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

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

March 25, 2026
First Version: November 19, 2024

Abstract

Leveraging a large, novel set of property-level operating statements, we analyze the drivers and consequences of rising commercial property insurance costs. We document a significant, persistent increase in insurance costs across the U.S. over the last decade. The increased pricing of local risk tracks the rising cost of reinsurance coverage; states with higher ex-ante exposure to reinsurance markets face steeper increases, even holding local risk fixed. Commercial insurance cost growth is more than double that of homeowners insurance in 95% of counties. Using a border county-pair difference-in-differences design, we show that this divergence arises from homeowner-market regulatory frictions spilling over into commercial pricing through cross-product subsidization. On average, 49% of the rise in insurance costs is passed through to rents, though this pass-through rate is declining over time. While the average impact on rents and profitability has been relatively small, the effect in high-risk areas is substantial. Finally, we show that larger owners and those with lower-risk portfolios secure lower insurance costs, particularly in high-risk areas. Consequently, property ownership in high-risk regions is increasingly being consolidated among larger entities. Our findings suggest that commercial insurance pricing reflects both localized and systematic risk exposure and is significantly influenced by owner portfolios.

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

[*]We thank Aydoğan Alti, William Fuchs, John M. Griffin, Shan Ge, Caitlin Gorback, Sam Kruger, Yifei Li (discussant), Kevin Mei, Philip Mulder, Xiang Li (discussant), Simon Oh, Yang Shi (discussant), Clemens Sialm, Laura Starks, Lin Tang (discussant), Sheridan Titman, Alex Van De Minne (discussant), Charles Yang (discussant), Yiyuan Zhang (discussant), and conference and seminar participants at the American Finance Association (AFA) Annual Meeting (PhD Poster Session), American Real Estate and Urban Economics Association (AREUEA) Conference, Baruch-JFQA Climate Finance and Sustainability Conference, Boca Finance and Real Estate Conference, Conference on Sustainable Finance at Deakin University, Financial Management Association (FMA) Annual Meeting, MRS International Risk Conference, Southern Finance Association Annual Meeting, the UT Dallas Fall Finance Conference, the University of Texas at Austin, and the University of Texas at San Antonio for their helpful comments. We gratefully acknowledge financial support from the Brookings Institution as part of the Hutchins Center on Fiscal & Monetary Policy's project on the "Challenges Climate Change Poses to U.S. Property-Casualty Insurance and Housing Markets."

[†]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

Property insurance is a cornerstone of the residential and commercial real estate markets. By transferring risk away from property owners and lenders, it stabilizes cash flows and sustains credit provision in the face of rare but costly disasters (Sastry and Sen, Forthcoming). However, this stability is under threat. As the frequency of billion-dollar disasters in the United States has surged—rising from roughly 3 per year in the 1980s to 23 per year over the previous five years—insurance markets have responded with aggressive repricing. While the inflation of homeowners premiums is well-documented (e.g., Keys and Mulder, 2025), the commercial real estate (CRE) sector has received little attention, despite its scale and economic importance, due to a scarcity of granular data.[1]

In this paper, we leverage a novel set of property-level operating statements from Agency Commercial Mortgage-Backed Securities (CMBS) to provide the first comprehensive analysis of insurance cost dynamics in the multifamily market over time and across geographies. Supplementing this data with a series of additional datasets, we examine the drivers of rising insurance costs, their pass-through effects on rental prices and profitability, and the role property owners play in mitigating these increases. Unlike the residential market, which is often distorted by state-level rate caps and political pressure, the commercial market is largely unregulated (Born and Klimaszewski-Blettner, 2013). This setting offers a unique advantage: it allows us to observe the "true" market pricing of climate risk, unencumbered by the regulatory frictions that dampen price signals in the homeowners insurance market.

We begin by documenting a regime shift in insurance costs across nearly all regions of the United States. Since 2019, properties have faced average annual cost increases exceeding 15%, peaking at nearly 30% in 2023. While these hikes are most acute in coastal states like Florida, Texas, Louisiana, and California, we document substantial increases across the U.S. interior as well, including Oklahoma, Colorado, Tennessee, and Indiana.

We identify three distinct mechanisms driving this surge: local risk, reinsurance exposure, and regulatory frictions in the homeowners insurance market. First, insurance pricing increasingly reflects

[1] Sastry and Sen (Forthcoming) highlights that "understanding the exposures of [commercial real estate] firms and the extent to which commercial insurance markets help mitigate exposures is largely unexplored." The U.S. CRE market is valued at $20.5 trillion as of 2025.

the underlying risk of a property's location, particularly its exposure to natural disasters. As climate risks intensify, insurers are placing greater weight on regional risk measures when setting premiums. 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. However, after 2018, insurers appear to have recalibrated their pricing models to incorporate risk exposure more directly.[2] Our empirical design includes property fixed effects to account for time-invariant characteristics and year fixed effects to control for aggregate time shocks. The results show that, controlling for property-specific features, location in a high-risk tract is associated with significantly steeper insurance cost curves, highlighting the growing role of local risk in driving premium adjustments. Similarly, we find that before 2018, realized climate risk due to natural disasters largely did not affect insurance prices; however, after 2018, realized climate risk leads to higher insurance costs.

Second, primary insurers often transfer a portion of their risk to global reinsurers, and rising reinsurance costs can be passed through to policyholders. We begin by showing that the increased pricing of local risk closely tracks the rising price of reinsurance. The extent to which rising reinsurance prices affect local insurance costs depends on insurer reliance on reinsurance markets. To quantify this, we follow Keys and Mulder (2025) and construct a state-level measure of ex-ante exposure to reinsurance markets, 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 cost increases when reinsurance prices rise. Our identification strategy leverages sharp discontinuities in reinsurance exposure across state borders, comparing neighboring areas with similar underlying physical risk but different insurer regulatory exposure. Using a triple-interaction regression design with property fixed effects, we show that when national reinsurance costs rise by 10 index points, the effect on insurance cost per unit is 250% as large in states with high exposure to reinsurance markets.

[2] As shown in Figure IA.5, property damages rise sharply around 2018, indicating a discrete increase in realized exposure. We interpret the post-2018 shift in pricing behavior as consistent with insurers updating their rating models in response to this change.

Third, comparing commercial property insurance to homeowners insurance—the primary focus of the existing literature—we find that commercial premiums have risen at a substantially faster pace in nearly every county. Specifically, 95% of the population resides in counties where the increase in commercial insurance costs is at least double that of homeowners insurance. This widening gap is driven largely by state-level regulations in the homeowners market that constrain risk-based pricing, preventing insurers from fully adjusting rates in response to local risk (Oh, Sen, and Tenekedjieva, Forthcoming). In contrast, commercial insurance pricing remains much more flexible. We show that the wedge between commercial and homeowners insurance prices widens with local risk in states with high regulatory frictions in the homeowners market; we find no such effect in low-friction states. Similarly, following a local disaster, the price wedge expands significantly more in high-friction states, particularly in the high-risk portions of those states.

In addition to commercial insurance pricing being more responsive to local risk, regulatory frictions in the homeowners market may spill over into commercial pricing through cross-product subsidization. We hypothesize that insurers, constrained by state regulations that limit homeowners premium adjustments after substantial losses, compensate by raising commercial rates.[3] To test this, we employ a border county-pair difference-in-differences design. We find that counties in states with strict homeowners insurance regulations experience significantly larger commercial premium increases following major disasters compared to neighboring counties across state borders. We estimate that commercial premium growth is roughly 19–22 percentage points larger on the high-friction side of the border in the post-disaster period. This suggests insurers actively engage in cross-product subsidization: when homeowners premium adjustments are constrained, multi-line insurers respond to major losses by shifting a larger share of post-disaster repricing toward commercial lines.

These rising costs have profound implications for the incidence of climate risk. We analyze whether higher premiums are passed through to tenants (via rents) or absorbed by owners (via reduced net operating income (NOI)). While higher insurance expenses typically incentivize rent increases, we find that owners face increasing constraints in doing so. We estimate that, on average, 49% of the

[3] As of 2017, conditional on an insurer offering commercial insurance in a given state, 44% (on a premium-weighted basis) also offer homeowners insurance in that state.

increase in insurance costs is passed through to rents. However, this pass-through rate is highly non-linear and has declined over the last decade. While landlords initially could pass on most of the cost increase to rents, their ability to do so has diminished, particularly since 2019. By 2024, the marginal pass-through to rents was near zero. For example, a 10% increase in insurance costs, which led to a 0.35% increase in rents in 2014, resulted in only a 0.02% increase by 2024. Conversely, the associated decline in NOI for a 10% increase in insurance costs grew to over 0.85% by 2024. Consequently, the economic incidence of climate risk is shifting from tenants to property owners, leading to a growing erosion of profitability in high-risk markets.

To quantify the cumulative effect of these rising costs on rents and profitability, we conduct a back-of-the-envelope calculation using our time-varying pass-through estimates and the distribution of insurance cost growth during each year. We find that the average impact on rents and profitability has been relatively modest over the 2014–2024 period, amounting to a 0.9% increase in rents and a 5.1% decrease in NOI. However, in areas most affected by rising costs, the effects are substantial. For example, at the 95th percentile of the insurance cost increase distribution, we estimate an 11% increase in rents and a 26% decrease in NOI over this decade-long period.

Given the substantial effects on profitability, we next examine how insurance costs vary by property owner characteristics. We find that the burden of insurance pricing is highly heterogeneous, with ownership size and portfolio risk playing critical roles. 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 profile of the owner's entire portfolio. We find that owners with lower aggregate risk scores receive lower premiums, even after controlling for the risk of the focal property. This suggests that insurers price risk at a broader level, incorporating the overall composition of an owner's holdings. Crucially, this relation-

ship 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 secure significantly lower insurance costs. These findings indicate that insurers reward lower portfolio risk, but primarily when coupled with the bargaining power of a large size.

Finally, we find that rising insurance costs have contributed to a consolidation of property ownership, shifting high-risk assets toward larger owners with the scale and diversification to manage mounting expenses. Before 2020, the cost advantage enjoyed by large owners was relatively uniform across risk categories. However, after 2020, this advantage narrowed for low-risk properties while expanding significantly for high-risk locations. Consequently, ownership of high-risk properties has increasingly shifted toward larger entities capable of negotiating better terms and absorbing higher costs. These patterns illustrate how bargaining power and portfolio composition interact to shape insurance outcomes, reinforcing the growing dominance of large owners in high-risk markets.

Our findings contribute to the growing literature on climate finance and insurance. While recent work has focused on the residential sector (e.g., Oh, Sen, and Tenekedjieva (Forthcoming); Keys and Mulder (2025); Sastry, Scharlemann, Sen, and Tenekedjieva (2025)), we demonstrate that the commercial sector faces distinct and more severe pricing pressures due to the lack of regulatory shielding. Further, our findings reveal that commercial insurance pricing is determined by a complex interplay of local physical risk and broader systemic exposures held by both insurers and property owners. Importantly, our results highlight the need to understand how these pricing dynamics translate into higher housing costs for tenants and lower profitability for owners, especially as climate risks continue to grow.

Related Literature. Our paper contributes to four main strands of literature. First, we add to the literature on insurance market pricing, which has predominantly focused on homeowners and climate risk insurance. Recent studies have provided valuable insights into the regulatory and informational factors shaping premiums. For instance, Oh, Sen, and Tenekedjieva (Forthcoming) emphasize the role of regulation and cross-subsidies in climate risk insurance, while Boomhower, Fowlie, and Plantinga (2023) highlight how information asymmetry complicates the alignment of premiums with underly-

ing risk. Similarly, Ge (2022) use evidence from weather and life insurance to explore how financial constraints affect pricing strategies. We build on the foundational work of Froot (2001) regarding capital constraints in reinsurance markets and Koijen and Yogo (2015) regarding regulatory frictions to examine how these supply-side dynamics transmit shocks to local markets. While Keys and Mulder (2025) illustrate how reinsurer exposure specifically shapes homeowners insurance premiums, commercial real estate (CRE) insurance remains relatively underexplored. We argue that the CRE market offers a cleaner setting for studying pricing dynamics because, unlike homeowners insurance, it is less distorted by strict regulatory constraints (Born and Klimaszewski-Blettner, 2013). Further, in contrast to the homeowners insurance market where owners facing rising premiums may reduce coverage or self-insure (Cookson, Gallagher, and Mulder, 2025; Sastry et al., 2025), CMBS lenders mandate comprehensive, "all-risk" coverage, which eliminates this selection channel. We extend this literature by documenting the drivers of rising premiums in the commercial sector and showing how regulatory frictions in the homeowners insurance market spill over into commercial insurance, underscoring the interconnectedness of insurance markets.

Second, we contribute to the literature on the financial impacts of climate risk. Prior studies demonstrate 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). For example, Sastry (Forthcoming) shows how climate exposure affects mortgage origination. Beyond housing, Seltzer, Starks, and Zhu (2022) and Sastry, Sen, Tenekedjieva, and Scharlemann (2024) illustrate implications for corporate bond pricing and insurance supply, respectively. Holtermans, Kahn, and Kok (2024) examine the impact of climate-related disasters on mortgage delinquency rates for commercial real estate mortgages. Buschbom, Eastman, Wang, and Zhou (2025) study the impact of realized climate shocks on insurance costs across multiple commercial property types. We contribute to this literature by using novel CMBS data to establish a direct link between rising climate risk and higher insurance costs, which are either passed through to tenants or result in reduced profitability.

Third, we extend the understanding of how rising insurance premiums affect 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 has generally focused on residential real estate owners, our research highlights the impact on the rental market. By documenting the extent to which operating cost shocks are passed through to rents, we show that higher insurance premiums directly drive up rents for tenants.[4]

Finally, we contribute to research on the role of property owners in real estate markets. Previous studies have primarily examined the long-term rental market, demonstrating how large institutional owners influence rents and asset quality (Mills, Molloy, and Zarutskie, 2019; Austin, 2022; Coven, 2023; Gorback, Qian, and Zhu, 2024). We extend this line of inquiry by showing that large property owners also benefit from lower insurance costs, particularly in high-risk areas. We find that even after controlling for individual property risk, owners with lower average portfolio risk secure reduced premiums. These findings underscore the significance of ownership structure in shaping market outcomes, highlighting how economies of scale and portfolio composition significantly influence commercial real estate insurance pricing.

II. Data

Our primary dataset focuses on multifamily properties with loans securitized through the Agency Commercial Mortgage-Backed Securities (CMBS) market (Freddie Mac and Fannie Mae). These two entities play critical roles in the U.S. residential and commercial mortgage markets; as of September 2023, they collectively owned or guaranteed roughly 40% of the $2.2 trillion in outstanding multifamily mortgage debt (Heeb, 2024). Given their prominence, Freddie Mac and Fannie Mae are subject to regulatory mandates requiring the public disclosure of comprehensive loan performance data for properties underlying their CMBS offerings. These data encompass key metrics including insurance costs, rent, and NOI, alongside property-level details such as address, number of units, year built, and year of last renovation. Our hand-collected dataset comprises 455,922 property-year observations across 102,995 unique properties.

We supplement this with similar property-level data for hospitality, office, industrial, and retail

[4] Our results on pass-through complement a literature on the pass-through of property taxes (Carroll and Yinger, 1994) and interest rates (Lee, 2024).

properties obtained from Bloomberg. However, for the majority of our analysis, we focus on multifamily properties in Agency CMBS deals for three reasons: (1) other property types are frequently subject to Triple Net Leases ("NNN"), where tenants cover both rent and operating expenses, which would render the pass-through of rising insurance costs to property-level revenues mechanical; (2) loans in Agency CMBS deals are subject to more standardized mandates regarding insurance coverage; and (3) multifamily properties constitute the largest share of our sample, and restricting the analysis to a single asset class facilitates cleaner comparisons and simplifies the interpretation of our results.

To examine the relationship between rising insurance costs and natural disaster risk, we utilize two datasets: the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and the National Risk Index (NRI). SHELDUS provides granular, county-level data on historical natural hazard events and associated losses, offering a robust measure of realized disaster impacts. The NRI offers a forward-looking assessment, providing expected loss estimates and risk scores for each census tract across the United States. To analyze the role of geographic location, we geocode all property addresses using the U.S. Census Geocoder and calculate each property's elevation and distance to the nearest coast using topographic data from the National Elevation Dataset and Natural Earth, respectively.

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

Finally, to accurately determine property ownership, we use Real Capital Analytics (RCA). Identifying ownership is often complicated by variations in recorded names, such as the use of subsidiaries, holding companies, and non-standardized conventions. RCA addresses this by standardizing ownership names and identifying the ultimate parent owner. Using these data, we calculate the total number of multifamily units owned by each entity annually across the United States to proxy for owner size.

III. The Rise

We begin by documenting the significant rise in insurance costs, distinguishing between time-series and cross-sectional trends. Figure 1 illustrates the time-series evolution, while Figure 2 details the cross-sectional variation.

A. Time-Series Variation

Figure 1, Panel A plots insurance costs for multifamily properties as a share of rent and total operating expenses. Both measures remained relatively stable prior to 2019, averaging below 2.7% of rent (5.7% of total operating expenses), but increased steadily thereafter, reaching 4.7% (9.9%) by 2024. Figure 1, Panel B (left subpanel) shows the median and average percentage change in insurance costs annually from 2011 to 2024. The average percentage change has exceeded 15% in every year since 2019, peaking at nearly 30% in 2023. Figure 1, Panel B (right subpanel) plots the percentage change in the ratio of insurance costs to operating expenses (OpEx) to control for broader inflationary pressure on operating costs. A similar pattern persists: the insurance-to-OpEx ratio has risen by at least 8% annually from 2019 onward, with a surge of nearly 20% in 2023.

Figure 1, Panel C replicates the analysis from Panel B (left) for non-multifamily property types using data from Bloomberg. A strikingly similar time-series pattern emerges across all asset classes. For the remainder of the paper, we focus exclusively on multifamily properties. We do so because they constitute the largest share of our sample, and restricting the analysis to a single property type facilitates cleaner comparisons and simplifies the interpretation of our results.

B. Cross-Sectional Variation

Figure 2, Panel A compares the median annual insurance cost per unit in the 2022–2024 period relative to the 2010–2017 baseline. Each bubble represents a Core-Based Statistical Area (CBSA), sized according to the number of properties in our sample. Bubbles are colored based on the magnitude of the cost increase, with dashed lines indicating 1x, 2x, and 3x multiples. The average property in our sample is located in a CBSA where median insurance costs per unit have increased by a factor of 1.94.

Notably, 37% of CBSAs—containing 34% of the properties in our sample—have seen median insurance costs at least double.

Figure 2, Panel B zooms in on the recent spike, displaying a heatmap of the percentage change in insurance costs between 2022 and 2023 across CBSAs. While the largest increases occurred in coastal regions—including Florida, Texas, Louisiana, and California—substantial hikes were also observed in the U.S. interior, such as in Oklahoma, Colorado, Tennessee, and Indiana. Only 12% (29%) of CBSAs, containing just 1% (9%) of sampled properties, experienced an increase of less than 10% (20%). Collectively, the panels in Figure 2 demonstrate that the surge in insurance costs is a pervasive, nationwide phenomenon.

IV. Pricing of Local Risk and Reinsurance

In the previous section, we documented the time-series and cross-sectional variation in the rise of insurance costs. We now turn to examining the potential causes of this rise. First, we assess how the local disaster risk of a property's location relates to rising insurance costs. To do so, we employ 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 realized historical losses at the county-year level. Second, we examine the rising cost of reinsurance and determine whether differential exposure to reinsurance markets affects commercial insurance costs. Finally, we discuss several alternative explanations for which we find limited empirical support, including property features, insurance market concentration, distance to the coast, and elevation.

A. Risk Scores and Expected Annual Losses

We begin by examining how risk scores and expected annual building losses relate to changes in insurance costs, presenting the results in Figure 3. We utilize census tract-level data from the Federal Emergency Management Agency's (FEMA) National Risk Index. Panel A presents binscatter plots showing the relationships over the entire sample period (2010 to 2023), while Panel B splits the analy-

sis into an early period (2017 and earlier) and a later period (2018 and later). In both panels, we include year fixed effects to control for time-specific unobserved factors; the lines 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 a comparable 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 sample. In the left subpanel, we find that risk scores had no significant effect on insurance cost changes prior to 2017, but the effect becomes significant post-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.4 illustrates the effect of risk scores (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 the percentage change in insurance costs. Across all subpanels, we find that the positive and statistically significant effect emerges only after 2018. These findings suggest that insurers have become increasingly sensitive to regional risk profiles over time.

B. Past Property Damages

Next, we explore the relationship between past property damages and the percentage change in insurance costs, presenting our results in Figure 4. We use county-level property damage data 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 and cluster standard errors at the county level. 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 five years, insurance costs have increased by more than 12%.

We build on Panel A by investigating 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 in 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 the early (pre-2017) and later (post-2018) periods. We find that before 2017, property damages had no significant effect on insurance cost increases. However, after 2018, the effect becomes significant, suggesting that insurers have begun to respond more aggressively to areas with a history of high damages. It is possible that this shift was driven by the abnormally high magnitude of property losses during 2017 (see Figure IA.5, Panel A). Alternatively, it may 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.

C. Cost of Reinsurance

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. Because reinsurance is priced in global markets, movements in reinsurance prices can also be understood as reflecting changes in the price of systematic catastrophe risk.

In recent years, the cost of reinsurance has increased substantially. The Guy Carpenter Rate-On-Line Index, as shown in Figure 5, Panel A, 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. Panel A also plots the estimated effect of local disaster risk on insurance costs over time. A striking feature is the close co-movement between the pricing of local disaster risk and this proxy for systematic risk

pricing, with both rising sharply in recent years. This pattern points to reinsurance as a potential driver of rising insurance costs and motivates tests that separate the effects of heightened global risk pricing from changes in local risk pricing. As reinsurance prices rise, insurers that rely more heavily on reinsurance may pass higher costs through to policyholders, increasing premiums even holding local disaster risk fixed.

To quantify the role of reinsurance exposure in driving insurance cost increases, we follow Keys and Mulder (2025) 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.[5]

Using the constructed reinsurance exposure measure, we calculate state-level reinsurance exposure and plot it in Figure IA.6, Panel A. 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:

[5]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, Panel B that the percentage of premiums ceded to reinsurers at the company level and the exposure to reinsurance markets at the state level are largely stable over time.

$$ChangeInsurancePerUnit_{i,s,t} = \beta \times ChangeReCost_t \times ReinsuranceExposure_s \times RiskScore_i + \delta_t \times ReinsuranceExposure_s + \zeta_t \times RiskScore_i + \gamma_i + \tau_t + \varepsilon_{i,s,t}$$

where $ChangeInsurancePerUnit_{i,s,t}$ represents the change in insurance costs per unit for property i in state s during year t, $ChangeReCost_t$ is the 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 (γ_i) to control for unobservable, time-invariant property characteristics, include year fixed effects (τ_t) to account for macroeconomic shocks or broader trends affecting insurance costs for all properties in that year, and control for time-varying effects of reinsurance exposure ($\delta_t \times ReinsuranceExposure_s$) and local risk ($\zeta_t \times RiskScore_i$). 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, consider two southeastern states, Florida and Georgia, as an example. Figure IA.6, Panel A plots reinsurance exposure, while Figure IA.1 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 5, Panel B. The left subpanel of Panel A presents the marginal effects of a 10 index point increase in reinsurance cost on the change in insurance cost per unit, 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 10 index point increase in reinsurance cost leads to a $19 change in insurance cost per unit. However, for the same property with a reinsurance exposure of 25% instead, the same increase in reinsurance cost leads to a $47 increase in insurance cost per unit. That is, the effect of the reinsurance cost shock is 250% as large in states with more exposure to reinsurance markets, even holding fixed the riskiness of the location.[6] 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 pass-through of changes in reinsurance cost into primary insurance premiums, with the effect increasing as disaster risk scores rise.

Table 1 provides corresponding regression estimates and examines robustness to varying fixed effects. Namely, columns (1) to (3) examine the interactions between reinsurance cost changes and state-level reinsurance exposures, and columns (4) to (7) introduce interactions with local risk score. Across varying sets of fixed effects, the most stringent of which (columns (3), (6), and (7)) includes year and property fixed effects and column (7) controls for time-varying effects of local risk and reinsurance exposure, we find that ex-ante exposure to reinsurance markets leads to higher insurance costs when reinsurance costs increase, especially in areas with heightened local risk.[7]

[6] Since the model is linear, this 250% difference in the effect between states with 10% and 25% exposure holds across any given level of risk score.

[7] Figure 5, Panel B is based on the regression specification shown in Column (7). Table IA.I replicates columns (4) to (7) of Table 1 using expected annual losses and finds similar results.

D. Other Potential Causes

Finally, we examine additional factors that could influence insurance cost changes, including geographic characteristics, property features, and insurance market concentration. We analyze the relationship between insurance cost increases and the distance from the coast and elevation (Figure IA.7). We also assess the impact of property-specific features, such as unit count and building age (Figure IA.8). Additionally, we investigate insurance market concentration at both the state level and the county level (for California), measured 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, a trend that contrasts with homeowners insurance markets. However, none of these factors meaningfully explain the variation in insurance cost increases.

V. Insurance for Multifamily vs. Single-Family Properties

In this section, we examine differences in insurance costs between multifamily and single-family properties. We find that 94.8% of the population resides in counties where commercial insurance costs increased at more than double the rate of homeowners insurance costs. We attribute this divergence to state-level regulatory constraints in the homeowners insurance market (Oh, Sen, and Tenekedjieva, Forthcoming). Specifically, the wedge between commercial and homeowners insurance costs increases with local disaster risk in states with high regulatory frictions. In contrast, in states with low regulatory frictions, local risk has no effect on this wedge. Furthermore, we find that the wedge expands when a local area suffers a disaster, but only if the state has high regulatory frictions and the area has high underlying risk. These findings are consistent with the decoupling of local risk and homeowners insurance prices highlighted by Oh, Sen, and Tenekedjieva (Forthcoming) and suggest that commercial property insurance costs are better able to adjust to reflect expected and realized climate risk.

We then examine whether regulatory frictions that constrain homeowners insurance pricing create spillovers to commercial property insurance through cross-product subsidization. Using a border county-pair difference-in-differences design within a property-year panel, we find that commercial insurance costs rise disproportionately more in counties facing high homeowners insurance market

frictions after a large disaster relative to their paired counties with low regulatory frictions. This raises the possibility that a disproportionate share of the cost of disaster risk is being borne by commercial property owners or renters. We return to examine whether renters, in particular, are bearing the rising cost of insurance in Section VI and how owners are responding in Section VII.

A. Differences in Rise

We begin by comparing the growth of commercial property insurance costs to that of homeowners insurance costs. This comparison is critical because prior literature has documented substantial increases in homeowners insurance costs in recent years (Keys and Mulder, 2025). However, homeowners insurance cost increases are often limited by state-level regulatory constraints (Oh, Sen, and Tenekedjieva, Forthcoming). In contrast, commercial property insurance costs are generally not subject to these strict rate caps, 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 homeowners insurance cost data from U.S. Department of the Treasury (2025). The data is available at the ZIP-year level, capturing average homeowners insurance costs per policy for each ZIP code annually from 2018 to 2022. We aggregate these 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.

Figure 6, Panel A presents scatterplots comparing the annual percentage change in commercial insurance costs to the percentage change in homeowners insurance costs for each county across three yearly intervals: 2019–2020, 2020–2021, and 2021–2022. Each bubble represents a county, sized based on its population. Three dashed lines are drawn for reference: a 1x line indicating equal percentage changes between commercial and homeowners insurance costs (the 45-degree line), a 2x line indicating commercial insurance increases at twice the rate of homeowners insurance, and a 5x line indicating

commercial insurance increases five times as large as homeowners 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 grew more than five times faster than homeowners insurance costs or increased despite homeowners costs decreasing. Furthermore, 98.1% (94.8%) of the population lived in counties where commercial insurance costs increased at least as much (at least twice as much) as homeowners insurance costs. Just 0.9% of the population lived in counties where the commercial increase was smaller than the homeowners increase, and merely 1.0% of the population resided in counties where commercial insurance costs decreased.[8]

The plots show that commercial insurance costs consistently rise at higher rates than homeowners insurance costs across most counties—a pattern that is stable across the three yearly intervals. If anything, the gap has widened in recent years, with commercial insurance cost increases accelerating while homeowners insurance cost increases remain relatively consistent in magnitude.

B. State-level Frictions in Homeowners Insurance Market

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

$$CoHoRatio_{i,z,t} = \frac{Commercial\ Insurance/Unit_{i,t}}{Average\ Homeowners\ Insurance\ Premiums_{z,t}}$$

and estimate the following regression equation:

[8] Counties where commercial insurance costs decreased are omitted from the figure for clarity.

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

where $LocalRisk_c$ denotes either the risk score or expected annual building losses scaled by building value of the census tract c containing commercial property i, and $\mathbb{1}(HighFriction)_s$ is a binary variable equal to one if state s is in the top tercile of the friction measure.[9] The regression includes state × year fixed effects, and standard errors are clustered at the state level. In Figure 6, Panel B (left subpanel), we plot the predicted effects of risk score on the ratio of commercial to homeowners insurance costs separately for high-friction (orange line) and low-friction (blue line) states. The results reveal that in high-friction states, the ratio of commercial to homeowners insurance costs is higher in riskier areas because commercial premiums more closely reflect underlying local risk due to fewer regulatory constraints. In contrast, in low-friction states, this ratio does not vary with geographic risk, presumably because homeowners premiums can also be adjusted for local risk factors. 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 homeowners insurance. In addition to the state × year fixed effects included previously, we also include property fixed effects to examine within-property changes in the wedge due to realized local losses. Table 2 presents the regression results. Column (1) shows that areas experiencing greater losses exhibit a higher ratio of commercial to homeowners insurance costs. While Column (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 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 homeowners insurance costs in high-friction states despite rising losses, while commercial insurance pricing remains flexible.

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

Moreover, as previously discussed, Figure 6, Panel B shows that the wedge between commercial and homeowners insurance markets in high-friction states increases with local risk. To examine this further, Columns (3) and (4) of Table 2 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 that the difference in insurers' ability to respond to heightened losses between the commercial and homeowners markets is largest in high-friction, high-risk areas. That is, the widening gap between commercial and homeowners insurance is most pronounced in these areas, consistent with the mismatch between risk and homeowners insurance prices highlighted by Oh, Sen, and Tenekedjieva (Forthcoming).[10]

C. Spillovers Due to Regulatory Frictions

This subsection extends our analysis of regulatory frictions by testing whether spillovers to commercial property insurance operate through cross-product subsidization. As of 2017, conditional on an insurer offering commercial insurance in a given state, 44% of insurers (on a premium-weighted basis) also wrote homeowners policies in that same state.[11] This overlapping market participation creates the possibility that multi-product insurers operating in jurisdictions with tighter constraints on homeowners rates may respond to large natural disasters by more aggressively adjusting commercial premiums to rebuild capital.[12]

To test this hypothesis, we adopt a stacked border county-pair difference-in-differences design using a property-year panel. We form county-pairs by matching adjacent counties that straddle a state border, under the assumption that properties on either side share similar economic fundamentals and exposure to regional shocks. Using the homeowners friction measure from Oh, Sen, and Tenekedjieva (Forthcoming), we classify counties on one side of the border as treated if they have high homeowners insurance market frictions, while the paired counties on the other side—serving as controls—do

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

[11] This percentage has remained stable over time; as of 2022, it was 42%.

[12] Similar cross-product subsidization behavior has been documented in other insurance contexts. For example, Ge (2022) finds evidence that insurance groups engage in cross-subsidization between life and property-casualty insurance divisions following financial shocks.

not. We additionally require that both states in the pair have low frictions in commercial property insurance rates. Specifically, we estimate the following regression:

$$PctChangeInsurance_{ipstc} = \beta \times HighFriction_s \times Post_{tc} \times Treat_{pc} + \mu_i + \gamma_{stc} + \delta_{psc} + \zeta_{ptc} + \varepsilon_{ipstc},$$

where $PctChangeInsurance_{ipstc}$ is the percentage change in insurance cost for property i located in county-pair p in state s during event year t within cohort c. $HighFriction_s$ equals one if state s is classified as having high homeowners insurance market frictions. For each county-pair p, we use historical property damage data to identify whether the pair experiences a major disaster during the sample period and, if so, define the disaster year.[13] County-pairs that experience a major disaster are defined as treated county-pairs. We define cohorts c at the event level: in each disaster year, the set of county-pairs experiencing a shock are the treated units, and the corresponding not-yet-treated and never-treated county-pairs serve as controls. Therefore, $Treat_{pc}$ is an indicator equal to one for treated county-pair p in its cohort c, and $Post_{tc}$ is an indicator equal to one for all county-pairs in cohort c in the disaster year and all subsequent years. The sample includes two years before and two years starting from the disaster year.

A key concern in this setting is endogeneity arising from unobserved differences in local economic conditions, insurance markets, or state-level policies that may simultaneously affect both disaster exposure and property outcomes. To mitigate these concerns, we employ a rich set of fixed effects, including property fixed effects (μ_i) to absorb time-invariant property characteristics. We also saturate the model with cohort $\times$ state $\times$ event-year fixed effects (γ_{stc}) that capture cohort-specific state-level shocks over time, cohort $\times$ state $\times$ county-pair fixed effects (δ_{psc}) that absorb time-invariant differences across county-pairs within states and cohorts, cohort $\times$ event-year $\times$ county-pair fixed effects (ζ_{ptc}) that flexibly control for county-pair-specific dynamics around the disaster within each cohort. These controls ensure that we effectively compare properties within the same local region facing the

[13] Using SHELDUS data, we construct annual property damage per capita for each county and take the average across the two counties in a pair. We classify a county-pair as experiencing a major disaster if its within-sample peak damage year (i) falls in the top decile of the county-pair damage distribution across all pairs and years and (ii) is at least 10 times the previous year's damage. This restriction ensures that the identified event reflects an unexpected shock rather than a gradual trend. We define the disaster year as the peak-damage year.

same disaster shock, isolating the differential effect of the state regulatory environment.

The coefficient β captures the differential post-disaster change in commercial insurance costs for treated county-pairs on the high-friction (homeowners) side of the border, relative to their low-friction counterparts, after conditioning on the above described fixed effects. Table 3 reports a consistently positive and statistically significant coefficient on *Treat* × *Post* across all specifications. The estimated magnitudes, ranging from roughly 19 to 22 percentage points, indicate that commercial insurance costs rise disproportionately more in counties facing high homeowners insurance market frictions after a large disaster relative to their paired counties. This pattern is consistent with insurers shifting a larger share of post-disaster repricing to commercial lines when homeowners premiums are restricted by regulation.

VI. Effects on Rents and Profitability

In previous sections, we documented the time-series and cross-sectional rise in insurance costs and explored the potential causes of these increases. In this section, we 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 estimate a regression of the following form:

$$Log(y)_{imt} = \beta Log(Insurance/Unit)_{imt} + \gamma_i + \eta_{mt} + \epsilon_{imt}$$

where $Log(y)$ represents our outcome variable—either *Log(Rents/Unit)* or *Log(NOI/Unit)*—for property i in CBSA m in year t. γ_i denotes property fixed effects, and η_{mt} denotes CBSA × year fixed effects. $Log(Insurance/Unit)_{imt}$ is our variable of interest, and β captures the pass-through rate to either rents or operating profits. Because both the dependent and independent variables are in logs and the specification includes property fixed effects, the coefficients can be interpreted as elasticities: the percentage

change in rent or NOI resulting from a 1% change in insurance costs.[14]

Table 4 presents the results. Columns (1) and (2) report the pass-through to rents, while columns (3) and (4) report the impact on operating income. All specifications include property fixed effects. Columns (1) and (3) include year fixed effects, while columns (2) and (4) include CBSA $\times$ year fixed effects to absorb time-varying local shocks. In the specification with CBSA $\times$ year fixed effects, a 10% increase in insurance costs is associated with a 0.16% increase in rents and a 0.46% decrease in NOI. Both estimates are statistically significant, with t-statistics exceeding 9 based on standard errors clustered at the CBSA level.[15]

To quantify the share of the insurance cost increase passed through to rents, consider a 25% increase in insurance costs. Based on Column (2) of Table 4, this increase is associated with a 0.41% increase in rents ($25\% \times 0.0162$). Since insurance costs account for approximately 3.3% of rent on average, a 25% hike in insurance costs would necessitate a 0.83% rent increase if fully passed through ($3.3\% \times 25\%$). Thus, we estimate that approximately 49% of the rise in insurance costs is passed through to rents ($0.41/0.83$). Note that because we estimate an elasticity, this 49% pass-through rate holds regardless of the magnitude of the insurance cost shock.

B. Non-linearity of Pass-through

Next, we graphically examine the pass-through of insurance costs to rents and NOI to identify potential nonlinearities. Figure 7, Panel A displays binscatter plots showing the relationship between log insurance costs per unit and two outcomes: log rents per unit (left subpanel) and log NOI per unit (right subpanel). As in the regression analysis, both plots include CBSA $\times$ year and property fixed effects. The black curves represent third-degree polynomial fits based on the residualized data, with the gray regions indicating 95% confidence intervals.

The binscatter in the left subpanel shows a positive relationship between insurance costs and rents, confirming that rising costs are partially passed on to tenants. However, the concave shape of the fitted

[14] We normalize both the dependent and independent variables by the number of units to ensure that the CBSA $\times$ year fixed effects precisely capture the average rent or NOI trends in each CBSA.

[15] Specifications including only year fixed effects (rather than CBSA $\times$ year) imply a higher pass-through to rents and a smaller negative impact on operating income.

polynomial indicates that this pass-through diminishes as insurance costs rise, implying that property owners face increasing difficulty in passing on higher costs to tenants. The binscatter in the right subpanel reveals a similar concave relationship: NOI initially increases as insurance costs rise (likely due to concurrent rent growth) but eventually declines at higher cost levels. This pattern suggests that while owners can absorb moderate cost increases through operational adjustments or rent hikes, their ability to maintain profitability weakens as insurance premiums escalate. At high levels of insurance costs, the inability to fully pass through expenses results in a net reduction in NOI.

C. Pass-through Over Time

Figure 7, Panel B examines how the pass-through of insurance costs to rents and operating profits has evolved over time. We estimate the baseline regression but interact the independent variable of interest (log insurance per unit) with year indicators. The left subpanel shows a decline in the rate of pass-through to rents over time, with a particularly sharp decrease between 2019 and 2020. In 2013, a 10% increase in insurance costs resulted in a rent increase of approximately 0.35%; by 2023, the same shock resulted in an increase of only 0.05%. Conversely, the impact on operating losses has intensified. Before 2018, changes in insurance costs had no economically or statistically significant association with NOI. By 2023, however, a 10% increase in insurance costs was associated with a decrease in NOI of more than 0.80%.

Note that the concavity observed in Panel A and the temporal trends in Panel B are driven by the same underlying dynamic: as insurance costs have surged in recent years, property owners have been unable to raise rents or adjust operations sufficiently to preserve profitability. It remains to be seen how owners will respond in the long term, particularly if insurance costs continue to rise at their current trajectory.

D. Cumulative Effect

Figure 7, Panel C illustrates the cumulative effect of rising insurance costs for rents and profitability using a back-of-the-envelope calculation that combines our time-varying pass-through estimates with

the distribution of insurance cost growth.[16] While the implied average effects over the 2014–2024 period are modest—corresponding to roughly a 0.9% increase in rents and a 5.1% decline in NOI—the cumulative impacts are substantial in the upper tail of the shock distribution. At the 95th percentile of insurance cost increases, the same calculation implies an approximately 11% increase in rents alongside a 26% decline in NOI over the decade.[17] These results indicate that because rent adjustments absorb only a fraction of higher insurance expenses, large cost shocks translate into economically meaningful and persistent reductions in profitability in the most exposed markets.

VII. Role of Property Owners

Given the substantial effects on profitability, we next examine how property owners are responding. In this section, we analyze how owner size and portfolio composition influence insurance pricing and how these dynamics may be reshape the market structure.

A. Owner Size

Ownership structure interacts significantly with rising insurance costs, with larger property owners demonstrating a notable advantage in securing lower per-unit insurance expenses. Figure 8, Panel A illustrates the relationship between property owner size and insurance costs, highlighting how this interaction varies across regions with different risk levels and over time. The data show that larger property owners typically incur lower insurance costs per unit and as a percentage of rent, reflecting economies of scale. This trend underscores their stronger bargaining power with insurers, which enables them to negotiate more favorable rates.[18]

The bargaining power and economies of scale for large owners are likely most pronounced in high-risk areas, where insurance companies exercise greater discretion in pricing. To test this hypothesis,

[16] We use the annual percentage increase in the ratio of insurance costs to total operating expenses to account for general inflation in operating expenses. Internet Appendix Figure IA.10 replicates this analysis using percentiles of the percentage change in insurance cost per unit and yields similar results.

[17] Implicitly, this analysis assumes that regions consistently face insurance cost shocks at the same percentile of the annual distribution. To the extent that shocks mean-revert, this back-of-the-envelope exercise will overestimate the cumulative effects in the tails.

[18] We include CBSA × year fixed effects in this figure to account for variation in insurance pricing across regions and time.

we estimate the following regression:

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

where $RiskScore_i$ is the risk score of the census tract in which property i is located, and $Log(OwnerSize)_{o,t}$ is the log of the total number of units owned by owner o in year t across the entire country. We include property fixed effects (γ_i) and CBSA-by-year fixed effects ($\eta_{c,t}$) to account for local market conditions over time. Note that the inclusion of property fixed effects ensures that our results are driven entirely by time-series variation in the size of the owner of a given property (e.g., as the owner grows or the property changes hands).

Figure 8, Panel B plots 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 risk scores, the effect is both economically sizable and highly statistically significant. Specifically, 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—roughly 7.8% of the average insurance cost per unit ($458). Notably, this estimated saving holds the property fixed and only varying owner size. We find similar results using the ratio of insurance cost to rent (right subpanel). Table 5 provides the corresponding regression estimates; Column (1) confirms that the insurance-to-rent ratio is lower for larger owners, while Column (2) shows that this size advantage increases with local risk.

B. Owner Portfolio Risk

We next examine whether an owner's overall (pooled) portfolio risk influences the insurance pricing of individual properties within that portfolio. 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 estimate the following equation:

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

where $PortfolioRiskScore_{o,t}$ reflects the weighted average riskiness of owner o's portfolio at time t. The specification controls for owner size, property fixed effects (γ_i), and CBSA $\times$ year fixed effects ($\eta_{c,t}$). The inclusion of property fixed effects isolates the effect of changes in the owner's portfolio risk over time—either due to the owner acquiring/divesting other assets or due to a change in ownership of the focal property.

Figure 9, Panel A shows that as an owner's average portfolio risk score declines, the insurance cost per unit for a given property also tends to decrease. This pattern indicates that insurers do not set premiums based solely on a property in isolation but also account for the risk profile of the entire portfolio held by the owner.[19]

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:

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

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 captures how the pricing sensitivity to a property's own risk depends on the owner's overall portfolio risk. The owner $\times$ year fixed effects ($\tau_{o,t}$) account for any unobserved time-varying factors unique to each owner.

In Figure 9, Panel B, 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 100), insurance costs are substantially lower if the property is part of a lower-risk portfolio. For example, consider an owner holding a mixed portfolio of high- and low-risk assets. If the owner divests a high-risk property and acquires a safer one, the overall portfolio risk score declines. Our results suggest that even if the risk of a remaining high-risk property is unchanged, its premium may fall simply because it is now pooled with safer assets. Table 6 provides corresponding estimates: Column (1) shows that

[19] Note that the effect of an owner's average portfolio risk is distinct from the owner size effect discussed in the previous section; both effects remain economically and statistically significant when considered jointly.

the insurance-to-rent ratio is higher for owners with higher portfolio risk, and Column (2) confirms that this portfolio effect is amplified in riskier areas.

C. Combined Effects of Owner Size and Portfolio Risk

We now consider the combined role of owner size and portfolio composition. Specifically, we estimate:

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

where $RiskScore_i$ denotes the risk score of property i, $PortRiskScore_{o,t}$ is the weighted average risk of the owner's full portfolio, and $Log(OwnerSize)_{o,t}$ is the log of number of units owned by owner o in year t across the entire country. The owner $\times$ year fixed effects ($\tau_{o,t}$) account for any unobserved time-varying factors unique to each owner. The triple interaction term ($PortRiskScore_{o,t} \times RiskScore_i \times Log(OwnerSize)_{o,t}$) captures the extent to which the portfolio risk channel described above varies by owner size, while holding the riskiness of the area fixed.

In Figure 10, Panel A, the left (right) subpanel shows the estimated effects for small owners (1,000 units) versus large owners (50,000 units). For small owners, regardless of their average portfolio risk, there is little difference in insurance costs per unit. In contrast, for large owners, insurance costs are substantially lower if the overall portfolio risk is low. Panel B shows similar results using the ratio of insurance cost to rent. This indicates that the benefits of portfolio diversification—specifically, pooling high-risk assets with safer ones—are largely realized by large owners.

D. Within Same Ownership Spell

Table 7 further shows that, holding ownership of the focal property fixed, increases in owner size are associated with declines in insurance costs for incumbent properties, especially for higher-risk properties. Conversely, increases in the owner's average portfolio risk are associated with higher insurance

costs that are likewise concentrated among higher-risk properties. Specifically, we restrict the sample to property-year observations where the property is owned by the same owner as three years earlier and examine how the three-year change in the insurance-cost-to-rent ratio varies with three-year changes in owner size and the owner's average portfolio risk, controlling for year fixed effects and year-by-property-risk controls. Columns (1)–(2) show that, within the same owner and property, increases in owner size predict declines in insurance costs, and that the decline is steeper for riskier properties. Columns (3)–(4) show that increases in average portfolio risk predict increases in insurance costs, with a larger increase for riskier properties. Together, these results mitigate concerns that our findings are driven by operational changes associated with ownership transitions and confirm that both scale and portfolio composition are critical determinants of risk pricing.

E. Effects Over Time

So far, we have shown that larger property owners enjoy a significant advantage in negotiating lower insurance costs and that insurers price risk partly based on the owner's overall portfolio. In this subsection, we investigate how this advantage has evolved over time.

We first examine the evolution of the size advantage. Figure 11, Panel A plots the annual effect of owner size on the insurance-to-rent ratio for low-, medium-, and high-risk properties. A negative coefficient indicates a cost advantage for larger owners. In the earlier years of the sample, the size advantage was comparable across risk categories. However, in recent years, a divergence has emerged: the size advantage has diminished in low-risk areas but grown substantially larger in high-risk areas. In other words, the benefits of scale are increasingly concentrated among risky properties. Similarly, Panel B illustrates the owner portfolio effect over time. It shows that in recent years, reducing portfolio risk has led to significantly larger insurance cost savings, particularly for large owners holding high-risk assets. Column (3) of Table 5 and Table 6 confirm these trends in a regression framework, showing that the interaction effects of size and portfolio risk with time have intensified.

F. Effects on Ownership Patterns

Finally, we investigate how property owners have adjusted their holdings in response to heightened insurance costs and, more broadly, climate risk. To do so, we analyze the relationship between local risk and owner size over time. Figure 12, Panel A presents binscatter plots for 2010 (left) and 2024 (right), relating local risk (log expected annual building losses per capita) to owner size. Both plots include CBSA fixed effects. In 2010, the relationship is flat, indicating no correlation between local risk and owner size. By 2024, however, a strong positive relationship emerges: properties in riskier areas are significantly more likely to be held by larger owners.

We quantify this shift using the following dynamic regression:

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

where the dependent variable is the log of the number of units owned by property i's owner o in year t across the entire country, 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 (γ_i), which means the regression relies entirely on within-property variation over time. Conceptually, this approach allows us to compare ownership size changes for the same property as if it were hypothetically located in areas with different risk levels. Year fixed effects (τ_t) are also included to account for general market trends that affect all properties.

Figure 12, Panel B plots the coefficients (β_t), showing that the positive relationship between risk and owner size strengthens progressively 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 25-point increase in the risk score. Table 8 provides the corresponding regression estimates. We observe that the effects become progressively stronger each year. These findings are consistent with a market sorting mechanism: as the insurance cost advantage for large owners in risky areas grows, ownership of these assets increasingly consolidates into the hands of larger entities.

VIII. Conclusion

We document a pervasive and substantial rise in commercial property insurance costs across the United States over the last decade. While recent literature has focused on the homeowners insurance market, we argue that the commercial real estate (CRE) sector offers a clearer view of the market's pricing of climate risk. This setting allows us to observe the 'true' market response to rising physical and reinsurance risks, unencumbered by the regulatory frictions that dampen price signals in the homeowners market.

We identify three primary mechanisms driving the rise in commercial insurance costs: the aggressive repricing of local climate risk, surging reinsurance costs, and cross-product subsidization where insurers compensate for capped homeowners premiums by raising commercial rates. Notably, 95% of the population resides in counties where commercial insurance cost growth has been at least double that of homeowners insurance. We show that the wedge between commercial and homeowners insurance costs is largest in high-risk areas of states with high regulatory frictions in the homeowners insurance market. Further, we provide causal evidence of cross-product subsidization using a border county-pair difference-in-differences design; following a major disaster, commercial insurance costs rise by approximately 19 to 22 percentage points more in counties located in states with strict homeowners insurance regulations compared to their neighboring counties across the border.

These rising costs have profound implications for the multifamily housing sector. Crucially, we document a regime shift in the economic incidence of these costs. While the average pass-through to rents is 49% over the last decade, this figure masks a sharp decline over time—from nearly complete pass-through in 2014 to near-zero marginal pass-through in 2024. Our analysis reveals a concave relationship: as insurance costs reach extreme levels, the ability to pass on these costs to tenants collapses. Consequently, the incidence of climate risk pricing has shifted from tenants to property owners, leading to a significant erosion of NOI in recent years.

However, the burden of these costs is not distributed equally. We find that larger property owners leverage economies of scale and superior bargaining power to secure lower per-unit premiums, an advantage that is most pronounced in high-risk regions. Furthermore, owners with geographically

diversified, lower-risk portfolios achieve lower costs even for their high-risk assets, indicating that insurers price risk at the portfolio level rather than solely at the property level. Consequently, this cost asymmetry is reshaping market structure: since 2020, ownership of high-risk properties has increasingly consolidated into the hands of large institutional investors capable of capitalizing on these insurance efficiencies.

Ultimately, our findings reveal that commercial insurance pricing is determined by a complex interplay of local physical risk and broader systemic exposures held by both insurers and property owners. Moreover, our results underscore the importance of understanding how these pricing dynamics translate into higher housing costs for tenants and lower profitability for owners, especially as climate risks continue to grow. In particular, the substantial effects on profitability in high-risk areas raise questions regarding the future flow of capital into these regions.

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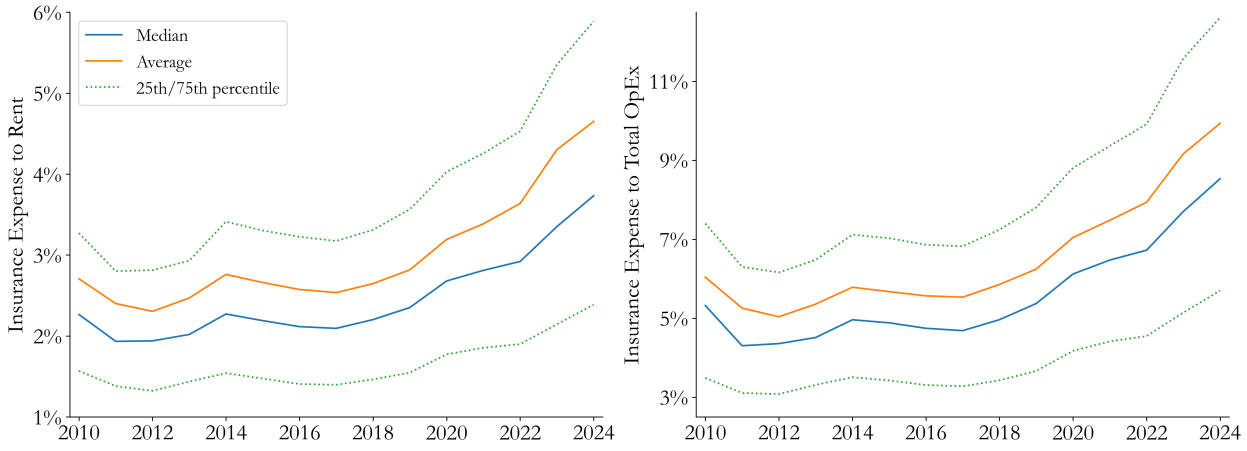
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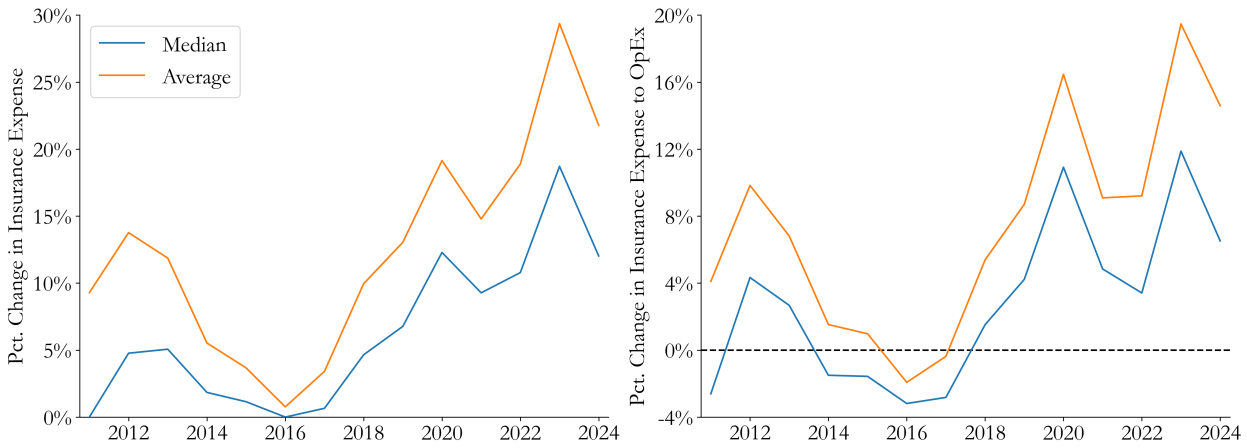
Figure 1: Time-Series Changes in Insurance Costs

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 shows the timeseries of insurance costs as a percentage of rent and total operating expenses for multifamily properties. Panels B and C shows the annual percentage increase in insurance costs, with Panel B focusing on multifamily properties and Panel C on other property types.

Panel A: Multifamily, As a Percentage of Rent and Total Operating Expenses



Panel B: Multifamily, Annual Percentage Change



Panel C: Other Property Types, Annual Percentage Change

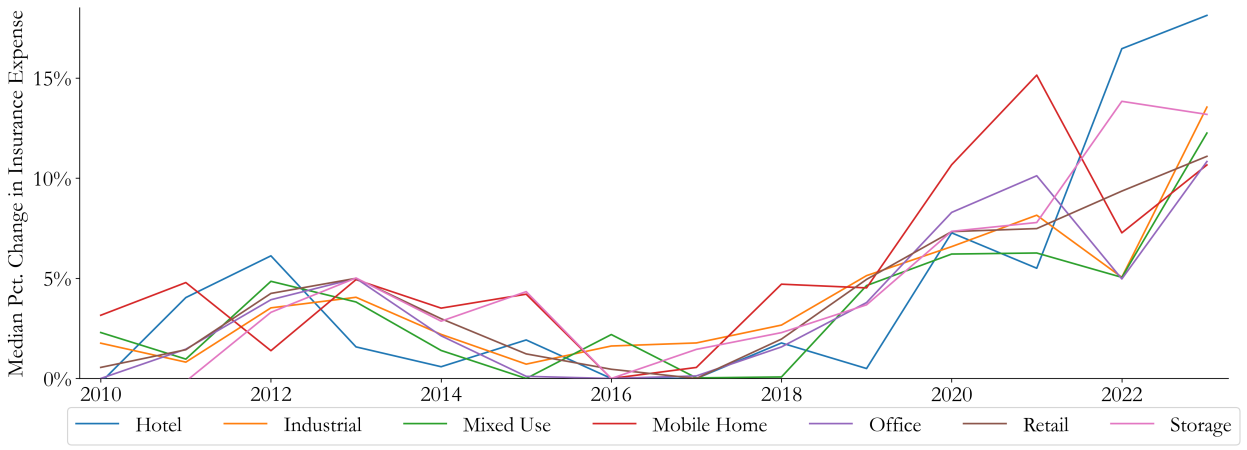
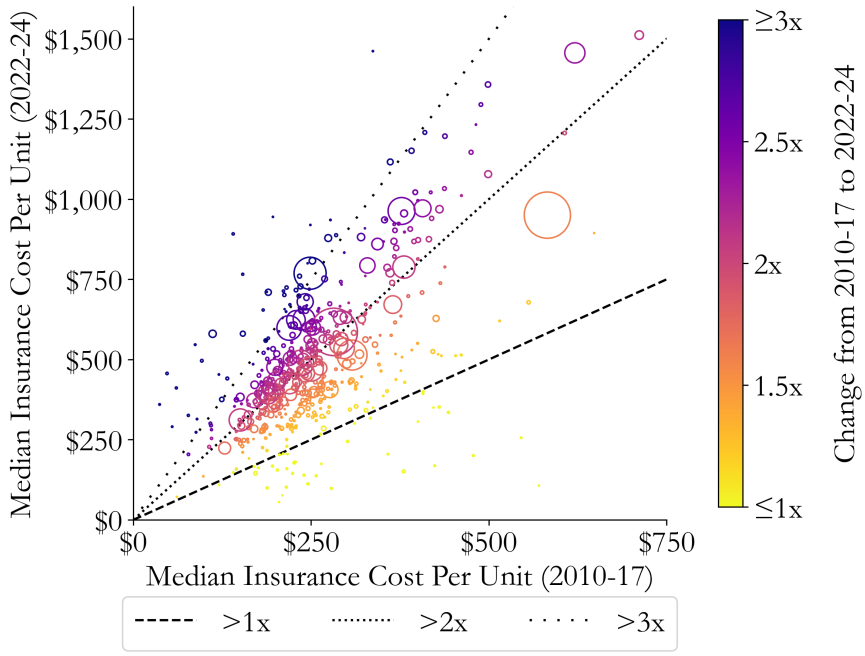


Figure 2: Cross-Sectional Differences in Insurance Cost Changes

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 2022-2024 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 2022-24 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

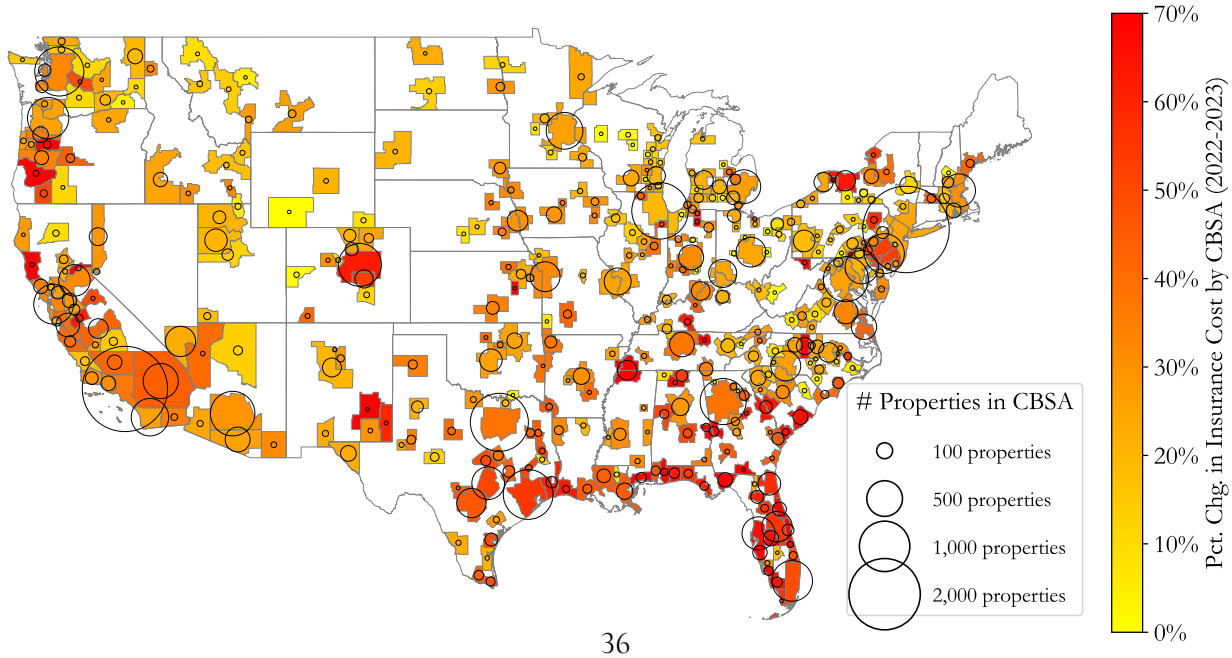


Figure 3: Risk Scores and Expected Annual Losses

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.

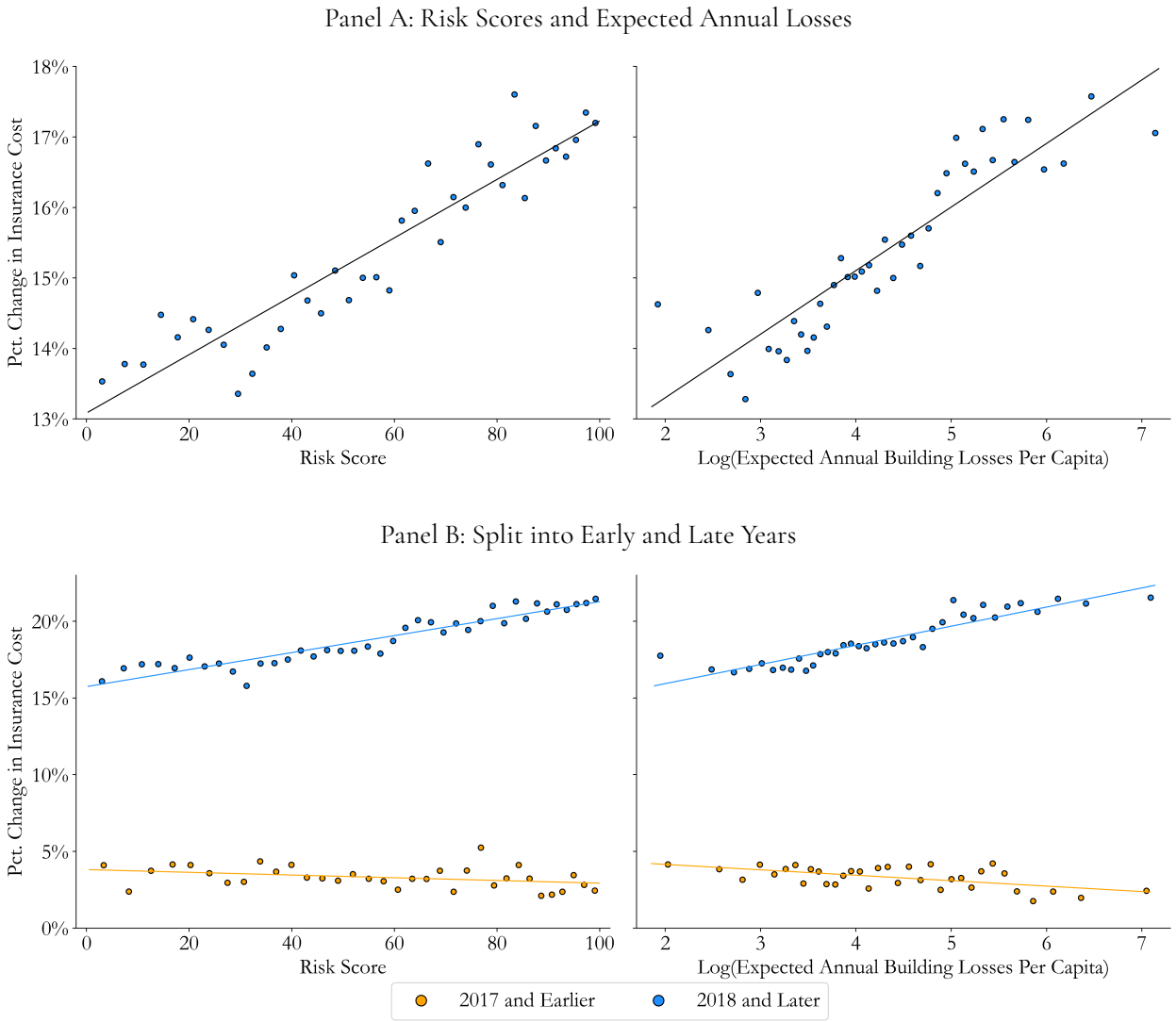
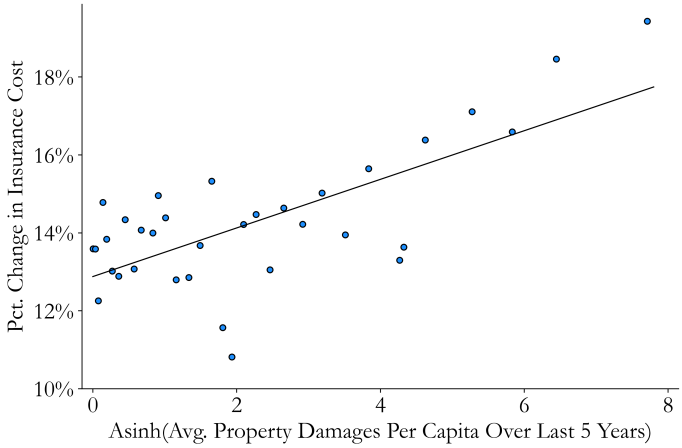


Figure 4: Past Property Damages and the Rise in Insurance Costs

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

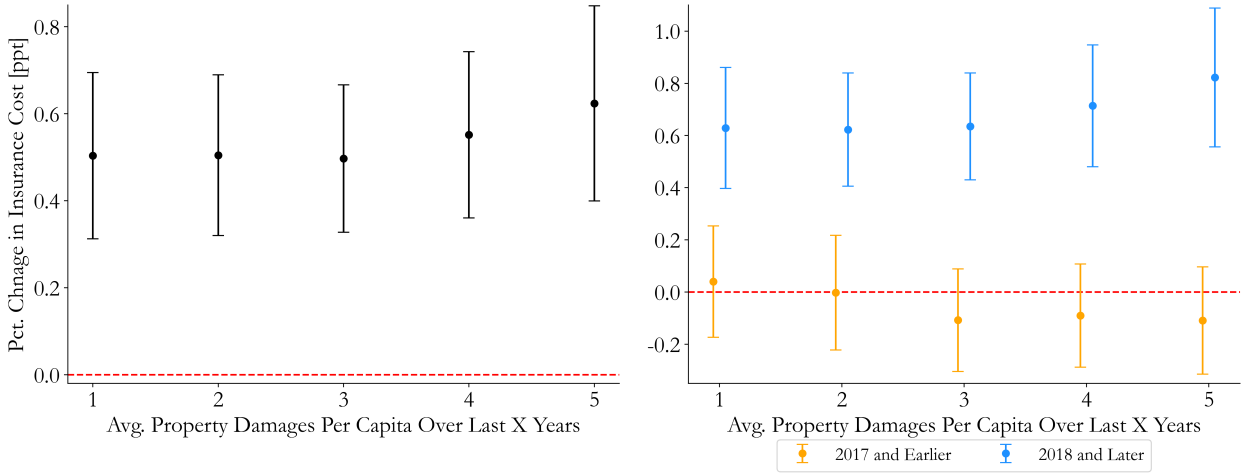
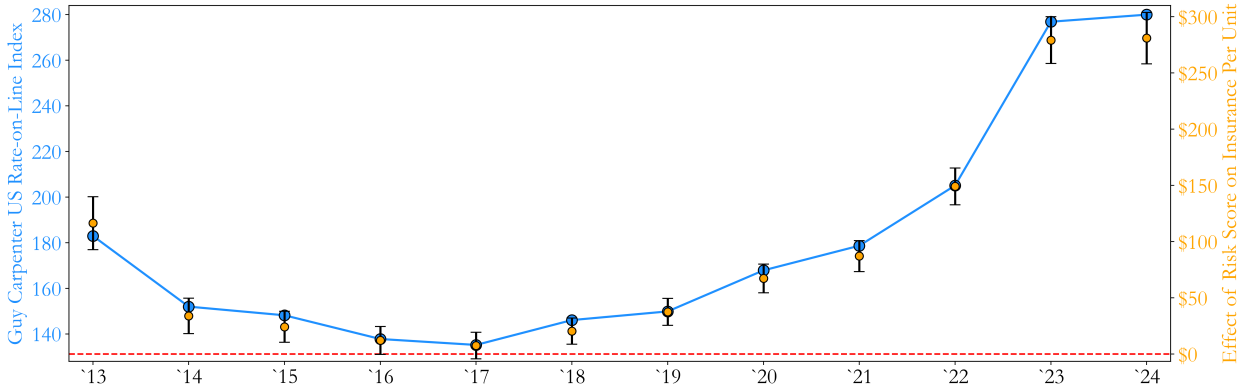


Figure 5: Rise in Reinsurance Costs

This figure examines the role of rising reinsurance costs. Panel A plots the reinsurance costs based on the Guy Carpenter US Property Catastrophe Rate-on-Line Index (blue series) and cross-sectional effect of local risk on insurance costs (orange series). The error bars represent 95% confidence intervals based on standard errors clustered at the census tract level. Panel B shows the effect of reinsurance cost increases across varying levels of reinsurance exposure (different colored lines) and local risk (horizontal axis) on insurance costs. Exposure on reinsurance markets defined at the state-level following Keys and Mulder (2025) 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: Effect of Reinsurance Cost Increase

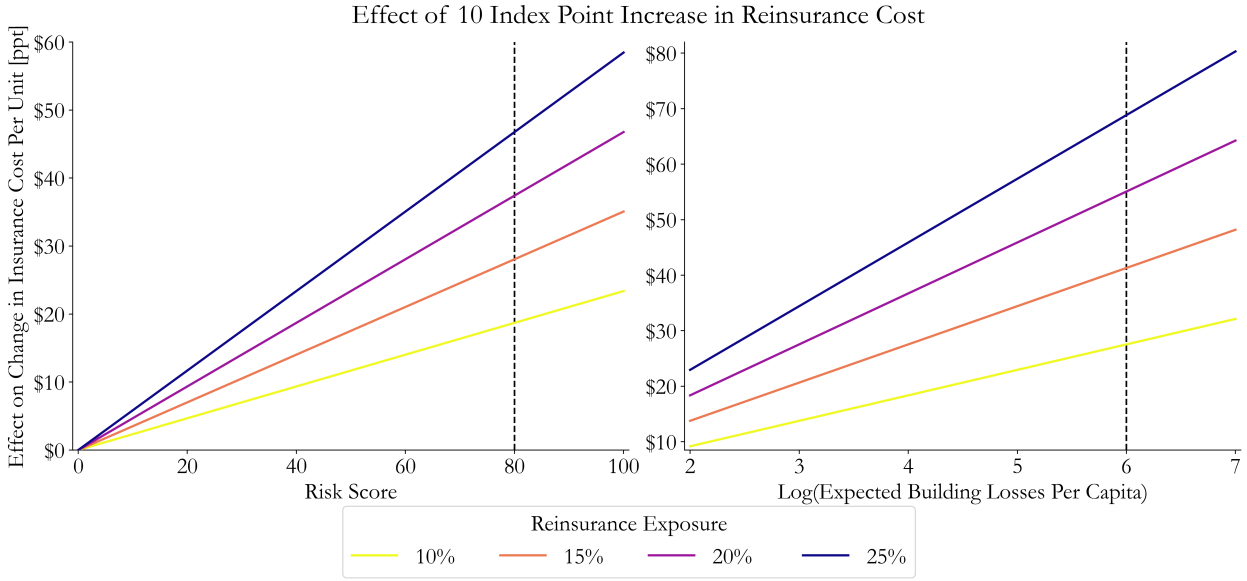
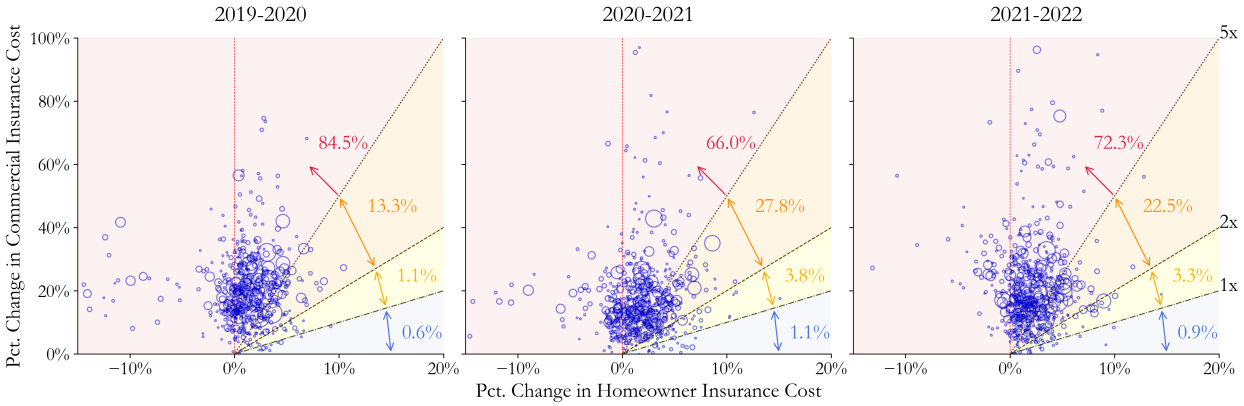


Figure 6: Commercial vs. Homeowners Insurance Costs

This figure compares commercial property insurance costs to homeowners insurance costs. Panel A presents scatterplots of the annual average percentage change in commercial insurance costs versus homeowners 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. Homeowners insurance cost data is sourced from U.S. Department of the Treasury (2025). Panel B further explores the differential rise between commercial and homeowners 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 (Forthcoming). 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 Homeowners Insurance, by Year



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

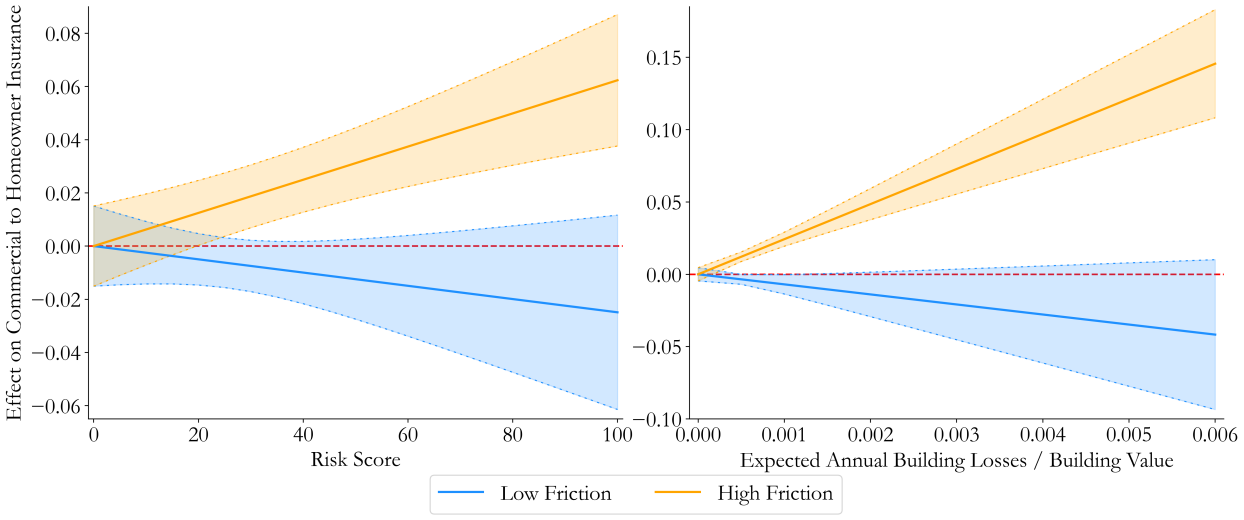


Figure 7: Effect of Insurance Cost Increase on Rents and Profits

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. Panel C shows the cumulative effect of insurance cost increases on rent and NOI across various percentiles of insurance cost increases. Specifically, the time-varying pass-through rates shown in Panel B and percentiles of percentage increase in insurance cost to operating expenses (to account for general expense inflation) during each year are used. All panels include CBSA × year and property fixed effects in the underlying regressions.

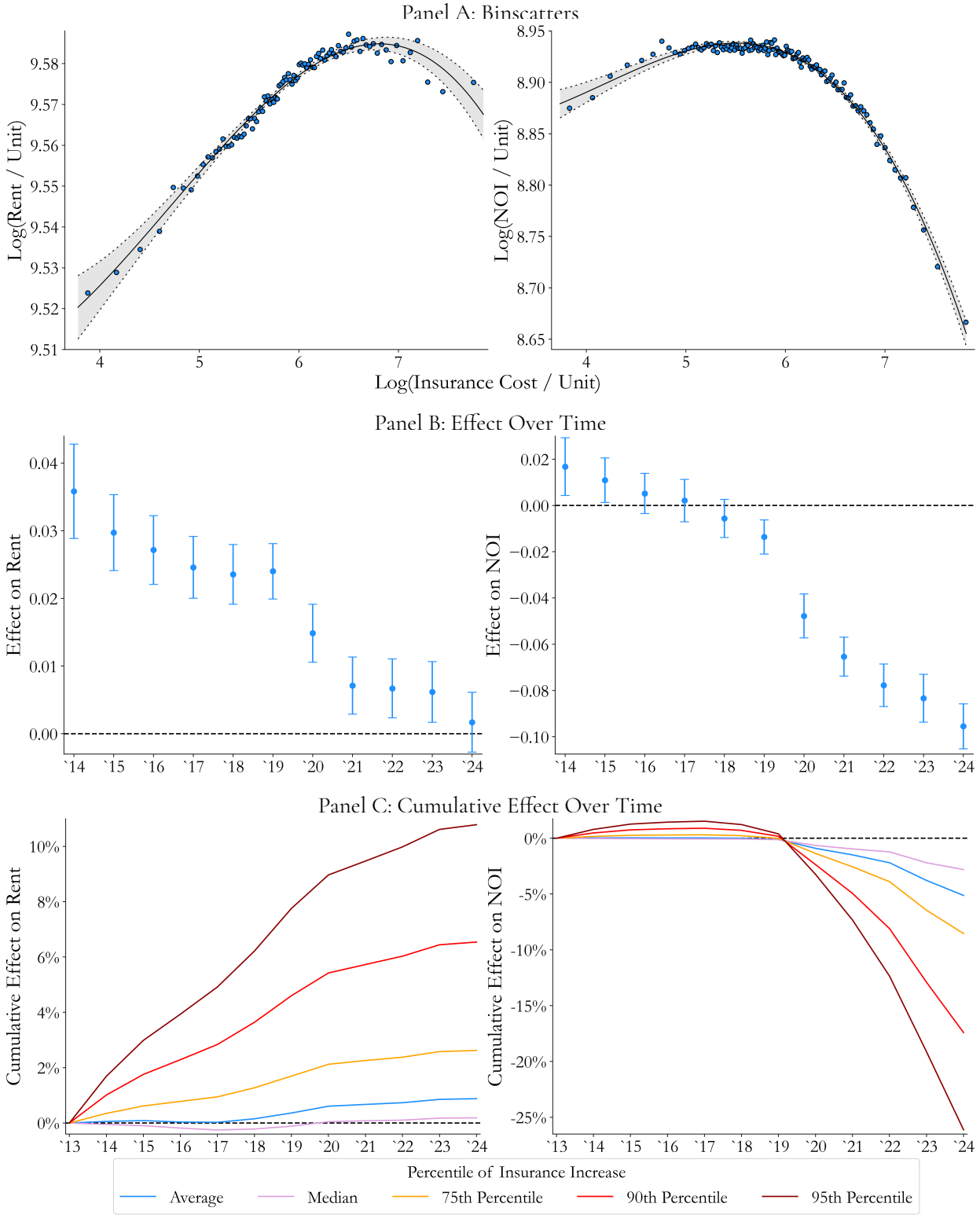


Figure 8: Role of Property Owner Size

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 3). Property ownership is based on transaction and holdings data from Real Capital Analytics.

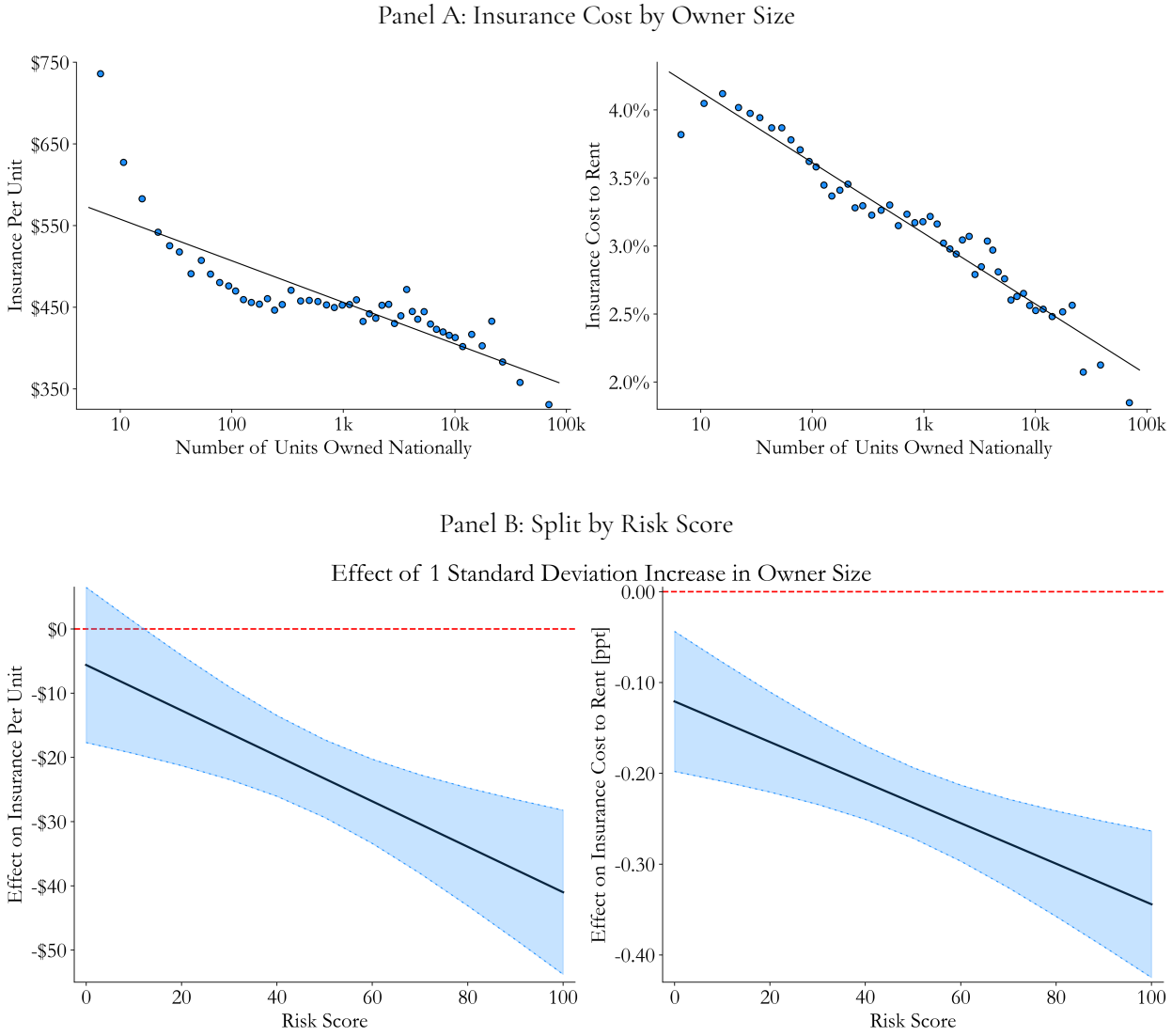
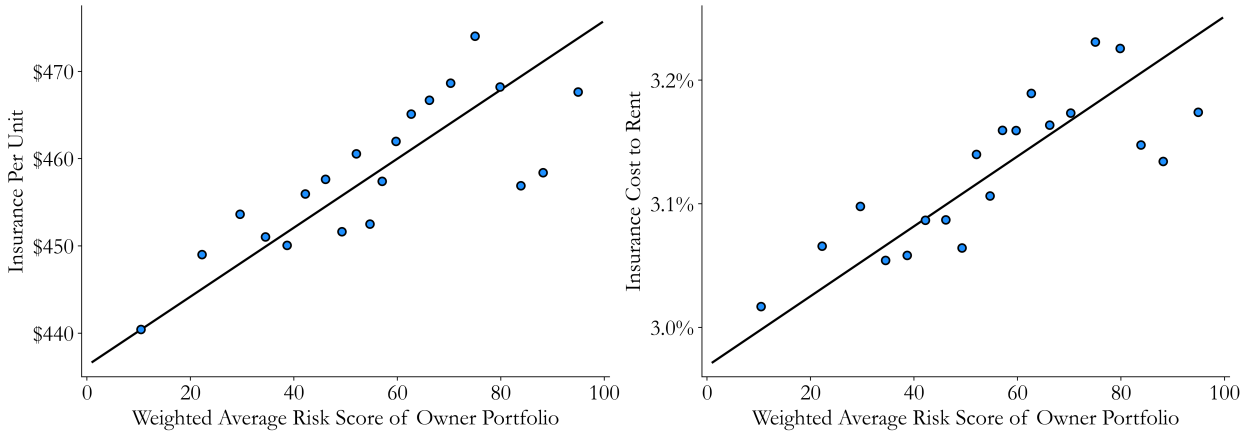


Figure 9: Role of Average Risk of Owner Portfolio

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 × 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 × 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

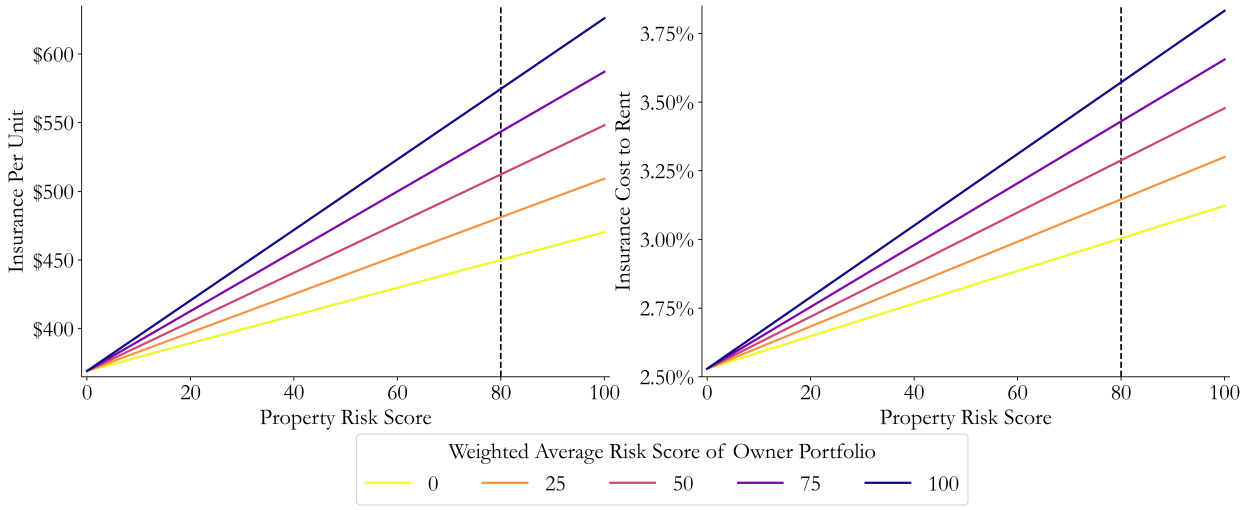
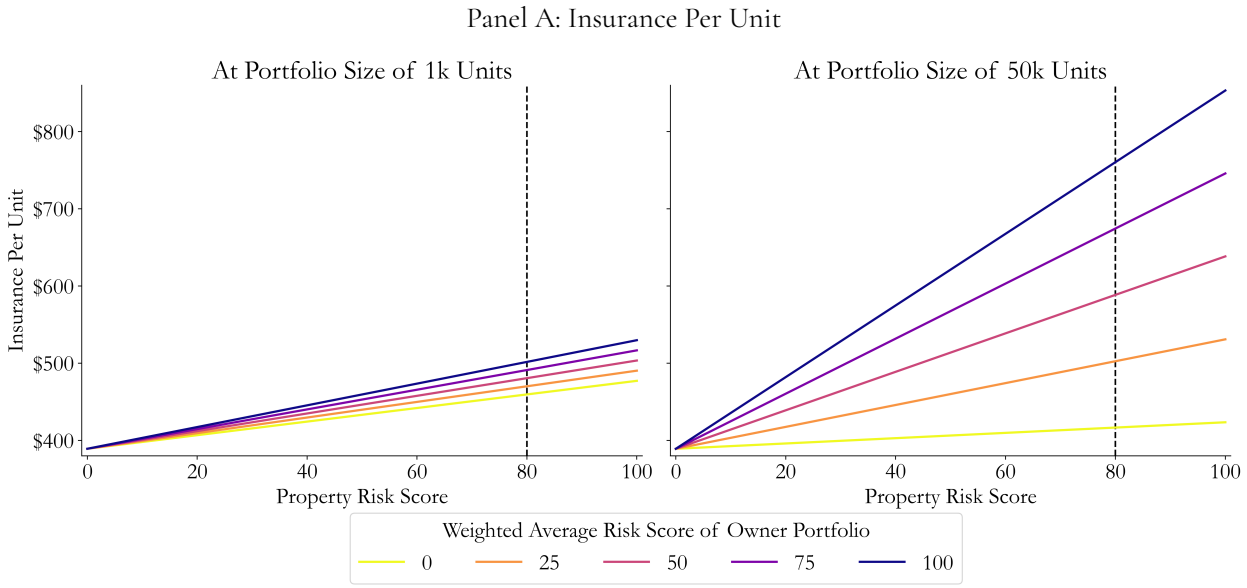


Figure 10: Role of Average Risk of Owner Portfolio Across Owner Size

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.



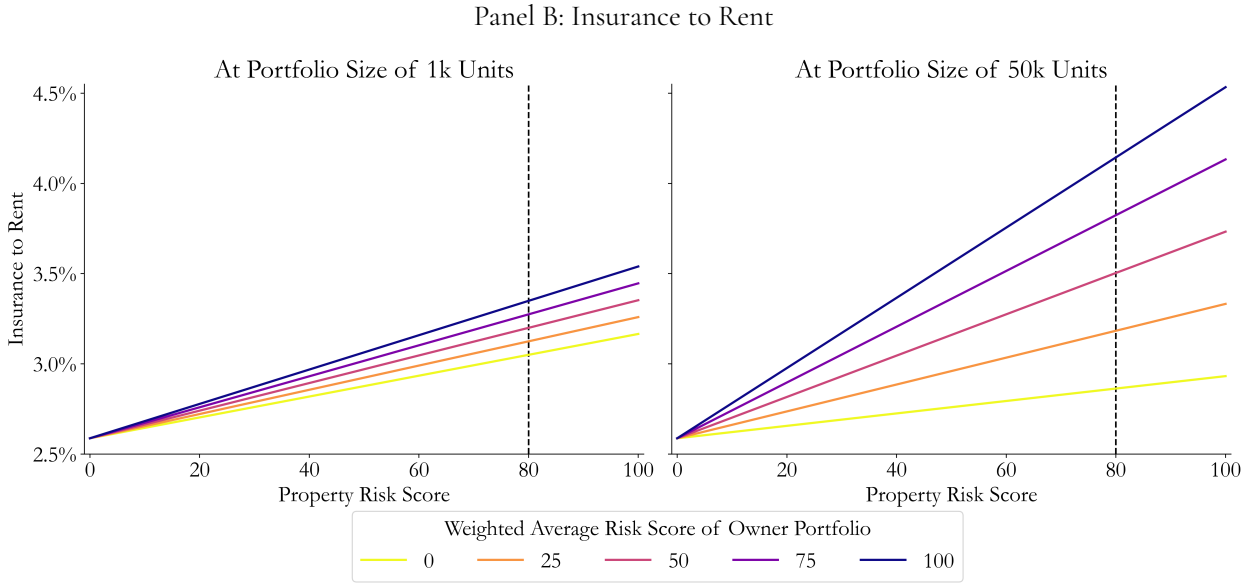
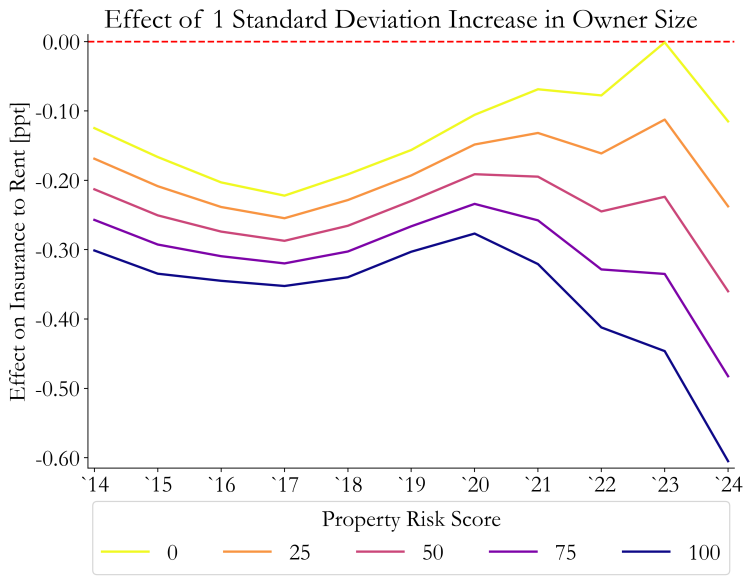


Figure 11: Role of Property Owner Size Over Time

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 25, while the right subpanel shows the same effects for properties with a risk score of 75. 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

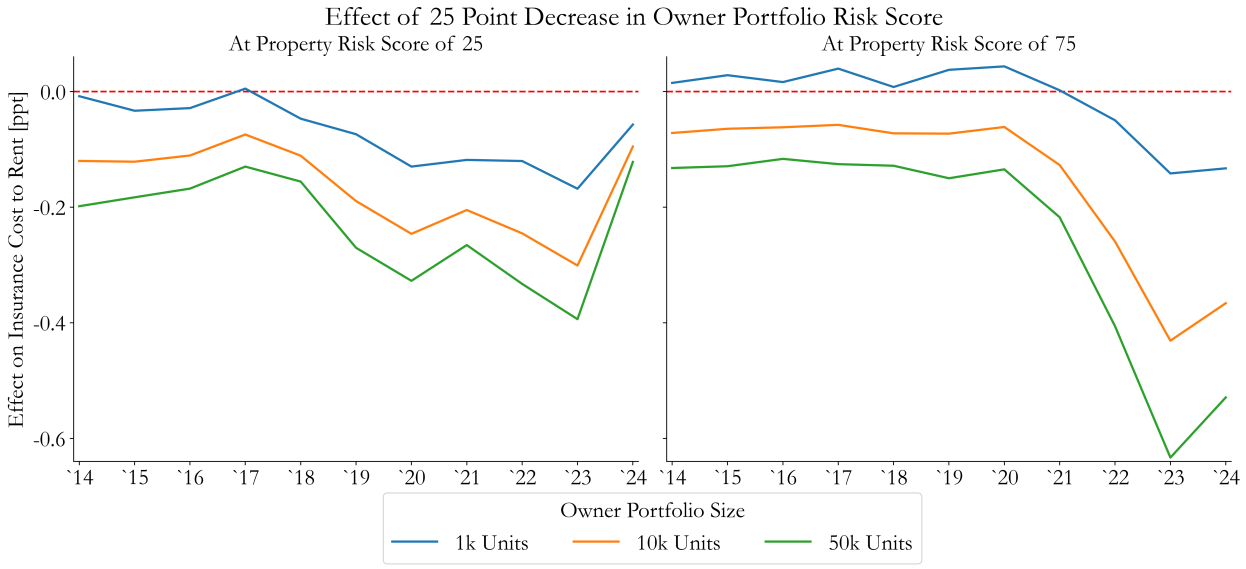


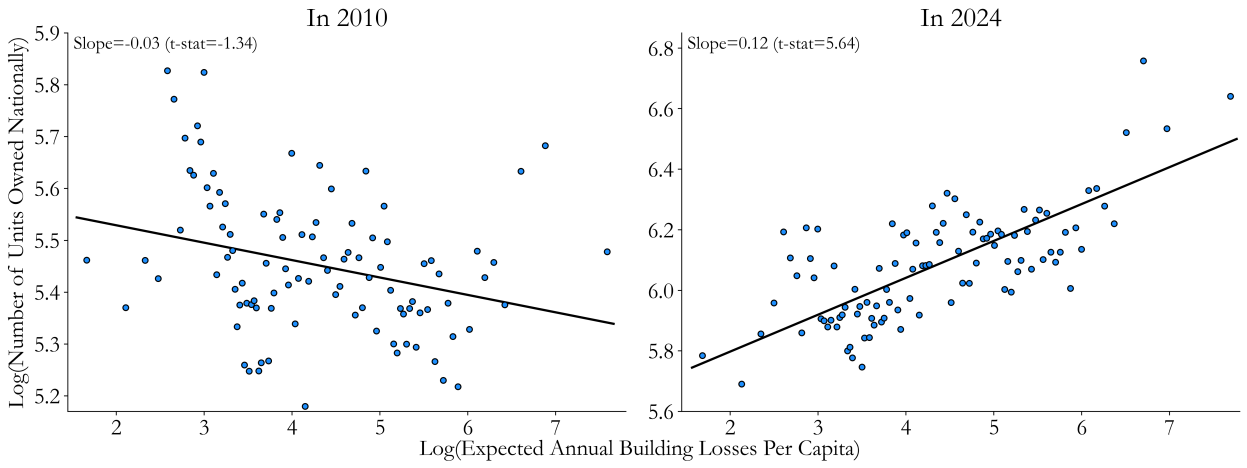
Figure 12: Effect of Property Risk on Owner Size

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

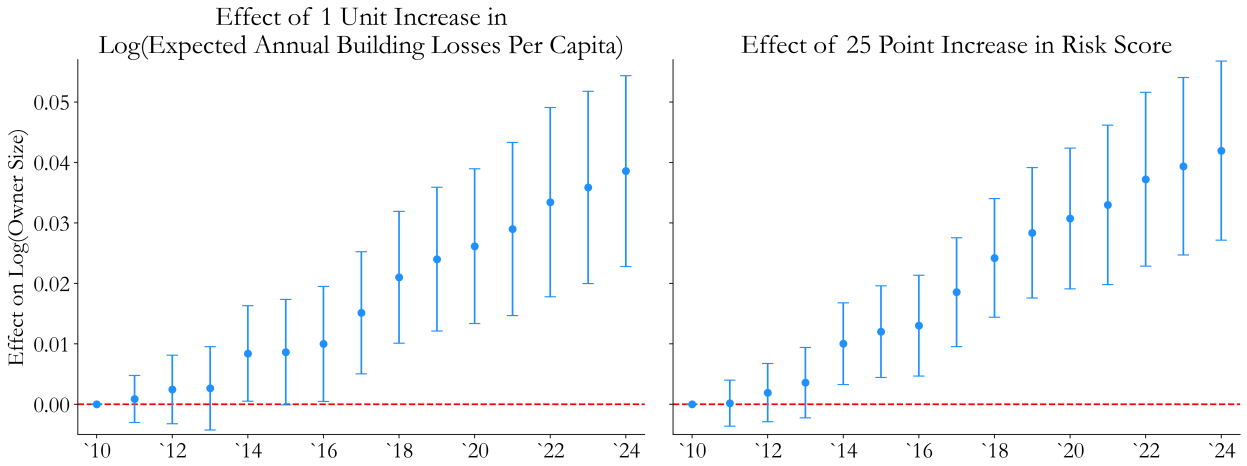


Table 1: Effects of Reinsurance Exposure on Rise in Insurance Cost

This table examines how state-level exposure to reinsurance markets influences the extent to which rising national reinsurance costs are passed through to commercial property insurance premiums. The dependent variable in all columns is the change in insurance cost per unit for property i in state s and year t. Reinsurance exposure is measured at the state level as the weighted average share of direct premiums ceded to unaffiliated reinsurers by insurers operating in the state, following the methodology of Keys and Mulder (2025). ΔReins. Cost denotes the annual change in the Guy Carpenter Rate-On-Line Index. Columns (1)-(3) estimate the interaction between reinsurance cost changes and state reinsurance exposure. Columns (4)-(7) introduce a triple interaction with FEMA tract-level disaster risk scores to examine whether the pass-through of rising reinsurance costs is more pronounced for properties in higher-risk locations. Robust standard errors are double clustered at the state and year levels.

Dep. Variable:	ΔInsurance Cost Per Unit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reins. Exposure	60.98*			111.5			
	(2.12)			(0.71)			
ΔReins. Cost× Reins. Exposure	1924.3***	1919.1***	1802.4***	−44.06	−38.03	15.99	
	(6.56)	(4.67)	(4.74)	(−0.25)	(−0.09)	(0.04)	
Risk Score				10.89	28.66		
				(0.55)	(1.03)		
ΔReins. Cost × Risk Score				−258.6***	−257.3***	−227.2***	
				(−6.05)	(−3.37)	(−3.09)	
Reins. Exposure × Risk Score				−84.19	−201.4		
				(−0.45)	(−0.98)		
ΔReins. Cost × Reins. Exposure				2617.3***	2593.9***	2346.0***	2338.2***
× Risk Score				(10.54)	(4.63)	(4.66)	(4.52)
Year FE	✓	✓	✓	✓	✓	✓	✓
State FE		✓			✓		
Property FE			✓			✓	✓
Year × Risk Score							✓
Year × Reins. Exposure							✓
Observations	325,695	325,695	312,907	325,637	325,637	312,851	312,851
Adjusted R^2	0.0849	0.0915	0.0413	0.0871	0.0934	0.0427	0.0432

t-statistics in parentheses.

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

Table 2: 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 (Forthcoming) 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 Homeowners Insurance Cost			
	(1)	(2)	(3)	(4)
Lagged Loss Ratio	0.00239***			
	(2.76)			
$\mathbb{1}$(Low Friction) × Lagged Loss Ratio		0.000870		
		(0.59)		
$\mathbb{1}$(High Friction) × Lagged Loss Ratio		0.00343***		
		(4.11)		
$\mathbb{1}$(Low Risk Score) × Lagged Loss Ratio			0.00232	0.000885
			(0.93)	(0.36)
$\mathbb{1}$(High Risk Score) × Lagged Loss Ratio			−0.000918	0.00515***
			(−0.59)	(4.89)
States Included	All	All	Low	High
Property FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Observations	158,045	158,045	80,517	77,528
Adjusted R^2	0.823	0.823	0.840	0.801

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

Table 3: Effects of Homeowners Insurance Market Frictions on Commercial Insurance Cost

This table implements a border county-pair stacked difference-in-differences design to evaluate whether frictions in homeowners insurance markets spill over to commercial property insurance. County-pairs are formed by matching adjacent counties that straddle a state border. Within each county-pair, one county is located in a state with high homeowners insurance frictions, i.e., *High-Friction* = 1, and the neighboring county across the border is located in a state with low homeowners frictions; the homeowners friction measure is adopted from Oh, Sen, and Tenekedjieva (Forthcoming). In addition, both states in the county-pair are required to have low frictions in commercial property insurance rates. *Treated* equals one for county-pairs that experience a large natural-disaster shock during the sample period. For each treated county-pair, the disaster year is defined as the peak-damage year for the pair's average county property damage per capita, conditional on the peak being in the top decile across all county-pairs and at least 10x the previous year's damage. Cohorts are defined at the event level: in each disaster year, the treated county-pairs and the corresponding not-yet-treated and never-treated county-pairs that serve as controls form a cohort. *Post* equals one for all county-pairs in a cohort in the disaster year and all subsequent years, and zero otherwise. The dependent variable in all columns is the annual percent change in commercial insurance cost at the property-year level. Fixed effects are indicated at the bottom of each column. Robust standard errors are double clustered by the county-pairs and the states.

Dep. Variable:	Pct. Change in Insurance Cost	
	(1)	(2)
$\mathbb{1}$(High Friction) × $\mathbb{1}$(Post) × $\mathbb{1}$(Treated)	0.193**	0.222***
	(2.79)	(9.51)
Cohort × State × Event-year FE	✓	✓
Cohort × State × County-pair FE	✓	✓
Cohort × Event-year × County-pair FE	✓	✓
Property FE		✓
Observations	49,707	49,624
Adjusted R^2	0.0912	0.2342

t statistics in parentheses

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

Table 4: Pass-through of Insurance Cost Rise

This table examines the pass-through 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)	0.0221***	0.0162***	−0.0411***	−0.0461***
	(9.09)	(10.03)	(−10.86)	(−13.48)
Property FE	✓	✓	✓	✓
Year FE	✓		✓	
CBSA × Year FE		✓		✓
Observations	411,276	411,276	411,276	411,276
Adjusted R^2	0.976	0.979	0.918	0.924

t statistics in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Role of Owner Size

This table examines how the size of a property owner affects insurance costs as a share of rent and how this relationship varies by property risk level and over time. The dependent variable in all columns is the ratio of insurance cost to rent. Owner size is defined as the log of the total number of multifamily units owned nationally by each owner in a given year. Columns (1) and (2) show the effect of owner size and its interaction with property risk scores, while column (3) adds an interaction with a post-2018 indicator to assess time-varying effects. All regressions include CBSA × year fixed effects and property fixed effects. Risk score data are from FEMA's National Risk Index. Property ownership information is sourced from Real Capital Analytics. Robust standard errors are clustered at the census tract level.

Dep. Variable:	Insurance Cost to Rent		
	(1)	(2)	(3)
Log(Owner Size)	−0.00109***	−0.000410**	−0.000694***
	(−12.19)	(−2.34)	(−3.79)
Log(Owner Size) × Risk Score		−0.00122***	−0.000894***
		(−3.91)	(−2.74)
$\mathbb{1}$(2018 or Later) × Log(Owner Size)			0.000365***
			(4.86)
$\mathbb{1}$(2018 or Later) × Risk Score			0.00297***
			(2.92)
$\mathbb{1}$(2018 or Later) × Log(Owner Size) × Risk Score			−0.000426***
			(−3.42)
CBSA × Year FE	✓	✓	✓
Property FE	✓	✓	✓
Observations	301,457	301,457	301,457
Adjusted R^2	0.767	0.767	0.767
Mean of Dep. Variable	0.0335	0.0335	0.0335

t statistics in parentheses.

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

Table 6: Role of Average Risk of Owner Portfolio

This table examines how the average riskiness of a property owner's national portfolio affects insurance costs. The dependent variable in all columns is the ratio of insurance cost to rent. The key independent variable is the owner's portfolio risk score, defined as the units-weighted average FEMA National Risk Index risk score across all properties owned nationally by that owner in a given year. Column (1) estimates the baseline relationship between portfolio risk and insurance costs, controlling for owner size. Column (2) adds an interaction between portfolio risk and the individual property's own risk score to assess whether insurers price a property differently depending on the broader risk characteristics of the owner's portfolio. Columns (3) and (4) introduce interactions with a post-2018 indicator to capture how the relevance of portfolio-level risk in insurance pricing has evolved in recent years. All regressions include property fixed effects and CBSA × year fixed effects. Robust standard errors are clustered at the census tract level.

Dep. Variable:	Insurance Cost to Rent			
	(1)	(2)	(3)	(4)
Portfolio Risk Score	0.00370***	−0.00159	0.00204**	−0.00587***
	(4.45)	(−1.03)	(2.30)	(−3.54)
Portfolio Risk Score × Property Risk Score		0.00986***		0.0137***
		(3.58)		(4.78)
$\mathbb{1}$(2018 or Later) × Portfolio Risk Score			0.00254***	0.00618***
			(4.48)	(6.37)
$\mathbb{1}$(2018 or Later) × Property Risk Score				0.00148
				(1.57)
$\mathbb{1}$(2018 or Later) × Portfolio Risk Score × Property Risk Score				−0.00542***
				(−3.54)
CBSA × Year FE	✓	✓	✓	✓
Property FE	✓	✓	✓	✓
Observations	301,457	301,457	301,457	301,457
Adjusted R^2	0.767	0.767	0.767	0.767
Mean of Dep. Variable	0.0335	0.0335	0.0335	0.0335

t statistics in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Role of Owner Size and Average Risk of Owner Portfolio, Holding Ownership of Focal Property Fixed

This table examines the role of owner size and owner portfolio risk while holding the ownership of the focal property fixed. The dependent variable is the change in the ratio of insurance cost to rent over the previous three years and the key independent variables (ΔLog(Owner Size) and ΔPortfolio Risk Score) are defined as changes over the same three-year period. Only property-year observations where the owner of the property remains the same as it was three years ago are included. All regressions include year fixed effects and control for time-varying effects of local risk. Robust standard errors are two-way clustered by owner and census tract.

Dep. Variable:	Insurance Cost to Rent$_t$ − Insurance Cost to Rent$_{t-3}$			
	(1)	(2)	(3)	(4)
ΔLog(Owner Size)	−0.00199***	−0.000747		
	(−6.66)	(−1.57)		
ΔLog(Owner Size) × Property Risk Score		−0.00223***		
		(−2.71)		
ΔPortfolio Risk Score			0.00370**	−0.00434
			(2.13)	(−1.54)
ΔPortfolio Risk Score × Property Risk Score				0.0148***
				(2.91)
Year FE	✓	✓	✓	✓
Year × Property Risk Score	✓	✓	✓	✓
Observations	132,649	132,649	132,649	132,649
Adjusted R^2	0.114	0.114	0.113	0.113
Mean of Dep. Variable	0.00731	0.00731	0.00731	0.00731

t statistics in parentheses.

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

Table 8: Effect on Owner Size

This table examines how the riskiness of a property's location relates to the size of its owner and how this relationship has changed over time. The dependent variable in all columns is the log of the total number of multifamily units owned nationally by the property's owner in a given year. Columns (1) and (2) use the FEMA risk score; columns (3) and (4) use expected annual building losses per capita from FEMA's National Risk Index as the measure of local risk. Each risk measure is interacted with an indicator for the post-2018 period to assess how the relationship between local risk and owner size has evolved. Columns (2) and (4) include property fixed effects, which allow the relationship to be estimated based on changes in ownership for the same property over time. All specifications include year fixed effects. Robust standard errors are two-way clustered by owner and year.

Dep. Variable:	Log(Owner Size)			
	(1)	(2)	(3)	(4)
$\mathbb{1}$(2018 or Later) × Risk Score	0.107***	0.104***		
	(4.76)	(4.63)		
Risk Score	−0.592***			
	(−9.29)			
$\mathbb{1}$(2018 or Later) × Log(Expected Building Annual Losses)			0.0241***	0.0237***
			(5.18)	(4.19)
Log(Expected Annual Building Losses)			−0.189***	
			(−9.15)	
Year FE	✓	✓	✓	✓
Property FE		✓		✓
Observations	1,932,802	1,932,750	1,932,802	1,932,750
Adjusted R^2	0.009	0.890	0.013	0.890

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: 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.

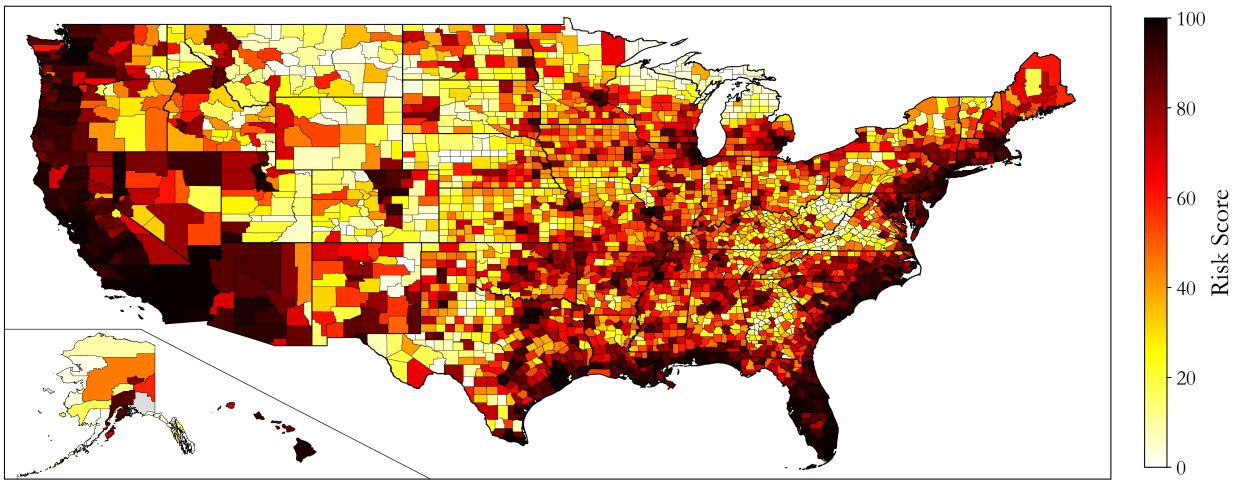
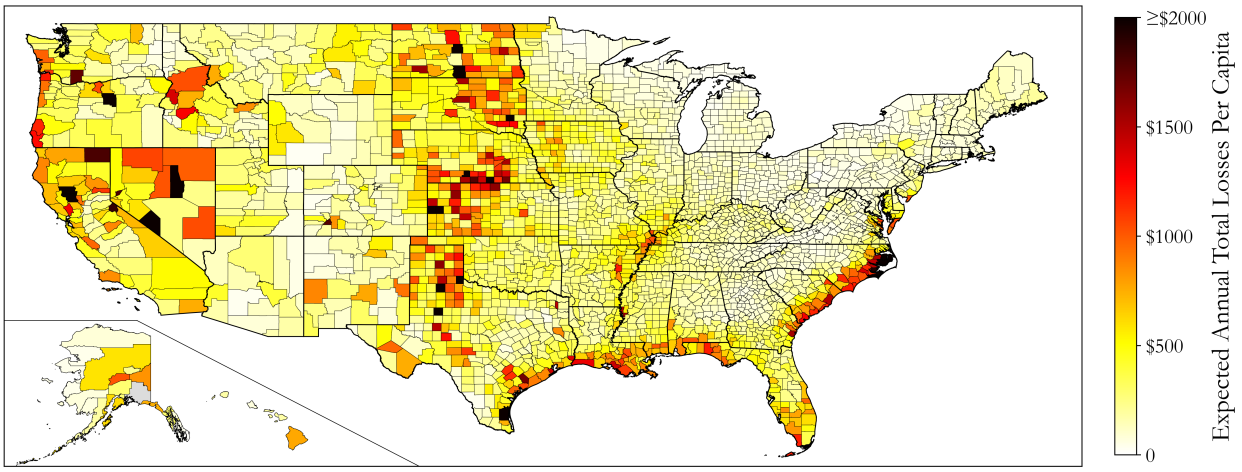


Figure IA.2: Expected Annual Losses, County-level Maps

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

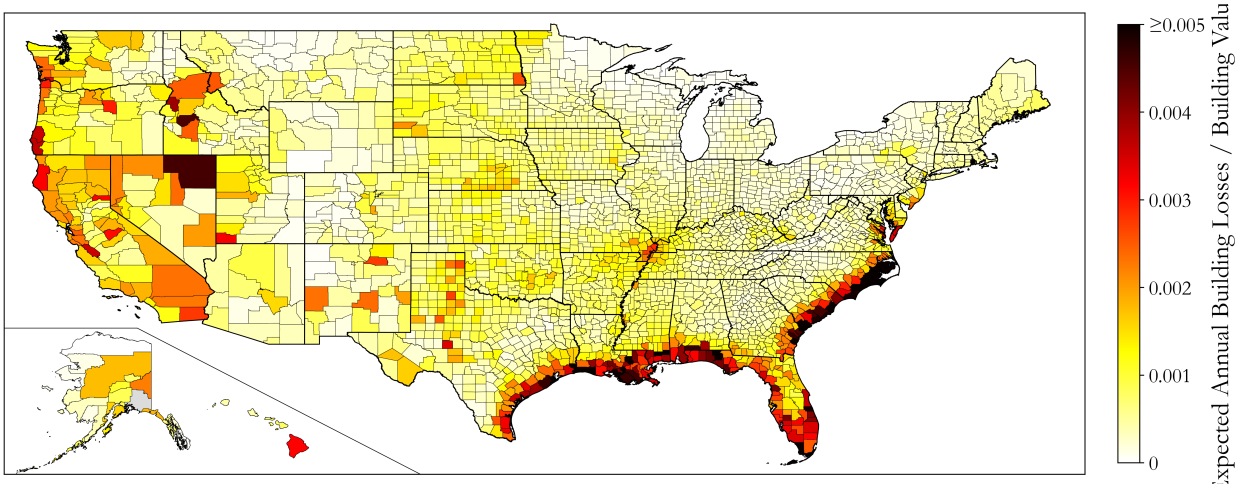


Figure IA.3: Risk Scores and Expected Annual Losses and the Rise in Insurance Costs, Additional Measures

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

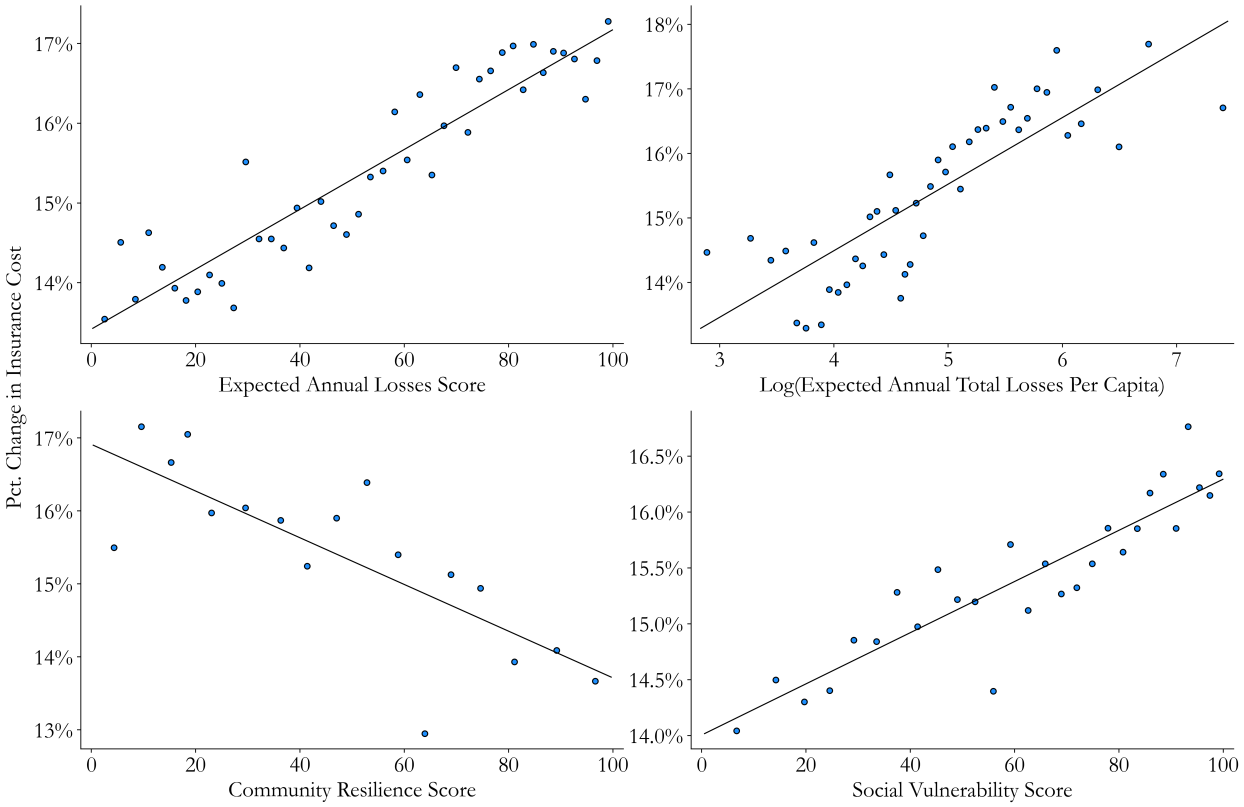
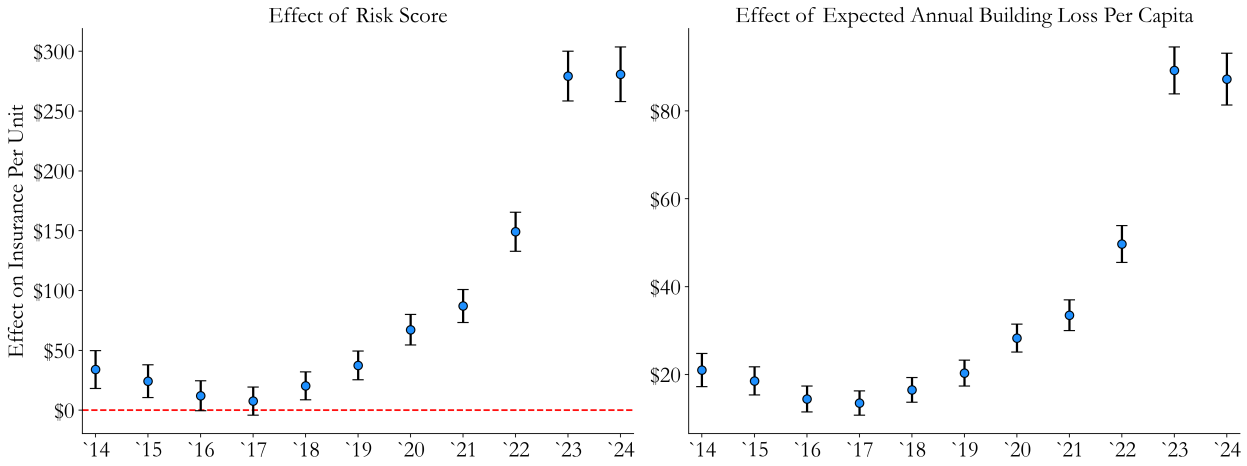


Figure IA.4: Risk Scores and Expected Annual Losses and the Rise in Insurance Costs, Over Time

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

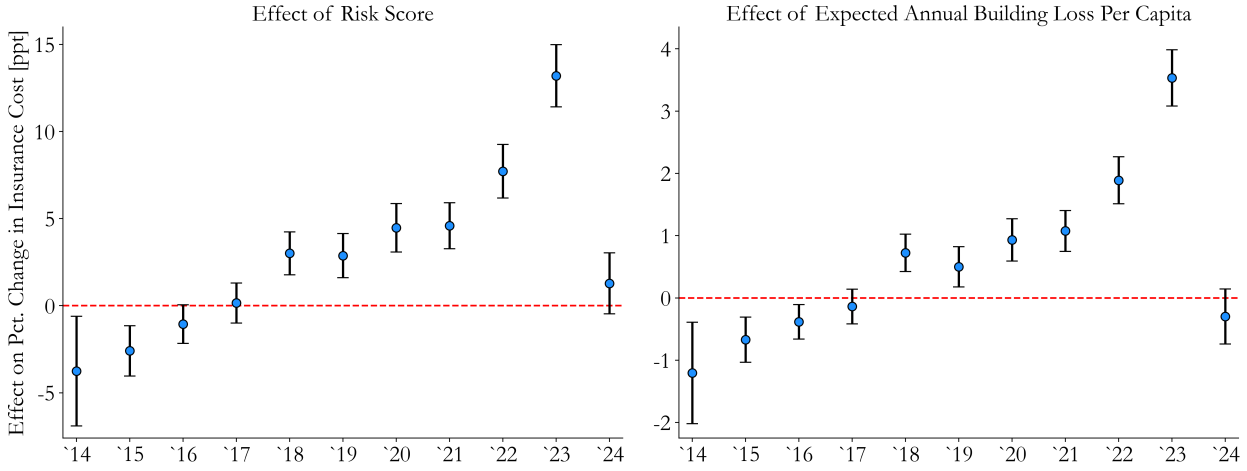
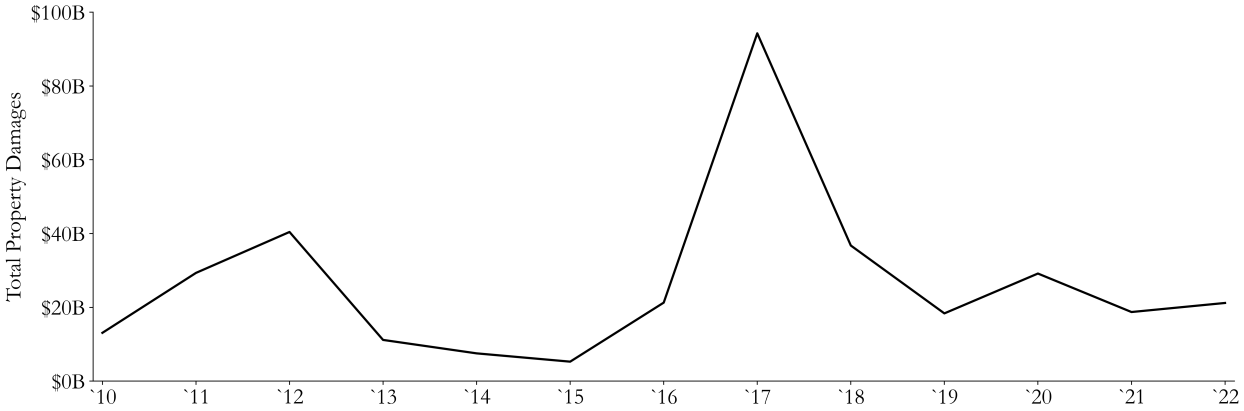


Figure IA.5: Property Damages Between 2010-22

This figure shows the time-series of national-level total property damages in each year (Panel A) and the average annual property 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

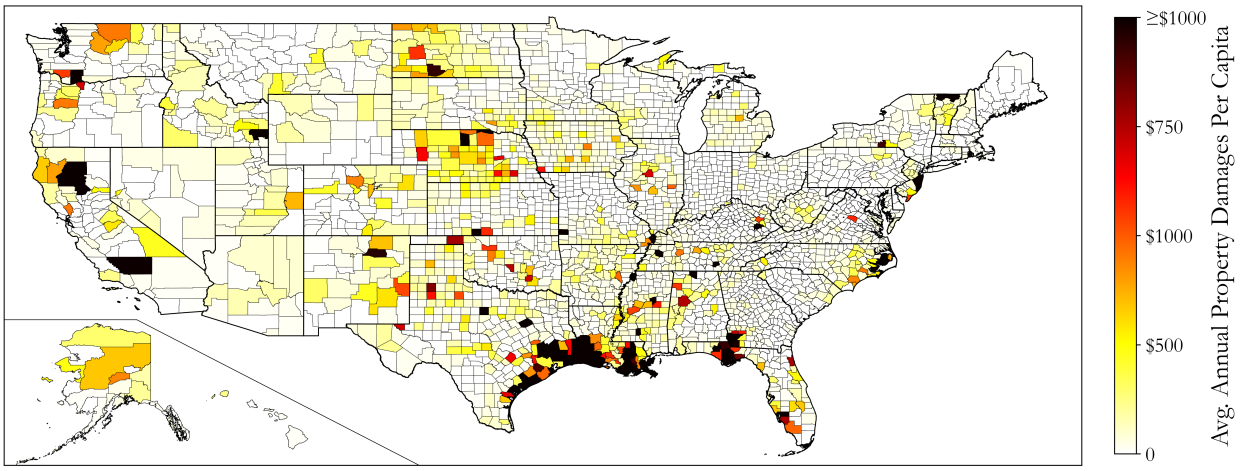
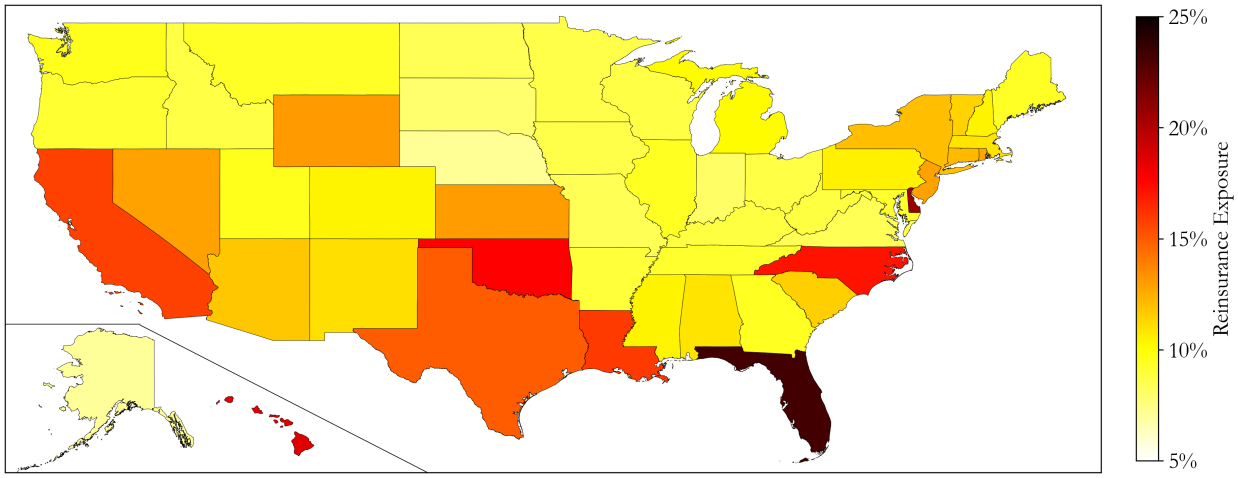


Figure IA.6: Reinsurance Exposure

This figure examines the state-level exposure to reinsurance markets (Panel A) and the stability of the percentage of risk ceded to unaffiliated reinsures at the company level and reinsurance exposure at the state level over time (Panel B).

Panel A: Reinsurance Exposure by State



Panel B: Stability of Reinsurance Exposure

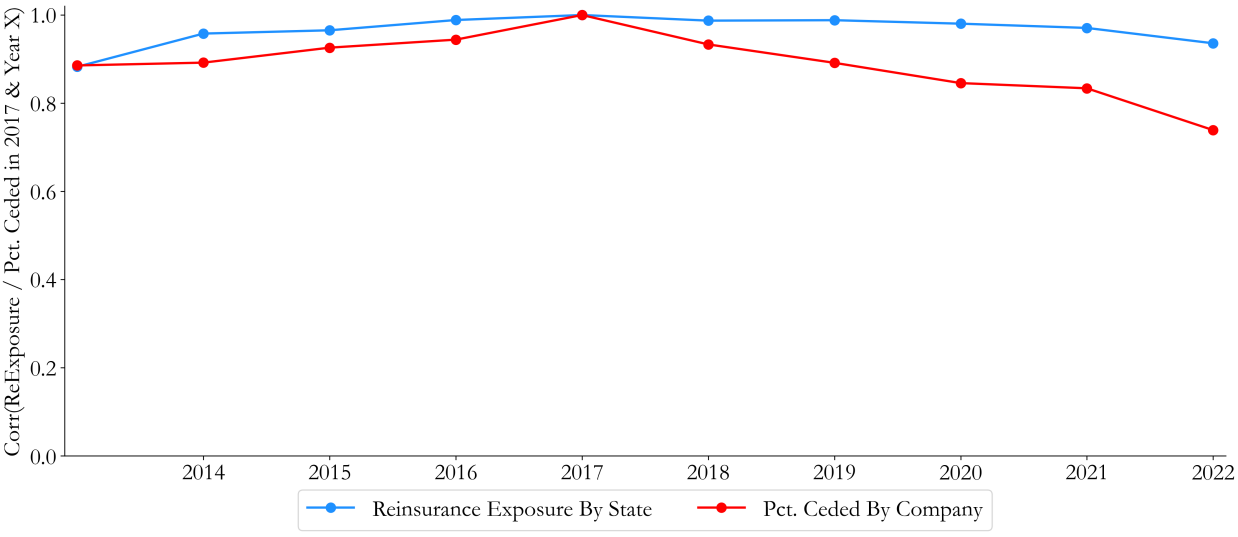
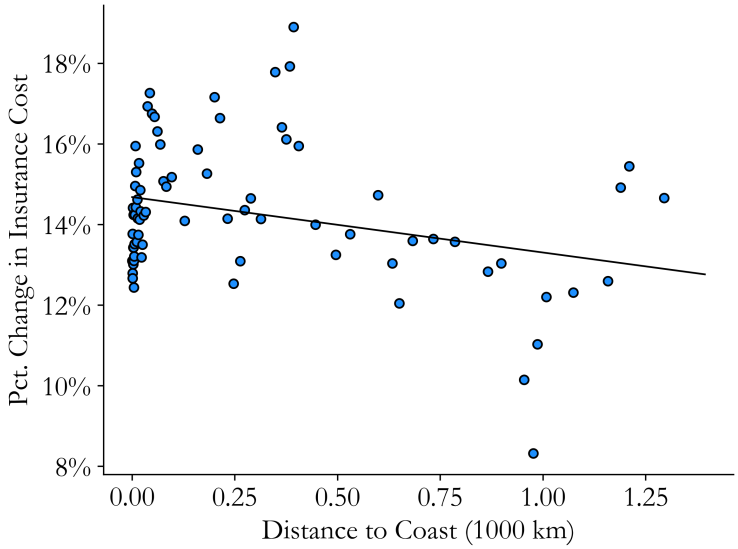


Figure IA.7: Location and the Rise in Insurance Costs

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

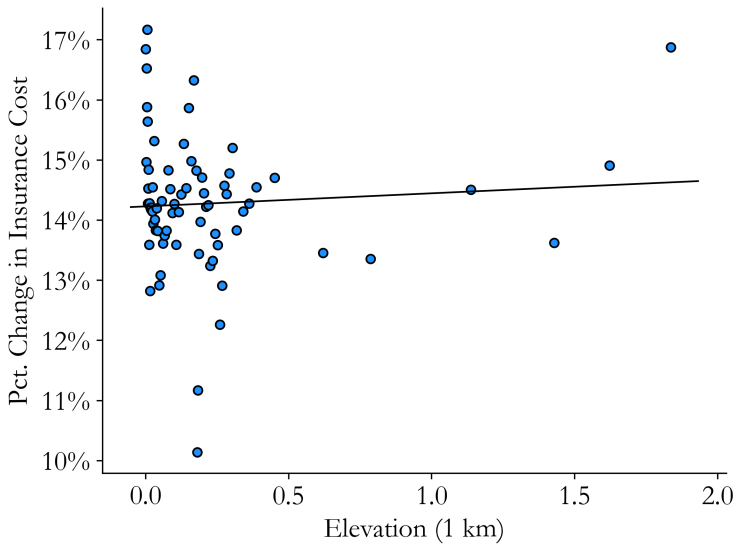


Figure IA.8: Property Features and the Rise in Insurance Costs

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.

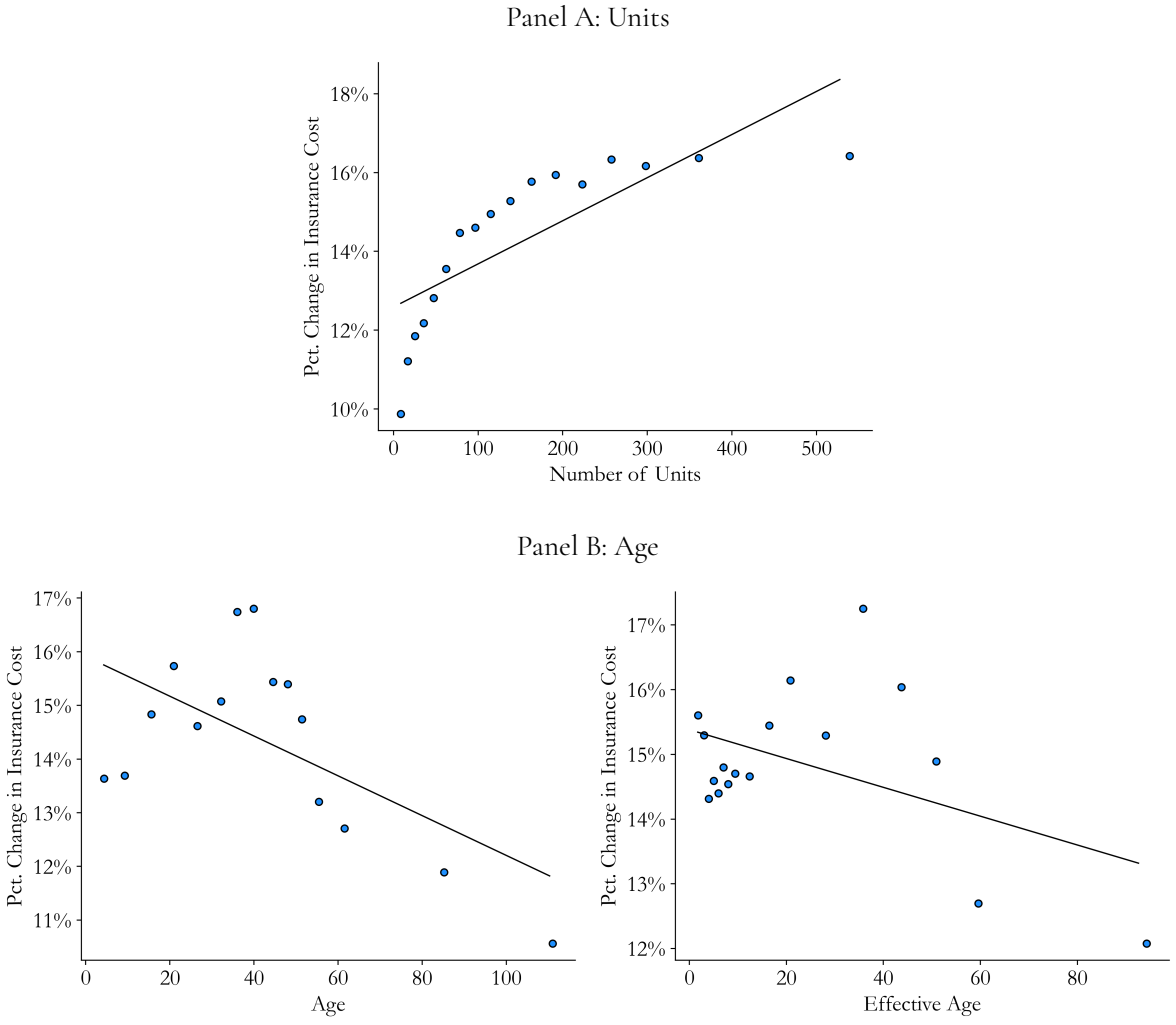
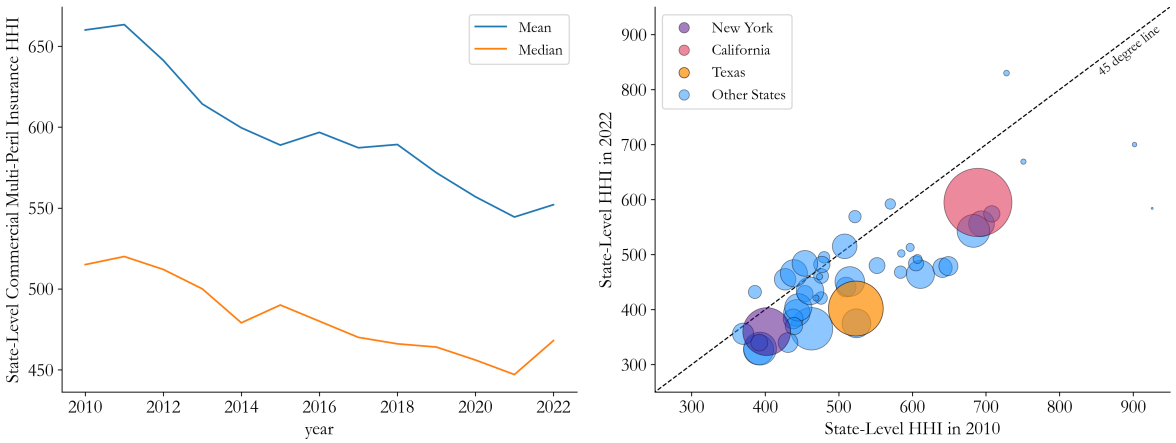


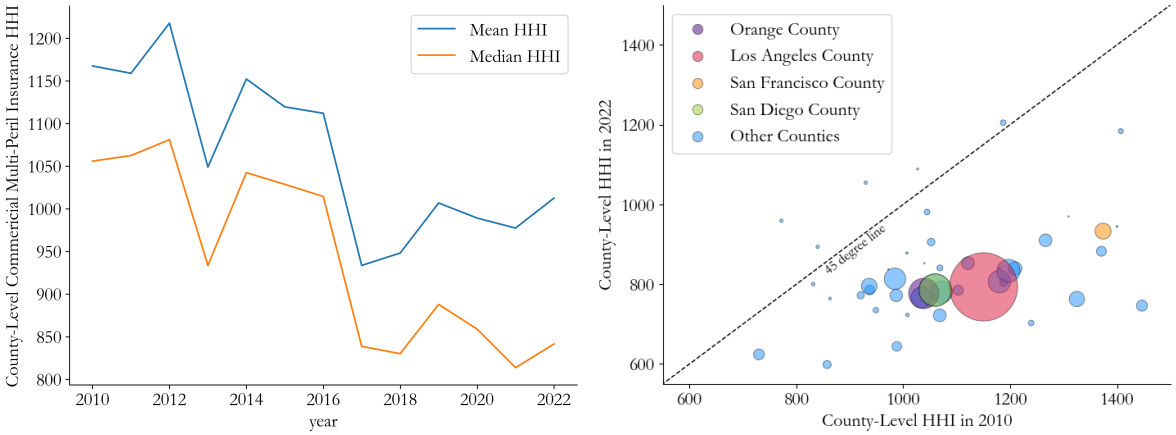
Figure IA.9: Insurance Market Concentration and the Rise in Insurance Costs

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

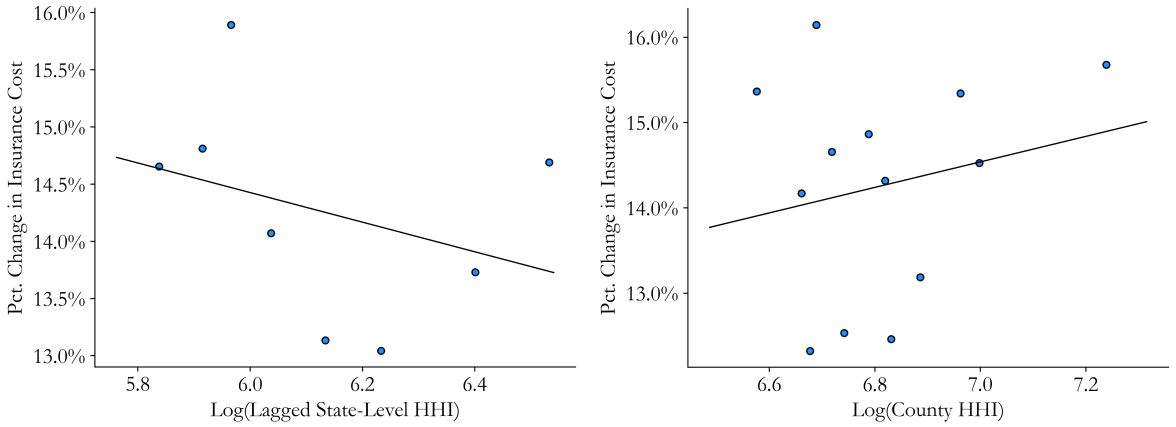


Figure IA.10: Cumulative Effect of Rise in Insurance Cost on Rent and NOI, Using Percentage Change in Insurance Cost Per Unit

This figure replicates Figure 7, Panel C using the percentiles of percentage change in insurance cost per unit instead of percentiles of percentage change in the ratio of insurance cost to total operating expenses.

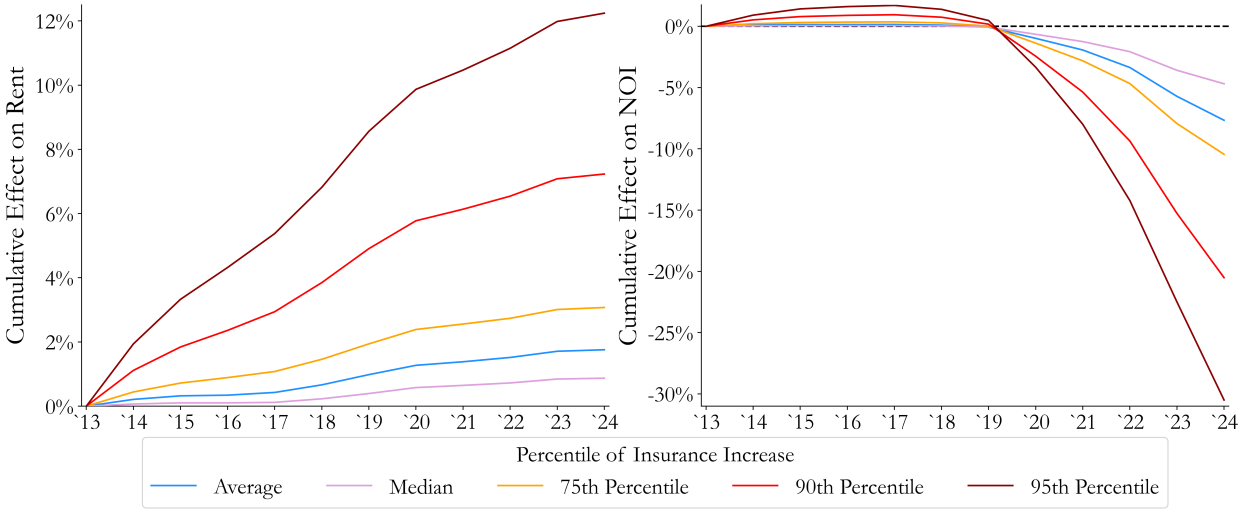


Figure IA.11: Role of Property Owner Size, Split by Expected Annual Losses

This figure replicates Figure 8, Panel B using expected annual losses rather than risk score.

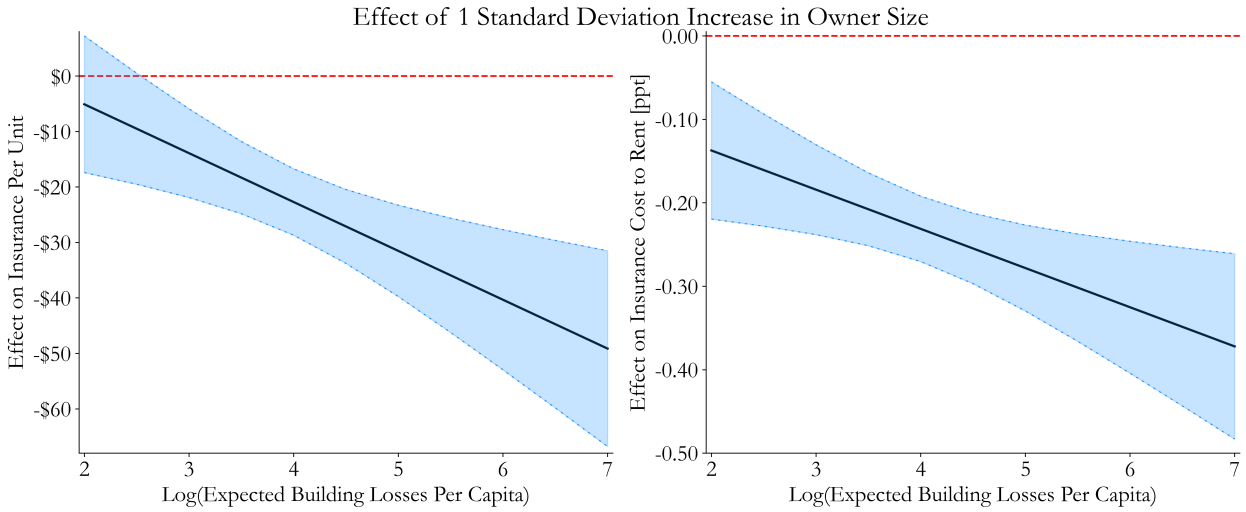


Figure IA.12: Role of Average Risk of Owner Portfolio, Weighted Expected Annual Losses

This figure replicates Figure 9, Panel A using the weighted expected annual losses across the owner's portfolio rather than the weighted risk score across the owner's portfolio.

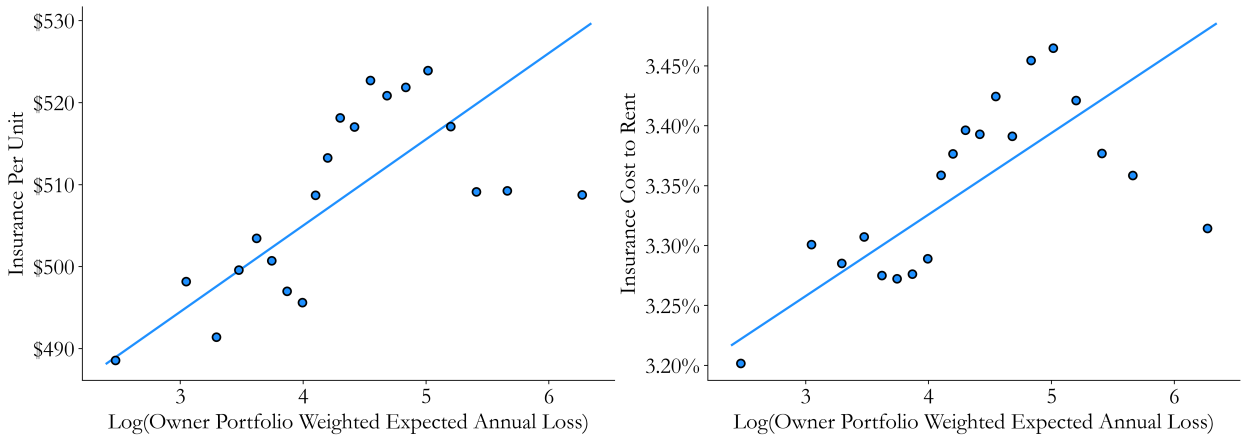


Table IA.I: Effects of Reinsurance Exposure on Rise in Insurance Cost

This table replicates columns (4) to (7) of Table 1 using expected annual losses per capita instead of risk score. The dependent variable in all columns is the change in insurance cost per unit for property i in state s and year t. Reinsurance exposure is measured at the state level as the weighted average share of direct premiums ceded to unaffiliated reinsurers by insurers operating in the state, following the methodology of Keys and Mulder (2025). ΔReins. Cost denotes the annual change in the Guy Carpenter Rate-On-Line Index. Robust standard errors are double clustered at the state and year levels.

Dep. Variable:	ΔInsurance Cost Per Unit			
	(1)	(2)	(3)	(4)
Reins. Exposure	34.88			
	(0.28)			
ΔReins. Cost× Reins. Exposure	-955.8*	-1044.9	-699.7	
	(-1.94)	(-1.37)	(-0.86)	
Log(Expected Annual Losses Per Capita)	-0.738	2.974		
	(-0.21)	(0.43)		
ΔReins. Cost × Log(Expected Annual Losses Per Capita)	-43.96**	-47.05*	-34.44	
	(-2.33)	(-2.13)	(-1.42)	
Reins. Exposure × Log(Expected Annual Losses Per Capita)	5.769	-16.43		
	(0.22)	(-0.37)		
ΔReins. Cost × Reins. Exposure	531.7***	551.5***	455.5***	457.8***
× Log(Expected Annual Losses Per Capita)	(5.99)	(4.06)	(3.22)	(3.23)
Year FE	✓	✓	✓	✓
State FE		✓		
Property FE			✓	✓
Year × Risk Score				✓
Year × Reins. Exposure				✓
Observations	325,705	325,705	312,920	312,920
Adjusted R^2	0.0878	0.0941	0.0430	0.0436

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

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

This table replicates Table 2 using the percentage of homeowners 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 Homeowners Insurance Cost			
	(1)	(2)	(3)	(4)
Lagged Pct. Claims	0.0201			
	(1.29)			
$\mathbb{1}$(Low Friction) × Lagged Pct. Claims		-0.0164		
		(-0.61)		
$\mathbb{1}$(High Friction) × Lagged Pct. Claims		0.0451***		
		(4.38)		
$\mathbb{1}$(Low Risk Score) × Lagged Pct. Claims			-0.000446	0.0265
			(-0.01)	(1.23)
$\mathbb{1}$(High Risk Score) × Lagged Pct. Claims			-0.0298	0.0628***
			(-1.36)	(3.18)
States Included	All	All	Low	High
Property FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Observations	158,045	158,045	80,517	77,528
Adjusted R^2	0.823	0.823	0.840	0.801

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

Table IA.III: Role of Owner Size, Expected Annual Losses

This table replicates columns (2) and (3) of Table 5 using expected annual losses instead of risk score. The dependent variable in all columns is the ratio of insurance cost to rent. Owner size is defined as the log of the total number of multifamily units owned nationally by each owner in a given year. All regressions include CBSA × year fixed effects and property fixed effects. Expected annual losses data are from FEMA's National Risk Index. Property ownership information is sourced from Real Capital Analytics. Robust standard errors are clustered at the census tract level.

Dep. Variable:	Insurance Cost to Rent	
	(1)	(2)
Log(Owner Size)	0.00000880	−0.000449
	(0.03)	(−1.28)
Log(Owner Size) × Log(Expected Annual Losses Per Capita)	−0.000256***	−0.000174**
	(−3.21)	(−2.10)
$\mathbb{1}$(2018 or Later) × Log(Owner Size)		0.00056***
		(3.99)
$\mathbb{1}$(2018 or Later) × Log(Expected Annual Losses Per Capita)		0.0004826*
		(1.89)
$\mathbb{1}$(2018 or Later) × Log(Owner Size) × Log(Expected Annual Losses Per Capita)		−0.0000988***
		(−3.11)
CBSA × Year FE	✓	✓
Property FE	✓	✓
Observations	301,457	301,457
Adjusted R^2	0.767	0.767
Mean of Dep. Variable	0.0335	0.0335

t statistics in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$