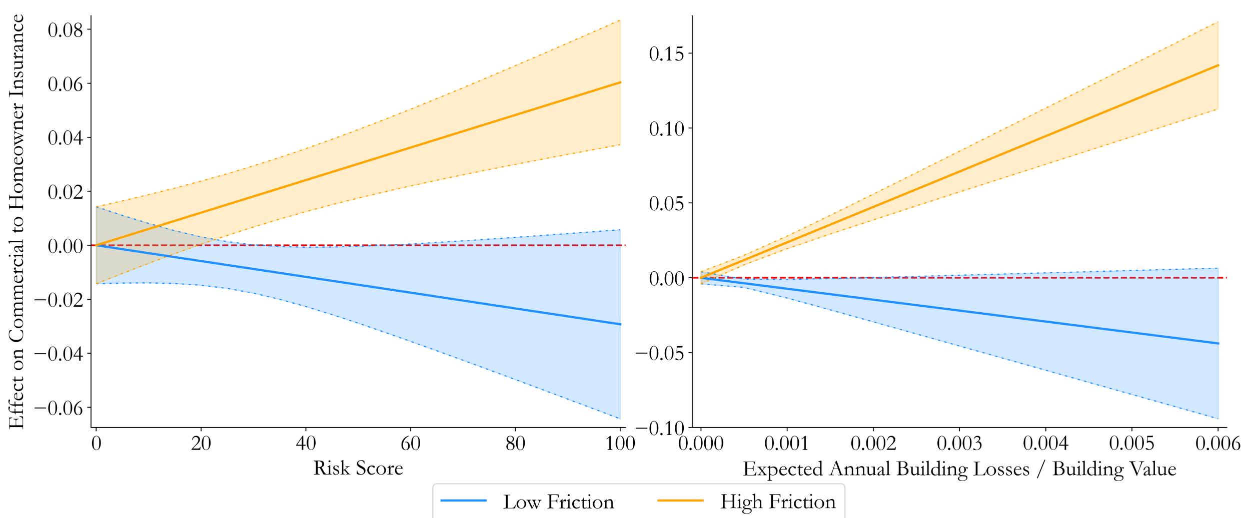
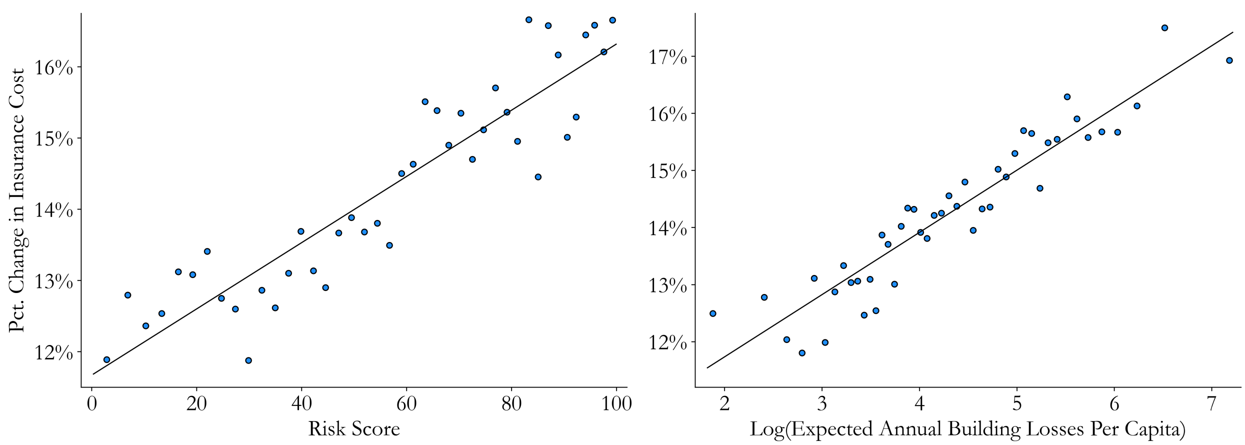


Figure 4: Risk Scores and Expected Annual Losses and the Rise in Insurance Costs

This figure explores how risk scores and expected annual building losses relate to changes in insurance costs. In both panels, these relationships are examined using binscatters; Panel A shows the relationships over the whole sample period (2010 to 2023), and Panel B shows the relationship separately during the early years (2017 and earlier) and later years (2018 and later). In both panels, the left subpanels plot the percentage change in insurance costs against risk scores, while the right subpanels plot the percentage change in insurance costs against the logarithm of expected annual building losses per capita. Both panels include a year fixed effect, and the lines shown are lines of best fit based on the underlying data. The risk score and expected annual loss data are at the census tract level and are from the Federal Emergency Management Agency's National Risk Index dataset.

Panel A: Risk Scores and Expected Annual Losses



Panel B: Split into Early and Late Years

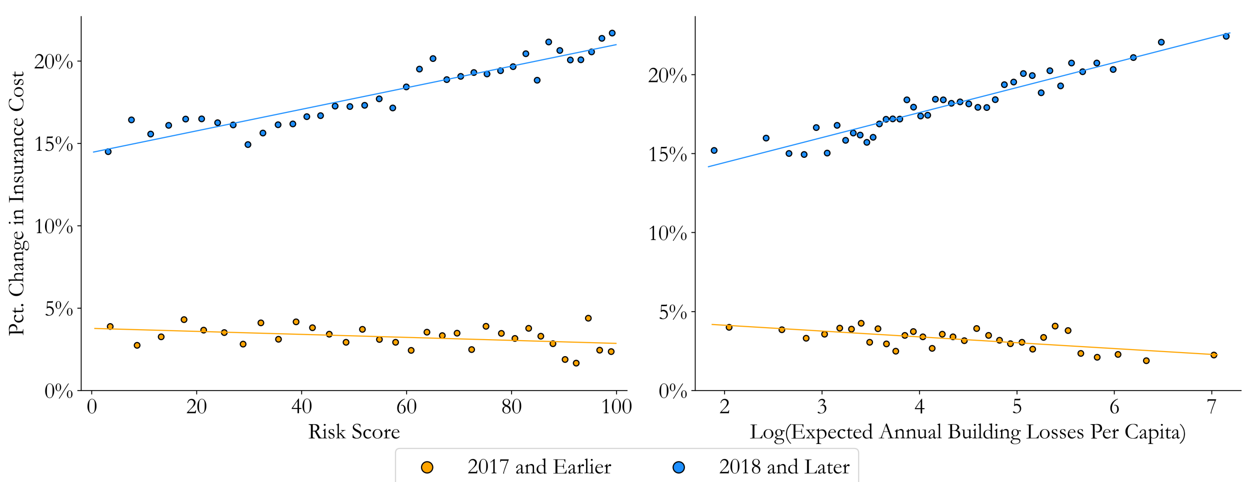
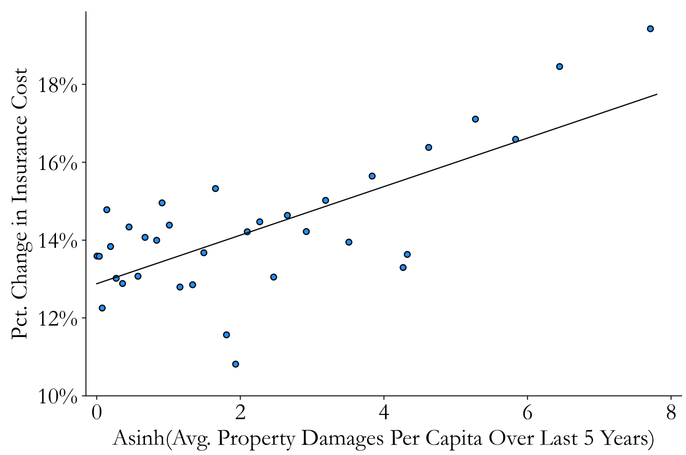


Figure 5: Past Property Damages and the Rise in Insurance Costs

This figure explores how past property damages relate to the percentage change in insurance costs. Panel A shows a binscatter plot of the percentage change in insurance costs against the inverse hyperbolic sine (asinh) transformation of average property damages per capita over the past five years. The line shown is a line of best fit based on the underlying data. Panel B considers different time horizons for past property damages (one to five years). The left subpanel shows the regression coefficients capturing the effect of property damages per capita over these time horizons on the percentage change in insurance costs, with error bars representing 95% confidence intervals based on standard errors clustered at the county level. Note that the rightmost coefficient (labeled 5) corresponds with the binscatter shown in Panel A. The right subpanel separates these effects into early years (2017 and earlier) and later years (2018 and later). Both panels include year fixed effects. Property damages data is at the county level and is from Arizona State University's Spatial Hazard Events and Losses Database.

Panel A: Binscatter



Panel B: Various Horizons and Split into Early and Late Years

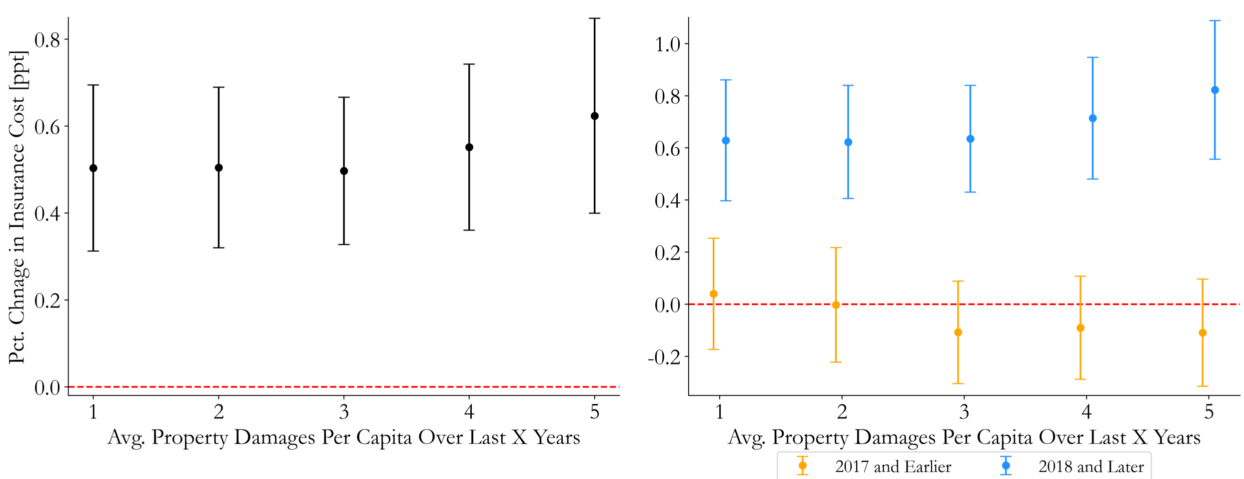
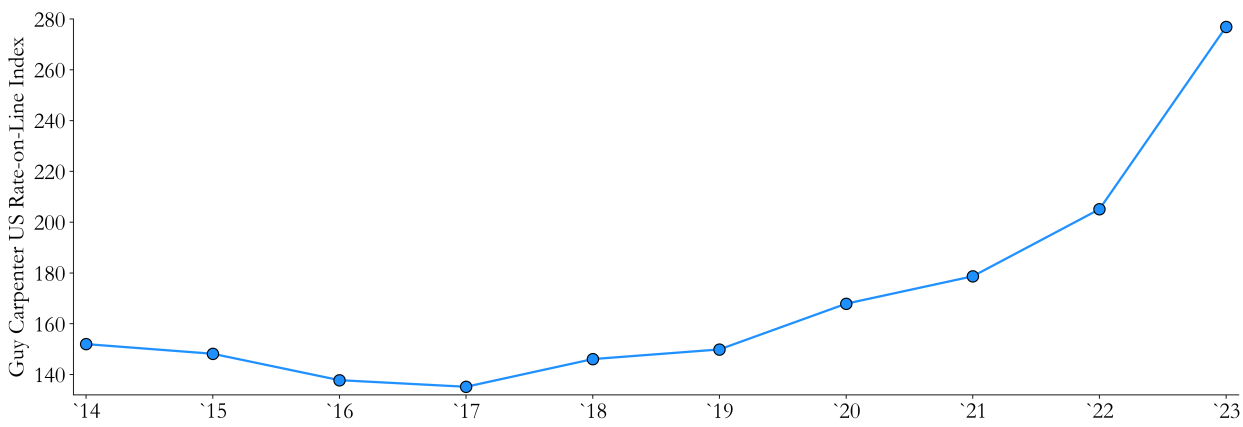


Figure 6: Rise in Reinsurance Costs and Reinsurance Exposure

This figure shows the rise in reinsurance costs (Panel A) and the exposure on reinsurance markets by state (Panel B). Reinsurance costs are based on the Guy Carpenter US Property Catastrophe Rate-on-Line Index. Reinsurance exposure is from Keys and Mulder (2024) and is based on the percentage of each insurer's risk ceded to unaffiliated reinsurers and the premiums written in each state in 2017. Specifically, $ReinsuranceExposure_s = \frac{\sum_{i \in I} DirectPremiumsWritten_{i,s} \times PctCeded_i}{\sum_{i \in I} DirectPremiumsWritten_{i,s}}$.

Panel A: Guy Carpenter US Property Catastrophe Rate-on-Line Index



Panel B: Reinsuance Exposure by State

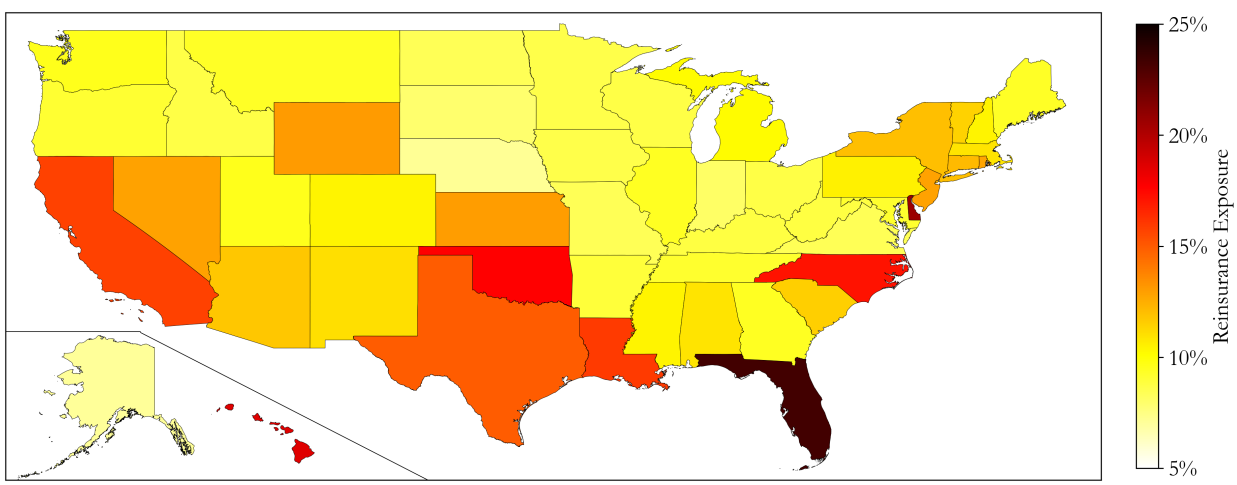


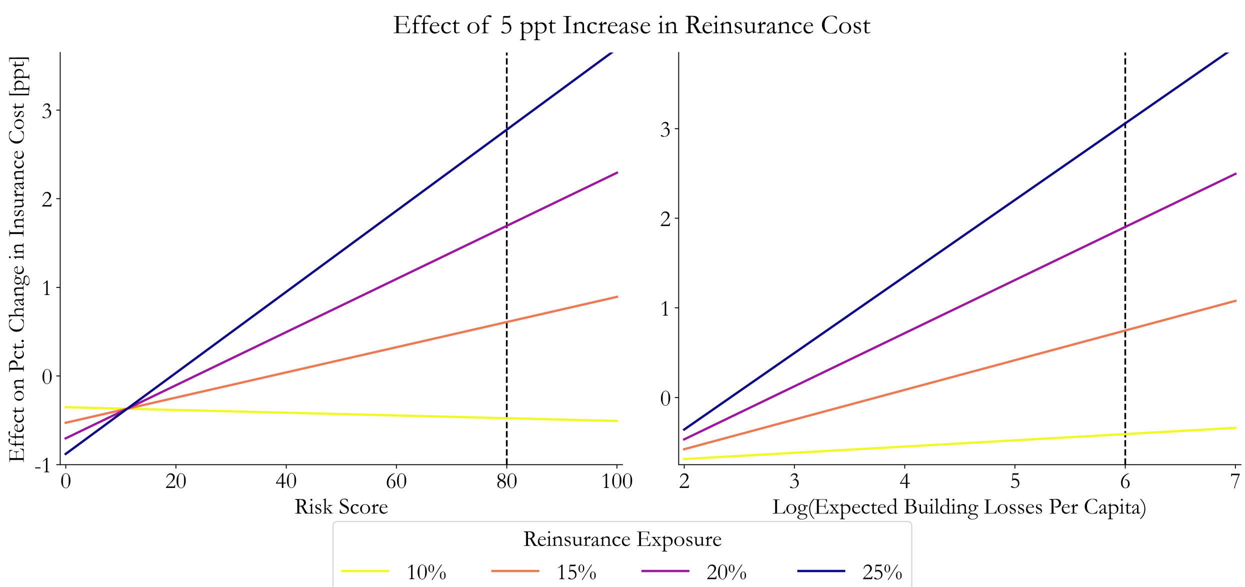
Figure 7: Reinsurance and the Rise in Insurance Costs

This figure shows the effects of interaction between rise in reinsurance costs at the national-level (Panel A of Figure 6), reinsurance exposure at the state-level (Panel B of Figure 6), risk scores across regions (Figure IA.2). Specifically, we estimate

$$\begin{aligned} PctChangeInsurance_{i,s,t} = & \beta \times PctChangeReCost_t \times ReinsurancExposure_s \times RiskScore_i \\ & + \gamma \times PctChangeReCost_t \times ReinsuranceExposure_s \\ & + \delta \times PctChangeReCost_t \times RiskScore_i \\ & + PropertyFE_i + YearFE_t + \varepsilon_{i,s,t}. \end{aligned}$$

Panel A shows the effects of a 5 ppt increase in reinsurance costs across varying levels of risk score or expected annual losses (horizontal axis) given different levels of reinsurance exposure (different colored lines) on percentage change in insurance costs. Panel B shows the effects of a 10-point increase in risk score or a 1-unit increase in expected annual losses at varying levels of reinsurance exposure (horizontal axis) given different levels of reinsurance cost increase (different colored lines) on percentage change in insurance costs.

Panel A: Effect of Reinsurance Cost Increase



Panel B: Effects of Risk Score and Expected Losses

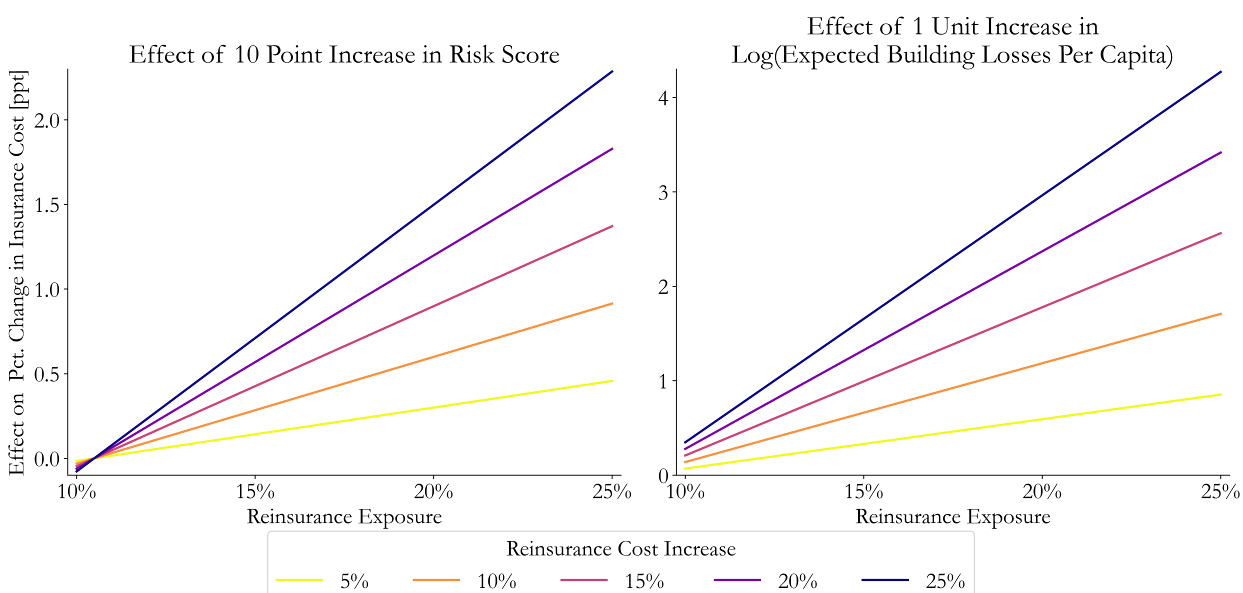
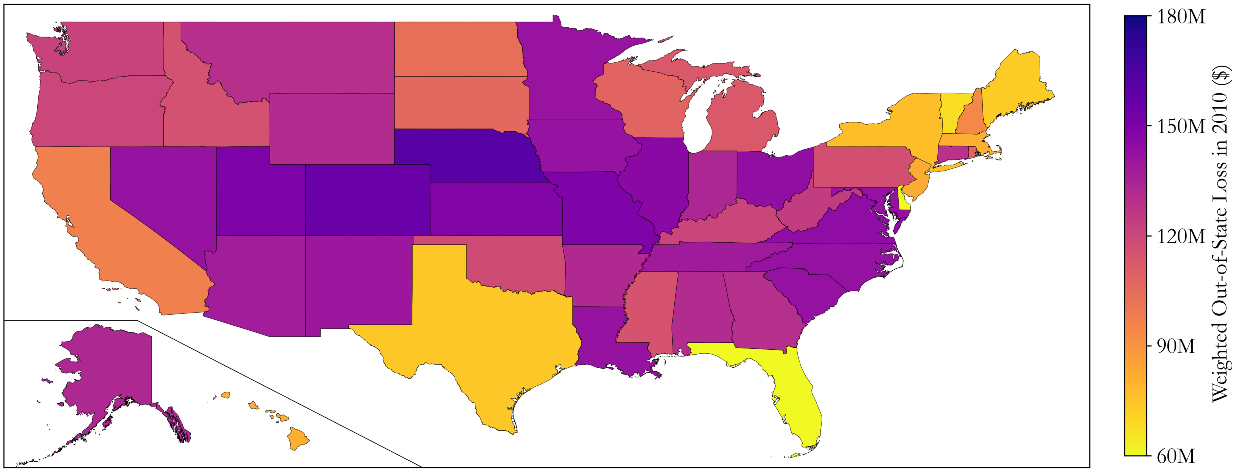


Figure 8: Out-of-State Losses

This figure shows variation in out-of-state losses. Out-of-state losses are defined as $OOSLoss_{s,t} = \frac{\sum_{i \in I} \text{DirectPremiumsWritten}_{i,s,t} \times \text{Losses}_{i,-s,t}}{\sum_{i \in I} \text{DirectPremiumsWritten}_{i,s,t}}$. Panel A shows variation in $OOSLoss_{s,2010}$ across states. Panel B shows abnormal $OOSLoss_{s,t}$ for a select group of states over time based on $\varepsilon_{s,t}$ from estimating $Log(OOSLosses)_{s,t} = StateFE_s + YearFE_t + \varepsilon_{s,t}$.

Panel A: Out-of-State Losses in 2010



Panel B: Abnormal Losses in Select States Over Time

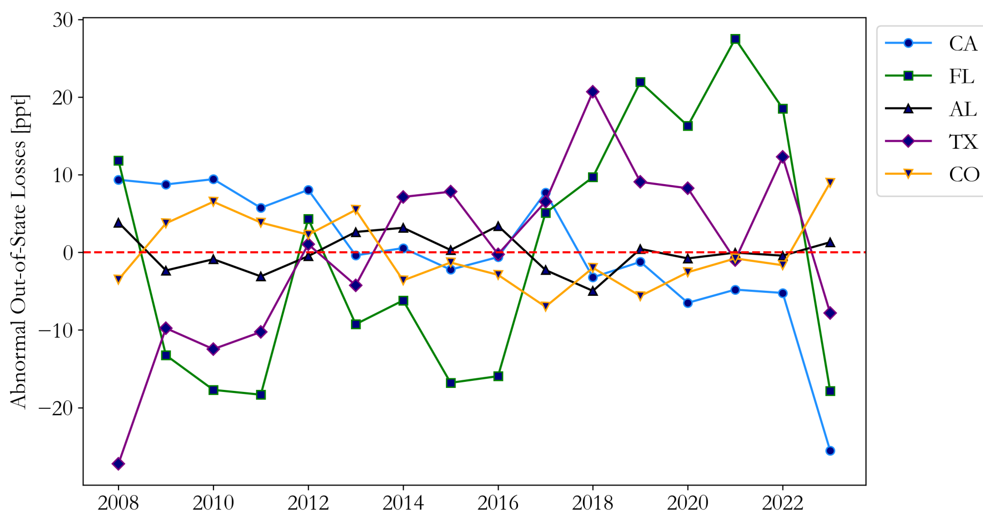
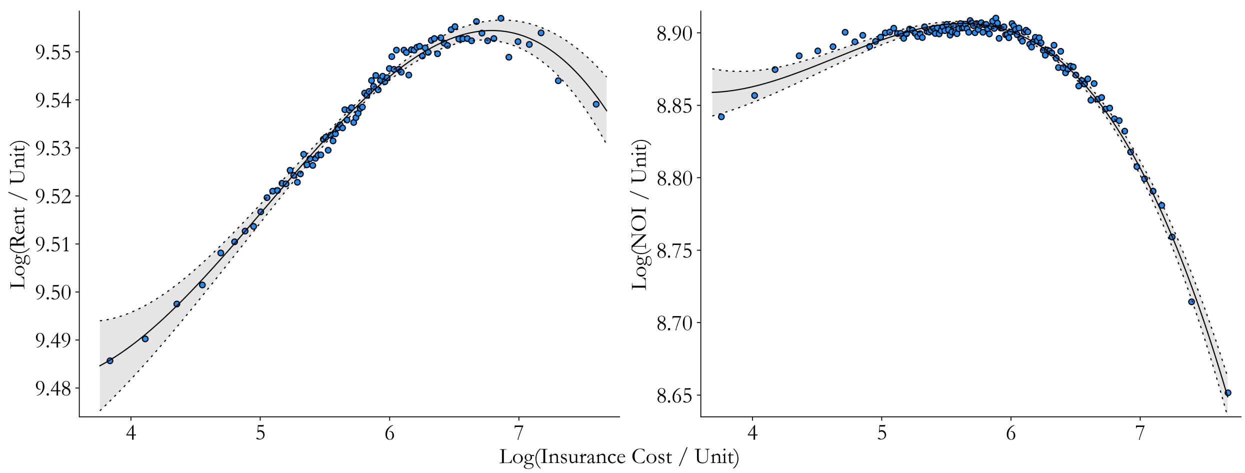


Figure 9: Effect of Insurance Cost Increase on Rents and Profits

This figure examines the impact of rising insurance costs on rents and net operating income (NOI) for properties. Panel A presents binscatter plots showing the relationship between insurance cost per unit and two outcomes: the left subpanel plots rents per unit, and the right subpanel plots NOI per unit. The black curves shown are third-degree polynomials fits based on the underlying data, and the grey regions represent 95% confidence intervals. Panel B illustrates how the effect of insurance costs on these outcomes evolves over time. The error bars represent 95% confidence intervals based on standard errors clustered at the CBSA level. Both panels include CBSA × year and property fixed effects.

Panel A: Binscatters



Panel B: Effect Over Time

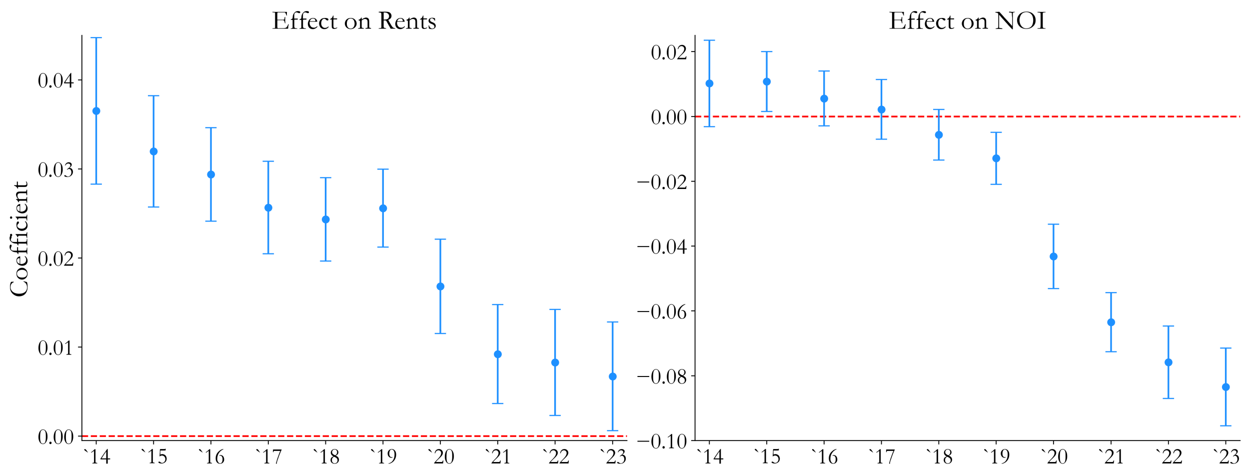
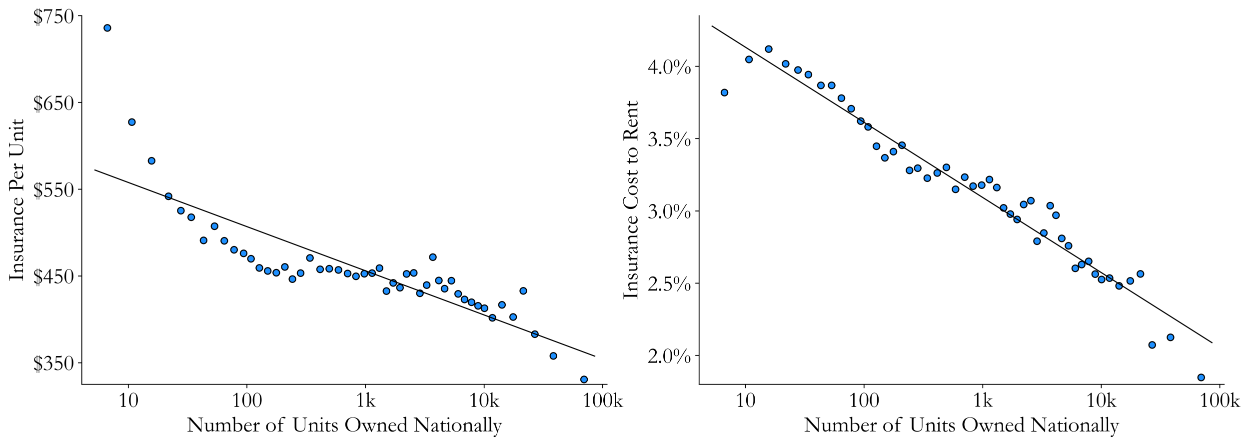


Figure 10: Role of Property Owner Size

This figure examines how owner size impacts insurance costs and how this relationship varies across regions with different risk score levels and over time. Panel A shows the relationship between owner size, measured as the number of units owned nationally, and insurance costs. The left subpanel plots the insurance cost per unit, while the right subpanel plots the insurance cost as a percentage of rent. The lines shown are lines of best fit based on the underlying data. Panel B examines how the effect of owner size varies across varying levels of risk scores for these same two cost measures. The error bars represent 95% confidence intervals based on standard errors clustered at the CBSA level. Panel A includes CBSA × year fixed effects, and Panel B includes property fixed effects and CBSA × year fixed effects. Risk scores are based on the National Risk Index (see Figure 4). Property ownership is based on transaction and holdings data from Real Capital Analytics.

Panel A: Insurance Cost by Owner Size



Panel B: Split by Risk Score

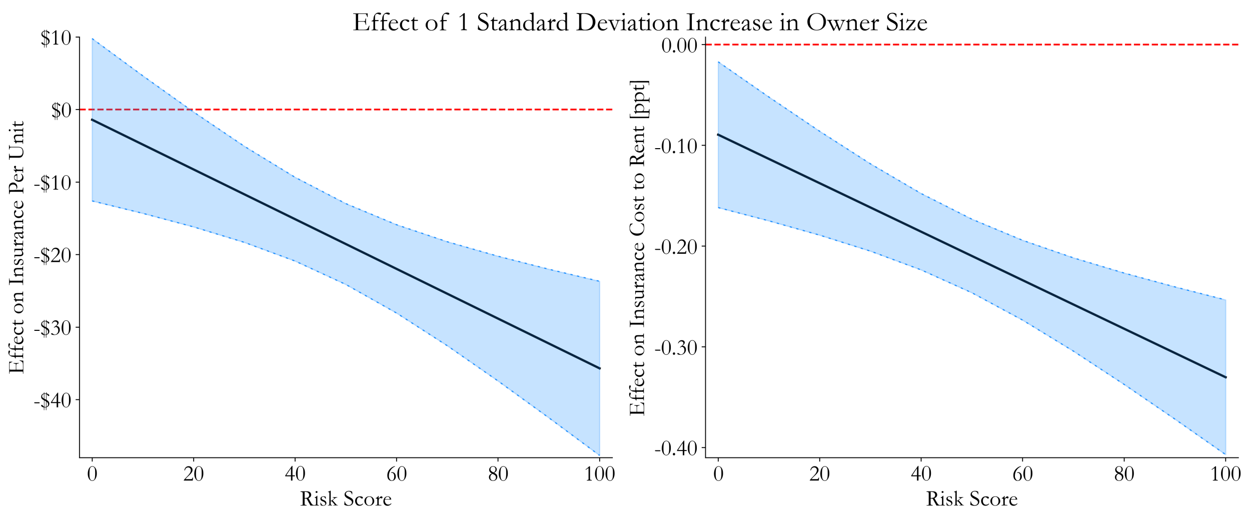
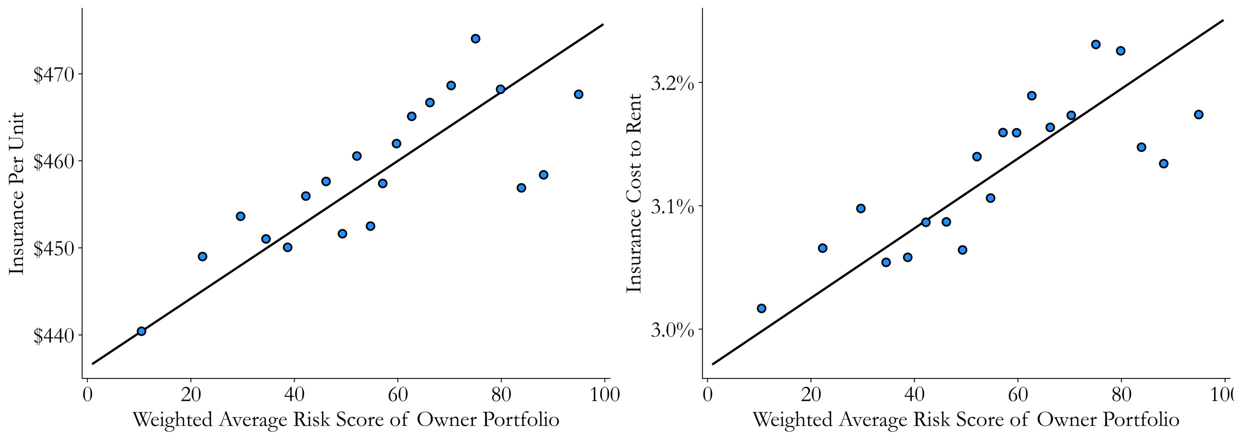


Figure 11: Role of Average Risk of Owner Portfolio

This figure examines how the average risk of an owner's portfolio affects insurance costs. Specifically, we define $PortfolioRiskScore_{o,t} = \frac{\sum_{i \in Portfolio_o} Units_i \times RiskScore_i}{\sum_{i \in Portfolio_o} Units_i}$. Panel A shows the binscatter of the relationship between insurance costs and $PortfolioRiskScore_{o,t}$ while controlling for owner size, property fixed effects, and CBSA $\times$ year fixed effects. Panel B shows how the effect of a property's risk score (horizontal axis) on insurance costs varies across different levels of average risk of its owner's portfolio (different colored lines) while controlling for owner $\times$ year fixed effects. Property ownership is based on transaction and holdings data from Real Capital Analytics.

Panel A: Insurance Cost vs. Portfolio Risk Score



Panel B: Across Property Risk Score

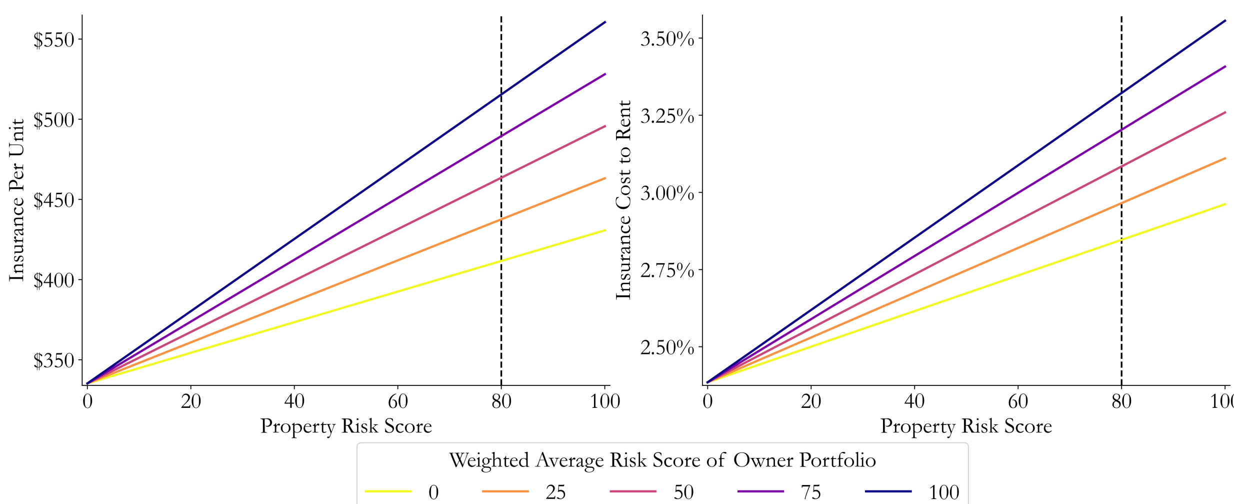
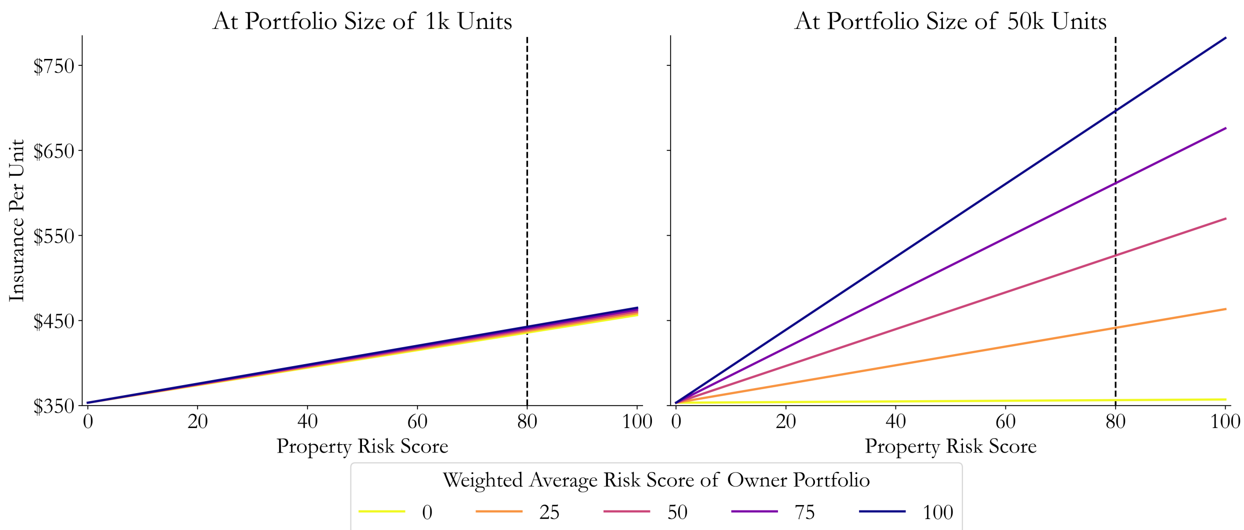


Figure 12: Role of Average Risk of Owner Portfolio Across Owner Size

This figure examines how the relationship between the effect of a property's risk score (horizontal axis) on insurance costs across different levels of average risk of its owner's portfolio (different colored lines) varies across different owner sizes. The left (right) subpanel shows the case when the property owner has 1,000 (50,000) units across the entire nation. Panel A examines effects on insurance cost per unit and Panel B on the ratio of insurance cost to rent. Owner × year fixed effects are included in the regression. Property ownership is based on transaction and holdings data from Real Capital Analytics.

Panel A: Insurance Per Unit



Panel B: Insurance to Rent

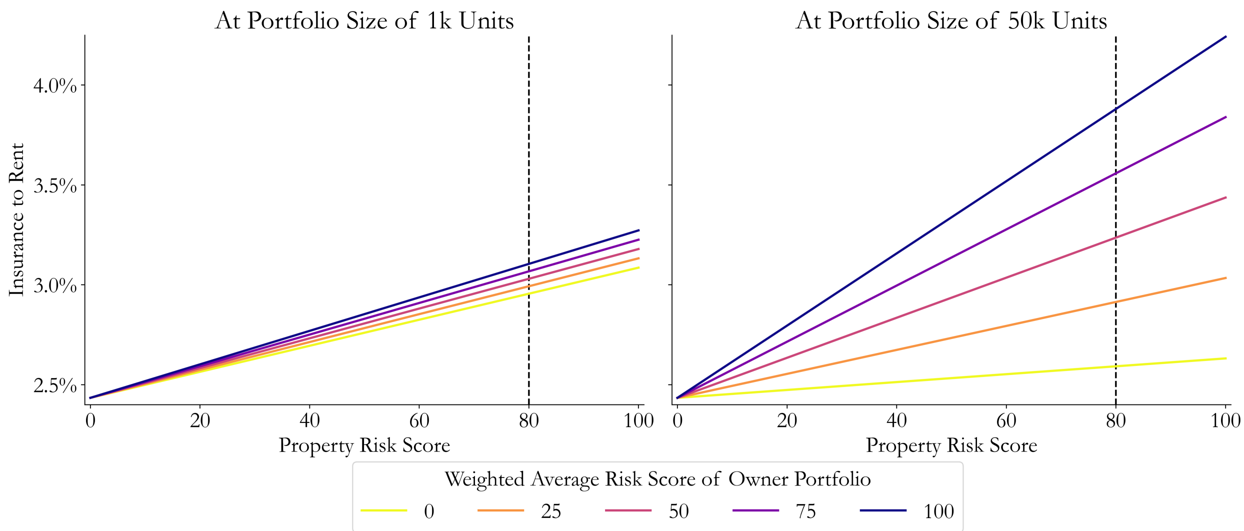
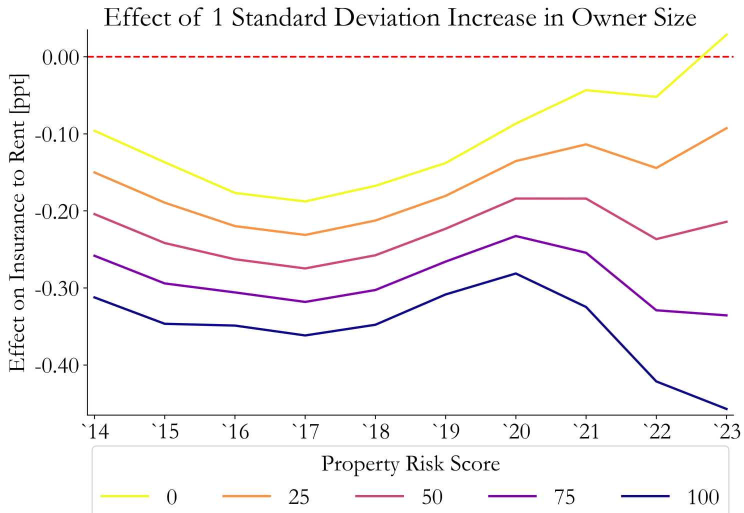


Figure 13: Role of Property Owner Size Over Time

This figure explores how the effects of property owner size and owner portfolio risk on insurance cost to rent vary over time and across different levels of property risk. Panel A shows the effect of a one-standard-deviation increase in owner size on insurance cost to rent over time for properties with different risk scores (0, 25, 50, 75, and 100). Each line represents properties at a specific risk score, plotting the yearly effect from 2014 to 2023. Panel B shows the effect of a 25-point decrease in owner portfolio risk on insurance cost to rent over time. The left subpanel displays these effects for properties with a risk score of 20, while the right subpanel shows the same effects for properties with a risk score of 80. Each line corresponds to a different owner portfolio size (1,000 units, 10,000 units, and 50,000 units), with effects plotted annually from 2014 to 2023. The risk score data are at the census tract level and are from the Federal Emergency Management Agency's National Risk Index dataset. Property ownership is based on transaction and holdings data from Real Capital Analytics.

Panel A: By Property Risk Score



Panel B: By Portfolio Risk Score

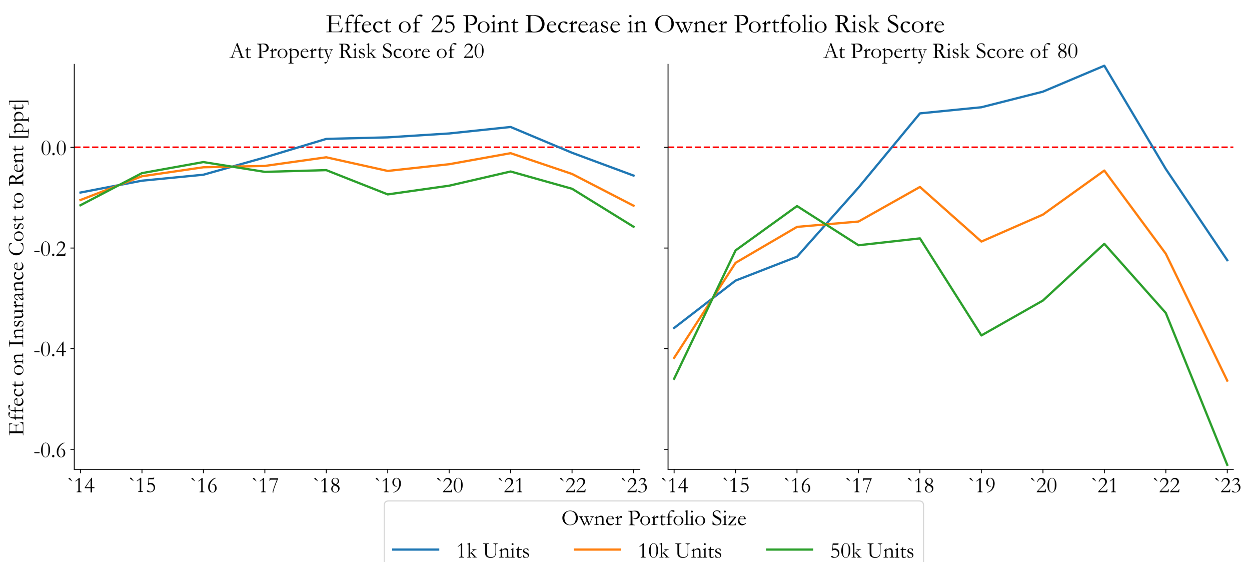


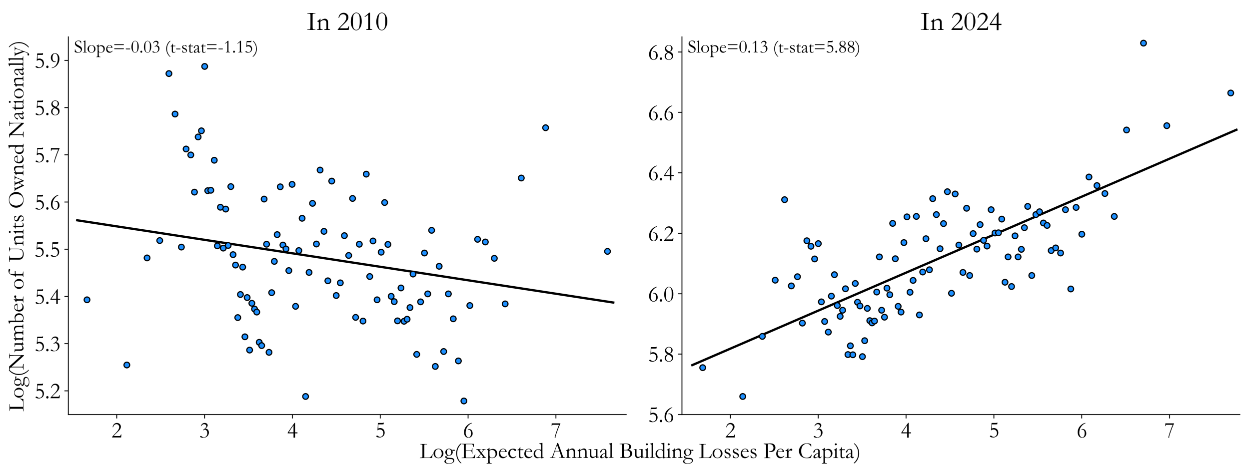
Figure 14: Effect of Property Risk on Owner Size

This figure examines the effect of property risk on owner size. Panel A shows two binscatter plots illustrating the relationship between the logarithm of expected annual building losses per capita (x-axis) and the logarithm of owner size, measured as the number of units owned nationally (y-axis), separately for the years 2010 (left subpanel) and 2024 (right subpanel). Each binscatter plot includes a fitted regression line controlling for CBSA fixed effects, with slopes and corresponding t-statistics provided. Panel B plots the yearly estimates of the effect of property risk on owner size over the period 2010 to 2024. Specifically, the following regression is estimated.

$$Log(OwnerSize)_{o,t} = \sum_{t \neq 2010} \beta_t \times \mathbb{1}(Year = t) \times RiskScore_i + PropertyFE_i + YearFE_t + \varepsilon_{i,o,t}$$

The regression coefficient (β_t) for each year is plotted, capturing the effect of a one-unit increase in log(expected annual building losses per capita) (left subpanel) and a 10-point increase in risk score (right subpanel) on log(owner size). The regression includes property and year fixed effects. The risk score and expected annual loss data are at the census tract level and are from the Federal Emergency Management Agency's National Risk Index dataset. Property ownership is based on transaction and holdings data from Real Capital Analytics.

Panel A: Binscatters



Panel B: Effect Over Time

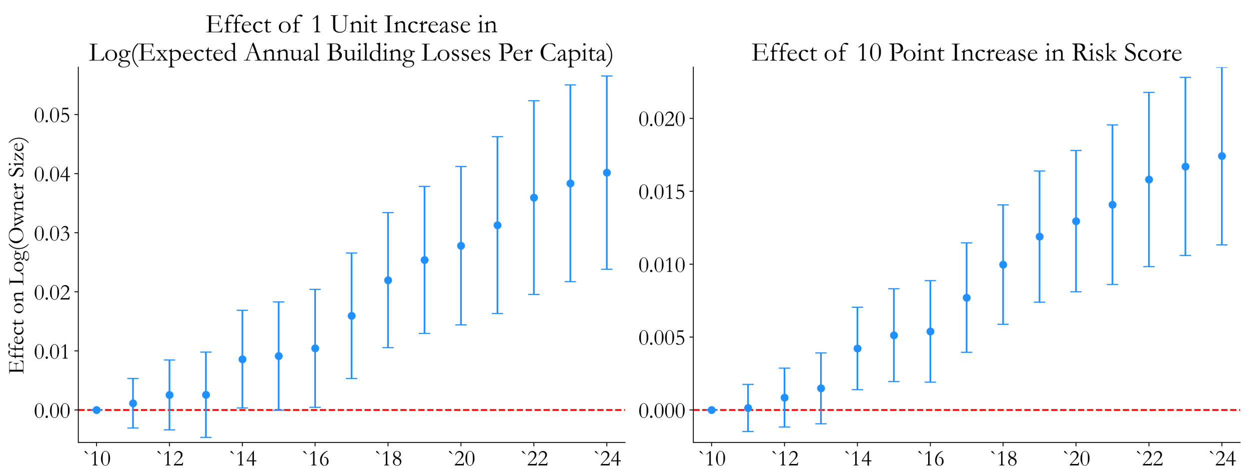


Table 1: Effects of Losses on Ratio of Commercial to Homeowners Insurance Costs

This table examines the effects of losses on the ratio of commercial to homeowners insurance costs. Zipcode-by-year-level average homeowners insurance premiums and losses ratios are from U.S. Department of the Treasury (2025). The dependent variable in all columns is the ratio of each commercial property's insurance per unit to homeowners insurance costs in the property's zipcode. $\mathbb{1}$(Low Friction) and $\mathbb{1}$(High Friction) are based on the state-level homeowners insurance market friction measures from Oh, Sen, and Tenekedjieva (2022) and are states in the bottom two terciles and top tercile, respectively. Columns (3) and (4) split the sample by the levels of friction. Fixed effects are specified at the bottom of each column. Robust standard errors are clustered at the state level.

Dep. Variable:	Commercial to Homeowner Insurance Cost			
	(1)	(2)	(3)	(4)
Lagged Loss Ratio	0.00227**			
	(2.63)			
$\mathbb{1}$(Low Friction) × Lagged Loss Ratio		0.00117		
		(0.73)		
$\mathbb{1}$(High Friction) × Lagged Loss Ratio		0.00302***		
		(4.49)		
$\mathbb{1}$(Low Risk Score) × Lagged Loss Ratio			0.00151	0.000135
			(0.68)	(0.08)
$\mathbb{1}$(High Risk Score) × Lagged Loss Ratio			0.000751	0.00504***
			(0.36)	(3.92)
States Included	All	All	Low	High
Property FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Observations	118,985	118,985	60,869	58,116
Adjusted R^2	0.850	0.850	0.881	0.816

t-statistics in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2: Effects of Out-of-State Losses on Rise in Insurance Cost

This table examines the effect of out-of-state losses on the percentage change in insurance cost. The dependent variable is the percentage change in insurance cost for property i in state s at year t. Out-of-state losses ($OOSLosses_{s,t}$) measure represents the average out-of-state losses for all insurers operating in state s in year t, weighted by each insurer's market share in that state and are calculated as: $OOSLosses_{s,t} = \frac{\sum_{i \in I} \text{DirectPremiumsWritten}_{i,s,t} \times \text{Losses}_{i,-s,t}}{\sum_{i \in I} \text{DirectPremiumsWritten}_{i,s,t}}$ where $\text{DirectPremiumsWritten}_{i,s,t}$ represents the direct premiums written by insurer i in state s at year t, and $\text{Losses}_{i,-s,t}$ denotes the losses incurred by insurer i in all states other than s. The variable $\log(OOSLosses)_{s,t}$ is the natural logarithm of out-of-state losses standardized by its standard deviation. The risk score variable is sourced from FEMA's National Risk Index and represents a tract-level measure of disaster risk, ranging from 0 to 100. Year fixed effects are included in all specifications, while the inclusion of state, county, and property fixed effects varies by column, as indicated in the table. Robust standard errors are clustered at the state level. The sample period covers the years 2010 to 2023.

Dep. Variable:	Pct. Change in Insurance Cost			
	(1)	(2)	(3)	(4)
Log(OOS Losses) Std. × Risk Score		0.0304***	0.0351***	0.0567**
		(3.17)	(2.82)	(2.21)
Log(OOS Losses) Std.	0.0620**	0.0356	0.0306	-0.0228
	(2.36)	(1.66)	(1.42)	(-1.33)
Risk Score		0.00607	0.00139	
		(1.00)	(0.17)	
Year FE	✓	✓	✓	✓
State FE	✓	✓		
County FE			✓	
Property FE				✓
Observations	264,591	264,591	264,531	251,508
Adjusted R^2	0.0692	0.0696	0.0701	0.00528

t-statistics in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: Passthrough of Insurance Cost Rise

This table examines the passthrough of the rise in insurance cost to rents [columns (1) and (2)] and to net operating income (NOI) [columns (3) and (4)]. All variables (both dependent and independent) are winsorised at the 1% tails within the year. Fixed effects are indicated at the bottom of each column. Robust standard errors clustered by CBSA.

Dep. Variable:	Log(Rent Per Unit)		Log(NOI Per Unit)	
	(1)	(2)	(3)	(4)
Log(Insurance Cost Per Unit)	0.0275***	0.0209***	-0.0292***	-0.0354***
	(9.48)	(8.68)	(-6.88)	(-8.83)
Property FE	✓	✓	✓	✓
Year FE	✓		✓	
CBSA × Year FE		✓		✓
Observations	351,174	351,174	351,174	351,174
Adjusted R^2	0.974	0.978	0.922	0.928

t statistics in parentheses.

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

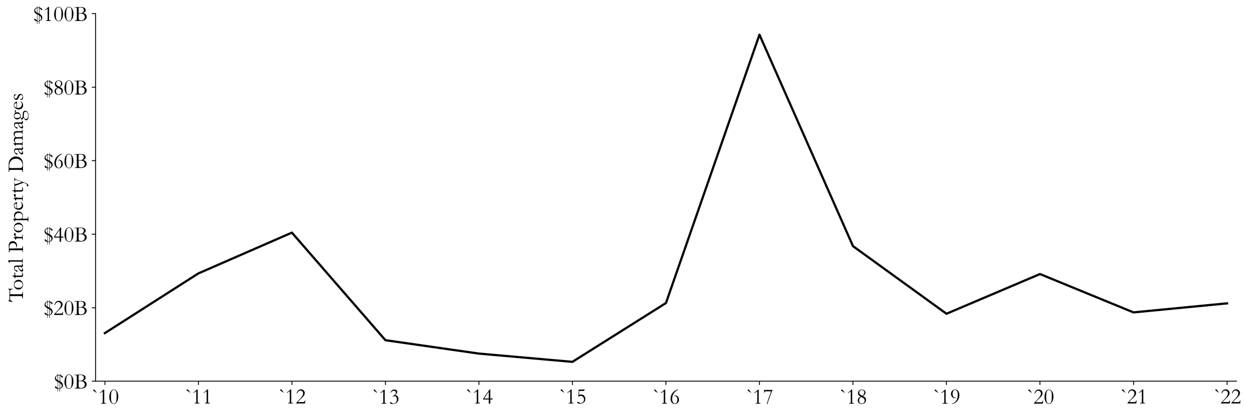
For Online Publication

Internet Appendix for:
“The Rise in Insurance Costs for Commercial Properties: Causes, Effects on Rents, and the Role of Owners”

Figure IA.1: Property Damages Between 2010-22

This figure shows the time-series of national-level total property damages in each year (Panel A) and the average annual propery damages per capita in each county (Panel B).

Panel A: Total Property Damages in Each Year



Panel B: Average Annual Property Damages Per Capita, County-level Map

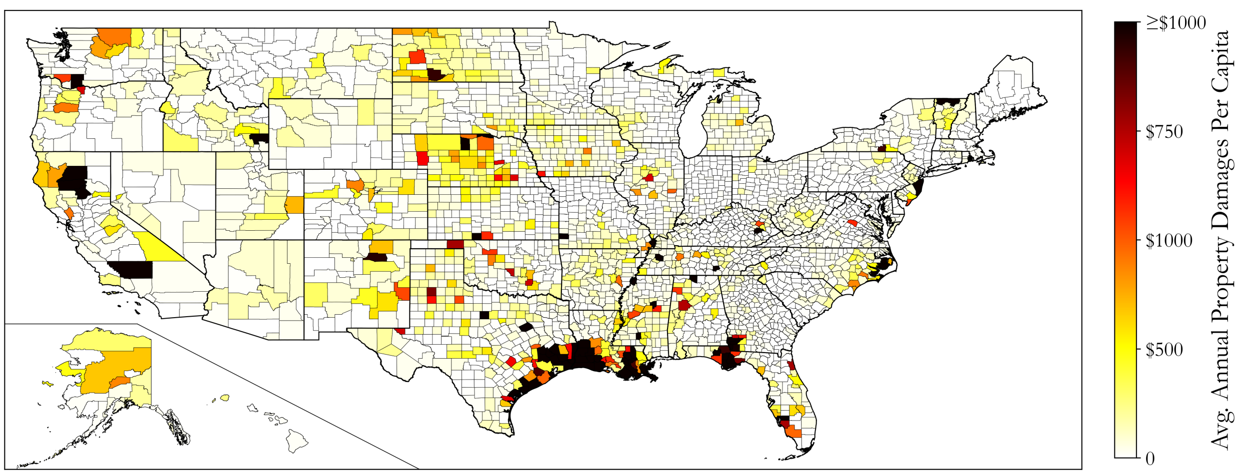


Figure IA.2: Risk Score, County-level Maps

This figure shows county-level heatmaps of the risk scores. Please note that the risk scores we use in the paper are on the tract-level from the National Risk Index by FEMA. For illustration purposes, we aggregate it to the county-level.

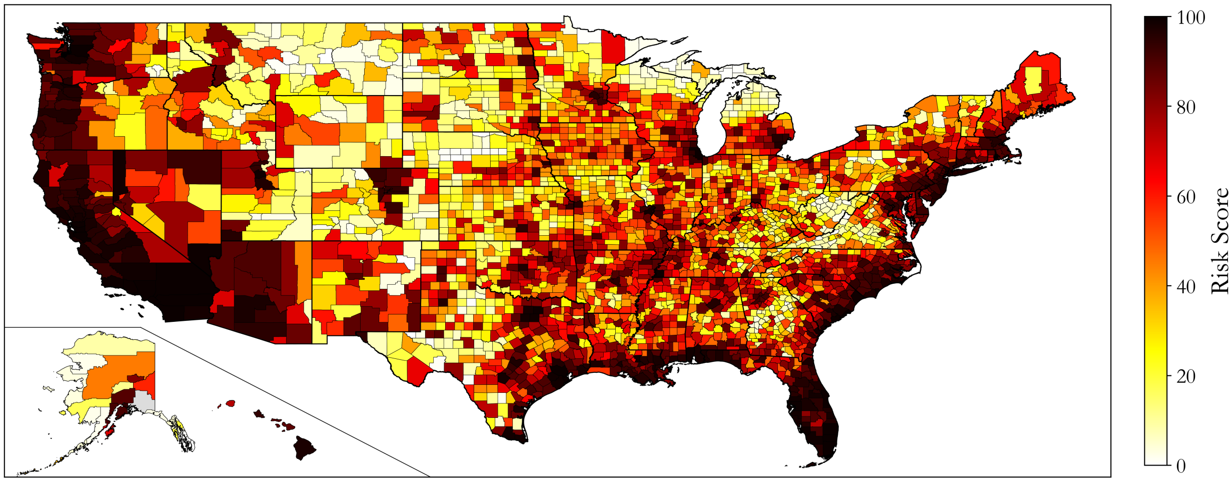
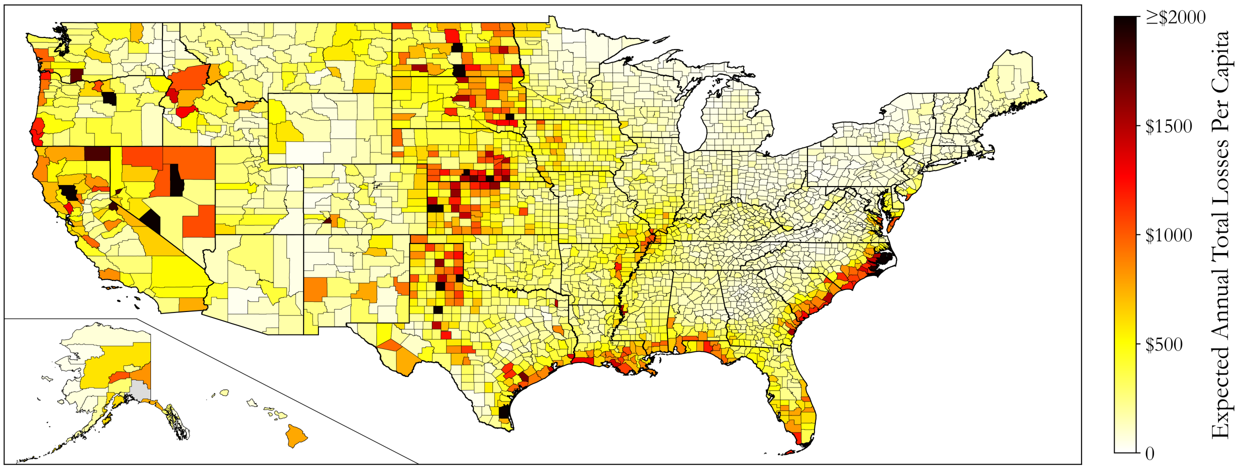


Figure IA.3: Expected Annual Losses, County-level Maps

This figure shows county-level heatmaps of expected annual total losses per capita (Panel A) and the ratio of expected annual property losses to building value (Panel B).

Panel A: Expected Annual Total Losses Per Capita



Panel B: Expected Annual Building Losses / Building Value

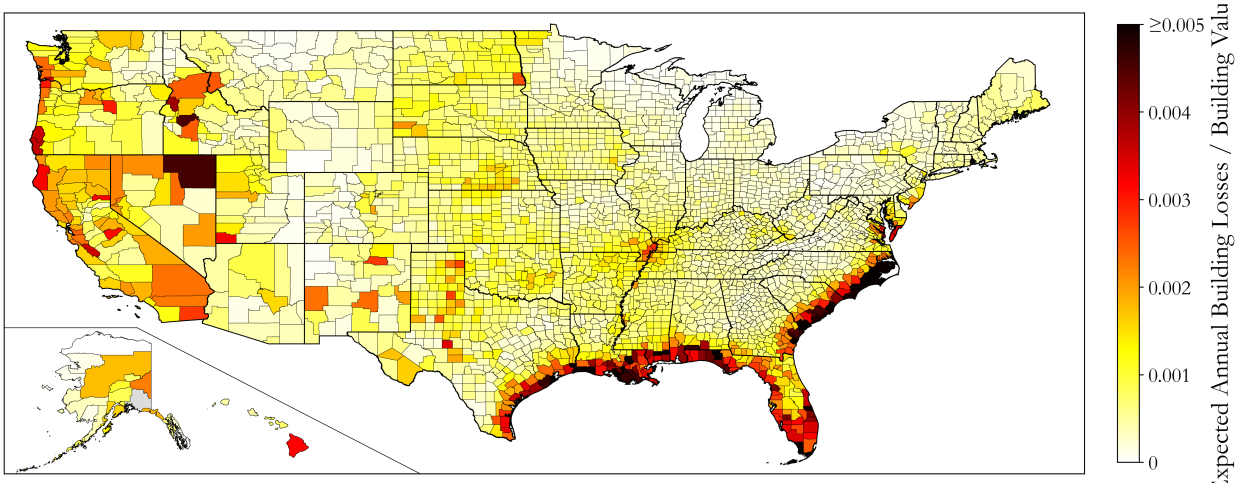


Figure IA.4: Risk Scores and Expected Annual Losses and the Rise in Insurance Costs, Additional Measures

This figure shows the effects of additional measures of risk scores and expected annual losses on the rise in insurance cost.

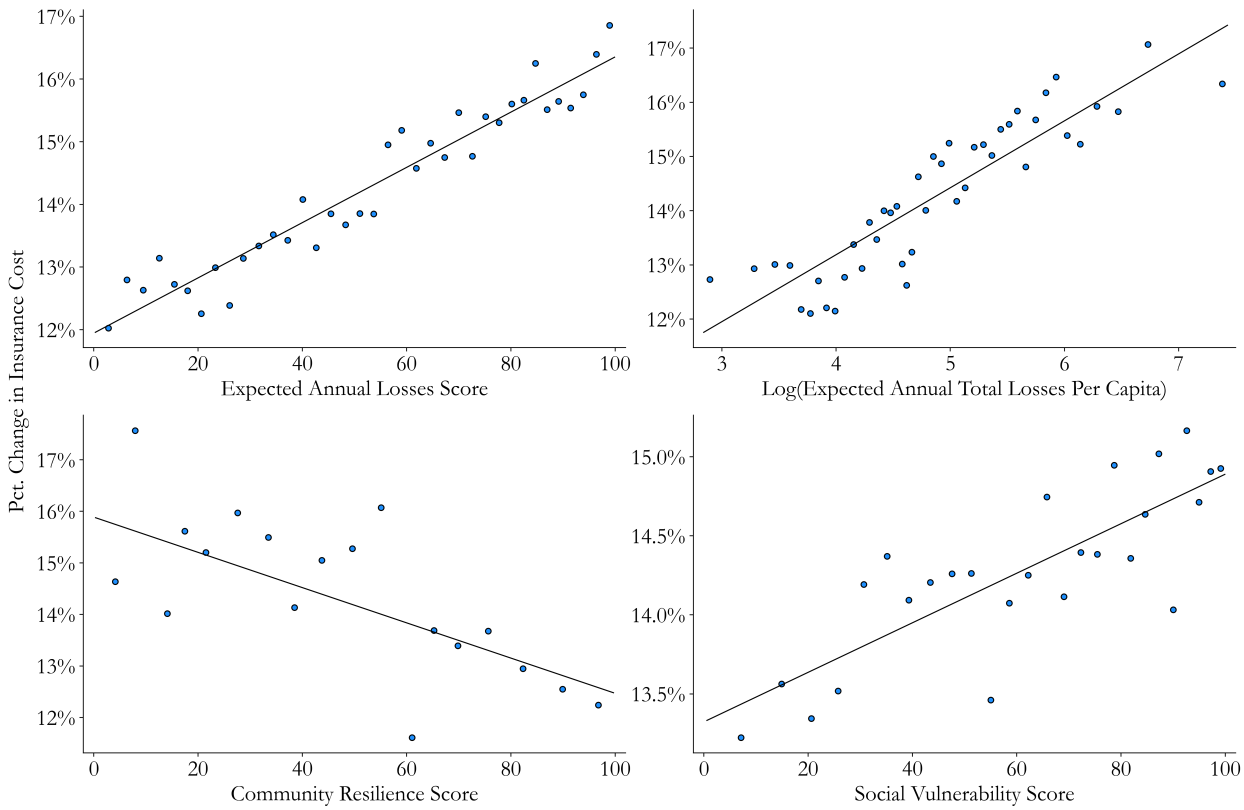
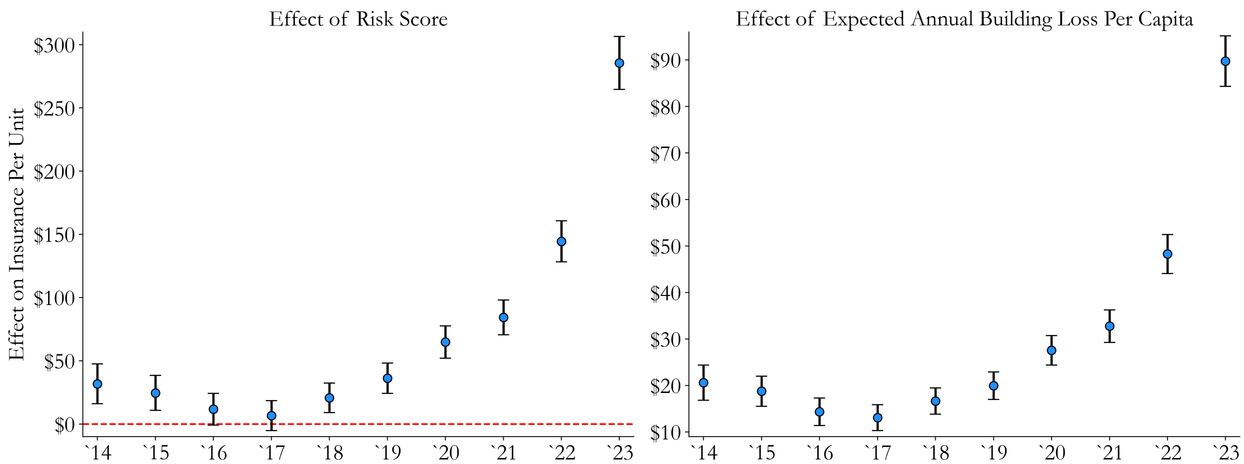


Figure IA.5: Risk Scores and Expected Annual Losses and the Rise in Insurance Costs, Over Time

This figure shows how the relationship between insurance costs and risk score/expected annual losses has changed over time. Panel A presents the effect on insurance cost per unit. The left subpanel shows the effect of the risk score, while the right subpanel shows the effect of expected annual building loss per capita. Panel B presents the effect on the percentage change in insurance cost. The left subpanel show the effect of the risk score, while the right subpanel shows the effect of expected annual building loss per capita.

Panel A: Effect on Insurance Cost Per Unit



Panel B: Effect on Percentage Change in Insurance Cost

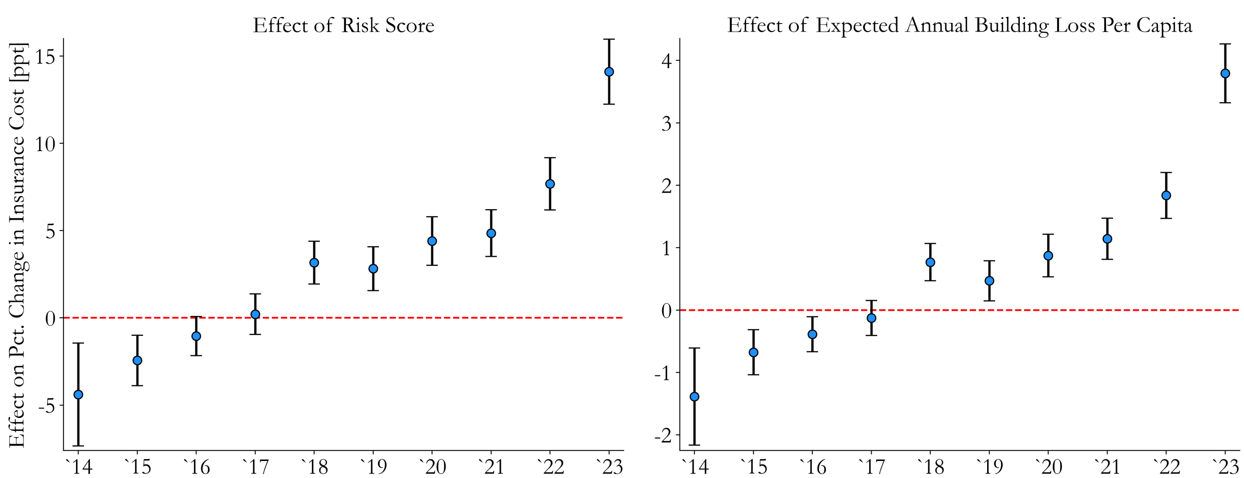


Figure IA.6: Stability of Reinsurance Exposure

This figure examines the stability of the percentage of risk ceded to unaffiliated reinsures at the company level and reinsurance exposure at the state level over time.

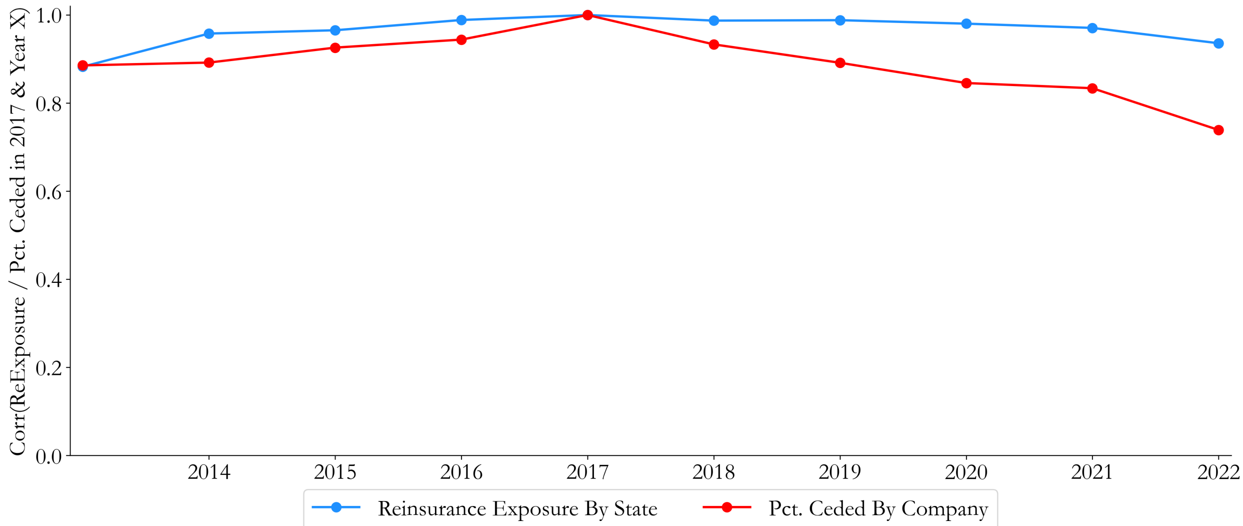
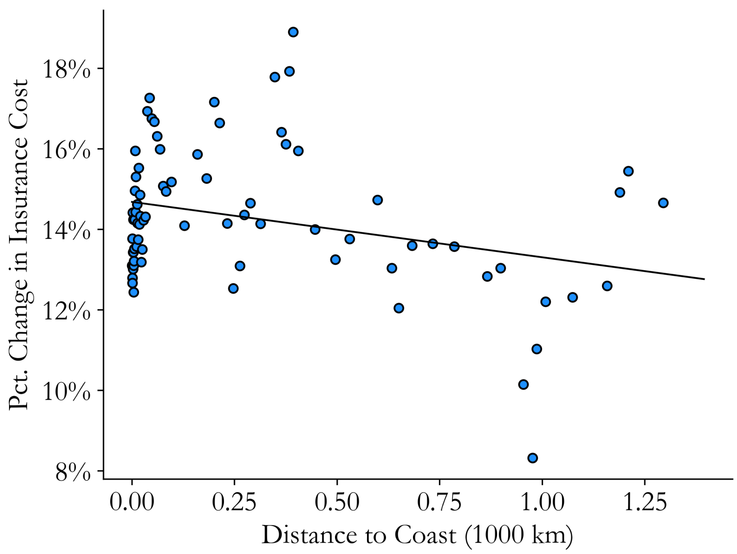


Figure IA.7: Location and the Rise in Insurance Costs

This figure explores the relationship between geographic location characteristics and changes in insurance costs. Panel A plots the percentage change in insurance costs against the distance to the nearest coast (measured in 1,000 km). Panel B plots the percentage change in insurance costs against elevation (measured in kilometers). Both panels include a year fixed effect and the lines shown are lines of best fit based on the underlying data. Both distance to coast and elevation are determined based on the property's latitude and longitude (based on geocoding addresses using the US Census Geocoder) and topographic maps (from Natural Earth for coastline and National Elevation Dataset for elevation).

Panel A: Distance to Coast



Panel B: Elevation

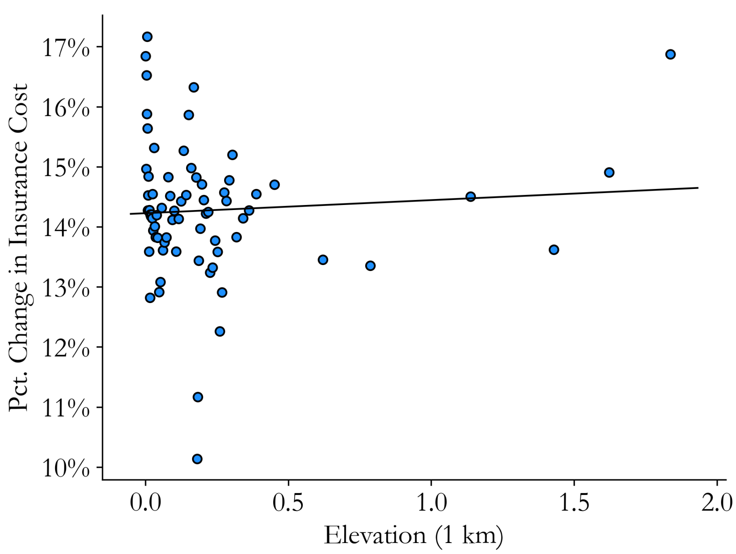
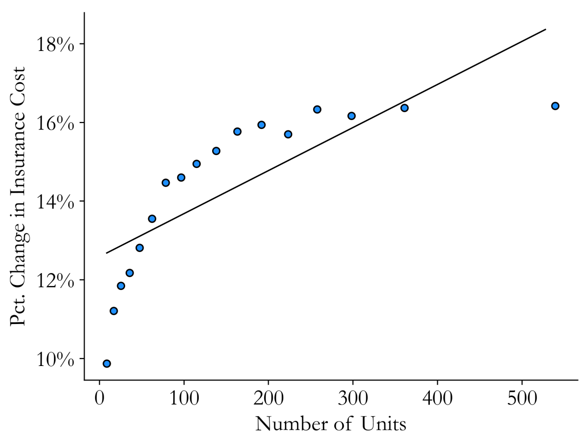


Figure IA.8: Property Features and the Rise in Insurance Costs

This figure explores how property-specific characteristics relate to changes in insurance costs. Panel A plots the percentage change in insurance costs against the number of units in a property. Panel B examines the relationship between property age and insurance cost changes, with the left subpanel showing results for actual age and the right subpanel focusing on effective age. Effective age is the number of years since the last renovation; if no renovation has occurred, it is the same as the building's age. Renovation data is only available for properties in the Freddie dataset. Both panels include a year fixed effect and the lines shown are lines of best fit based on the underlying data.

Panel A: Units



Panel B: Age

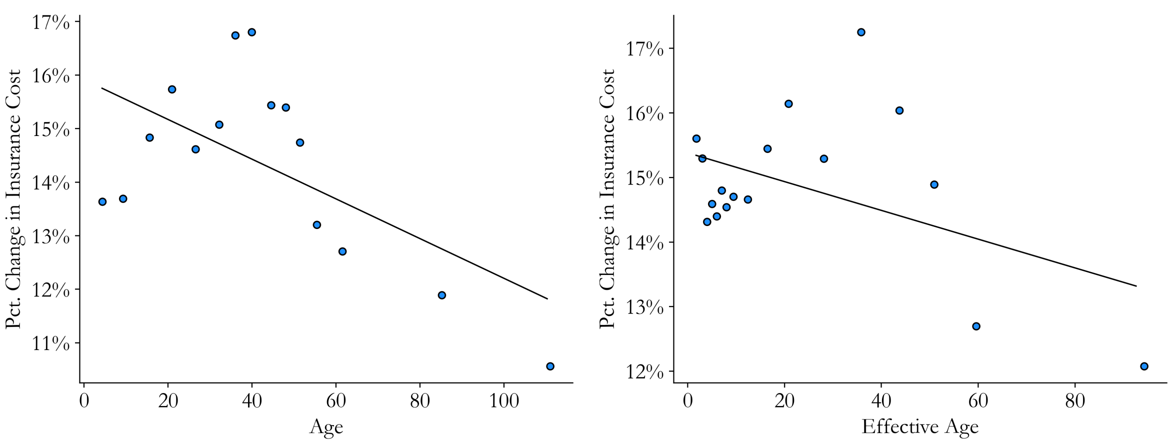
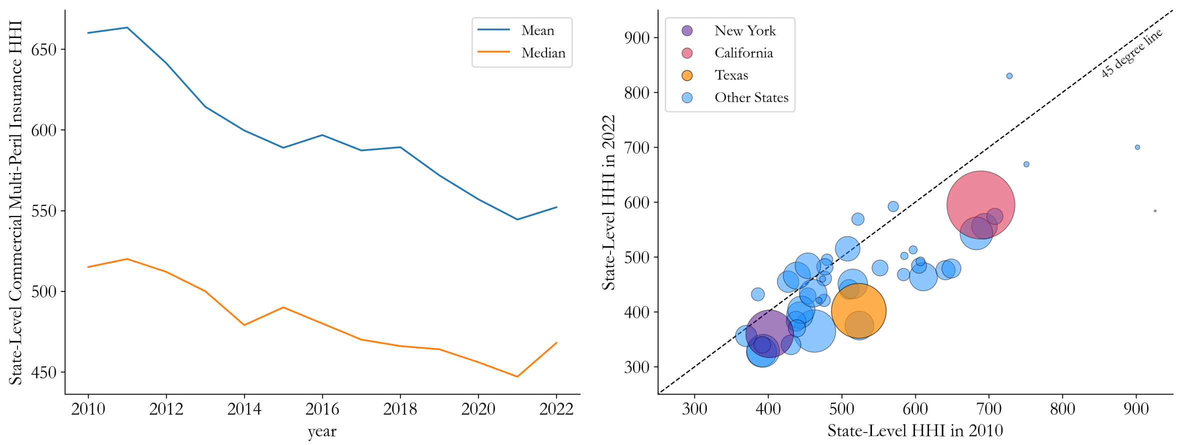


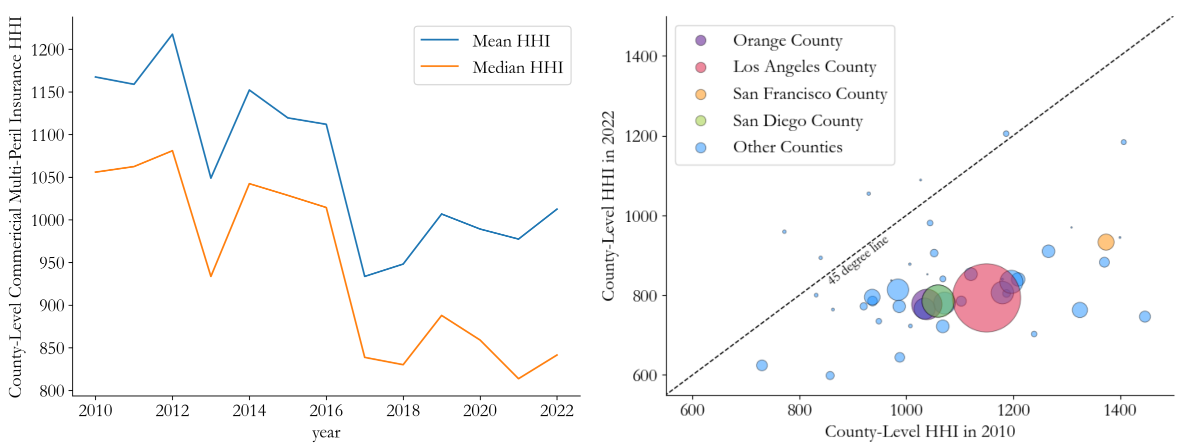
Figure IA.9: Insurance Market Concentration and the Rise in Insurance Costs

This figure explores the role of insurance market concentration, measured by the Herfindahl-Hirschman Index (HHI), in explaining changes in insurance costs. Panel A and the left subpanel of Panel C focus on state-level HHI, and Panel B and the right subpanel of Panel C focus on county-level HHI for only California. The left subpanel of Panel A (B) shows the average and median state-level (county-level) commercial multi-peril insurance HHI during each year from 2010 to 2022, while the right subpanel of Panel A (B) compares state-level (county-level) HHI in 2010 to HHI in 2022, with circle sizes scaled by the number of properties in each state (county) in 2022 and several large states (counties) highlighted. The left (right) subpanel of Panel C explores the relationship between lagged state-level (county-level) HHI and changes in insurance costs. Both subpanels include a year fixed effect and the lines shown are lines of best fit based on the underlying data. State-level HHIs are from the National Association of Insurance Commissioners' annual Competition Database Report and county-level HHIs for California are from the California Department of Insurance's Community Service Statement data.

Panel A: State-Level HHI



Panel B: County-Level HHI for California



Panel C: Effect of HHI on Insurance Cost

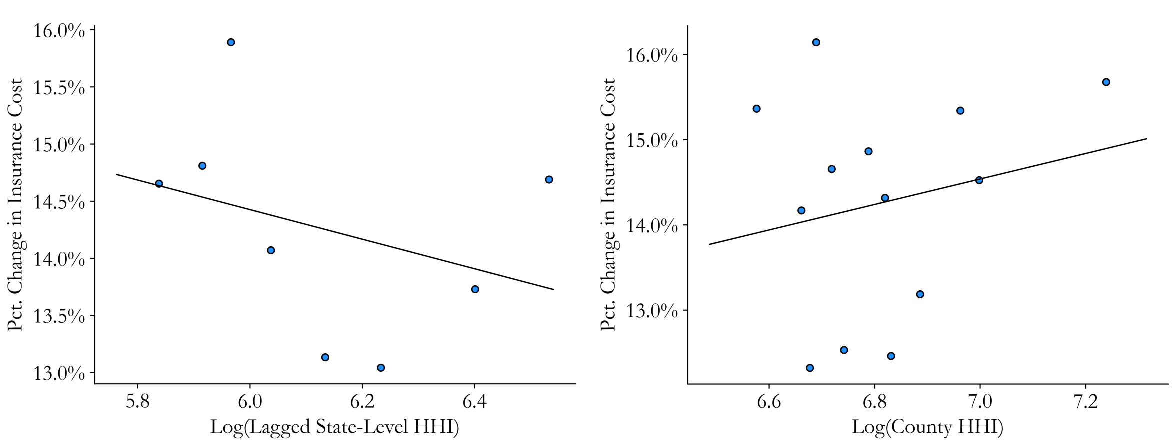


Figure IA.10: Heterogeneity in Effect of Insurance Cost Increase on Rents and Profits

This figure shows cross-sectional heterogeneity in the passthrough of insurance cost increases to rents and NOI. Panel A examines heterogeneity by supply elasticity (based on tract-level data from Baum-Snow and Han (2024)), Panel B by lagged rent (based on splits within CBSA × year), and Panel C by building age (based on splits within CBSA × year).

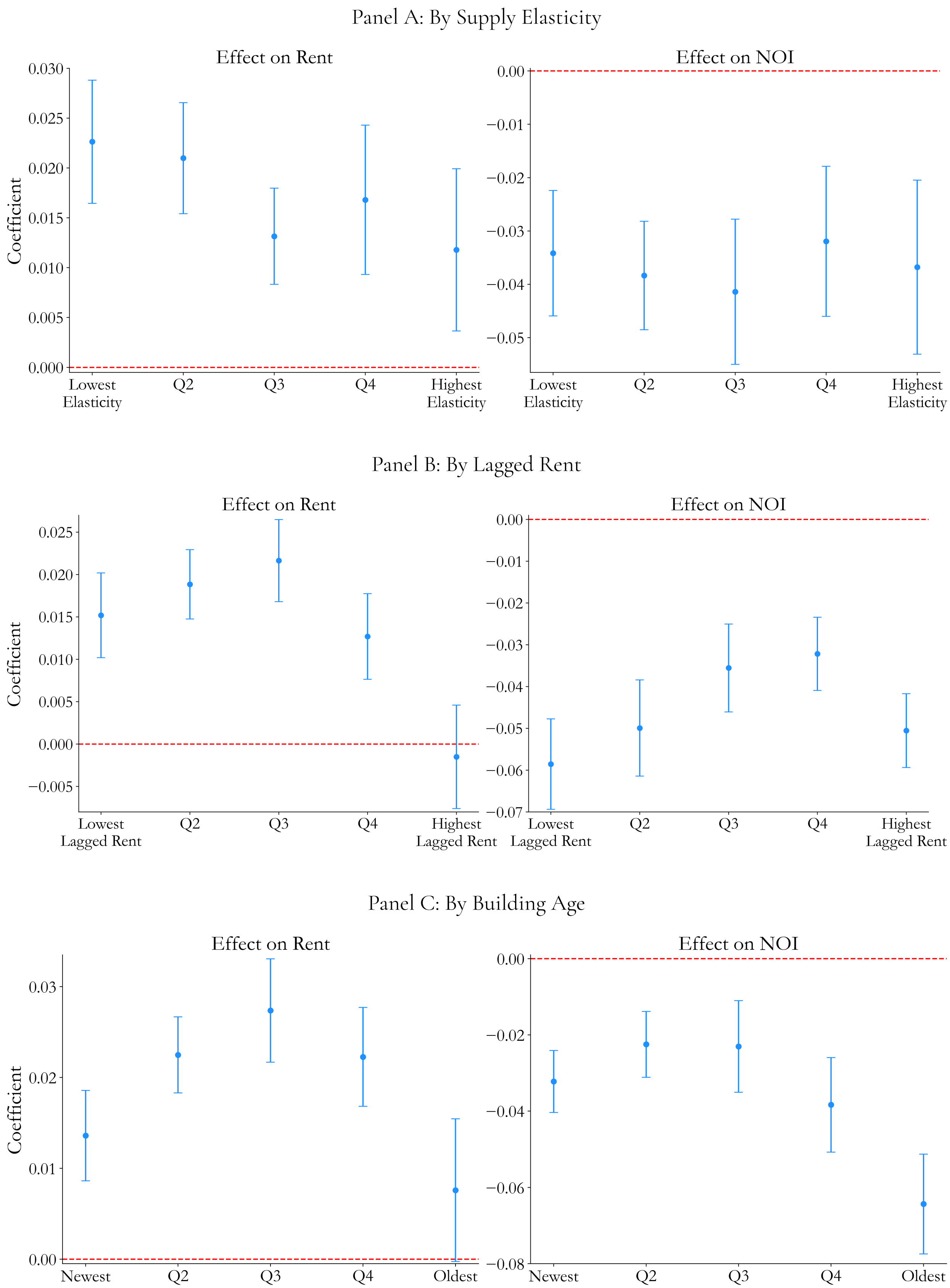


Table IA.I: Summary Statistics

This table provides summary statistics for the main variables used throughout the paper.

					Quartiles			
	Observations	Mean	Std	Min	1st	2nd	3rd	Max
Pct. Change in Insurance Cost	285,963	0.1415	0.3451	-0.7984	-0.0012	0.0677	0.2166	2.6642
Log(Insurance Cost Per Unit)	282,400	5.8880	0.6868	3.2209	5.4653	5.8874	6.3367	7.9046
Log(Insurance to Operating Expense)	286,089	-2.8575	0.6035	-5.4747	-3.2420	-2.8532	-2.4564	-1.2007
Log(Rent Per Unit)	282,567	9.5532	0.4743	8.4396	9.2275	9.5303	9.8420	10.9848
Log(NOI Per Unit)	281,584	8.8923	0.6071	6.7883	8.4915	8.9048	9.3074	10.4077
Number of Units	282,574	159.452	181.2651	2	44	116	230	11,244
Property Age	279,439	42.2365	28.1258	1	21	39	53	231
Effective Age	124,890	23.3453	25.2343	-3	5	12	37	190
Min Distance to Coast (1000km)	267,608	0.0003	0.0004	0.0000	0.0000	0.0001	0.0004	0.0015
Elevation	267,429	0.2234	0.3519	-0.0545	0.0275	0.1246	0.2497	3.0939
Log(Damage Per Capita)	220,945	-0.6652	3.2011	-11.5129	-2.3888	-0.8328	1.1490	11.6379
Log(Expected Loss Per Capita)	267,599	4.8805	0.9789	2.0438	4.1705	4.7821	5.5702	12.2040
Risk Score	267,599	55.9163	28.1882	0.2664	32.3229	57.7641	81.1599	99.9988
State-level HHI	283,080	478.3773	202.5496	316	376	441	551	4,585
County-level HHI	48,528	920.2684	189.5710	585.1318	794.6330	893.2257	986.1418	3,283.958
Owner Size (Units)	152,848	3,303.165	6,689.341	5	100	636.5	3,214	86,266

Table IA.II: Effects of Claims on Ratio of Commercial to Homeowners Insurance Costs

This table replicates Table 1 using the percentage of homeowner policies with claims instead of loss ratios. Fixed effects are specified at the bottom of each column. Robust standard errors are clustered at the state level.

Dep. Variable:	Commercial to Homeowner Insurance Cost			
	(1)	(2)	(3)	(4)
Lagged Pct. Claims	0.0167			
	(0.94)			
$\mathbb{1}$(Low Friction) × Lagged Pct. Claims		-0.0244		
		(-0.81)		
$\mathbb{1}$(High Friction) × Lagged Pct. Claims		0.0435***		
		(6.30)		
$\mathbb{1}$(Low Risk Score) × Lagged Pct. Claims			-0.0235	0.0258
			(-0.46)	(1.73)
$\mathbb{1}$(High Risk Score) × Lagged Pct. Claims			-0.0250	0.0616***
			(-0.93)	(5.00)
States Included	All	All	Low	High
Property FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Observations	118,985	118,985	60,869	58,116
Adjusted R^2	0.850	0.850	0.881	0.816

t-statistics in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table IA.III: Horse Race of Explanations for Insurance Cost Rise

This table examines the various explanations for the rise in insurance cost both separately (columns (1) to (8)) and together (column (9)). Historic property damage data is at the county level and is from Arizona State University's Spatial Hazard Events and Losses Database. Risk score and expected annual loss data are at the census tract level and are from the Federal Emergency Management Agency's National Risk Index dataset. Distance to coast and elevation are determined based on the property's latitude and longitude (based on geocoding addresses using the US Census Geocoder) and topographic maps (from Natural Earth for coastline and National Elevation Dataset for elevation). State-level HHIs are from the National Association of Insurance Commissioners' annual Competition Database Report. The percentage change in insurance cost is winterized at the 1% tails within each year. Fixed effects are as indicated at the bottom of each column. Robust standard errors clustered by state.

Dep. Variable:	Pct. Change in Insurance Cost								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(Property Damage$_{t-1}$)	0.00227*								0.00183*
	(1.90)								(1.86)
Risk Score		0.000554***							0.000166
		(4.36)							(1.34)
log(Expected Loss)			0.0161***						0.0117***
			(4.77)						(3.58)
Distance to Coast				-0.0196					-0.0153*
				(-1.38)					(-1.72)
Elevation					-0.00276				0.0109
					(-0.23)				(1.22)
Number of Units						0.0000604***			0.0000522***
						(3.79)			(3.48)
Property Age							-0.000371***		-0.000185***
							(-4.22)		(-2.88)
State-level HHI								-0.00171	-0.00631
								(-0.36)	(-1.30)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	215,605	215,605	215,605	215,605	215,605	215,605	215,605	215,605	215,605
Adjusted R^2	0.0555	0.0569	0.0572	0.0555	0.0551	0.0560	0.0559	0.0552	0.0589
Within-Year R^2	0.000383	0.00186	0.00223	0.000351	0.00000571	0.000960	0.000809	0.0000134	0.00401
Dep. Var. Mean	0.145	0.145	0.145	0.145	0.145	0.145	0.145	0.145	0.145
Dep. Var. Std	0.377	0.377	0.377	0.377	0.377	0.377	0.377	0.377	0.377

t statistics in parentheses.

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