

Adapting to Risk? How Investor Beliefs Shape Climate Adaptation in Real Estate Portfolios

Simon Büchler^{a,b}, Juan Palacios^{b,c}, Xudong Sun^c, Siqi Zheng^b

^a*Miami University Farmer School of Business, 83 N Patterson Ave, Oxford, OH 45056.*

^b*MIT Center for Real Estate, 77 Massachusetts Avenue, Cambridge, MA 02139-4307.*

^c*Maastricht University School of Business and Economics, Minderbroedersberg 4-6, 6211 LK Maastricht, The Netherlands.*

Abstract

As environmental and physical risks intensify, investors face mounting pressure to adapt their investment strategies to physical climate risks. This paper examines the impact of climate risks on real estate portfolio investment decisions. We build a unique dataset where we can identify changes in the composition of purchases and sales for real estate portfolios across the US and the investments in the resilience of individual assets. Using localized heat events as quasi-exogenous shocks and a difference-in-differences approach, we find that portfolio managers adjust their strategies in two key ways. First, they shift investments toward properties with lower-risk exposure. Second, they increase spending on protective building improvements and risk-related insurance for vulnerable properties. This paper contributes to the literature by analyzing how institutional investors integrate physical climate risks into portfolio strategies for their real estate investments.

Email addresses: buechlsc@miamioh.edu (Simon Büchler), jpalacio@mit.edu (Juan Palacios), x.sun@maastrichtuniversity.nl (Xudong Sun), sqzheng@mit.edu (Siqu Zheng)

1. Introduction

This paper examines how institutional investors adapt to physical climate risks through their acquisition and resilience decisions regarding real assets and their investments in climate resilience measures. Real estate has become a cornerstone of institutional investment portfolios, with pension funds allocating an average of 8.3% of their assets to it, totaling approximately \$10 trillion in private real estate holdings and \$1.2 trillion in listed REITs (Carlo et al., 2021; Andonov et al., 2015). This allocation reflects institutional investors' expectation that real estate provides diversification benefits and reduces portfolio volatility (Andonov et al., 2021; Chambers et al., 2021).¹

Despite the prominent role of the real estate sector for investors and the growing evidence of the threat of climate in real estate markets (Bernstein et al., 2019; Addoum et al., 2024), there is scant evidence of how institutional investors actively adapt their investment strategies to address climate risk. This knowledge gap is critical, as extreme weather events' increasing severity and frequency pose significant risks to assets and investments (IPCC, 2022; Hsiang et al., 2017). Over the past four decades, the associated losses have increased nearly 10-fold globally (Smith and Matthews, 2015). In 2023 alone, there were 28 separate climate disaster events with losses exceeding 1 billion each in the US (NOAA, 2024). At the same time, insured losses hit record highs, and uninsured losses are growing even faster, amplifying financial risks (Munich Re, 2025). In recent survey data, Krueger et al. (2020) document that institutional investors rank climate risk lower than financial and operational risks but still consider it important.

Against this background, institutional investors are increasingly pushed to adapt their portfolio strategies in response to the growing vulnerability of properties to physical climate risks. CRE holders have recently faced growing pressure from debt and equity providers and regulators to disclose how (physical) climate risks affect their assets (Ilhan et al., 2023). Mar-

¹According to MSCI Inc., in 2022, approximately US\$13.5 trillion of global real estate assets were under institutional management for investment purposes. The National Association of Real Estate Investment Trusts (NAREIT) (2022) estimated that the total value of commercial real estate (CRE) in the US in 2021 was \$20.7 trillion. Additionally, pension, endowment, and foundation funds controlled over \$12 trillion in total assets, with almost \$900 billion invested in real estate as of 2021.

ket participants’ inadequate response to climate risks through misallocation of capital could lead to significant portfolio losses and broader economic impacts. Yet, these adjustments are not uniform—while some investors proactively integrate climate risks into their strategies, many others hesitate to act due to short-term financial incentives, uncertainty about climate risk projections, or future regulatory enforcement.² Therefore, understanding whether and how institutional investors adapt to physical climate risks is critical for the investment industry and policy design. This insight is essential for developing effective macroeconomic policies and portfolio management strategies to address climate risk adaptation.

This paper examines how investors adapt to climate risks in their real asset investments through two different channels: portfolio reallocation decisions and investments in climate resilience measures of individual assets. We integrate transaction data on commercial real estate (CRE) properties from Real Capital Analytics (RCA) with property-level financial and accounting data from the National Council of Real Estate Investment Fiduciaries (NCREIF) to track the real estate portfolios of 40,371 institutional investors from 2015 to 2021. To assess climate risk exposure, we incorporate property-level climate risk data from Moody’s, covering a comprehensive set of physical climate hazards for our sample of each property in the portfolio (N=649,723), including floods, hurricanes, cyclones, typhoons, sea-level rise, wildfires, water stress, and extreme temperatures. In addition to hazard-specific risk scores, we also utilize the Average Damage Rate (ADR) provided by Moody’s. ADR quantifies the expected annual damage as a percentage of property value and enables consistent monetary comparisons of climate risk exposure across properties and hazard types.

We exploit localized heat events at institutional investors’ primary office sites as quasi-exogenous shocks to their climate beliefs (Alekseev et al., 2022; Di Giuli et al., 2022) and examine how these shocks influence subsequent investment decisions. Specifically, we identify idiosyncratic shifts in portfolios’ climate risk beliefs and employ a difference-in-differences approach to model their decisions to acquire or divest CRE assets across different levels of climate risk.

²In March 2024, the US Securities and Exchange Commission (SEC) adopted final rules requiring publicly traded companies to disclose climate-related risks and their potential material impacts (U.S. Securities and Exchange Commission, 2024).

Our findings reveal that, after the climate risk perception shift, institutional investors reallocate their portfolios toward lower-risk properties and increase capital expenditures on building improvements and insurance coverage, exceeding prevailing market trends. These results offer valuable insights into how climate risks are integrated into institutional investment strategies and their influence on asset pricing.

This paper relates to a growing body of literature investigating how climate risks affect real estate assets.³ Current studies, which mostly focus on residential real estate, consistently show that climate risks such as floods, wildfires, hurricanes, or extreme temperatures result in price discounts on exposed properties (Ortega and Taşpınar, 2018; Bernstein et al., 2019; Murfin and Spiegel, 2020; Baldauf et al., 2020a; Giglio et al., 2021). However, the extent to which physical climate risk affects CRE is unclear (Hino and Burke, 2021; Baldauf et al., 2020a; Giglio et al., 2021). This paper contributes to the literature by focusing explicitly on portfolio management adaptation strategies. It offers a detailed examination of how institutional investors adapt their strategies in their real estate portfolios in response to climate risks.

We also contribute to the growing body of research that examines how investor beliefs about climate risk shape financial decision-making. Choi et al. (2019) find that retail investors respond to abnormal local temperatures by increasing attention to climate change, reflected in Google search volume and stock market behavior, while institutional investors do not.⁴ Alekseev et al. (2022) identifies climate-related belief shocks of fund managers to build hedge portfolios for climate risks. Alok et al. (2019) show that professional money managers overreact to nearby climate disasters, significantly underweighting disaster-zone stocks, which harms fund performance. Complementing these findings, Di Giuli et al. (2022) examine mutual fund voting on environmental proposals, showing that climate beliefs influence institutional investor engagement strategies. Together, these studies highlight the role of climate beliefs in shaping investment decisions and corporate governance. Our research

³See Clayton et al. (2021) for a literature review.

⁴Similarly, exposures to climate hazard incidents, such as heat stress (Choi et al., 2020), flood (Bruine de Bruin et al., 2014; Niu et al., 2023), or hurricane (Holtermans et al., 2023), also influence beliefs regarding climate issues.

extends this discussion to real estate, providing unique insights into how climate risks influence asset allocation decisions. We also examine the channels through which climate risks shape asset allocation and investments in the resilience of their portfolios.

The remainder of the paper is structured as follows. Section 2 describes the different data sets. Section 3 presents the empirical methodology and discusses the identifying assumptions. Section 4 discusses the results. Section 5 concludes.

2. Data

We combine CRE transaction records, property-level climate risk assessments, detailed financial information, and localized extreme weather events to examine how CRE institutional investors adapt their portfolios to climate risks. Table 1 shows descriptive statistics.

2.1. Real estate transactions and property-level financial records

We utilize property transaction records from RCA between 2015 and 2021, which cover 807,290 transactions across 649,723 unique properties by 40,371 unique investors, 34,703 unique buyers, and 25,472 unique sellers. This period captures the recently growing awareness of climate risks in the CRE industry. RCA’s data provides rich information about each transaction, accurately identifying the actual buyers and sellers and detailing their characteristics. The dataset features the property transaction price, the age of the building, its net operating income, the capital intensity, and the size of the plot of land on which the building is located. It also includes property characteristics like the type of commercial building (office, industrial, residential, or retail), a quality index based on the building’s physical characteristics, and the building’s number of units.

Moreover, the data set contains detailed information on buyer and seller characteristics, such as the geographic scope of the buyer/seller (local, national, continental, and global), whether the buyer is foreign, the type of deal between buyer and seller, and whether the building owner resolved a situation of distress.

We complement the RCA dataset with detailed quarterly property financial records from NCREIF. The quarterly NCREIF data contains acquisition dates and transaction prices for

Variable	Mean	Std Dev	0.25	Median	0.75
<i>PANEL A: Transaction and Property Details: (N = 807,290)</i>					
Price (million \$)	51.17	102.04	10.55	26.67	57.80
Building age (year)	29.81	23.46	14.00	28.00	38.00
Recent renovation (year)	116.43	444.48	4.00	10.00	20.00
Floor area (1000 sq.ft)	250.77	476.87	70.51	153.69	297.69
Walkscore (0-100)	46.19	28.64	24.00	42.00	67.00
Transitscore (0-100)	42.66	30.96	25.00	37.00	61.00
Caprate (percentage)	0.06	0.01	0.05	0.05	0.06
Occupancy (percentage)	0.90	0.18	0.90	0.96	1.00
<i>PANEL B: Financial Information (N = 99,113) ($\times 1000$ \$):</i>					
Quarterly CapEx	365.68	2,702.23	0.00	8.10	141.63
CapEx on building improvements	241.20	2,824.03	0.00	0.00	31.11
Quarterly Opex	446.37	946.00	63.66	203.56	491.72
Insurance expenditures	14.88	33.49	2.27	6.91	16.35
Net operating income (NOI)	433.82	1,192.25	33.09	198.44	525.82
<i>PANAL C: Climate Risk Impact Score (N = 649,723) (0-100):</i>					
All categories	57.61	28.13	31.00	55.00	89.00
Floods	11.53	23.53	0.00	0.00	8.00
Heat stress	65.65	12.25	57.00	65.00	75.00
Hurricanes typhoons	39.26	40.42	0.00	50.00	78.00
Sea level rise	2.42	11.96	0.00	0.00	0.00
Water stress	39.43	21.80	29.00	33.00	49.00
Wildfires	18.55	26.83	0.00	0.00	28.00
Earthquakes	51.68	27.30	30.00	44.00	72.00
<i>PANEL D: Annualized Climate Risk Damage (N = 649,723) ($\times 1000$ \$):</i>					
All categories	54.71	220.42	3.82	11.25	37.64
Floods annualized	4.94	86.04	0.00	0.00	0.04
Heat stress	5.89	11.78	1.13	2.89	6.81
Hurricanes typhoons	12.60	60.52	0.00	0.05	2.73
Sea level rise	6.63	122.16	0.00	0.00	0.00
Water stress	1.79	4.15	0.21	0.69	1.76
Wildfires	0.77	6.36	0.00	0.00	0.08
Earthquakes	22.10	97.76	0.12	0.45	5.32

Table 1: **Descriptive Statistics**

approximately 30,000 US properties. In addition, the data features information about market value appraisals, net operating income, quarterly capital expenditures, insurance expenditures, operating expenses, and the property’s hedonic characteristics (property location, age, property type, leverage, ownership structure, owning fund, and type of fund). Our analysis uses expenditure categories most responsive to climate risk considerations, specifically capital expenditure on building improvements and insurance costs. These line items are particularly relevant as they directly reflect adaptive responses to climate challenges— increased building improvement allocations may signify investments in energy efficiency enhancements or resilience features. At the same time, elevated insurance expenditures potentially indicate

climate risk pricing by insurers. This targeted approach isolates financial decisions most likely influenced by climate risk management strategies.

2.2. CRE portfolio construction

We first track changes in their property holdings over time to understand how CRE investors adapt their portfolios to climate risks. A primary challenge is the absence of a comprehensive database directly recording the complete portfolio holdings of all CRE investors. To address this, we reconstruct investor portfolios using RCA data. Cvijanović et al. (2022) demonstrate the reliability and breadth of RCA data. RCA transaction histories allow researchers to accurately identify actual institutional buyers and sellers, enabling a credible reconstruction of investment portfolios and investment behavior. Specifically, RCA’s extensive coverage allows us to identify each investor’s initial holdings by observing properties that appear only as sales without prior purchase records, indicating these properties were owned at the beginning of the study period. Subsequently, we dynamically track portfolio changes through subsequent purchases and sales.

Formally, let $T_{i,(j_1,j_2),t}$ denote a transaction where property i is transferred from seller j_1 to buyer j_2 at time t . Define $J = \{j_k\}_{k=1}^N$ as the set of all investors (buyers or sellers). For each investor $j_k \in J$, we construct their portfolio $P_{j_k,t}$ as follows:

For any transaction $T_{i,(j_1,j_2),t}$ – meaning investor j_2 buys from investor j_1 at time t – we update the buyer’s portfolio by adding property i :

$$P_{j_2,t} = P_{j_2,t-1} \cup \{i\}$$

We identify each investor’s initial holdings by observing properties only appearing as sales (without prior purchase records). These form the initial portfolio $P_{j_k,0}$. Subsequently, we dynamically update portfolios at each transaction $T_{i,(j_1,j_2),t}$ by adding property i to the buyer’s portfolio and removing it from the seller’s portfolio:

$$P_{j_2,t} = P_{j_2,t-1} \cup \{i\}, \quad P_{j_1,t} = P_{j_1,t-1} \setminus \{i\}.$$

For instance, an investor j_k with initial holdings $P_{j_k,0} = \{i_1, i_2, i_3\}$ acquiring property i_4 at t_1 will have an updated portfolio $P_{j_k,t_1} = \{i_1, i_2, i_3, i_4\}$. If the same investor later sells property i_3 at t_2 , their portfolio adjusts to $P_{j_k,t_2} = \{i_1, i_2, i_4\}$.

While acknowledging certain limitations – such as incomplete ownership transparency or multi-layered investment structures (e.g., joint ventures or LLC ownership) – RCA remains the most robust dataset for capturing actual institutional investment patterns. RCA’s meticulous identification of counterparties enables accurate mapping of property transfers to institutional portfolios, providing strong assurance of the reconstructed portfolios’ validity as realistic proxies.

After constructing portfolios, we integrate transaction data with property-level financial records from NCREIF using unique building identifiers. We then aggregate expenditures related to climate risks, such as capital improvements and insurance, at the portfolio level. Formally, for portfolio $P_{j_k,t}$ at time t , the total expenditure is:

$$Ex_{j_k,t} = \sum_{i \in P_{j_k,t}} Ex_i,$$

where Ex_i denotes the expenditure for property i from NCREIF records.

2.3. Property-level climate risk assessment

To understand how investors adapt to climate risks, we examine the data environment shaping these decisions. Most institutional CRE investors rely on the same source for property-level climate risk assessments: Moody’s Risk Management Solutions (RMS), our primary data source for property-level climate risk assessment. RMS is a widely recognized market leader in climate hazard modeling (Moody’s Corporation, 2021). The widespread adoption of RMS means that investors operate with a shared understanding of risk exposure, shaping consistent expectations across the market and influencing portfolio strategies accordingly. RMS provides standardized exposure scores for key climate hazards, including floods, hurricanes & typhoons, sea level rise, water stress, and wildfires. The methodology combines location-specific hazard modeling based on publicly available climate model datasets (e.g.,

the North American CORDEX program NA-CORDEX or the World Climate Research Program [WCRP]’s Coupled Model Intercomparison Project Phase 5 [CMIP5] and Phase 6 [CMIP6]), together with detailed property characteristics, including construction type, age, and building quality.⁵ Specifically, the hazard model estimates each location’s severity of climate-related hazards. Then, this estimate is combined with the property characteristics to get an overall risk exposure evaluation (e.g., risk score, financial loss) of the property. Moody’s validates hazard and property-level loss modeling results by back-testing against historical disaster events and financial losses.

For each hazard, properties receive a risk score ranging from 0 (no risk) to 100 (highest risk) measuring the probability of getting hit by climate risk hazards, derived from over 25 risk indicators based on various public and private data sources.⁶ These risk scores are time-invariant under a given climate model.

Apart from providing detailed risk scores, the RMS dataset also includes the *Average Damage Rate* (ADR) – the expected annual damage expressed as a share of the property’s total value. This measure is central to our analysis, as it translates diverse physical climate hazards into a standard financial metric that allows for consistent, portfolio-level exposure comparisons. By normalizing risks across perils, geographies, and asset types, ADR enables us to evaluate how institutional investors perceive and respond to different types of climate threats in monetary terms. ADR is foundational in translating complex hazard models into expected financial impacts directly relevant to investment decisions (Moody’s Investors Service, 2023). Given RMS’s status as an industry standard in real estate climate risk modeling, ADR provides a consistent and credible basis for analyzing investor adaptation behavior in response to climate risk.

2.4. Climate Information Shock Events

A key challenge in studying investor adaptation is identifying when investors become more aware of climate risks and adjust their commercial real estate (CRE) portfolios. We cannot

⁵See Appendix Appendix A for details.

⁶Table A.8 in Appendix A shows the climate risk categories and severity levels.

directly observe changes in beliefs. Instead, we infer shifts in perception from changes in investor behavior following extreme local weather events. This approach builds on the idea that direct exposure to climate events makes risks more salient to decision-makers.

We identify climate events using data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). This county-level dataset reports natural hazards such as thunderstorms, hurricanes, floods, wildfires, tornadoes, and perils like flash floods and heavy rainfall (CEMHS, 2024). The data span from 1960 to the present and include the event date, location (county and state), and associated damages. These damages include property and crop losses, injuries, and fatalities. Following Di Giuli et al. (2022), we define a local heat shock as any event that reports injuries or deaths due to extreme heat. These events indicate severe disruption and serve as our baseline measure of investor exposure.

Other studies identify climate shocks using temperature anomalies based on historical weather records. However, Alekseev et al. (2022) show that using injuries and deaths offers a more robust identification strategy. We include robustness checks using alternative definitions to verify the consistency of our results.

Next, we determine which investors are exposed to each climate event. We use the Google Maps API to identify primary office locations for each investor. These include the main headquarters and up to five active branch offices. We base this identification on activity patterns such as user visits and online reviews. This method better reflects where investment decisions are likely made.⁷

3. Empirical Analysis

We examine whether investors exposed to localized environmental risks adjust their CRE portfolios. In particular, we test whether institutional investors change their property acquisition and disposition behavior after experiencing extreme heat events near their primary office locations. Our approach builds on evidence that localized exposure to climate shocks can influence decision-making. For example, Di Giuli et al. (2022) show that fund managers

⁷We avoid using registered legal addresses, which often correspond to administrative or legal entities rather than operational centers (Menz et al., 2013).

who experience abnormal heat are more likely to support climate-related proposals.

3.1. Empirical Setting

We focus on local extreme heat events as a channel through which investors may update their beliefs about climate risks. Long-term environmental changes unfold slowly and may not be directly observable. In contrast, extreme heat events provide immediate and salient experiences that can shape investor perceptions. We use these localized shocks at investors' operational headquarters as a source of quasi-exogenous variation in climate risk salience.

Our identification strategy relies on attribute substitution, where individuals respond to complex, abstract risks by focusing on more tangible cues such as local temperature anomalies (Kahneman et al., 2002). Investors may not fully grasp the long-term financial implications of climate change. However, a severe heatwave in their community can prompt them to reassess climate risks. Several studies document similar belief-updating behavior after exposure to local climate events (Bernstein et al., 2019; Baldauf et al., 2020b; Kang et al., 2024).

Localized heat events offer several advantages over broader natural disasters. They vary across space and time, allowing us to compare affected (treatment group) to unaffected (control group) portfolios. In contrast to large-scale disasters that elicit market-wide responses, these events enable more precise identification of behavioral change.

To evaluate investor behavior, we examine CRE portfolio transactions before and after heat shocks. We test whether investors increase acquisitions of lower-risk properties or shift capital expenditures in response to local climate events. Figure 1 displays the geographic distribution of portfolio headquarters and the occurrence of extreme heat events at the county level.

We use a difference-in-differences framework to estimate how climate belief shocks affect investment decisions. Because heat events occur at different times across different locations, traditional two-way fixed effects models may yield biased estimates (Baker et al., 2022; Roth et al., 2023). When treatment timing varies, already-treated units may enter the control group, distorting causal inference.

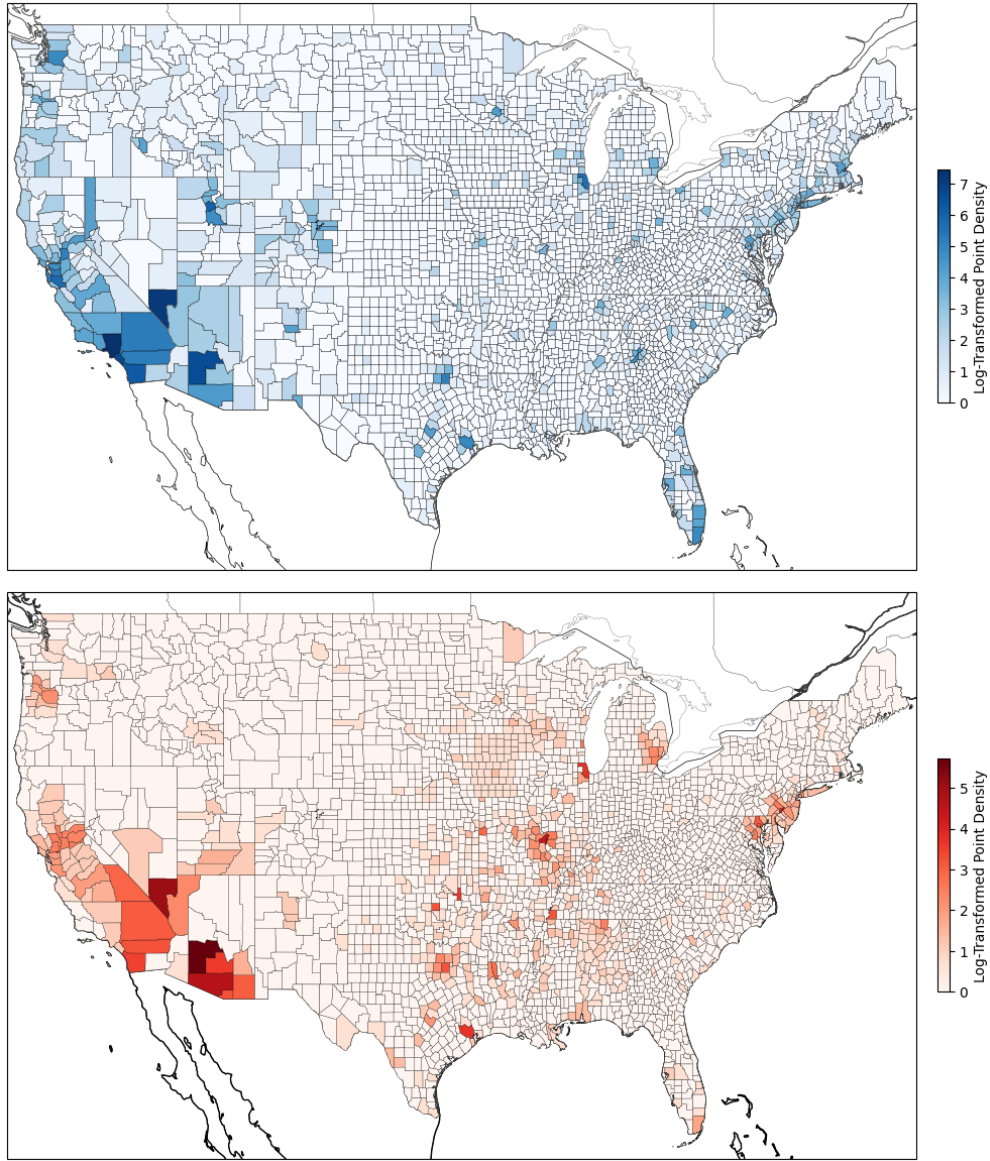


Figure 1: County-level heatmap of primary office locations of CRE portfolios (top) and number of severe extreme heat events (bottom)

To avoid these pitfalls, we adopt a stacked-regression approach (Cengiz et al., 2019; Di Giuli et al., 2022; Wing et al., 2024). This method creates independent event-study cohorts for each shock, ensuring clean comparisons between treated and never-treated portfolios. For a given shock g occurring in location A at time t_0 , we define a time window of $(t_0 - dt, t_0 + dt)$, where $dt = 4$ quarters. Within each window, we identify treated portfolios as those with offices in A and control portfolios as those never exposed to any heat shock over the sample period.

Figure 2 shows the number of treated and control transactions by cohort. The distribution supports our choice of 2015 as the starting year. Before 2015, the treatment group was small relative to the control group, consistent with industry reports suggesting that most CRE investors began to take climate risk seriously only in the mid-2010s. The rise in heat shock exposure aligns with a broader shift in climate risk awareness across the real estate sector.

3.2. Climate Risk and Portfolio Adaptation

We use a difference-in-differences model to analyze how climate belief shocks affect CRE portfolio decisions. The analysis uses a stacked dataset covering all shock cohorts from 2015 to 2021. We estimate the model separately for property acquisition (buying) and disposition (selling) transactions:

$$\begin{aligned} RiskScore_{i,j,g,t} = & \beta_0 + \beta_1(Treatment_{i,j,g,t} \times PostShock_{i,j,g,t}) \\ & + \beta_2 X_{i,t} + \sigma_j + \delta_g + \tau_t + \varepsilon_{i,j,g,t} \end{aligned} \quad (1)$$

The subscripts indicate property (i), portfolio (j), climate shock cohort (g), and time (t). The dependent variable, $RiskScore_{i,j,g,t}$, measures the climate risk probability associated with property i that portfolio j buys or sells at time t during shock cohort g .

Our primary explanatory variable is the interaction between two indicator variables: $Treatment_{i,j,g,t}$ and $PostShock_{i,j,g,t}$. The variable $Treatment_{i,j,g,t}$ equals one if portfolio j 's primary office experiences climate shock g . The variable $PostShock_{i,j,g,t}$ equals one for periods after the shock event. Thus, the interaction term captures whether investors exposed to shocks subsequently alter their property selection toward lower-risk assets compared to

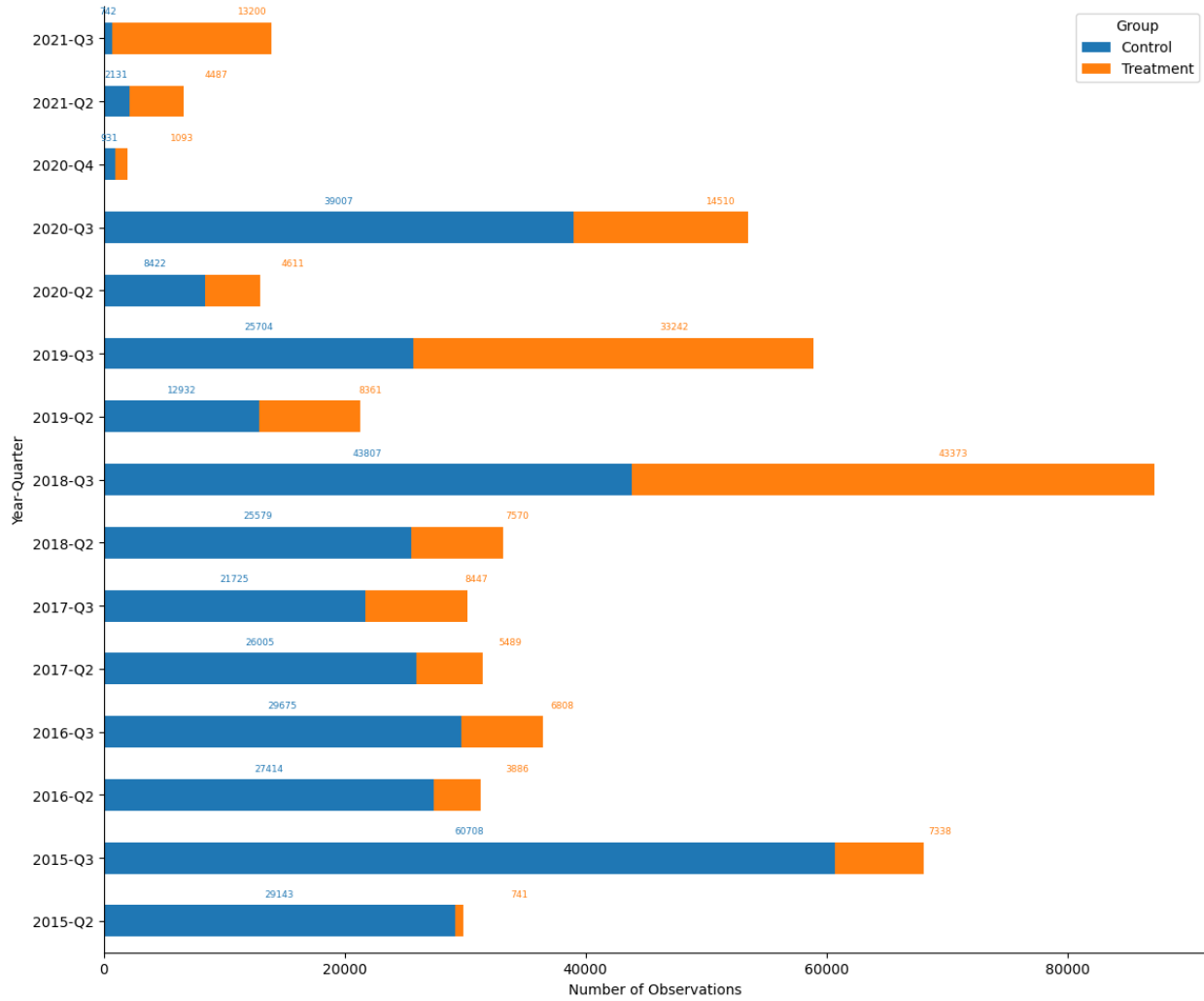


Figure 2: **Stacked-regression cohorts on property transactions** This figure reports the number of transactions by treated and control CRE portfolios in each cohort, defined by the year-quarter of the temperature shock. Each cohort includes transactions within four quarters before and after the shock.

unaffected investors.

We include portfolio fixed effects (σ_j) to control for portfolio-specific characteristics that do not vary over time. Shock cohort fixed effects (δ_g) control for cohort-specific differences in the severity or type of climate event. Time fixed effects (τ_t) account for broader temporal trends affecting all portfolios. The vector $X_{i,t}$ includes property-level control variables. Specifically, we control for net operating income, property size, type, year built, and renovation status. We cluster standard errors at the cohort-portfolio level. The coefficient of interest, β_1 , measures how affected investors change the climate risk profile of properties they buy or sell relative to unaffected investors.

In addition to analyzing property-level risk probabilities ($RiskScore_{i,j,g,t}$), we examine the expected financial impacts of these hazards using the Average Damage Rate (ADR). The ADR provides a standardized financial metric across different climate hazard types. While $RiskScore_{i,j,g,t}$ reflects the likelihood of physical climate events, ADR translates these probabilities into economic terms, allowing direct comparison across hazard types. By supplementing our probability-based results with ADR, we assess whether investor decisions reflect economically rational adjustments based on anticipated financial consequences of climate risks, beyond mere awareness of abstract probabilities. This dual approach demonstrates investors' sensitivity to both scientific climate projections and their tangible financial implications.

3.3. Climate Risk Adaptation and Expenditures: New Purchases

Next, we investigate whether investors exposed to climate shocks adapt their portfolios by strategically selecting properties based on their expenditure profiles. Specifically, we test whether treated portfolios systematically buy or sell properties associated with different levels of capital expenditures or insurance costs. We estimate the following model:

$$\begin{aligned} Expenditure_{i,j,g,t} = & \beta_0 + \beta_1(Treatment_{i,j,g,t} \times PostShock_{i,j,g,t}) \\ & + \beta_2 X_{i,t} + \sigma_j + \delta_g + \tau_t + \varepsilon_{i,j,g,t} \end{aligned} \quad (2)$$

Here, the dependent variable, $Expenditure_{i,j,g,t}$, captures expenditures related to prop-

erty i when portfolio j buys or sells it during period t of cohort g . We consider various expenditure types, including total capital expenditures, building improvements, and insurance costs. Higher building improvement expenses indicate proactive investments in resilience or energy efficiency upgrades. Similarly, higher insurance expenditures could reflect a strategic choice to protect against future climate risks.

The NCREIF dataset reports Expenditure measures quarterly. Therefore, we face a timing challenge when interpreting results. Observed expenditure changes could reflect two distinct scenarios. First, investors exposed to heat shocks might selectively target properties with favorable recent expenditure histories. Alternatively, these investors might actively increase spending immediately after acquisition, implementing climate resilience measures post-purchase.

To address this ambiguity, we separately analyze property expenditures for several quarters before and after each transaction. Pre-transaction analyses clarify whether investors prefer properties with specific expenditure histories. Post-transaction analyses reveal whether investors directly invest in resilience measures after acquiring new properties. By differentiating between these two scenarios, we gain deeper insight into how climate belief shocks influence property selection and subsequent investment behavior.

Another concern is distinguishing between proactive responses by investors to climate information and passive reactions triggered by actual climate damage to properties. Increased expenditures might represent proactive investments anticipating future climate events, or they might reflect necessary repairs from recent damage. Likewise, rising insurance expenses could indicate strategic decisions to increase coverage or simply higher premiums after properties suffer climate-related losses.

Our baseline specification in Equation 2 addresses proactive investor behavior by defining treatment based on climate shocks experienced at the investors' main office locations. To isolate and separately assess reactive spending due to actual building-level events, we alternatively define $Treatment_{i,j,g,t}$ and $PostShock_{i,j,g,t}$ based on shocks occurring at the properties themselves. This distinction enables us to identify investor reactions to climate belief shocks, separately from direct responses to physical property damage.

3.4. Climate Risk Adaptation and Expenditures: Existing Properties

The previous analyses (Equations 1 and 2) examine climate adaptation strategies based on property transactions. However, investors can also adapt to climate risks without trading properties. Instead, they may maintain existing holdings and invest directly in climate resilience measures. These investments could include upgrading HVAC systems, installing flood protection, enhancing insulation, or improving water conservation.

To assess whether portfolios invest in existing properties as an adaptation strategy, we estimate the following portfolio-level regression:

$$\begin{aligned} PortfolioExpenditure_{j,g,t} = & \beta_0 + \beta_1(Treatment_{j,g,t} \times PostShock_{j,g,t}) \\ & + \tau_t + \varepsilon_{j,g,t} \end{aligned} \quad (3)$$

The dependent variable, $PortfolioExpenditure_{j,g,t}$, aggregates expenditures at the portfolio level. It includes the same expenditure categories analyzed previously: total capital expenditures, building improvements, and insurance costs. This portfolio-level approach complements our earlier transaction-based analyses by capturing investor responses that do not involve altering portfolio composition.

For example, a portfolio exposed to a climate shock might undertake a significant renovation program to enhance climate resilience across multiple existing properties. Such investment decisions would significantly increase portfolio-level expenditures but would not be detected through transaction-based measures like $RiskScore_{i,j,g,t}$ or $Expenditure_{i,j,g,t}$. Adaptation through direct investments (“adaptation-in-place”) can be particularly relevant for portfolios with limited flexibility to buy or sell properties or locations where targeted resilience upgrades effectively mitigate climate risks.

Considering transaction behavior and investments in existing holdings, we offer a comprehensive picture of how institutional investors adjust their portfolios following climate belief shocks.

4. Results

4.1. Climate Risk and Portfolio Adaptation

Table 2 presents the estimation results of Equation 1. We find clear evidence that institutional investors adjust their climate risk preferences after experiencing climate information shocks. These adaptations occur consistently across multiple risk categories, including aggregate climate impact, flood, wildfire, and sea level rise risks.

Column (1) of Table 2 shows that investors choose properties with significantly lower average climate risk scores after exposure to abnormally high temperatures near investors' primary offices. Specifically, the estimated coefficient (β_1) is -2.389 (SE = 0.18). This reduction is economically meaningful, representing approximately 8.5% of the sample's standard deviation in climate risk scores. Conversely, Column (2) indicates investors also strategically divest higher-risk properties following these climate shocks, with an average risk score increase of 1.987 points (7.1% of standard deviation). Together, these results show investors pursue a deliberate rebalancing strategy, mitigating climate exposure by acquiring safer properties and disposing of riskier ones.

The adaptation response varies across specific hazard categories. Flood risk shows the largest magnitude effects, with a substantial decrease of 2.382 points in purchased properties' risk scores (8% of standard deviation, $p < 0.01$) and an increase of 2.974 points in sold properties (10% of standard deviation, $p < 0.01$). Wildfire risk follows a similar but less pronounced pattern, with purchased properties having a reduced risk score of 0.5396 (3.4% of standard deviation) and sold properties increasing by 0.4347 (2.7% of standard deviation). For sea level rise, investors primarily respond by selling higher-risk properties (+2.367 points, 13.4% of standard deviation, $p < 0.01$), with no significant adjustment in purchases.

	All Categories Risk Score		Floods Risk Score		Sea Level Rise Risk Score		Wildfires Risk Score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
<i>Variables</i>								
Treated $\times$ Post	-2.389***	1.987***	-2.382***	2.974***	-0.0365	2.367***	-0.540***	0.435***
	(0.1789)	(0.2475)	(0.2734)	(0.3921)	(0.1633)	(0.1015)	(0.1100)	(0.1449)
<i>Fixed-effects</i>								
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Portfolio FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>								
Observations	259,670	223,992	259,520	223,992	259,670	223,992	259,670	223,992
R ²	0.53338	0.53174	0.45587	0.49050	0.46367	0.49578	0.46955	0.55692

Table 2: **Climate Risk Adaptation in CRE Portfolio** This table shows the treatment effects of climate risk information shock on properties' risk scores (higher score = riskier) in buying and selling transactions. All specifications include cohort, portfolio, and year-quarter fixed effects. Standard errors are clustered at the portfolio-cohort level.

Analysis of expected financial impacts, measured using the Annualized Damage Rate (ADR), further supports these findings. Table 3 reports these results. Column (1) shows that investors purchase properties with significantly lower expected financial damage after climate shocks. The estimated coefficient is -0.0968 (SE = 0.0066), indicating that purchased properties have approximately 9.58% lower expected annualized damage rates. Conversely, Column (2) demonstrates investors sell properties with higher expected damage rates, with an estimated coefficient of +0.1007 (SE = 0.0128). These results are economically significant, as even modest percentage changes in ADR translate into considerable financial impacts given the high asset values typical in commercial real estate markets.

	All Categories Annualized Damage Rate (log)	
	(1)	(2)
	Buy	Sell
<i>Variables</i>		
Treated $\times$ Post	-0.0958*** (0.0066)	0.1007*** (0.0128)
<i>Fixed-effects</i>		
Cohort FE	Yes	Yes
Portfolio FE	Yes	Yes
Year-Quarter FE	Yes	Yes
<i>Fit statistics</i>		
Observations	264,397	228,220
R ²	0.52188	0.51588
Within R ²	0.00056	0.00144

Table 3: **Financial Impact of Climate Risk in CRE Portfolio** This table shows the treatment effects of climate risk information shock on properties' annualized damage rates (log) in buying and selling transactions. All specifications include cohort, portfolio, and year-quarter fixed effects. Standard errors are clustered at the portfolio-cohort level.

These results highlight how institutional CRE investors adjust their portfolios in response to increased awareness of climate risks. The observed rebalancing strategy reflects nuanced differences between acute hazards (floods and wildfires) and chronic risks (sea level rise). The pronounced reaction to flood risk aligns with its widespread and immediate implications for property values and insurability. The selective divestment pattern observed for sea level rise suggests that investors prioritize avoiding long-term value erosion in highly exposed coastal assets. Overall, our findings indicate that climate risk perceptions influence tangible investment behaviors, potentially accelerating market-wide repricing of climate risk in the commercial real estate sector.

4.2. Climate Risk Adaptation and Expenditures

Table 4 presents the estimated DiD effects showing how investors adjust their expenditure patterns following climate information shocks. Column (1) reports that capital expenditures on building improvements increase by 102.2% (SE=0.06) relative to the pre-shock period. This result implies a significant rise in investments aimed at enhancing structural resilience. Similarly, Column (2) shows total capital expenditure increasing by 39.56% (SE=0.05), indicating broader renovations beyond routine maintenance. Insurance expenditures also increase by 11.51% (SE=0.02), suggesting heightened investor attention to managing climate risks through insurance coverage. Column (4) shows total expenditures rising by 9.59% (SE=0.03), confirming an overall systematic increase in property-related spending following shocks.

	CapEx Building Improvement	CapEx Total	Insurance Expenditure	Total Expenditure
	(1)	(3)	(7)	(9)
<i>Variables</i>				
Treated $\times$ Post	1.022*** (0.0645)	0.396*** (0.0490)	0.115*** (0.0224)	0.096*** (0.0265)
<i>Fixed-effects</i>				
Cohort FE	Yes	Yes	Yes	Yes
Owner FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	18,735	26,739	43,184	44,090
R ²	0.85895	0.84257	0.78932	0.79181
Within R ²	0.06515	0.02659	0.01257	0.00061

Clustered standard-errors in (cohort_portfolio)

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

Table 4: Expenditure Changes in Property Acquisitions after Climate Shock This table reports difference-in-differences estimates of expenditure changes in properties acquired by treatment portfolios after climate risk information shocks. The dependent variables include building improvement CapEx, total CapEx, insurance expenditure, and total expenditure. All coefficients represent percentage changes. Standard errors clustered at the cohort-portfolio level.

The observed changes in expenditures could reflect two mechanisms: investor preference (selecting properties with recent investments) or investor intervention (actively enhancing properties after purchase). To distinguish between these, we analyze expenditures separately for k quarters before and after transactions, denoted $Expenditure_{i,j,g,t}^{(k)}$.

Table 5 examines capital expenditures on building improvements before and after transactions, excluding the transaction quarter. Two distinct patterns emerge. First, we find evidence of investor selection. Treated investors tend to purchase properties with recent expenditure increases, especially in the third (61.47%), fourth (49.35%), and second quarters (18.91%) before the acquisition. However, we observe substantially stronger effects after acquisition. Post-acquisition expenditures rise significantly across all four quarters, ranging from 117.5% (first quarter) to 199.7% (fourth quarter). These results indicate that while treated portfolios somewhat prefer recently improved properties, their main strategy involves actively investing in resilience upgrades after acquisition.

Model:	CapEx Building Improvement							
	4Q Before	3Q Before	2Q Before	1Q Before	1Q After	2Q After	3Q After	4Q After
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Variables</i>								
Treated $\times$ Post	0.494*** (0.0741)	0.615*** (0.0738)	0.189** (0.0888)	-0.1129 (0.1378)	1.175*** (0.0529)	1.406*** (0.1161)	1.325*** (0.0883)	1.997*** (0.1036)
<i>Fixed-effects</i>								
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Owner FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>								
Observations	28,850	27,690	29,061	29,809	28,114	25,272	27,050	26,496
R ²	0.85227	0.88167	0.90299	0.83416	0.88752	0.88773	0.91154	0.88079
Within R ²	0.07281	0.03517	0.02519	0.00743	0.08968	0.08595	0.12113	0.15463

Clustered standard-errors in (cohort-portfolio)

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

Table 5: **Pre- and Post-acquisition Building Improvement Expenditure** This table reports difference-in-differences estimates of quarterly building improvement CapEx up to 4 quarters before and after property acquisitions, excluding the transaction quarter. Columns (1)-(4) show selection effects (pre-acquisition), while columns (5)-(8) show investment effects (post-acquisition). Treatment portfolios are those experiencing climate risk information shocks. Standard errors clustered at the cohort-portfolio level.

An important consideration is whether these expenditure increases represent proactive investments or reactive responses to physical damage from climate hazards. To explore this distinction, we conduct a separate DiD analysis at the building level, evaluating expenditures directly after climate hazards impact properties.

Table 6 presents these building-level results. Surprisingly, building improvement expenditures decrease by 30%

	CapEx Building Improvement		Insurance Expenditure	
	1Q-4Q Total.	1Q After	1Q-4Q Total.	1Q After
	(1)	(2)	(3)	(4)
<i>Variables</i>				
Treated $\times$ Post	0.2120*** (0.0267)	-0.2994*** (0.0299)	-0.1860*** (0.0063)	-0.1421*** (0.0108)
<i>Fixed-effects</i>				
Cohort FE	Yes	Yes	Yes	Yes
Owner FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	143,950	232,958	310,424	337,107
R ²	0.99414	0.96561	0.96466	0.96313
Within R ²	0.10964	0.01755	0.00906	0.17432

Clustered standard-errors in (cohort_portfolio)

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

Table 6: **Expenditure Change: Effect of Building-level Hazards** This table reports difference-in-differences estimates for building improvement and insurance expenditures as the impact of climate hazards on *buildings*, instead of *investors* (as in Table 4 and 5). Column (1) and (3) shows the effect on aggregated expenditures of 4 quarters after impact; column (2) and (4) for expenditures during the first quarter after impact. Coefficients represent percentage changes; standard errors are clustered at the cohort-portfolio level.

4.3. Climate Risk Adaptation in Existing Portfolios

Table 7 shows the effect of climate information shocks on portfolio-level expenditures for existing properties. The results show significant expenditure increases for treated portfolios. Specifically, capital expenditures on building improvements rise by 9.18%, and insurance expenditures increase by 14.53%. These findings highlight a comprehensive adaptation strategy. Portfolios do not merely adjust their property transactions. Instead, they actively

invest in climate resilience upgrades within their existing property holdings. The observed spending increases likely reflect deliberate, strategic enhancements to mitigate future climate risks.

Model:	Portfolio Aggregated Expenditures		
	CapEx Building Improvement	CapEx Total	Insurance Expenditure
	(1)	(2)	(3)
<i>Variables</i>			
Treated $\times$ Post	0.0918*** (0.0199)	-0.0125 (0.0115)	0.1453*** (0.0076)
<i>Fixed-effects</i>			
Cohort FE	Yes	Yes	Yes
Owner FE	Yes	Yes	Yes
<i>Fit statistics</i>			
Observations	81,754	86,197	90,539
R ²	0.89083	0.93731	0.98031
Within R ²	0.00130	0.00237	0.03446
<i>Clustered standard-errors in (cohort_portfolio)</i>			
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>			

Table 7: **Portfolio-level Expenditure Changes After Climate Shock:** This table reports difference-in-differences estimates of expenditure changes for existing properties in treatment portfolios, excluding properties within ± 4 quarters of any transaction. The results show changes in building improvement CapEx, total CapEx, and insurance expenditure. All coefficients represent percentage changes. Standard errors clustered at the cohort-portfolio level.

5. Conclusion

This paper provides robust evidence on how institutional real estate investors adjust their portfolios in response to localized climate information shocks, such as extreme heat events. We document two primary adaptation strategies by exploiting these events as quasi-exogenous

shocks. First, investors actively rebalance their portfolios toward properties with lower climate risk exposure. Second, they significantly increase capital expenditures on building improvements and insurance coverage, exceeding typical market behavior. These findings demonstrate that institutional investors recognize and proactively integrate climate risks into their investment decisions. Our results offer critical insights for policymakers, regulators, and industry practitioners aiming to enhance climate resilience in commercial real estate, a sector pivotal for economic stability and societal well-being.

References

- Addoum, J. M., Eichholtz, P., Steiner, E., and Yönder, E. (2024). Climate change and commercial real estate: Evidence from hurricane sandy. *Real Estate Economics*, 52(3):687–713.
- Alekseev, G., Giglio, S., Maingi, Q., Selgrad, J., and Stroebel, J. (2022). A quantity-based approach to constructing climate risk hedge portfolios. *Available at SSRN 4283192*.
- Alok, S., Kumar, N., and Wermers, R. (2019). Do fund managers misestimate climatic disasters? *The Review of Financial Studies*, 32(4):1330–1367.
- Andonov, A., Eichholtz, P., and Kok, N. (2015). Intermediated investment management in private markets: Evidence from pension fund investments in real estate. *Journal of Financial Markets*, 22:73–103.
- Andonov, A., Kräussl, R., and Rauh, J. (2021). Institutional investors and infrastructure investing. *The Review of Financial Studies*, 34(8):3880–3934.
- Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2):370–395.
- Baldauf, M., Garlappi, L., and Yannelis, C. (2020a). Does Climate Change Affect Real Estate Prices? Only If You Believe In It. *The Review of Financial Studies*, 33(3):1256–1295.
- Baldauf, M., Garlappi, L., and Yannelis, C. (2020b). Does climate change affect real estate prices? only if you believe in it. *The Review of Financial Studies*, 33(3):1256–1295.
- Bernstein, A., Gustafson, M. T., and Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of financial economics*, 134(2):253–272.
- Bruine de Bruin, W., Wong-Parodi, G., and Morgan, M. G. (2014). Public perceptions of local flood risk and the role of climate change. *Environment Systems and Decisions*, 34:591–599.

- Carlo, A., Eichholtz, P., and Kok, N. (2021). Three decades of global institutional investment in real estate. *Available at SSRN 3802518*.
- CEMHS (2024). Spatial hazard events and losses database for the united states, version 22.0. Online Database.
- Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454.
- Chambers, D., Spaenjers, C., and Steiner, E. (2021). The rate of return on real estate: Long-run micro-level evidence. *The Review of Financial Studies*, 34(8):3572–3607.
- Choi, D., Gao, Z., and Jiang, W. (2019). Attention to global warming. *The Review of Financial Studies*, 32(5):2063–2093.
- Choi, D., Gao, Z., and Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, 33(3):1112–1145.
- Clayton, J., Devaney, S., Sayce, S., and van de Wetering, J. (2021). Climate risk and commercial property values: a review and analysis of the literature. unep fi available at—unepfi. org/publications/investment-publications/climate-risk-and-commercial-prop-erty-values. *Climate Risk & Commercial Property Values*, 3:3.
- Cvijanović, D., Milcheva, S., and Van de Minne, A. (2022). Preferences of institutional investors in commercial real estate. *The Journal of Real Estate Finance and Economics*, 65(2):321–359.
- Di Giuli, A., Garel, A., Michaely, R., and Romec, A. (2022). Climate change and mutual fund voting on environmental proposals. *European Corporate Governance Institute–Finance Working Paper*, (815).
- Giglio, S., Maggiori, M., Rao, K., Stroebel, J., and Weber, A. (2021). Climate change and long-run discount rates: Evidence from real estate. *The Review of Financial Studies*, 34(8):3527–3571.

- Hino, M. and Burke, M. (2021). The effect of information about climate risk on property values. *Proceedings of the National Academy of Sciences*, 118(17).
- Holtermans, R., Niu, D., and Zheng, S. (2023). Quantifying the impacts of climate shocks in commercial real estate markets. *Journal of Regional Science*.
- Hsiang, S., Kopp, R. E., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D., Muir-Wood, R., and Wilson, P. (2017). Estimating economic damage from climate change in the united states. *Science*, 356(6345):1362–1369.
- Ilhan, E., Krueger, P., Sautner, Z., and Starks, L. T. (2023). Climate risk disclosure and institutional investors. *The Review of Financial Studies*, 36(7):2617–2650.
- IPCC (2022). The physical science basis. contribution of working group i to the sixth assessment report of the intergovernmental panel on climate change.
- Kahneman, D., Frederick, S., et al. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. *Heuristics and biases: The psychology of intuitive judgment*, 49(49-81):74.
- Kang, Y., Niu, D., Song, J., and Sun, W. (2024). Feeling the heat: Extreme temperatures and housing prices in china. *Journal of Economic Surveys*, 38(5):1956–1982.
- Krueger, P., Sautner, Z., and Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3):1067–1111.
- Menz, M., Kunisch, S., and Collis, D. J. (2013). What do we know about corporate headquarters? a review, integration, and research agenda. *A Review, Integration, and Research Agenda (August 19, 2013). Harvard Business School Strategy Unit Working Paper*, (14-016).
- Moody’s Corporation (2021). Moody’s to Acquire RMS, Leader in Climate Natural Disaster Risk. Online. Press Release, retrieved from <https://ir.moody.com/press-releases/news-details/2021/>

Moody's-to-Acquire-RMS-Leader-in-Climate--Natural-Disaster-Risk/default.aspx.

Moody's Investors Service (2023). Climate-related risks and opportunities assessment: Framework and methodology. Online. Retrieved from https://www.moody's.com/researchdocumentcontentpage.aspx?docid=PBC_1352372.

Munich Re (2025). Climate change is showing its claws: The world is getting hotter, resulting in severe hurricanes, thunderstorms and floods. Munich Re Group Report.

Murfin, J. and Spiegel, M. (2020). Is the risk of sea level rise capitalized in residential real estate? *The Review of Financial Studies*, 33(3):1217–1255.

National Association of Real Estate Investment Trusts (NAREIT) (2022). The role of real estate in pension funds. Accessed: [Insert Date].

Niu, D., Eichholtz, P., and Kok, N. (2023). Asymmetric information provision and flood risk salience. *MIT Center for Real Estate Research Paper*, (23/20).

NOAA (2024). Billion-dollar weather and climate disasters.

Ortega, F. and Taşpınar, S. (2018). Rising sea levels and sinking property values: Hurricane sandy and new york's housing market. *Journal of Urban Economics*, 106:81–100.

Roth, J., Sant'Anna, P. H., Bilinski, A., and Poe, J. (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2):2218–2244.

Smith, A. B. and Matthews, J. L. (2015). Quantifying uncertainty and variable sensitivity within the us billion-dollar weather and climate disaster cost estimates. *Natural Hazards*, 77:1829–1851.

U.S. Securities and Exchange Commission (2024). Sec adopts rules to enhance and standardize climate-related disclosures for investors. <https://www.sec.gov/newsroom/press-releases/2024-31>. Accessed: 2025-02-04.

Wing, C., Freedman, S. M., and Hollingsworth, A. (2024). Stacked difference-in-differences. Technical report, National Bureau of Economic Research.

Appendix

Appendix A. Moody's Climate Data

Appendix A.1. Risk modeling methodology

Our research uses data from RMS's hazard risk scoring systems to assess climate-related perils.⁸ These systems utilize outputs from leading publicly available climate models, such as the North American CORDEX program (NA-CORDEX) and the World Climate Research Program's Coupled Model Intercomparison Project Phases 5 and 6 (CMIP5 and CMIP6). For specific perils, RMS generates scores across various locations using relative rankings. RMS assigns each asset a score for each peril within a portfolio, which they then aggregate to provide an overall risk assessment. While these systems offer valuable insights, they have notable limitations. Climate model outputs alone are insufficient for creating high-resolution, empirically validated, multivariate hazard distributions. Factors such as parameterized sub-grid scale processes inherent to all climate models, computational constraints, and model inaccuracies necessitate additional tools to ensure accurate and well-validated estimates of the full multivariate hazard distribution, including extreme events like hurricanes and wildfires. Moreover, hazard-based systems primarily provide comparative analyses of climate change effects across locations but fall short in quantifying damages and costs essential for assessing credit, investment, and insurance risks. They also struggle to facilitate risk comparisons across different perils or to aggregate risk metrics comprehensively. Consequently, evaluating the financial impact and quantifying physical climate risk are critical next steps for effective climate change risk assessment, mitigation, adaptation, management, and disclosure. We utilize advanced solutions like Moody's Climate on Demand Pro to address these challenges. This platform provides detailed hazard and financial impact metrics, enabling us to assess climate risk across various perils and asset types. Offering expected damage and impact scores on a scale from 0 to 100 allows for quick comparisons between assets and portfolios, categorizing locations into different risk zones. The platform delivers expected damage and impact scores for five lines of business: commercial, industrial, single-family dwelling,

⁸See www.rms.com. for more details.

multi-family dwelling, and unknown. These lines of business are mapped from user inputs for the asset’s activity, using the activity types already established in Climate on Demand. RMS then uses the subset of non-zero risk metrics to form a benchmark against which the risk metric computed for the location of interest can be compared. For example, if the risk metric computed for a location lies at the 75th percentile of the benchmark set of results, then an impact score of 75 is assigned to that location. The impact score for a portfolio is evaluated in a similar manner using the results from a representative sample of corporations and their locations drawn from Moody’s proprietary corporate facility database to define the peril benchmarks. In contrast, RMS employs a comprehensive approach by simulating extensive catalogs of potential events, representing up to a million simulated years, depending on the frequency-severity distribution of the peril. They characterize each event by its location or path, intensity, evolution, and probability of occurrence. These simulations are grounded in scientific principles, historical data, and climate and numerical weather models. For instance, the hurricane model calculates the strength of the winds around a storm, the amount of rainfall and flooding, and the storm surge impact, considering the region’s terrain and built environment and its proximity to the coast. RMS assesses the degree to which structures and their contents are likely damaged by the hazard severity experienced in an event that affects a location. Different assets (residential buildings, commercial properties, large industrial facilities) experience different damage from the same hazard. To gauge these differences, vulnerability curves reflect variations in building codes, building characteristics, construction type, age, and building quality across regions and between countries. Similarly, business interruption losses depend on the type of occupancy of the building and the performance of critical lifelines (e.g., electricity and water supply) servicing the building or the broader area. RMS also translates physical damage into monetary terms, such as the costs of repair and reconstruction, damage to contents and equipment, alternative living expenses, and business interruption and loss of income. RMS’s damage modeling includes the effect of inflation in repair and materials costs due to the surge in demand following major catastrophes, the impact of rebuilding older properties to higher modern-day building standards and codes, and the consequences of infrastructure damage such as roads, bridges, and power networks on business interruption. Moreover, the insured loss component can be estimated

utilizing Moody’s RMS advanced insurance modeling engine. However, the damages and impact scores expressed in Climate on Demand Pro reflect the total damage, excluding consideration of insurance policy terms and coverages. Moody’s RMS solutions have historically focused on key peril regions for acute perils (e.g., hurricanes, floods, wildfires) in developed markets and economies. Since 2021, Moody’s RMS has released climate change-conditioned versions of natural catastrophe models across North America, Europe, and Japan, enabling various stakeholders to project risk profiles under different climate change scenarios. By integrating such advanced analytics, we can better quantify and manage the financial impacts of climate risks, leading to more informed decision-making and enhanced resilience against future climate-related challenges.

Risk Type	No Risk	Low Risk	Medium Risk	High Risk	Red Flag
Floods	0: No risk	0-27: Not susceptible, future rainfall increase likely	28-49: Some susceptibility	50-74: Susceptible to floods	≥75: High frequency/severe flooding
Heat Stress	0: No risk	0-32: Minor warming	33-65: Average warming	66-94: Above average	≥95: Severe changes
Hurricanes	0-24: No history	25-61: Minimal activity	62-87: Frequent activity	88-95: Regular path	≥96: Regular severe storms
Sea Level	0-4: Not coastal	5-45: Coastal, low risk	46-59: Possible flooding	60-69: Some flooding	≥70: High flood risk
Water Stress	0: No risk	0-32: Minor changes	33-65: Increasing competition	66-94: High stress	≥95: Extreme stress
Wildfires	0: Not burnable	1-46: Low potential	47-73: Moderate risk	74-96: High potential	≥97: Very high risk
<i>Note:</i> Risk scores range from 0 (no risk) to 100 (highest risk). Source: Moody’s.					

Table A.8: Climate Risk Categories and Severity Levels

Appendix A.1.1. Validation

Moody’s RMS employs a rigorous, multi-layered validation process to ensure the reliability of its models. Throughout model development, both internal and external experts independently assess methodologies and outputs. The validation framework operates at two key

levels: (1) Component validation, which systematically tests individual modules—including stochastic event generation, hazard modeling, vulnerability assessment, and financial loss estimation—to confirm their accuracy and robustness; and (2) Overall model validation, which evaluates the combined outputs of these modules to ensure they produce realistic and reliable damage estimates.

For the validation of stochastic event modules across different peril models, RMS utilizes historically recognized datasets widely accepted in the scientific community, such as the HURDAT2 hurricane database. In cases where publicly available historical data is incomplete or insufficient, RMS collaborates with local and global scientific institutions to construct proprietary historical catalogs, sometimes supplementing existing records or developing entirely new datasets in data-sparse regions. As more historical records become available—whether through new catastrophic events, advancements in scientific research (e.g., sediment core analysis for long-term earthquake activity), or the release of previously restricted datasets—RMS continuously integrates these updates to refine and improve its models.