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Dear NBER Climate finance workshop organizing committee,

I am a third year PhD student in Finance at Maastricht University's School of Business and Economics, in the Netherlands. My main advisor is Professor Nils Kok at the Finance department. My co-advisor is Professor Mark Sanders, at the Macro, International and Labour Economics department, both at Maastricht University. Additionally, I am a PhD fellow at the Central Bank of the Netherlands (De Nederlandsche Bank) in the Financial Stability department under the supervision of Dr. Robert Vermeulen and Dr. Lu Zang. My expected PhD completion date is September 2027.

My doctoral research investigates how physical climate risks impact financial markets, specifically commercial real estate, corporate credit and insurance markets. My first project explores how extreme weather events affect the insurability of commercial real estate in the United States. There is growing literature addressing the impacts of natural disasters on homeowners' insurance. However, research remains limited on how rising insurance costs, due to more frequent and severe natural disasters, affect commercial properties. This gap matters because commercial real estate insurance seems to operate different from residential insurance and may respond uniquely to climate risks. Using property-level insurance cost data and hurricane paths from 2010 to 2023, we find that properties exposed to climate shocks have, on average, a 20% higher ratio of insurance costs to total operating expenses compared to properties not exposed. We also find that properties managed within geographically diverse portfolios experience smaller insurance cost increases than those in concentrated portfolios.

My second project investigates whether European banks price physical climate risk in their lending decisions. We use a big dataset on nearly all euro-area corporate loans combined with records of major natural disasters in Europe. Our main hypothesis is that banks do not initially price climate risks but update risk assessments after borrowers experience extreme weather events. This project is currently in the exploratory data phase.

For my third project (job market paper), I am exploring ideas at the intersection of credit and insurance markets in the context of climate risk. Potential research questions include how interactions between insurance and credit markets influence investment decisions, or how climate risk alters market structures and equilibrium prices. I plan to develop a structural model of insurance demand that depends on credit access and climate risk exposure. The main challenge is obtaining asset-level insurance policy data. I am currently seeking data access from major insurance firms or commercial real estate funds in the Netherlands.

My future research agenda will continue exploring physical climate risks and their impacts on insurance and real estate markets. However, I plan to address broader questions about financial market structures in a climate-changed world, using industrial organization methods to study market power, efficiency, and compounded climate risks. Furthermore, I am interested in studying climate finance dynamics in developing economies, with a particular focus on Latin America. For this line of research, I already have access to comprehensive data on commercial loans in Colombia, including balance sheets for medium and large companies. This is an essential gap, as climate finance research predominantly focuses on developed markets, even though developing countries experience severe climate impacts.

This workshop represents a unique opportunity to refine my research and expand my understanding of climate finance. The feedback on my commercial real estate insurability paper would be invaluable, as well as insights about my other projects. Moreover, the opportunity to engage with leading researchers in the field, receive career guidance, and learn about the future direction of the climate finance field could significantly shape my professional path.

Thank you very much for considering my application and for creating this valuable platform to advance the climate finance field.

Stefany Burbano

Stefany Burbano, CV

Personal

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Education

2023 – 2027	PhD candidate, Maastricht University
	Main supervisor: Nils Kok n.kok@maastrichtuniversity.nl
	Co - supervisor: Mark Sanders m.sanders@maastrichtuniversity.nl
	Thesis: Extreme weather events and financial markets
2021 – 2023	MSc. Economic Analysis, University Carlos III Madrid
	Master thesis: Long-term contracts, environmental pledges, and bank lending channel
2015	Master in Economics, Javeriana University
	Master thesis: Vertical integration in Colombian industries, (text in spanish)
2012	BSc. Economics, Universidad del Valle

Experience

2014 – 2021	Expert Economist – Central Bank of Colombia
	Center for Studies on Production and Trade
2012 – 2014	Economist – Central Bank of Colombia
	Center for Regional Studies

Work in progress

"Climate risk and the Insurability of commercial real estate", 2025, with Nils Kok (Maastricht University) and Rogier Holtermans (University of Guelph).

"Are climate related risks priced in corporate loan interest rates?", 2025, with Mark Sanders (Maastricht University), Robert Vermeulen (Central Bank of the Netherlands), and Lu zhang (Central Bank of the Netherlands).

Publications

"Loans and Real Effects in Colombia 2000-2017", (in spanish), 2020, *ESPE Journal*, issue 94, with López, M., Bohorquez-Penuela, C., Carranza, J., Grajales-Olarte, A., Pinzón, M. and Pulido, J.

Working papers before PhD

"The effect of a bank liquidity shock on the performance of firms", 2020, *Working paper - Central Bank of Colombia*, num 1133, with Carranza, J.E.

"Interest rate dispersion in commercial loans", 2019, *Working paper - Central Bank of Colombia*, num 1088, with Vargas, R. and Vélez, J.S.

"Vertical structure of Colombian manufacture industry 1990 - 2013", (text in Spanish), 2016, *Working paper - Central Bank of Colombia*, num 925.

"Size and vertical structure of the Colombian industrial production chain since 1990", (text in Spanish), 2013, *Working paper - Central Bank of Colombia*, num 751.

Insurability of Commercial Real Estate and Climate Risk *

Stefany Burbano† Rogier Holtermans‡ Nils Kok§

Abstract

In recent years, the real estate market has seen a significant increase in average insurance costs. We examine the impact of extreme weather events and climate-related risks on insurance costs for commercial properties in the United States. Leveraging data on commercial property insurance expenditures, exposure to hurricanes, and forward-looking climate risk indicators, we provide evidence that properties expose to extreme weather events, such us hurricanes, face higher insurance costs relative to total operating expenses. Using a stacked differences-in-differences approach, we show that properties expose to hurricanes experienced between 1 to 2 percentage point increase in their ratio of insurance expenses to total operating expenses, approximately an average increase of 16% in the ratio, within forth quarters following the event.

Keywords: *Insurance; Climate risk; Commercial real estate*

*We thank NCREIF and Jupiter for the access to the data. For comments and discussions, we thank seminar participants at Maastricht University, University of Amsterdam, MORSE Conference.
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1 Introduction

Households and investors in the real estate market are increasingly exposed to the direct consequences of extreme weather events. [1] Secondary effects such as price fluctuations, shifts in market preferences and increased insurance cost, come on top of that. Insurance plays a critical role in real estate markets by providing financial protection against unanticipated events (Wagner, 2022). However, since 2018, insurance premiums have risen substantially: for homeowners around 8.7 to 14.7 average annual[2], and for commercial real estate we estimated growth rates as high as 40%, affecting both the availability and affordability of coverage. In this paper, we study how climate-related disasters affect the insurability of commercial real estate.

The sharp rise in insurance premiums in recent years can be attributed to a combination of factors, including a growing frequency of climate-related disasters (Keys and Mulder, 2024), persistent inflation in construction costs, and substantial increases in property catastrophe reinsurance rates. Reinsurance rates have shown annual growth rates of 7.5% in 2018, 14.8% in 2022 and 35% in 2023. [3] These pressures are evident nationwide, but their impact varies by state due to differences in regulatory frameworks, market structure, and differential exposure to natural disasters. For instance, Florida was among the first states to face large-scale insurance losses, starting with Hurricane Andrew in 1992. Recent hurricanes caused unprecedented damages reflecting in higher looses, insurers bankruptcies, and even some insurance companies exiting the market (Sastry et al., 2023). Similar, in the aftermath of the severe California wildfire seasons of 2017 and 2018, local homeowners faced rising premiums, an increase in policy cancellations, and a shift in market structure characterized by private insurer withdrawals (Boomhower et al., 2024).

While much of the literature has focused on the housing market, the commercial real estate market is also increasingly vulnerable to physical climate risks. Commercial properties, previously considered in low climate-related risk locations, have recently suffered damages from extreme weather events. This situation has led to unexpected financial consequences, raising repair costs and affecting both property prices and their income-generating potential (Addoum et al., 2023). Commercial properties located in regions prone to hurricanes, floods, or wildfires have also faced notable increases in

[1] In the U.S. alone, more than 15 million homes and businesses are located in high-risk flood zones, with a combined value exceeding $5 trillion (Wing et al., 2018) The total losses due to natural disasters worldwide were some $250 billion in 2023, with less than 40% of these losses insured (MunichRE, 2024). Hurricanes Helen and Milton as recent examples causing as high as $55 billion in private losses https://www.rms.com/newsroom/announcement/2024-10-14/moodys-rms-event-response-us-private-market-insured-loss-estimate-for-hurricanes-helene-and-milton.

[2] https://home.treasury.gov/news/press-releases/jy1375

[3] https://www.artemis.bm/us-property-cat-rate-on-line-index/

average insurance premiums (Preudhomme et al., 2023). All else equal, higher insurance costs raise total operating expenses, and may reduce net operating income, affecting the equilibrium property values. Climate risk is thus reshaping the financial profile of commercial real estate markets.

This paper contributes to the literature by providing empirical evidence on the link between climate-related risk and insurance costs in the commercial real estate market. Existing literature primarily addresses housing markets, leaving a gap in understanding the commercial real estate market despite its significant economic value. [4] We use NCREIF property-level data on revenue and operating expenses for U.S. commercial properties from 2000 to 2024. This dataset is combined with multiple data sources of physical climate-related risk indicators, that allow us to explore disaster exposure and accumulation effect, information provision, and forward looking climate risk. We use data on Atlantic basin hurricanes best paths, county-level disaster declarations from FEMA, flood maps from the National Flood Hazard Layer (NFHL), and climate scores from Jupiter Intelligence, a private climate risk data provider. Our main variable of interest is the ratio of insurance expenditures to total operating expenses. Unlike studies that focus on one major event, our analysis incorporates data from all hurricanes that made landfall in US since 2010.

We begin by documenting some trends. Since 2018, the ratio of insurance expenses to total operating expenses has increased sharply, especially in counties repeatedly affected by hurricanes. This pattern mirrors the trend observed in the homeowners insurance market (Keys and Mulder, 2024). When examining the spatial distribution of hurricane impacts, we observe that counties more expose to these events register larger increases in the ratio of insurance cost to total operating expenses. However, states with limited exposure to natural disasters also have experienced increases in insurance costs, likely reflecting cross-subsidization as insurers redistribute losses across the U.S. market (Oh et al., 2022).

The baseline specification relies on a stacked difference-in-differences framework using property-level panel data from 2010–2024, and hurricane exposure as the primary treatment. The analysis exploits 24 storms that made landfall in the U.S. We find that exposed properties experience a statistically significant increase of around 1.2 percentage points in the ratio of insurance expenses to total operating costs. That implies an increase of around 20% relative to the sample mean. When comparing only properties in hurricane-prone states, the effect rises to 1.69 percentage points, approximately an increase of 26% with tespect to the average insurance ratio.

[4] For instance, in the United States, the commercial real estate market comprised approximately $5.9 million buildings and 96.4 billion square feet of total floor space (Department of Energy, 2018), with a valuation estimated between $14.4 and $17 trillion dollars in 2018 (Nareit, 2019).

We then examine the dynamic effects of hurricane exposure using an event study specification covering four quarters after the climate shock. The estimated increase in the insurance ratio peaks at approximately 3 percentage points in the fourth quarter post-event, about a 50% rise relative to the average insurance ratio in the sample. This delayed response is consistent with the annual insurance policy renewal cycle, as insurers typically adjust premiums at renewal dates, potentially incorporating new climate-related risks information into pricing decisions.

Natural disasters frequently strike the same areas multiple times. Some counties in our sample experienced as many as 13 hurricane events between 2010 and 2023. Existing literature on physical climate risk rarely addresses the cumulative effects of multiple weather-related shocks. We explore the cumulative impact of repeated hurricane exposure with a non-parametric analysis. Our results indicate that properties exposed to three hurricanes have higher average insurance ratios than those exposed to fewer events. The increase becomes statistically meaningful after the fourth exposure. A non-linear pattern emerges: the more hurricanes a property experiences, the higher its insurance cost ratio. Building on this observation, we attempt to isolate the effect of a second hurricane exposure using a carefully designed difference-in-differences strategy. Following De Chaisemartin and D'haultfœuille (2023) intuition, our treated group consists of properties that experienced a transition ("switchers") from exposure to one hurricane to a second hurricane, while the control group includes properties exposed only once. We find no statistically significant effects for this second hurricane exposure, likely due to limited statistical power. However, the magnitude and direction of point estimates remain consistent with potential compounding effects.

One potential mechanism that could moderates the impact of extreme weather events on insurance costs is portfolio diversification of property management. The hypothesis is that managers with geographically diversified portfolios, in our case properties across multiple states, may have some bargaining power to negotiate favorable insurance terms. To test this, we calculate a Herfindahl–Hirschman Index (HHI) for each manager based on property locations, capturing the geographic concentration of their portfolios. Our results indicate that properties within highly concentrated portfolios experience significantly larger increases (2.3 to 2.8 percentage points) in the ratio of insurance expenses to total operating expenses following hurricane events. In contrast, properties managed by highly diversified portfolios across different states exhibit smaller or statistically no significant increases in insurance costs.

We further investigate heterogeneity in the impact of hurricanes along two key dimensions: storm severity and property type. First, properties exposed to stronger wind speeds (64 knots or more)

experience insurance cost increases between 6 and 9 percentage points, more than double the baseline estimate. This supports the idea that insurance markets respond to the severity of physical risk, not just its occurrence. Second, we explore heterogeneity by property type. The largest increases occur for office and industrial assets (1.6–2.3 percentage points). Multifamily properties experience increases of around 1.9 percentage points, but estimates are not statistically significant in almost all the specifications, potentially related with regulatory constraints common in residential insurance markets. Retail properties, in contrast, show no statistically significant changes in insurance costs, possibly due to differences in underlying risk profiles.

To consider alternative explanations, we evaluate whether publicly available information about climate risk influences commercial property insurance costs. Using flood maps (NFHL), we identify properties located within designated high-risk flood zones and compare their insurance expenses to similar properties located outside these zones. Prior research has demonstrated that regulations designating certain areas as flood-prone introduce market distortions and prompt adaptation measures in residential markets (Ostriker and Russo, 2022). Although the impact on commercial properties is less established, public flood risk information may influence property valuations and business location decisions (An et al., 2023), potentially increasing business density in designated flood-prone commercial districts. Consistent with this channel, we find that commercial properties within high-risk flood zones exhibit higher insurance expenses relative to total operating expenses.

Finally, we analyze the relationship between forward-looking climate risk scores and insurance costs. Our results demonstrate a positive correlation between property-level hazard scores and the ratio of insurance expenses to operating costs. This relationship is robust when examining specific perils for wind, precipitation, and drought as well as a compound hazard that aggregate all the risks. However, we find no statistically significant effect for flood risk alone.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature. Section 3 describes the data, outlines the construction of our sample, and presents key stylized facts. Section 4 details our empirical strategy and baseline results, including robustness checks and additional analyses. Section 5 concludes.

2 Related literature

Our research is framed within the literature examining how both physical and transition climate risks influence asset pricing. There are well-established connections between climate risk and asset values, including stocks [5], bonds [6], loans [7], and real estate (Bernstein et al., 2019; Baldauf et al., 2020; Bakkensen and Barrage, 2022; Boustan et al., 2020; Addoum et al., 2023; Holtermans et al., 2024a).

Despite the extended research on residential real estate, the understanding of physical climate risk impact on commercial real estate is still limited. Existing literature has primarily focused on pricing mechanisms such as capitalization rate to capture these impacts (Fisher and Rutledge, 2021; Addoum et al., 2023), the risk premium and operating income channels as transmission channels of climate shocks to transaction prices (Holtermans et al., 2024b). A recent study by Holtermans et al. (2024a) investigate delinquency rates in commercial properties after climate events, revealing that such shocks undermine the income-generating capacity of exposed properties. As a consequence, the borrowers' ability to make timely and complete payments of interest and principal. Interestingly, there is no anticipation effect, suggesting lenders do not typically account for flood risk at the underwriting stage. We contribute to this branch

Our research also contributes to an emerging body of literature on the relationship between extreme weather events and the property insurance market. Early discussions focus on the effect of natural disasters on insurance markets, primarily addressing private market failures and proposing solutions to maintain insurance as a viable tool for covering extreme weather risks (Kunreuther, 1996; Jaffee and Russell, 1997). Over time, interest about how insurance markets respond to such events (Born and Viscusi, 2006) have evolved into broader research on insurance demand (Kousky and Cooke, 2012; Bradt et al., 2021; Hennighausen et al., 2023; Wagner, 2022), climate risk information provision (Mulder, 2021), market structure (Sastry et al., 2023) and the intersection of insurance and land regulation (Oh et al., 2022; Druckenmiller et al., 2024) .

With increasingly costly natural disasters, the public provision of insurance has become a central topic of debate, raising concerns about the government's financial burden and the affordability of policies. Wagner (2022) estimate homeowners' willingness to pay for natural disaster insurance, and find that in high-risk flood zones, the average cost of flood insurance corresponds to only about two-thirds of homeowners' own expected payouts. One challenge associated with research in property

[5] Lanfear et al. (2019)
[6] Auh et al. (2022); Goldsmith-Pinkham et al. (2023)
[7] Koetter et al. (2020)

insurance, in the context of natural disasters, is data limitations. To address this, Keys and Mulder (2024) develop a novel dataset using mortgage escrow payments to analyze the causes and consequences of the recent surge in insurance premiums. They find an increase in premiums, in real values, of 13% across states from 2020 to 2023.

The recent surge in insurance premiums has drawn attention not only to the direct impact of more severe natural disasters on catastrophic insurance markets, but also to the unintended consequences on market structure. Oh et al. (2022) investigate the trend of property insurance rates becoming increasingly detached from underlying risk measures, meaning premiums do not rise proportionally with expected losses after disasters. This disconnection between rates and risk facilitates cross-subsidization, where states with lower regulatory constraints and lower climate risk help offset losses in more highly regulated, high-risk states. Sastry et al. (2023) examine the implications for mortgage markets of established insurers withdrawing from high-risk areas, a gap increasingly filled by smaller, less capitalized insurers with concentrated exposure to areas at risk. These newer insurers are typically rated by emerging rating agencies, and government-sponsored enterprises (GSE) requirements for them are less stringent.

Regarding the supply of property insurance, Boomhower et al. (2024) rise an additional complication related with the catastrophe risk models. Insurers face significant difficulties to accurately price policies for catastrophic events, mainly due to inconsistent quality of risk information available, which leads to variation in pricing strategies. Insurers relying on less detailed assessments may overprice policies to avoid selling unprofitable policies to high-risk customers or withdraw from high-risk markets, reducing the availability of insurance coverage. State-level regulations exacerbate these challenges, where laws restrict how much insurers can raise premiums.

One of the few studies examining the relationship between extreme weather events and insurance in the commercial real estate market is (An et al., 2023), which looks at business relocation due to flood map regulations. The study finds that businesses that choose to localize in flood-prone areas grew at a rate 10% faster, than those in non-flood zones over the past two decades. This counterintuitive is attributed to a free-rider problem in the flood insurance market. Commercial property owners avoid paying for flood insurance but still benefit from government assistance when floods occur, allowing them to offer lower rents and attract more businesses to high-risk areas. However, this dynamic is only true in areas with a high concentration of commercial properties. Our contribution to this literature highlights that natural disasters has had a tangible effect on insurance costs for commercial properties.

3 Data

3.1 Commercial properties

We use data on commercial real estate assets from the National Council of Real Estate Investment Fiduciaries (NCREIF). NCREIF is a not-for-profit trade association of large institutional real estate investors that share data on their institutional-quality portfolios, established with the objective to provide improved commercial real-estate data, performance measurement, investment analysis and information standards (Ghosh and Petrova, 2017). NCREIF collects data on operating income, expenses and sub-categories on a quarterly basis, based on data provided by large institutional real estate investors. We geo-reference the assets using reported information on state, county, city, and street address. Properties with missing or incomplete location information are excluded from the sample.

We focus on the four main property types: industrial, office, retail and multifamily. The sample is restricted to stabilized properties, excluding those in development stage or undergoing renovations or expansions, to avoid confounding effects unrelated to climate shocks. To ensure data quality, we trim income and operating expenditure variables at the 1% level in both tails of the distribution and exclude properties with incomplete full-year data. We focuses on commercial properties located in the contiguous United States, with a minimum of four quarters of available data. The variable of interest *Insurance expenses* is only consistently reported starting in 2000 Q1. We exclude observations where this line item is repeatedly reported missing or negative. Our main variable of interest, insurance expenditures, captures the total premiums paid to insure each property. Specifically, the *Property Insurance Expenses* variable include flood insurance expense, hazard liability expense, and other property insurance expense, following NCREIF's reporting definitions[8].

One feature of this dataset is its coverage of assets held mainly by institutional investors, which may introduce sample selection bias. To our knowledge, this is the first study using NCREIF data to investigate the impact of physical climate risk, specifically hurricanes, on insurance expenditures. Prior research employing NCREIF data includes Young and Brown (2023); Li et al. (2009); Geltner and Goetzmann (2000); Hardin III et al. (2025).

[8]This is the exact definition in the NCREIF Manual

3.2 Climate-related events

We obtain detailed hurricane best-track data from the National Hurricane Center (NHC). For each tropical cyclone, the NHC conducts a comprehensive post-storm analysis and produces an official historical record in its Tropical Cyclone Reports. These reports include synoptic history, meteorological statistics, and a post-event reconstruction of the storm's path and intensity. The best-track dataset records six-hourly information on storm position, wind speed, landfall timing, peak intensity, and wind radii, which represent the maximum spatial extent of a given wind speed in each quadrant of the storm system.

Tropical cyclones are classified into depressions, storms, and hurricanes based on the Saffir-Simpson Hurricane Wind Scale. A wind swath refers to the geographic area affected by damaging winds during a storm, especially in the case of hurricanes or tropical cyclones. Figure 7 in the Appendix illustrates the spatial distribution of hurricane Ian wind swaths used in our analysis.

We focus on hurricanes as our acute climate-related shock due to their potential for extreme damage and their direct impact on property-level outcomes. Unlike flooding, where insurance is heavily covered by federal government, hurricanes provide a setting in which market-driven insurance pricing may respond more directly to physical exposure.

For each hurricane, we collect three key variables: the storm path (based on the eye of the hurricane), maximum sustained wind speed (as a proxy for intensity), and wind radii (to identify the geographic extent of damaging winds). We mainly use wind radii to construct an indicator of exposure that captures whether a given property was located within the area affected by hurricanes and, if so, the intensity level it experienced.

Between 2010 and 2023, we identify 31 tropical cyclones that made landfall in the United States and were classified as hurricanes. Of these, 24 storms affect areas containing commercial real estate properties included in our dataset.

3.3 FEMA disaster declarations

We use disaster declarations from the Federal Emergency Management Agency (FEMA) as an alternative measure of exposure to climate shocks. FEMA records all major disaster events across the United States, including hurricanes, floods, and severe storms. For our analysis, we focus on disaster

declarations related to these hazards between 2000 and 2023. These declarations contain detailed information on the timing and geographic scope of each event, enabling us to construct a panel dataset at the county-quarter level that tracks disaster exposure over time (Figure 9).

FEMA disaster declarations allow us to identify the counties impacted by hurricanes and other extreme weather events during the study period. Because declarations are issued only for events that meet certain thresholds of severity, often triggering federal assistance, they serve as a useful proxy for identifying high-impact disasters.

However, this measure has limited geographic granularity. Because declarations are made at the county level, all properties within a declared county are flagged as exposed, regardless of their actual proximity to the storm path or damage zone. As a result, properties that were not directly affected may be misclassified as treated. This spatial imprecision introduces measurement error, particularly in large counties, where storm impacts may be highly localized.

3.4 Flood maps

The flood maps used in this analysis are derived from the National Flood Hazard Layer (NFHL), maintained by FEMA's Flood Map Service Center. This digital dataset covers approximately 90% of the U.S. surface area and delineates flood zones as defined by the National Flood Insurance Program (NFIP). The maps identify Special Flood Hazard Areas (SFHAs)—zones with at least a 1% annual chance of flooding, also known as the 100-year floodplain.

We classify properties located within SFHAs at risk of flooding. For properties outside the flood zone, we implement a spatial buffer strategy to define the control group. Properties located within one mile of the flood zone boundary are designated as controls, while those located farther than one mile from the floodplain are excluded from the analysis. This approach ensures that treated and control properties are geographically proximate and more likely to be comparable in unobservable characteristics. We also calculate alternative buffer distances (0.5 miles, 2 miles, and 5 miles) to evaluate whether different definitions of proximity to flood zones affect the estimates.

3.5 Climate Risk

To measure property-specific climate risk, we use Climate Scores developed by Jupiter Intelligence. These scores quantify physical climate risk across eight distinct perils: flood, wind, heat, hail, drought,

wildfire, precipitation, and cold. For the purposes of this study, we focus on four key hazards, flood, wind, precipitation, and drought, as they provide the most relevant metrics for assessing exposure to climate-related events at the property level. Moreover, flood, wind, and precipitation risks are directly linked to the impacts of hurricanes.

The Climate Score framework provides two core indicators for each peril: the Hazard Score and the Change Score. The Hazard Score captures the absolute level of physical climate risk for a location in the base year (2020), on a scale from 0 to 100. The Change Score reflects the projected change in that risk over a 30-year period (2020–2050), based on the SSP5–RCP8.5 scenario. Change Scores range from -100 to 100, with higher values indicating greater increases in risk. The SSP5–RCP8.5 scenario represents the "Fossil-fueled Development" pathway, one of the most extreme emissions trajectories, which is projected to result in a 2.6–4.8°C increase in global temperatures by 2100, relative to a 1986–2005 baseline.

Both Hazard and Change Scores are computed using peril-specific physical metrics. For example, flood risk is measured in meters of flood depth, wind risk in meters per second, and wildfire risk in terms of the probability of a total structural loss.

3.6 Sample

We combine property-level data on insurance expenditures and asset characteristics with information on climate shocks, specifically hurricanes, to examine how commercial insurance costs respond to acute weather events and how this relationship varies across property groups and risk profiles.

Table 3 presents summary statistics for the key variables used in our analysis. Our primary outcome variable is the ratio of insurance expenses to total operating expenses, which averages 6.05%, with a median of 4.15%. When scaled by total revenue, insurance expenditures account for approximately 1.90% on average. Across all property-quarter observations, the mean quarterly insurance expenditure is roughly €15,000, while the median is €8,600. Notably, by the end of 2023, average insurance costs reached nearly €24,000, up from previous peaks of around €16,000 in 2003 and 2007, signaling a long-run increase in the cost of insuring commercial real estate.

The distribution of climate risk indicators and exposure variables highlights the heterogeneity of risks faced by properties in the sample. Around 2.6% of the properties in the sample are expose to hurricane level storms. Approximately 5.3% of buildings are located within designated flood zones.

Broader climate hazard scores reveal significant variation in underlying physical risks. The All Peril hazard score has a mean of 39.12, while peril-specific averages include 11.41 for flood, 24.77 for wind, 45.51 for precipitation, and 50.36 for drought. These values reflect meaningful geographic and environmental variation in exposure to physical climate risk.

Our empirical strategy relies on a stacked difference-in-differences design to estimate the average impact of hurricane exposure on insurance costs. The "stacked" data is a set of sub-experiments, each defined by a specific hurricane event and its corresponding treatment timing. For each hurricane that made landfall, we compare the treated properties (those in the affected area during that quarter) to a control group composed of properties not exposed to any hurricane during the same event window (or not-yet-treated). This design ensures that comparisons are made between units observed in the same relative time period around an event (Wing et al., 2024b).

If multiple hurricanes occurred in the same quarter, each is treated as a separate sub-experiment because the affected regions differ in general. We consider several event windows —±2, ±4, and ±8 quarters— to examine both short and medium-term effects. We also vary the control group definition by using either never-treated properties or not-yet-treated properties.

These sub-experiments are then assembled into a stacked dataset, where each observation is defined at the property $\times$ event-time $\times$ sub-experiment level. Because clean control properties may qualify for multiple sub-experiments, the same property may appear in multiple stacked rows, either as treated in one cohort or as control in another. For example, a property never exposed to any hurricane during the sample period may serve as a control for all sub-experiment. While another property might serve as a control in one cohort and as treated in a later sub-experiment. This approach allows us to estimate the average treatment effect while controlling for treatment timing heterogeneity.

On average, properties are observed for approximately four to six years, resulting in an unbalanced panel with varying entry and exit across the 2000–2023 period. As a consequence, some empirical exercises are based on smaller sample sizes, which may reduce statistical power and lead to imprecise or non-significant estimates.

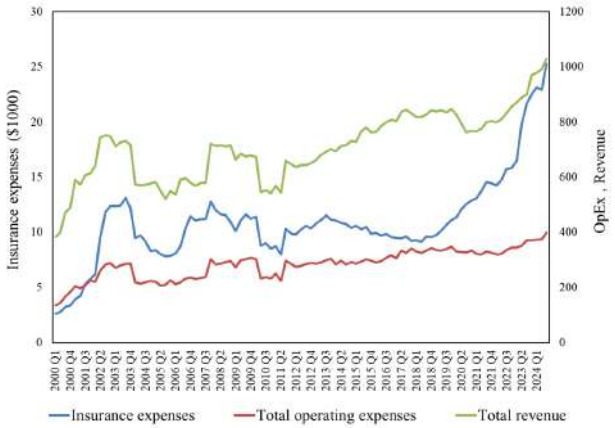
3.7 Stylized facts: Rising Insurance Costs in Commercial Real Estate

Figure 1 presents the time series of average nominal insurance expenses, total operating expenses, and total revenue for commercial properties in the NCREIF dataset, spanning from 2000 to the third

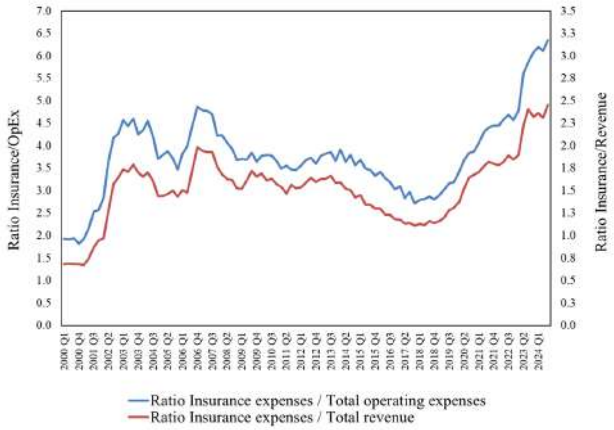
quarter of 2024. Insurance costs have risen sharply since 2018, increasing from approximately $8,000 on average in 2018Q3 to nearly 24,000 by 2024Q3. Although total revenue has followed a similar upward trend, its growth has been less steep than that of insurance expenditures. In contrast, total operating expenses have remained relatively stable, as shown in Panel A of Figure 1a. This pattern of insurance cost is similar to the one observed in homeowners' insurance markets over the same period (Sastry et al., 2023; Keys and Mulder, 2024; Boomhower et al., 2024).

Panel B of Figure1b illustrates that the ratio of insurance expenses to total operating costs has more than doubled, rising from 4.47% in 2018 to 8.73% in 2024. A similar increase is observed in the ratio of insurance expenses to total revenue, an increase from 1.5% to 3.3% over the same period.

Figure 1: The rise in insurance costs for commercial properties



(a) Insurance expenses, total operating expenses and total revenue



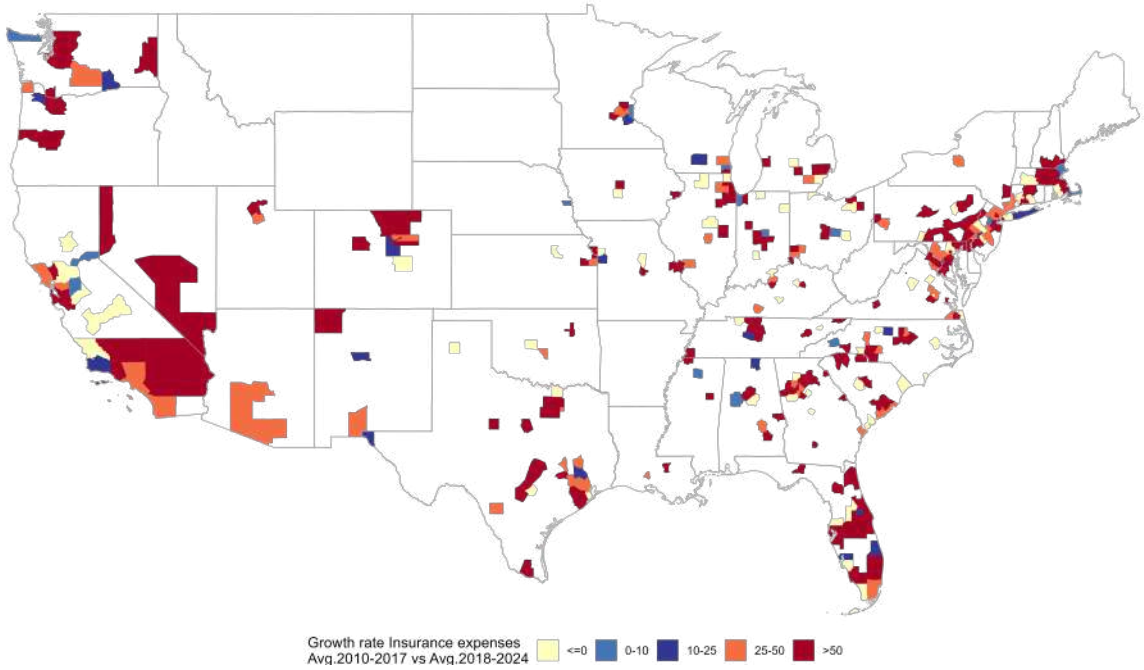
(b) Average ratio of insurance expenses relative to total revenue and total operating expenses

These facts raise the central question of this study: to what extent is the increase in insurance expenditures driven by physical climate risk? The intense hurricane season of the second half of 2017 was followed by an important increase in commercial property insurance rates, a trend not seen since 2012. The catastrophic losses associated with Hurricanes Harvey, Maria, and Irma in 2017, triggered significant reactions in the reinsurance markets. [9]

Figure 2 shows the county-level growth rate in insurance expenses, comparing average costs from 2010–2017 to those in the post-2017 period. Counties along the coastline, particularly those exposed to hurricanes in Florida and wildfires in California, exhibit higher increase in insurance expenses. Figure 13 further supports this observation: counties in coastal areas tend to register greater insurance expense ratios in 2023.

[9] https: //www.reuters.com /article /business /north- american- commercial- property- insurance- rates- seen- rising- sharply-in- 2018-idUSKBN1D62G5/

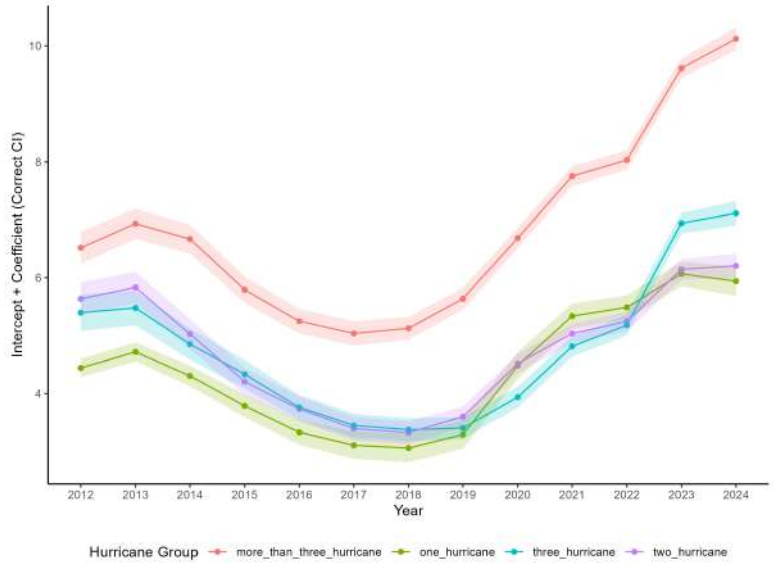
Figure 2: Growth rate of Insurance expenses, average 2010-2017 versus average, by counties



To contextualize these trends, Figure 10 plots the U.S. Property Catastrophe Rate-On-Line Index, which tracks the price of reinsurance. The post-2017 surge in this index coincides with the increase in insurance expenses for commercial properties. As demonstrated by Boomhower et al. (2024), reinsurance is a key driver of rising homeowners insurance premiums, and similar dynamics appear to be working in the commercial real estate markets.

The relationship between exposure to climate-related disasters and insurance expenses appears cumulative. Reinsurance markets have reacted to an accumulation of losses that exceed income from premiums. Figure 3 plots the average insurance ratio by number of hurricane exposures. Properties exposed to more than three hurricanes exhibit a statistically higher average ratio compared to those affected by one or two hurricanes. After 2022, the difference in the average ratio between properties affected by three hurricanes and properties affected by two or less of those events becomes both larger and statistically significant. This supports the view that markets have begun to price physical climate risk more explicitly in recent years.

Figure 3: Cumulative relationship between exposure to climate-related events and insurance costs



To further examine heterogeneity in the relationship between climate risk and the ratio of insurance expenses to operating costs, we stratify properties by their forward-looking climate risk scores. Figure 12a shows that properties in higher climate risk quintiles experienced more pronounced increases in their insurance expense ratios. Figure 12b compares properties located inside and outside designated floodplains, showing that real assets in flood-prone areas have seen sharper increases in insurance expenses relative to operating costs.

4 Empirical Analysis

Our main objective is to evaluate how exposure to climate related disasters, particularly hurricanes, contribute to the rise in insurance expenses for commercial properties. To identify potential causal effects, we employ different difference-in-differences specifications, exploiting hurricane exposure as our primary treatment. We implement a stacked difference-in-differences design, forming cohorts based on hurricane landfall dates and varying our control groups and geographic scope to ensure robustness. Additionally, we use an event-study approach to assess the dynamic impacts over subsequent quarters. Next, we examine cumulative effects related with the repeated nature of hurricanes, testing both parametric and non-parametric relationships. We explore portfolio diversification as a potential moderating mechanism. The hypothesis is that managers of more geographically diversified portfolios may benefit from some bargaining power in insurance negotiations. Further, we explore heterogeneity in treatment effects by storm severity (measured by wind speed) and property type.

4.1 Disaster exposure and the increase of insurance expenses in commercial real estate markets

To investigate whether the increase in insurance cost is linked to physical climate risks, the baseline analysis relates hurricane exposure to the ratio of insurance expenses in total operating expenses at property level. Since our treatment (hurricanes) occurs at different points in time, estimating the relationship between natural disaster and insurance cost using a two-way fixed effects (TWFE) model (Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020) may lead to biased estimates in the presence of heterogeneous treatment effects. Moreover, hurricane season typically occurs in the third or fourth quarter of almost every year. This timing structure introduces a challenge: properties previously expose to hurricanes would enter in the control group of later-expose properties. The two-way fixed effects estimates would be biased towards zero if the impact of the treatment is larger for early-expose properties. If the impact is larger for properties expose to hurricanes in recent years, then the bias would be positive.

We adopt a stacked difference-in-differences framework that analyze the effect of 24 hurricanes making landfall in U.S.[10] between 2010 and 2023. We use a stacked design, which helps us to avoid the

[10] contiguous US

challenges related to staggered difference-in-differences estimations. [11]. The sample for the empirical analysis was constructed following the description in subsection 3.6.

Two alternative control group were implemented. First, we use a "never-treated" group compose of properties never expose to any hurricane during the sample period. Second, we use a *not-yet-treated* group of properties that had not been exposed to any hurricane prior to the treatment quarter. We also define two different control samples using spatial scopes: i) all properties and ii) a sample restricted to states potentially (or previously) exposed to hurricanes[12].

To estimate treatment effects, we compare changes in the insurance ratio for properties expose to hurricanes, before and after the shock, to changes in the insurance ratio for properties never-expose (or not-yet-expose) to hurricanes. We begin with the following baseline specification:

$$Y_{ith} = \beta \, Expose_{ih} \times Post_{th} + \gamma_{ih} + \delta_{th} + X'_{it}\xi + \varepsilon_{ith} \tag{1}$$

where Y_{its} denotes the ratio of insurance expenses to total operating expenses for property i in event time t associated with hurricane cohort h. $Expose_{ih}$ is an indicator equal to 1 if property i is treated in event h, and 0 otherwise. $Post_{th}$ is a post-treatment indicator that equals 1 for all quarters from the hurricane event onwards. $Expose_{ih} \times Post_{th}$ is the interaction between exposure to the storm and the post dummy. β captures the average change in insurance expense ratios for treated properties, relative to pre-treatment periods. We include property-by-cohort fixed effects γ_{ih} and event-time-by-cohort fixed effects δ_{th} and control for observable property-level characteristics X'_{it} such as occupancy rates. Standard errors are clustered at the property level.

To examine the dynamics of insurance cost responses following extreme weather events, we estimate an event study specification:

$$Y_{ith} = \sum_{\substack{j=-\kappa_{\text{pre}},\ldots,\kappa_{\text{post}} \\ j\neq -1}}^{T} \left[\beta_j \, Expose_{ih} \times \mathbb{1}(t=j)\right] + \gamma_{ih} + \delta_{th} + X'_{it}\xi + \varepsilon_{ith} \tag{2}$$

where Y_{its} and $Expose_{ih} = 1$ are same as before. $\mathbb{1}(t = j)$ is an event-time indicator taking the value 1 if the observation corresponds to quarter j relative to the hurricane date. The event-time window spans from $-\kappa_{\text{pre}}, \ldots, \kappa_{\text{post}}$ in every cohort, omitting the period immediately prior to the

[11] Initially seen in Guryan (2004) and Cengiz et al. (2019), and increasingly used in recent applications Gormley and Matsa (2011); Deshpande and Li (2019); Fadlon and Nielsen (2021); Jeffers (2024)

[12] Alabama (AL), Connecticut (CT), District of Columbia (DC), Delaware (DE), Florida (FL), Georgia (GA), Louisiana (LA), Massachusetts (MA), Maryland (MD), Mississippi (MS), North Carolina (NC), New Hampshire (NH), New Jersey (NJ), New York (NY), Ohio (OH), Pennsylvania (PA), South Carolina (SC), Tennessee (TN), Texas (TX), and Virginia (VA).

event $j = -1$ as the reference category. T is the set of event-time periods (quarters) before and after the hurricane. γ_{ih} are property by cohort fixed effects, and δ_{th} are event-time by cohort fixed effects, meaning that we are comparing only changes in insurance ratios for properties expose to the same hurricane and within the same event-time. The fixed effects account for time-invariant property characteristics and control for macroeconomic or regional shocks coinciding with each storm. X'_{it} are property-level time-varying controls (occupancy rates). Standard errors are clustered at the property level. In stacked designs, the same observations may appear in multiple sub-experiments because clean controls may be used in several cohorts. Then, clustering at property level take into account the dependency across the different cohorts (Wing et al., 2024a).

Identification relies on the standard assumptions of no anticipatory behavior and parallel trends within each sub-experiment. Equations (1) and (2) are structured to account for both time-invariant and time-varying confounders across treatment cohorts. Unobserved property characteristics, such as building quality, insurer-property relationships, or state-level regulatory environment, are captured by property fixed effects. Changes in these confounders across cohorts are accounted for with the property by cohort fixed effects. Omitted confounders may only bias the estimates if such shocks occur contemporaneously with the hurricane itself. The probability is low given that hurricanes are as good as a random treatments in terms of location, timing, and intensity. However, our binary treatment indicator may not fully capture the variation in storm severity or actual damages, which are key drivers of premium adjustments. The identify assumption implies that, without natural disasters, treated and control properties would have experienced similar changes in insurance cost ratios. This is a plausible assumption in light of the relatively rigid and regulated structure of insurance pricing across states. Nonetheless, Oh et al. (2022) highlight that cross-subsidization from low-risk, less-regulated states to high-risk, highly regulated ones may distort insurance pricing, and bias our estimates, being a potential concern for our identification strategy.

Since the specification always include cohort fixed effects, we are comparing properties expose to hurricanes with the control group in the same year-quarter. The coefficients of interest β_j identify the effect of hurricane exposure at event time j, relative to the omitted pre-treatment period. Our baseline control group consists of properties never exposed to hurricanes during the study period. Our treatment group consist in properties expose to only one natural disaster in the study period. In the Appendix, we provide additional results using a not-yet-treated sample.

Wing et al. (2024a) recently state that stacked estimators using a fixed effects specification do not identify the aggregate causal effects of all treatment cohorts. To address that concern we estimate

Table 1: Effect of hurricane exposure on the ratio of insurance expenses to total operating expenses

	$Insurance\ expenses/Total\ operating\ expenses$			
	(1)	(2)	(3)	(4)
Exposure (=1) × Post (=1)	1.217***	1.090***	1.691*	1.691*
	(0.4347)	(0.4175)	(0.9617)	(0.9987)
Control group	All	All	Expose states	Expose states
Property × cohort FEs	Yes	Yes	Yes	Yes
Event-time × cohort FEs	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes
Control variable		Occup.rate		Occup.rate
Quarter-Property	538,636	521,792	169,030	163,233
R^2	0.17710	0.17693	0.19191	0.19129

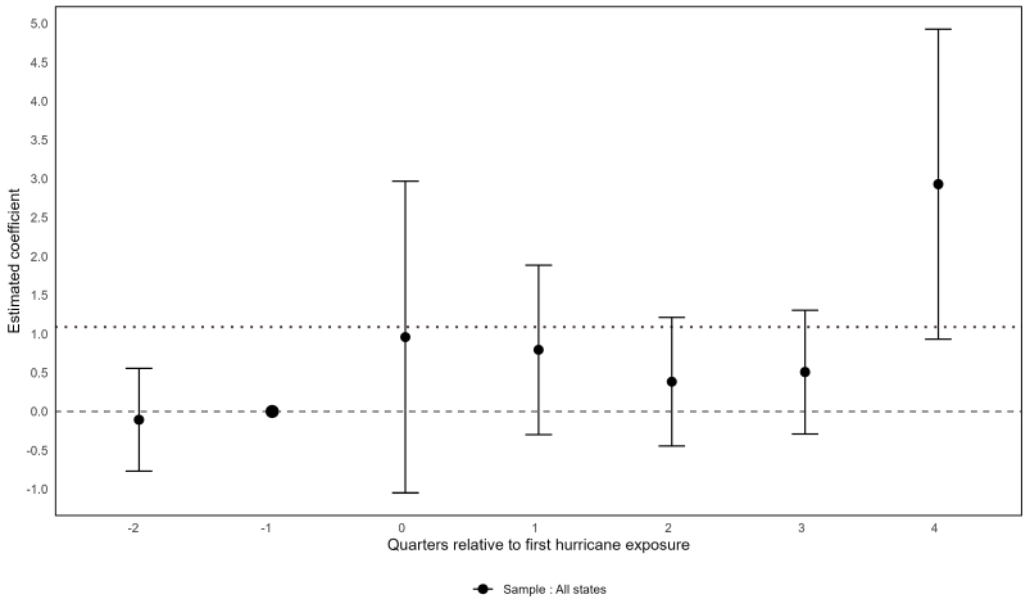
Standard errors are clustered at property level.
***, **, * indicate significance at 1%, 5%, and 10% level.

the previous equations using weighted least squares with their proposed weights. While we do not fully adopt their exact specification, additional robustness checks using their recommended approach (Equation 10) show that the results are similar.

Table 1 shows the estimated average treatment effects of hurricane exposure on the ratio of insurance expenses to total operating expenses using the stacked difference-in-differences specification from Equation(1). Across all columns, we find consistent evidence that exposure to natural disasters increase insurance costs for commercial properties. Column (1) reports the estimate using the full sample and never-treated properties as the control group. Also controlling for property-cohort and event-time by cohort fixed effects. The estimated coefficient indicate that properties exposed to hurricanes, increase, on average, by 1.2 percentage points the share of insurance costs relative to operating expenses in the post-storm period. Column (2) includes occupancy rate as additional control variable. The estimated coefficient is slightly attenuated but still significant, suggesting the result is not driven by contemporaneous changes in tenant demand.

Columns (3) and (4) use as control group properties located in hurricane-prone states only, tightening the comparison to states more similar in underlying climate risk. The point estimates increase in magnitude, however the standard errors are higher potentially due to the smaller sample size. On average, properties expose to hurricanes increase their insurance cost ratio by 1.69 percentage points after the event. These results suggest that the observed rise in insurance expenditures reflects a response to hurricane-related risk in commercial real estate markets. The estimated effects are eco-

Figure 4: Event study estimates of hurricane exposure on insurance expenses ratio



nomically meaningful: a 1.2 (1.6) percentage point increase represents roughly a 20% (26%) rise in the insurance ratio relative to the sample mean.

Figure 4 presents the dynamic treatment effects from the stacked difference-in-differences event study specification described in Equation(2). The analysis is restricted to properties exposed to a single hurricane during the study period and compares them to a control group of properties that were never exposed to any hurricane. We include two quarters prior to the event and four quarters after. We also explore alternative window lengths to evaluate the robustness of our results (Appendix). However, expanding the event window imposes stricter requirements on panel balance, as not all properties are observed in every quarter throughout the study period.

Figure 4 shows the estimated quarterly impact of hurricane exposure on the ratio of insurance expenses to total operating expenses, relative to the quarter immediately preceding the storm (event-time = -1), which is normalized to zero. The pre-treatment coefficients are statistically equal to zero, providing support for the parallel trends assumption[13]. The horizontal red line represents the average treatment effect on the treated across all post-treatment quarters, estimated at approximately 1.1 percentage points (Table 1 column (2)).

Following hurricane exposure (event-time=0 onwards), we observe a persistent increase in the insurance cost ratio. The point estimate increase to approximately 0.9 percentage points in the quarter of the storm and remains slightly above 0.5 percentage points for three quarters post-event. A sig-

[13] trade-off between more pre-treatment quarters and small power because it becomes difficult to observe properties with complete information for long windows

nificant effect emerges in the fourth quarter post-event, where the insurance cost ratio increases by nearly 3 percentage points. This delayed response is consistent with the annual cycle of insurance contract renewals. Because insurance policies are typically renegotiated on a yearly basis, the adjustment in premiums tends to occur at the point of renewal, allowing insurers to incorporate newly revealed climate-related risks into pricing decisions.

Additional regressions (Appendix 20) using the not-yet-treated control group show positive but mainly statistically insignificant estimates, though the coefficients are similar in magnitude to those in the main specification. Two potential -and completely different- explanations may account for this pattern. First, the estimates may be sensitive to sample composition (never-treated versus not-yet-treated), that it is also related with limited statistical power in some hurricane-specific cohorts. Second, it is possible that the observed increase in insurance costs is primarily driven by the initial shock, when insurers and investors revise their expectations regarding physical climate risk.

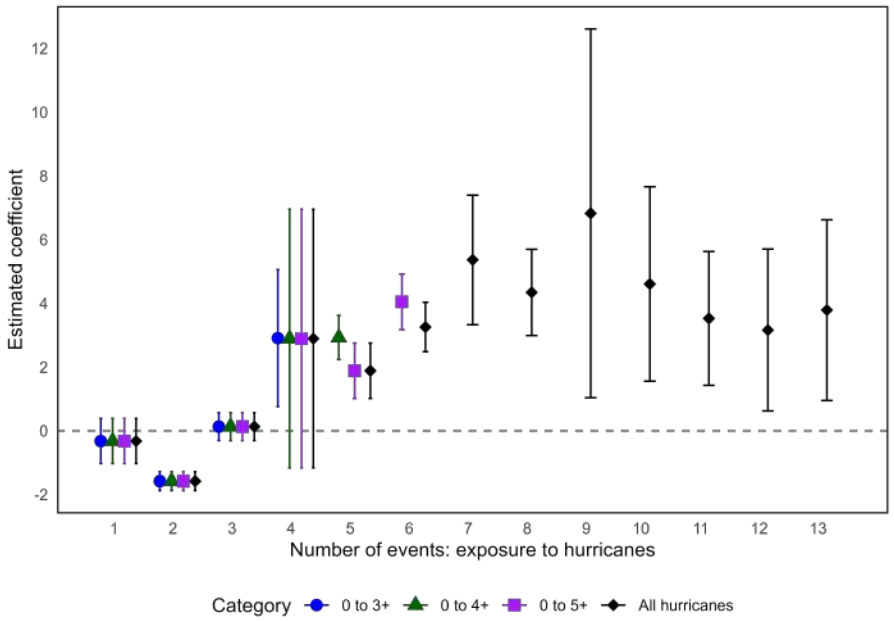
The properties in the "not-yet-treated" group are on average located in areas with high climate risk. These properties are going to be treated in the future. Then, the climate shock is not "new news" (Holtermans et al., 2024b) that could potentially affect the insurance premiums. The next section attempts to shed light on this issue.

4.2 Cumulative effects of multiple climate shocks on insurance cost

The previous empirical exercise explored the staggered exposure to natural disasters, restricting the sample to properties affected by a single hurricane event. This is the usual approach of the existing literature, which often emphasizes on first-time unexpected exposures to major disasters such as Hurricane Sandy (2012) or Hurricane Harvey (2017) (Addoum et al., 2023; Holtermans et al., 2024a) [14]. However, available data on weather-related disasters such as floods, hurricanes, and, more recently, wildfires (NOAA, EM-DAT, among others) indicate that it is common that natural disasters strike the same regions multiple times (Deryugina, 2017). For instance, according to our hurricane best-path data, some counties in Florida experienced as many as 13 hurricane exposures between 2010 and 2023. The repetitive nature of these events not only amplifies direct physical damage but also may contribute to an accumulation of climate-related economic losses. These dynamics can lead to long-term structural changes in regional economies, including disruptions in insurance markets (Sastry et al., 2023).

[14] also wildfires such as the Southern California wildfires in January 2025

Figure 5: Non-linear cumulative effect of climate-related shocks



In this section, we explore the effects of repeated hurricane exposure to assess the cumulative impact of physical climate risk on commercial property insurance costs.

We begin with a non-parametric analysis presented in Figure 5. Each point represents the estimated coefficient on an indicator equal to one if the property was exposed to a first, second, third, or subsequent hurricane. By construction, exposure to a second hurricane implies prior exposure to at least one earlier event. Each successive coefficient reflects the average insurance cost ratio associated with an increasing number of hurricane exposure. This allows us to examine the correlation between repeated exposure and potential compound effects on insurance expenditures.

Figure 5 illustrates the potential non-linear relationship between cumulative hurricane exposure and insurance costs. The black points show estimated average insurance ratios by number of hurricane exposures, with never-treated properties normalized to zero (reference category). For instance, properties exposed to seven hurricanes show an average increase of the insurance ratio in approximately 6 percentage points. Alternative groupings (blue, green, and purple points) aggregate higher exposure levels to certain thresholds. For instance, the blue series collapses all properties expose to fourth events or more into a single category at the fourth level. Then, the point at four (horizontal axis) represents the average insurance cost ratio for properties exposed to four or more hurricanes. The green and purple series follow a similar logic, using different thresholds to group higher levels of exposure.

Across all specifications, we observe minimal or statistically insignificant effects for one to two hurri-

cane exposures. Exposure to two hurricanes appears to be associated with a slightly lower insurance cost ratio compared to the never-treated group. From the fourth hurricane exposure onwards, there is a noticeable upward shift in insurance cost ratios, with average effects ranging between 2 and 4 percentage points above the baseline. This increasing trend continues with increasing exposure to natural disasters. However, the estimates become imprecise beyond nine events due to small sample sizes, as indicated by wider confidence intervals. Overall, this evidence suggests a non-linear relationship between cumulative climate shocks and insurance costs. The increase in the insurance expenses ratio following repeated exposure to hurricanes may reflect both the accumulation of losses but also general shifts in local insurance markets related with more frequent and severe natural disaster. Potential drivers would be: increasing climate-related risk awareness among insurers and investors, and rising reinsurance costs.

Next, we investigate the effect of a second hurricane exposure using the same stacked difference-in-differences framework. We estimate equation (1) for a treated group consisting of properties that transition from a first to a second hurricane exposure, treatment *switchers* (following the intuition in **?**). We consider two sub-samples of treated properties: (i) properties exposed to exactly two hurricanes, and (ii) properties exposed to two or more hurricanes, but restricting the observation window to quarters between the first and second event (pre-treatment), and between the second and third event (post-treatment), in order to avoid contamination from future treatments. We estimate weighted least squares using the weights proposed by Wing et al. (2024a), and cluster standard errors at the property level. As control groups, we use: (i) never-treated properties, (b) properties exposed only once, and (c) properties exposed to multiple hurricanes but with observation windows limited to periods before a third event.

Figure 21 in the Appendix show the estimated average treatment effects of a second hurricane exposure on the ratio of insurance expenses to operating costs, using different control groups and treatment histories (combination of treated and control group, more information in the section 6 in the Appendix). The point estimates for the second treatment are statistically insignificant. In some specifications, the estimated coefficients are negative, but still statistically insignificant. The wide confidence intervals across specifications reflect limited statistical power, likely due to smaller sample sizes. Overall, these results do not provide evidence that repeated hurricane exposure leads to additional insurance cost increases in the short term. We interpret this lack of significance primarily as a result of limited statistical power, rather than conclusive evidence that repeated hurricane exposure has no effect on commercial property insurance costs.

4.3 Mechanisms

Next, we study whether portfolio diversification moderates the effect of climate shocks on insurance costs. The central hypothesis is that properties managed within larger, more geographically diversified portfolios may experience smaller increases in insurance premiums following extreme weather events.

This could reflect some bargaining power hold by managers with presence in different states, during insurance negotiations. Standalone assets, for instance multifamily buildings, or properties managed by less diversified owners, may lack such leverage and face higher insurance cost increases after exposure to natural disasters.

This mechanism implies that among properties exposed to climate shocks or located in high-risk areas, those managed by highly diversified managers may exhibit attenuated increases in insurance expenses relative to similar properties under more geographically concentrated management.

To test this hypothesis, we extend the stacked design by introducing an additional interaction term, resulting in a triple-differences specification:

$$Y_{ith} = \sum_{\substack{j=-\kappa_{\text{pre}},\ldots,\kappa_{\text{post}} \\ j\neq -1}}^{T} \left[\beta_j \, Expose_{ih} \times \mathbb{1}(t=j) \times \mathbb{1}(Pre\ HHImgr = \tau) \right] + \gamma_{ih} + \delta_{th} + X'_{it}\xi + \varepsilon_{ith} \quad (3)$$

where $Pre\ HHImgr$ is a discrete categorical variable ranging from 1 to 3 (highly diversified, diversified and highly concentrated), indicating the level of geographic concentration of property managers based on the Herfindahl–Hirschman Index (HHI) calculated across states. The classification is based on manager portfolio composition in the quarter prior to hurricane exposure. Higher values of $Pre\ HHImgr$ indicate greater concentration in a single state, and thus lower diversification and bargaining power. In the regression, we include indicator variables for each HHI category.

Table 6 and figure 22a in the Appendix present the results. We find that properties managed by highly concentrated owners (HHI category 3) experience significantly higher increases in the insurance ratio after hurricane exposure. The estimated effects range from 2.3 to 2.8 percentage points, which is notably higher than the baseline effect of a single hurricane exposure.

In contrast, properties held by highly diversified managers (HHI category 1) show smaller increases in insurance costs. When the control group includes all properties, the insurance ratio increases slightly but remains below the baseline estimate. When the control group is restricted to properties

in hurricane-exposed states, the insurance cost ratio does not increase for properties under highly diversified management. These results are consistent with the interpretation that portfolio structure and scale moderates the effect of physical climate risk on insurance cost, potentially through bargaining power or underwriting practices at the insurer level.

4.4 Heterogeneity

To test for potential heterogeneity in the effect of climate shocks on commercial insurance costs along three dimensions: wind speed, property type, and state-level characteristics.

First, we examine whether the effect of climate shocks on commercial insurance costs varies by storm severity, measure by maximum wind speed exposure at the property level. The underlying hypothesis is that higher wind speed are associated with greater physical damage and thus a higher likelihood of post-storm insurance premium increases. We expect properties exposed to stronger wind intensities to experience more pronounced increases in the ratio of insurance expenses to total operating costs. To test this hypothesis, we extend the stacked design with a triple-differences specification, interacting hurricane exposure, post-event timing, and a discrete wind speed indicator. The variable wind speed takes three levels (34, 50, and 64 knots) corresponding to different wind thresholds during each hurricane event. These categories reflect increasing severity. Wind speed varies by property across sub-experiments, since not all properties are expose to all hurricanes.

Table 7 show the estimated coefficients. Results across all specifications confirm that properties exposed to higher wind speeds experience larger increases in insurance cost ratios. In columns (1) and (2), properties exposed to 34-knot winds experience on average increase in the insurance ratio of approximately 1 percentage point, similar to the baseline estimates. This rises to over 2.2 percentage points for those exposed to 50-knot winds, and to more than 5 percentage points for properties facing 64-knot winds. When the control group is only properties located in hurricane-exposed states (columns 3 and 4) the exposure to the most severe wind speeds (64 knots) is associated with a 6 to 9 percentage point increase in the insurance expense ratio, that is substantially larger than the baseline hurricane effect estimated. These results provide evidence that storm severity amplifies the impact of climate shocks on commercial insurance costs. The insurance market appears to respond not only to the occurrence of an event but also to its wind intensity, which is a proxy for expected damages.

Second, we investigate differences by property type, focusing on four main categories: multifamily (residential), office, industrial, and retail. The hypothesis is that these property types differ in their

regulatory exposure and market flexibility, which may influence how insurance costs respond to climate shocks. For instance, multifamily properties may be more affected by insurance regulation for housing markets, resulting in insurance price dynamics that are more aligned with residential insurance trends. In contrast, office, retail, and industrial assets may operate in more market-driven environments, potentially showing greater variation in insurance cost responses. To test this hypothesis, we use our stacked design and estimate triple-differences model that interacts hurricane exposure, post-event timing, and property type. Table 8 in the Appendix presents the results.

The largest and most robust effects are for office and industrial properties. After hurricane exposure, the insurance ratio increases by 1.6 to 2.3 percentage points for offices and 1.1 to 1.8 percentage points for industrial assets, depending on the specification. These estimates are statistically significant across all models and are consistently above the average treatment effect found in the baseline. Multifamily assets also experience significant increases in insurance expenses, with effects ranging from 0.87 to 1.95 percentage points. The magnitudes are comparable to office and industrial properties, though statistically significance vary across specifications, potentially reflecting differences in regulation.

Retail properties show smaller and statistically insignificant effects. Across all specifications, the estimated coefficients for retail assets range from 0.18 to 0.76 percentage points, and none are statistically different from zero. This may reflect either better diversification of risk for retail portfolios, greater flexibility in passing costs to tenants, or lower vulnerability to climate-related damage.

4.5 Alternative channels

4.5.1 Forward looking climate risk

We examine whether insurance expenditures respond not only to realized natural disasters but also to forward-looking measures of physical climate risk at the property level. This question is especially relevant in assessing whether insurers are incorporating expectations about future climate hazards into their pricing behavior. If insurance premiums increasingly reflect projected risk, rather than just historical exposure, this may indicate that insurers are actively integrating climate models into underwriting and pricing. Actuarially fair premiums that account for future risk could help discourage development in high-risk areas, such as coastal zones vulnerable to sea-level rise or regions frequently exposed to hurricanes and extreme precipitation.

To test this hypothesis, we use the Climate Score dataset developed by Jupiter Intelligence, which provides current and projected physical climate risk scores across a range of hazards, including flooding, wind, heavy precipitation, and drought. These scores are provided at the property level, range from 0 to 100, and summarize the intensity of climate-related threats under different scenarios. We focus both on individual hazards and a composite "All Perils" score that aggregates risks from multiple hazards, including wildfire, hail, and extreme cold.

To estimate the relationship between insurance costs and climate risk scores, we use the following regression specification:

$$Y_{it} = \alpha + \beta_1 \, ClimateRisk_i + \gamma_i + \delta_t + X'_{it}\xi + \varepsilon_{it} \tag{4}$$

The dependent variable, Y_{it}, is the ratio of insurance expenses divided by total operating expenses, expressed as a percentage, for property i in quarter t. $ClimateRisk_{it}$ captures the level of physical climate risk at the property, based on different hazard-specific and composite scores. The usual property and time fixed effects are included, as well as the control variable occupancy rate.

Table 9 presents the estimation of Equation 4. Column 1 reports the estimated coefficient for the climate score summarizing hazards across all perils. We find a positive and statistically significant relationship between overall physical climate risk and higher insurance expenses. A one standard deviation increase in the climate risk score for all perils is associated with a 0.56 percentage point increase in the ratio of insurance expenses to total operating expenses.

For individual hazards, we find that flood risk is not significantly correlated with insurance costs in this specification. Other hazards, such us wind, drought, and heavy precipitation, show strong and statistically significant effects. A one standard deviation increase in the wind hazard score (17.2 points) is associated with an estimated 0.78 percentage point increase in the insurance-to-operating-expense ratio. For drought, a one standard deviation increase (37.5 points) is associated with a 0.23 percentage point increase, and for precipitation, a one standard deviation increase (23.4 points) corresponds to an increase of roughly 0.79 percentage points. These patterns are consistent with our previous findings that acute and recurrent climate hazards—particularly hurricanes, which often combine wind and precipitation—drive rising insurance costs more than chronic risks such as sea-level rise.

4.5.2 Public information about Climate Risk

We test whether publicly available information on potential risks from acute weather events is reflected in insurance pricing. To capture this *information provision channel*, we estimate the following equation:

$$Insurance\ Ratio_{it} = \alpha + \beta\ Floodplain_i + W_{it}'\Gamma + Z_i'\Xi + \gamma_t + \varepsilon_{it} \tag{5}$$

The dependent variable is $Insurance\ Ratio_{it}$, is the total amount spent on insurance divided by total operating expenses in the same quarter, expressed as a percentage. The key explanatory variable, $Floodplain_i$, is a binary indicator equal to one if the property lies within a high-risk flood zone and zero otherwise. The comparison group consists of properties located outside the floodplain at distances of 0.5, 1, or 2 miles from its border. The vector W_{it} includes time-varying property-level controls (e.g., occupancy rate), Z_i are property type dummies and state fixed effects. γ_t represents time-fixed effects. Standard errors are clustered at the year level.

Table 11 presents the estimation results from Equation 5. Properties situated in high-risk flood zones report higher insurance expenditures as a share of total operating expenses. In Column (1), we compare properties inside the highest-risk flood zone to those located just outside the floodplain (within 0.5 miles), finding an estimated coefficient of 0.83 percentage points. Column (2) employs a 1-mile buffer, and Column (3) extends this to a 2-mile buffer, with similarly sized coefficients of 0.80 and 0.77 percentage points, respectively. These estimates suggest that, on average, commercial properties within the floodplain incur approximately 0.8 percentage points higher insurance costs due to their location.

5 Conclusion

In this paper, we examine the impact of climate-related disasters, specifically hurricanes, on the insurability of commercial real estate. Using detailed property-level data and a stacked difference-in-differences framework, we document significant increases in the ratio of insurance expenses to total operating expenses following hurricane exposure. On average, properties exposed to hurricanes experience 1.1 to 1.6 percentage point increase in their insurance cost ratios, representing approximately 20% to 26% rise relative to the sample average.

We further explore cumulative exposure effects, revealing a clear non-linear pattern: properties re-

peatedly exposed to hurricanes show disproportionately higher insurance cost increases, with jumps of up to 4 percentage points after four or more events.

Our analysis identifies portfolio diversification as a key moderating factor. Properties managed within geographically concentrated portfolios experience significantly insurance cost increases (2.3 to 2.8 percentage points), whereas diversified portfolios exhibit smaller or negligible effects. This indicates that potential bargaining power in negotiations with insurers may mitigate insurance cost pressures arising from climate shocks.

We find substantial heterogeneity in responses by storm severity and property type. Properties experiencing severe hurricanes (wind speeds of 64 knots or higher) face increases of 6 to 9 percentage points, more than double the baseline estimate. By asset class, office and industrial properties show notable increases of 1.6 to 2.3 percentage points, while multifamily properties experience moderate and generally insignificant changes, possibly due to regulatory influences. Retail assets display no statistically significant effects.

Additionally, our findings confirm that publicly available flood risk information from FEMA's floodplain maps is priced into current premiums, as properties within designated high-risk flood zones consistently pay higher insurance rates. Furthermore, forward-looking climate risk scores capturing wind, drought, and heavy precipitation risks are positively correlated with higher insurance expenses, suggesting insurers increasingly integrate anticipated climate risk into premium pricing.

Existing literature examines how regulations, such as flood zone designations, influence location decisions and adaptation efforts, although these regulations can sometimes lead to market distortions (Ostriker and Russo, 2022). More compelling evidence indicates that the removal of public aid in post-disaster recovery efforts in coastal areas can deter development in high-risk zones (Druckenmiller et al., 2024). A key follow-up question is whether accurately pricing climate risk into insurance policies would facilitate better location choices. In this context, higher premiums that fully reflect the underlying risks could guide development away from more exposed areas.

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6 Appendix

Data

Table 2: Hurricanes category 3,4 and 5 that made landfall in US from 2010 to 2023

Hurricane	Year-Quarter	Landfall	Index
H Alex	2010 Q3	July 2, 2010	al012010
H Earl	2010 Q3	August 25, 2010 (formed)	al072010
H Irene	2011 Q3	August 27, 2011	al092011
H Isaac	2012 Q3	August 28, 2012	al092012
H Sandy	2012 Q4	October 29, 2012	al182012
H Arthur	2014 Q3	July 3, 2014	al012014
H Hermine	2016 Q3	September 2, 2016	al092016
H Matthew	2016 Q4	October 8, 2016	al142016
H Harvey	2017 Q3	August 25, 2017	al092017
H Irma	2017 Q3	September 10, 2017	al112017
H Nate	2017 Q4	October 8, 2017	al162017
H Florence	2018 Q3	September 14, 2018	al062018
H Michael	2018 Q4	October 10, 2018	al142018
H Barry	2019 Q3	July 13, 2019	al022019
H Dorian	2019 Q3	September 6, 2019	al052019
H Hanna	2020 Q3	July 25, 2020	al082020
H Isaias	2020 Q3	August 3, 2020	al092020
H Laura	2020 Q3	August 27, 2020	al132020
H Sally	2020 Q3	September 16, 2020	al192020
H Delta	2020 Q4	October 9, 2020	al262020
H Zeta	2020 Q4	October 28, 2020	al282020
H Eta	2020 Q4	November 8, 2020	al292020
H Elsa	2021 Q3	July 7, 2021	al052021
H Henri	2021 Q3	August 22, 2021	al082021
H Ida	2021 Q3	August 29, 2021	al092021
H Nicholas	2021 Q3	September 14, 2021	al142021
H Fiona	2022 Q3	September 23, 2022	al072022
H Ian	2022 Q3	September 28, 2022	al092022
H Nicole	2022 Q4	November 10, 2022	al172022
H Idalia	2023 Q3	August 30, 2023	al102023
H Lee	2023 Q3	September 16, 2023	al132023

Figure 6: Commercial properties NCREIF

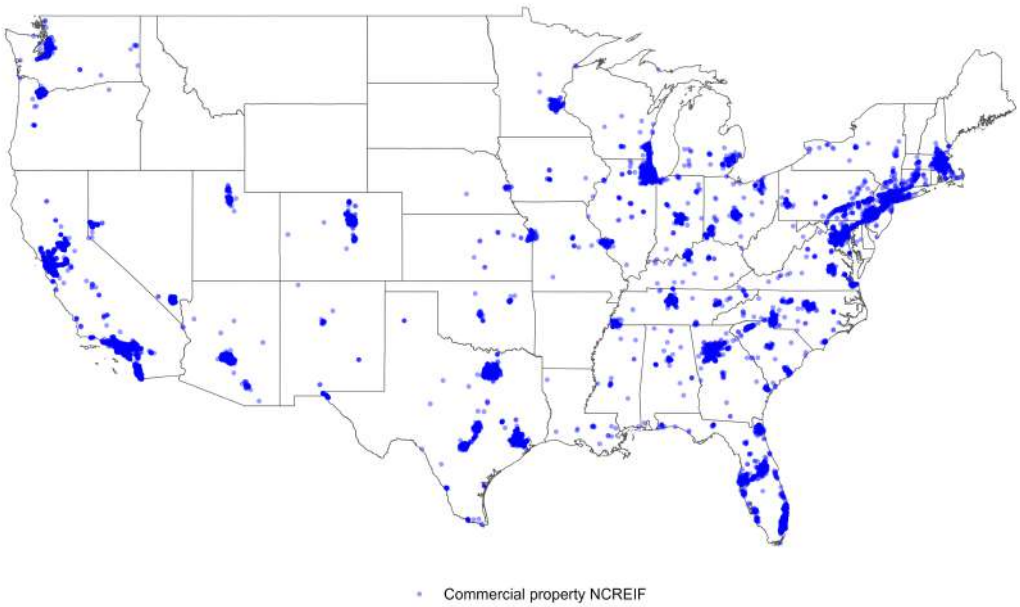


Figure 7: Hurricane Ian wind swath

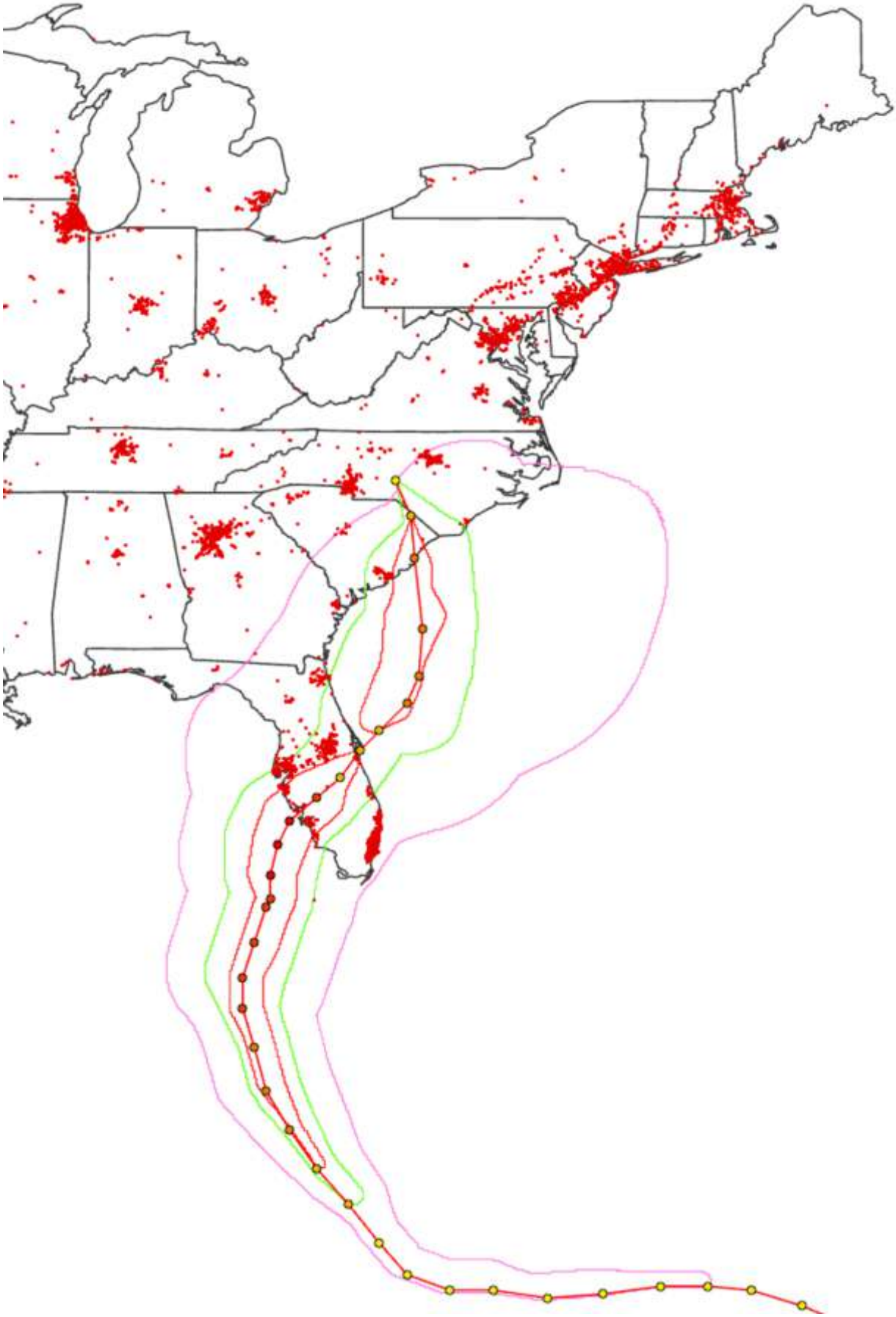
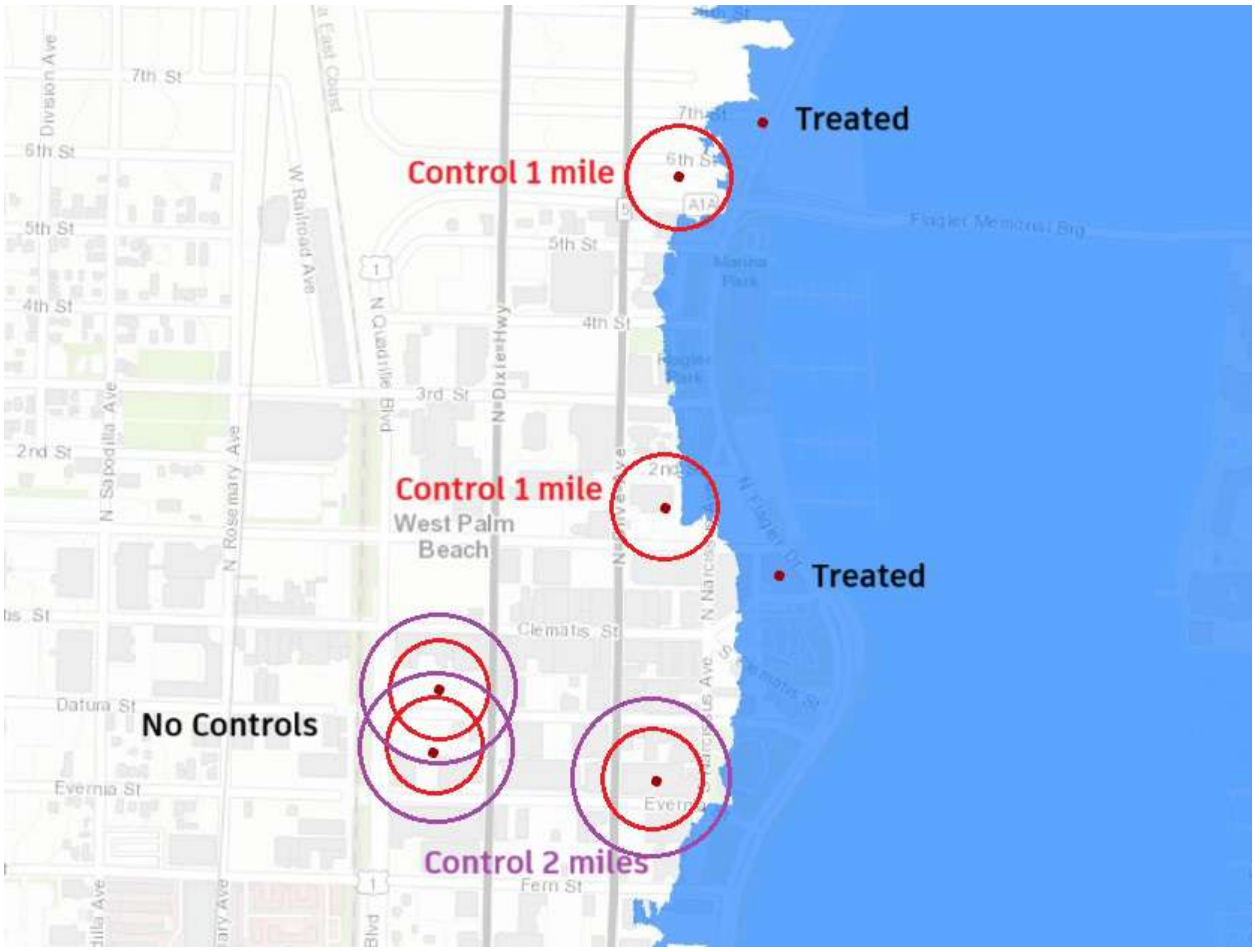


Figure 8: FEMA floodmaps: graphical representation of Inside floodplain and outside floodplain



Descriptive statistics

Table 3: Summary Statistics at Property - Quarter

Variable	Mean	Median	SD
Insurance Expenses / Total Operating Expenses (%)	6.05	4.15	9.00
Insurance Expenses / Total Revenue (%)	1.90	1.36	2.69
Insurance expenditures (€1,000)	15.03	8.59	18.25
Total Operating Expenses (€1,000)	349.45	204.99	402.90
Total Revenue (€1,000)	923.09	618.63	978.28
Occupancy rate (0-100%)	94.03	99.69	13.68
Exposed to Hurricane ==1 (%)	0.026	0.00	0.16
Inside Flood plain ==1 (%)	5.35	0.00	22.49
Apartments ==1 (%)	22.67	0.00	41.87
Industrial ==1 (%)	44.43	0.00	49.69
Offices ==1 (%)	20.26	0.00	40.19
Retail ==1 (%)	12.64	0.00	33.23
All peril Hazard Score (0-100)	39.12	33.00	26.61
Flood Hazard Score (0-100)	11.41	0.00	19.99
Wind Hazard Score (0-100)	24.77	19.00	17.25
Drought Hazard Score (0-100)	50.36	40.00	37.55
Precipitation Hazard Score (0-100)	45.51	46.00	23.40

Figure 9: FEMA declarations on Hurricanes, by county

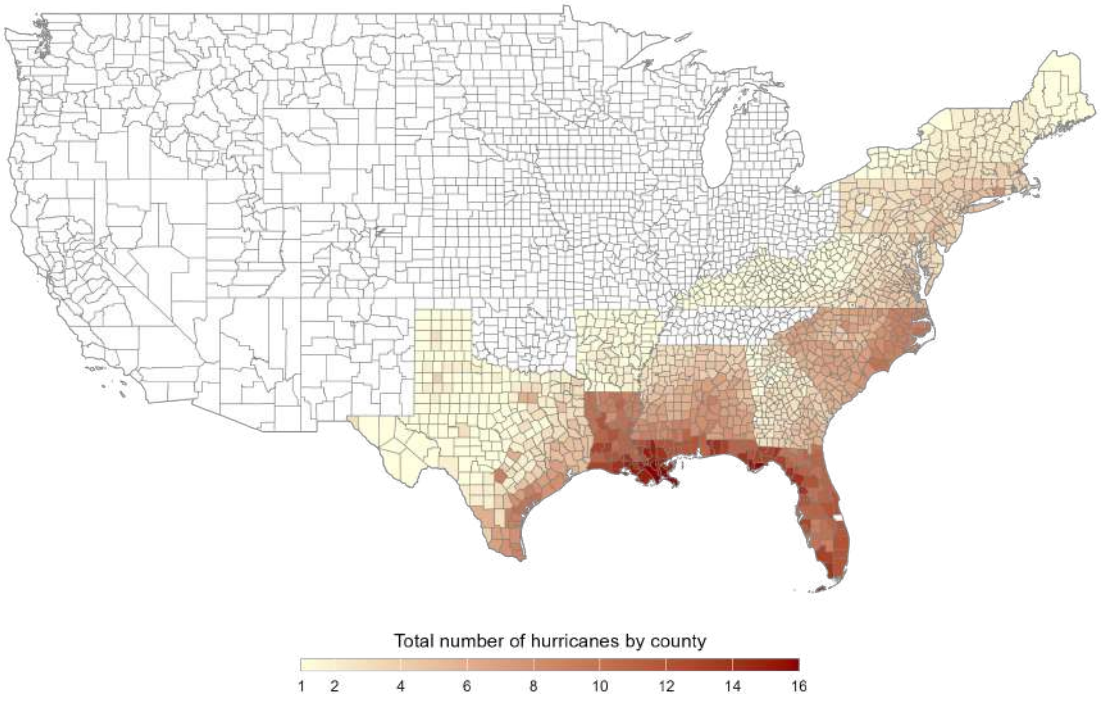


Figure 10: Average ratio of insurance expenses relative to total operating expenses and U.S. Property Catastrophe Rate-On-Line Index

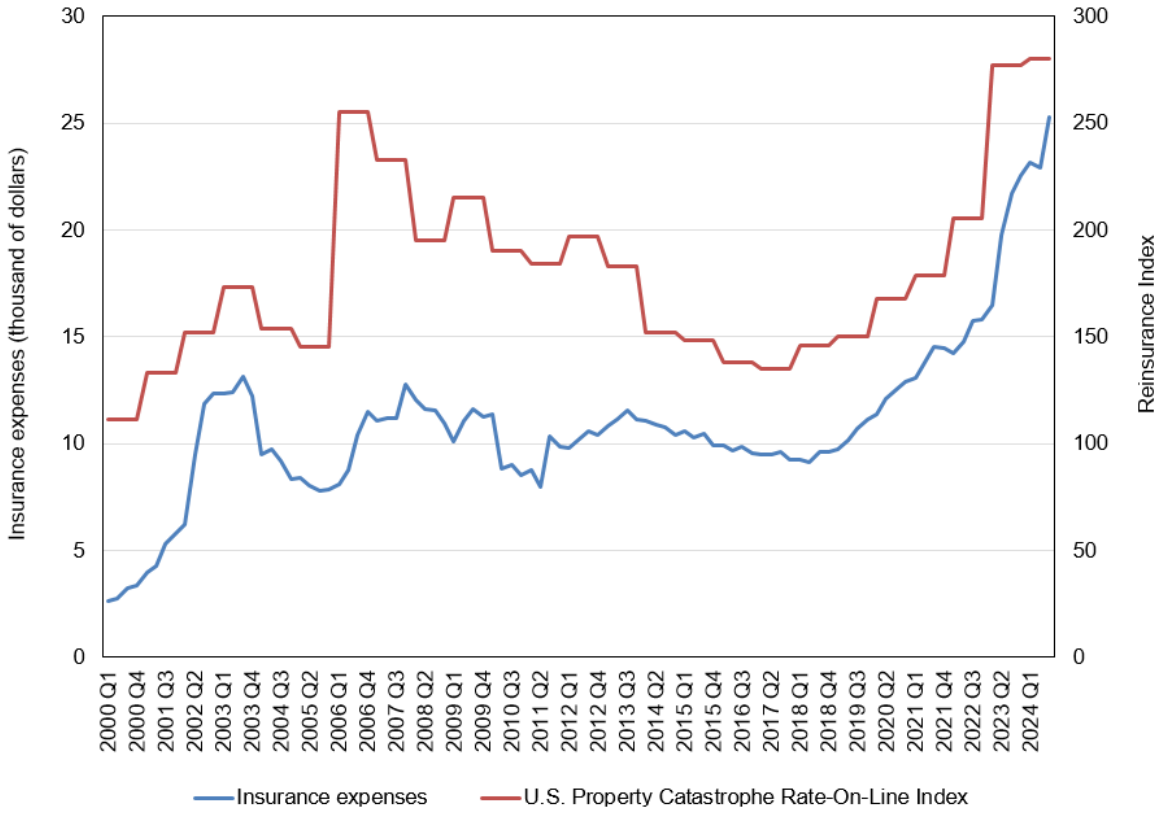


Figure 11: Average Ratio of Insurance Expenses to Operating Expenses by State

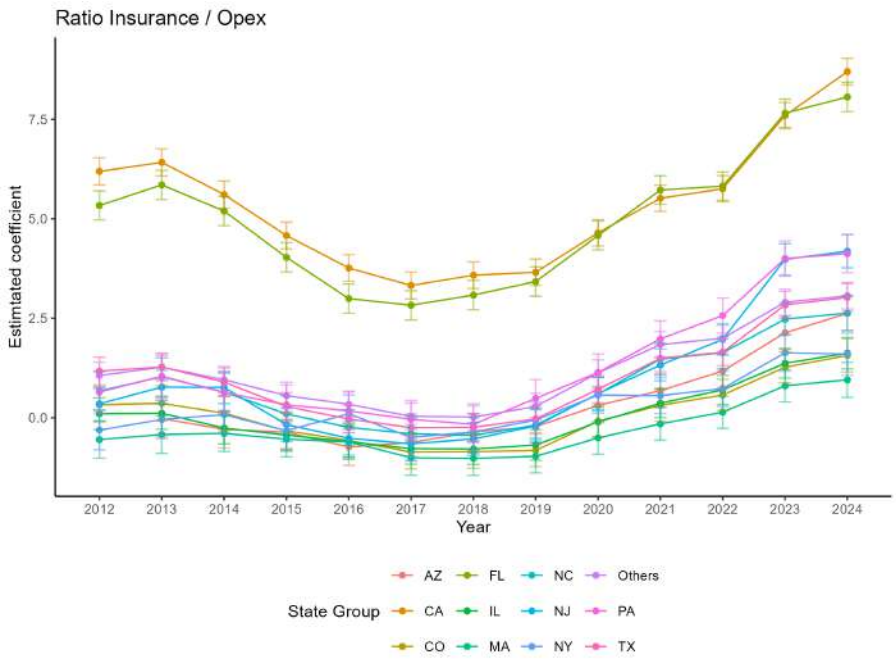
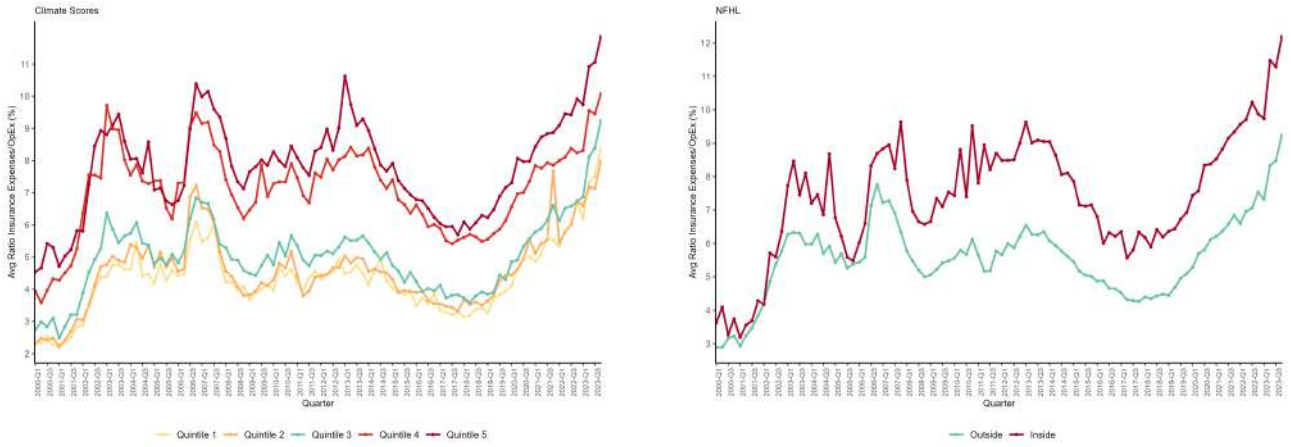


Figure 12: Average Ratio of Insurance Expenses to Operating Expenses by Quintile of Climate Score and by Flood Zone



(a) (b)

Descriptive maps

Figure 13: Average ratio Insurance expenses to total operating expenses, by counties

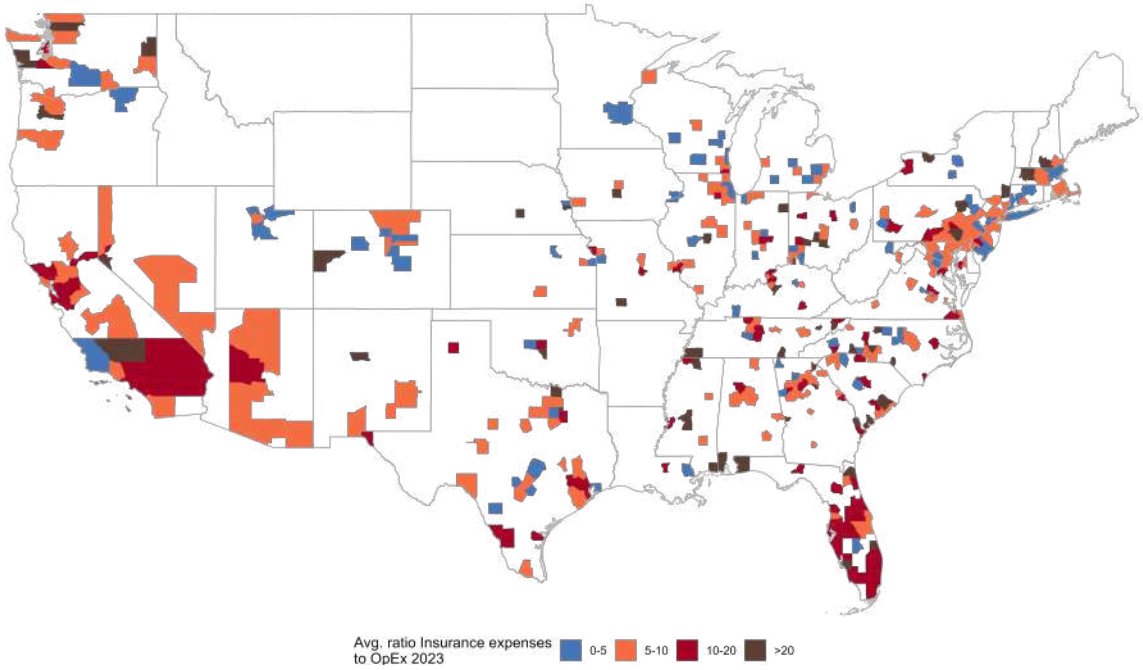


Figure 14: Average annual insurance expenses 2023, by county

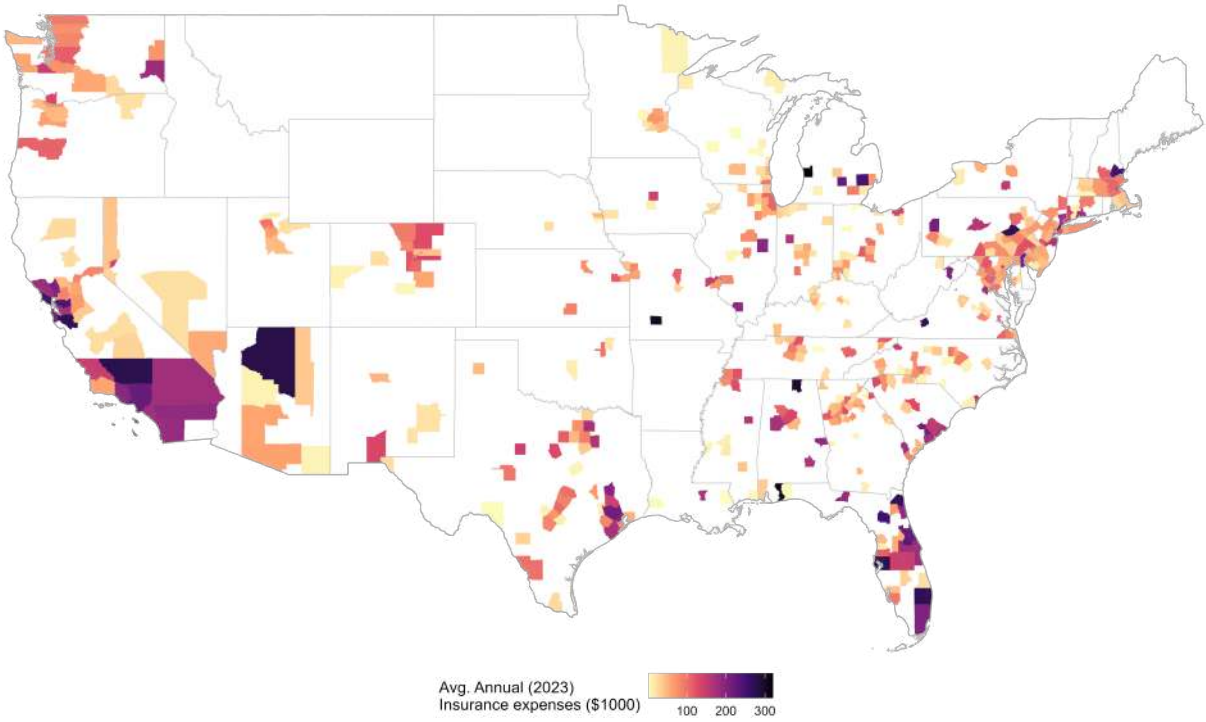


Figure 15: Average annual insurance expenses per sqft, 2023, by county

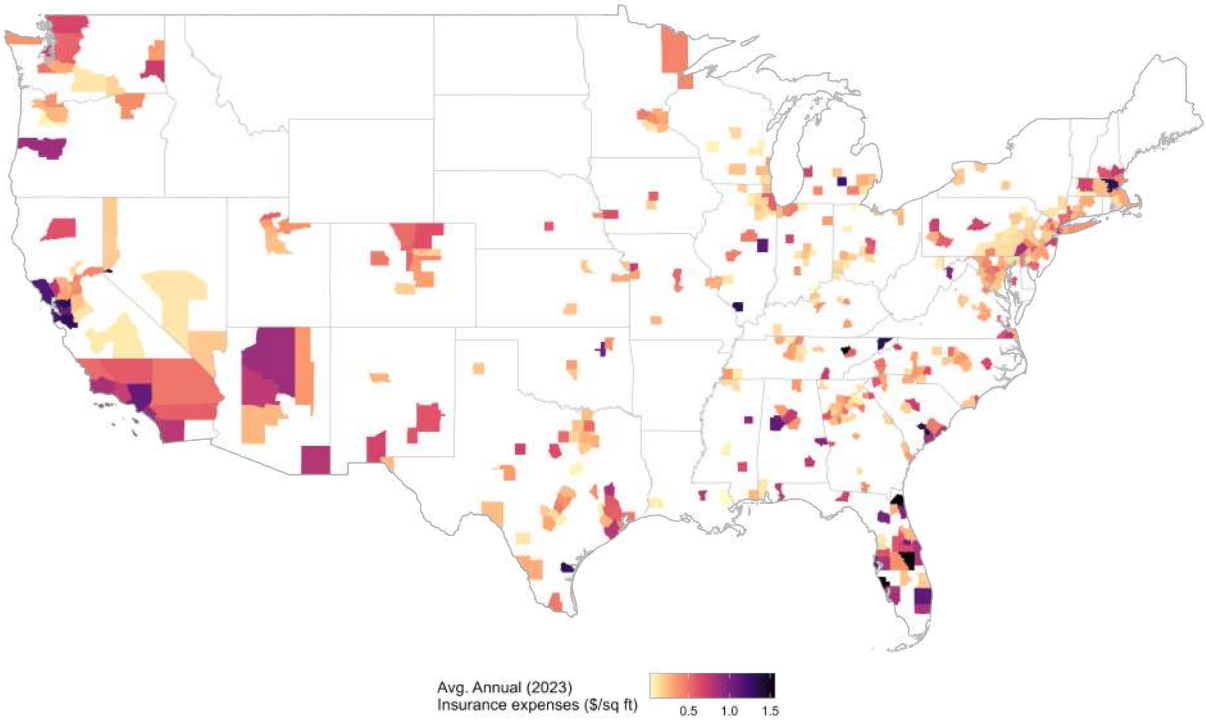
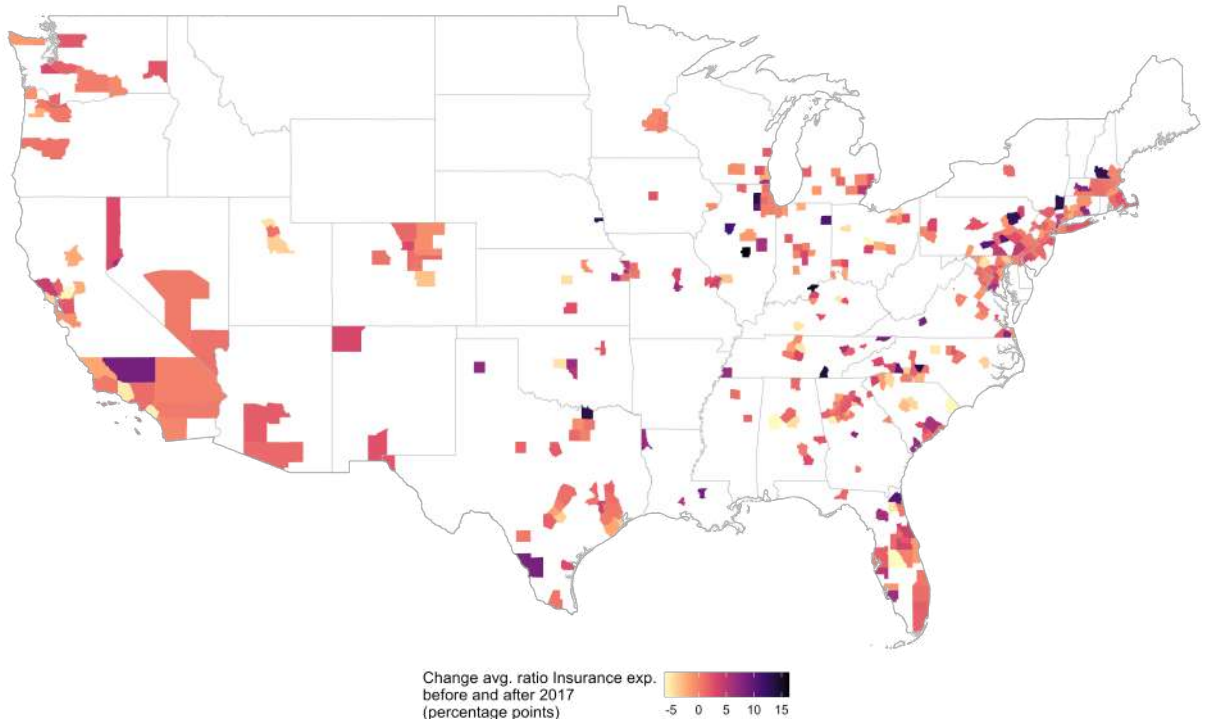


Figure 16: Change in ratio of insurance expenses to operating expenses, 2017–2024, by county



Weights

In order to ensure that the control group in each sub-experiment–time mimics the treated group, we construct weights through the following steps. First, for each event-time t, we compute the total number of observations N_t, the number treated T_t, and the number of controls C_t. These aggregate counts capture the overall sample composition at each time point:

$$N_t \;=\; \#\{i : \text{event_time}_i = t\}, \quad T_t \;=\; \sum_{i:\,\text{event_time}_i = t} D_i, \quad C_t \;=\; N_t - T_t. \tag{6}$$

Next, within each sub-experiment s at time t, we compute the subgroup counts: the total number of units $n_{s,t}$, the number treated $t_{s,t}$, and the number of controls $c_{s,t}$. This decomposes the overall counts into the contribution of each subgroup:

$$n_{s,t} \;=\; \#\{i : s_i = s,\ \text{event_time}_i = t\}, \quad t_{s,t} \;=\; \sum_{i:\,s_i = s,\ \text{event_time}_i = t} D_i, \quad c_{s,t} \;=\; n_{s,t} - t_{s,t}. \tag{7}$$

We then form the relative shares of each subgroup within the total at time t:

$$\text{sub_share}_{s,t} = \frac{n_{s,t}}{N_t}, \quad \text{sub_treat_share}_{s,t} = \frac{t_{s,t}}{T_t}, \quad \text{sub_control_share}_{s,t} = \frac{c_{s,t}}{C_t}. \tag{8}$$

Finally, we assign weights to each unit i at time t so that treated observations receive weight one, and control observations are scaled to match the treated share of their subgroup:

$$w_{i,t} = \begin{cases} 1, & D_i = 1, \\ \dfrac{\text{sub_treat_share}_{s,t}}{\text{sub_control_share}_{s,t}}, & D_i = 0. \end{cases} \tag{9}$$

These weights guarantee that, for each property-event-time , the re-weighted control distribution aligns with the treated distribution, thereby balancing the comparison in the event-study analysis.

Baseline

Table 4: Estimation of the effect of exposure to one Hurricane on insurance ratio

	Insurance expenses/Total operating expenses			
	(1)	(2)	(3)	(4)
Panel A. Post-exposure average effect				
Treated (=1) × Post (=1)	1.217***	1.090***	1.691*	1.691*
	(0.435)	(0.418)	(0.962)	(0.999)
Panel B. Event-study				
Treated (=1) × Event-time -2 (=1)	-0.152	-0.107	-0.164	-0.102
	(0.326)	(0.338)	(0.431)	(0.437)
Treated (=1) × Event-time 0 (=1)	1.249	0.959	3.432	3.457
	(1.061)	(1.024)	(2.773)	(2.820)
Treated (=1) × Event-time +1 (=1)	0.757	0.795	0.418	0.473
	(0.538)	(0.557)	(0.782)	(0.821)
Treated (=1) × Event-time +2 (=1)	0.450	0.385	0.619	0.678
	(0.417)	(0.423)	(0.503)	(0.552)
Treated (=1) × Event-time +3 (=1)	0.543	0.509	1.144**	1.135*
	(0.395)	(0.407)	(0.570)	(0.606)
Treated (=1) × Event-time +4 (=1)	3.006***	2.930***	2.079***	2.143**
	(1.014)	(1.019)	(0.773)	(0.855)
Control group	All states	All states	Expose states	Expose states
Event × time FEs	Yes	Yes	Yes	Yes
Event × property FEs	Yes	Yes	No	Yes
Weights	Yes	Yes	Yes	Yes
Control variable		Occup.rate		Occup.rate
Quarter-Property	538,636	521,792	169,030	163,233
R^2	0.177	0.177	0.192	0.191

***, **, * indicate significance at 1%, 5%, and 10% level. Standard errors clustered at the property level.

Baseline different windows

Figure 17: Event study baseline window 8 quarters after the Hurricane

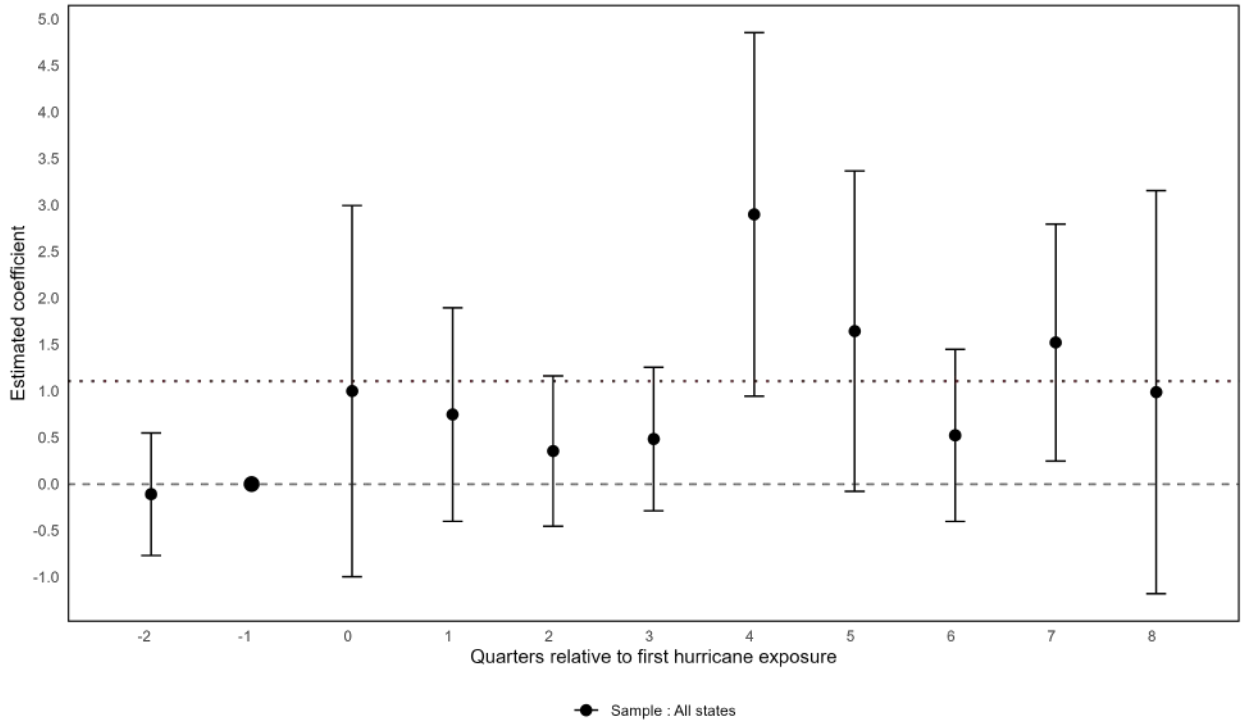
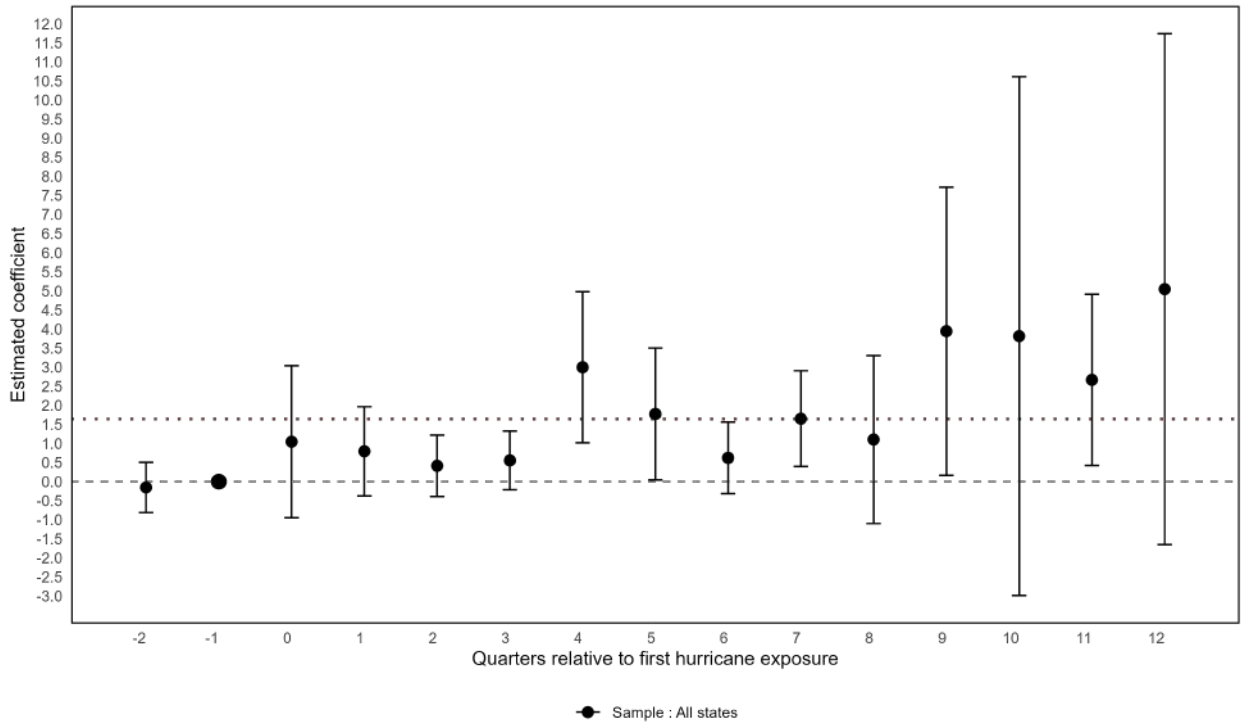
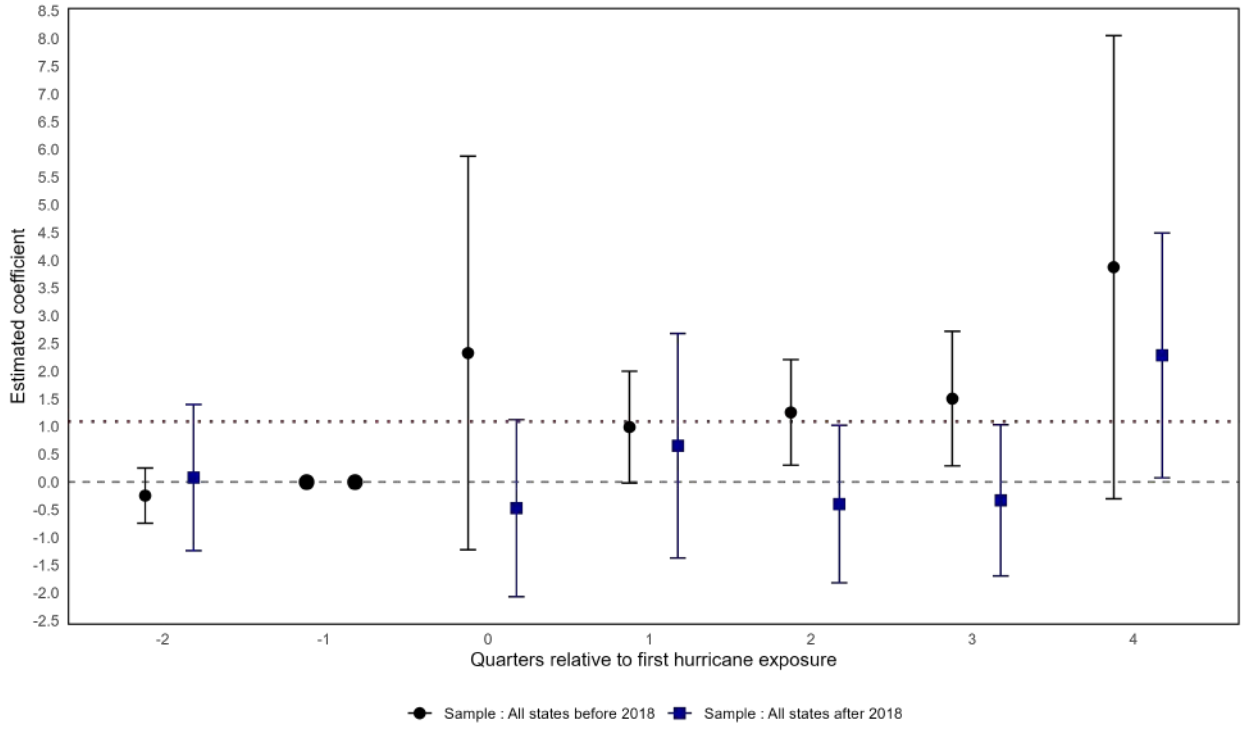


Figure 18: Event study baseline window 12 quarters after the Hurricane



Baseline: before and after 2018

Figure 19: Event study baseline: before and after 2018



Alternative estimation: Weighted lest squared following Wing et al. (2024b)

$$Y_{ith} = \alpha_1 D_{ih} + \sum_{\substack{j=-\kappa_{\text{pre}},\ldots,\kappa_{\text{post}} \\ j\neq -1}} \Big[\lambda_t 1[t=j] + \delta_t D_{is} \times 1[t=h]\Big] + \gamma_i + \tau_t + + \Xi' X_{it} + \varepsilon_{its} \tag{10}$$

Table 5

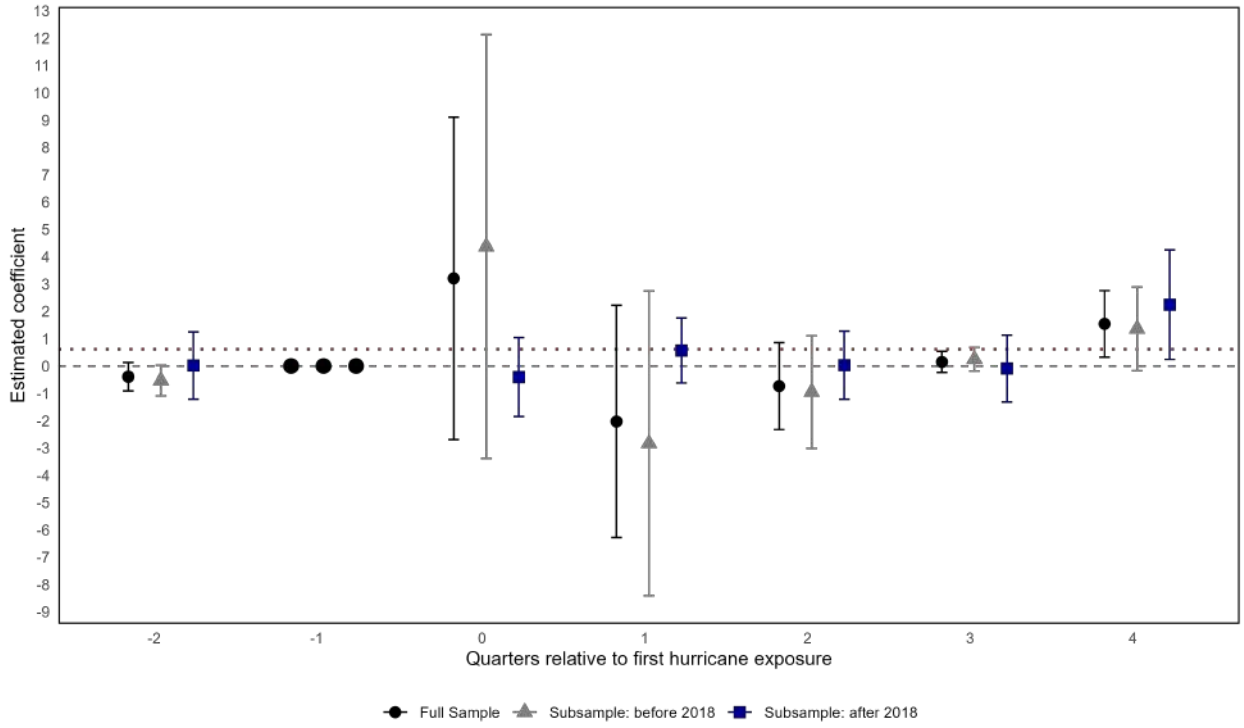
	Insurance expenses/Total operating expenses			
	(1)	(2)	(3)	(4)
Panel A. Post-exposure average effect				
Exposed (=1) × Post (=1)	1.032***	0.967***	1.095*	1.149*
	(0.340)	(0.340)	(0.624)	(0.611)
Panel B. Event-study				
Exposed	-0.621*	0.005	0.995***	1.237***
	(0.341)	(0.364)	(0.327)	(0.352)
Event-time -2 (=1)	0.198	0.123	0.189	0.105
	(0.168)	(0.168)	(0.305)	(0.318)
Event-time 0 (=1)	-0.939	-1.033	-3.366	-3.841
	(0.877)	(0.896)	(3.015)	(3.131)
Event-time +1 (=1)	0.500*	0.450*	0.930	0.797
	(0.260)	(0.269)	(0.671)	(0.706)
Event-time +2 (=1)	0.361**	0.328*	0.515**	0.412*
	(0.182)	(0.181)	(0.205)	(0.217)
Event-time +3 (=1)	0.482***	0.363***	0.383*	0.295
	(0.130)	(0.139)	(0.204)	(0.205)
Event-time +4 (=1)	-0.767	-0.940	0.657***	0.537**
	(0.786)	(0.872)	(0.235)	(0.245)
Treated (=1) × Event-time -2 (=1)	-0.060	0.030	-0.051	0.031
	(0.335)	(0.345)	(0.415)	(0.435)
Treated (=1) × Event-time 0 (=1)	1.299	1.083	3.727	3.909
	(1.031)	(0.999)	(3.057)	(3.125)
Treated (=1) × Event-time +1 (=1)	0.653	0.746	0.223	0.402
	(0.594)	(0.621)	(0.852)	(0.887)
Treated (=1) × Event-time +2 (=1)	0.318	0.320	0.164	0.264
	(0.383)	(0.390)	(0.406)	(0.416)
Treated (=1) × Event-time +3 (=1)	0.295	0.314	0.395	0.429
	(0.342)	(0.357)	(0.372)	(0.383)
Treated (=1) × Event-time +4 (=1)	2.617***	2.643***	1.192**	1.243**
	(0.934)	(0.984)	(0.540)	(0.565)
Control group	All	All	Expose states	Expose states
Event × time FEs	No	No	No	No
Event × state FEs	No	No	No	No
Weights	Yes	Yes	Yes	Yes
Control variable		Occup.rate		Occup.rate
Quarter-Property	538,636	521,792	169,030	163,233
R^2	0.001	0.001	0.001	0.001

Standard errors clustered at the property level. * p <0.1, ** p <0.05, *** p <0.01

Baseline: Not yet treated group

The subsample correspond to properties expose to the first hurricane, that could be expose to hurricanes later. But we only take into account the quarters before and after the first exposure and we trimmed the sample in the quarter where the property is exposure to the second hurricane (if any). The window is the same as the baseline two quarters before and 4 quarters after.

Figure 20: Event study not yet treated: All, before 2018 and after 2018



Effect of Second Hurricane Exposure

To study how a second hurricane affects insurance costs, we follow the intuition developed in De Chaisemartin and d'Haultfoeuille (2023) and compare properties exposed to two hurricanes with those exposed to only one or none.

The treated group consists of all properties that were initially exposed to one hurricane and subsequently exposed to a second hurricane during the study period. We refer to these properties as switchers, that transition from first-time exposure to repeat exposure. We define two variants of this group:

- Properties exposed to exactly two hurricanes (no additional exposures).
- Properties exposed to two or more hurricanes, but for whom we restrict the analysis window to post-first exposure and pre-third exposure, to avoid contamination from subsequent events.

For comparison, we use multiple control groups, depending on the specific comparison we aim to isolate:

- Group 1: Treated units (switchers with exactly two hurricane exposures) vs. never-treated properties. This specification captures the cumulative effect of two hurricanes relative to no exposure at all.
- Group 2: Treated units (switchers with exactly two exposures) vs. properties exposed to only one hurricane during the entire study period. This isolates the marginal effect of the second hurricane relative to the effect of the first.
- Group 3: Treated units (switchers with exactly two exposures) vs. properties exposed to two or more hurricanes, where the observation window includes only the period after the first hurricane and before the second. This ensures the control group experienced similar history but not yet the second treatment.

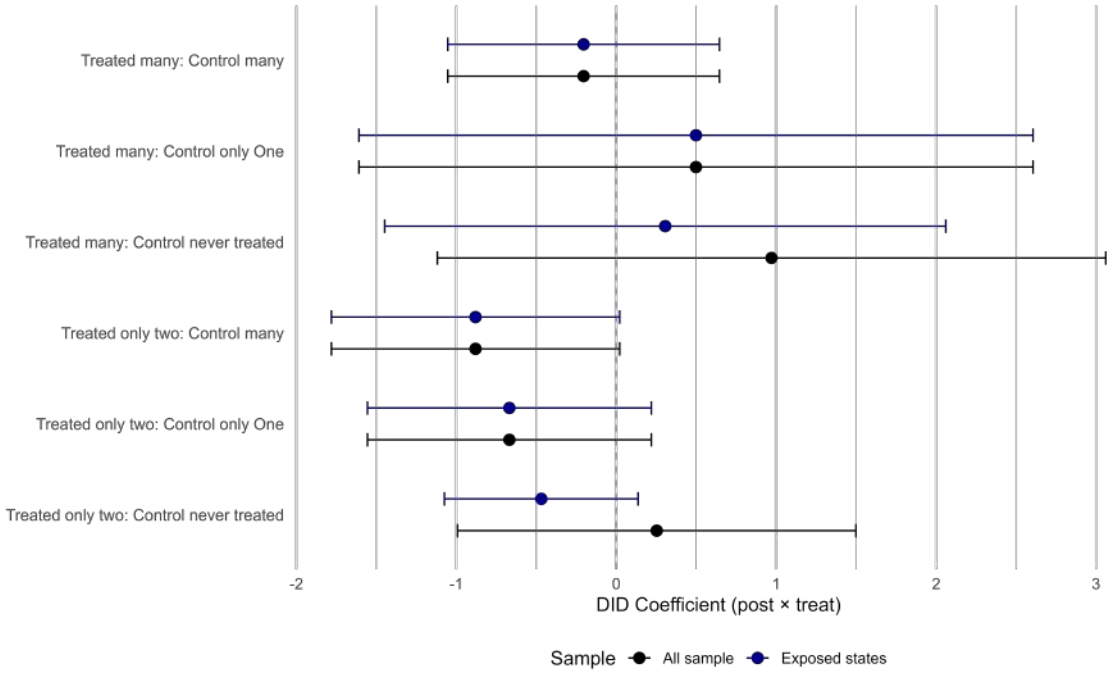
We repeat this logic for properties with more than two hurricane exposures, using similar control group definitions:

- Group 4: Switchers with two or more exposures vs. never-treated properties.

- Group 5: Switchers with two or more exposures vs. properties exposed to only one hurricane.
- Group 6: Switchers with two or more exposures vs. properties exposed to multiple hurricanes, using the window between the first and second exposure.

In all specifications, we use an event window of two quarters before and four quarters after the second hurricane, ensuring symmetric comparison around the treatment time and minimizing overlap with future shocks.

Figure 21: Estimation of the effect of the second hurricane exposure on the insurance ratio



Mechanisms

Pre Hurricane Manager diversification

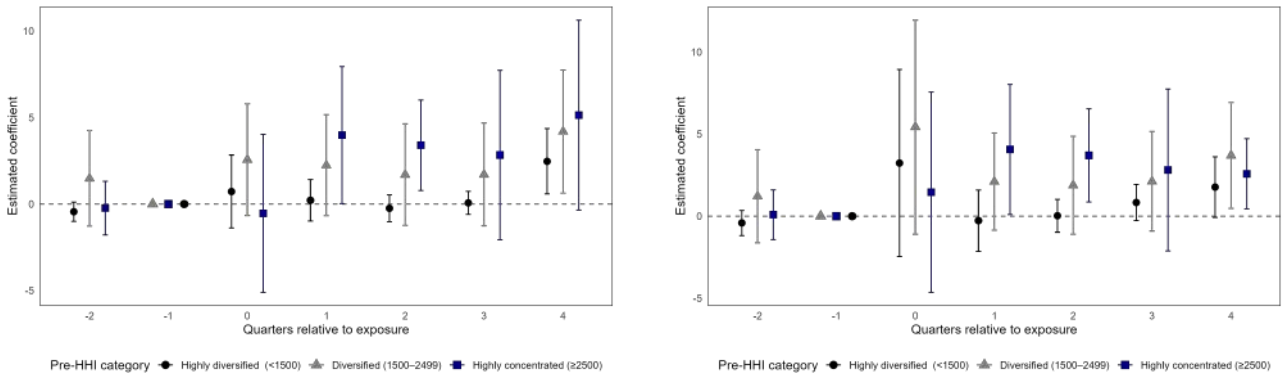
Table 6: Triple difference: Hurricane exposure × Post × Pre hurricane manager HHI category

	Insurance expenses/Total operating expenses			
	(1)	(2)	(3)	(4)
Exposure (=1) × Post (=1) × Pre-HHI=1 (=1)	0.9623**	0.7977*	1.406	1.388
	(0.4520)	(0.4076)	(0.9632)	(0.9978)
Exposure (=1) × Post (=1) × Pre-HHI=2 (=1)	1.888**	1.714**	2.621**	2.575**
	(0.8319)	(0.8634)	(1.277)	(1.293)
Exposure (=1) × Post (=1) × Pre-HHI=3 (=1)	2.332**	2.790**	2.514**	2.879**
	(1.021)	(1.202)	(1.282)	(1.394)
Control group	All	All	Expose states	Expose states
Property × cohort FEs	Yes	Yes	Yes	Yes
Event-time × cohort FEs	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes
Control variable		Occup.rate		Occup.rate
Quarter-Property	532,390	516,078	165,658	160,199
R^2	0.17691	0.17672	0.19173	0.19112

Standard errors are clustered at property level.

***, **, * indicate significance at 1%, 5%, and 10% level.

Figure 22: Event-study Difference-in-Difference-in-Difference: Insurance ratio and Pre hurricane manager diversification



(a) All states

(b) Expose states

Heterogeneity

Wind speed

Table 7: Triple difference: Hurricane exposure × Post × Wind speed category

	$Insurance\ expenses/Total\ operating\ expenses$			
	(1)	(2)	(3)	(4)
Exposure (=1) × Post (=1) × windspeed 34	1.001**	0.8381**	1.196*	1.108*
	(0.3941)	(0.3514)	(0.6377)	(0.6310)
Exposure (=1) × Post (=1) × windspeed 50	2.202**	2.283*	3.980	4.472
	(1.092)	(1.168)	(2.896)	(3.135)
Exposure (=1) × Post (=1) × windspeed 64	5.069***	6.655***	5.967***	9.096***
	(1.925)	(1.186)	(2.308)	(1.616)
Control group	All	All	Expose states	Expose states
Property × cohort FEs	Yes	Yes	Yes	Yes
Event-time × cohort FEs	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes
Control variable		Occup.rate		Occup.rate
Quarter-Property	538,636	521,792	169,030	163,233
R^2	0.17710	0.17693	0.19191	0.19129

Standard errors are clustered at property level.

***, **, * indicate significance at 1%, 5%, and 10% level.

Property type

Table 8: Triple difference: Hurricane exposure × Post × Property type

	$Insurance\ expenses/Total\ operating\ expenses$			
	(1)	(2)	(3)	(4)
Exposure (=1) × Post (=1) × Industrial	1.252**	1.139*	1.677*	1.808*
	(0.5866)	(0.6073)	(0.8733)	(0.9530)
Exposure (=1) × Post (=1) × Office	1.554**	1.768**	2.190*	2.345*
	(0.6342)	(0.7176)	(1.324)	(1.358)
Exposure (=1) × Post (=1) × Multifamily	1.461**	0.8729*	1.951*	1.553
	(0.6889)	(0.4533)	(1.147)	(1.075)
Exposure (=1) × Post (=1) × Retail	0.1818	0.3976	0.4766	0.7624
	(0.6173)	(0.5669)	(0.9873)	(0.9540)
Control group	All	All	Expose states	Expose states
Property × cohort FEs	Yes	Yes	Yes	Yes
Event-time × cohort FEs	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes
Control variable		Occup.rate		Occup.rate
Quarter-Property	538,636	521,792	169,030	163,233
R^2	0.17710	0.17693	0.19191	0.19129

Standard errors are clustered at property level.

***, **, * indicate significance at 1%, 5%, and 10% level.

Forward looking climate scores

Table 9: Regression Climate-related hazard scores on Ratio Insurance expenses/OpEx

	Insurance expenses / OpEx (%)				
	(1)	(2)	(3)	(4)	(5)
All perils	0.0209***				
	(0.0019)				
Flood		0.0004			
		(0.0013)			
Wind			0.0454***		
			(0.0040)		
Drought				0.0062**	
				(0.0010)	
Precipitation					0.0336***
					(0.0036)
Occupancy rate (0-100%)	0.0147***	0.0146***	0.0146***	0.0147***	0.0140***
	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Mean ind. var	39.1	11.4	24.8	50.4	45.5
Sd ind. var	26.6	20.0	17.2	37.5	23.4
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Property type FE	Yes	Yes	Yes	Yes	Yes
Quarter-Prop	522,917	522,917	522,917	522,917	522,917
R^2	0.11679	0.11568	0.11673	0.11578	0.11696
Within R^2	0.00176	0.00050	0.00169	0.00062	0.00195

Clustered (year-state) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Regression Climate-related change scores on Ratio Insurance expenses/OpEx: forward looking indicators

	Insurance expenses / OpEx (%)				
	(1)	(2)	(3)	(4)	(5)
All perils	0.0024				
	(0.0024)				
Flood		-0.0006			
		(0.0018)			
Wind			0.0713***		
			(0.0077)		
Drought				0.0232***	
				(0.0041)	
Precipitation					-0.0140***
					(0.0030)
Occupancy rate (0-100%)	0.0145***	0.0146***	0.0150***	0.0143***	0.0146***
	(0.0031)	(0.0031)	(0.0032)	(0.0032)	(0.0032)
Mean ind. var	34.5	3.32	7.16	-6.3	46.8
Sd ind. var	20.0	13.5	7.89	10.5	14.6
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Property type FE	Yes	Yes	Yes	Yes	Yes
Quarter-Prop	522,917	522,917	522,917	522,917	522,917
R^2	0.11569	0.11568	0.11685	0.11592	0.11587
Within R^2	0.00052	0.00050	0.00183	0.00078	0.00072

Clustered (year-state) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Impact of High-risk flood zone as Treatment on Insurance Expenses

	Insurance expenses / OpEx (%)		
	0.5 miles	1 miles	2 miles
Inside Floodplain	0.83***	0.8004***	0.7744***
	(0.0744)	(0.0726)	(0.0736)
Prop-Qtr	365,955	471,616	511,566
R^2	0.11936	0.12832	0.11826
Prop. type FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Clustered (year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*