Climate Change and Commercial Property Markets

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Abstract:

The economic effect of climate hazard events varies by time and by location. This paper investigates how climate shocks to local property markets transmit to capital markets. We also provide evidence of how forward-looking climate risk is capitalized into the public valuations of those property markets. We first quantify the exposure of real estate portfolios to locations that recently experienced climate events (*Event Exposure*). Using an event study framework, we find that, in the post-event period, a one-standard-deviation increase in ex-ante *Event Exposure* is associated with a 0.2 to 1.4 percentage points decrease in quarterly stock returns. Cross-sectional analyses reveal that differences in return effects can be explained by variation in the extent to which local media focus on climate change. Similarly, we find that forward-looking climate risk assessment negatively affects firm valuations only in markets with high media attention. Consistent with these findings, we provide evidence that climate events (shocks) induce retail investors (noise traders) to decrease their stock holdings and that blockholders tend to take the opposite side in these transactions. We also show that conditioning on consumer sentiment helps to explain cross-sectional variation in the response of stock returns to climate events.

Keywords: Climate risk, Commercial real estate, Media attention, Retail investors, Sentiment channel

JEL classification: G11, D80, R10

1 Introduction & Background

The frequency and severity of climate events continue to increase at an alarming rate (Figure 1). In the 1980's, the mean number of natural disasters exceeding $1 billion of inflation-adjusted damages was 3 per year. From 2011 to 2021, the U.S. suffered an average of over 14 natural hazards per year that exceeded $1 billion in inflation-adjusted damages. Similarly, in no single year in the 1980's did damages exceed $200 billion. However, from 2012 to 2022 this threshold was exceeded every year.

In response to these climate events, a fast-growing climate finance literature identifies climate risk as a material force shaping asset valuations and returns. For example, the empirical literature demonstrates that the prices of equities (Alok et al., 2020), bonds (Flammer, 2021), residential mortgages (Ouazad and Kahn, 2022), municipal bonds (Painter 2020), and derivatives contracts (Schlenker and Taylor, 2021) respond to extreme weather events (physical risk). However, much less is known about the extent to which expectations about future climate risk affect asset values and returns, or how these effects vary with the physical location of the firm's or portfolio's underlying assets. In particular, the effect of actual climate events, and estimates of future climate risk, on the stock prices of listed firms should depend critically on the location of the firm's assets; that is, on its "geographic footprint."

Our focus is on the commercial real estate (CRE) assets owned by listed U.S. equity Real Estate Investment Trusts (REITs), which own approximately $3 trillion in CRE assets and had an equity market capitalization of $1.3 trillion in September of 2023. REITs are a useful lens through which to study the impact of both actual climate events and expectations of future climate risks on stock price valuations and returns for several reasons. First, to remain a "qualified" REIT and enjoy the (unique) ability to deduct dividends paid from corporate taxable income, equity REITs must invest primarily in CRE (Goetzmann et al., 2021; Ouazad and Kahn, 2022).[1] These diversified portfolios of capital-intensive, fixed-location CRE assets are relatively easier for market participants to locate and value than the tangible (e.g., plant

[1] At least 75% of a REIT's assets must be invested in real estate, cash, or government securities and at least 75% of gross income must come from real estate assets. In exchange for conforming to these and other restrictions, REIT dividends are tax-deductible, which allows most REITs to avoid the double-taxation of the income produced by their assets.

and equipment) and intangible assets (e.g., intellectual property) owned by many conventional firms.

Second, the accurate measurement of the magnitude of a firm's economic interests in a location affected by a climate event is crucial. Several recent papers have recognized the limitation of using the location of a firm's headquarters as a proxy for the geographic distribution of its economic interests and activities (e.g., Garcia and Norli, 2012; Bernile et al., 2015). These papers instead employ a text-based approach to infer a firm's geographic footprint by tabulating the number of times a U.S. state's name appears in the firm's 10-K. However, state citation measures may be inadequate proxies for cross-sectional variation in the degree of asset allocation and information dispersion.[2] In sharp contrast, the dollar value of an equity REIT's time-varying portfolio allocations to each property type and to each U.S. county are available in the S&P Global Real Estate Properties database. Further, as professionally managed listed firms, REITs are also subject to intense scrutiny and traded by a variety of investor types (Gupta and Van Nieuwerburgh, 2021; Sagi, 2021). Although the lack of high-frequency, transaction-based, price movements in private CRE markets prevents the detection of portfolio valuation changes in "real time," we argue that the effects of actual and expected future climate events we observe in the highly liquid REIT market are indicative of the effects occurring in the much larger private CRE market.[3]

We begin by providing a conceptual framework for understanding the potential effects of actual climate events, as well as assessments of future climate risk/events, on the stock prices and returns of listed REITs. The empirical analysis that follows is designed to address three primary questions. First, to what extent do actual climate events affect REIT returns, controlling carefully for the exposure of each REIT's CRE portfolio to the MSA in which the

[2] State counts (citations) implicitly assume states with different sizes and economic relevance are identical. The use of states as the unit of measure for geography also masks the potential variation across metropolitan areas within a state in economic activity, labor markets, and information availability. Moreover, the number of appearances of a particular state's name in a firm's 10-K report may not directly identify the state's economic significance to the firm. For example, consider a situation in which two states are mentioned the same number of times in a firm's 10-K report and are therefore given equal weights as locations of the firm's economic activity. However, if the firm plans to close operations in the first state but expand operations in the second, a 10-K based measure of this firm's economic activity would clearly overweight the economic importance of the first state relative to the second.

[3] Nareit estimates that the value of investible CRE not held by equity REITs to be $14 to $18 trillion (www/reit.com/data-research).

event occurred? Climate events may cause a temporary shift in perceived risk that affects stock valuations, and therefore returns. However, sustained and accretive changes in experience or perceptions about climate change and its attendant risk could become embedded in risk premiums after a climate risk event and therefore affect firm valuations and returns beyond the period during which the climate shock occurred (i.e., they become a known and priced risk factor).[4] Second, are the return effects we document amplified by the amount of (geographically weighed) media attention given to climate risk topics or by the intensity of climate related Google searchers in the MSAs in which the REIT's properties are located? Third, to what extent are REIT stock price valuations affected by their geographically-weighted exposure to future climate risks and to what extent do these valuation effects vary with local media attention or the intensity of climate related Google searchers.

Potential extreme weather events are increasingly included in financial decision-making models (Bolton and Kacperczyk, 2021; Hsu et al., 2022; Krueger et al., 2020; Nordhaus 2017; Pástor et al., 2022). However, future-oriented estimates of climate risk represent a significant challenge to model development given scientific complexity, the pace of change of climate science, multiple types of uncertainty, and the conditional nature of predicting future events and mean average global temperatures (Allen et al., 2009; Barnett et al 2020). These predictions are confounded by the possibility that historical data may not offer much predictive capability as well as the non-linear, non-stationary, and spatially varied nature of future physical risk (Bartram et al., 2022). Wide variation in human beliefs and biases further confound the predictive capabilities of forward-looking models (Baldauf et al., 2020; Bakkensen et al., 2022). It is the role and path of information in financial markets, the dynamism and uncertainty embedded in forward-looking climate risk models, and the challenge of converting science into future estimates of risk (Fiedler et al., 2021) that motivate our analysis of future climate risks.

[4] We focus here on physical risk. Physical risk is both acute and chronic. Acute physical risks refer to increased frequency and severity of extreme weather events, such as cyclones, hurricanes, or floods. Chronic physical risks refer to longer-term shifts in climate patterns (e.g., sustained higher temperatures) that may cause sea-level rise or chronic heat waves. For the remainder of the document, we use the terms physical risk and climate risk interchangeably.

The existing climate risk literature has also uncovered differential patterns of risk pricing among investor types with different access to climate information and different capacities to incorporate complex scientific information into valuation models. For example, Bauer et al. (2021) show that retail investors in equity markets prefer more sustainable investments. Choi et al. (2020) demonstrate that retail investors tend to sell carbon-intensive firms when the temperatures in their local areas are abnormally high, while institutional investors do not. We therefore augment our empirical analysis by examining differences in the trading behavior of retail investors and large blockholders after actual climate events. Finally, we examine the extent to which cross-sectional variation in REITs' sensitivity to consumer sentiment affects stock price reactions to climate events.

Our analyses produce several important findings. First, consistent with prior literature on non-real estate firms, we observe that equity REIT returns decline for at least three quarters following a physical risk event to which their property portfolio is exposed. Our event study shows statistically and economically significant declines in value following a salient climate event.

Second, we find that variation in local media attention to climate change and variation in the intensity of Google searches for information on climate change in the MSAs in which a REIT's property portfolio is concentrated significantly affect how firm valuations and returns respond to both observed climate events and forward-looking risk forecasts. More specifically, the interaction of strong media coverage (or the intensity of Google searches) and either observed physical hazards or forward physical risk forecasts are statistically and economically significant predictors of variation in REIT returns and valuations, respectively. This supports the findings of Barnett et al. (2020) that the role of climate science is to explain the transmission mechanisms through which greenhouse gasses influence or alter the environment while the role of valuation models is to explain the economic damage associated with climate change.

Third, we observe significant differences in the trading patterns of retail investors and institutional blockholders—suggesting information asymmetry between investor types and/or the (in)ability to integrate geo-physical science into financial valuation models. This is consistent with Farrell et al., (2022) and interview-based evidence from Urban Land Institute (2022). We also find evidence that, during a physical risk event, retail investors tend to sell REIT shares; blockholders do not. This may be indicative of asymmetrical long-term information or beliefs about climate risk. It also indicates that perceptual salience can have different manifestations relative to climate change. This is consistent with the findings of Alok et al. (2019) who observe that fund managers in areas experiencing climate events tend to underweight the securities of firms in proximity to a major climate event to a far greater extent than managers who are less proximate. Here, a salience bias is evident between investor types—suggesting that institutional investors perceive climate information and physical risk differently than do retail investors.

Fourth, we find that consumer sentiment indicators impact the degree to which stock prices change subsequent to a climate hazard. REITs whose returns are more sensitive to changes in consumer sentiment exhibit statistically significant greater stock price declines when their portfolios are impacted by a climate hazard. This further supports differential investor-type trading patterns.

Our empirical analysis is among the first to present empirical evidence on the extent to which forward-looking climate risk is capitalized into stock prices and thereby provides new information about climate change uncertainty to investors and policy makers working to understand the implications of physical risk across markets (Barnett et al., 2020). This is timely and important given that the United States Securities and Exchange Commission's (SEC) proposed rule, S7-10-22, would require disclosure of material climate risk by all publicly traded firms. Similarly, the European Union, Japan, Australia, India and several other countries are already mandating climate risk disclosures for larger firms. Thus, developing a deeper understanding of the impact of prior and anticipated climate events and risk on asset returns and valuations is increasingly relevant.

Below, we first provide a conceptual framework for understanding the potential effects of actual climate events, as well as assessments of future climate risk/events, on the stock prices and returns of listed real estate companies. Described in Section 2, and used in all analyses, are REIT data from the CRSP-Ziman database and from the S&P Global Real Estate database, which details REIT property holdings by MSA. In Section 3, we describe the Spatial Hazards Events and Losses Database for the United States (SHELDUS) and discuss its summary statistics. Then we describe our SHELDUS event study regressions. In Section 4, we perform a cross-sectional analysis of the reaction of REIT returns to climate events and detail our use of data from Yale University on climate change related media attention. In Section 5, we describe our forward-looking climate risk data from RisQ and discuss its characteristics and summary statistics. We also report and discuss the results of Tobin's Q valuation-oriented regressions. In section 6, we present our REIT ownership and investor data followed by a discussion of the results of our ownership regressions. Finally, in Section 7, we discuss the University of Michigan Consumer Sentiment Index we employ to examine the impact of consumer sentiment on stock price reactions to climate events.

2 Conceptual Framework

We motivate our asset-level analysis of the effects of actual and expected climate events by first examining the channels through which climate events can affect the income-producing ability, and therefore the value, of the CRE assets from which REITs derive their value. Formally, the valuation by the marginal investor in a REIT's stock of the unlevered annual cash inflows and outflows associated with an existing CRE property owned by the REIT can be represented by the following expression:

$$PropValue_{i,r,0} = \sum_{t=1}^{y} \frac{(Rent_t - OE_t - CapX_t)}{(1+k)^y} + \frac{PropValue_{i,r,y}\,(1-SC_y)}{(1+k)^y}$$

$PropValue_{i,r,0}$ is the present value of the expected pretax cash flows on portfolio property i owned by REIT r at time "zero" that is expected to be held in portfolio by the REIT for y years. $Rent_t$ is the expected gross rental income in year t of the expected y-year holding period, OE_t are expected property level operating expenses in year t, and $CapX_t$ represents expected capital expenditures. Unlike operating expenses, capital expenditures are defined as non-recurring cash outflows that increase the market value of the property, such as roof replacements and replacements of heating and air conditioning systems. $PropValue_{i,r,y}$ represents the expected property value at the end of year y, at which time proportional selling costs equal to SC_y will be incurred. Finally, k is the unlevered, pretax discount rate the marginal investor in the REIT's stock applies to the expected income stream to determine the unlevered value of the i^{th} property owned by REIT r.

Actual climate events (hurricanes, floods, wildfires, etc.) can negatively affect rental income by rendering properties inaccessible or inoperable and by inducing a negative rental demand shock to the market. For example, hurricanes may cause migrations from higher-risk areas to safer regions, thereby leading to vacancies and/or reduced rental rates. However, the removal from the market of some damaged space due to a climate event may, at least in the short run, increase the rental rates of competing properties that did not sustain damage. A climate event may also increase the cost of hazard insurance, for both affected and unaffected properties, as well as other operating costs, especially in the short run, if the cost of materials and labor increases. Owners may also expect/fear higher local property taxes to support increased local governmental expenditures and to compensate for the potential reduction in the assessed values of damaged or destroyed properties.

Climate events may also increase actual and expected future capital expenditures. Even if local building codes do not change for existing properties, more owners may feel the need to increase building resilience by elevating mechanical equipment, installing flood doors, or related measures. Owners may also anticipate that costly regulations will be promulgated by federal, state, or local governments in the wake of climate events that require increased future compliance expenditures. Globally, numerous regional and national policies related to physical building risk and resilience have been codified or proposed.[5] Any of these potentially long-lived impacts of climate events/shocks can negatively impact property values.

In addition to direct reductions in annual net operating income, property valuations may be negatively affected if the marginal investor becomes more uncertain about the effects of exposure to climate events on expected future cash flows. This increased uncertainty could raise required risk premiums and therefore the discount rate (k) applied to the future cash flows of the portfolio property. Some evidence suggests that investors price downside risk more than upside risk (Easley and Yang, 2015; Daniel et al., 2020; Olijslagers and Van

[5] Several new policies, both announced and pending at the time of this writing, happen(ed) in 2023. In the European Union, the Corporate Sustainability Reporting Directive (CSRD) was announced with implementation set for the 2024 fiscal year. The International Sustainability Standards Board (ISSB) announced its final guidelines in June 2023. The United States Securities and Exchange Commission (SEC) expects to finalize its proposed climate rules in 2023. ISSB standards require, among other items related to physical risk, that firms disclose quantitative and qualitative information about: "costs arising from physical damage to assets from climate events; and expenses associated with climate adaptation or mitigation (16.d)." Notably, the International Organization of Securities Commissions (IOSCO), which includes the SEC and CFTC endorsed the ISSB standards.

Wijnbergen, 2019); in any case, actual climate events and the increased media coverage given to climate events/change, can increase cash flow uncertainty and CRE discount rates.

Aggregating across the individual properties owned by a REIT, the current value of REIT *r*'s CRE portfolio can be depicted as

$$PortValue_{r,0} = \sum_{i=1}^{n}(PropValue_{i,0}\ x\ Weight_{i.0})$$

where $PortValue_{r,0}$ is the current value placed on REIT *r*'s property portfolio by the REIT's marginal investor and $Weight_{i,0}$ is the percentage of the REIT's total assets invested in the i^{th} property. In addition to the severity of the climate event, its negative effect on the perceived value of a particular REIT's property portfolio should depend critically on the percentage of its portfolio located in local markets affected, or potentially affected, by a climate event. However, REIT investors may not know at the time of a climate event the extent to which a particular REIT's portfolio is exposed to the event. This is why, for example, all REITs may decline in value in response to a localized climate event that raises uncertainty/discount rates, even though many REITs were not directly affected.

The reactions of institutional and retail investors to climate events/risk also may differ. For example, better-informed institutional investors may discount only the stock prices of the REITs most affected by a climate event. However, arguably less well-informed retail investors ("noise traders") may discount the stock prices of all REITs regardless of the climate event's impact on a specific REIT's holdings. Similarly, REITs whose marginal investor is more sensitive to changes in market-wide consumer sentiment may exhibit larger stock price declines when some of their portfolio assets are impacted by a climate hazard. Overall, the impact of a climate event on a REIT's marginal investor can affect assessments of operating cash flows, risk-adjusted discount rates, and property valuations.

In sum, there are numerous channels through which a climate event/hazard can reduce the current and future valuations of REIT-owned properties and therefore REIT stock prices and returns. The risk of future climate events, which we also examine, should impact stock valuations and returns through these same channels; that is, lower expected future rental income, higher operating and capital expenditures, and higher discount rates.

2 REIT Descriptive Data

Data on publicly-traded U.S. equity REITs are obtained from the CRSP-Ziman database. Observations must contain the following information to be included in our sample: REIT PERMNO, returns, stock price, property (sub-property) type focus, and stock market capitalization. Our initial sample contained 417 unique equity REITs traded on the NYSE, Amex, and Nasdaq exchanges from 1996 to 2019. Quarterly accounting data for each REIT are obtained from Compustat as well as the S&P Global Real Estate database. Table 1 shows descriptive statistics for the REIT data.

We use two REIT-based dependent variables in our regressions. *RetRf* measures the chain-linked return of firm *i* in quarter *t+1* in excess of the one-month Treasury bill rate and has a mean value of 2.83%. Tobin's Q, a widely used measure of firm value (Capozza and Seguin, 2003; Hartzell et al., 2014) is defined as the market value of a company divided by the replacement cost of its assets. In practice, the market value of a firm's equity is available for publicly-traded REITs; however, the book value of debt is generally used as a proxy for its market value. In addition, the (depreciated) book value of all assets is used to proxy their replacement cost. In our sample, Tobin's Q has a mean of 1.45.

A firm's time-varying portfolio allocations to each property type and to each U.S. county are based on data from the S&P Global Real Estate Properties database. These portfolio allocations are measured at the end of each calendar year for each property held by a listed equity REIT during the period 1996–2019. These data include landlord (institution name), property type and sub-type, county location, acquisition date, sale date, net book value, initial cost, and historic cost. Our analysis begins in 1996 (end of 1995) because this is the first period for which S&P Global provides historic cost and book value information at the property level. After matching our initial sample with data from the S&P Global Real Estate Properties database, our REIT property-level data set contains 282 unique REITs and 851,648 property-year observations. Data identifying the property type focus of each REIT (industrial, multifamily, office, retail, etc.) are utilized as control variables.

We estimate aggregated county-level measures of climate shocks at the firm level, using a firm's time-varying allocation to each county as weights. Specifically, for each firm that owns any property in county l at the beginning of year t, its calculated *Event Exposure* for each climate hazard event, c, is

$$Event\ Exposure_{i,c,t} = \frac{\sum_l I_{l,c,t} \times \$Prop_{i,l,t}}{\sum_l \$Prop_{i,l,t}} \tag{1}$$

where $I_{l,c,t}$ indicates whether county l was exposed to climate shock c in time t. c is one of five salient climate shocks discussed below. $\$Prop_{i,l,t}$ is the total book value of properties owned by firm i in county l in year t. Panel A of Figure 2 displays the geographic distribution of U.S. REIT property holdings based on book values. Properties held by a typical REIT in our sample tend to be in locations with higher perceived asset productivity, such as the six U.S. "gateway cities" (New York, Los Angeles, Chicago, Boston, San Francisco, and Washington DC), as well as in southern California, Florida, and other more populated areas.

Finally, we construct a set of time-varying firm-level controls, identified in the prior literature as REIT return drivers. Summary statistics are reported in Table 1. *Size* is the logarithm of the book value of assets and has a mean of 14.01. *B/M* is defined as the ratio of book equity to market equity and has a mean of 0.66. With a mean of 0.14, *Momentum* is a firm's cumulative return over the prior quarter. *Leverage* is the ratio of the total book value of debt to the book value of total assets and has a mean of 0.47. *Profitability* is defined as annual revenues divided by book equity and *Investment* is the quarterly growth rate in noncash assets. Finally, we define *ILLIQ* as the logarithm of a stock's Amihud (2002) illiquidity measure and *IVOL* as the idiosyncratic volatility of a firm's stock price. *ILLIQ* (*IVOL*) has a mean of 0.09 (1.46). After deleting observations with missing firm-level controls, our final sample contains 9,491 firm-quarter observations (corresponding to 513,492 property-year observations) for 197 equity REITs.

3 Event Study—Publicly Traded REITs and Historical Climate Events

This section reports the results of an event study of the reaction of REIT returns to climate hazards during 1996-2019 period. Our REIT data is described in Section 1.1. SHELDUS data is defined and described below. Tables 2 and 3 report regression results obtained using the REIT and SHELDUS data.

3.1 Historical Climatic Disaster Data

SHELDUS reports information on U.S. counties impacted by an extreme weather event during 1996-2019; this information includes the quarter and year of the event, what hazard occurred (e.g., hurricane, flood, tornado), and estimates of nominal and per capita property damage. We can observe the quarter in which a climate event occurred but not the exact date within the quarter.

To measure the extent to which climate events predict equity REIT stock returns, we construct five measures of salient climate shocks at the county level. First, following Alok et al. (2020), we construct a dichotomous variable, *Top4Event*, that is set equal to one if a major climate event (hurricanes/tropical storm, flood, tornado, or wildfire) occurred in the county during the quarter; zero otherwise. The mean value of *Top4Event* is 0.429 (Table 1); that is, on average, 43% of REITs had some exposure to a major climate event in a given quarter. Panel B of Figure 2 displays the geographic distribution of top-4 climate events across U.S. counties using an average of data from 1996 through 2019. A comparison of Panels A and B in Figure 2 reveals a clear overlap of REIT geographic asset allocations and major climate events.

An indicator of both a significant climate event and the potentially mitigating impact of federal insurance assistance is the declaration of the event as a disaster by the Federal Emergency Management Association (FEMA). A dummy variable, *FEMADec*, is set equal to one in quarter t if FEMA announced federal funding for disaster recovery efforts in an affected county. The announcement of FEMA funding could potentially have bi-directional effects. It certainly indicates a high severity climate event. However, a declaration of FEMA funding may signal to investors that federal compensation and broader insurance coverage for damages will mitigate owner losses. Moreover, federal involvement in recovery efforts could be based, at least partially, on socio-political considerations in addition to the severity of the climactic event. This "noise" could affect the ability of *FEMADec* to predict stock price reactions. On average, 8% of the typical REIT's portfolio in any quarter was located in a county declared a disaster area by FEMA (Table 1). A comparison of the mean values of *Top4Event* and *FEMADec* reveals that FEMA funding is associated with a relatively small percentage of climate events. Panel C of Figure 2 shows the geographic pattern of FEMA events across the U.S. counties. It is evident that FEMA events are more frequent in the vicinity of the Mississippi River, which tends to produce flooding.

The increasing frequency and severity of climate shocks may make it more difficult to measure their salience (Smith and Matthews, 2015). For example, Schlenker and Taylor (2022) demonstrate that the prices of financial derivatives can be impacted by both near-term and longer-term climate event predictions. If the probability of a future event (e.g., flood) is reflected, at least in part, in current asset prices, then distinguishing between an "expected" or "unexpected" event becomes important. To capture an "unexpected" climate event, we construct two measures.

Hewing closely to both geophysical science traditions and the existing climate finance literature (e.g. Li and Thompson, 2021; Moon et al., 2019), we first estimate the mean and standard deviation of the dollar damages of all climate events that occurred in the same county during the available data period (1970-2020). The dichotomous variable *Extreme1* is set equal to one in quarter *t* if an event produced damages more than two standard deviations greater than the county's long-run average damages associated with weather events.

The literature also demonstrates that investors update their perceptions of what constitutes an extreme weather event as additional climate shocks occur (Addoum et al., 2021; Gibson and Mullins, 2020; Ouazad and Kahn, 2021). To capture evolving expectations, we construct a second indicator of an extreme weather event. *Extreme2* is set equal to one in quarter *t* if an event occurred that produced damages that exceeded two standard deviations of the county's average damages from weather events that occurred in the preceding ten years. The mean values of *Extreme1* and *Extreme2* are *0.*117 and 0.174, respectively. Because the data is left-skewed with many zero damage observations, the percentages for *Extreme1* and *Extreme2* do not follow a normal distribution. The left skew biases the data towards including additional events with potentially weaker impact; thus, findings of statistical significance would strengthen the assertion that physical climate risk impacts prices.

Although our two county-based sample standard deviations of damages provide a localized measure of the salience of a weather event, nominal dollar damage may not fully reflect the impact in each market. In particular, the impact of dollar damages may be related to the population density of a county. We therefore create a dummy variable that indicates non-zero property damages in a particular county and quarter. We then aggregate this variable to the REIT level using each REIT's quarterly exposure (in book value) to the property damage in each county (*DMGPerCap*) as weights. The mean value of *DMGPerCap* is 0.568 (Table 1), which means that about 57 percent of a typical REIT portfolio is exposed to at least one county with non-zero property damages over our sample period.

3.2 Event Study of Climate Events and REIT Returns

To examine the effects of exposure to climate events on REIT returns, we use an event study methodology similar to Alok et al. (2020). Specifically, we use five quarters of data surrounding the climate event to estimate the following regression model:

$$\begin{aligned} RetRf_{i,t} = {} & \beta_0 + \beta_1 Event\ Exposure_i + \beta_2 Post\ Event_t \\ & + \beta_3 Post\ Event_t \times Event\ Exposure_i + \gamma X_{i,t-1} + \sigma_{p,t} + \epsilon_{i,t} \end{aligned} \tag{2}$$

where $RetRf_{i,t}$ is REIT *i*'s return in quarter *t*. Quarter zero is the quarter in which a climate event occurred. Quarters *t*-1 and *t*-2 are the preceding two quarters; quarters *t*+1 and *t*+2 define the two quarters following the event. *Post-Event*$_t$ is a dichotomous variable set equal to one for quarters zero, *t*+1, and *t*+2, and zero otherwise. *Event Exposure*$_i$ is the previously defined geographically weighted exposure of the firm's property portfolio to climate events at the beginning of the calendar year. The interaction term, *Post-Event*$_t$ *x Event Exposure*$_i$, captures the extent to which the return effects associated with exposure to a climate event differ post-event. *Size*, *B/M*, *Momentum*, *Leverage*, *Profitability*, *Investment*, *ILLIQ*, *IVOL*, property type (specialization) and time (quarter) fixed effects are included in all specifications. $\sigma_{p,t}$ denotes property-type-time fixed effects.

The event study results from estimating equation (2) are presented in Table 2. The coefficient estimate on *Post-Event *Event Exposure* is negative and highly significant across all specifications. That is, relative to the two quarters prior to the climate event, REIT returns tend to be lower during the quarter in which the climate event occurred, as well as the following two quarters. In terms of magnitudes, a one-standard-deviation increase in the *ex-ante* Event Exposure is associated with a 0.2 to 1.4 percentage points decrease in quarterly stock returns in the post-event period. This is economically meaningful relative to an average quarterly return of 2.8 percentage points during the sample period.

Interestingly, the use of *FEMADec* to measure a significant climate event produces the strongest return signal followed by the two salience measures, *Extreme1* and *Extreme2*. Our ex-ante expectation that events that generate damage greater than two standard deviations from mean damage would produce stronger return effects was met. However, as discussed above, FEMA events could influence returns positively or negatively. Sophisticated investors likely understand that FEMA involvement also means federal insurance dollars to support the area and the asset. Alternatively, FEMA involvement could signal, especially to a less sophisticated investor, that the hazard was large and serious enough to merit federal involvement. It appears the greater media attention associated with FEMA declarations offsets the expected positive effects of a FEMA declaration. This is explored later in more detail.

Consistent with prior literature, REIT returns are positively related to return momentum, profitability, and idiosyncratic stock price volatility but negatively related to a stock's illiquidity (Zhang and Hansz, 2022). A firm's book-to-market value ratio and leverage are not predictive of post-event returns.

Our results reveal another interesting finding. The estimated coefficient on *Event Exposure* is positive and significant at the 1% level in all specifications, indicating that REIT returns in quarters *t*-1 and *t*-2 are positively related to a typical firm's exposure to a major climate event in the two quarters prior to the event. This suggests that prior to an event, REITs with portfolios tilted toward areas more exposed to a weather-related disaster outperformed REITs less exposed to these weather events. Inspection of Figure 2, Panel A reveals that the typical REIT has significant exposure to the gateway markets, which have been shown to have outperformed their non-gateway peers, likely due to higher asset productivity. Thus, the positive coefficient estimate on *Event Exposure* is consistent with the literature.[6] It is also consistent with Dougal et al. (2020) who find that traditional indicators of urban market desirability are positively related to stock prices.

[6] Hoesli and Johner (2022) and Ling et al. (2022) show that gateway markets exhibit greater price appreciation and total returns than non-gateway markets, which is likely due to greater liquidity and market depth (Ghent, 2021; Wang et al., 2022).

The estimated coefficient on *Post-Event* is positive and significant in all five specifications. In a classic two-period difference-in-difference model, *Post-Event* captures the average cross-sectional return increase among all observations, both those in the control group and those in the treated group. The majority of quarter observations, greater than 95% in some specifications, include at least one climate event, albeit many of them quite minor. As a result, since it is almost universally activated, the *Post-Event* variable serves a similar function as in a two period model. Part of what this coefficient captures is the consistent upward trend of REIT share prices and returns over the sample period; more specifically, the mean annual REIT return in the 1996-2020 period on the FTSE NAREIT All REIT index was 11.36%.

The results presented in Table 3 are based on models in which the post-event period is broken into three separate quarters: the event quarter (q+0) and the two following quarters (q+1, q+2). The estimated coefficients on our control variables are unaffected by this disaggregation of event time and are therefore suppressed. The results displayed in Table 3 reveal that the estimated coefficients on all three interaction variables are negative and highly significant across most specifications. This indicates a negative relation between a firm's geographically-weighted exposure to climate events and stock returns in the quarter in which the event occurs, as well as the following two quarters, relative to returns in quarters t-1 and t-2.

Overall, the results presented in Tables 2 and 3 provide evidence that the negative effect of climate events on stock returns is proportional to the firm's portfolio exposure to the event; moreover, the negative return effects tend to persist for at least three quarters.

4 Cross-sectional Analysis—Media and Investor Attention Data

This section reports the results of a cross-sectional analysis of the reaction of REIT returns to climate events during the 1996-2000 period. The results presented in Table 4 are estimated using the same set of REIT-level and SHELDUS variables previously defined. Table 5 builds on that analysis by including the impact of media and investors' attention (Baldauf et al. 2020). Our media and investor attention variables are first defined, followed by a description of the research method and results of the analysis.

4.1 Media and Investors Attention

An expanding literature suggests that beliefs about climate change are material factors in asset pricing. Baldauf et al. (2020) and Holtermans et al (2023) demonstrate this in both housing and private CRE markets, while Goldsmith-Pinkham et al. (2022) explore the relationship in the municipal bond market. The extent to which various media outlets focus on climate events/change has been shown to be an important determinant of cross-sectional variation in responses to climate events (Fang and Peress, 2009; He and Tanaka, 2023).

An ideal control instrument would capture longitudinal variation in the extent to which REIT investors, located in any MSA, pay attention to climate events/exposure in, say, Boston, or any other market in which a REIT owns property. We do not believe such an instrument exists. As proxies for the extent to which investors pay attention to climate events in a particular market, we use data from two sources. First, we obtain data on media attention from the Yale Climate Opinions Maps (Howe et al., 2015), which contains survey data at the county level on perceptions of climate change (risk). The model uses 13,000 individual survey responses since 2008 collected by Howe et al. (2015) to estimate differences in opinion across geographic and demographic groupings. According to Howe et al. (2015), their model produces "high-resolution estimates of public climate change understanding, risk perceptions, and policy support in all 50 states, 435 Congressional districts, and 3,000+ counties across the United States."[7]

Following Baldauf et al. (2020), Bernstein et al. (2019), and Murfin and Spiegel (2020), we use county-level data from the Yale survey to measure the extent to which local respondents are exposed to climate-related information. Specifically, we focus on survey responses to the question: "How often do you hear about global warming in the media?" Five options were available to respondents for selection: "At least once a week," "At least once a month," "Several times a year," "Once a year or less often," and "Never." The proportion of respondents in each county who selected "At least once a week" was used to construct our time-varying, cross-sectional, measure of media attention, *High Media Attention*. This proxy suffers from two potential limitations. First, it primarily captures the supply of media coverage in a particular county, not the demand for climate change information by current or potential future REIT investors. Second, it captures media coverage of climate-related news in, say,

[7] Howe et al. (2015) validated the model estimates using a variety of techniques, including independent state and city-level surveys."

Boston, not the media coverage of Boston climate news in the multiple local markets in which REIT investors are located. Nevertheless, we assume that the media coverage of climate news and events to which residents of Boston are exposed is a reasonable proxy for the amount of information REIT investors in any location are provided on climate news that affects Boston. Of course, to the extent *High Media Attention* is a noisy proxy for the media coverage of Boston climate news available to investors in any location, our coefficient estimates on *High Media Attention* will be biased downwards.

As an additional empirical test, we download search query-based index values from Google Trends. These indexes are available from 2004 onward and vary by year and by subregion (e.g., a U.S. state). Specifically, they contain information about how the popularity of a topic (e.g., "Climate Change") has fluctuated over time for each location.[8] A value of 100 for a given geography (MSA, state, etc.) and time period indicates the date (day, month, quarter, etc.) during which search volume for the topic peaked; a value of 50 for a given geography and time period indicates the date in which the search volume was 50% of the maximum volume. To illustrate the time series variation in Google searches for information on climate-related topics, we searched for "climate change" at the national level. As depicted in Figure 3, there has been significant monthly variation in the search volume for climate change since 2005. Movements in the index are relative to an index value of 100 in April of 2022 when the search volume for the topic over the sample period peaked.

Chauvet et al. (2016) and He and Tanaka (2023) conclude that Google Trends indexes are more likely to capture demand effects (i.e., the popularity of a topic among information recipients) rather than supply effects (i.e., the availability of news content). In addition, investors are likely to receive similar output when searching for a topic at a given time point, regardless of their physical location. The homogeneity of the search results helps us to make inferences about the variation across states in the intensity of interest in the topic of climate change. Similar to *High Media Attention*, we construct a time-varying measure of search intensity for each state: *High Google Trends*. Compared to *High Media Attention*, *High Google Trends* directly proxies for the popularity of "climate change" among information recipients and is therefore less likely to be influenced by the intensity of local media coverage.

[8] Google dominates the global search engine market by retaining approximately 85% of the total market. Source: https://www.impressiondigital.com/blog/bing-differ-google/.

However, this proxy potentially suffers from the limitation that it measures the demand for information on climate change from, say, Massachusetts-based investors, not the demand for climate change information on Massachusetts by investors located in any state/market. Nevertheless, we assume that the demand for climate news among individuals and investors located in Massachusetts is a reasonable proxy for the demand by investors in any location for climate news that affects Massachusetts. To the extent *High Google Trends* is a noisy proxy for the demand by all REIT investors for information on climate change in Massachusetts, our coefficient estimates on *High Google Trends* will be biased downwards.

Overall, increasing coverage and awareness of climate risk should expand potential pricing beyond local geographies. As evidence towards this, our two measures of investor awareness, the Yale Climate Survey and Google Trends data, provide an additional signal for REIT investors not strictly tied to the geography of the asset. Simply, if a REIT analyst maintains a Google news alert on the property holdings of the firm, these measures reflect variation in attention paid to the phenomenon of climate change and its geography. That information can be added to the awareness/salience of individual climate events in both catastrophic (NOAA/SHELDUS) and forward climate risk (RisQ) data. We note the broad geographic relationship between this attention measure and where risk-related events occur (Figure 2).

4.2 Price Impact of Climate Event on REIT Returns—Panel Regressions

Table 4 presents estimates from the following panel regression equation:

$$RetRf_{i,t+1} = \alpha + \beta_1 Event\ Exposure_{i,c,t} + \gamma X_{i,t} + \sigma_p + \delta_{t+1} + \epsilon_{i,t+1}, \qquad (3)$$

where $RetRf_{i,t+1}$ is the return of firm i in quarter t+1 in excess of the one-month Treasury bill rate. $X_{i,t}$ is a vector of firm-level controls. σ_p and δ_{t+1} are fixed effects pertaining to the firm's property type focus (p) and year-quarter (t+1), respectively. The coefficient of interest, β_1, is expected to be negative if a larger portfolio exposure to climate events is perceived by investors as value-destroying.

In column (1), we report panel regression results using *Top4Event* as our climate event variable. The estimated coefficient on portfolio exposure to a *Top4Event* cannot be distinguished from zero. Firm size, return momentum from the prior quarter, and the idiosyncratic volatility of the firm's stock price in the prior quarter are positively and significantly related to returns; the firm's book-to-market value ratio is negatively related to returns. In column (2), we report the results obtained when *FEMADec* is used as our measure of the REIT's exposure to climate events in quarter *t*. In the results reported in columns (3)–(5), we use *Extreme1*, *DMGPerCap*, and *Extreme2*, respectively, as our measure of a firm's geographically-weighted climate risk exposure. In all specifications, the estimated coefficient on our climate exposure variable is insignificant, suggesting that firm-level quarterly returns are not responsive to a weighted average of each firm's climate risk exposure in the prior quarter.

We next examine whether the ability of our climate event variables to predict REIT returns is related to the amount of media exposure that global warming receives in the counties where climate events are occurring. To explore the cross-sectional heterogeneity in the impact of salient climate shocks on returns, we augment Equation (3) by adding the previously defined *High Media Attention* to each regression specification. We then multiply *High Media Attention* by *Event Exposure* to create an interaction variable that captures the extent to which the predictive power of *Event Exposure* is moderated by the amount of media attention given to global warming in the same markets to which the firm's portfolio is exposed. The functional form of this augmented regression is:

$$\begin{aligned} RetRf_{i,t+1} = \alpha &+ \beta_1 Event\ Exposure_{i,c,t} + \beta_2 High\ Media\ Attention_{i,t} \\ &+ \beta_3 Event\ Exposure_{i,c,t} \times High\ Media\ Attention_{i,t} + \gamma X_{i,t} + \sigma_p \\ &+ \delta_{t+1} + \epsilon_{i,t+1} \end{aligned} \tag{4}$$

We expect the negative impact of *Event Exposure* on excess return to be more pronounced among REITs whose portfolios are titled toward markets in which more media attention is focused on climate-related issues.

The results obtained from estimating these augmented panel regression specifications are reported in Table 5, Panel A. The coefficient estimates on our control variables are little changed from those reported in Table 4 and are therefore suppressed. In column (1), we report the results from a baseline model that includes *High Media Attention* but not a climate event variable or an interaction term. The estimated coefficient on *High Media Attention* is positive and weakly significant. As shown in Panel D of Figure 2, the upper quartile of *High Media Attention* includes Boston, Los Angeles, Miami, New York, San Diego, Seattle, and other cities that tend to have outperformed during our sample periods. Likely, the *High Media Attention* independently captures the higher rental growth and demand in these markets leading to increased returns, although we do not test this hypothesis.

The results presented in column (2) are estimated with a model that also contains *Top4Event* and *Top4Event × High Media Attention.* The estimated coefficient on *Top4Event* event exposure cannot be distinguished from zero. However, the estimated coefficient on the interaction term is negative and significant at the 5% level. This suggests that negative stock price reactions to a major climate event tend to occur in the cross-section only among REITs whose portfolios are tilted toward counties (1) in which a climate event has occurred and (2) media attention to global warming/climate change is high.

We replicate the analysis presented in Column (2) of Table 5, Panel A by interacting the remaining four climate event variables with *High Media Attention.* The estimated coefficients on the *FEMADec*, *Extreme1*, and *Extreme2* interactions are negative and significant at the 1% level; the coefficient estimate on the *DMGPerCap* interaction variable is negative and significant at the 10% level. These results confirm the important relation between geographically-weighted media attention and stock price reactions to a REIT's exposure to climate events. The positive and significant coefficient estimates on *High Media Attention* in all specifications are noteworthy as they suggest that a firms' exposure to local markets in which global warming receives significant media attention is predictive of returns.

We next replace *High Media Attention* in Equation (4) with *High Google Trends*. Results from estimating this augmented Equation (4) are reported in Table 5, Panel B. We again focus on the estimated coefficients on the interaction term, *Event Exposure × High Google Trends*. Except for FEMA events, the estimated coefficients on the interaction terms are negative and significant at the 1% or 5% level. This indicates that major climate events predict negative stock returns in the cross-section only among REITs whose property holdings are disproportionally allocated to locations in which both a climate event has occurred and the demand for information on the topic "Climate Change" is high.

5 Price Capitalization of Forward-Looking Climate Risk—Data and Results

The pricing of catastrophic risk insurance is typically backward-looking and is the catalyst for our use of the SHELDUS data. Forward-looking climate risk involves the different Relative Concentration Pathways (RCPs) or forecasts published by the Intergovernmental Panel on Climate Change (IPCC). Each represents a different scenario, based on the expected degree of global warming, to estimate the likelihood of future climate risk. Many highly specialized firms now offer physical risk assessments and, in recent years, most institutional investors and their advisors have acquired access to forward-looking physical climate risk analytics. This information is typically offered as a bundle of information services. Our data on forward-looking climate risk was provided by RisQ.

This section analyzes the extent to which forward-looking climate risk is capitalized into REIT valuations. Typically, forward-looking climate risk data providers aggregate individual hazard risks (e.g., pluvial flood, hail, hurricane, storm surge, wildfire, etc.) into a single property level risk. However, no scientific consensus has emerged as to how these physical risk assessments should be developed. As a result, data providers use different assumptions for both the likelihood of a hazard and the likely damage when one occurs (Urban Land Institute, 2022). We use the 2019 RisQ data made available to us to analyze the effects of climate risk projects on REIT valuations in 2017-2019.[9] Given the heterogeneity in value-at-risk estimates for property, we focus on the physical risk of an event itself.

5.1 Forward-Looking Climate Risk Assessments from RisQ

Our RisQ data are based on estimates of forward-looking climate risk as of 2020. Although these data provide only a single cross-sectional "snapshot," typically the movement in these forward-looking risk assessments is slow. The spatial scale used by industry providers (e.g., 100-meter grid) varies; RisQ uses a transportation isochrone based on minutes of drive time as their spatial scale. This provides some measure of the risk of site accessibility in addition to the climate risk of the localized site.

[9] We restrict our analysis to pre-2020 REIT data to avoid the effects of the COVID19 pandemic. Although forward looking climate risk assessments are not static, we assume the 2019 RisQ risk assessment data are relevant to firm valuations in 2017 and 2018, as well as 2019.

The RisQ score combines flood (multiple typologies), wildfire, and hurricane-related catastrophe models (e.g., Grossi et al. 2005; Jindrová and Pacáková 2019) into one composite relative risk score on a 0-5.0 scale for each property.[10] The scale is exponential with each integer increase representing approximately a doubling of risk (e.g., a risk of three is double that 2). RisQ suggests that a risk weight of three or greater would be considered a "high" risk. To avoid representing the data as ordinal, we transform all data as $2^{\text{RisQ Score}}$ to better match the rating in a continuous scale.

Our baseline analysis uses a drive time isochrone of six minutes although other available isochrones provide qualitatively similar results. We also used the 4.5-degree RCP as our base analysis. Since the IPCC has already stated that human activity has increased the global temperature approximately 1.0°C above its pre-industrial level, this seems a reasonable choice relative to the use of an 8.5-degree RCP scenario—given both IPCC methodology and the attendant uncertainty associated with such a significant global mean temperature change. Since different investors may focus on different investment timelines, we employ multiple time horizons over which the risk is assessed. We use *base, 10-year, and 30-year* time horizons, with base meaning current risk and forward scenarios estimating the likely risk in a 10 year or 30 year period respectively; of course, the longer the time horizon with increased global warming, the larger the expected physical risk.

The option of equal weighting (EW) or value weighting (VW) each property's contribution to a REIT's overall risk exposure was considered. Since this is among the first papers assessing forward-looking climate risk, we elected to include both typologies. When equal weighting, each property's forward climate risk assessment contributes equally to the firm level risk; that is, total risk is summed and divided by the number of properties owned by the REIT in each period. We additionally construct a value-weighted risk assessment where the percentage contribution of each asset to firm risk is based on the book value of the asset divided by the total book value of the firm.

As shown in Table 1, the means for equal-weighted risk using the *base, 10-year, and 30-year* time horizons are 1.793, 1.982, and 2.255, respectively. Similarly, the value-weighted mean risk for the *base, 10-year, and 30-year* time horizons are 1.744, 1.953, and 2.259, respectively.

[10] Detailed data descriptions may be found at https://www.risq.io/

5.2 Capitalization of Forward-Looking Climate Risk into Firm Valuations

To examine whether forward-looking climate risk impacts firm valuations, we estimate the following regression:

$$Q_{i,t+1} = \alpha + \beta_1 RISQ_{i,c,t} + \gamma X_{i,t} + \sigma_p + \delta_{t+1} + \epsilon_{i,t+1} \quad (5)$$

where $Q_{i,t+1}$ is the Tobin Q of firm i in quarter $t+1$. $RISQ_{i,c,t}$ is the one of the six projected climate risk exposures: *Base (EW)*, *10Y (EW)*, *30Y (EW)*, *Base (VW)*, *10Y (VW)*, and *30Y (VW)*. $X_{i,t}$ is a vector of firm-level controls. σ_p and δ_{t+1} are the fixed effects pertaining to the firm's property type focus (p) and year-quarter ($t+1$), respectively. The estimated coefficient of interest, β_1, is expected to be negative if larger projected climate risk exposures, based on each REIT's weighted average allocations to each county, are perceived by the marginal investor as likely to reduce operating cash flows or require higher discount rate. However, the results displayed in the first row of Table 6 reveal that none of the coefficient estimates on our six *RisQ* measures are statistically significant. That is, estimates of the exposure of REIT portfolios to future county-specific climate risk are not predictive of current REIT valuations.

This outcome could accommodate a number of explanations. First, we observe in our event study (Table 2) that firms more exposed to an event tend to outperform their peers in the quarter prior to the event. We also observe that climate events were more likely to occur in gateway markets (Figure 2) where property prices tended to appreciate at faster rates during our sample period. It is therefore plausible that, cross-sectionally, the higher risk of climate hazards in these areas is offset by the expectation of higher rent and price growth in those markets. Also, prior research (Baldauf et al., 2020) shows that belief systems and media coverage impact the capitalization of physical climate risk into residential homes, which is largely driven by households. It is unclear whether similar results will be found in listed CRE markets, which are dominated by institutional investors.[11]

To test the impact of belief systems and media attention on REIT pricing, we first include *High Media Attention* in revised panel regressions of firm value on future climate risk exposures, along with interactions of *High Media Attention* with our six forward-looking *RisQ* measures. These results are reported in Table 7, Panel A. To provide a baseline, the

[11] According to S&P Global, in 2023, 72 percent of outstanding REIT share were owned by institutional investors.

regression results reported in column (1) include *High Media Attention* but not a *RisQ* measure or a media attention interaction term. The estimated coefficient on *High Media Attention* is not statistically significant. That is, *High Media Attention* has no direct, independent impact on REIT valuations. However, the estimated coefficients on the six interaction terms of *RisQ* × *High Media Attention* are consistently negative and statistically significant; that is, the valuations of REITs more exposed to climate risk are lower only in areas in which climate change receives extensive media coverage. The economic magnitude of this effect is relatively modest—as shown in column (1), a one-standard-deviation change in *RisQ* corresponds to a decrease of -0.072 (-0.051 x 1.411) in Tobin Q (mean: 1.448). These results suggest that the findings of Baldauf et al. (2020) in housing markets extend to CRE pricing, at least as reflected in listed REITs.

The results presented in Table 7, Panel A provide some of the first direct evidence that forward-looking physical climate risk is capitalized into REIT valuations when local media attention is high. We extend the analyses displayed in Panel A by interacting our six forward-looking *RisQ* variables with *High Google Trends.* These results are tabulated in Table 7, Panel B. The estimated coefficients on the interaction terms of *RisQ × High Google Trends* are consistently negative and significant at the 1% level. In terms of the economic magnitude of this effect, in column (1), a one-standard-deviation increase in *RisQ* is associated with a decrease of -0.171 (-0.121 x 1.411) in Tobin Q, or 12% (-0.171/1.448) of its mean. These results provide further evidence that forward-looking climate risk affects firm valuations when local demand for climate risk information is high. This sheds light on the importance of cross-sectional heterogeneity in the demand for climate news and information in predicting REIT valuations.

6 Institutional and Retail Ownership Holdings and Climate

We have documented that, in the cross-section, (1) stock returns tend to react to actual climate events and (2) forward-looking climate risk assessments tend to be reflected in firm valuations only when REIT portfolios are more heavily allocated to markets in which media attention to climate change or the where the demand for information on climate change is high. We next seek possible explanations for these findings. Although institutional investors have ready access to climate risk analytics, retail investors frequently do not. The potential influence of this information asymmetry is testable and our results reveal differing climate event reactions between institutional and retail investors.

6.1 Blockholder Data

Ownership data from Thomson Reuters, which provides quarterly data on the common stock holdings of 13(f) institutions, is merged with our existing sample. Total stock ownership percentages are disaggregated into three components: outstanding shares owned by blockholders, shares owned by non-block institutional investors, and shares owned by retail investors.[12] Blockholders typically act as the "buyer of last resort" for a firm's shares. For instance, if retail investors exhibit salience bias and overreact to climate disasters, blockholders may cater to their disposition requests. As shown in Table 1, on average, 27% of REIT shares are owned by blockholders, 48% by non-block holders, and 25% by retail investors during our sample period. We examine how these ownership percentages change after climate events.

6.2 Institutional and Retail Stockholder Reaction to Climate Events

We re-estimate Equation (2) using the percentage of outstanding shares of each REIT held each quarter by retail investors as the dependent variable. *Post-Event* is again set equal to one if the level of institutional ownership is being measured in the post-event period that includes the quarter in which the climate event occurred and the two subsequent quarters. Quarters t-1 and t-2 are the omitted quarters. The interaction term, *Post-Event x Event Exposure*, captures the extent to which a firm's exposure to a climate event predicts reduced retail ownership after the event.

Table 8 contains the results from estimating our event study models separately for retail investors, non-blockholder institutional investors, and blockholders. The results for retail investors are reported in Panel A. The estimated coefficient on *Post-Event* is negative and highly significant in the *FEMADec*, *Extreme1*, and *Extreme 2* specifications, suggesting lower levels of retail ownership post-event. Moreover, except for *DMGPerCap* , the estimated coefficient on the post-event interaction term is negative and significant at the 5% level or

[12] A blockholder is the owner of a large block of a company's outstanding shares. These owners are often able to influence the company with the voting rights awarded with their holdings. Thomson Reuters defines a blockholder as an investor that holds 5% of a voting class or more beneficial ownership for control purposes.

greater. The estimated coefficient on the *Top4Event* interaction term, for example, suggests that a standard deviation increase in a firm's exposure to top-four events is associated with a decline of 0.5 percentage points in retail ownership post-event. To whom are these retail investors selling? The results displayed in Panel B suggest that blockholders eventually buy the majority of the shares sold by retail investors. In fact, the estimated coefficient on *Post-Event x Event Exposure* is positive and significant in all five specifications for Blockholders.

Among non-blockholder institutional investors (Panel C), the *Post-Event x Event Exposure* coefficient cannot be distinguished from zero in any of the five specifications. However, *Post-Event* is positive and significant at the 5% level or greater in all five specifications. This indicates that non-blockholder institutional investors tend to buy some of the shares sold by retail investors in the aftermath of a climate event. However, among these non-blockholder institutional investors, this increase does not appear to be related to the degree to which a REIT's portfolio is exposed to the climate event.

Taken together, the results reported in Table 8 suggest that retail investors tend to dispose of shares in REITs most exposed to climate events, while the REIT's large blockholders take the opposite side of many of these transactions. However, our return results suggest that the majority of these offsetting purchases by blockholders (likely the firms themselves) occur after prices have declined in response to a climate event (Hong et al., 2008; Choi et al., 2020). It is often argued that the trades of retail investors are based on "noise," and therefore, these trades provide little or no relevant new information to the market (Kumar and Lee, 2006; Kaniel et al., 2008; Alok et al., 2020). This could explain why, in our cross-sectional panel regressions (Table 4), we find no relation between a firm's exposure to a climate event and returns in the subsequent quarter. If institutional investors and blockholders are not selling in response to climate events, little or no relevant new information is provided to the market.

7 Investor Sentiment and Price Impact of Climate Event

Given our findings that a) forward-looking climate risk tends to be capitalized into REIT stock prices in areas with extensive media coverage or where the demand for climate news (as reflected in Google searches) is high and b) retail investors tend to react differently to climate hazard events than institutional investors, it is plausible that consumer sentiment may also influence post-hazard REIT returns. We therefore investigate if consumer (investor) sentiment is partially driving our return results by conditioning on the extent to which each REIT's stock returns are exposed to consumer sentiment.

In the last month of each quarter in our sample, we regress firms' monthly excess stock returns on one-month lags of the Michigan Consumer Sentiment Index and Carhart's four risk factors (Carhart, 1997) using data over the prior 60 months.[13] The Michigan index is a widely used measure of consumer (i.e., retail) sentiment.[14] These rolling return regressions are estimated over a sample period that runs from January 1991 through December 2019. At the beginning of each quarter (last month of the prior quarter), we separate REITs into "high" sentiment firms and "low" sentiment firms based on the magnitude of the sentiment beta estimated in the last month of the prior quarter. We then separately re-estimate our five event study regression models for firms with high and low exposure to consumer sentiment. These results are reported in Table 9. The estimated coefficient of interest is the *Post-Event x Event Exposure* interaction.

The estimated coefficient on *Post-Event x Event Exposure* for *Top4Event* (columns (1) and (2)) is negative and significant among both high and low sentiment firms. However, the magnitude of the estimated coefficient among high sentiment firms is three times larger than among low sentiment firms (-5.995 versus -1.954). A test for the difference in these two interaction coefficient estimates produces a chi-square statistic of 9.27, which is highly significant. Inspection of the results presented in columns 3-10 reveals similar results for the remaining four definitions of climate events. Overall, the results presented in Table 9 suggest that REITs whose returns are more sensitive to consumer sentiment tend to suffer larger stock price declines post climate events. This is consistent with our findings that retail investors tend to dispose of REIT shares most exposed to climate events.

8 Limitations of Forward Looking Risk Measures

Numerous forward physical risk providers offer varying levels of detail and sophistication. Most major financial service providers acquired a system over the last several years, a small

[13] Carhart's four factors include the monthly return of the CRSP value-weighted index less the risk-free rate (*MKTRF*), monthly premium of the book-to-market factor (*HML*) the monthly premium of the size factor (*SMB*), and the monthly premium on winners minus losers (*UMD*).
[14] Data on the Michigan Consumer Sentiment Index are downloaded from the Federal Reserve of Saint Louis (FRED) website (https://fred.stlouisfed.org/series/UMCSENT).

number of insurers or re-insurers provide climate risk services, and numerous third-party start-ups remain in an evolving industry. RisQ, the data used herein, is considered one of the more sophisticated and robust physical climate risk modeling systems.

However, significant confusion remains among industry practitioners in how to interpret the data. Among other areas, some vendors are opaque in the data sources used for risk identification, the nature of the model used (e.g., proprietary, peer-reviewed, etc.), the extent to which municipal or regional mitigation measures (if any) were included, whether accessibility or transit isochrones were used, the RCP and time horizons used—all of which impact the level of risk. Further, as shown in a recent Urban Land Institute publication (2022), different firms can produce different estimates of risk for the same set of assets.

Lastly, based on qualitative interviews with leading institutional asset managers and real estate investment trust climate experts, little consensus exists on how to use this data[15]. While outside the scope of this paper, most firms rely on physical risk analytics primarily as a signal to perform more due diligence. However, REITs offer greater transparency than other real estate investment vehicles, particularly in portfolio-level disclosures. While no evidence has been found that REITs are either ahead of or behind the broader CRE market in assessing climate risk, the public nature of their holdings provide opportunities for investors making informed use of these analytics to make better informed investment decisions.

Our findings therefore represent a pre-regulatory finding and should be interpreted with the caveat that required disclosures, future convergence of climate science, and more advanced decision-making around physical risk will continue to impact the market capitalization of forward looking risk (Cloutier et al., 2021, Robinson and McIntosh, 2022).

As much of the industry currently relies on intuition and a "common sense" approach to physical climate risk, we contend that media and household attention strongly factor into market capitalization. Where media highlights the physical risk in certain areas, this often translates into either national coverage or hits the media stream of the analysts covering REITs with assets in those locations. As the measurement and decision-making around

[15] Based on pre-publication version of Physical Risks and Underwriting Practices in Assets and Portfolios, ULI 2023 forthcoming.

physical risk matures, we would expect this variable to diminish in importance but, at this time, it reflects an awareness of risk that is difficult to measure elsewhere.

9 Conclusion

Motivated by the challenges of introducing climate science into asset pricing models, this paper exploits data describing both realized climate events and estimates of future climate risk to study the stock return and valuation effects of climate hazards across time and by location. Utilizing both event study and cross-sectional models, we investigate how climate shocks to local property markets affect the stock returns of listed Real Estate Investment Trusts (REITs). We also examine the extent to which forward-looking measures of climate risk are capitalized into the firm valuations of publicly-traded equity REITs. This provides the opportunity to explore returns and valuations for firms that hold assets that are fixed in location and capital intensive. Moreover, REITs are professionally managed, highly regulated, and the subject of intense analytical scrutiny.

The analysis produces four stylized conclusions. First, we observe statistically and economically significant declines in REIT returns for at least three quarters following a significant climate event. Second, we find that variation in media attention to climate change or variation in the demand for information on climate change (as proxied for by the intensity of Google searches) in the markets in which REITs' properties are located has a significant relation to both asset pricing and risk capitalization--relative to both observed climate events and forward-looking climate risk forecasts. Further, the interactive effects of strong media coverage or the demand for climate change information in the markets in which REITs' properties are located with either observed physical hazards or forward physical risk forecasts are also statistically and economically significant predictors of variation in REIT returns and valuations, respectively. Third, we uncover significant differences in the trading patterns of retail and institutional blockholders following physical climate events. Retail investors tend to sell REIT shares whereas blockholders do not. Finally, extending the findings around differential investor-type trading patterns, we observe that REITs whose returns are more sensitive to changes in consumer sentiment exhibit statistically significant greater stock price declines when impacted by a climate hazard.

Together, the results echo and extend findings from the climate finance literature as well as from industry research. Climate change is an array of individual risks and looking ahead requires anticipating significant scientific, market, and behavioral uncertainty. Thus, its analysis using asset pricing models will continue to require analyses across an array of signals, channels, and future pathways. Our findings speak to the information diffusion of climate risk into financial markets. Institutions and informed investors like blockholders react differently than retail consumers to climate events. Given the preponderance of physical climate risk analytics available to informed capital, arguably their investment behavior reflects some level of understanding about that risk. However, the combination of its complicated scientific underpinnings and comparatively slow recognition of climate risk by the U.S. public, perhaps their trading behavior reflects a gap in knowledge of climate risk. Although we cannot rule out that the tendency of blockholders/institutional investors to purchase the shares sold by retail investors in response to a climate event is simply "buy the dip" trading behavior, the pattern reflects market integration of other previously new risks, like environmental risk, Government bodies, and financial markets' level of understanding and willingness to react preceded a more general public acceptance and awareness of the same.

Finally, our results are important relative to the arc of public policy in the U.S. With the SEC poised to introduce new rules on climate risk disclosure, it is useful to see evidence of climate as a driver of values and returns and to observe the contours of different types of investors and how they perceive and effectuate climate-related information in financial analyses. Future work should evaluate changes in the patterns as disclosure becomes mandatory among other related questions.

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Figure 1: Billion-Dollar Disasters in the United States, 1980-2022

This figure shows the billion-dollar disasters in the United States from 1980-2022. Property and related damages are presented in the Consumer Price Index (CPI) adjusted dollars. Source: https://www.ncei.noaa.gov/access/billions/time-series/US (accessed Sep 2022)

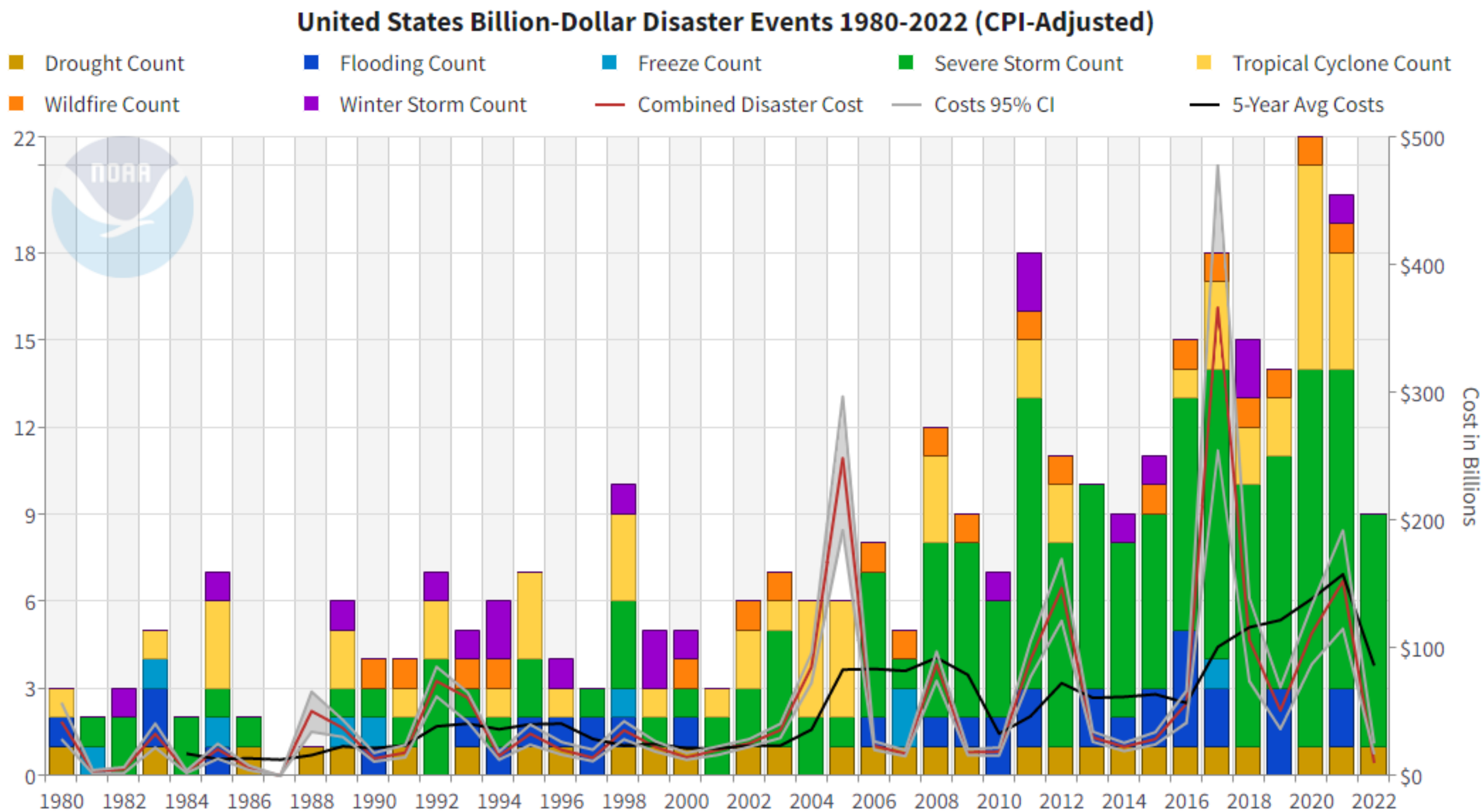

Figure 2: Disaster Counties, Property Holdings, and Media Attention

This figure shows the geographical distribution of our county-level measures. Panel A is based on the total book value of properties owned by REITs. Panel B (Panel C) depicts the geographic patterns of county-level exposure to top-4 climate events (FEMA events) from 1996 through 2019. Geographic patterns are shown in terms of quartiles. Panel D is based on geographic patterns of Median Attention. See Appendix 1 for variable descriptions.

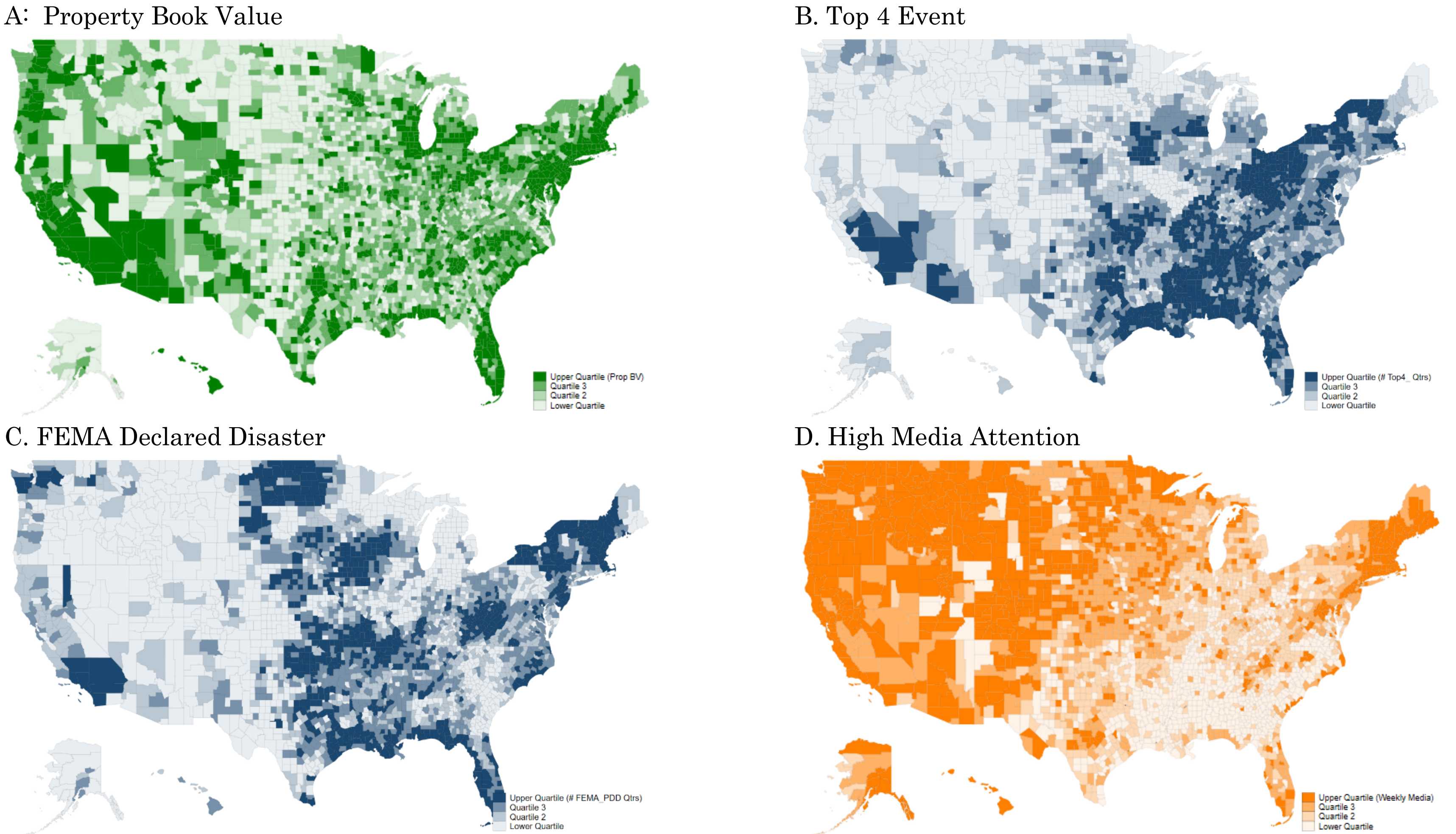

Figure 3: Google Trends Index (U.S.)

This figure shows the monthly Google Trends index for the topic "Climate Change" from Jan 2004 to Aug 2023 for the U.S.. A value of 100 is the peak popularity (Apr 2022) for the topic.

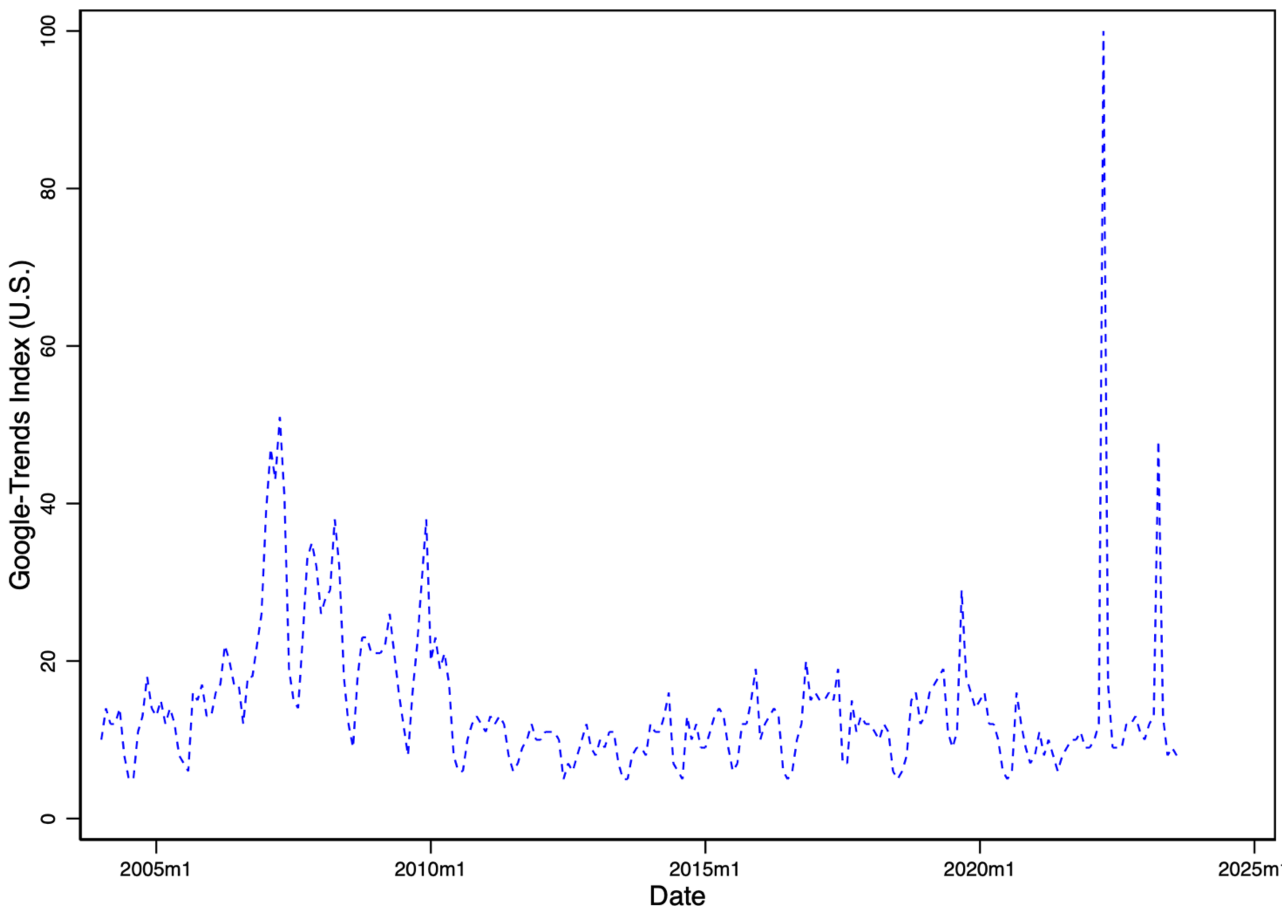

Table 1: Summary Statistics

This table shows summary statistics (mean, median, standard deviation, and 25th, and 75th percentiles) of key variables used in our analysis. Appendix 1 in the appendix defines all variables and lists all data sources.

	Mean	Median	SD	PCT25	PCT75
REIT Data (N=9,491)					
RetRf (%)	2.830	2.628	15.140	-4.372	9.880
Size	14.012	14.182	1.619	13.184	15.050
B/M	0.655	0.551	0.614	0.391	0.754
Momentum	0.135	0.126	0.308	-0.017	0.270
Leverage	0.471	0.482	0.160	0.397	0.571
Profitability	1.821	1.517	11.215	0.372	2.824
Investment	3.624	0.893	14.113	-0.487	4.039
ILLIQ	0.090	0.002	0.410	0	0.007
IVOL	1.464	1.184	0.928	1.010	1.501
Tobin's Q	1.448	0.478	1.136	1.343	1.625
SHELDUS Data (N=9,491)					
Event Exposure (Top4Event)	0.429	0.418	0.237	0.245	0.603
Event Exposure (FEMADec)	0.080	0.039	0.117	0.005	0.107
Event Exposure (Extreme1)	0.117	0.123	0.029	0.086	0.166
Event Exposure (DMGPerCap)	0.568	0.578	0.211	0.440	0.711
Event Exposure (Extreme2)	0.174	0.147	0.147	0.071	0.241
Yale Climate Survey Data (N=9,491)					
Media Attention	0.447	0.111	1.738	-0.699	1.419
Google Trends	0.433	0.067	0.387	0.424	0.471
RisQ Climate Risk Data (N=1,733)					
RisQ Base (Equal Weight)	1.793	0.657	1.411	1.685	1.949
RisQ 10Y (EW)	1.982	1.018	1.441	1.761	2.096
RisQ 30Y (EW)	2.255	1.641	1.476	1.863	2.212
RisQ Base (Value Weight)	1.744	0.744	1.340	1.645	1.946
RisQ 10Y (VW)	1.953	1.213	1.353	1.701	2.103
RisQ 30Y (VW)	2.258	2.019	1.390	1.773	2.197
Institutional Investor Data (N=1,733)					
Block	0.265	0.275	0.158	0.146	0.370
Non-Block	0.481	0.506	0.177	0.376	0.602
Retail	0.254	0.176	0.277	0.052	0.418

Table 2: Market Reactions to Climate Disasters

This table reports the event study results on the relationship between REIT excess returns and alternative measures of climate event exposure interacted with a dummy variable that indicates the post-disaster period. We focus on two quarters before to two quarters after a climate event. *RetRf*, the quarterly REIT excess returns, are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 1-month Treasury bills. In columns (1)-(5), we specify one of the five climate hazard measures as *Event Exposure*, including *Top4Event*, *FEMADec*, *Extreme1*, *DMGPerCap*, and *Extreme2* and interact *Event Exposure* with *Post-Event*, which equals 1 for the disaster quarter and the two following quarters and 0 otherwise. See Appendix 1 for variable descriptions. The property type focus times year-quarter fixed effects are included in the regressions. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
RetRf	*Top4Event*	*FEMADec*	*Extreme1*	*DMGPerCap*	*Extreme2*
Post-Event × Event Exposure	-3.967***	-12.043***	-6.595***	-3.253***	-8.634***
	(-5.62)	(-8.57)	(-3.99)	(-3.93)	(-6.01)
Event Exposure	2.022***	7.076***	4.290***	2.022***	6.286***
	(3.62)	(7.65)	(4.11)	(3.25)	(7.16)
Post-Event	1.837***	1.108***	0.872***	1.989***	1.603***
	(6.31)	(8.85)	(4.56)	(4.19)	(6.50)
Size	0.081	0.085	0.085	0.085	0.084
	(1.20)	(1.28)	(1.28)	(1.28)	(1.29)
B/M	-0.123	-0.120	-0.120	-0.122	-0.116
	(-0.25)	(-0.24)	(-0.24)	(-0.24)	(-0.23)
Momentum	8.914***	8.921***	8.925***	8.923***	8.929***
	(11.93)	(11.96)	(11.95)	(11.94)	(11.97)
Leverage	-0.358	-0.375	-0.374	-0.377	-0.373
	(-0.54)	(-0.57)	(-0.56)	(-0.57)	(-0.56)
Profitability	0.043***	0.043***	0.044***	0.043***	0.044***
	(3.24)	(3.25)	(3.27)	(3.26)	(3.37)
Investment	0.002	0.002	0.002	0.002	0.002
	(0.31)	(0.35)	(0.35)	(0.35)	(0.32)
ILLIQ	-2.486***	-2.496***	-2.489***	-2.498***	-2.478***
	(-2.68)	(-2.67)	(-2.66)	(-2.67)	(-2.67)
IVOL	1.522***	1.522***	1.520***	1.523***	1.517***
	(4.06)	(4.04)	(4.03)	(4.04)	(4.03)
Constant	-1.858	-1.606	-1.511	-2.187	-2.101
	(-1.33)	(-1.24)	(-1.17)	(-1.53)	(-1.62)
Prop # Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes
R-squared	0.118	0.119	0.117	0.117	0.119
# Obs	30,415	30,415	30,415	30,415	30,415

Table 3: Dynamics of Market Reactions to Disasters

This table reports the event study results on the relationship between REIT excess returns and alternative measures of climate event exposure interacted with quarter fixed effects. We focus on two quarters before to two quarters after a climate event. *RetRf*, the quarterly REIT excess returns, are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 1-month Treasury bills. In columns (1)-(5), we specify one of the five climate hazard measures as *Event Exposure*, including *Top4Event*, *FEMADec*, *Extreme1*, *DMGPerCap*, and *Extreme2* and interact *Event Exposure* with quarter fixed effects, including *Q+0*, *Q+1*, and *Q+2*. *Q+n* equals 1 for the *n* quarters after a climate event and 0 otherwise. See Appendix 1 for variable descriptions. The property type focus times year-quarter fixed effects are included in the regressions. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

RetRf	(1) *Top4Event*	(2) *FEMADec*	(3) *Extreme1*	(4) *DMGPerCap*	(5) *Extreme2*
Q+0 × Event Exposure	-4.037***	-16.798***	-9.613***	-3.030***	-9.032***
	(-4.07)	(-8.05)	(-4.90)	(-2.88)	(-5.41)
Q+1 × Event Exposure	-3.538***	-10.826***	-1.152	-0.746	-5.987***
	(-4.17)	(-6.31)	(-0.59)	(-0.85)	(-4.36)
Q+2 × Event Exposure	-4.327***	-8.505***	-9.019***	-5.982***	-10.883***
	(-5.16)	(-5.58)	(-4.23)	(-5.20)	(-5.05)
Event Exposure	2.022***	7.076***	4.290***	2.022***	6.286***
	(3.62)	(7.65)	(4.11)	(3.25)	(7.16)
Q+0	1.828***	1.459***	1.177***	1.822***	1.633***
	(4.17)	(7.86)	(5.03)	(2.92)	(5.41)
Q+1	1.656***	1.013***	0.258	0.555	1.153***
	(4.61)	(6.82)	(1.12)	(1.09)	(4.78)
Q+2	2.026***	0.852***	1.181***	3.589***	2.022***
	(5.93)	(6.20)	(4.84)	(5.54)	(5.57)
Controls	Yes	Yes	Yes	Yes	Yes
Prop # Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes
R-squared	0.118	0.120	0.118	0.118	0.119
# Obs	30,415	30,415	30,415	30,415	30,415

Table 4: Panel Regression Results of Excess Returns on Climate Risk

This table shows the panel regression results on the relationship between REIT excess returns and alternative measures of climate event exposure. Results are based on a quarterly sample of 9,491 firm-quarter observations from 1996-2019. *RetRf*, the quarterly REIT excess returns, are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 1-month Treasury bills. In columns (1)-(5), we specify one of the five climate hazard measures as *Event Exposure*, including *Top4Event*, *FEMADec*, *Extreme1*, *DMGPerCap*, and *Extreme2*. All independent variables are lagged by one quarter. See Appendix 1 for variable descriptions. Fixed effects pertaining to a firm's property type focus and time (year-quarter) are included in the regressions. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

RetRf	(1) *Top4Event*	(2) *FEMADec*	(3) *Extreme1*	(4) *DMGPerCap*	(5) *Extreme2*
Event Exposure	-1.317	0.142	-0.901	-1.298	0.194
	(-1.53)	(0.11)	(-0.79)	(-1.17)	(0.23)
Size	0.438***	0.449***	0.447***	0.445***	0.449***
	(2.72)	(2.77)	(2.75)	(2.76)	(2.76)
B/M	-4.077***	-4.085***	-4.083***	-4.071***	-4.085***
	(-4.56)	(-4.54)	(-4.54)	(-4.56)	(-4.54)
Momentum	3.889***	3.902***	3.906***	3.895***	3.903***
	(3.90)	(3.90)	(3.91)	(3.90)	(3.90)
Leverage	-1.670	-1.675	-1.691	-1.705	-1.673
	(-1.54)	(-1.53)	(-1.54)	(-1.58)	(-1.52)
Profitability	0.957	1.006	0.991	1.014	1.008
	(0.30)	(0.31)	(0.31)	(0.32)	(0.31)
Investment	2.215	2.274	2.267	2.227	2.275
	(1.04)	(1.06)	(1.06)	(1.05)	(1.06)
ILLIQ	1.841	1.774	1.783	1.832	1.772
	(1.17)	(1.16)	(1.18)	(1.17)	(1.16)
IVOL	2.614***	2.631***	2.627***	2.615***	2.632***
	(4.38)	(4.44)	(4.44)	(4.37)	(4.45)
Constant	-3.819	-4.565*	-4.414*	-3.727	-4.589*
	(-1.50)	(-1.80)	(-1.71)	(-1.47)	(-1.78)
Prop FEs	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes
R-squared	0.438	0.437	0.437	0.438	0.437
# Obs	9,491	9,491	9,491	9,491	9,491

Table 5: Panel Regressions of Excess Returns on Climate Risk Interacted with Media Attention

This table shows the panel regression results on the relationship between REIT excess returns and alternative measures of climate event exposure interacted with local investors' attention to global warming. Results in Panel A (B) are based on a quarterly sample of 9,491 (6,022) firm-quarter observations from 1996-2019 (from 2004-2019). *RetRf*, the quarterly REIT excess returns, are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 1-month Treasury bills. In Panel A, column (1), we re-estimate our baseline specification with *High Media Attention*, which is the aggregate percentage of adults who hear about global warming in the media at least once a week across all counties in which a REIT owns properties. In columns (2)-(5), we specify one of the five climate hazard measures as *Event Exposure*, including *Top4Event*, *FEMADec*, *Extreme1*, *DMGPerCap*, and *Extreme2* and interact *Event Exposure* with *High Media Attention*. In Panel B, we replicate our specifications in Panel A by replacing *High Media Attention* with *High Google Trends*, with the latter indicating that a firm's aggregate search queries pertaining to the topic "Climate Change" are above the sample median during a particular year. All independent variables are lagged by one quarter. Control variables are the same as in Table 2 and are suppressed for brevity. See Appendix 1 for variable descriptions. Fixed effects pertaining to a firm's property type focus and time (year-quarter) are included in the regressions. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
RetRf (t+1)	*Base*	*Top4Event*	*FEMADec*	*Extreme1*	*DMGPerCap*	*Extreme2*
Event Exposure × High Media Attention		-0.958**	-2.249***	-1.730***	-0.735*	-1.359***
		(-2.47)	(-4.04)	(-3.26)	(-1.79)	(-3.33)
Event Exposure		-0.458	2.594**	0.557	-0.557	1.401
		(-0.66)	(2.02)	(0.44)	(-0.62)	(1.45)
High Media Attention	0.121*	0.432***	0.271***	0.277***	0.477**	0.323***
	(1.94)	(2.80)	(3.23)	(3.27)	(2.09)	(3.32)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prop FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.436	0.438	0.438	0.438	0.438	0.438
# Obs	9,491	9,491	9,491	9,491	9,491	9,491

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)
RetRf (t+1)	*Base*	*Top4Event*	*FEMADec*	*Extreme1*	*DMGPerCap*	*Extreme2*
Event Exposure × High Google Trends		-3.026***	-0.019	-3.403**	-2.603**	-3.662***
		(-3.16)	(-0.01)	(-2.15)	(-1.99)	(-2.70)
Event Exposure		0.861	-1.017	-0.039	1.733*	3.225**
		(0.67)	(-0.62)	(-0.02)	(1.68)	(2.47)
High Google Trends	-0.357	0.820*	-0.357	-0.057	1.141	0.195
	(-1.60)	(1.89)	(-1.19)	(-0.19)	(1.54)	(0.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prop FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.510	0.510	0.510	0.510	0.510	0.510
# Obs	6,022	6,022	6,022	6,022	6,022	6,022

Table 6: Panel Regression Results of Firm Value on Forward-Looking Climate Risk

This table shows the panel regression results on the relationship between REIT Tobin Q and alternative measures of projected climate risk exposure. Results are based on a quarterly sample of 1,733 firm-quarter observations from 2017-2019. *Q*, the quarterly REIT Tobin Q, is calculated as the market value of equity plus the book value of debt divided by the book value of assets. In columns (1)-(6), we specify one of the six projected climate risk exposures as *RISQ*, including *Base (EW)*, *10Y (EW)*, *30Y (EW)*, *Base (VW)*, *10Y (VW)*, and *30Y (VW)*. All independent variables are lagged by one quarter. Control variables are the same as in Table 2 and are suppressed for brevity. See Appendix 1 for variable descriptions. Fixed effects pertaining to a firm's property type focus and time (year-quarter) are included in the regressions. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Q (t+1)	(1) *Base (EW)*	(2) *10Y (EW)*	(3) *30Y (EW)*	(4) *Base (VW)*	(5) *10Y (VW)*	(6) *30Y (VW)*
RISQ	0.005	0.013	0.012	0.039	0.031	0.020
	(0.08)	(0.29)	(0.45)	(0.73)	(0.83)	(0.93)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prop FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.527	0.527	0.528	0.529	0.531	0.533
# Obs	1,733	1,733	1,733	1,733	1,733	1,733

Table 7: Regression Results of Firm Value on Forward-Looking Climate Risk Interacted with Media Attention

This table shows the panel regression results on the relationship between REIT Tobin Q and alternative measures of projected climate risk exposure interacted with local investors' attention to global warming. Results are based on a quarterly sample of 1,733 firm-quarter observations from 2017-2019. *Q*, the quarterly REIT Tobin Q, is calculated as the market value of equity plus the book value of debt divided by the book value of assets. In Panel A, column (1), we re-estimate our baseline specification with *High Media Attention*, which is the aggregate percentage of adults who hear about global warming in the media at least once a week across all counties in which a REIT owns properties. In columns (2)-(7), we specify one of the six projected climate risk exposures as *RISQ*, including *Base (EW)*, *10Y (EW)*, *30Y (EW)*, *Base (VW)*, *10Y (VW)*, and *30Y (VW)* and interact *RisQ* with *High Media Attention*. In Panel B, we replicate our specifications in Panel A by replacing *High Media Attention* with *High Google Trends*, with the latter indicating that a firm's aggregate search queries pertaining to the topic "Climate Change" are above the sample median during a particular year. All independent variables are lagged by one quarter. Control variables are the same as in Table 2 and are suppressed for brevity. See Appendix 1 for variable descriptions. Fixed effects pertaining to a firm's property type focus and time (year-quarter) are included in the regressions. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A

Q (t+1)	(1) *Attention*	(2) *Base (EW)*	(3) *10Y (EW)*	(4) *30Y (EW)*	(5) *Base (VW)*	(6) *10Y (VW)*	(7) *30Y (VW)*
RisQ × High Media Attention		-0.051**	-0.028***	-0.021***	-0.031*	-0.035**	-0.028***
		(-2.11)	(-2.80)	(-2.74)	(-1.81)	(-2.48)	(-2.99)
RisQ		0.041	0.051	0.051*	0.055	0.067*	0.054**
		(0.72)	(1.32)	(1.66)	(1.04)	(1.66)	(2.41)
High Media Attention	0.018	0.104**	0.071**	0.063***	0.072**	0.084***	0.078***
	(1.40)	(2.14)	(2.57)	(2.65)	(2.02)	(2.62)	(2.93)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prop FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.531	0.541	0.545	0.549	0.542	0.554	0.562
# Obs	1,733	1,733	1,733	1,733	1,733	1,733	1,733

Panel B

Q (t+1)	(1) *Attention*	(2) *Base (EW)*	(3) *10Y (EW)*	(4) *30Y (EW)*	(5) *Base (VW)*	(6) *10Y (VW)*	(7) *30Y (VW)*
RisQ × High Google Trends		-0.121***	-0.087***	-0.060***	-0.117***	-0.085***	-0.058***
		(-3.22)	(-3.95)	(-4.69)	(-3.31)	(-4.33)	(-5.66)
RisQ		0.051*	0.065***	0.053***	0.081***	0.084***	0.060***
		(1.86)	(3.25)	(4.31)	(3.07)	(4.71)	(6.62)
High Google Trends	0.051***	0.260***	0.227***	0.193***	0.254***	0.222***	0.187***
	(3.23)	(3.69)	(4.62)	(5.45)	(3.83)	(4.90)	(5.90)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prop FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.578	0.583	0.587	0.593	0.587	0.597	0.604
# Obs	1,733	1,733	1,733	1,733	1,733	1,733	1,733

Table 8: Regression Results of Ownership Percentages on Climate Risk

This table reports the event study results on the relationship between REIT ownership percentages and alternative measures of climate event exposure interacted with a dummy variable that indicates the post-disaster period. We focus on two quarters before to two quarters after a climate event. The dependent variable is the ownership percentages of retail investors in Panel A, non-block institutional investors in Panel B, and blockholders in Panel C, respectively. In columns (1)-(5), we specify one of the five climate hazard measures as *Event Exposure*, including *Top4Event*, *FEMADec*, *Extreme1*, *DMGPerCap*, and *Extreme2* and interact *Event Exposure* with *Post-Event*, which equals 1 for the disaster quarter and the two following quarters and 0 otherwise. Control variables are included and are suppressed for brevity. See Appendix 1 for variable descriptions. The property type focus times year-quarter fixed effects are included in the regressions. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Top4Event	(2) FEMADec	(3) Extreme1	(4) DMGPerCap	(5) Extreme2
Panel A: Retail Investors					
Post-Event × Event Exposure	-0.016***	-0.013**	-0.021**	-0.007	-0.018**
	(-4.06)	(-2.13)	(-2.30)	(-1.07)	(-2.35)
Event Exposure	0.160***	-0.025	0.004	0.086*	0.007
	(3.20)	(-0.69)	(0.08)	(1.85)	(0.18)
Post-Event	-0.002	-0.008***	-0.007***	-0.005	-0.006***
	(-1.18)	(-7.54)	(-5.07)	(-1.36)	(-3.91)
R-squared	0.628	0.621	0.621	0.623	0.621
Panel B: Blockholders					
Post-Event × Event Exposure	0.015***	0.013**	0.013*	0.014***	0.016***
	(4.10)	(2.13)	(1.78)	(3.03)	(2.74)
Event Exposure	-0.112***	-0.018	-0.003	-0.072***	-0.015
	(-3.50)	(-0.69)	(-0.13)	(-2.62)	(-0.70)
Post-Event	-0.002	0.004***	0.003***	-0.003	0.002
	(-0.91)	(4.04)	(3.00)	(-1.13)	(1.65)
R-squared	0.433	0.423	0.423	0.427	0.423
Panel C: Non-Block Institutional Investors					
Post-Event × Event Exposure	0.002	0.000	0.008	-0.007	0.002
	(0.43)	(0.04)	(1.41)	(-1.20)	(0.37)
Event Exposure	-0.048**	0.043**	-0.000	-0.014	0.008
	(-2.02)	(2.18)	(-0.01)	(-0.56)	(0.34)
Post-Event	0.004**	0.005***	0.004***	0.008**	0.004***
	(2.13)	(4.80)	(3.43)	(2.54)	(3.10)
R-squared	0.614	0.613	0.613	0.613	0.613

Table 9: Regression Results of Consumer Sentiment on Returns

This table reproduces the event study results in Table 4 for high- and low-sentiment groups. We focus on two quarters before to two quarters after a climate event. *RetRf*, the quarterly REIT excess returns, are calculated using the chain-linked monthly excess returns of firm *i* in quarter *t* in excess of the rate of return of 1-month Treasury bills. At the beginning of each quarter, we separate REITs into "high" sentiment firms and "low" sentiment firms by comparing the sentiment beta estimates with the sample median. Sentiment betas are estimated using rolling-window regressions of 60 months over a sample period that runs from January 1991 through December 2019. In columns (1)-(5), we specify one of the five climate hazard measures as *Event Exposure*, including *Top4Event* (*Top4*), *FEMADec* (*FEMA*), *Extreme1* (*X1*), *DMGPerCap* (*DMG*), and *Extreme2* (*X2*), and interact *Event Exposure* with *Post-Event*, which equals 1 for the disaster quarter and the two following quarters and 0 otherwise. See Appendix 1 for variable descriptions. The property type focus times year-quarter fixed effects are included in the regressions. The *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

RetRf	(1) High SENT *Top4*	(2) Low SENT *Top4*	(3) High SENT *FEMA*	(4) Low SENT *FEMA*	(5) High SENT *X1*	(6) Low SENT *X1*	(7) High SENT *DMG*	(8) Low SENT *DMG*	(9) High SENT *X2*	(10) Low SENT *X2*
Chi2: High - Low	chi2= 9.27***		chi2=1.82*		chi2=4.06***		chi2=7.22***		chi2=5.69***	
Post-Event × Event Exposure	-5.995***	-1.954**	-13.802***	-10.257***	-7.250***	-5.858**	-5.271***	-1.294	-10.969***	-6.045***
	(-5.54)	(-2.22)	(-7.87)	(-4.52)	(-3.07)	(-2.51)	(-3.77)	(-1.25)	(-5.11)	(-3.16)
Event Exposure	4.828***	0.135	8.291***	5.454***	5.379***	3.527**	4.399***	0.149	7.653***	5.078***
	(6.37)	(0.16)	(5.82)	(3.72)	(3.38)	(2.12)	(4.23)	(0.17)	(5.58)	(4.17)
PostEvent	2.736***	0.983**	1.307***	0.970***	0.990***	0.802***	3.188***	0.878	2.055***	1.169***
	(5.66)	(2.49)	(6.17)	(4.69)	(3.38)	(2.68)	(3.89)	(1.45)	(5.10)	(3.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prop # Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.135	0.148	0.136	0.150	0.134	0.148	0.135	0.148	0.136	0.149
# Obs	15,047	15,338	15,047	15,338	15,047	15,338	15,047	15,338	15,047	15,338

Appendix 1: Variable Definitions

Variable	Source	Definition
Dependent Variables		
RetRf$_{i,t}$	CRSP	The chain-linked monthly stock returns of firm *i* in period *t* in excess of the rate of return of 1-month Treasury bills
Q$_{i,t}$	Compustat	The market value of equity shares plus the book value of debt divided by the book value of assets
Event Exposure		
Top4Event$_{i,t}$	SHELDUS, S&P Global	The event exposure of a REIT portfolio to counties with any major climate events
FEMADec$_{i,t}$	SHELDUS, S&P Global	The event exposure of a REIT portfolio to counties that experienced high-impact events resulted in a Presidential Disaster Declaration (PDD)
Extreme1$_{i,t}$	SHELDUS, S&P Global	The event exposure of a REIT portfolio to counties with climate events that produced property damages more than two standard deviations greater than the county's long-run average damages associated with weather events
DMGPerCap$_{i,t}$	SHELDUS, S&P Global	The event exposure of a REIT portfolio to counties with non-zero property damages
Extreme2$_{i,t}$	SHELDUS, S&P Global	The event exposure of a REIT portfolio to counties with climate events that produced property damages that exceeded two standard deviations of the county's average damages from weather events that occurred in the preceding 10 ten years
RisQ		
Base	RisQ	(Equally- or value-weighted) near-term forward-looking climate risk
10Y	RisQ	(Equally- or value-weighted) 10-year forward-looking climate risk
30Y	RisQ	(Equally- or value-weighted) 30-year forward-looking climate risk
Channels		
Media Attention$_{i,t}$	Yale, S&P Global	The aggregate percentage of adults who hear about global warming in the media at least once a week across all counties in which a REIT owns properties
Google Trends$_{i,t}$	Google, S&P Global	A firm's aggregate search queries pertaining to the topic "Climate Change" during a particular year.
Ownership Percentages		
Block$_{i,t}$	Thomson Reuters	The ratio of the number of shares held by blockholders to the total number of shares outstanding. A blockholder is an institutional investor that block owns at least 5% of the common equity
Non-Block	Thomson Reuters	The ratio of the number of shares held by non-block institutional investors to the total number of shares outstanding
Retail	Thomson Reuters	The ratio of the number of shares held by retail investors to the total number of shares outstanding

Appendix 1 (cont')

Variable	Source	Definition
Control Variables		
$Size_{i,t}$	Compustat	The logarithm of the product of stock price and shares outstanding
$B/M_{i,t}$	Compustat	The ratio of book equity to market equity.
$Momentum_{i,t}$	CSRP	Cumulative stock returns over the past quarter (in percentage)
$Leverage_{i,t}$	Compustat	Sum of total long-term debt and debt in current liabilities divided by total assets
$Profitability_{i,t}$	Compustat	Revenues minus revenues minus cost of goods sold, interest expense, and selling, general, and administrative expense divided by the sum of book equity and minority interest at the end of the previous period (in percentage)
$Investment_{i,t}$		The percentage growth rate in non-cash assets of firm i during period t
$ILLIQ_{i,t}$	CRSP	The logarithm of the average Amihud (2002) daily volume price impact firm i during period t
$IVOL_{i,t}$	CRSP	The standard deviation of residuals of monthly Fama-French 3-factor-model regressions of daily stock returns (in percentage)
δ_i		Property type focus of the REIT in Fama–MacBeth cross-sectional regressions or firm fixed effects in panel regressions
θ_t		Time (year-quarter) fixed effects