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

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**Abstract**

Using a large, novel set of property-level operating statements for multifamily properties, we analyze the drivers and consequences of rising commercial property insurance costs. We document a large and persistent increase in insurance costs across the United States over the last decade. We identify three forces behind this repricing: more aggressive pricing of local climate risk after 2018, rising reinsurance costs that amplify increases in states with greater exposure to reinsurance markets, and homeowners-market frictions that both widen the commercial-homeowners wedge and spill over into commercial policies through cross-product subsidization. On average, rent increases offset roughly 49% of the increase in insurance costs, but this burden-sharing breaks down as shocks become larger and more recent, shifting more of the burden onto owners through lower net operating income and resulting in lower property values. While average effects are modest, the upper tail of insurance shocks generates meaningful rent increases and substantial profitability losses. Finally, larger owners and owners with lower-risk portfolios obtain more favorable insurance pricing; these advantages also appear within continuing ownership relationships and as discrete insurance-cost declines following M&A events, and they increasingly coincide with a reallocation of high-risk assets toward larger owners.

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# I. Introduction

Property insurance is a cornerstone of residential and commercial real estate markets. By transferring risk away from property owners and lenders, it stabilizes cash flows and supports credit provision in the face of rare but costly disasters (Sastry and Sen, Forthcoming). That stabilizing role is under growing strain. As the frequency of billion-dollar disasters in the United States has surged, rising from roughly 3 per year in the 1980s to an average of 23 per year since 2020, insurance markets have responded with aggressive repricing.[1] While the rise in homeowners insurance premiums is now well documented (e.g., Keys and Mulder, 2025), we know much less about insurance dynamics in the commercial real estate (CRE) sector, despite its scale and economic importance.[2] How is climate risk being repriced in commercial property insurance markets? Who ultimately bears those higher costs? How does insurance repricing reshape ownership patterns and the allocation of risky real estate assets?

Answering these questions is challenging because granular property-level data on commercial insurance have been scarce. We address this gap by hand-collecting a novel set of property-level operating statements from Agency Commercial Mortgage-Backed Securities (CMBS), which allows us to observe multifamily properties and track them over time. By combining these data with additional datasets on local disaster risk, reinsurance exposure, homeowners insurance pricing, and ownership structure, we provide the first comprehensive analysis of insurance cost dynamics in the multifamily market over time and across geographies.

The commercial sector provides a particularly informative setting for studying climate-risk repricing for several reasons. First, commercial lines are less constrained by state rate regulation than homeowners insurance (Born and Klimaszewski-Blettner, 2013; Kim, Leverty, and Liu, 2025), and Agency CMBS loan covenants require comprehensive insurance coverage. Together, these features imply that observed insurance expenses in our setting provide a cleaner measure of the non-discretionary market price of climate risk than in homeowners markets, where financially constrained households may respond to higher premiums by reducing coverage or self-insuring (Cookson, Gallagher, and Mulder, 2025; Sastry, Scharlemann, Sen, and Tenekedjieva, 2025). Second, this setting allows us to study interactions across insurance lines. As we show below, commercial pricing is not frictionless: it is shaped not only by local physical risk and reinsurance markets, but also by regulatory spillovers from frictions in the homeowners insurance market, providing evidence on how multi-line insurers transmit shocks

[1] Disaster damage estimates are from the National Centers for Environmental Information (NCEI) and have been adjusted for inflation to 2024 dollars using the CPI.

[2] Sastry and Sen (Forthcoming) highlights that "understanding the exposures of 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.

across products. Third, multifamily properties separate owners from tenants, creating adjustment margins that differ from those in homeowners markets, where the same household typically purchases insurance, consumes housing, and owns the asset. Our property-level data on rents, net operating income (NOI), and ownership structure allow us to trace how insurance cost increases are reflected in rents, quantify how much of the shock is absorbed by owners through lower NOI, and examine how repricing reshapes ownership and the allocation of climate-exposed assets.[3]

We begin by documenting a broad regime shift in insurance costs. Since 2019, average annual insurance cost growth has exceeded 15%, peaking at nearly 30% in 2023. This break coincides with the transition from a soft to a hard commercial insurance market, in which catastrophic loss years were followed by tighter underwriting and substantially higher premiums. Although the largest increases appear in coastal states such as Florida, Texas, Louisiana, and California, the surge is national: we also document substantial increases in interior states, including Oklahoma, Colorado, Tennessee, and Indiana. Moreover, the same time-series pattern appears in other commercial asset classes using Bloomberg data. Although the rise in insurance costs is broad across commercial asset classes, we focus on multifamily properties because they constitute the largest share of our sample and because this setting allows us to study rents, net operating income (NOI), and ownership structure most cleanly. The remainder of the paper has three parts. We first study the supply-side repricing of commercial insurance. We then examine how the resulting cost increases are divided between tenants and owners and capitalized into property valuations. Finally, we analyze which owners are best positioned to absorb these shocks and how repricing reshapes ownership patterns and the allocation of risky assets.

We identify three supply-side mechanisms behind this repricing. First, insurance pricing increasingly reflects the underlying risk of a property's location, particularly its exposure to natural disasters. As climate risks intensify, insurers place 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 experience significantly larger increases in insurance costs, particularly after 2018. Before 2018, insurance costs were relatively insensitive to local risk measures. From 2018 onward, however, insurers appear to have recalibrated their pricing models to incorporate risk exposure more directly.[4] Our empirical design includes property fixed effects to account for time-invariant characteristics and year fixed effects to control for aggregate shocks over time. These results show that insurers placed

[3] Our data allow us to study the pricing margin through realized insurance expenses, but not non-price supply responses such as coverage restrictions, insurer exit, or rationing, which remain important topics for future work.

[4] As shown in Figure IA.8, 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.

substantially greater weight on local climate risk after 2018, and we find a similar break when we use realized disaster damages rather than forward-looking risk measures.

Second, rising reinsurance costs amplified this repricing by raising the cost of supplying insurance in places more exposed to correlated catastrophe risk.[5] We begin by showing that the increased pricing of local risk closely tracks the rising price of reinsurance. The extent to which higher reinsurance prices affect local insurance costs depends on insurers' 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, defined by the share of direct premiums ceded to unaffiliated reinsurers. We find that states with greater reinsurance exposure, such as Florida, Louisiana, and Texas, experience significantly larger cost increases when reinsurance prices rise. Our identification strategy exploits sharp discontinuities in reinsurance exposure across state borders, comparing neighboring areas with similar underlying physical risk but different exposure to reinsurance markets. 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 2.5 times as large in states with high exposure to reinsurance markets as in states with low exposure.

Third, comparing commercial property insurance to homeowners insurance, which is the primary focus of the existing literature, we find that commercial premiums have risen substantially faster in nearly every county. Specifically, 95% of the population resides in counties where the increase in commercial insurance costs is at least twice as large as the increase in homeowners insurance costs. 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 appears better able to adjust. 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, but not 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 being more responsive to local risk, commercial insurance pricing also reflects spillovers from regulatory frictions in the homeowners market 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.[6] To test this hypothesis,

[5] Primary insurers often transfer a portion of their risk to global reinsurers, and rising reinsurance costs can be passed through to policyholders.

[6] 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.

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 than 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 pattern suggests that insurers 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 important implications for who bears climate risk in multifamily housing. We examine whether higher premiums are reflected in rents paid by tenants or absorbed by owners through reduced net operating income (NOI), and whether these shocks are also capitalized into property valuations. Although higher insurance expenses create pressure to raise rents, we find that owners face increasing constraints in doing so. We estimate that, on average, the rent response offsets roughly 49% of the increase in insurance costs. However, this response is highly nonlinear and has declined over the last decade. Although landlords were initially able to offset much of the increase in costs through rents, their ability to do so has diminished, particularly since 2019. By 2024, the marginal rent response to insurance cost increases was near zero. For example, a 10% increase in insurance costs, which was associated with a 0.35% increase in rents in 2014, was associated with only a 0.02% increase by 2024. Conversely, the associated decline in NOI from a 10% increase in insurance costs grew to more than 0.95% by 2024. Consequently, climate-risk repricing is shifting the burden of insurance costs from tenants toward property owners, leading to a growing erosion of profitability in the most exposed markets. We also show that this repricing is increasingly capitalized into property valuations, with riskier properties trading at lower prices per unit and higher cap rates relative to pre-2018.

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 rent-response estimates and the distribution of insurance cost growth in each year. We find that the average impact on rents and profitability was relatively modest over the 2014–2024 period, amounting to a 0.9% increase in rents and a 5.1% decrease in NOI. However, in the 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. Climate-risk repricing therefore affects not only insurance costs themselves, but also who ultimately bears climate risk in rental housing and how that repricing is capitalized into asset values.

Given the substantial effects on profitability, we next examine how insurance costs vary with property owner characteristics. We find that the burden of insurance pricing is highly heterogeneous, with

owner size and portfolio risk playing central roles. Larger property owners benefit from economies of scale and greater bargaining power, allowing them to negotiate lower per-unit insurance costs than 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 also 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 relationship 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 it is coupled with the bargaining power associated with large size. These relationships are not solely cross-sectional: within continuing ownership relationships, increases in owner size lower insurance costs for incumbent properties, while increases in portfolio risk raise them, especially for higher-risk assets. We also find that insurance costs fall discretely following M&A events, consistent with acquired properties gaining access to the scale and bargaining leverage of the acquiring owner.

Finally, we find that rising insurance costs have contributed to a reallocation of high-risk properties toward larger owners with the scale needed to manage mounting expenses. Before 2020, the cost advantage enjoyed by large owners was relatively uniform across risk categories. After 2020, however, this advantage narrowed for low-risk properties while expanding significantly in high-risk locations. After 2018, high-risk properties owned by smaller owners also become more likely to transact, and conditional on sale, they are increasingly acquired by larger buyers. 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 interact to shape insurance outcomes, reinforcing the growing dominance of large owners in high-risk markets. In this sense, climate-risk repricing in insurance markets affects not only rents and profitability, but also who can hold risky assets and how capital is allocated across high-risk regions.

Our findings contribute to the growing literature on climate finance and insurance. While recent work has focused primarily on the residential sector (e.g., Oh, Sen, and Tenekedjieva (Forthcoming); Keys and Mulder (2025); Sastry et al. (2025)), we show that commercial insurance markets are a central channel through which climate risk affects real estate outcomes. More broadly, the paper shows

that commercial insurance pricing is shaped by the interaction of local physical risk, global reinsurance markets, regulatory frictions, and owner characteristics. The paper therefore speaks not only to the pricing of insurance, but also to the incidence of climate risk, the capitalization of that risk into property values, and the allocation of risky assets. Because insurance is a required input into multifamily finance, these dynamics are relevant not only for rents and profitability, but also for how climate risk is transmitted into commercial real estate credit, asset valuations, and capital allocation in high-risk regions. By raising operating expenses and compressing NOI, rising insurance costs threaten the income-return component that has historically made commercial real estate attractive to institutional capital. Unlike in homeowners markets, where rising risk may also manifest through under-insurance, in our setting the cost is absorbed through rents, lower profitability, lower valuations, and ownership reallocation.

**Related Literature.** Our paper contributes to four main strands of literature. Our paper speaks directly to the agenda outlined in Sastry and Sen (Forthcoming) by providing asset-level evidence on supply-side repricing of insurance, incidence, and capital allocation in commercial real estate. First, we add to the literature on insurance supply and pricing, which has focused primarily on homeowners insurance and climate risk. Recent studies have emphasized the role of regulation, information, and insurer balance-sheet constraints in shaping premiums and supply. For instance, Oh, Sen, and Tenekedjieva (Forthcoming) highlight the role of regulation and cross-subsidies in climate risk insurance, while Boomhower, Fowlie, and Plantinga (2023) emphasize how information asymmetries complicate the alignment of premiums with underlying risk. Similarly, Ge (2022) uses evidence from weather and life insurance to explore how financial constraints affect pricing strategies. We build on the foundational work of Froot (2001) on capital constraints in reinsurance markets and Koijen and Yogo (2015) on financial frictions in insurance to show that commercial insurance repricing reflects not only local physical risk, but also reinsurance-market conditions and regulatory spillovers from homeowners insurance.[7] While Keys and Mulder (2025) show how reinsurer exposure shapes homeowners insurance premiums, commercial real estate insurance remains relatively understudied. We argue that the commercial sector offers a useful complement to the homeowners setting because lender-mandated coverage limits endogenous take-up responses and because commercial lines are less constrained by rate regulation (Born and Klimaszewski-Blettner, 2013). In addition, unlike the home-

[7] Our reinsurance results also connect to classic work on insurance-market capacity and catastrophe pricing, which emphasizes that shocks to intermediary capital can generate cyclical hard markets and sharp increases in the price of bearing catastrophe risk (Gron, 1994; Winter, 1994; Froot and O'Connell, 1999; Jaffee and Russell, 1997; Eastman and Kim, 2024).

owners 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, largely eliminating 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 climate finance and real estate by identifying insurance as a central transmission channel through which climate risk affects property cash flows. Prior studies show 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, while Seltzer, Starks, and Zhu (2022) and Sastry, Sen, Tenekedjieva, and Scharlemann (2024) illustrate implications for corporate bond pricing and insurance supply, respectively.[8] Holtermans, Kahn, and Kok (2024) examine the impact of climate-related disasters on mortgage delinquency rates for commercial real estate mortgages. Foerster, Ryan, and Scheid (2025) documents an increasing physical-risk penalty in euro-area commercial real estate, while Fang, Li, Scofield, and Yavas (2024) finds negative transaction-price effects of realized hurricane risk in parts of the U.S. commercial market. Buschbom, Eastman, Wang, and Zhou (2025) study commercial property insurance across major CRE sectors and emphasizes the pricing of realized climate risk in CMBS settings.[9] We contribute to this literature by showing how climate-risk repricing in insurance markets translates into higher operating costs, lower profitability, lower property values, and reallocation across owners in multifamily housing. In doing so, we connect the insurance market more directly to the broader climate-finance question of who bears climate risk and how that burden propagates through real estate markets.

Third, we extend the understanding of the incidence of insurance cost increases. 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). Although this work has generally focused on homeowners, our research highlights the rental market and asks how rising insurance costs reflected in rents and absorbed by property owners. By documenting both a partial average rent response and a sharp decline in that response over time, we show that climate-risk

[8] Kalda, Sharma, Soni, and Wenning (2025) shows that climate-related stress in homeowners markets can spill over across locations and can be reflected not only in premiums but also in non-price margins such as claim rejections.

[9] Relative to that work, our paper focuses on multifamily properties and contributes new evidence on supply-side amplification through reinsurance, spillovers from homeowners-market frictions, the division of costs between tenants and owners, and the reallocation of risky assets toward larger and more diversified owners.

repricing increasingly shifts the burden of insurance costs onto owners through lower NOI. We also show that the heightened pricing of climate risk is increasingly capitalized into property values, with riskier properties trading at lower prices per unit and higher cap rates relative to pre-2018.[10]

Finally, we contribute to research on the role of ownership structure in real estate markets. Previous studies have primarily examined the long-term rental market, showing 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 owner scale and portfolio composition shape insurance pricing itself.[11] Larger owners obtain lower insurance costs, especially in high-risk areas, and owners with lower-risk portfolios secure lower premiums even for otherwise similar high-risk properties. These owner-side advantages are not merely cross-sectional: they also appear within continuing ownership relationships, are reflected as discrete insurance-cost declines following M&A events, and increasingly coincide with a reallocation of risky assets toward larger, more diversified owners. Our results therefore connect ownership structure not only to rents and profitability, but also to who can hold risky assets and how climate risk is allocated in commercial real estate.

## II. Data

Our primary dataset focuses on multifamily properties with loans securitized through the Agency Commercial Mortgage-Backed Securities (CMBS) market, specifically 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 public disclosure of comprehensive loan performance data for the properties underlying their CMBS offerings. These data include key metrics such as insurance costs, rent, and NOI, along with 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.[12]

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

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

[11] More broadly, these results connect to the corporate demand-for-insurance literature, which studies why firms insure and how insurance demand covaries with financing constraints, investment, and organizational structure (Mayers and Smith, 1990; Hoyt and Khang, 2000; Aunon-Nerin and Ehling, 2008).

[12] Figure IA.1 shows that the CMBS sample expands substantially over time and tracks the cross-sectional distribution of multifamily units across MSAs reasonably well.

retail properties obtained from Bloomberg. However, for most 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"), under which tenants cover both rent and operating expenses, rendering the pass-through of rising insurance costs to property-level revenues largely mechanical; (2) loans in Agency CMBS deals are subject to more standardized requirements 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 interpretation.

To examine the relationship between rising insurance costs and natural disaster risk, we use two datasets: the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and the National Risk Index (NRI). SHELDUS provides granular county-level data on historical natural hazard events and associated losses, offering a measure of realized disaster impacts. The NRI provides a forward-looking assessment, including expected loss estimates and risk scores for each census tract in 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 insurer-level 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 reports reinsurance activity. We focus on non-liability commercial lines and extract annual measures of direct written premiums, direct earned premiums, incurred losses, and reinsurance transactions.

Finally, to identify property ownership, we use Real Capital Analytics (RCA). Ownership identification is often complicated by variation in recorded names, including subsidiaries, holding companies, and nonstandard naming 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 as a proxy for owner size.[13]

# III. The Rise in Commercial Property Insurance Costs

We begin by documenting the substantial rise in commercial property insurance costs along two dimensions: time-series and cross-sectional. This section establishes three facts that motivate the

[13] Figure IA.2 shows that RCA provides broad coverage of the multifamily market, closely tracking the number of units over time and across MSAs. Figure IA.3 shows that, relative to the broader RCA multifamily universe, properties matched to the CMBS sample tend to be larger, have fewer floors, be newer, be less expensive, and have higher cap rates, while still broadly tracking the geographic distribution of multifamily units across MSAs.

rest of the paper. First, the rise has been rapid and sustained, with average annual growth exceeding 15% in every year since 2019. Second, it is broad-based, extending across commercial asset classes and reaching well beyond the highly exposed coastal markets typically associated with climate-related insurance stress. Third, the rise is large relative to property cash flows: by 2024, insurance had grown into a meaningful share of rent and operating expenses, with important implications for incidence, profitability, and owner-side adjustment that we examine in later sections. Figure 1 presents the time-series evidence, and Figure 2 presents the cross-sectional evidence.

## A. Time-Series Variation

Figure 1, Panel A plots insurance costs for multifamily properties as shares of rent and total operating expenses (OpEx). Both measures were stable before 2019, averaging below 2.7% of rent and 5.7% of total operating expenses. By 2024, they had risen to 4.7% and 9.9%, respectively — roughly a doubling in five years. Thus, by 2024, insurance had grown from a modest line item into a meaningful share of property cash flows. Moreover, the widening in the 25th–75th percentile band after 2019 indicates that the rise has become more dispersed across properties, foreshadowing the heterogeneity in incidence and owner-side adjustment that we examine later in the paper.

Figure 1, Panel B (left) shows the median and average annual percentage change in insurance costs from 2011 to 2024. Average annual growth exceeded 15% in every year since 2019 and peaked at nearly 30% in 2023. Figure 1, Panel B (right) plots the percentage change in the ratio of insurance costs to operating expenses to account for broader inflation in operating costs. A similar pattern emerges: the insurance-to-OpEx ratio rose by at least 8% annually from 2019 onward, including a surge of nearly 20% in 2023. Taken together, these patterns point to a sharp upward shift in insurance costs beginning in the late 2010s, with the most rapid acceleration occurring after 2019. As we show in the next section, this aggregate surge coincides with a broader shift after 2018 in how insurers price local risk and reinsurance exposure.

Figure 1, Panel C replicates the analysis in Panel B (left) for non-multifamily commercial property types using Bloomberg data. A similar broad time-series pattern emerges across hospitality, industrial, mixed use, mobile homes, office, and storage properties, although the magnitude of the increase varies across asset classes. The recent rise in insurance costs is therefore not unique to multifamily properties, but reflects a broader repricing across commercial real estate. For the remainder of the paper, we focus on multifamily properties because they constitute the largest share of our sample and because this setting allows us to examine how rising insurance costs affect rents, net operating income, and ownership structure.

### B. Cross-Sectional Variation

Figure 2, Panel A compares median annual insurance cost per unit in 2022–2024 with the 2010–2017 baseline. Each bubble represents a Core-Based Statistical Area (CBSA) and is sized according to the number of properties in our sample. Bubbles are colored according to the magnitude of the cost increase, and dashed lines indicate 1x, 2x, and 3x multiples. For the average property in our sample, median CBSA-level insurance costs per unit rose by a factor of 1.94. Notably, 37% of CBSAs, containing 34% of the properties in our sample, saw median insurance costs at least double. These large relative increases are not confined to CBSAs with high initial insurance costs: many markets with only moderate pre-period insurance costs still experienced roughly two- to three-fold increases. The rise in insurance costs is therefore is widespread across local commercial property markets rather than driven by a small set of outlier markets.

Figure 2, Panel B focuses 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 states, including Florida, Texas, Louisiana, and California, substantial increases were also observed in the U.S. interior, including Oklahoma, Colorado, Tennessee, and Indiana. Only 12% of CBSAs, containing just 1% of sampled properties, experienced increases of less than 10%, and only 29% of CBSAs, containing 9% of sampled properties, experienced increases of less than 20%. Thus, although climate-related insurance stress is often associated with a narrow set of highly exposed coastal markets, the recent repricing is better understood as a pervasive national phenomenon.

Taken together, Figure 1 and Figure 2 establish that the rise in commercial property insurance costs is large, broad-based, and economically meaningful. These descriptive patterns motivate the remainder of the paper. The next two sections examine the forces behind this repricing, focusing on local disaster risk, reinsurance exposure, and regulatory spillovers from homeowners insurance markets. We then study how these cost increases are split between tenants and owners and how differences in owner size and portfolio composition shape the ability to absorb them.

## IV. Repricing of Local Risk and the Role of Reinsurance

The previous section documents a large and widespread increase in commercial property insurance costs. In this section, we examine two forces behind that increase. First, we show that insurers began pricing local climate risk much more aggressively after 2018. Second, we show that rising reinsurance costs amplified this repricing, especially in states with greater ex ante exposure to reinsurance markets. The next section then turns to a third mechanism: regulatory frictions in the homeowners insurance

market and their spillovers into commercial pricing.

## A. Repricing of Local Risk

We begin by examining whether the relationship between local climate risk and insurance cost growth changed over time. We use two complementary sets of measures. The first comes from FEMA's National Risk Index (NRI), which provides census tract-level measures of expected annual losses and risk scores. These measures capture forward-looking assessments of local disaster risk. The second comes from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which provides county-level measures of realized historical property damages. Together, these data allow us to study whether insurers responded more strongly over time to both expected and realized local risk.

Figure 3 shows a clear regime shift in the pricing of local risk. Before 2018, insurance cost growth was only weakly related to tract-level risk scores and expected annual building losses. After 2018, both relationships became strongly positive. Panel A shows that, over the full sample, higher-risk areas experienced larger increases in insurance costs. More informative, however, is the time-series break in Panel B, which shows that the relationship between local risk and insurance cost growth emerges only after 2018.[14] Figure IA.7 confirms the same pattern year by year: the effects of both risk scores and expected annual losses on insurance cost growth become economically meaningful only after 2018. Insurers did not simply continue a pre-existing pattern of risk-based repricing; rather, they began placing substantially greater weight on local climate risk after 2018.

We find the same break when we turn to realized disaster damages. Using county-level property damage data from SHELDUS, Figure 4 relates insurance cost growth to historical disaster losses. Before 2018, historical damages had little predictive power for insurance cost growth; after 2018, the relationship became positive and significant. Panel A shows a positive relationship between insurance cost growth and average property damages per capita over the previous five years, while Panel B shows that this relationship is driven by the post-2018 period.[15] This finding reinforces the interpretation that insurers revised their pricing of local climate risk after 2018. At the same time, even low-damage areas experienced substantial insurance cost growth, indicating that local risk repricing is an important part of the recent increase but not the only force behind it.

Taken together, the evidence from expected risk and realized damages points to the same conclusion: insurers began pricing local climate risk much more aggressively after 2018. This repricing helps

[14] Both panels include year fixed effects, so the figures examine differential repricing of riskier relative to safer places within the same year.

[15] Both panels include year fixed effects, so the figures examine whether higher-damage areas experienced larger relative increases in insurance costs within the same year.

explain why insurance costs rose most sharply in higher-risk areas, but it does not by itself account for why the aggregate rise was so broad. We next show that rising reinsurance costs amplified these local pricing effects.

## B. Reinsurance Amplification

Reinsurance functions as insurance for insurers, transferring catastrophic risk to global reinsurers that specialize in absorbing large-scale losses and allowing primary insurers to remain solvent through extreme events such as hurricanes and wildfires. Because reinsurance is priced in global markets, movements in reinsurance prices can be interpreted as changes in the price of systematic catastrophe risk. If primary insurers differ in how heavily they rely on reinsurance, then a common increase in reinsurance costs should have larger effects in states where insurers are more exposed to reinsurance markets. This interpretation is consistent with theories of catastrophe-risk intermediation in which the supply of reinsurance capital is less than perfectly elastic, so that correlated losses raise the marginal cost of bearing risk (Froot, 1997; Froot and O'Connell, 2008).

In recent years, the cost of reinsurance has increased substantially. As shown in Figure 5, Panel A, the Guy Carpenter Rate-On-Line Index, a widely used benchmark for reinsurance pricing, has risen steadily 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 close co-movement points to reinsurance as a supply-side amplification channel, insurers with greater reliance on reinsurance face stronger pressure to raise premiums, even holding fixed local disaster risk. This motivates tests that separate the effects of heightened global risk pricing from changes in local risk pricing.

To quantify the role of reinsurance exposure in driving insurance cost increases, we follow Keys and Mulder (2025) and construct a state-level measure of how much insurers operating in a given state depend on reinsurance to manage risk:

$$ReinsuranceExposure_s = \frac{\sum_{i \in I} DirectPremiumsWritten_{i,s} \times PctCeded_i}{\sum_{i \in I} DirectPremiumsWritten_{i,s}} \tag{1}$$

where $DirectPremiumsWritten_{i,s}$ is the total direct insurance premiums written by insurer $i$ in state $s$ and $PctCeded_i$ is the share of insurer $i$'s total direct premiums ceded to unaffiliated reinsurers.[16]

Using this measure, we calculate state-level reinsurance exposure and plot it in Figure IA.9, Panel A.

[16] We construct this measure using 2017 data so that it captures exposure prior to the sharp rise in reinsurance costs. Figure IA.9, Panel B shows that both insurer-level cession rates and state-level exposure are broadly stable over time.

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 in the southeastern United States, including Florida, Louisiana, and Texas, exhibit the highest reinsurance exposure, exceeding 20% in some cases. This pattern is consistent with the fact that insurers in these states face elevated hurricane risk and therefore rely more heavily on reinsurance markets to hedge catastrophic losses. In contrast, states in the Midwest and parts of the Northeast show relatively low 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:

$$\begin{aligned}\Delta(\textit{Insurance/Unit})_{i,s,t} = \beta \times \Delta(\textit{ReinsuranceCost})_t \times \textit{ReinsuranceExposure}_s \times \textit{RiskScore}_i \\ + \delta_t \times \textit{ReinsuranceExposure}_s + \zeta_t \times \textit{RiskScore}_i + \gamma_i + \tau_t + \varepsilon_{i,s,t}\end{aligned} \tag{2}$$

where $\Delta(\textit{Insurance/Unit})_{i,s,t}$ represents the change in insurance costs per unit for property $i$ in state $s$ during year $t$, $\Delta(\textit{ReinsuranceCost})_t$ is the change in the Guy Carpenter Rate-On-Line Index, capturing changes in national reinsurance pricing, $\textit{ReinsuranceExposure}_s$ measures the extent to which insurers in state $s$ rely on reinsurance markets, and $\textit{RiskScore}_i$ represents the tract-level disaster risk score of property $i$. We include property fixed effects ($\gamma_i$) to control for time-invariant property characteristics and year fixed effects ($\tau_t$) to account for macroeconomic shocks or broader trends affecting insurance costs in a given year. We also control for time-varying effects of reinsurance exposure ($\delta_t \times \textit{ReinsuranceExposure}_s$) and local risk ($\zeta_t \times \textit{RiskScore}_i$). Identification comes from differential state exposure to common national reinsurance shocks, comparing properties with similar local risk while absorbing time-invariant property heterogeneity and time-varying effects of both reinsurance exposure and local risk.

To illustrate the identifying variation in reinsurance exposure, consider Florida and Georgia. Figure IA.9, Panel A plots reinsurance exposure, while Figure IA.4 displays the corresponding county-level risk scores. A key feature is the sharp discontinuity in state-level reinsurance exposure at the Florida-Georgia border even though local risk varies smoothly across the region. This pattern is intuitive: natural disaster risks, such as hurricane exposure, do not abruptly change at state borders, but insurers 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 substantially higher reinsurance exposure than those in Georgia, even for areas with similar underlying risk.

This sharp cross-state difference in reinsurance exposure, combined with relatively smooth variation in geographic risk, provides the identifying variation we exploit in the regressions below. Our regression compares properties located in states with different reinsurance exposure, including properties near state borders where underlying disaster risk is similar. The property fixed effects absorb time-invariant differences across properties, while the interactions with local risk and year effects allow us to distinguish common reinsurance shocks from differences in baseline exposure to disaster risk. Thus, identification comes from whether properties with similar local risk experience larger insurance cost increases when national reinsurance costs rise if they are located in states that are more exposed to reinsurance markets. While the Florida-Georgia border serves as a useful illustration, our formal empirical test uses the full sample across the United States.

The results of estimating equation 2 are shown in Figure 5, Panel B. The left subpanel of Panel B presents the marginal effect of a 10 index point increase in reinsurance costs on the change in insurance cost per unit for different combinations of risk scores and reinsurance exposure. 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 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 costs leads to a $19 increase in insurance cost per unit. However, for the same level of local risk but with reinsurance exposure of 25%, the same increase in reinsurance costs leads to a $47 increase in insurance cost per unit. Thus, the effect of a common reinsurance shock is roughly 2.5 times as large in high-exposure states as in low-exposure states, holding fixed local risk.[17] Replacing the risk score with $\log(\textit{Expected Building Losses per Capita})$ yields a very similar pattern, as shown in the right subpanel.

Table 1 provides the corresponding regression estimates and examines robustness across different fixed-effects specifications. Columns (1) to (3) examine the interaction between reinsurance cost changes and state-level reinsurance exposure, progressively adding year and property fixed effects to absorb aggregate insurance-market shocks and time-invariant differences across properties. Columns (4) to (7) then introduce interactions with local risk scores. In the most demanding specification, Column (7), the property fixed effects absorb permanent property heterogeneity, while the year-specific controls for reinsurance exposure and local risk absorb any direct time-varying relationship between those characteristics and insurance costs. The remaining triple interaction therefore asks whether properties with similar local risk experience larger insurance cost increases when national reinsurance costs rise if they are located in states whose insurers were more exposed to reinsurance markets ex ante.

[17] Because the model is linear, this relative difference holds at any fixed level of the risk score.

Across these increasingly stringent specifications, we find that ex ante exposure to reinsurance markets leads to larger insurance cost increases when reinsurance costs rise, especially in areas with heightened local risk.[18] Reinsurance shocks therefore do not raise insurance costs uniformly across exposed states. Once the interaction with local risk is introduced, the lower-order interaction between reinsurance cost changes and reinsurance exposure becomes small, while the triple interaction remains large and statistically significant, indicating that reinsurance amplification is concentrated in riskier places.

To further tighten the test around the identifying variation described above, we implement a border county-pair difference-in-differences design. Specifically, we restrict the sample to properties located in counties near state borders and estimate the following dynamic specification:

$$\Delta(\textit{Insurance/Unit})_{i,p,s,t} = \sum_{\tau \neq 2017} \beta_t \times \mathbb{1}(\textit{Year} = t) \times \textit{HighReinsuranceExposure}_s + \gamma_i + \eta_{p,t} + \theta_p \times \textit{RiskScore}_i + \varepsilon_{i,p,s,t}, \tag{3}$$

where property $i$ is located in state $s$ and border county pair $p$, and $\textit{HighReinsuranceExposure}_s$ is an indicator equal to one if state $s$ has above-median commercial reinsurance exposure. We include property fixed effects ($\gamma_i$) and county-pair × year fixed effects ($\eta_{p,t}$). We also include county-pair-specific controls for local risk ($\theta_p \times \textit{RiskScore}_i$) to allow the pricing of local disaster risk to vary flexibly across border county-pairs. Panel C of Figure 5 presents the annual estimates ($\beta_t$). The estimates are close to zero before 2018 and become positive afterward, indicating that properties located on the high-reinsurance-exposure side of a state border experienced larger increases in insurance costs relative to nearby properties across the border. The effects are also larger in the most recent years, which is consistent with the sharp increase in reinsurance cost shown by the Guy Carpenter Index during this period.

## C. Other Potential Causes

We also examine several alternative explanations for the recent rise in insurance costs, including distance to the coast, elevation, property features, and insurance market concentration. Figure IA.10, Figure IA.11, and Figure IA.12 show that these factors provide limited explanatory power relative to local risk repricing and reinsurance exposure. In particular, simple geographic proxies such as distance to the coast or elevation do not account for the broad national rise in insurance costs, and we find no evidence that increasing market concentration in commercial insurance explains the recent surge. If

[18] 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.

anything, concentration declines over time in this market.

Overall, the evidence in this section points to a repricing of local climate risk after 2018 that was further amplified by rising reinsurance costs. These forces explain an important part of the recent increase in commercial insurance costs, especially in higher-risk areas. The next section shows that this repricing was also shaped by regulatory frictions in the homeowners insurance market, which both widened the wedge between commercial and homeowners premiums and spilled over into commercial insurance through cross-product subsidization.

# V. Commercial vs. Homeowners Insurance and Regulatory Spillovers

The previous section shows that commercial insurance costs rose because insurers began pricing local climate risk more aggressively and because higher reinsurance costs amplified that repricing. This section turns to a third mechanism: regulatory frictions in the homeowners insurance market (Oh, Sen, and Tenekedjieva, Forthcoming). These frictions matter for commercial insurance in two distinct ways. First, they dampen repricing in homeowners lines, creating a widening wedge between commercial and homeowners insurance costs. Second, because many insurers write both products, constraints on homeowners repricing may spill over into commercial lines through cross-product subsidization.

## A. The Commercial-Homeowners Pricing Wedge

We begin by comparing the recent rise in commercial property insurance costs with the rise in homeowners insurance costs. This comparison is informative because prior work has shown that homeowners insurance pricing is often constrained by state-level regulation (Oh, Sen, and Tenekedjieva, Forthcoming), whereas commercial property insurance is generally less tightly constrained by rate regulation.[19] The contrast therefore provides a useful way to evaluate how regulatory frictions shape the pricing of climate risk across insurance lines.

To construct this comparison, we use homeowners insurance premium data from U.S. Department of the Treasury (2025). These data are available at the ZIP-year level and report average homeowners insurance costs per policy annually from 2018 to 2022. We aggregate them to the county-year level and compute annual percentage changes. We then compare these changes with county-year changes in commercial insurance costs from our property-level dataset. Accordingly, the analysis in this section

[19] This distinction is also consistent with recent evidence that compliance costs associated with insurance contract regulation have become less important in commercial lines than in personal lines as commercial markets have deregulated (Kim, Leverty, and Liu, 2025).

focuses on the post-2018 period for which comparable homeowners premium data are available.

Figure 6, Panel A presents scatterplots comparing annual percentage changes in commercial and homeowners insurance costs across counties for 2019–2020, 2020–2021, and 2021–2022. 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 rose while homeowners costs declined. More broadly, 98.1% of the population lived in counties where commercial insurance costs increased at least as much as homeowners insurance costs, and 94.8% lived in counties where commercial insurance costs increased at least twice as much.[20] Thus, the recent rise in insurance costs has been far more pronounced in commercial lines than in homeowners lines, and this gap is pervasive across local markets. This pattern is visible in all three subperiods shown in the figure: the wedge is already pronounced in 2019–2020, narrows somewhat in 2020–2021, and then widens again in 2021–2022.

We next examine whether state-level frictions in the homeowners insurance market help explain this wedge. Following Oh, Sen, and Tenekedjieva (Forthcoming), we use their state-level friction measure and estimate whether the ratio of commercial to homeowners insurance costs rises more steeply with local risk in high-friction states.[21] Specifically, we define

$$CoHoRatio_{i,z,t} = \frac{Commercial\ Insurance/Unit_{i,t}}{Average\ Homeowners\ Insurance\ Premiums_{z,t}} \tag{4}$$

and estimate

$$CoHoRatio_{i,z,t} = \beta \times LocalRisk_c \times \mathbb{1}(High\ Friction)_s + \delta \times LocalRisk_c + \gamma_{s,t} + \varepsilon_{i,z,t}, \tag{5}$$

where property $i$ is located in census tract $c$, zip code $z$, and state $s$. $LocalRisk_c$ denotes either the tract-level risk score or expected annual building losses scaled by building value for census tract $c$ and $\mathbb{1}(High\ Friction)_s$ indicates whether state $s$ is in the top tercile of the homeowners-friction measure.[22] The regression includes state × year fixed effects, and standard errors are clustered at the state level.

Figure 6, Panel B shows that in high-friction states, the ratio of commercial to homeowners insurance costs rises sharply with local risk. In low- and medium-friction states, by contrast, the ratio is roughly flat with respect to local risk. Because the regression includes state × year fixed effects, this pattern is not driven by statewide premium cycles, aggregate regulatory changes, or other shocks

[20] Counties where commercial insurance costs declined are omitted from the figure for clarity.

[21] This ratio should be interpreted as a reduced-form relative pricing wedge across sectors rather than a matched-contract premium ratio. Our commercial measure is realized insurance expense per unit for Agency CMBS properties, where lender requirements impose broad and relatively standardized coverage, while the homeowners measure is the average premium per policy from Treasury data. Note that our main cross-product-subsidization result below does not rely on homeowners premium data; it is identified using only commercial insurance costs in a border county-pair design.

[22] Both risk scores and expected annual losses are from FEMA's NRI.

common to all local areas within a state-year. Instead, the identifying variation comes from whether, within the same state-year, higher-risk local areas exhibit a steeper commercial-homeowners wedge in high-friction states. This pattern is consistent with regulatory constraints preventing homeowners premiums from fully adjusting to geographic risk in high-friction states, while commercial premiums remain is better able to do so. We find a similar result when we move from expected risk to realized losses. Table 2 shows that areas experiencing greater recent losses exhibit a higher ratio of commercial to homeowners insurance costs, but this relationship is driven primarily by high-friction states. Moreover, when we interact losses with local risk, the wedge expands most strongly in high-risk areas within high-friction states.[23] In other words, the divergence between commercial and homeowners insurance pricing is largest precisely where underlying disaster risk is greatest, even after netting out common state-year shocks. Frictions in homeowners markets distort relative pricing across insurance lines by muting observed repricing — either through direct rate constraints or through reductions in effective coverage, such as higher deductibles or narrower protection. We next test whether those same frictions also spill over directly into commercial premiums.

## B. Spillovers Through Cross-Product Subsidization

We now test whether regulatory frictions also spill over directly into commercial premiums 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 the state.[24] This overlapping market participation creates scope for multi-line insurers operating in jurisdictions with tighter constraints on homeowners rates to respond to large natural disasters by adjusting commercial premiums more aggressively to rebuild capital.[25] A natural question is why commercial-only insurers do not undercut multi-line insurers undertaking such cross-product subsidization. Commercial property insurance remains segmented by state-specific carrier participation, broker relationships, underwriting specialization, and capacity constraints tied to insurer and reinsurer capital, which may limit the ability of commercial-only insurers to immediately compete away the higher commercial premiums after large disasters.

To test this mechanism, we adopt a stacked border county-pair difference-in-differences design

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

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

[25] 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. Powell, Sommer, and Eckles (2008) also find evidence that insurer groups use internal capital markets to reallocate funds across affiliates and business lines after shocks.

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, which serve as controls, do not. We additionally require that both states in the pair have low frictions in commercial property insurance rates, so that the identifying difference comes from homeowners-market regulation rather than direct regulation of commercial lines. Specifically, we estimate the following regression:

$$PctChangeInsurance_{ipstc} = \beta \times HighFriction_s \times Post_{tc} \times Treat_{pc} + \mu_i + \gamma_{stc} + \delta_{psc} + \zeta_{ptc} + \varepsilon_{ipstc}, \tag{6}$$

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 identify major disasters using historical property damage data and define the peak-damage year as the event year.[26] 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 county pairs $p$ in cohort $c$ that experience a major disaster shock, 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 window covers the two years before each disaster, the disaster year itself, and the year after.

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 ($\mu_i$) to absorb time-invariant property characteristics. We also saturate the model with cohort $\times$ state $\times$ event-year fixed effects ($\gamma_{stc}$), which capture cohort-specific state-level shocks over time; cohort $\times$ state $\times$ county-pair fixed effects ($\delta_{psc}$), which absorb time-invariant differences across county pairs within states and cohorts; and cohort $\times$ event-year $\times$ county-pair fixed

[26] 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.

effects ($\zeta_{ptc}$), which flexibly control for county-pair-specific dynamics around the disaster within each cohort. These controls ensure that we are effectively comparing properties within the same local region facing the same disaster shock, while isolating the differential effect of the state regulatory environment. That is, the coefficient $\beta$ 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 fixed effects described above.

Table 3 reports a consistently positive and statistically significant coefficient on *HighFriction* × *Post* × *Treat* across specifications, with the estimate increasing slightly when property fixed effects are added.[27] The estimated magnitudes imply that after a major disaster, commercial insurance costs rise by roughly 19–22 percentage points more in counties on the high-friction homeowners side of the border than in their neighboring counterparts. This pattern is consistent with cross-product subsidization: when multi-line insurers cannot fully reprice homeowners coverage after large losses, they shift a larger share of post-disaster repricing toward commercial lines.

Taken together, the evidence in this section shows that homeowners-market frictions matter for commercial insurance in two distinct ways. They widen the wedge between commercial and homeowners premiums by suppressing observed repricing in residential lines, and they spill over into commercial pricing through cross-product subsidization after disasters. These findings help explain why commercial insurance costs have risen much faster than homeowners insurance costs. They also matter for the remainder of the paper because any repricing shifted into commercial lines must ultimately be absorbed either through rents, lower NOI, or reallocation toward owners better able to bear the shock.

# VI. Incidence of Insurance Cost Increases

The previous sections show that commercial property insurance costs rose because insurers began pricing local climate risk more aggressively, because higher reinsurance costs amplified that repricing, and because homeowners-market frictions distorted commercial pricing. We now turn to the economic incidence of these cost increases. The central question is whether higher insurance costs are reflected in higher rents paid by tenants or absorbed by property owners through lower net operating income (NOI). When owners absorb the cost, those shocks may also be capitalized into lower property valuations and elevated cap rates. We show that insurance cost increases are initially shared between tenants and owners, but that this sharing breaks down as shocks become larger and more recent, shift-

[27] This increase suggests that the result is not driven by time-invariant differences in properties on the two sides of the border.

ing a growing share of the burden onto owners through lower NOI. We also show that transaction markets increasingly reflect this repricing, consistent with investors treating higher insurance costs as a persistent drag on expected cash flows rather than a temporary expense shock.

## A. Average Incidence on Rents and NOI

We begin by estimating the average relationship between insurance costs, rents, and NOI for multifamily properties. Specifically, we estimate

$$Log(y)_{imt} = \beta Log(Insurance/Unit)_{imt} + \gamma_i + \eta_{mt} + \epsilon_{imt}, \tag{7}$$

where $Log(y)$ represents the outcome variable—either *Log(Rents/Unit)* or *Log(NOI/Unit)*—for property $i$ in CBSA $m$ in year $t$. $\gamma_i$ denotes property fixed effects, and $\eta_{mt}$ denotes CBSA $\times$ year fixed effects. $Log(Insurance/Unit)_{imt}$ is the variable of interest. Because both the dependent and independent variables are in logs, $\beta$ measures the elasticity of rents or NOI with respect to insurance costs within a property over time. We interpret these estimates as reduced-form incidence relationships rather than causal pass-through elasticities. Property fixed effects absorb time-invariant property heterogeneity, and CBSA $\times$ year fixed effects absorb common local market-year shocks, but time-varying property-level confounds may still remain. To address the most salient version of this concern, we also estimate specifications that additionally control for occupancy, non-insurance operating expenses, capital expenses, renovation indicators, and measures of property age and effective age.[28]

Table 4 presents the results, with columns (1)–(3) reporting the relationship with rents and columns (4)–(6) reporting the relationship with net operating income (NOI). All specifications include property fixed effects. Columns (1) and (4) include year fixed effects, while the remaining columns include CBSA $\times$ year fixed effects to absorb time-varying local shocks. Columns (3) and (6) add the property-level controls described above in the subset of properties for which those variables are observed.[29] The estimates are similar in economic magnitude and remain statistically significant, based on standard errors clustered at the CBSA level, across specifications. In the baseline 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. In the richer-control specification, the corresponding estimates are 0.16% and 0.39%, respectively.[30] The stability of the estimates in the subsample with these added controls suggests

[28] We normalize both the dependent and independent variables by the number of units so that the CBSA $\times$ year fixed effects capture average rent and NOI trends within each local market.

[29] We observe renovations in the Freddie Mac data, but not in the Fannie Mae data.

[30] Specifications including only year fixed effects, rather than CBSA $\times$ year fixed effects, imply a larger rent response and a smaller negative relationship with NOI.

that the main patterns are not driven solely by observable time-varying property-level changes such as renovations, even though unobserved confounds may still remain. Overall, the estimates indicate that insurance cost shocks are shared between tenants and owners on average, but that the rent response is far from complete.

To quantify the economic magnitude of the rent response, consider a 25% rise in insurance costs. Based on the baseline estimate in Column (2) of Table 4, this implies a 0.41% rent increase ($25\% \times 0.0162$). Because insurance costs account for approximately 3.3% of rent on average, to fully offset a 25% rise in insurance costs would require a 0.83% rent increase ($3.3\% \times 25\%$). Dividing the implied rent response by the full pass-through benchmark, we estimate that roughly 49% of the insurance costs increase is reflected in rents ($0.41/0.83$). Using the estimate from Column (3), which includes time-varying property-level controls, yields a nearly identical estimate of 48%.[31] Thus, both specifications suggest that only about half of the average increase in insurance costs is reflected in rents, while the remainder is borne by owners through lower NOI.

## B. Nonlinearity and Time Variation in Incidence

The average incidence estimate masks substantial heterogeneity. Figure 7, Panel A presents binscatters plots of 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 gray regions indicating 95% confidence intervals.

The binscatter in the left subpanel indicates that higher insurance costs are associated with higher rents on average. However, the concave shape of the fitted polynomial indicates that this rent response diminishes as insurance costs rise, implying that property owners face increasing difficulty offsetting higher costs through rents. The binscatter in the right subpanel reveals a similarly concave relationship: NOI is initially little changed as insurance costs rise because rents appear to increase enough to offset part of moderate cost shocks, but it eventually declines at higher cost levels. This pattern suggests that owners can partly offset moderate shocks through rent increases, but their ability to maintain profitability weakens as insurance premiums escalate.

Figure 7, Panel B traces how the relationship between insurance costs and rents and NOI has evolved over time. We estimate the baseline regression but interact the variable of interest, log insurance cost per unit, with year indicators. The left subpanel shows a decline in the rent response over

[31] Because the model is estimated in elasticities, these implied rent-response shares do not depend on the magnitude of the insurance cost shock.

time, with a particularly sharp decrease between 2019 and 2020. In 2014, a 10% increase in insurance costs was associated with a rent increase of approximately 0.35%; by 2024, the same shock was associated with an increase of only 0.02%. Conversely, the relationship with NOI has become more negative. Before 2018, changes in insurance costs had no economically or statistically significant association with NOI. By 2024, however, a 10% increase in insurance costs was associated with a decline in NOI of more than 0.95%.

The nonlinearity in Panel A and the time-series pattern in Panel B reflect the same underlying shift in incidence. As insurance costs have risen and large shocks have become more common, owners have become increasingly constrained in their ability to offset those costs through rents. The result is a regime shift in incidence: the burden of climate-risk repricing is now falling more heavily on owners than earlier in the sample.

## C. Cumulative Effect

To quantify the economic significance of this shift, Figure 7, Panel C combines our time-varying rent-response estimates with the distribution of insurance cost growth over time.[32] This calculation highlights an important distinction between average and tail outcomes.

On average, the cumulative effects over 2014–2024 are modest: roughly a 0.9% increase in rents and a 5.1% decline in NOI. However, the effects are much larger in the upper tail of the distribution. At the 95th percentile of insurance cost increases, the same calculation implies an approximately 11% increase in rents and a 26% decline in NOI over the decade.[33] These results show that while average incidence effects are limited, properties facing the largest insurance shocks experience economically meaningful rent increases and substantial profitability losses.

## D. Transaction Prices and Cap Rates

If local climate risk and the associated rise in insurance costs are increasingly viewed as persistent rather than transitory, that repricing should also appear in transaction markets through lower valuations and higher required yields. Table 5 shows that the repricing of local climate risk is increasingly capitalized into multifamily asset values after 2018.[34] In the specifications without property fixed ef-

[32] 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.13 replicates the analysis using percentiles of the percentage change in insurance cost per unit and yields similar results.

[33] This exercise assumes that areas remain at a given percentile of the annual insurance-shock distribution over time. To the extent that shocks mean-revert, the cumulative effects in the tails may be overstated.

[34] These results are based on the full sample of completed multifamily property sales in the RCA data from 2010 to 2024, excluding refinancing and construction transactions.

fects, local climate risk is positively associated with transaction prices and negatively associated with cap rates, consistent with the fact that riskier properties are often located in otherwise attractive markets where valuations are high and yields are compressed. The interaction terms show that this relationship weakens materially after 2018: riskier properties now transact at lower prices per unit and higher cap rates than they did before. This pattern is even clearer in the specifications with property fixed effects and CBSA × year fixed effects, which absorb time-invariant property heterogeneity and time-varying regional shocks.[35] In this specification, a one log-point increase in expected annual building losses is associated with a 6.5% lower transaction price per unit and an 11.8 basis point higher transaction cap rate in the post-2018 period. The joint movement in prices and cap rates suggests that investors are not treating higher insurance costs and climate risk as a temporary expense shock, but instead are capitalizing them as a more persistent drag on expected net cash flows and, potentially, requiring additional compensation for bearing that risk.

Overall, this section shows that rising insurance costs are only partially reflected in rents and that owners' ability to offset them through rents has weakened sharply over time. As a result, owners increasingly bear the burden of climate-risk repricing through lower NOI, especially when shocks are large. The transaction-market evidence complements these results by showing that the same repricing is increasingly capitalized into lower asset values and higher cap rates. This shift in incidence is especially important in the upper tail, where rent adjustment is weakest and NOI losses are largest, and it motivates the next section, which examines which owners are best positioned to absorb these shocks.

# VII. Owner Heterogeneity and Reallocation

The previous section shows that the rent response to insurance cost increases has weakened sharply over time, especially in the upper tail of the shock distribution, so a growing share of climate-risk repricing is now absorbed by owners through lower net operating income (NOI). This section asks which owners are best positioned to absorb those shocks. We show three main results. First, insurance pricing is highly heterogeneous across owners: larger owners and owners with lower-risk portfolios obtain cheaper coverage, especially for high-risk properties. Second, these relationships are not driven solely by cross-sectional sorting; they also appear within continuing ownership relationships and insurance costs decline discretely when properties move into new ownership structures through M&A

[35]The CBSA × year fixed effects absorb local time-varying conditions common to all properties in the same market, such as broad shifts in local demand, financing conditions, or market-wide appreciation. The property fixed effects absorb time-invariant differences in quality, location, and other persistent property characteristics; thus, the estimates aim to isolate how the pricing of local climate risk changes within properties over time rather than reflecting cross-sectional differences between high- and low-risk assets.

events. Third, these owner-side advantages have intensified over time and increasingly coincide with a reallocation of high-risk properties toward larger owners. This reallocation operates on two margins: high-risk properties become more likely to transact when held by smaller owners, and conditional on sale, they are increasingly acquired by larger buyers.

## A. Heterogeneity in Insurance Pricing

We begin by examining whether insurance costs vary systematically with owner size. Figure 8, Panel A plots insurance costs against owner size, measured as the total number of multifamily units held nationally by the property's owner. Larger owners pay lower insurance costs per unit and lower insurance costs as a share of rent, consistent with economies of scale and stronger bargaining power in insurance procurement. This size advantage is especially relevant in the current setting because the previous sections show that insurance repricing is strongest in high-risk areas, where insurer pricing discretion is greater.[36]

To quantify this pattern, we estimate

$$Log(Insurance/Unit)_{i,o,c,t} = \beta \times RiskScore_i \times Log(OwnerSize)_{o,t} + \gamma \times Log(OwnerSize)_{o,t} + \gamma_i + \eta_{c,t} + \varepsilon_{i,o,c,t}, \tag{8}$$

where $RiskScore_i$ is the risk score of the census tract containing property $i$, $Log(OwnerSize)_{o,t}$ is the log of the number of multifamily units owned by owner $o$ in year $t$ across the country, $\gamma_i$ denotes property fixed effects, and $\eta_{c,t}$ denotes CBSA $\times$ year fixed effects. This specification therefore compares how the insurance cost of a given property evolves over time with movements in the size of its owner, either because ownership shifts across owners or because the incumbent owner expands or contracts elsewhere.

Figure 8, Panel B shows that the size advantage is economically small in low-risk areas but becomes large and statistically significant in high-risk areas. For the riskiest properties, a one-standard-deviation increase in owner size is associated with a reduction in insurance cost per unit of more than $35, or about 7.8% of the average insurance cost per unit. Table 6 confirms that the insurance-to-rent ratio is lower for larger owners and that this advantage increases with local risk. Since both Figure 8, Panel B and Table 6 include property fixed effects and CBSA $\times$ year fixed effects, this pattern is not driven simply by larger owners holding systematically different properties or operating in cheaper markets. Instead, the effects are identified from within-property changes in insurance costs as owner

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

size shifts, after netting out local market-year conditions common to all properties. Thus, owner size matters most precisely where insurance repricing is most severe.

We next examine whether an owner's broader portfolio composition is also associated with the pricing of insurance for individual properties. We define portfolio risk as the unit-weighted average risk score of the owner's multifamily holdings:

$$PortfolioRiskScore_{o,t} = \frac{\sum_{i \in Portfolio_o} Units_i \times RiskScore_i}{\sum_{i \in Portfolio_o} Units_i}. \tag{9}$$

We first estimate

$$Log(Insurance/Unit)_{i,o,c,t} = \beta \times PortfolioRiskScore_{o,t} + \gamma \times Log(OwnerSize)_{o,t} + \gamma_i + \eta_{c,t} + \varepsilon_{i,o,c,t}, \tag{10}$$

where the specification includes property fixed effects and CBSA × year fixed effects, and additionally controls for owner size. These controls and fixed effects ensure that the relationship between portfolio risk and insurance costs is not simply reflecting differences in owner scale, persistent differences in the properties themselves, or common pricing conditions in a given local market and year. Figure 9, Panel A shows that properties owned by lower-risk portfolios tend to face lower insurance costs even after netting out those factors. This pattern suggests that insurers may take portfolio composition into account when pricing coverage.[37]

To sharpen the interpretation, we next allow a property's own risk to interact with the owner's portfolio risk and include owner × year fixed effects:

$$Log(Insurance/Unit)_{i,o,c,t} = \beta \times PortfolioRiskScore_{o,t} \times RiskScore_i + \gamma \times RiskScore_i + \tau_{o,t} + \varepsilon_{i,o,c,t}, \tag{11}$$

where $\tau_{o,t}$ denotes owner × year fixed effects. This specification absorbs all owner-level time-varying shocks — changes in bargaining conditions, capital constraints, or insurer relationships that move all of an owner's properties at once. Identification therefore comes from differences across properties within an owner's portfolio in a given year. Figure 9, Panel B therefore asks whether higher-risk properties are priced differently depending on whether they sit inside a lower- or higher-risk portfolio, holding fixed everything common to that owner-year. The figure shows that high-risk properties face lower insurance costs when they are held within lower-risk portfolios. Table 7 confirms that the insurance-to-rent ratio is higher for owners with riskier portfolios and that this portfolio effect is strongest in

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

riskier locations.

Finally, we examine the joint role of owner size and portfolio composition by estimating

$$\begin{aligned} \textit{Log(Insurance/Unit)}_{i,o,c,t} = \beta \times \textit{PortfolioRiskScore}_{o,t} \times \textit{RiskScore}_i \times \textit{Log(OwnerSize)}_{o,t} \\ + \gamma \times \textit{PortfolioRiskScore}_{o,t} \times \textit{RiskScore}_i \\ + \delta \times \textit{RiskScore}_i \times \textit{Log(OwnerSize)}_{o,t} \\ + \eta \times \textit{RiskScore}_i + \tau_{o,t} + \varepsilon_{i,o,c,t}. \end{aligned} \tag{12}$$

Figure 10 shows that the portfolio-diversification channel is concentrated among large owners. For small owners, insurance costs vary little with portfolio risk. For large owners, by contrast, high-risk properties are materially cheaper to insure when the owner's overall portfolio risk is low. Thus, portfolio diversification appears to generate insurance-pricing benefits primarily when coupled with scale.

## B. Validation Within Continuing Ownership Relationships

The preceding evidence indicates that owner size and portfolio composition are strongly associated with insurance pricing. A natural concern, however, is that these relationships may simply reflect cross-sectional differences across owners or operational changes around ownership transitions. To address this concern, Table 8 restricts the sample to property-year observations whose owner is unchanged from three years earlier and examines three-year changes in insurance costs.

Within these continuing ownership relationships, increases in owner size are associated with declines in the insurance-cost-to-rent ratio, and the decline is steeper for higher-risk properties. Conversely, increases in the owner's average portfolio risk are associated with increases in insurance costs, again concentrated among higher-risk properties. Because the sample restricts attention to properties whose owner is unchanged over a three-year window, these estimates are not driven by selection into acquisitions or dispositions. In addition, the year fixed effects and controls for time-varying local risk absorb broad repricing trends that affect risky places more generally. The remaining variation therefore comes from changes in owner scale or portfolio composition within incumbent ownership relationships. These results indicate that scale and portfolio composition matter for insurance pricing even for incumbent owners — not just through selection across properties or one-time changes around ownership transitions. The continuing-ownership results show that owner scale and portfolio composition matter even absent a sale; we next ask whether insurance costs also change discretely when properties move into new ownership structures through M&A events.

## C. Insurance Costs Around Mergers and Acquisitions Events

The preceding results show that larger owners and owners with lower-risk portfolios obtain more favorable insurance pricing, both cross-sectionally and within continuing ownership relationships. We next examine how insurance costs evolve around ownership transitions generated by mergers and acquisitions (M&A) events. This evidence complements the continuing-ownership analysis by asking whether insurance costs change discretely when properties move into larger ownership structures through acquisitions. If so, that would provide additional support for the view that owner-side scale and the associated bargaining advantages affect insurance pricing directly, rather than merely sorting lower-cost properties toward certain owners.

Using the RCA property transaction data, we identify M&A events as concentrated portfolio-level ownership transfers. For each seller-year, we track the properties that exit the seller's portfolio and classify the seller-year as an M&A event if at least 70% of those properties are acquired by a single buyer. This threshold identifies cases in which the seller's portfolio is largely absorbed by one acquiring entity, consistent with an M&A transaction rather than property-by-property sales.[38,39]

To estimate the insurance-cost response to an acquisition, we use a stacked difference-in-differences design. For each acquisition cohort year $g$, we construct a stack that combines treated properties acquired in year $g$ with control properties drawn from the never-treated pool. The never-treated pool consists of properties whose owners never appear as either an acquirer or a target in our M&A registry. Treated and control properties are observed over an event-time window spanning three years before and three years after the transaction. We estimate a stacked difference-in-difference specification:

$$Log(Insurance/Unit)_{i,t,g} = \beta \times Post_{t,g} \times Treated_{i,g} + \gamma_{i,g} + \eta_{c,t,g} + \varepsilon_{i,t,g}, \tag{13}$$

where $Post_{t,g} = \mathbb{1}\{t \geq g\}$. The coefficient $\beta$ provides an average estimate of the insurance-cost response after acquisition, capturing whether insurance costs change when properties are absorbed into acquiring owners' portfolios. Further, we estimate a dynamic specification:

$$Log(Insurance/Unit)_{i,t,g} = \sum_{\tau \neq -1} \beta_\tau \times \mathbb{1}\{t - g = \tau\} \times Treated_{i,g} + \gamma_{i,g} + \eta_{c,t,g} + \varepsilon_{i,t,g}, \tag{14}$$

[38] We then impose several restrictions to exclude single-asset transactions and foreclosure-related transfers. Specifically, we exclude targets with fewer than five properties at $t-1$, which removes single-property sales and very small investors. In addition, we exclude transactions in which the acquirer is a bank, loan servicer, Fannie Mae, Freddie Mac, or mortgage trust company, as such transactions are more likely to reflect foreclosure or loan-resolution activity. Finally, we require the acquirer's pre-deal portfolio, measured by total units, to exceed the target's pre-deal portfolio. Together, these filters restrict the sample to transactions in which properties move into larger ownership structures.

[39] We validate the classification by manually matching a random 3% sample of identified events to publicly reported M&A transactions.

which traces the year-by-year path of insurance costs around the acquisition. This dynamic specification allows us to assess whether treated properties were already on differential insurance-cost trends before the transaction and to examine how quickly the post-acquisition response emerges. In both specifications, $i$ denotes property, $t$ year, and $g$ cohort; $\gamma_{i,g}$ and $\eta_{c,t,g}$ denote property $\times$ cohort fixed effects and CBSA $\times$ year $\times$ cohort fixed effects. Standard errors are clustered at the owner level.[40] The property $\times$ cohort fixed effects absorb all time-invariant differences across properties, while the CBSA $\times$ year $\times$ cohort fixed effects absorb common shocks to insurance pricing within a local market and year. The remaining variation therefore comes from whether insurance costs for the same property change discretely around the ownership transition relative to other properties in the same market-year and cohort.

Table 9, Panel A reports the corresponding estimates from the specification in Equation 13. Column (1) shows that log insurance cost per unit declines by 13.4 log points after acquisition. Columns (2) and (3) show similar reductions in alternative insurance-cost measures: the insurance-cost-to-rent ratio falls by 0.80 percentage points, and the insurance-cost-to-operating-expenses ratio falls by 1.33 percentage points.

Figure 11 plots the event-time coefficients from the dynamic specification in Equation 14. The estimated pre-trends are small and statistically insignificant, which suggests that properties involved in M&A are not already on systematically different insurance-cost paths before the ownership change. After the event, however, insurance costs decline materially. In the transaction year, log insurance cost per unit falls by roughly 13 log points relative to the pre-event benchmark, and the decline persists over the following three years, reaching roughly 12 to 11 log points. The persistence of the decline suggests that the effect is not merely a temporary adjustment around the transaction itself. Panels B and C show the same qualitative pattern: the insurance-cost-to-rent and insurance-cost-to-operating-expenses ratios display little evidence of pre-trends and decline persistently after the transaction.

We next examine heterogeneity in the M&A effect along two margins: the size gap between the acquirer and the target, and the acquired property's own disaster exposure. We begin with the acquirer–target size gap, which speaks directly to the owner-size channel. If the post-M&A decline reflects gains from owner size, bargaining leverage, and insurer relationships, then those gains should be more pronounced when target properties are acquired by substantially larger owners. We define the size gap at $t-1$ as the difference between the acquirer's and target's total portfolio units.[41] This design tests

[40] Specifically, we cluster by acquiring owner for treated observations. For control observations, ownership remains unchanged throughout the event window.

[41] Because the size gap is a deal-level characteristic, it is observed only for acquired properties. We therefore classify treated properties according to whether their acquisition is above or below the median acquirer–target size gap, while

whether acquisitions that move properties into substantially larger owners generate larger insurance savings. Columns (1) and (2) of Table 9, Panel B show that the post-M&A decline in insurance costs is concentrated in deals with larger acquirer–target size gaps. Log insurance cost per unit falls by 20.1 log points for high-size-gap deals, compared with 5.9 log points for low-size-gap deals, with only the high-size-gap estimate statistically significant.[42] This heterogeneity is consistent with the interpretation that larger jumps in owner size generate larger insurance-pricing benefits for the acquired properties.

We next examine whether the M&A effect varies with the acquired property's own disaster exposure. This test is motivated by the earlier owner-size estimates in Figure 8, Panel B and Table 6, which show that the insurance-cost advantage of larger owners is strongest for properties in high-risk locations. We measure the risk exposure using the FEMA NRI risk score at the census-tract level.[43] This comparison tests whether acquisition-induced insurance savings are larger for properties located in riskier areas. Columns (3) and (4) of Table 9, Panel B show that the post-M&A decline in insurance costs is larger for properties located in higher-risk census tracts. Insurance cost per unit falls by 17.9 log points for high-risk properties, compared with 7.2 log points for low-risk properties, with only the high-risk estimate statistically significant. This result is consistent with the earlier cross-sectional evidence that the insurance-cost advantage of larger owners is concentrated among high-risk properties.

Taken together, the continuing-ownership and M&A results indicate that owner-side insurance advantages are not merely static correlations across properties or owners. Insurance costs decrease when incumbent owners become larger and increase when their portfolios become riskier. Insurance costs also decrease when properties move into larger ownership structures through acquisition, with the largest post-M&A declines appearing when the increase in owner size is greatest and when acquired properties are more exposed to disaster risk. These patterns reinforce the interpretation that owner scale and related bargaining advantages are economically meaningful determinants of insurance pricing. We next examine how the importance of these owner-side advantages has evolved over time and whether, as climate-risk repricing has intensified, they are increasingly reflected in transaction behavior and the broader reallocation of high-risk properties toward larger owners.

using the same never-treated control pool in both comparisons.

[42] Table **??** shows similar heterogeneity when insurance cost to rent or insurance cost to operating expenses is used as the dependent variable.

[43] Unlike the size-gap measure, property risk is observed for both treated and never-treated properties. We therefore partition the entire stacked panel at the global median of the property-level risk score, so that high-risk treated properties are compared with high-risk controls and low-risk treated properties are compared with low-risk controls.

## D. Dynamics and Reallocation

We next examine how these owner-side pricing advantages have evolved over time. Figure 12, Panel A plots the annual effect of owner size on the insurance-to-rent ratio separately for low-, medium-, and high-risk properties. In the early years of the sample, the size advantage is relatively similar across risk categories. In recent years, however, the pattern diverges: the size advantage weakens in low-risk areas but becomes substantially stronger in high-risk areas. Panel B shows an analogous result for portfolio risk. In recent years, lower portfolio risk has generated larger insurance cost savings, particularly for large owners holding high-risk properties. Table 6 and Table 7 confirm this intensification in regression form.

These dynamics suggest that owner heterogeneity has become more consequential precisely as climate-risk repricing has intensified. This change is especially visible after 2020, and even more so after 2021, when the pricing advantages associated with owner size and portfolio composition become much more concentrated in high-risk properties. When the rent response to rising insurance costs was larger, owner-side differences in insurance pricing mattered less for profitability. As owners' ability to offset costs through rents has weakened — especially in the upper tail, where rent adjustment is weakest and NOI losses are largest — differences in owner scale and diversification have become increasingly important determinants of who can absorb rising insurance costs.

We then examine whether these pricing advantages are reflected in ownership patterns and transaction behavior. Figure 13, Panel A compares the relationship between local risk and owner size in 2010 and 2024. In 2010, owner size is essentially unrelated to local risk, and if anything the relationship is slightly negative. By 2024, this pattern has reversed: properties in riskier areas are significantly more likely to be held by larger owners. Figure 14 provides complementary evidence on the sale margin.[44] Before 2018, high-risk properties are not systematically more likely to sell across the owner-size distribution. After 2018, however, a clear monotonic pattern emerges: high-risk properties become substantially more likely to transact when they are held by the smallest owners, with the effect largest in owner-size deciles 1 and 2, smaller but still positive in deciles 3 and 4, and close to zero for middle and larger owners. This pattern is consistent with climate-risk repricing pushing high-risk assets out of smaller owners and toward larger owners better able to absorb rising insurance costs.[45]

To quantify this shift, we estimate

[44] The underlying regressions include CBSA × year fixed effects, so the estimates are identified from within-market comparisons that absorb common local shocks to transaction activity in a given year.

[45] Figure IA.16 shows that this sale-margin effect strengthens over time, becoming statistically significantly positive after 2018.

$$Log(OwnerSize)_{i,o,t} = \sum_{t \neq 2010} \beta_t \times \mathbb{1}(Year = t) \times RiskScore_i + \gamma_i + \tau_t + \varepsilon_{i,o,t}, \tag{15}$$

where the dependent variable is the log of the number of units owned by property $i$'s owner $o$ in year $t$ across the country, and the independent variable is the risk score of the property's location, interacted with a set of year indicators. Because property fixed effects ($\gamma_i$) are included, this specification isolates within-property changes in the size of the owner of a given property. Year fixed effects ($\tau_t$) absorb aggregate changes in owner size common to all properties. Accordingly, the coefficients $\beta_t$ trace how the relationship between local risk and owner size evolves over time relative to the omitted base year, 2010.

Figure 13, Panel B shows that the positive relationship between local risk and owner size strengthens steadily over time. Table 10, Panel A confirms that properties in riskier locations become progressively more likely to be owned by larger entities. The property fixed-effects estimates are particularly informative because they show that the same property becomes more likely to be held by a larger owner after 2018 when it is located in a riskier area, rather than reflecting only static cross-sectional sorting across properties.

Table 10, Panel B then shows that, conditional on a sale occurring, high-risk properties owned by smaller owners are transferred to significantly larger buyers after 2018. All columns include CBSA $\times$ year fixed effects, so the comparison is among transactions taking place in the same local market and year. Columns (2) and (3) further absorb year-specific effects for small owners and for high-risk properties separately.The triple-interaction coefficient therefore captures whether being both high-risk and held by a small owner predicts a larger buyer after 2018, beyond any general post-2018 change in buyer size along either dimension alone. The triple-interaction coefficient is stable across specifications and remains precisely estimated as the controls become more demanding. Thus, after 2018, high-risk assets sold by smaller owners are acquired by buyers that are 16–18% larger on average. At the same time, the interaction between high risk and small-owner status, which captures the pre-2018 relationship, is close to zero and statistically insignificant. Together, these patterns are consistent with an active market-sorting mechanism: as the insurance-pricing advantages of large, diversified owners become more valuable in risky areas, high-risk assets are not only more likely to be sold when held by smaller owners, but are also systematically reallocated toward larger buyers.

Taken together, the evidence in this section shows that climate-risk repricing is reshaping the multifamily market along both the ownership and transaction margins. Larger owners and owners with lower-risk portfolios obtain more favorable insurance pricing, especially for high-risk properties, and

these advantages have intensified as owners' ability to offset insurance cost increases through rents has weakened. These patterns are not merely cross-sectional: they also appear within continuing ownership relationships and are reinforced by discrete declines in insurance costs following M&A events, consistent with properties gaining access to the acquiring owner's scale, bargaining leverage, and diversification. As a result, differences in owner scale and diversification have become increasingly important for profitability and are accompanied by a greater likelihood that high-risk properties owned by smaller owners are sold and reallocated toward buyers better able to absorb insurance shocks. More broadly, climate-risk repricing is increasingly determining who can hold risky assets, pushing high-risk properties toward larger and more diversified owners.

# VIII. Conclusion

We document a large and widespread rise in commercial property insurance costs in the United States over the last decade. Although recent work has focused primarily on homeowners insurance, the commercial sector provides a particularly informative setting in which to study the pricing of climate risk because commercial lines are less tightly constrained by state rate regulation and lender-mandated coverage limits reduce endogenous take-up responses. At the same time, our results show that commercial pricing is not frictionless. Instead, it is shaped by the interaction of local physical risk, global reinsurance markets, regulatory spillovers from homeowners insurance, and owner-level characteristics.

We identify three forces behind this repricing. First, insurers began pricing local climate risk much more aggressively after 2018, with insurance cost growth becoming substantially more sensitive to both expected and realized disaster risk. Second, rising reinsurance costs amplified local repricing, especially in states with greater ex ante exposure to reinsurance markets. Third, frictions in the homeowners insurance market distorted relative pricing across insurance lines and spilled over into commercial policies through cross-product subsidization, with our border county-pair estimates showing that after major disasters commercial insurance costs rose 19–22 percentage points more on the high-friction side of a state border. Notably, the recent surge in insurance costs is not unique to multifamily properties: we observe a similar time-series pattern across other commercial asset classes.

These pricing changes have materially altered who bears climate risk in multifamily housing. On average, rent increases offset roughly 49% of the rise in insurance costs. However, this average masks a sharp decline in rent adjustment over time. Early in the sample, landlords were able to offset much of the increase in insurance costs through rents, but by 2024 the marginal rent response had fallen

to nearly zero. The sharing of insurance shocks between tenants and owners breaks down as shocks become larger and more recent, shifting an increasing share of the burden onto owners through lower net operating income. The average effects over 2014–2024 are modest, but the upper tail is much more severe: for properties facing the largest insurance shocks, rent increases remain meaningful while profitability declines sharply. We also find that this repricing is increasingly capitalized into property valuations, with riskier properties trading at lower prices per unit and higher cap rates relative to before 2018. Climate-risk repricing therefore affects not only insurance costs themselves, but also who ultimately bears the risk and how it is capitalized in multifamily asset values.

The burden of this repricing is also highly uneven across owners. Larger owners obtain cheaper coverage than smaller owners, especially in high-risk areas, and owners with lower-risk portfolios receive lower premiums even for otherwise similar high-risk properties. These advantages are not solely cross-sectional: they also appear within continuing ownership relationships, where increases in owner size lower insurance costs for incumbent properties while increases in portfolio risk raise them, especially for higher-risk assets. We also show that insurance costs decline discretely following M&A events, consistent with acquired properties gaining access to the scale and bargaining leverage of the new owner. Since 2020, these pricing advantages have become increasingly concentrated in high-risk properties and have coincided with a reallocation of high-risk assets toward larger owners with the scale and diversification needed to absorb rising costs. After 2018, high-risk properties owned by smaller owners also become more likely to transact and, conditional on sale, are more likely to be acquired by larger buyers. Thus, climate-risk repricing in insurance markets affects not only rents and profitability, but also ownership patterns and the allocation of risky assets, helping shift high-risk properties toward larger owners.

Our findings show that commercial insurance pricing is shaped by a complex interplay between local physical risk and broader systemic exposures borne by both insurers and property owners. The paper identifies how insurance supply reprices, how the resulting costs are divided between tenants and owners, how owner scale and diversification shape pricing, how repricing reshapes the allocation of risky assets across owners, and how these effects are increasingly capitalized into property values. More broadly, because insurance is a required input into multifamily finance, these dynamics matter not only for rents and profitability, but also for commercial real estate credit, required yields, and the allocation of capital in high-risk regions.

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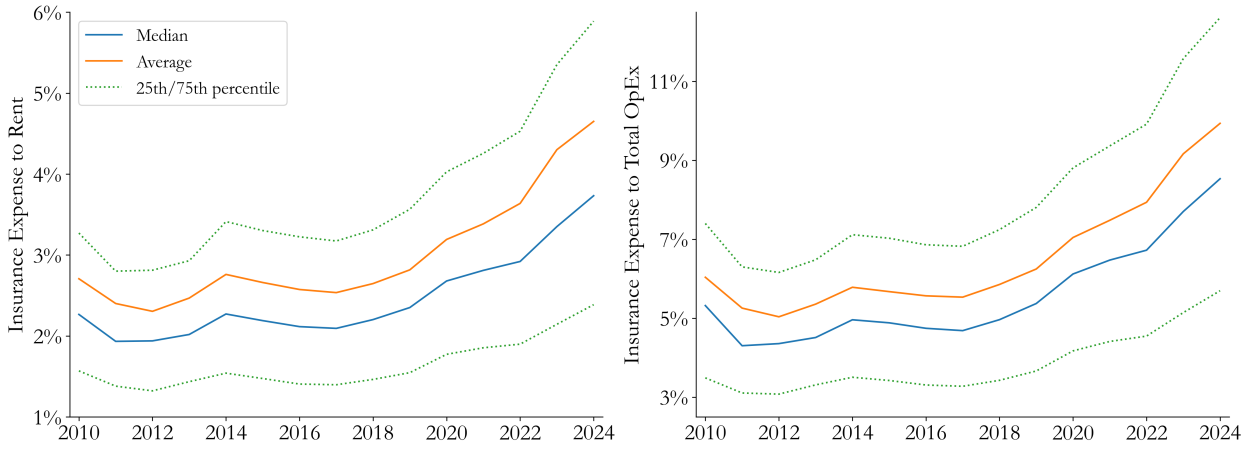
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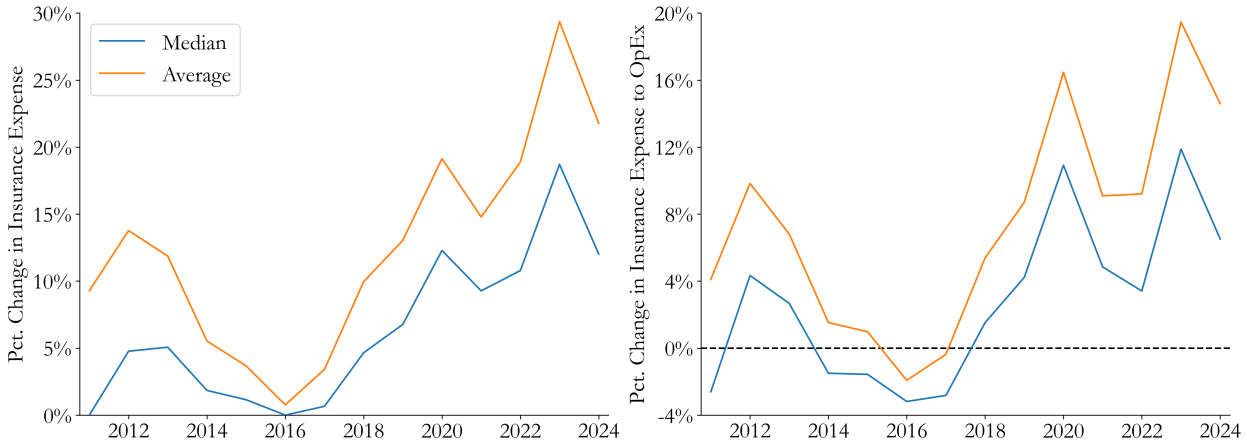
**Figure 1: Time-Series Changes in Insurance Costs**

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 2024. Panel A shows the timeseries of insurance costs as a percentage of rent and total operating expenses for multifamily properties. Panels B and C show 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

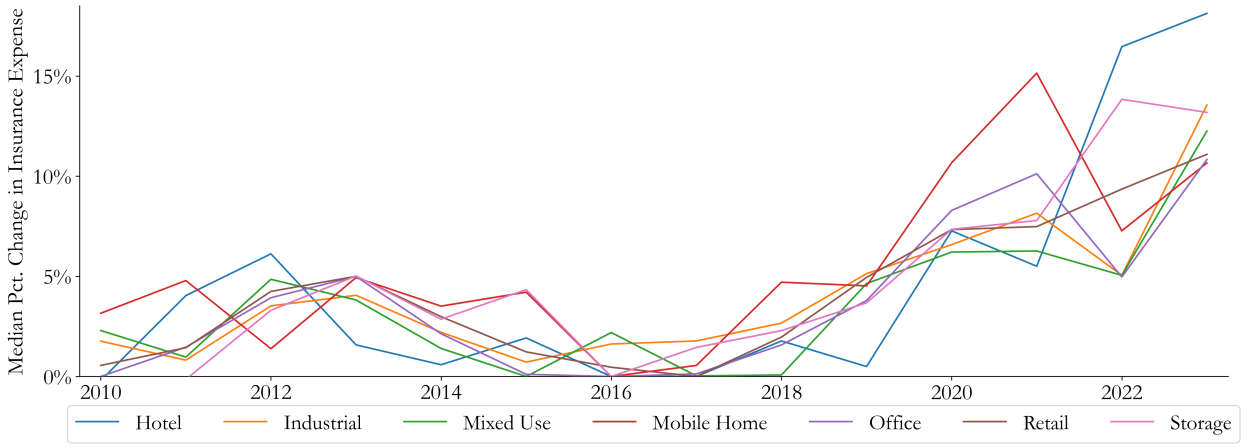
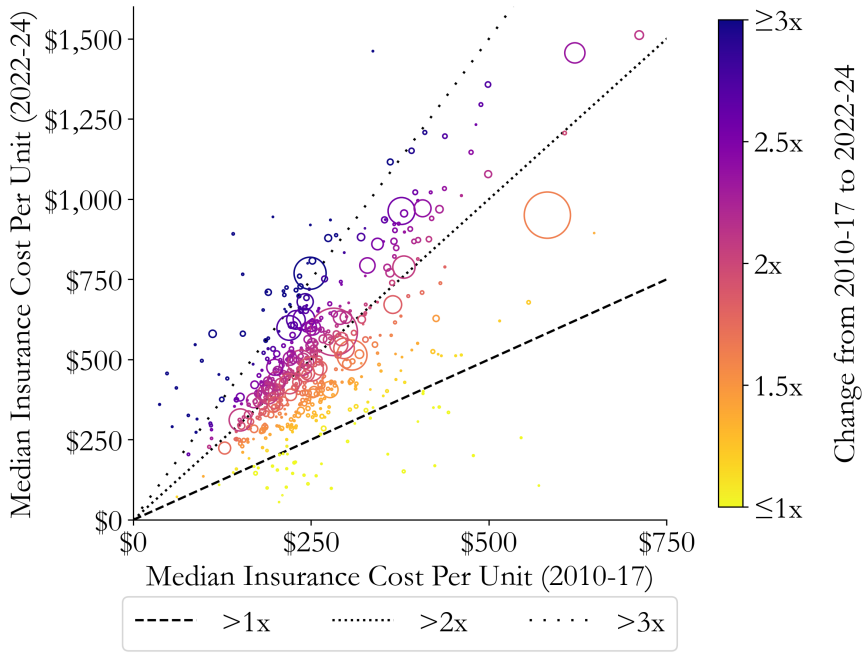


**Figure 2: Cross-Sectional Differences in Insurance Cost Changes**

This figure shows cross-sectional variation in the rise in insurance costs for multifamily properties across Core-Based Statistical Areas (CBSAs). Panel A compares median insurance cost per unit in 2010–2017 with median insurance cost per unit in 2022–2024 for each CBSA, where each circle represents a CBSA, circle size is proportional to the number of properties, and dashed lines indicate one-, two-, and three-fold increases. Panel B maps the percentage change in insurance costs between 2022 and 2023 across CBSAs. 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 2022-24




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

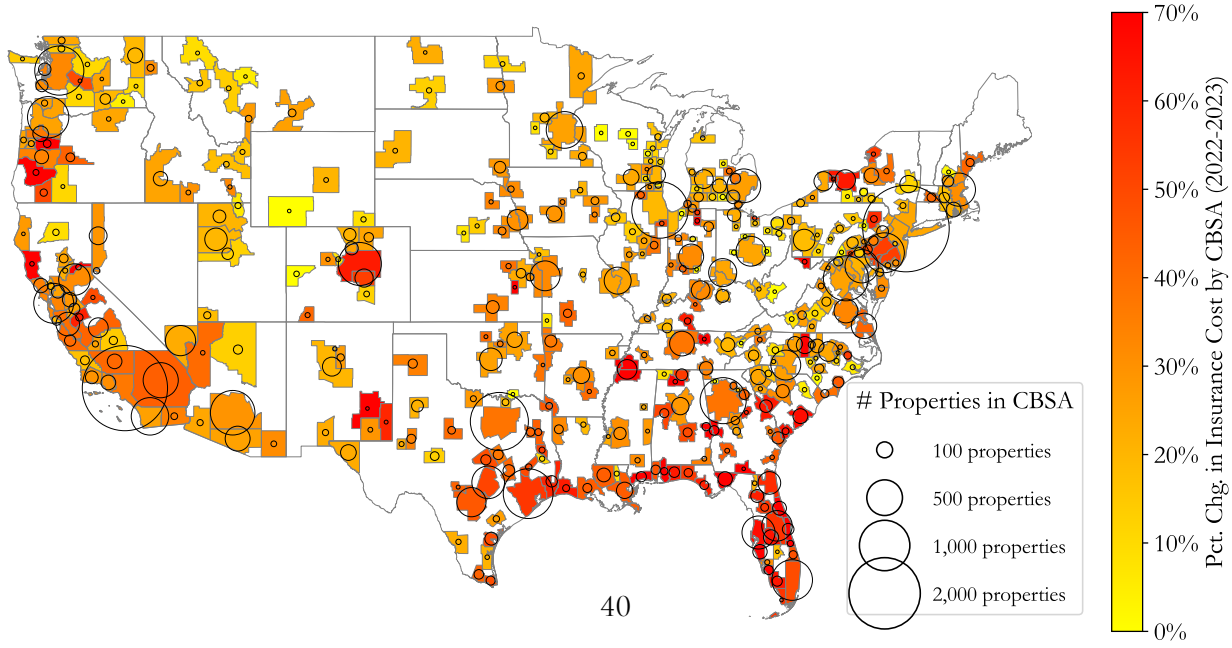


**Figure 3: Risk Scores and Expected Annual Losses**

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 2024), 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.

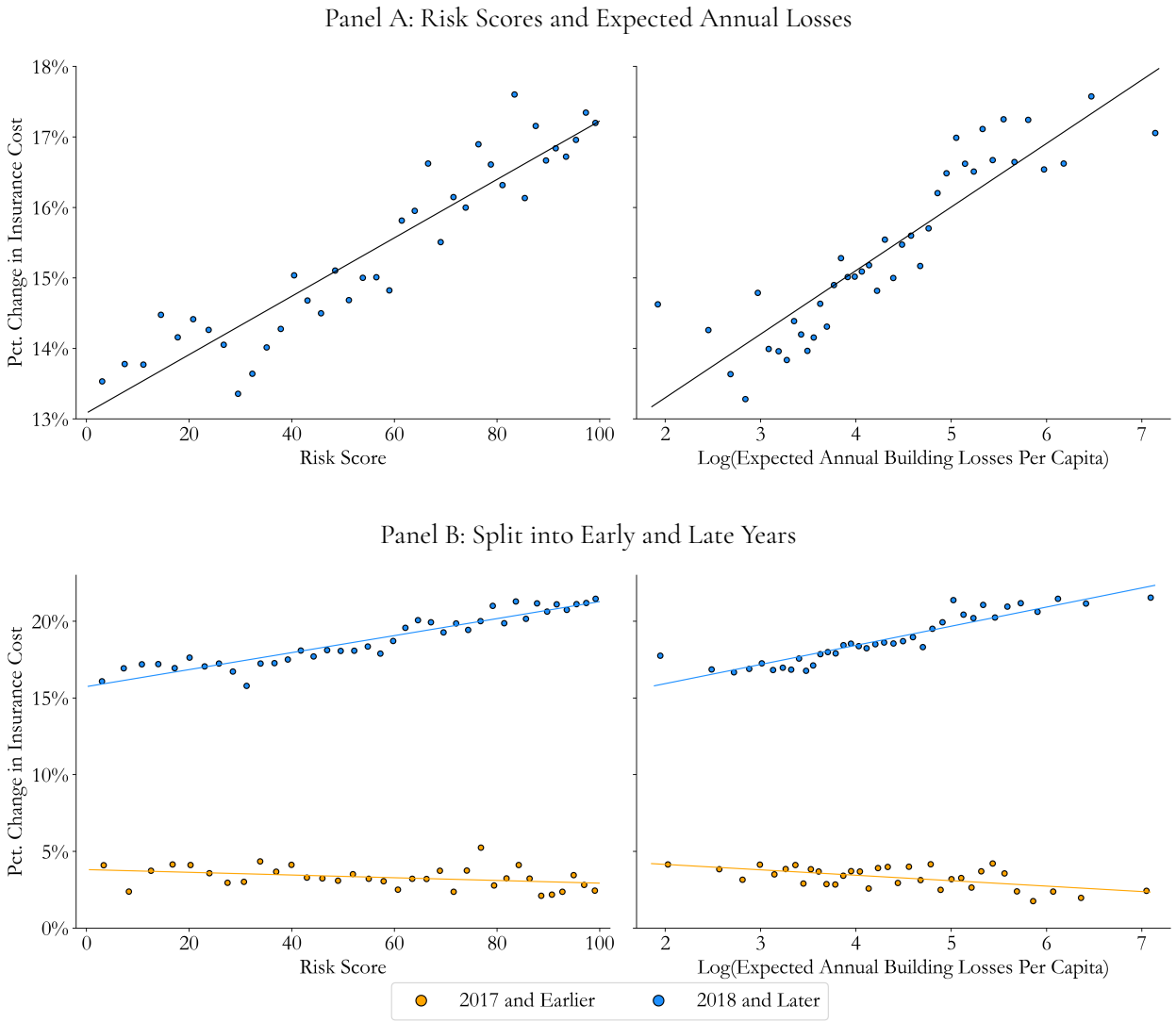
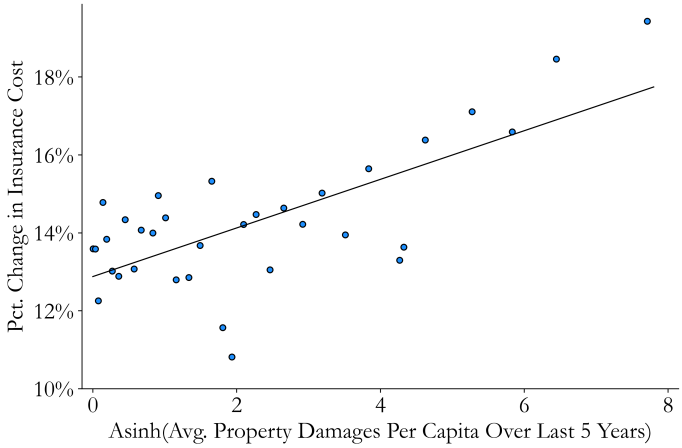


**Figure 4: Past Property Damages and the Rise in Insurance Costs**

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

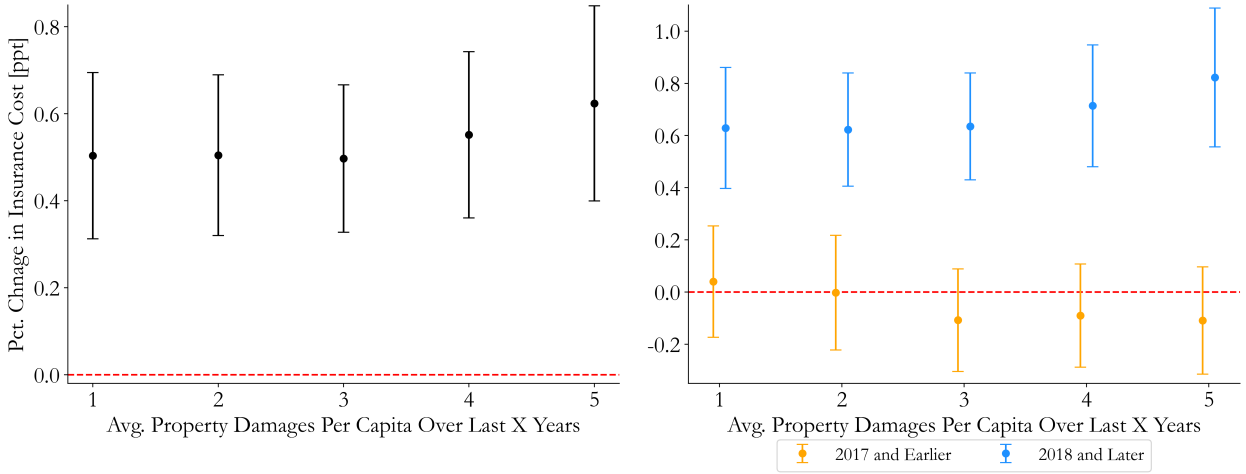
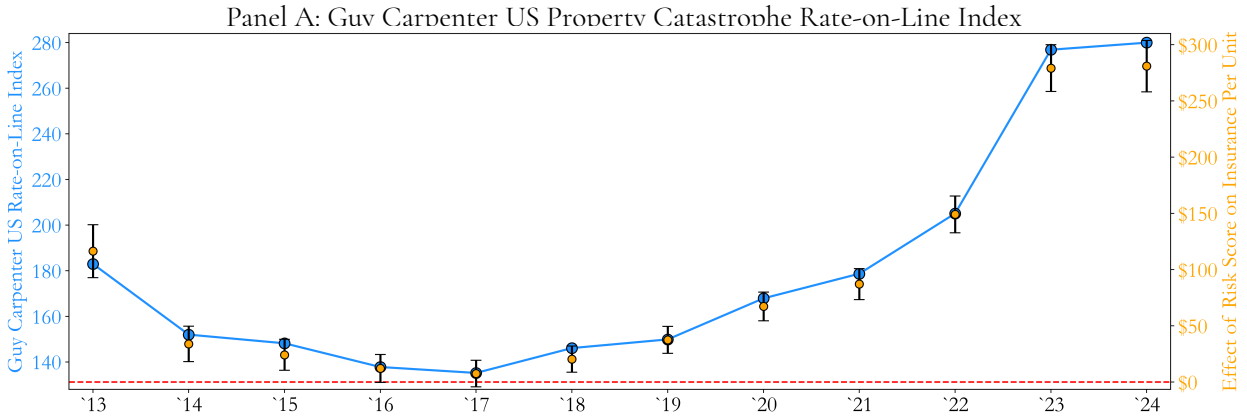
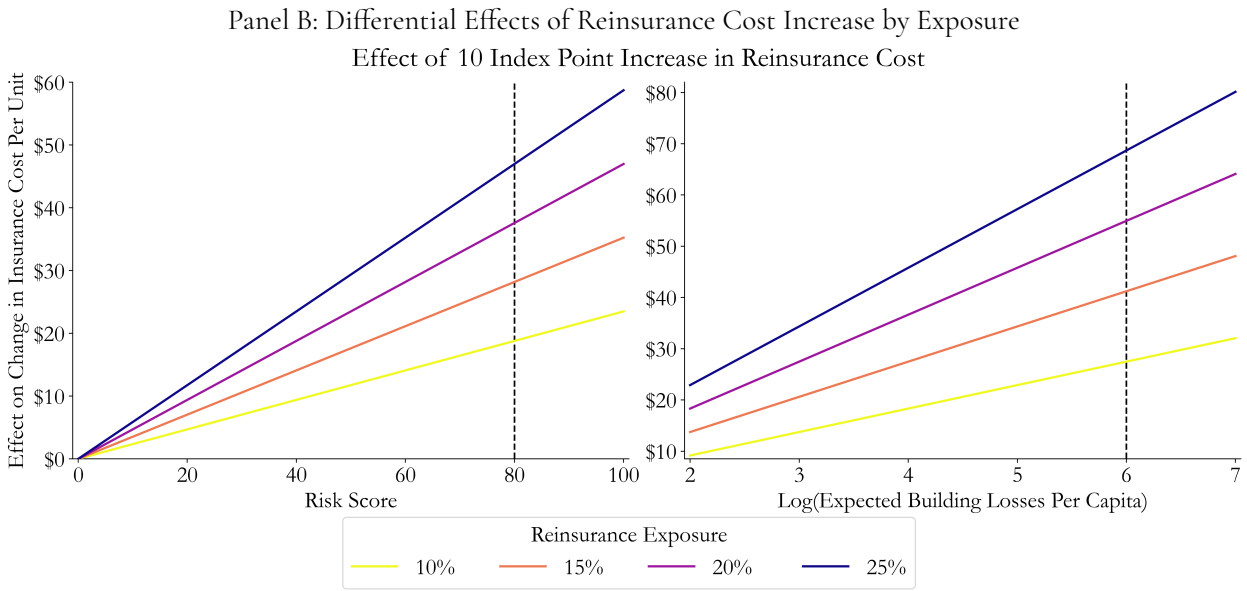


**Figure 5: Rise in Reinsurance Costs**

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 is 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 C presents the annual estimates from the border county-pair difference-in-differences specification in Equation (3), where the sample is restricted to properties located in counties near state borders. The error bars represent 95% confidence intervals based on standard errors double clustered at the state and year levels.



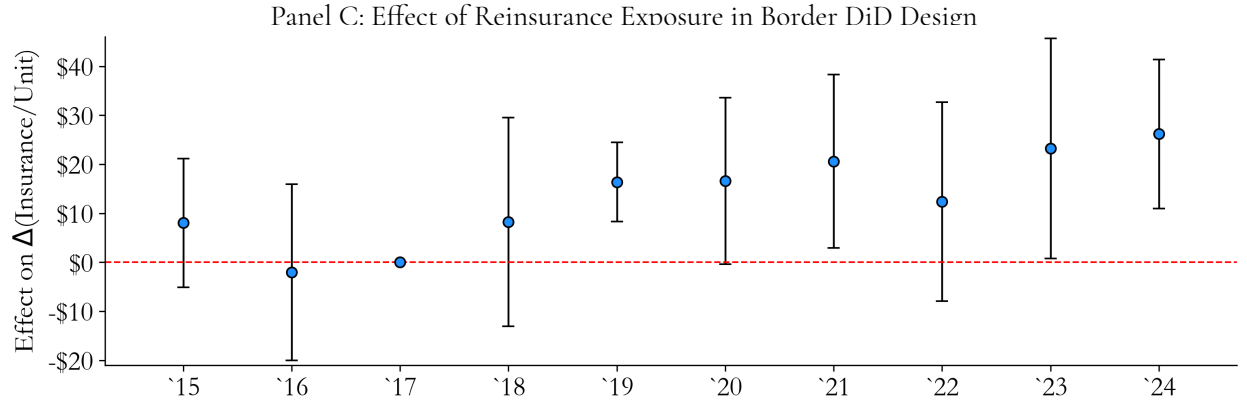
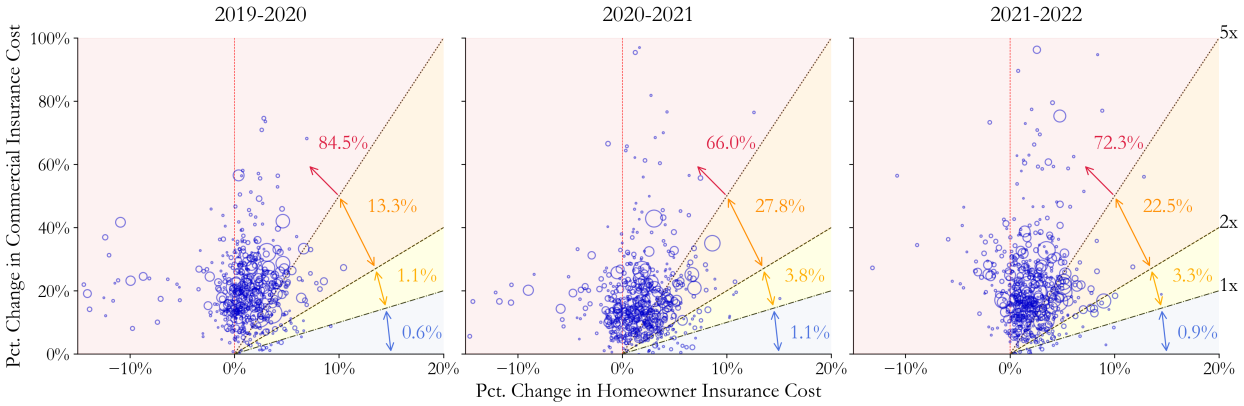



**Figure 6: Commercial vs. Homeowners Insurance Costs**

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

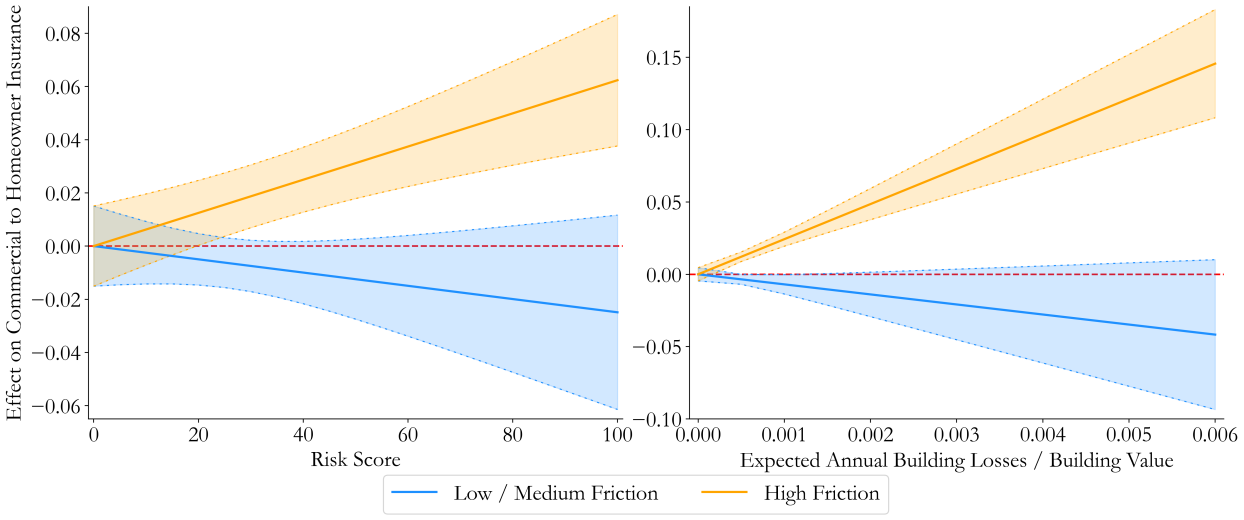
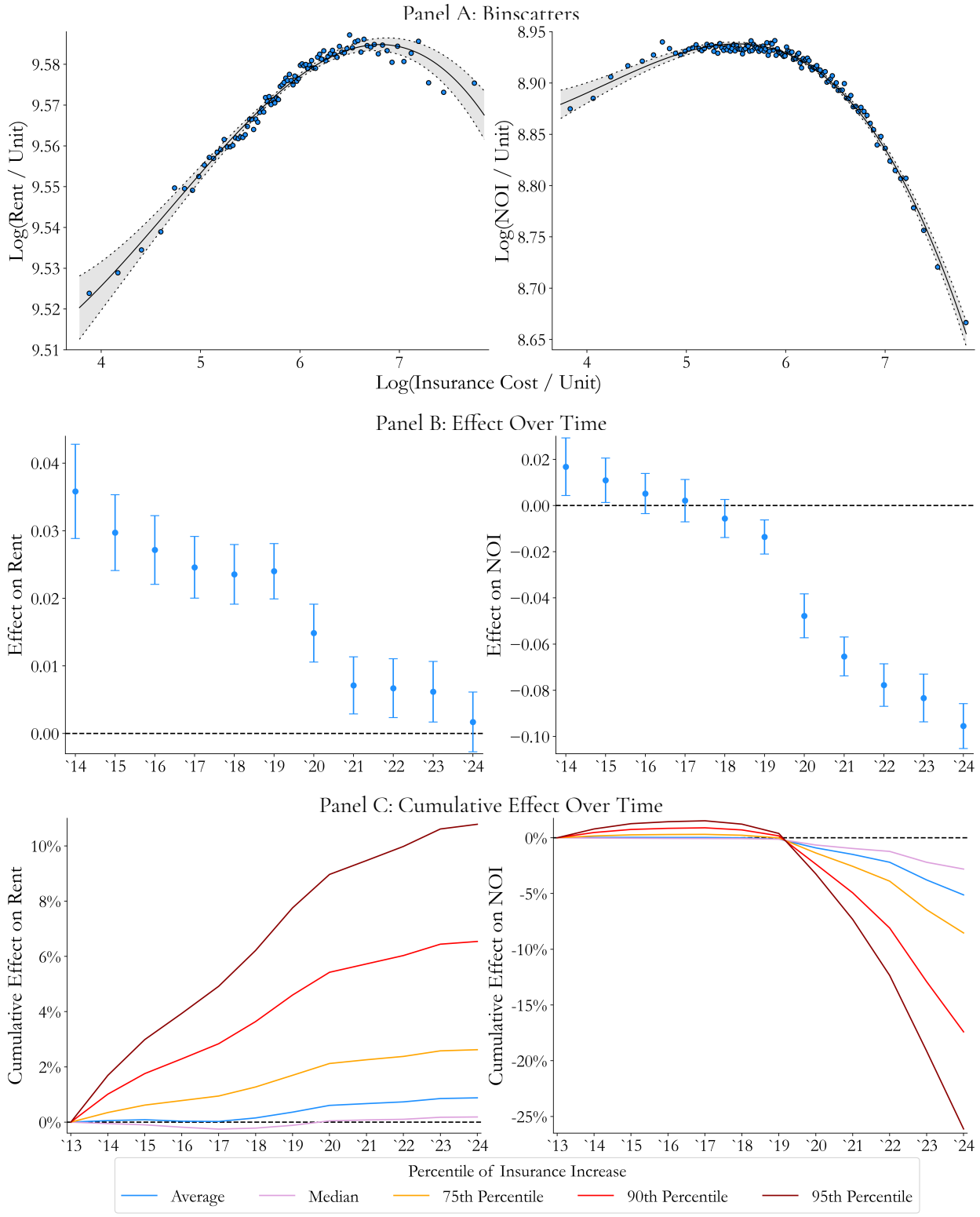


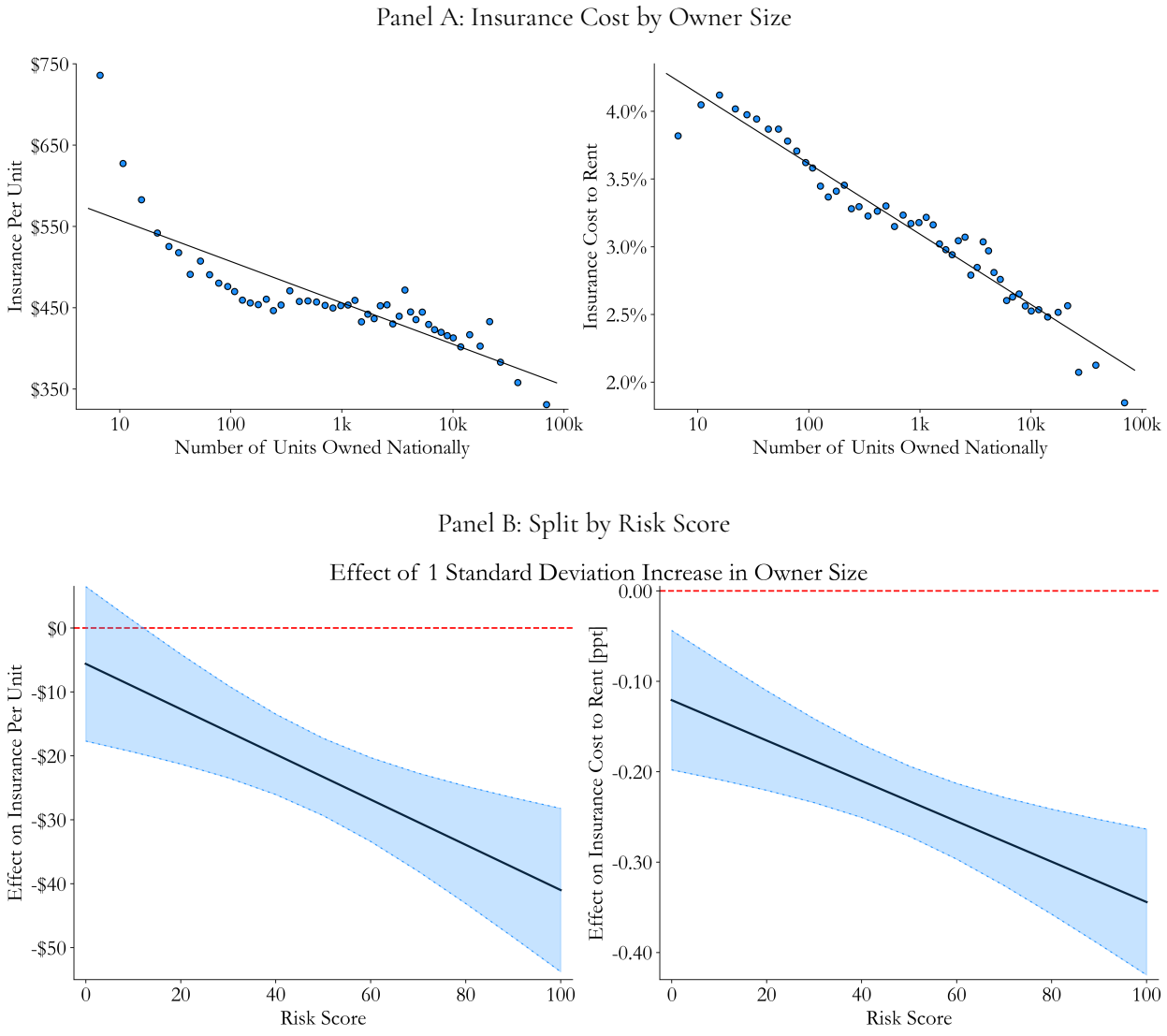
**Figure 7: Incidence of Insurance Cost Increases on Rents and NOI**

This figure examines the incidence 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 polynomial fits based on the underlying data, and the gray regions represent 95% confidence intervals. Panel B illustrates how these relationships evolve 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 estimates shown in Panel B and percentiles of the percentage increase in insurance cost relative 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

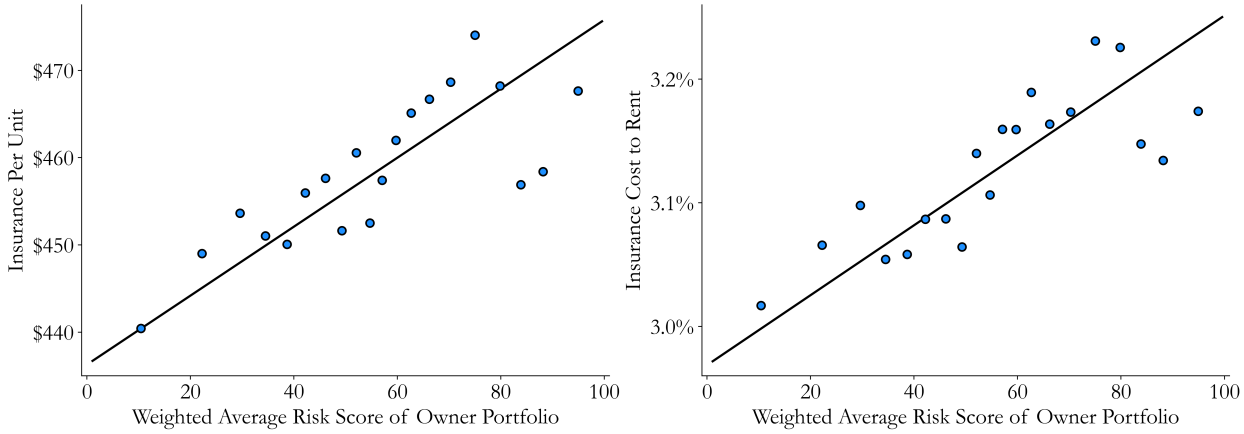
This figure examines how owner size is related to insurance costs and how that relationship varies with property risk. Panel A shows the relationship between owner size, measured as the number of units owned nationally, and insurance costs. The left subpanel plots the insurance cost per unit, while the 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

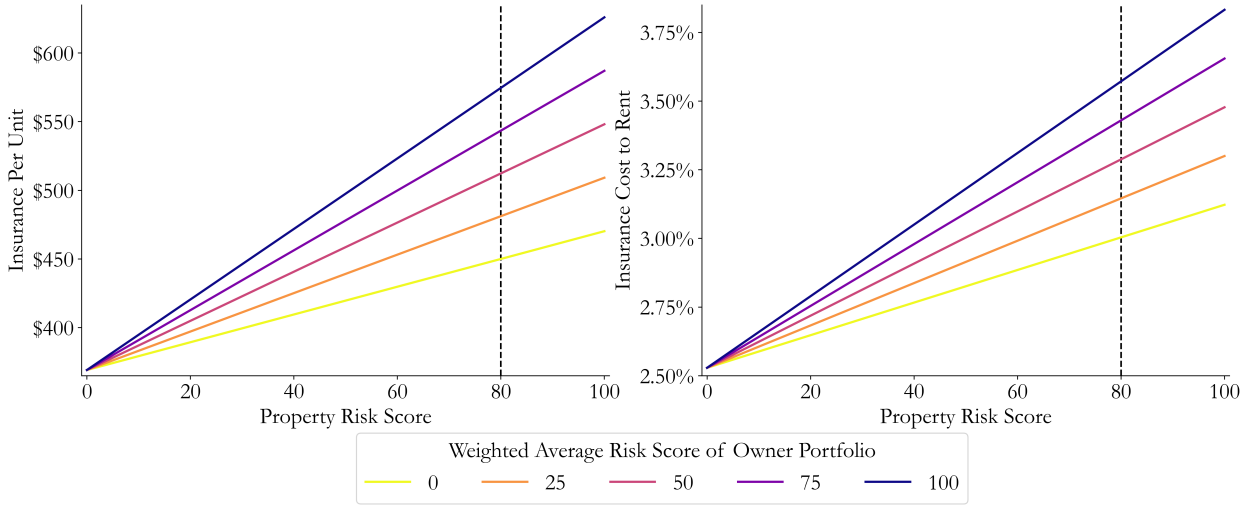


**Figure 10: Role of Average Risk of Owner Portfolio Across Owner Size**

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.

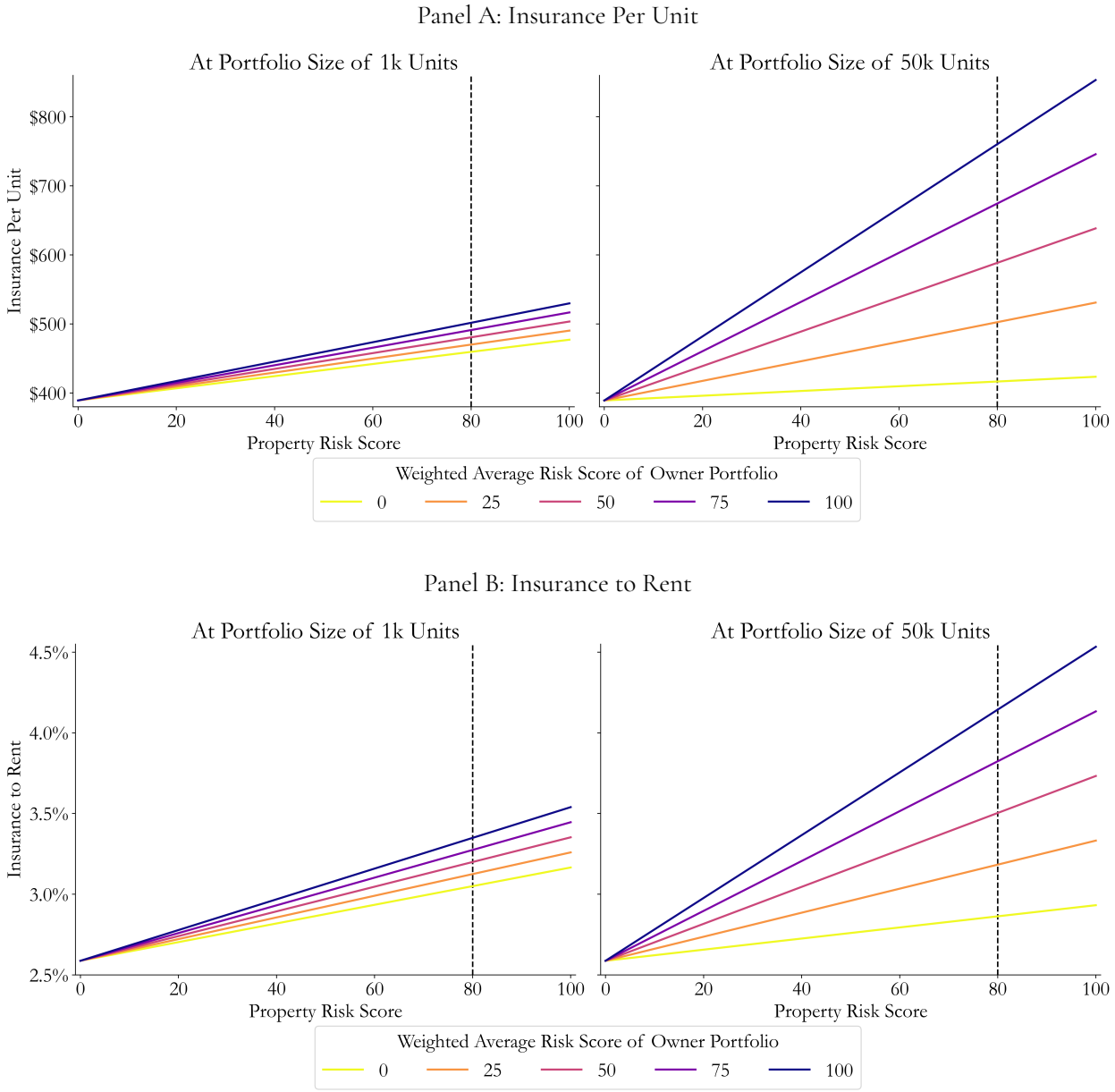


**Figure 11: Insurance Costs Around Mergers and Acquisitions Events**

This figure examines how insurance costs evolve around mergers and acquisitions (M&A) events using a stacked difference-in-difference framework. Event time is measured in years relative to the M&A transaction, with the year immediately before the event ($t = -1$) omitted as the reference period. Panel A plots the effects on *Log(Insurance Cost Per Unit)*, Panel B on insurance-cost-to-rent ratio, and Panel C on insurance-cost-to-operating-expenses ratio. All panels are based on regressions with property × cohort fixed effects and CBSA × year × cohort fixed effects. Error bars denote 95% confidence intervals based on standard errors clustered by owner.

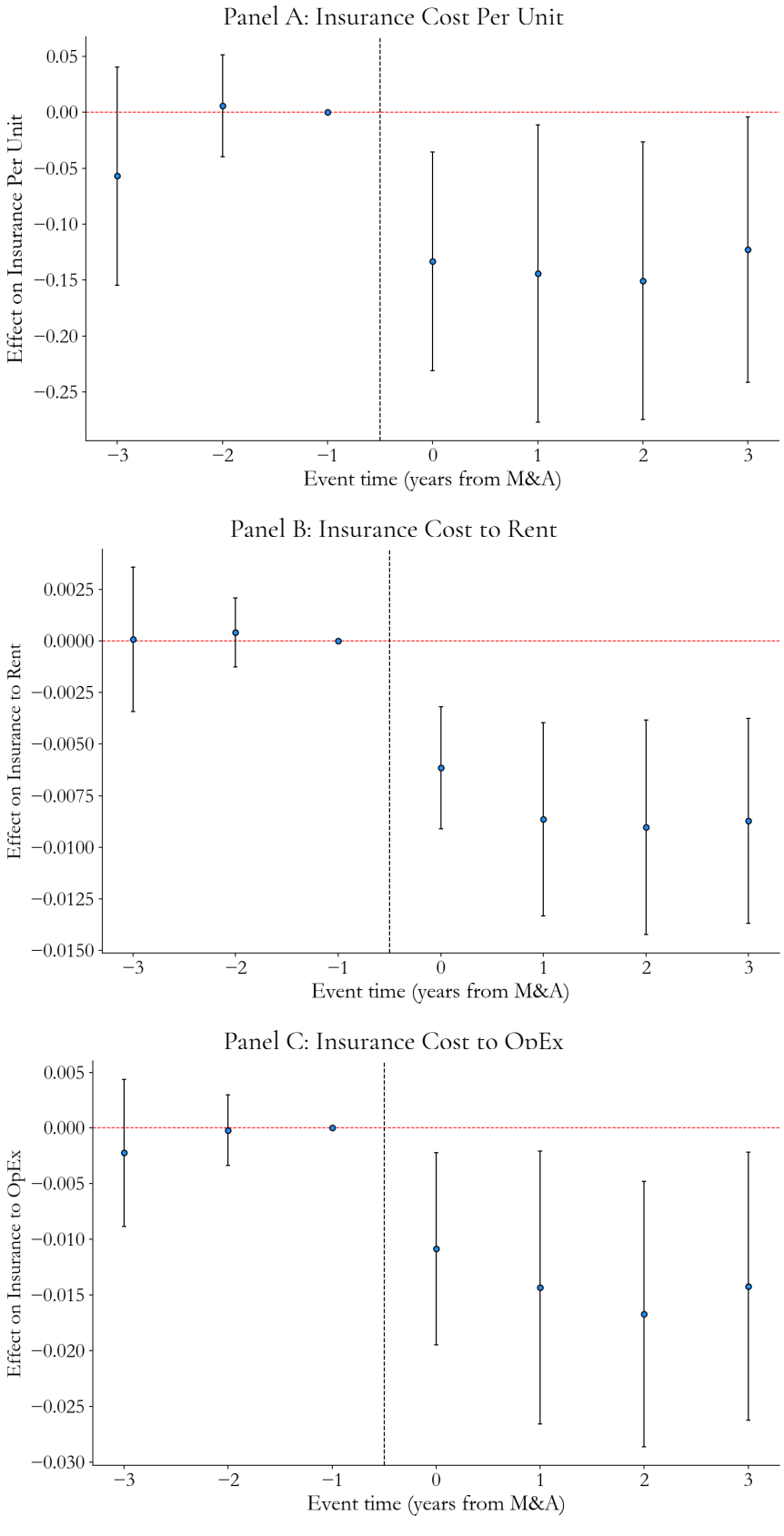


**Figure 12: Role of Property Owner Size Over Time**

This figure examines 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.

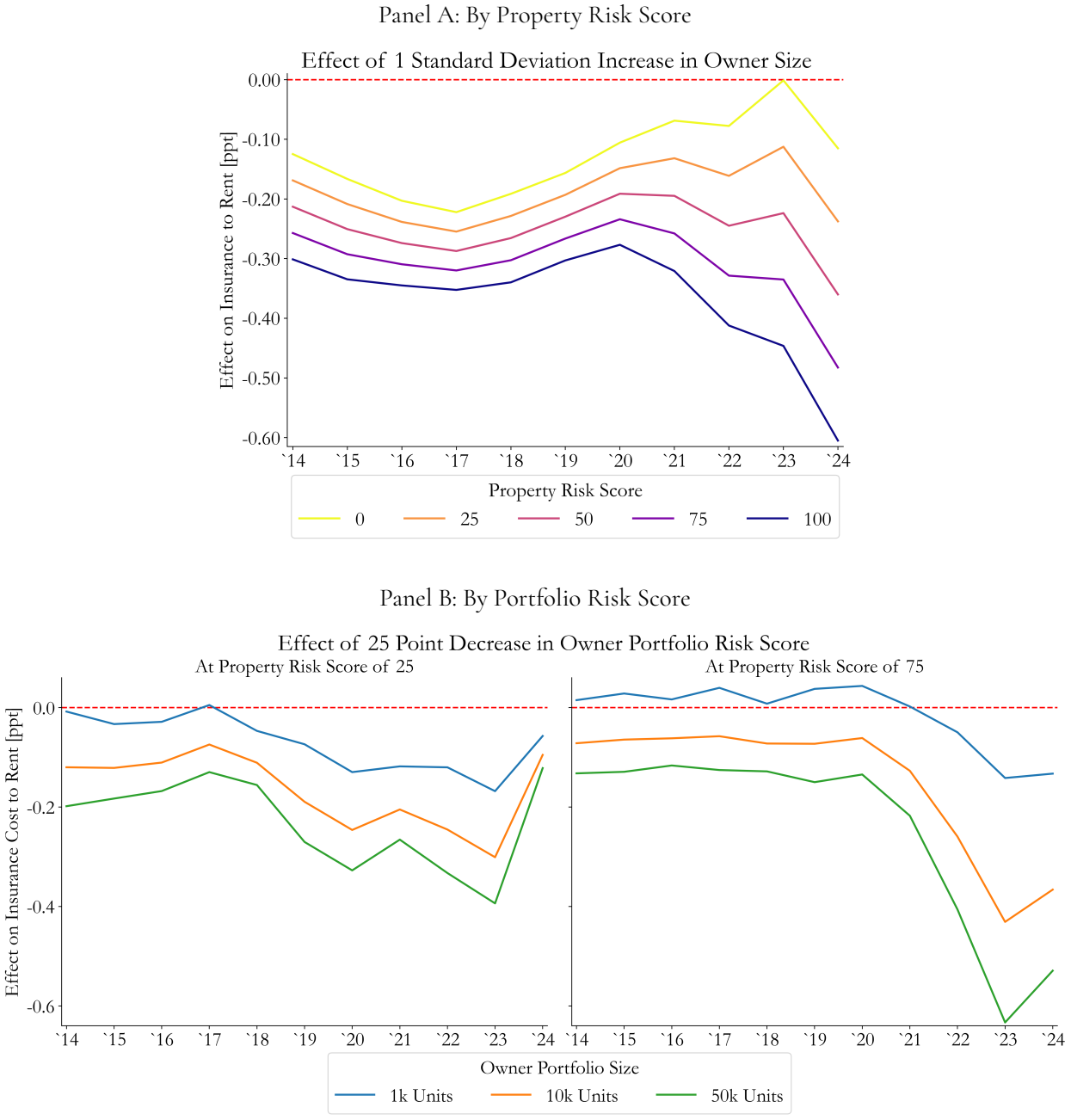


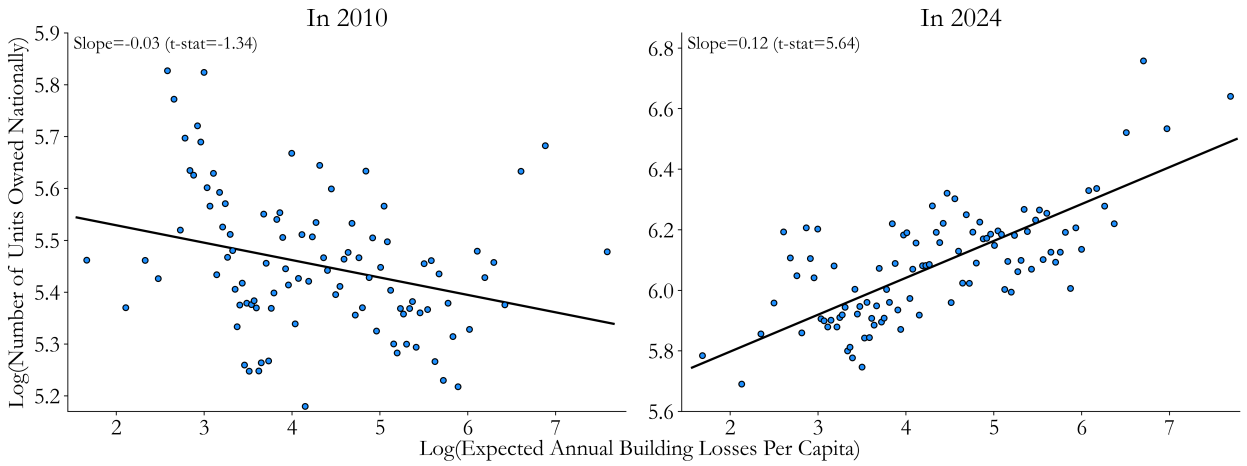
**Figure 13: Effect of Property Risk on Owner Size**

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 ($\beta_t$) 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 25-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

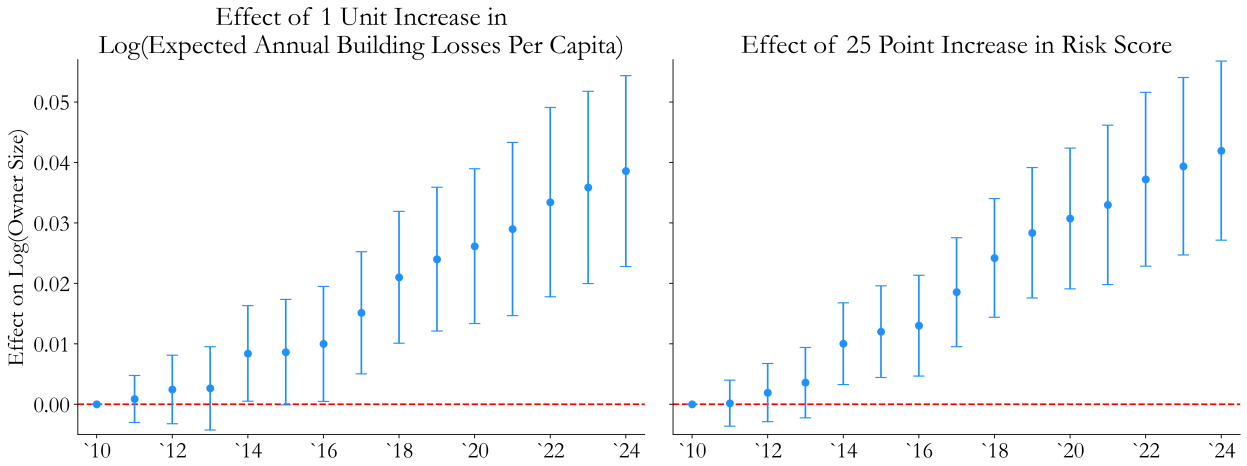


**Figure 14: Effect of Property Risk and Owner Size on Property Sales**

This figure examines how the effect of being in a high-risk location on the probability that a property is sold varies by owner size and period. For each subperiod, we estimate the following regression:

$$Sale_{i,o,m,t} = \sum_{d \neq 5} \beta_d \times HighRisk_i \times \mathbb{1}(OwnerSizeDecile_{o,t} = d) + \sum_{d \neq 5} \delta_d \times \mathbb{1}(OwnerSizeDecile_{o,t} = d) + \alpha \times HighRisk_i + \eta_{m,t} + \varepsilon_{i,o,m,t}.$$

The dependent variable is an indicator equal to one if property $i$, located in CBSA $m$ and owned by owner $o$, is sold in year $t$. *HighRisk* is an indicator variable defined as above-median expected annual building losses. The specification includes CBSA × year fixed effects ($\eta_{m,t}$) to absorb common local shocks to transaction activity in a given year. The omitted owner-size category is decile 5, and the plotted points ($\beta_d$) report the estimated differential effect of high risk on sale probability for each owner-size decile relative to decile 5. The orange series shows estimates for 2010–2017, while the blue series shows estimates for 2018–2024. Error bars denote 95% confidence intervals based on standard errors clustered by CBSA.

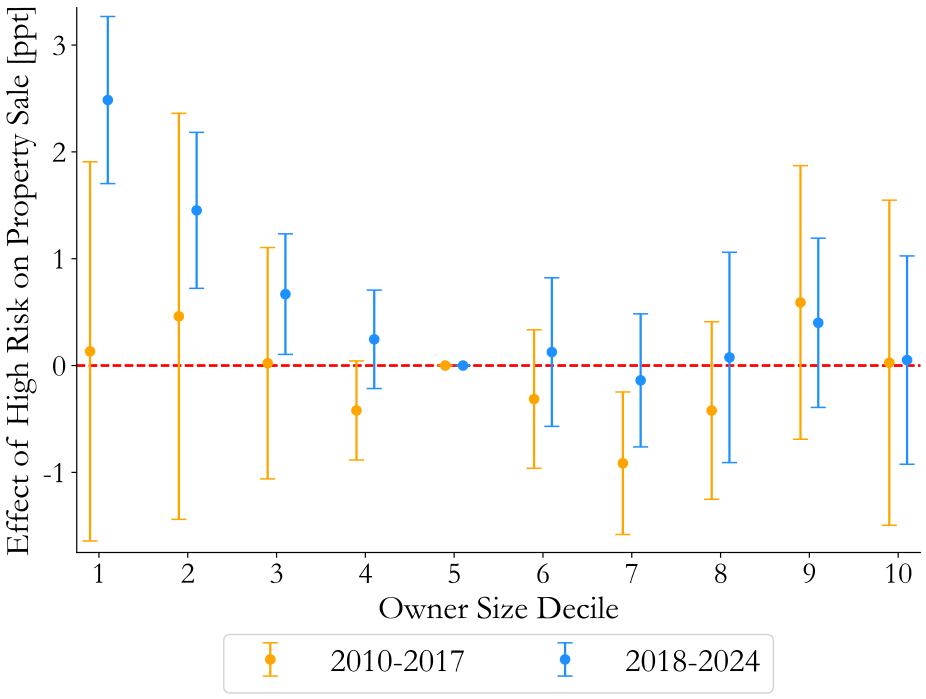


**Table 1: Effects of Reinsurance Exposure on Rise in Insurance Cost**

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 | 0.00238*** | | | |
| | (2.76) | | | |
| $\mathbb{1}$(Low Friction) × Lagged Loss Ratio | | 0.000862 | | |
| | | (0.58) | | |
| $\mathbb{1}$(High Friction) × Lagged Loss Ratio | | 0.00342*** | | |
| | | (4.14) | | |
| $\mathbb{1}$(Low Risk Score) × Lagged Loss Ratio | | | 0.00230 | 0.000888 |
| | | | (0.92) | (0.36) |
| $\mathbb{1}$(High Risk Score) × Lagged Loss Ratio | | | −0.000911 | 0.00513*** |
| | | | (−0.58) | (4.84) |
| States Included | All | All | Low | High |
| Property FE | ✓ | ✓ | ✓ | ✓ |
| State × Year FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 158,047 | 158,047 | 80,519 | 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: Incidence of Insurance Cost Increases on Rents and NOI**

This table examines the incidence of rising insurance costs on rents [columns (1)–(3)] and on net operating income (NOI) [columns (4)–(6)]. All variables, both dependent and independent, are winsorized at the 1% tails within each year. Fixed effects and controls are indicated at the bottom of each column. Columns (3) and (6) additionally control for occupancy, Log(Operating Expenses Excluding Insurance Cost Per Unit), Log(Capital Expenses), an indicator for renovations in the previous year, an indicator for renovations in the previous five years, Log(Property Age), and Log(Effective Property Age). Robust standard errors are clustered by CBSA.

| Dep. Variable: | Log(Rent Per Unit) | | | Log(NOI Per Unit) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log(Insurance Cost Per Unit) | 0.0223*** | 0.0164*** | 0.0158*** | −0.0410*** | −0.0460*** | −0.0391*** |
| | (8.99) | (9.95) | (9.76) | (−10.74) | (−13.55) | (−8.63) |
| Property FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | | | ✓ | | |
| CBSA × Year FE | | ✓ | ✓ | | ✓ | ✓ |
| Additional Controls | | | ✓ | | | ✓ |
| Observations | 411,669 | 411,669 | 173,388 | 411,669 | 411,669 | 173,388 |
| Adjusted $R^2$ | 0.976 | 0.979 | 0.977 | 0.918 | 0.924 | 0.929 |

*t* statistics in parentheses.

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

**Table 5: Effect on Transaction Prices and Cap Rates**

This table examines how local climate risk is reflected in multifamily transaction prices and cap rates, and whether that relationship changes after 2018. The dependent variable is either the log of transaction price per unit [columns (1) and (2)] or the transaction cap rate [columns (3) and (4)]. The key explanatory variable is log(*Expected Annual Building Losses*), measured using FEMA's National Risk Index, and its interaction with an indicator for 2018 or later. All specifications include CBSA × year fixed effects, and columns (2) and (4) additionally include property fixed effects. Robust standard errors are two-way clustered by CBSA and year.

| Dep. Variable: | Log(Transaction Price Per Unit) | | Transaction Cap Rate | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}$(2018 or Later) | −0.0747*** | −0.0653*** | 0.000872** | 0.00118*** |
| × Log(Expected Annual Building Losses) | (−3.50) | (−5.94) | (2.64) | (3.18) |
| Log(Expected Annual Building Losses) | 0.230*** | | -0.00230*** | |
| | (5.39) | | (-5.42) | |
| CBSA × Year FE | ✓ | ✓ | ✓ | ✓ |
| Property FE | | ✓ | | ✓ |
| Observations | 102,294 | 49,955 | 38,551 | 10,535 |
| Adjusted $R^2$ | 0.564 | 0.902 | 0.452 | 0.650 |
| Dep. Variable Mean | 11.84 | 11.74 | 0.0555 | 0.0558 |

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

**Table 6: 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 7: 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 8: Insurance Costs Within Continuing Ownership Relationships**

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 $\text{Rent}_t$ − Insurance Cost to $\text{Rent}_{t-3}$ | | | |
|---|---|---|---|---|
| | (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 9: Insurance Costs Around Mergers and Acquisitions Events**

This table examines how insurance costs change around mergers and acquisitions (M&A) events. Panel A reports baseline stacked difference-in-differences estimates of the effect of an M&A event on three outcomes: *Log(Insurance Cost Per Unit)* [column (1)], the insurance-cost-to-rent ratio [column (2)], and the insurance-cost-to-operating-expenses ratio [column (3)]. The key independent variable is the interaction between an indicator for treated properties (i.e., those that undergo an M&A event) and an indicator for the post-M&A period. Panel B examines heterogeneity in the effect on *Log(Insurance Cost Per Unit)* by the change in owner size and by property risk. Columns (1) and (2) split the sample according to whether the difference in owner size between the acquiring and acquired firms is above or below the median, while columns (3) and (4) split the sample according to whether the property's risk score is above or below the median. In columns (1) and (2), the treated properties are split by the difference in owner size, while the full set of control properties is retained in both specifications. Fixed effects and controls are indicated at the bottom of the table. Robust standard errors are clustered by owner.

Panel A. Baseline

| Dep. Variable: | Log(Insurance / Unit) | Insurance to Rent | Insurance to OpEx |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\mathbb{1}$(Treated) × $\mathbb{1}$(Post) | -0.1340** | -0.0080*** | -0.0133** |
| | (2.38) | (4.05) | (2.49) |
| Property × Cohort FE | ✓ | ✓ | ✓ |
| CBSA × Year × Cohort FE | ✓ | ✓ | ✓ |
| Observations | 1,046,494 | 1,048,096 | 1,048,096 |
| Adjusted $R^2$ | 0.906 | 0.839 | 0.845 |

Panel B. Heterogeneity

| Dep. Variable: | Log(Insurance / Unit) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Sample: | High Diff. Size | Low Diff. Size | High Risk | Low Risk |
| $\mathbb{1}$(Treated) × $\mathbb{1}$(Post) | -0.2012*** | -0.0589 | -0.1788*** | -0.0723 |
| | (2.66) | (0.90) | (3.13) | (0.86) |
| Property × Cohort FE | ✓ | ✓ | ✓ | ✓ |
| CBSA × Year × Cohort FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 1,044,690 | 1,045,126 | 524,111 | 516,311 |
| Adjusted $R^2$ | 0.906 | 0.906 | 0.898 | 0.914 |

*t* statistics in parentheses.

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

**Table 10: Effects of Local Risk on Owner Size and Reallocation**

This table examines how local climate risk relates to owner size and how that relationship changes over time. Panel A studies the relationship between the riskiness of a property's location and the size of its current owner. The dependent variable is the log of the total number of multifamily units owned nationally by the property's owner in a given year. 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. Panel B examines whether, conditional on a sale occurring, high-risk properties owned by smaller owners are sold to larger new owners after 2018. The dependent variable is the log of the new owner's national multifamily unit count at the time of sale, and the key variable is the triple interaction between indicators for the post-2018 period, high risk, and small-owner status. High risk is defined as above-median expected annual building losses, and small owner is defined as being in the bottom 20% of the owner-size distribution. The regressions in Panel B also include the lower-order interaction terms, but only the coefficients of primary interest are reported for space. Fixed effects and controls are indicated at the bottom of the table. In Panel A, robust standard errors are two-way clustered by owner and year; in Panel B, robust standard errors are two-way clustered by CBSA and year.

Panel A. Local Risk and Owner Size

| 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 Annual Building 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 |

Panel B. Reallocation of High-Risk Properties from Small Owners

| Dep. Variable: | Log(New Owner Size) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\mathbb{1}$(2018 or Later) × $\mathbb{1}$(High Risk) × $\mathbb{1}$(Small Owner) | 0.151*** | 0.161*** | 0.162*** |
| | (3.35) | (3.33) | (4.74) |
| $\mathbb{1}$(High Risk) × $\mathbb{1}$(Small Owner) | 0.0510 | 0.0469 | 0.0479 |
| | (0.19) | (0.18) | (0.18) |
| CBSA × Year FE | ✓ | ✓ | ✓ |
| Year × $\mathbb{1}$(Small Owner) | | ✓ | ✓ |
| Year × $\mathbb{1}$(High Risk) | | | ✓ |
| Observations | 100,583 | 100,583 | 100,583 |
| Adjusted $R^2$ | 0.308 | 0.308 | 0.309 |

*t* statistics in parentheses.

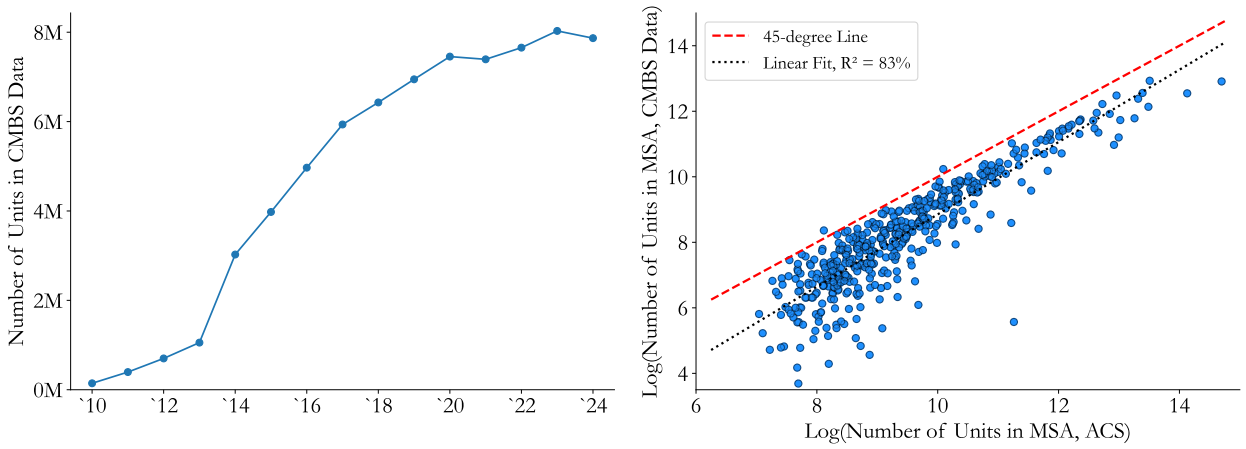
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**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: Coverage of CMBS Data

This figure evaluates the coverage of multifamily units in the CMBS operating statement data. The left panel plots the total number of units in the CMBS data from 2010 to 2024. The right panel compares the number of multifamily units (as of 2024) by Metropolitan Statistical Area (MSA) in the CMBS data with benchmark counts from the American Community Survey (ACS). The dashed red line is the 45-degree line, and the dotted black line is the fitted linear relationship.



## Figure IA.2: Coverage of RCA Data

This figure compares the coverage of multifamily units in the RCA data to benchmark estimates from the American Community Survey (ACS). The left panel plots the total number of multifamily units in the RCA data and in the ACS from 2010 to 2024. The right panel compares the number of multifamily units (as of 2024) by Metropolitan Statistical Area (MSA) in the RCA data and the ACS. The dashed red line is the 45-degree line, and the dotted black line is the fitted linear relationship.

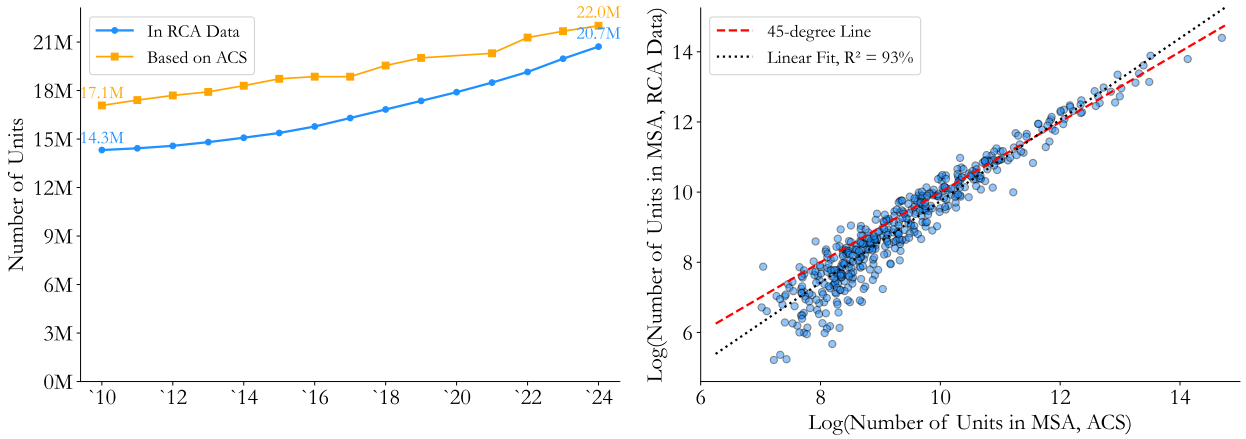
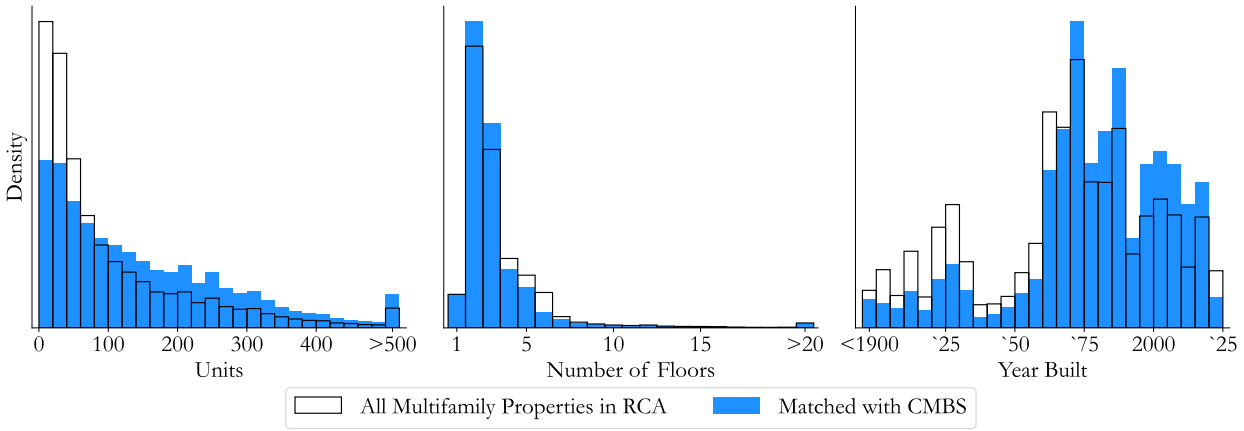


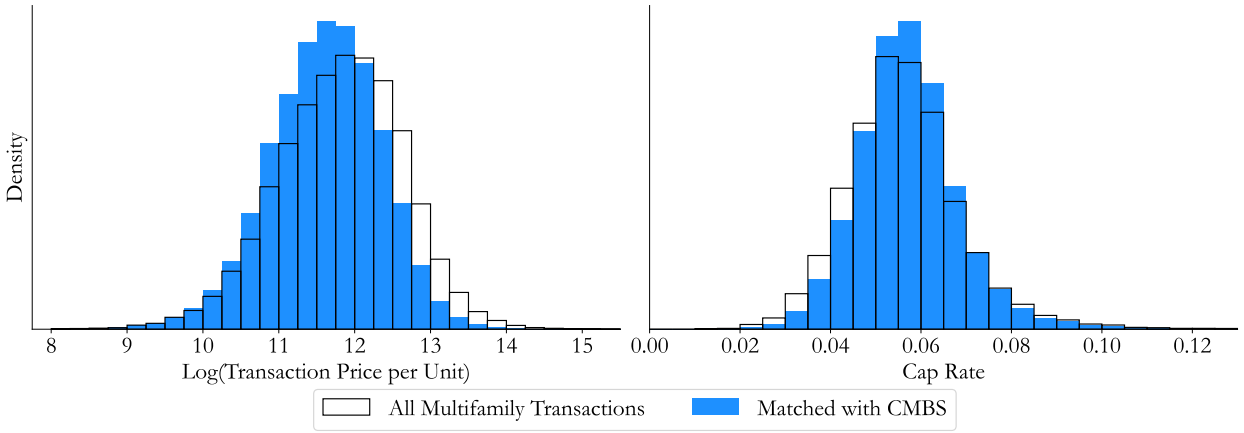
**Figure IA.3: Comparison of RCA Population to CMBS Matched Properties**

This figure compares all properties in the RCA data to those matched to the CMBS sample. Panel A compares property characteristics, with the left, middle, and right panels showing the distributions of the number of units, the number of floors, and year built, respectively. Panel B compares transaction prices per unit and cap rates, based on transaction data from RCA. Panel C compares each Metropolitan Statistical Area's (MSA's) share of all RCA multifamily units with its share of CMBS-matched units.

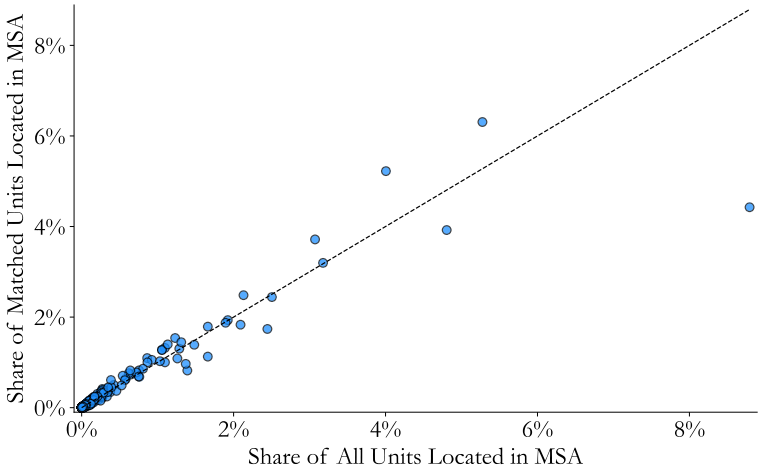
Panel A: Property Features




Panel B: Transaction Prices and Cap Rates

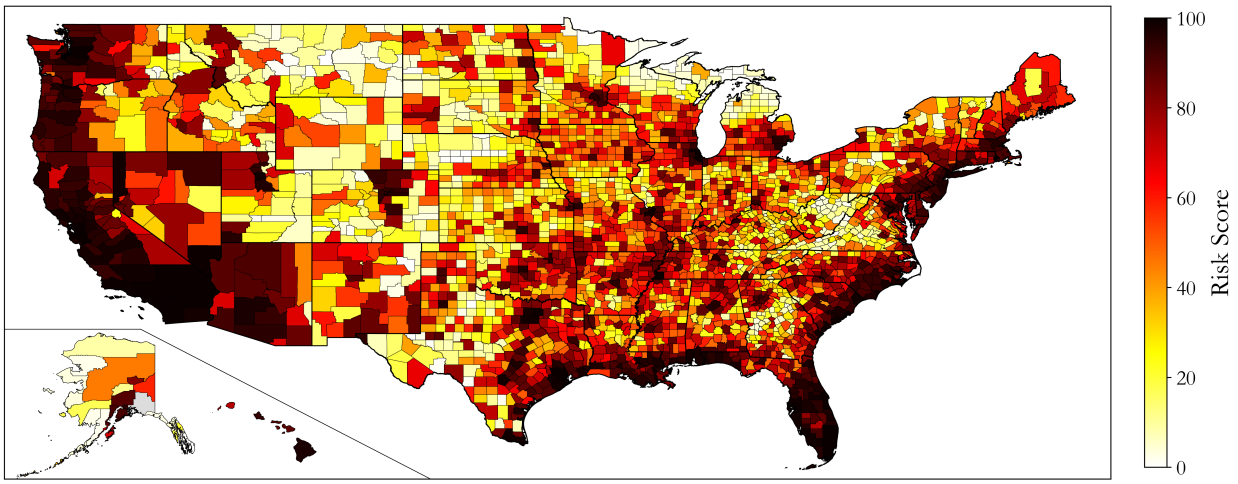



Panel C: Location



## Figure IA.4: Risk Score, County-level Maps

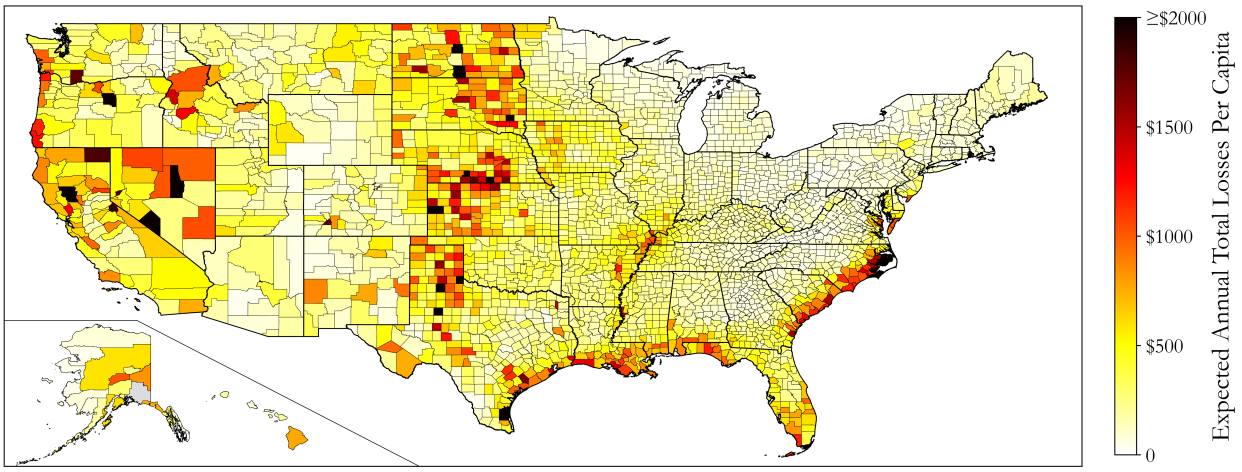
This figure shows county-level heatmaps of the risk scores. Please note that the risk scores we use in the paper are on the tract-level from the National Risk Index by FEMA. For illustration purposes, we aggregate it to the county-level.



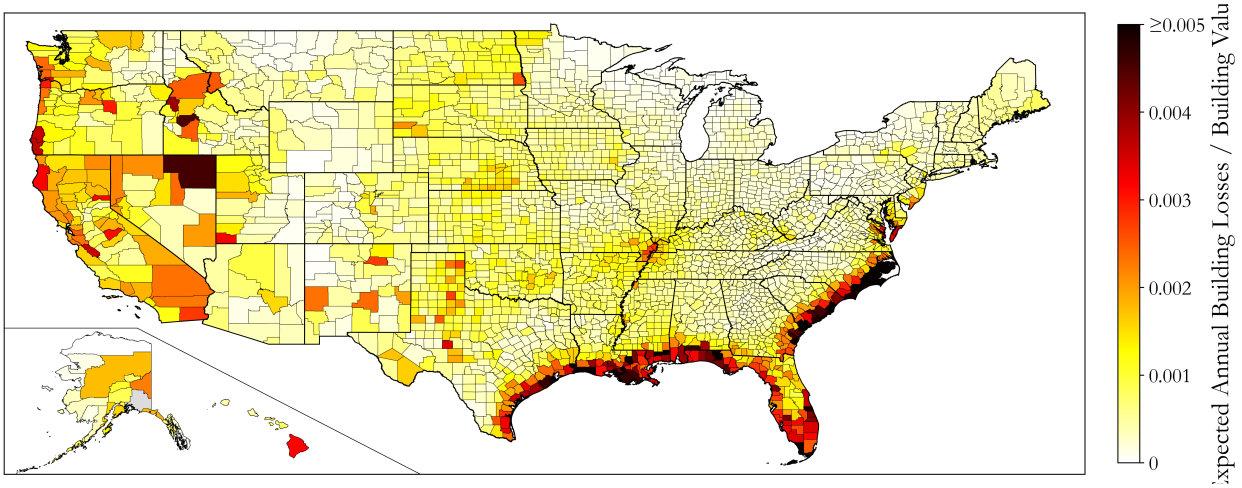
## Figure IA.5: Expected Annual Losses, County-level Maps

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.6: 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.

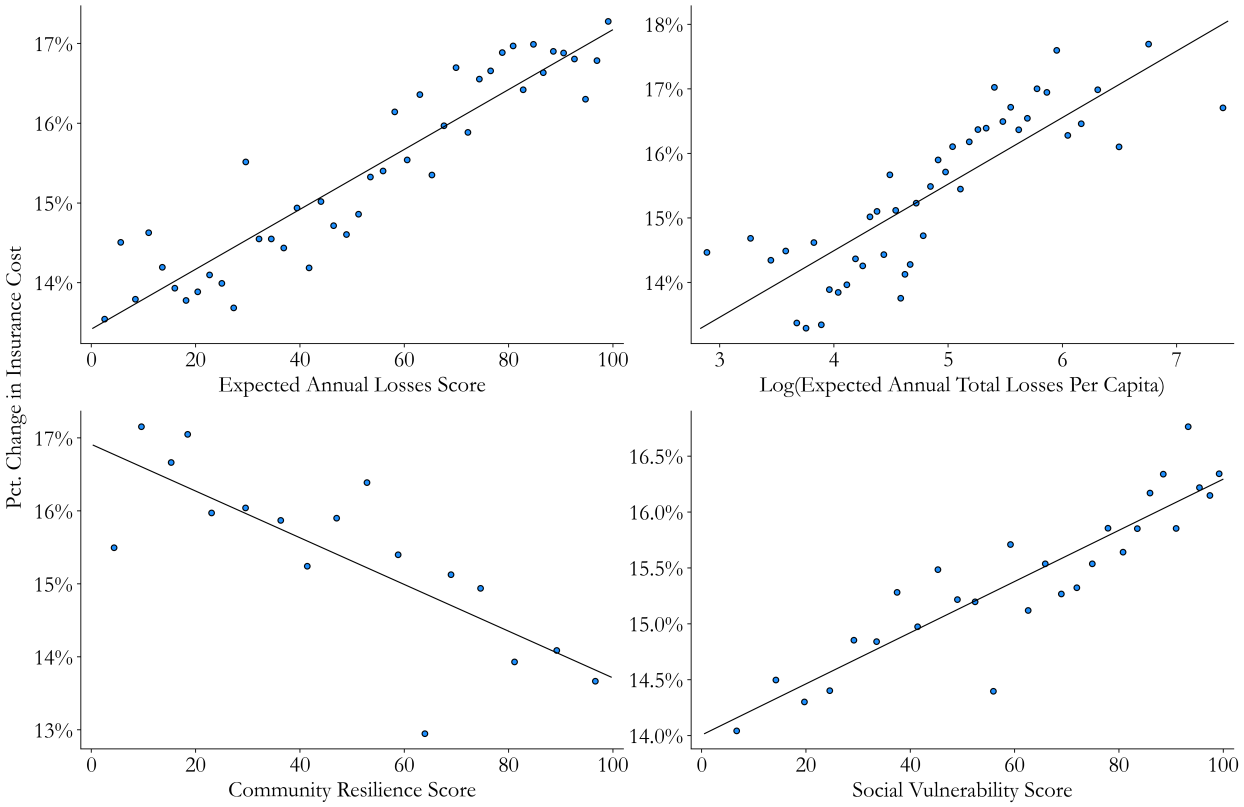
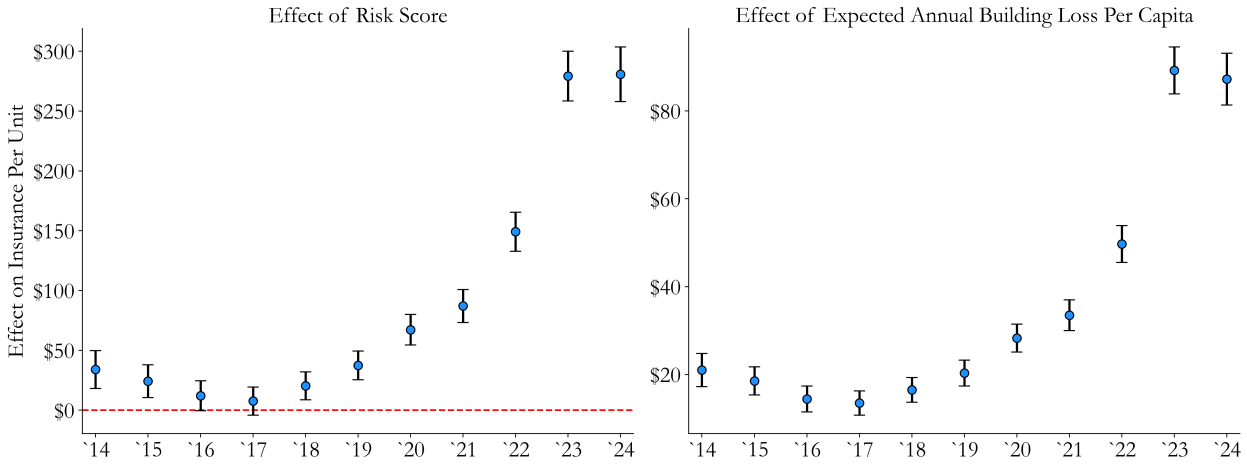


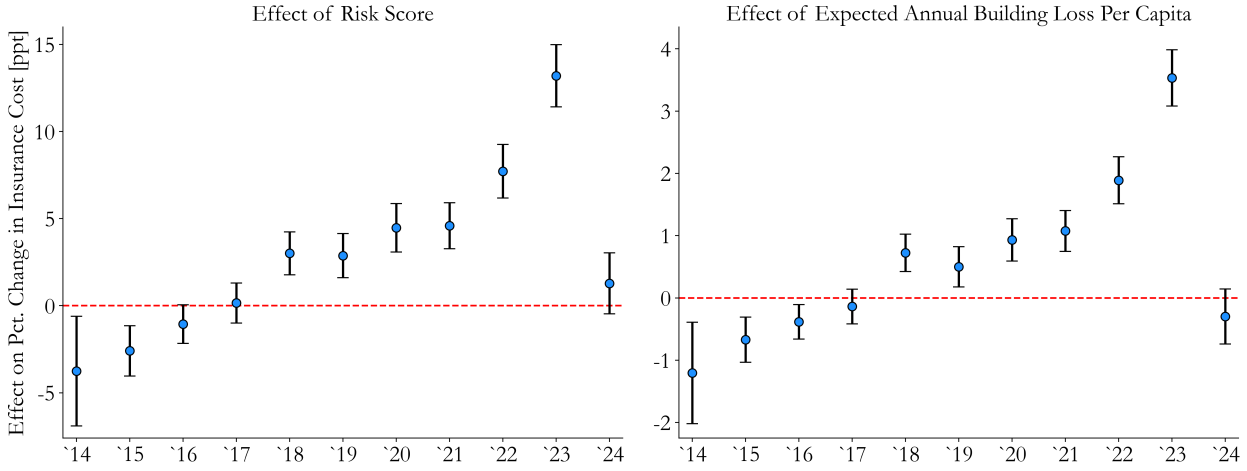
**Figure IA.7: Risk Scores and Expected Annual Losses and the Rise in Insurance Costs, Over Time**

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 shows 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



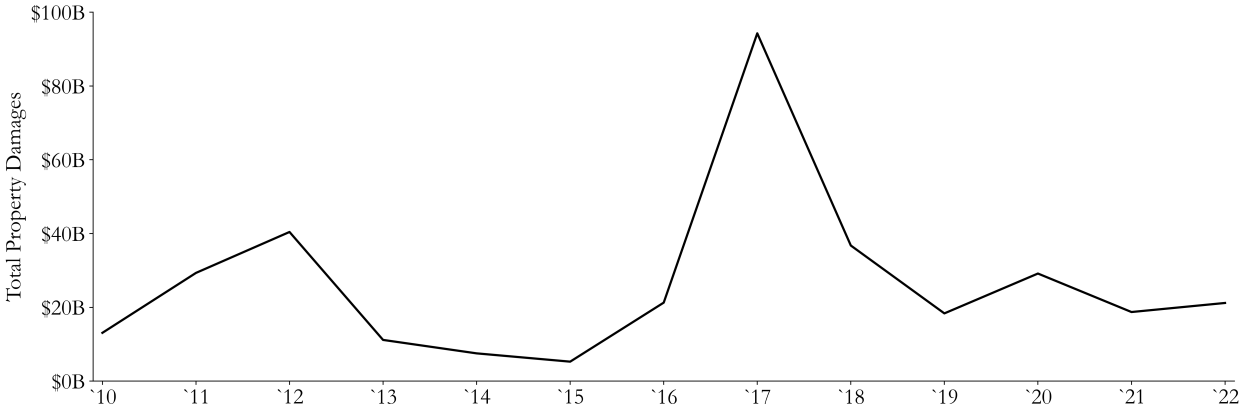

Panel B: Effect on Percentage Change in Insurance Cost



## Figure IA.8: 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

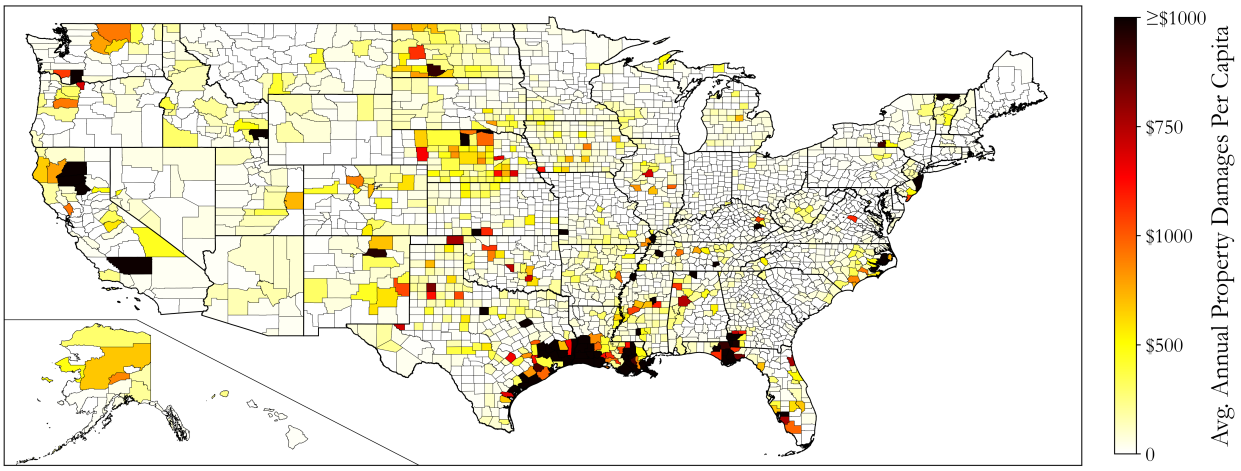
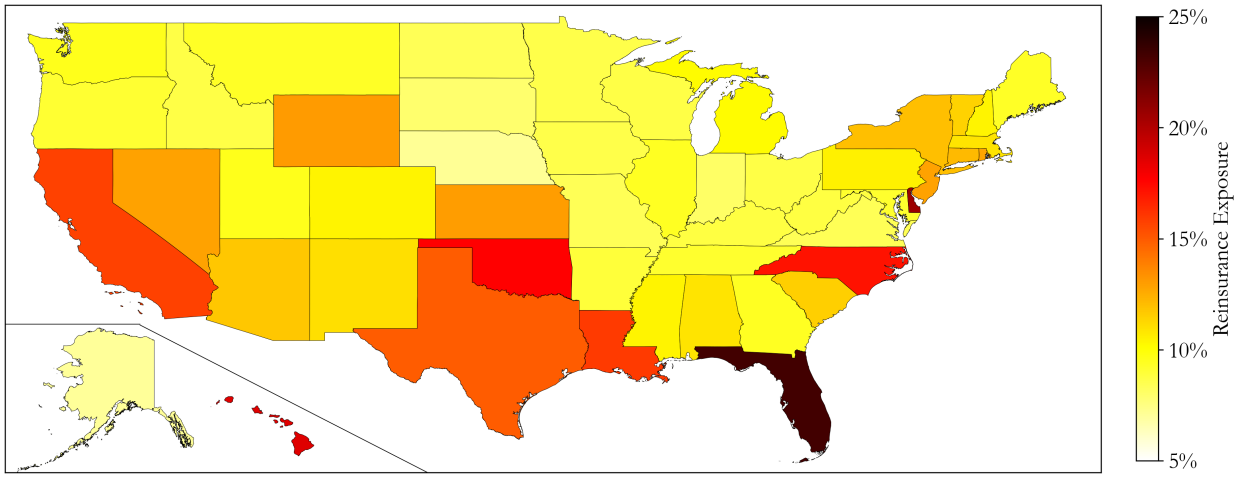


**Figure IA.9: Reinsurance Exposure**

This figure examines the state-level exposure to reinsurance markets (Panel A) and the stability of the percentage of risk ceded to unaffiliated reinsurers 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

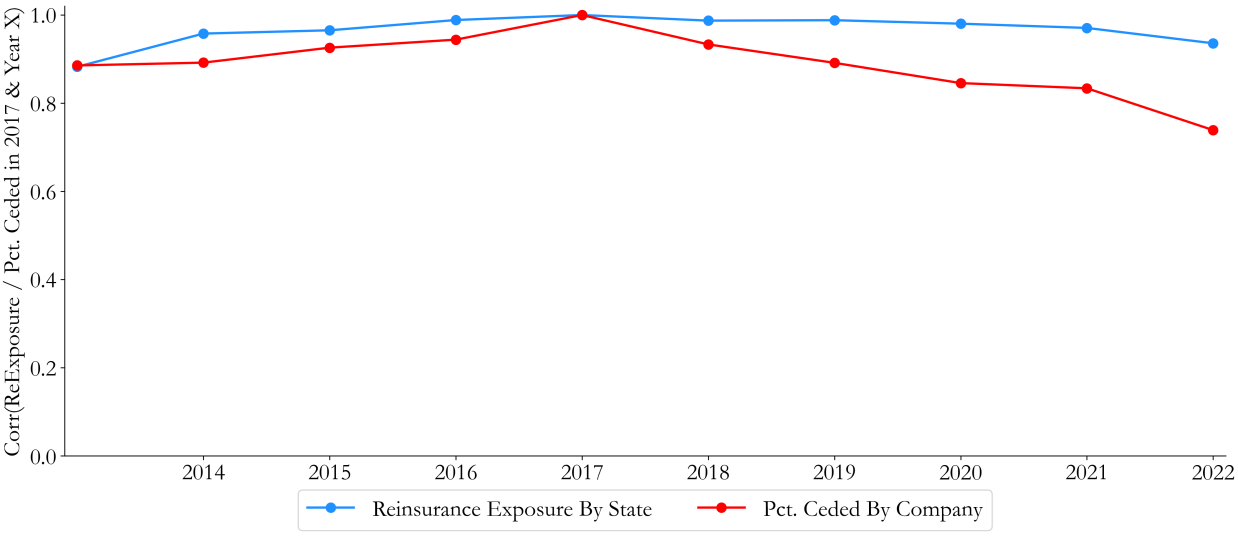
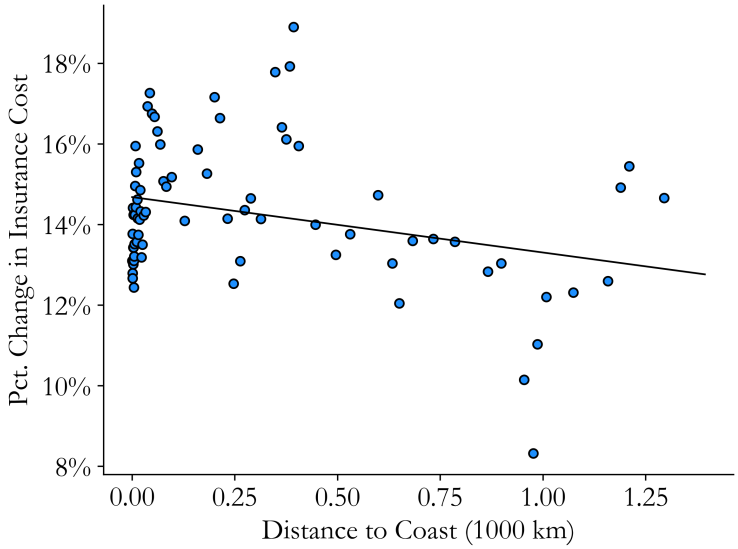


**Figure IA.10: Location and the Rise in Insurance Costs**

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

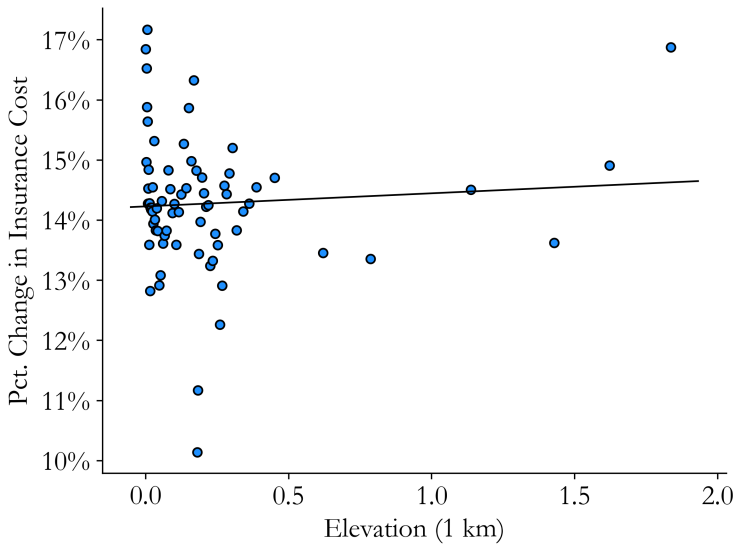


**Figure IA.11: Property Features and the Rise in Insurance Costs**

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.

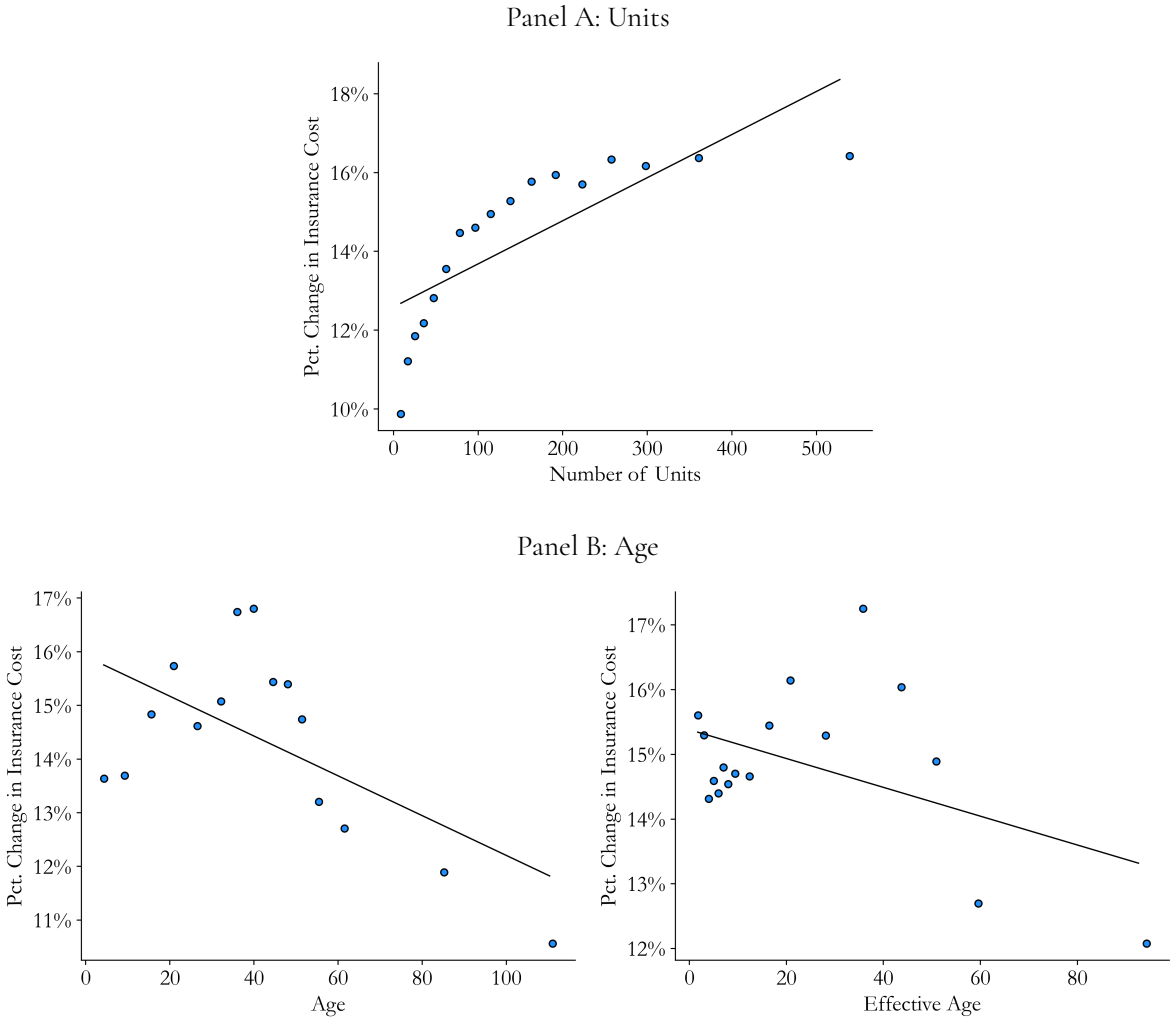
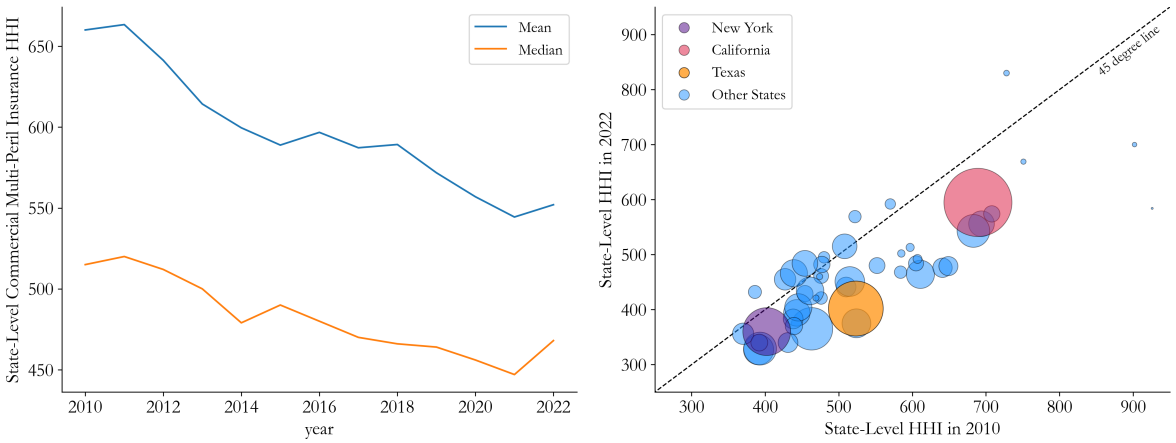


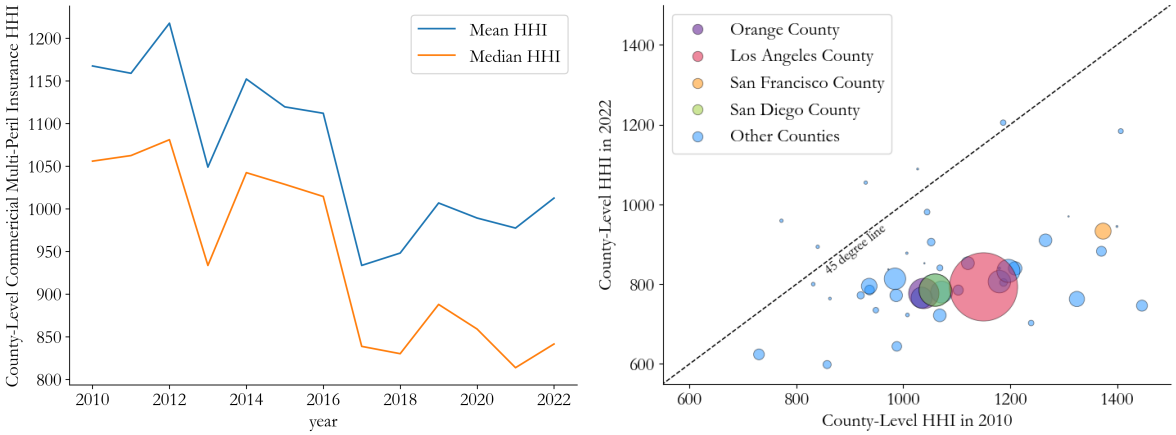
**Figure IA.12: Insurance Market Concentration and the Rise in Insurance Costs**

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

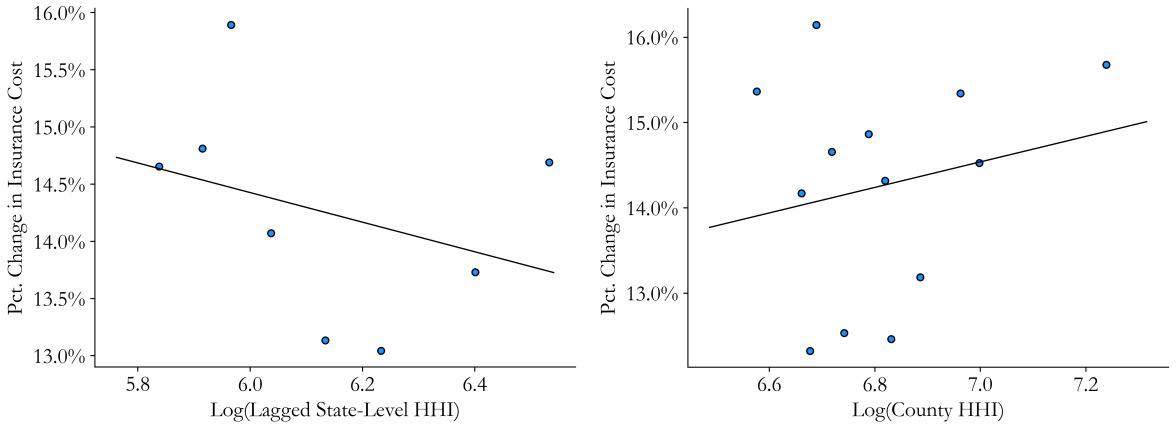
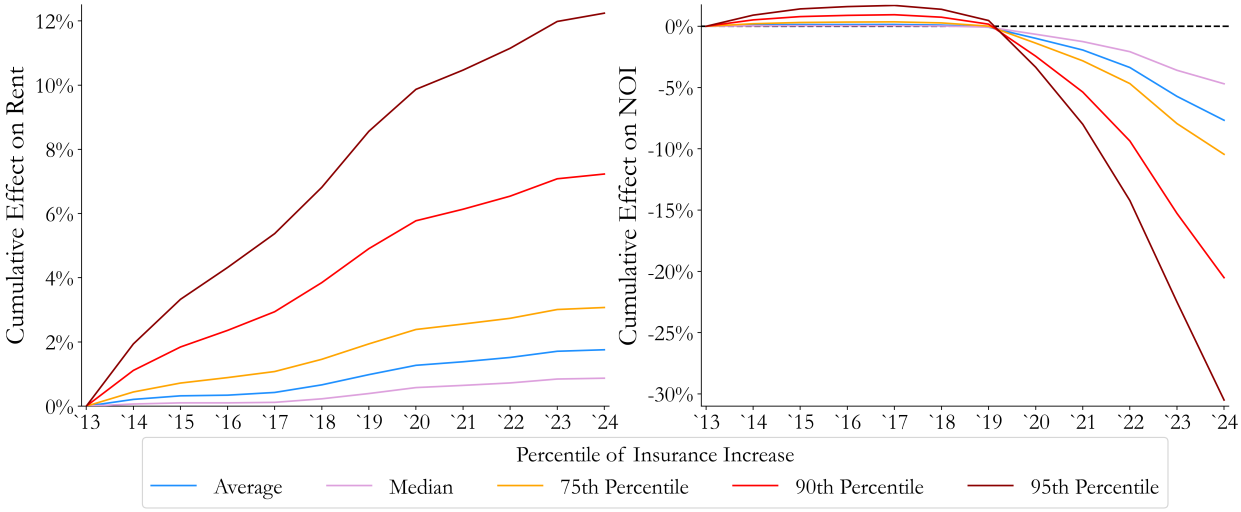


**Figure IA.13: Cumulative Effect of Rise in Insurance Cost on Rent and NOI, Using Percentage Change in Insurance Cost Per Unit**

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.14: 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.

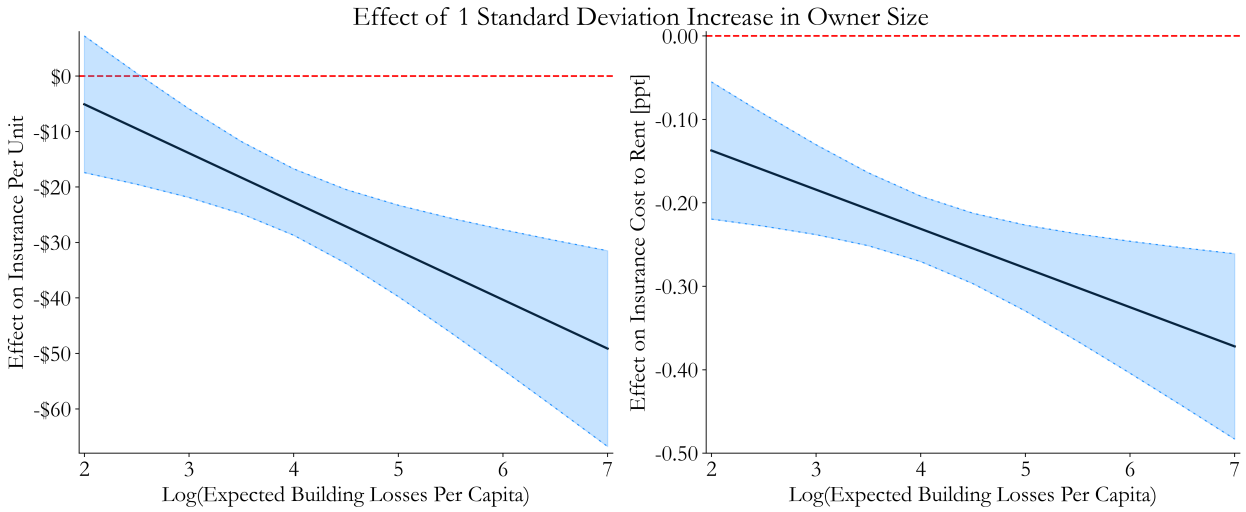


**Figure IA.15: Role of Average Risk of Owner Portfolio, Weighted Expected Annual Losses**

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.

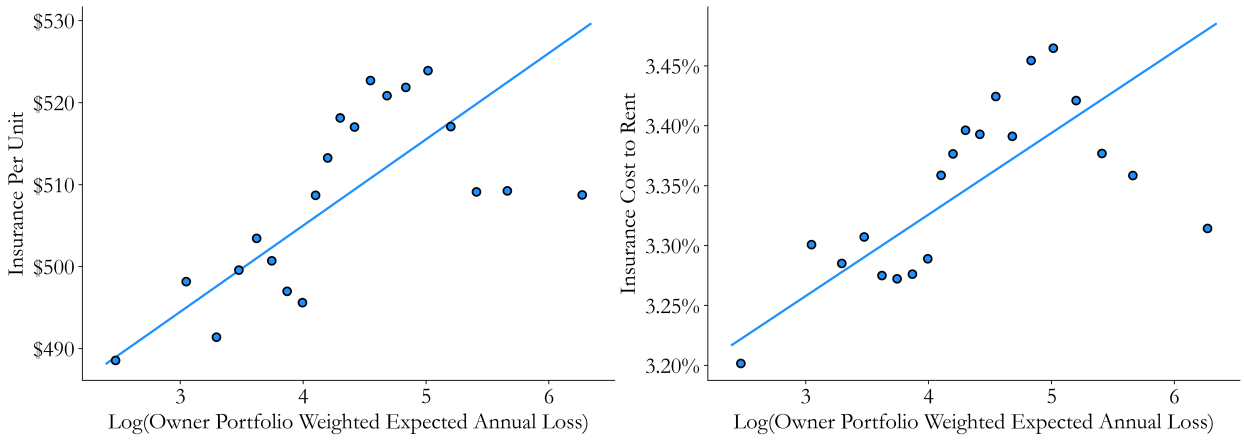


**Figure IA.16: Effect of Property Risk and Owner Size on Property Sales, Over Time**

This figure plots the annual estimated effect of being in a high-risk location on the probability that a property is sold by owners in size deciles 1–2 relative to the omitted owner-size decile 5. For each year, a regression of the transaction indicator on interactions between the high-risk indicator and owner-size deciles with CBSA fixed effects is estimated. High risk is defined as above-median expected annual building losses. Error bars denote 95% confidence intervals based on standard errors clustered by CBSA.

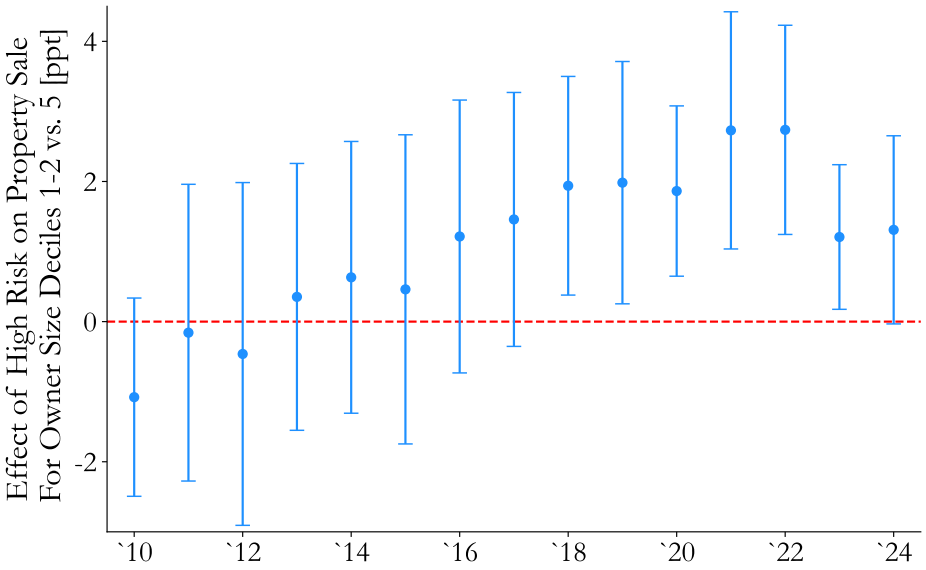


**Table IA.I: Effects of Reinsurance Exposure on Rise in Insurance Cost**

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 × Log(Expected Annual Losses Per Capita) | | | | ✓ |
| 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*** | | |
| | | (4.39) | | |
| $\mathbb{1}$(Low Risk Score) × Lagged Pct. Claims | | | -0.000554 | 0.0265 |
| | | | (-0.01) | (1.23) |
| $\mathbb{1}$(High Risk Score) × Lagged Pct. Claims | | | -0.0297 | 0.0628*** |
| | | | (-1.36) | (3.18) |
| States Included | All | All | Low | High |
| Property FE | ✓ | ✓ | ✓ | ✓ |
| State × Year FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 158,047 | 158,047 | 80,519 | 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 6 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) | | −0.0000988*** |
| × Log(Expected Annual Losses Per Capita) | | (−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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table IA.IV: Insurance Costs Around Mergers and Acquisitions Events, Heterogeneity Robustness**

This table reports heterogeneity robustness tests for the effects of mergers and acquisitions (M&A) events on two alternative insurance-cost measures. Panel A examines the insurance-cost-to-rent ratio, and Panel B examines the insurance-cost-to-operating-expenses ratio. The key independent variable is the interaction between an indicator for treated properties (i.e., those that undergo an M&A event) and an indicator for the post-M&A period. In both panels, columns (1) and (2) split the sample according to whether the difference in owner size between the acquiring and acquired firms is above or below the median, while columns (3) and (4) split the sample according to whether the property's risk score is above or below the median. In columns (1) and (2), the treated properties are split by the difference in owner size, while the full set of control properties is retained in both specifications. All regressions include property × cohort fixed effects and CBSA × year × cohort fixed effects. Robust standard errors are clustered by owner.

Panel A. Insurance Cost to Rent

| Dep. Variable: | Insurance Cost to Rent | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Sample: | High Diff. Size | Low Diff. Size | High Risk | Low Risk |
| $\mathbb{1}$(Treated) × $\mathbb{1}$(Post) | -0.0106*** | -0.0052** | -0.0109*** | -0.0044* |
| | (4.76) | (1.99) | (5.35) | (1.66) |
| Property × Cohort FE | ✓ | ✓ | ✓ | ✓ |
| CBSA × Year × Cohort FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 1,044,690 | 1,045,126 | 524,111 | 516,311 |
| Adjusted $R^2$ | 0.839 | 0.839 | 0.839 | 0.839 |

Panel B. Insurance Cost to OpEx

| Dep. Variable: | Insurance Cost to OpEx | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Sample: | High Diff. Size | Low Diff. Size | High Risk | Low Risk |
| $\mathbb{1}$(Treated) × $\mathbb{1}$(Post) | -0.0224*** | -0.0031 | -0.0180*** | -0.0071 |
| | (4.63) | (1.08) | (2.81) | (1.56) |
| Property × Cohort FE | ✓ | ✓ | ✓ | ✓ |
| CBSA × Year × Cohort FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 1,044,690 | 1,045,126 | 524,111 | 516,311 |
| Adjusted $R^2$ | 0.845 | 0.845 | 0.845 | 0.845 |

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