

## **Physical climate risks and equity markets: a survey of empirical evidence**

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**POVZETEK:** Točno 47 raziskovalnih članek je pregledano, ki raziskuje učinek fizikalnih okoljskih težav na trge sodobnih akcij. Raziskava ukazuje, da so okoljske dogodki pomembni za vratke, volatilnost, korelacije in, če je manjši učinek, za likvidnost. Negativni učineki prevladajo, posebej za ekstremno toploto, tropske torklone, ščetine in opalbe. Učinek je raznolik v različnih področjih in se enačno prikazuje v podatkih o Združenih državah in akutnih dogodkih.

**METODA:** Raziskava je zgrajena na 47 raziskavah, ki se strinjajo, da so okoljske dogodki pomembni za trge sodobnih akcij. Metodologija vključuje analizo dogodkov in presek analiza, ki uporabljajo različne vrste okoljskih težav.

### **KLJUČNE UGOTOVITVE:**

- Okoljske dogodke imajo značilne učinek na vratke, volatilnost in korelacije sodobnih akcij.
- Negativni učineki prevladajo, posebej za ekstremno toploto, tropske torklone, ščetine in opalbe.
- Učinek je raznolik v različnih področjih in se enačno prikazuje v podatkih o Združenih državah in akutnih dogodkih.

**POMEN ZA TRGOVANJE:** Raziskava je pomembna za razumevanje učinkov fizikalnih okoljskih težav na trge sodobnih akcij. To vprašanje je ključno za razumevanje in upravljanje težav, ki jih prinašajo okoljske dogodki. To vprašanje je posebno pomembno za upravljane in regulirane entitete, ki morajo razumevati in upravljati težave, ki jih prinašajo okoljske dogodki.

# Physical climate risks and equity markets: a survey of empirical evidence

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## ABSTRACT

This paper reviews the empirical finance literature on the effects of realized physical climate hazards on equity markets. Synthesizing evidence from 47 studies, it shows that climate-related events have significant impacts on stock returns, volatility, correlations, and, to a lesser extent, liquidity. From an investor perspective, negative effects dominate, particularly for extreme heat, tropical cyclones, droughts, and wildfires, but positive abnormal returns arise in specific sectors and contexts. The review documents substantial heterogeneity across hazards, regions, and firm characteristics, as well as a pronounced bias toward United States data and acute events. Finally, the paper discusses how these results on realized climate-related events can inform and enhance forward-looking frameworks for managing climate risks.

*JEL classification:* G122, G14, G54, G32

*Keywords:* Climate finance; Physical climate risk; Extreme weather events; Equity markets; Asset pricing; Event studies

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# 1 Introduction

Physical manifestations of climate change—such as rising temperatures, sea-level rise, and the growing frequency of extreme weather events—are increasingly recognized as potential sources of financial instability (Carney, 2015; Bolton et al., 2020). Despite escalating geopolitical tensions, “extreme weather events” are still identified as the second most probable risk to precipitate a material crisis on a global scale and are regarded as the most severe perceived risk over a longer horizon (World Economic Forum, 2025). While these hazards do not necessarily pose an immediate systemic financial threat, their cumulative and correlated effects across sectors, regions, and asset classes may amplify existing vulnerabilities within the financial system (Battiston et al., 2017; Dafermos et al., 2018; Kruttli et al., 2025). From a financial perspective, understanding how physical climate risks affect asset valuations is therefore critical for both investors and regulators. In this paper, we review and synthesize the existing literature to assess how financial markets react to different types of climate-related events.

From a regulatory standpoint, the integration of climate risk into financial decision-making has become a formal requirement. Climate-related financial risks are commonly divided into transition risks and physical risks. Transition risks arise from policy, technological, and market changes associated with decarbonization, including carbon pricing, regulatory constraints, and asset stranding in carbon-intensive sectors (Krueger et al., 2020; Bolton et al., 2022). Physical risks, by contrast, stem from the direct material impacts of climate change on economic activity, asset values, and financial stability. The recommendations of the Task Force on Climate-related Financial Disclosures (FSB, 2017) and the recent adoption of sustainability reporting standards by the International Sustainability Standards Board (ISSB, 2023) have made the identification and disclosure of physical climate risks mandatory for asset owners and managers. Within the European Union, regulations such as the sustainable finance disclosure regulation and the corporate sustainability reporting directive, together with climate stress-testing exercises, have further reinforced the need to assess exposure and sensitivity to climate hazards (ECB, 2022). As a result, understanding how physical risks translate into financial valuations has become both a fiduciary and a regulatory imperative.

Asset pricing theory suggests that exposure to physical climate hazards should affect firm value through fundamental cash-flow and financing channels. By damaging physical capital, disrupting production processes, and interrupting transportation and supply networks, adverse climate events directly affect revenues and costs, with potential spillovers to customers and upstream suppliers (Barrot and Sauvagnat, 2016). Repeated or severe events may further raise insurance premia, reduce coverage availability, accelerate asset depreciation, and constrain external financing. From a standard asset-pricing perspective, these effects should lead to downward revisions of expected cash flows and potentially to higher required returns.

However, whether these theoretical mechanisms are reflected in observed asset prices remains an open question. Physical climate risk is heterogeneous across hazard types, regions, exposure profiles, and time horizons, with potentially offsetting effects on cash-flow and discount-rates. In practice, investors may anticipate damages, diversify exposures, rely on insurance, or respond behaviourally to salient events, complicating the mapping from physical risk to realized returns. This raises several core questions that motivate this review: Which types of physical climate hazards are associated with significant stock-market reactions? How do these reactions vary across regions, sectors, and empirical designs? And to what extent do observed market responses align with the transmission channels emphasized in asset-pricing theory?

This paper addresses these questions by focusing explicitly on realized market responses to physical climate hazards. To do so, we review the empirical finance literature examining how equity markets react to physical climate risks. Related contributions include [Giglio et al. \(2021\)](#) and [Campiglio et al. \(2023\)](#), which provide broad syntheses of climate risk in asset pricing and financial stability. While these studies integrate both approaches based on realized events and forward-looking scenario-based approaches, their emphasis on modelled projections leaves the empirical evidence on *realized* physical impacts in equity markets relatively dispersed. We fill this gap by systematically synthesizing event-study and cross-sectional analyses that exploit variation in firms' exposure to acute and chronic climate-related hazards. By emphasizing realized events rather than modelled scenarios, this review provides a benchmark for the frequency, magnitude, and concentration of physical risk exposures across listed firms, offering a complementary perspective to forward-looking climate-finance frameworks.

The review delivers two central findings. First, realized physical climate events significantly affect equity markets across regions and empirical designs, with effects that are predominantly negative from the investor perspective. However, this aggregate result masks substantial heterogeneity across hazard types. Multiple-hazard studies are consistently associated with negative abnormal returns in both the United States and the rest of the world. Temperature-related hazards exhibit asymmetric effects: extreme heat is predominantly associated with negative market reactions, whereas evidence for extreme cold is mixed. Wind-related hazards show the strongest and most consistent effects, with tropical cyclones and tornadoes generating large and statistically significant negative impacts, while other storm events yield less clear-cut results. Evidence on wet and dry hazards remains comparatively sparse; nonetheless, floods and droughts are generally associated with negative stock market responses, whereas wildfire-related effects are mixed. Beyond returns, a growing body of studies documents higher volatility, stronger comovement, and, in fewer cases, reduced liquidity following physical climate events. The sign and persistence of market reactions depend critically on hazard type, geographic exposure, sectoral characteristics, and firm-level attributes such as diversification, carbon intensity, and environmental performance.

Second, the literature reveals a systematic mismatch between the economic relevance of certain hazards and regions and their academic coverage, pointing to important blind spots—particularly for chronic risks, emerging economies, and non-return dimensions of financial risk. By organizing more than 700 results across 47 studies within a coherent framework, this review clarifies what can—and cannot—be inferred from historical market reactions and highlights how real-world evidence complements forward-looking climate-finance assessments.

The rest of the paper is organized as follows. Section 2 introduces the conceptual framework, listing the different types of physical risk and describing the theoretical channels through which they may affect financial assets. Section 3 illustrates the scope of this review and the approach used. Section 4 provides an in-depth analysis concerning the evolution of the literature, its geographic and time coverage, and the methods used, dedicating a brief section for each one of the latter. Section 5 reviews the empirical evidence from equity markets, highlighting common findings and differences across existing studies. This is the core section of the paper and can be read independently by readers who wish to abstract from ancillary details. Section 6 discusses the results and summarizes the main takeaways. Section 7 concludes, providing suggestions for future research.

## **2 Conceptual foundations: physical climate hazards and financial transmission channels**

Climate is conceptualised as the coupled dynamics of the atmosphere, ocean, cryosphere, land surface and biosphere. Formally, it is characterised by the statistical distribution of key physical variables—such as temperature, precipitation, wind, humidity, sea level—evaluated over multi-decadal time horizons. Certain hazards, such as hail or convective storms, may involve multiple physical mechanisms spanning both precipitation- and wind-related processes. These dynamics and their long-run patterns—whether observed historically or anticipated in projections—can affect equity markets through shifts in expected cash flows and the stochastic discount factor.

### **2.1 Defining physical risk and its drivers**

According to the Intergovernmental Panel on Climate Change (IPCC), physical climate risk emerges from the interaction among (i) climate-related hazards, (ii) the exposure of human and ecological systems, and (iii) their vulnerability (Ara Begum et al., 2022). Hazards are defined as the potential occurrence of natural or anthropogenically induced physical events or trends that may lead to loss of life, injury, environmental degradation or economic disruption. Exposure denotes the presence of assets in locations where they may be adversely affected by

such hazards.<sup>1</sup> Vulnerability reflects the propensity of these exposed assets to experience harm, determined by their sensitivity and adaptive capacity. Finally, impacts are the realised outcomes of this interaction, and can be either detrimental or beneficial. This conceptual disaggregation is useful for interpreting empirical studies, as individual contributions may focus on the marginal effects of any one of these three components.

Financial regulators distinguish climate physical risks as either acute or chronic (FSB, 2017; ISSB, 2023; ECB, 2022): acute risks are linked to short-duration, high-intensity events such as tropical cyclones, riverine flooding or severe storms, whereas chronic risks arise from enduring changes in the average state of the climate system, including long-term warming, sea-level rise or shifts in mean precipitation. There is, however, less guidance on the more detailed list of hazards or climate-trend indicators that financial institutions should use within these broad groups. The Emergency Events Database (EM-DAT)—which is widely employed in the reviewed articles—defines natural disaster subtypes organized into geophysical, meteorological, hydrological and climatological classes. Yet this taxonomy focuses solely on acute disaster events and does not encompass slow-onset climatic changes. To address this gap, and to foster a tighter integration between climate science and finance, this paper uses a classification closely related to the climatic impact drivers proposed by the IPCC. When reorganized according to the acute–chronic distinction and mapped onto EM-DAT hazard families, climate impact drivers can function as a bridge between the scientific, regulatory, and empirical classification systems (Table B.1).

A further distinction of direct importance is that between climate risk and climate *change* risk. Climate risk refers to the cross-sectional distribution of climate-related hazards and variability under approximately stationary, current climatic conditions. By contrast, climate change risk originates from the non-stationarity of the climate system itself: persistent shifts in the mean state of key physical variables redefine both expected event frequencies and intensity. The empirical analysis conducted by Hong et al. (2019) exemplifies this distinction between climate and climate change. Their study analyses the relationship between droughts and the financial performance of firms operating in the agricultural sector, using a drought index. Instead of focusing on drought events per se—i.e., short-term fluctuations in the index—the authors examine the long-run trend component of the index over several decades to capture the climate *change* risk associated with droughts.

## 2.2 Observed trends and projections of physical risk

Climate-related hazards examined in the literature exhibit distinct statistical properties under current climatic conditions. Based on EM-DAT, Table 1 summarises these contrasts for acute

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<sup>1</sup>The Intergovernmental Panel on Climate Change (IPCC) adopts a broad notion of assets, including physical capital, ecosystems, human populations, infrastructure networks and productive systems.

hazards. First, the occurrence and characteristics of hazards are highly region-dependent. In particular, low-latitude regions closer to the equator are generally characterized by greater exposure to high-temperature conditions and heat stress. At the same time, extreme heat events such as heatwaves are defined relative to local climatic baselines, although their frequency and intensity are projected to increase across most regions under continued global warming. Second, average duration and frequency differ substantially across hazard types. For example, droughts may persist for several months or even multiple years, whereas tornadoes are typically confined to few hours; however, they affect the United States extremely often (more than 24,000 times annually compared to approximately 50 for hurricanes). These temporal characteristics shape the choice of the empirical methods used for assessing their effects on the stock market: event-study designs may for example be appropriate for short-lived, high-intensity phenomena, but they are less inadequate for longer-lasting events.

[Table 1 here](#)

In addition to the current characteristics of climate hazards, some climate impact-drivers characteristics—such as their frequency or intensity—have already shifted due to anthropogenic forcing or will evolve in the future. Yet both observed trends and projected changes differ substantially across drivers and regions. Key state variables associated with chronic risks exhibit robust and often monotonic trends under all warming scenarios ([Table 2](#)). Global mean surface temperature has increased by approximately 1.1°C between 1850 and 1900 and exceeds 4.0°C in several end-century projections. Ocean heat content, which measures the thermal energy accumulated in ocean waters, has risen steadily over recent decades. This heat uptake, combined with ice-sheet mass loss, drives a sustained increase in global mean sea level, rising 0.20 m over 1901–2018, with rates accelerating (from 1.3 mm per year between 1901 and 1971, to 3.7 mm per year between 2006 and 2018). Ocean acidification has also intensified everywhere ([IPCC, 2021](#)).

[Table 2 here](#)

These chronic changes underpin a first group of acute hazards whose trends are highly robust. Temperature extremes show virtually certain increases in the frequency and intensity of hot extremes and simultaneous declines in cold extremes across most land regions ([IPCC, 2021](#)). Coastal flooding and coastal erosion intensify in all coastal regions due to sea-level rise alone, with historical 1-in-100-year extreme sea-level events projected to occur annually in many regions by 2100. Agricultural and ecological droughts<sup>2</sup> have increased in many regions since the

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<sup>2</sup>Following the IPCC AR6 glossary framework, droughts may be distinguished according to the affected com-

mid-20th century (medium confidence), and are projected to intensify across most continents under high-warming levels (medium to high confidence) (Seneviratne et al., 2021). Hydrological droughts also show increasing trends in regions such as the Mediterranean, parts of Africa, and western North America (medium to high confidence), with further widespread increases expected under high global warming scenarios. By contrast, hazards governed mainly by humidity or wind—heavy convective storms, tornadoes, hail, tropical cyclones and extratropical cyclones—display greater regional heterogeneity and substantially lower confidence in both observed and projected trends. Heavy precipitation extremes have increased over most land areas (IPCC, 2021), yet attribution of changes in cyclone frequency, intensity, or storm-track structure remains basin-specific, with global-scale projections still assessed with medium to low confidence (Seneviratne et al., 2021). This heterogeneity in hazard persistence, regional exposure, and confidence levels is central for financial markets, as it shapes both the predictability and the magnitude of potential economic damages that firms and investors may face.

### 2.3 Transmission channels from physical climate hazards to stock prices

Standard return-decomposition approaches (Campbell and Shiller, 1988) and recent models that embed climate dynamics into equilibrium asset-pricing frameworks (Pástor et al., 2021; Giglio et al., 2021) highlight two conceptually distinct mechanisms through which physical climate hazards can affect asset valuations: revisions in expected future cash flows and discount rates. Table 3 offers a summary of the various channels.

Climate hazards and climate change can affect expected cash flows through the macroeconomic environment as well as via firm-specific transmission channels (Campiglio et al., 2023).

At the macroeconomic level, physical climate hazards can reduce aggregate productive capacity by lowering labour productivity, constraining the utilisation of physical capital, and damaging critical infrastructure on a scale sufficient to influence sectoral and regional output. Climate hazards may also modify relative input prices: heat stress, water scarcity, and drought can amplify the volatility of energy, water, and agricultural commodity prices. Finally, as households and firms adapt to evolving climatic conditions, sectoral demand patterns and the spatial distribution of economic activity may be reallocated.

Firm specificities might mitigate or exacerbate these macro dynamics. Acute events such as hurricanes, floods, and wildfires might destroy firm physical assets, disrupt its production processes, and cause unplanned operational downtime (Addoum et al., 2023). Over longer horizons,

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ponent of the Earth system, including meteorological drought (persistent precipitation deficits), agricultural and ecological drought (soil-moisture deficits affecting crop production or ecosystem functioning), and hydrological drought (abnormally low surface or subsurface water availability).

chronic climatic shifts, including rising sea levels or persistent heat, may accelerate asset depreciation, necessitate costly adaptation investments, and increase ongoing maintenance expenditures (Kling et al., 2021). In addition to these direct impacts, physical risks can propagate through firm supply chains and market access channels. Extreme weather events can damage transport networks, incapacitate critical suppliers, thereby amplifying revenue volatility and exposing firms to second-order shocks (Barrot and Sauvagnat, 2016). Furthermore, as physical risks become more frequent or severe, insurance markets respond with higher premia, reduced coverage availability, or increased self-insurance requirements. These changes can raise firms' cost of capital and, through liability-side deterioration, exacerbate financing constraints (Batten et al., 2020; Bank for International Settlements, 2021). Finally, information dynamics play a crucial role: new data on climate exposure, adaptation strategies, or resilience plans can prompt investors to revise expectations about future cash flows and asset valuations (Sautner et al., 2023).

The mechanisms above operate through revisions in expected future cash flows. However, changes in expected cash flows alone do not determine equilibrium prices. A climate risk premium arises only if climate-related cash-flow realizations covary with investors' marginal utility, that is, if physical climate risks load on non-diversifiable aggregate sources of risk. This leads to the second transmission channel: revisions in discount rates. When climate-related hazards tend to impact firms in macroeconomic states that investors particularly care about (such as recessions), the asset's systematic risk profile is modified and its required return adjusts accordingly (assets providing insurance against aggregate downturns will typically have lower discount rates). Depending on whether climate-related payoffs covary more strongly with favourable or adverse aggregate states, the resulting climate premium may be positive or negative (Giglio et al., 2021). On the one hand, acute events typically prompt rapid adjustments in short-horizon discount rates as investors reassess near-term risk and liquidity conditions. On the other hand, longer-horizon discount rates can also evolve when chronic climate dynamics shape expectations about aggregate productivity or consumption growth.

[Table 3 here](#)

### 3 Review scope and methodology

The literature on financial climate risk can be divided into two major analytical approaches: forward-looking approaches and approaches based on realized events (Campiglio et al., 2023). Forward-looking approaches include model-based projections of macroeconomic and financial impacts under alternative climate pathways, resulting in climate scenarios or stress tests. Central banks and financial regulators have increasingly adopted this approach, exemplified by the

Network for Greening the Financial System (NGFS). Forward-looking methods often rely first on the outputs of climate integrated assessment models coupled with asset pricing models to quantify potential valuation impacts over multi-decade horizons (Dietz et al., 2021). Approaches based on realized events, by contrast, focus on historical climate-related hazards and their observed effects on financial markets. This review concentrates on the latter, to provide a solid primary informational basis for prospective assessments.

### 3.1 Search and inclusion strategy

The literature search followed a two-stage strategy. First, climate-related search terms were derived from the IPCC climate impact-drivers taxonomy and from an initial exploratory review of the empirical finance literature, while the equity-market terminology was iteratively refined after examining the first set of retrieved articles. The search strategy explicitly included terms associated with both acute hazards and chronic physical risks, including “physical climate risk”, “climate risk”, “temperature anomaly”, “precipitation”, “drought”, “sea level”, and “heat stress”. The final search query returned 357 articles classified under Economics, Econometrics and Finance.<sup>3</sup>

Second, titles and abstracts were systematically screened to exclude studies that did not analyse realised impacts of climate-related events on equity markets, resulting in a group of 35 suitable articles. A subsequent citation search based on these papers yielded additional relevant studies (often appearing in journals not indexed under finance), which led to a final corpus of 47 articles, including 4 working papers (see Table A.1). Figure 1 summarizes the literature search and article selection procedure.

### 3.2 Extraction and classification of results

Table A.1, which is placed in the section A for reasons of space, summarizes the result of the literature review, ordered by publication year. For each paper, it reports the type of hazard analysed, the geographical region and the time period considered, the methodological approach adopted, and the financial variable analysed, together with the main findings and the direction (sign) of the impact of climate-related events investigated.

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<sup>3</sup>Search conducted in Scopus as of October 2025, with the following query: "TITLE-ABS-KEY ( ( "extreme weather\*" OR ( climat\* W/2 physical W/2 risk\* ) OR ( physical W/2 climat\* W/2 risk\* ) OR "climate risk" OR "temperature extreme\*" OR "temperature shock\*" OR "temperature anomal\*" OR storm\* OR cyclon\* OR hurricane\* OR tornado\* OR flood\* OR wildfire\* OR bushfire\* OR "natural disaster\*" OR "climate disaster\*" OR "natural catastroph\*" OR precipitation\* OR drought\* OR ( "sea" W/2 level\* ) OR ( "heat" W/2 stress\* ) ) AND ( ( ( stock\* OR equity\* ) W/2 ( market\* OR return\* OR price\* OR volatilit\* OR performance ) ) OR ( cost W/2 capital\* ) OR ( cost W/2 equity\* ) ) ) AND ( LIMIT-TO ( SUBJAREA , "ECON" ) ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) )".

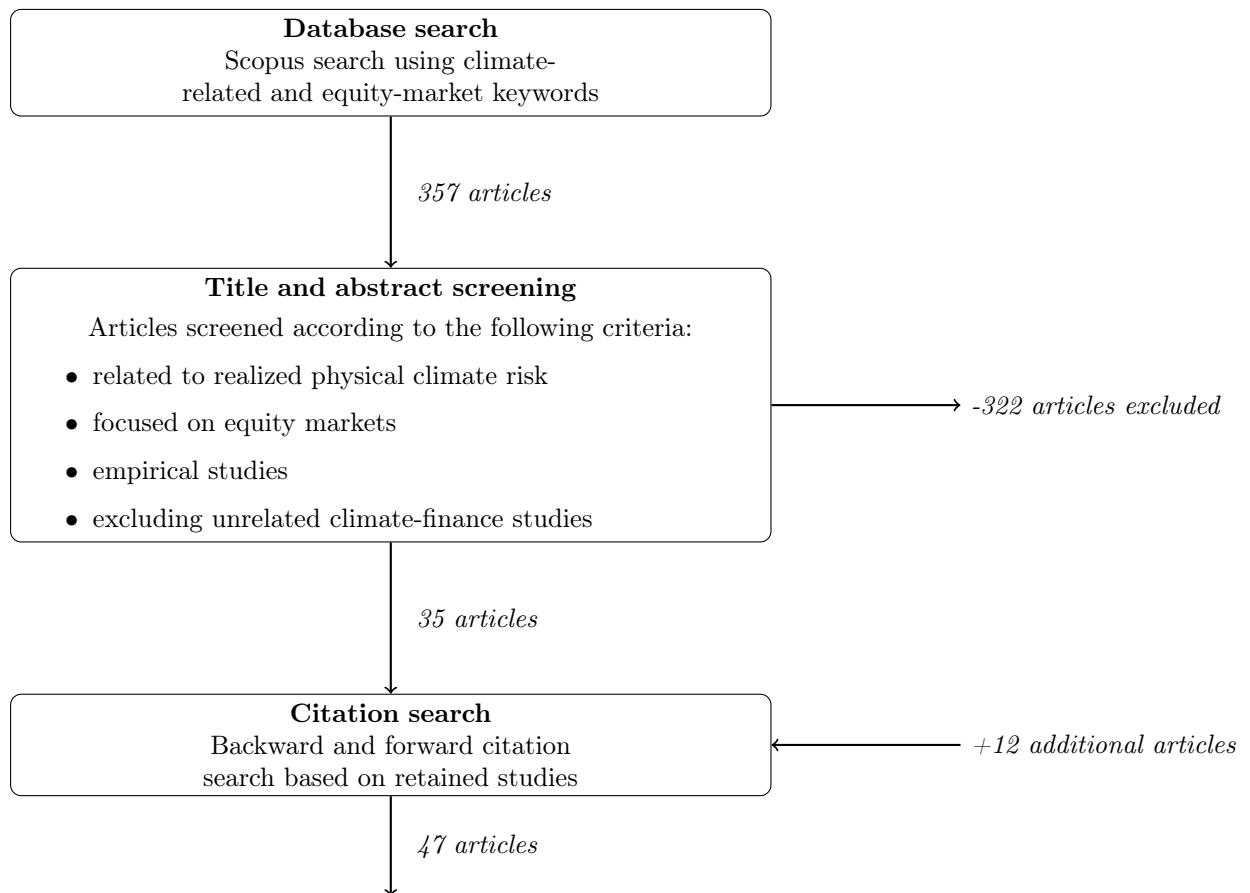


Figure 1: Literature search and article selection process.

The summary of findings corresponds to the perspective of an investor holding an asset exposed to physical climate risk *ex-ante*, such that an increase in returns is interpreted as a favourable outcome. Although, a rise in the required cost of capital is economically adverse from the firm’s perspective, we consistently adopt the investor viewpoint throughout the review. In cases where a study conducts multiple empirical exercises yielding conflicting results (for instance, [Huynh and Xia \(2023\)](#) document that firms exposed to disasters experience lower contemporaneous returns but higher future returns), we classify the overall effect as positive (negative) if the majority of reported results are positive (negative), and as “mixed” when the direction of the net effect is not evident or when positive and negative findings appear to offset each other to a substantial degree. Secondary analyses, alternative specifications, and robustness checks are not included in the key results unless they produce meaningfully novel insights.

### 3.3 Limitations of the evidence base

This review process is subject to several limitations that are important to acknowledge. First, the analysis focuses exclusively on a single asset class—equities—which inherently constrains the external validity and generalizability of the findings. Market responses to physical climate risks may vary substantially across different asset classes, and extending the scope beyond equities would likely introduce additional dimensions of heterogeneity. Second, the review is restricted to physical climate risks and does not consider non-climate-related natural hazards (e.g., earthquakes), nor does it incorporate transition or policy-related climate risks. This exclusion reflects a deliberate decision aimed at preserving comparability. Third, the review concentrates on realized manifestations of climate change, rather than on expectations, projections, or model-based forecasts, thus prioritizing empirical, real-world observations over simulated outcomes. Also, while insurance protection constitutes an important channel through which climate-related losses may be redistributed, this review focuses specifically on studies examining the impact of physical climate risk on stock market valuations rather than on the effectiveness of insurance systems themselves. Finally, as with any literature review, the analysis is constrained by the timing of publication. It is possible that relevant studies are still unpublished at the time of writing and are consequently not incorporated into this synthesis.

## 4 Empirical research designs in the literature

The literature examining the impact of realized climate-related events on stock markets emerged in the late 1990s and has accelerated markedly in recent years. The majority of these studies focus on the United States, with hurricanes constituting the most extensively analysed hazard.

Event-study of abnormal stock returns remain the predominant methodological design, although it has progressively been complemented by more sophisticated techniques.

#### 4.1 Literature evolution over time

The earliest article in our selection was published in 1995 ([Lamb, 1995](#)), whereas the most recent contributions date from 2025 (e.g. [Kruttli et al., 2025](#)). The pronounced upward trend in the number of publications seems to indicate that growing societal concern about climate change is increasingly mirrored in academic research. This pattern is particularly evident from 2019 onwards, when at least three papers were published each year, culminating in eight publications in 2025.

[Figure 1](#) here

An examination of the keywords provided by the authors indicates that climate-related hazards are predominantly conceptualized within the broader category of “natural disasters”, and that specific types of events, such as “hurricanes”, have received particular attention ([Figure 2](#)). A further relevant group of keywords reflects the empirical methods most employed: event-study designs are the most frequently adopted, as discussed below. In addition, generalized autoregressive conditional heteroscedasticity (GARCH) models are also relatively popular. Finally, recurrent keywords concern the variables analysed, with stock returns and the cost of capital being the most commonly investigated.

[Figure 2](#) here

#### 4.2 Geographic, temporal, and hazard coverage of the samples used

The classification of studies by region and hazard type discussed in this section is based on the final corpus summarized in [Table A.1](#).

The geographical scope of the empirical samples used in the literature is heavily concentrated on the United States, which is the focus of 34 studies (e.g. [Kruttli et al., 2025](#)). The European region has attracted substantially less attention, with only 4 publications covering the European Union ([Bauer et al., 2024](#); [Schuster et al., 2025](#)), France ([Peillex et al., 2021](#)), and the United Kingdom ([Panetsidou and Synapis, 2025](#)), while Australia is examined in 3 studies (e.g. [Worthington, 2008](#)). The Asian and African regions are markedly under-represented, with only a single study

focusing on Japan (Wang and Kutan, 2013). Finally, seven studies adopt a multi-regional approach, comparing different geographical areas (e.g. Pagnottoni et al., 2022).

On the time dimension, the mean temporal coverage of the samples used in the literature is 22 years. However, there is considerable heterogeneity in these windows: nine studies analyse data spanning fewer than 10 years, whereas only two studies encompass periods exceeding 50 years (Figure 3).

Figure 3 here

The reviewed publications encompass 14 distinct categories of climate hazards: temperature shocks, extreme cold, extreme heat, tropical cyclones (hurricanes), tornadoes, winter storms, other storms (e.g., hailstorms), floods, droughts, wildfires, as well as multiple-hazard studies and information signals related to weather alerts or heightened weather attention. Most studies focus either on hurricanes (19 papers, e.g. Schuh and Jaeckle, 2023) or on multiple hazards (14 papers, e.g. Xu et al., 2025), with the latter category frequently including hurricanes among the phenomena under analysis. Overall, wind-related hazards receive considerably more attention than other categories of events.

Figure 4 here

### 4.3 Financial variables and empirical models

Existing studies focus mainly on stock market (abnormal) returns, while volatility, correlation, and liquidity have received far less attention. To evaluate the impact of climate-related hazards, a broad spectrum of empirical modelling frameworks are used, ranging from event-study to more advanced econometric approaches.

Twenty-five studies analyse abnormal returns as the main outcome variable. Because abnormal returns are realized returns in excess of those predicted by a benchmark factor model, their prevalence reflects the dominance of event-study methods. These abnormal returns are also often used as dependent variables in panel regressions. The second most common outcome is (raw) returns, including excess returns over the risk-free rate, examined in 19 studies and encompassing various settings: GARCH models, multi-factor asset-pricing models, and portfolio-sorting approaches. Regarding the risk dimension of stock markets, only 8 studies analyse the impact of climate-related events on return volatility and 3 on correlations or comovements. Other financial variables such as bid-ask spreads, trading volume, and (il)liquidity appear each in only one

study. Regarding the aggregation level, the reviewed literature is relatively balanced: 24 studies use portfolio-level analyses, 25 use security-level analyses, and 2 combine both approaches.

Event-studies constitute the most commonly applied approach to assess the effects of climate-related hazards, employed in 21 cases. Time-series econometric models, such as GARCH and its extensions, are also frequently utilised (12 cases), as are panel regression frameworks (13 cases). In addition, 6 studies rely on differences in means ( $t$ -tests), primarily in conjunction with portfolio sorts (4 studies), and cross-sectional regression analyses (5 studies). More traditional factor-model specifications (e.g. [Fama and French \(1993, 2015\)](#)) are implemented in 4 cases, whereas single-equation time-series regressions (not explicitly formulated in terms of risk factors) appear in 3 studies. Mimicking-portfolio approaches (e.g. [Breedon et al. \(1989\)](#); [Lamont \(2001\)](#)) are used in 2 studies. Finally, we identify 2 applications of two-stage least squares (instrumental-variable estimation) and 2 applications of difference-in-differences designs ([Alok et al., 2020](#); [Krutli et al., 2025](#)). The following subsections explain how each method is used in climate-related analysis, the methods being presented in order of increasing complexity and typical dependence.

#### 4.3.1 Difference in means

The most elementary model-free procedure for assessing the impact of climate-related variables across groups is the test for difference in means, commonly implemented as Welch’s  $t$ -test ([Welch, 1947](#)). The  $t$ -statistic is computed as

$$t = \frac{\bar{r}_1 - \bar{r}_2}{\sqrt{\sigma_1^2/N_1 + \sigma_2^2/N_2}},$$

where  $\bar{r}_1$  ( $\bar{r}_2$ ) denotes the sample mean return of the first (second) group,  $\sigma_1^2$  ( $\sigma_2^2$ ) the corresponding sample variance, and  $N_1$  ( $N_2$ ) the group sample size. Under the null hypothesis of equal means, the statistic follows a Student  $t$  distribution with degrees of freedom that depend on the sample variances and sample sizes.

Using this test, [Peillex et al. \(2021\)](#) compares trading volumes on the French stock market between the hottest days (top temperature quartile) and cooler days to examine whether elevated temperatures reduce trading activity. Moreover,  $t$ -tests are widely employed to assess the average returns of portfolios constructed by sorting assets according to a particular characteristic, as well as for evaluating the performance of mimicking portfolios, as detailed below.

### 4.3.2 Portfolio sorts

Another model-free approach is based on portfolio sorting, where stocks are grouped according to a characteristic of interest (e.g. per decile). In the context of climate-related events, [Xu et al. \(2025\)](#) construct for example portfolios of highly exposed and non-exposed stocks using a climate risk index corresponding to the climate risk of the country in which each firm is located, and then compare the performance of these portfolios. Differences in performance are formally assessed using  $t$ -tests for differences in mean returns. Other studies employ more traditional sorts based on firm characteristics such as value or momentum ([Lanfear et al., 2019](#)), in order to identify which attributes are more sensitive to climate-related events.

Portfolio sorts are straightforward to implement, but they exhibit some limitations: for a given cross-section of assets, they can accommodate only a small number of sorting dimensions (typically no more than two or three) before becoming infeasible ([Fama and French, 2015](#)). Moreover, they approximate the underlying relationship of interest with a coarse, step-wise function, which may hinder their ability to accurately capture behaviour in the tails of the distribution ([Fama and French, 2008](#)).

### 4.3.3 Factor models

Linear factor models are widely used in empirical asset pricing to study whether exposure to systematic sources of risk explains the cross-section of expected returns (e.g. [Fama and French \(1993, 2015\)](#)). A standard time-series specification is

$$r_{i,t} = \alpha_i + \sum_{k=1}^K \beta_{i,k} f_{k,t} + \varepsilon_{i,t} \quad (1)$$

where  $r_{i,t}$  denotes the return of asset  $i$  at time  $t$  (or the return in excess of the risk-free rate),  $f_{k,t}$  is the return of risk factor  $k$  at time  $t$  with corresponding factor loadings  $\beta_{i,k}$  (assumed time-independent for simplicity) and  $\varepsilon_{i,t}$  is the error term such that  $\mathbb{E}[\varepsilon_{i,t}] = \mathbb{E}[\varepsilon_{i,t} f_{k,t}] = 0 \forall k = 1, \dots, K$ .

In time-series regressions, the intercept  $\alpha_i$  measures the average abnormal return unexplained by the factor exposures and is often interpreted as a pricing error under the maintained factor specification.<sup>4</sup> If the factor model fully explains expected returns,  $\alpha_i$  should not be statistically different from zero.

Depending on the research question, factor models are used in different ways. In their standard

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<sup>4</sup>In this review, we distinguish factor models from time-series regressions to stress whenever regressions do not contain classical factor returns on the right-hand side.

time-series implementation, as in [Fama and French \(1993\)](#), the factors are taken as given and Eq. (1) is estimated separately for each asset or portfolio to obtain factor loadings and abnormal returns. This approach is useful for assessing whether a set of factors explains the time-series variation in returns, or whether a portfolio earns an alpha relative to a benchmark model.

When the objective is instead to estimate the compensation investors require for bearing exposure to a given factor, the analysis moves to a cross-sectional asset-pricing test. In that case, estimated factor loadings are used to infer factor risk premia, such as in Fama–MacBeth regressions ([Fama and MacBeth, 1973](#)). In climate-finance applications, climate-related variables can therefore enter either as additional factors in time-series benchmark models to capture exposure to disaster frequency, weather variability, or physical risk (e.g. [Bolton and Kacperczyk \(2021\)](#)), or as sources of priced risk whose premia are estimated in the cross-section (e.g. [Gregory \(2021\)](#)).

Factor models have a long tradition in asset pricing and benefit from extensive work on their estimation and use. A drawback is that noisy data (e.g., at the stock level) can yield imprecise estimates, and including many regressors risks multicollinearity.

#### 4.3.4 Mimicking portfolios

The mimicking portfolio method ([Breedon et al., 1989](#); [Lamont, 2001](#)) constructs a traded portfolio whose returns mimic the behaviour of a non-traded economic variable. The approach consists in regressing the target (non-traded) variable on a set of traded asset returns. The resulting regression coefficients define portfolio weights that produce a return series tracking the target variable as closely as possible. More explicitly, start from the regression (e.g. [Ang et al. \(2006\)](#)):

$$\Delta z_t^{NONTRAD} = a + \sum_{j=1}^N r_{j,t}^{TRAD} b_j + X_t + u_t$$

where  $\Delta z_t^{NONTRAD}$  represent innovations in a non-traded variable  $z$ ,  $r_{j,t}^{TRAD}$  is the time  $t$  return of traded asset  $j$ , for  $j = 1, \dots, N$  which represent the base assets,  $X_t$  is a vector of (optional) controls that depends on the application, and  $u_t$  is the error term. The mimicking portfolio is  $\sum_{j=1}^N r_{j,t}^{TRAD} \hat{b}_j$  where  $\hat{b}_j$  is the estimated ordinary least square coefficient. This allows researchers to estimate risk premia and test asset-pricing models using observable market data even when the underlying state variable is not directly traded. Then, similarly to any other factor, one can evaluate the significance of the risk premium of the the mimicking portfolio, or assess whether it is spanned by other known risk factors.

Examples of climate mimicking portfolios are given by [Balvers et al. \(2017\)](#) and [Gregory \(2021\)](#), who build a temperature shock factor by projecting a time-series of temperature on [Fama and](#)

French (2015) factors plus momentum (Carhart, 1997) or on industry portfolios.

#### 4.3.5 Event studies

Event studies remain the predominant empirical approach for assessing the short-term financial effects of physical climate shocks, following the methodology established by Fama et al. (1969), refined by Brown and Warner (1985), and formalized by MacKinlay (1997). These models estimate abnormal returns, i.e., deviations from expected returns, around the occurrence of an event, using an estimation window to calibrate expected returns and an event window to capture market reactions. More formally, let us first denote with  $AR_{i,t}$  the abnormal return of asset  $i$  at time  $t$ , computed as the return in excess of a factor model like that of Eq.(1):

$$AR_{i,t} = r_{i,t} - (\hat{\alpha}_i + \sum_{k=1}^K \hat{\beta}_{i,k} f_{k,t})$$

The second step in event studies consists in aggregating the abnormal returns into *cumulative abnormal returns* over the event window starting in  $\tau_1$  and ending in  $\tau_2$ :

$$CAR_i(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} AR_{i,t} \quad (2)$$

The distribution of  $CAR_i$  is known if one makes some assumptions about the distribution of single-period returns (MacKinlay, 1997), and thus statistical tests and confidence intervals can be computed. Some researcher prefer working with  $CARs$  normalized by the length of the event window, i.e. effectively average  $AR$  over time,  $\widetilde{AR}_i = (1/(\tau_2 - \tau_1 + 1)) \sum_{t=\tau_1}^{\tau_2} AR_{i,t}$ , to have a more balanced take on the return reaction over the event window (e.g. Lanfear et al. (2019)).<sup>5</sup>

Abnormal returns can also be aggregated cross-sectionally to form a portfolio, for example through an equal-weighted average of  $AR_i$  across  $N$  different securities:

$$AAR_{i,t} = \overline{AR}_t = \frac{1}{N} \sum_{n=1}^N AR_{i,t}$$

This definition of  $AAR$  is the most commonly used (e.g. Feria-Domínguez et al. (2017); Liu et al. (2021)). If the aggregation across firms occurs using  $CARs$ , then we obtain the cumulative

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<sup>5</sup>The definitions of average AR, average cumulative AR and cumulative average AR are not always consistent across papers. For example, Lanfear et al. (2019) use  $ACAR$  to denote what we define  $\widetilde{AR}_i$ . While we are aware of these differences, here we follow a coherent framework that presents all potential definitions consistently. Since an average of  $AR_{i,t}$  can be taken both cross-sectionally and over time, we use “ $\sim$ ” to denote the first case ( $\widetilde{AR}$ ) and “ $-$ ” for the second case ( $\overline{AR}$ ).

average abnormal returns, or *CAARs*, such as in [Barrot and Sauvagnat \(2016\)](#):

$$CAAR_i = \overline{CAR} = \frac{1}{N} \sum_{n=1}^N CAR_i = \sum_{t=\tau_1}^{\tau_2} AAR_{i,t}$$

As shown in the left-hand side of the last equation, *CAAR* can also be obtained aggregating *AAR* through all event days. The *CAAR* is sometimes further averaged over all events, e.g. [Bauer et al. \(2024\)](#). For instance, [Malik et al. \(2023\)](#) compares the average  $\overline{CAR}$  across events for corporate social responsible (CSR) firms to that of non-CSR firms.

Event studies constitute a simple and transparent methodology with a long tradition in empirical finance. Their strength lies in their ability to isolate and quantify market reactions to discrete, time-limited events with minimal model dependence. Crucially, they require only market price data, making them particularly valuable when analysing long historical periods or datasets where firm-level fundamentals, asset locations, or exposure variables are unavailable or inconsistent. As we explain in more detail in Section 5.2, 21 of the reviewed papers employ this method, which allowed the collection of 506 detailed results in total (each article can carry out several different studies).

Most studies in our sample use a simple market model or capital asset pricing model (CAPM) (332 results); the remainder use either the [Fama and French \(1993\)](#) 3-factor model (110), the same plus Momentum (18), or the [Fama and French \(2015\)](#) 5-factor model (46). One possible explanation for favouring simple market model is that, although the inclusion of additional factors enhances statistical control, it can also absorb event-related effects and hinder their identification. For instance, when examining how firm size affects reactions to hurricanes, the size factor in [Fama and French \(1993\)](#) may fully absorb this effect, making the research question unanswerable.

Estimation-window length varies widely, though most papers use at least 100 observations, with a few exceptions ([Bauer et al., 2024](#); [Addoum et al., 2023](#)). Some studies adopt a "seasonal" event window, which is particularly suited to events like hurricanes (e.g. [Lanfear et al. \(2019\)](#); [Malik et al. \(2020, 2023\)](#)).

There is no clear pattern regarding the length of the event window used in the literature. It varies according to the data frequency (e.g. more data points are possible with higher-frequency data), and can be both symmetrical or asymmetrical around the event date. Generally, we observe more frequently longer event windows (20-30 days), but there are also several analyses on shorter time windows (2-5 days). For instance, a short event window is sometimes used to measure the short-term asset movements around the event, while a longer event window tend to capture persistent effects. Furthermore, out of the 506 results, 54 measure the effect on a time window that starts *and ends* before the event.

The literature has applied this framework to various hazards such as hurricanes, tornadoes, heatwaves, and droughts. Studies including [Lanfear et al. \(2019\)](#), [Donadelli et al. \(2020\)](#), and [Peillex et al. \(2021\)](#). More recent contributions extend the methodology to account for asymmetric volatility ([Kreuzer et al., 2024](#)), investor attention ([Horváth et al., 2025](#)), and market comovements ([Ma et al., 2022](#)).

However, several limitations arise when applying event studies to climate-related phenomena. First, large-sample applications can increase the likelihood of false positives if multiple-testing adjustments are not carefully implemented. Second, for slow-onset or diffuse events, such as droughts or gradual temperature anomalies, the definition of an unambiguous event date becomes challenging, weakening causal attribution.

#### 4.3.6 Panel regressions

Panel data (i.e. multiple data over time are available for each entity) allow the use of specific regression models<sup>6</sup>:

$$r_{i,t} = \alpha_i + \beta c_{i,t} + \gamma_t + \epsilon_{i,t} \quad (3)$$

where  $c_{i,t}$  the variable of interest,  $\alpha_i$  captures entity-specific effects and  $\gamma_t$  captures time-fixed effects. Further controls can be added to the regression. Panel regressions enable to control for unobserved heterogeneity across entities through  $\alpha_i$  and to remove commonalities specific to certain times through  $\gamma_t$  for a better identification of the effect of  $c_{i,t}$ . Typically, the papers analysed either regressed firm- or portfolio-level returns directly on physical risk measures, such as heat score measures ([Acharya et al., 2023](#)), a disaster indicator ([Huynh and Xia, 2023](#)) or tornado activity dummies ([Donadelli et al., 2020](#)), often controlling for financial characteristics. However, the left-hand side variable is often the CAR computed with event studies at an earlier step (e.g. [Kruttli et al. \(2025\)](#)).

#### 4.3.7 Two-stage least squares

A popular way to mitigate endogeneity problems is to use instrumental variables within a two-stage least squares (2SLS) methodology. The 2SLS replaces the problematic regressor of interest  $c$  with a component that is exogenous using *valid* instruments (or instrumental variables). Valid instruments must satisfy two conditions ([Wooldridge, 2010](#)): relevance, i.e., they must explain part of the variation of the regressor of interest; and exogeneity, i.e., they must be uncorrelated

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<sup>6</sup>There are several approaches to panel regressions, mainly pooled OLS, fixed effects models and random effects models. For more details, see e.g. [Wooldridge \(2010\)](#).

with the error term in Eq. (3). The 2SLS estimator is then obtained as follows. In the first step, the variable of interest  $c$  is regressed onto a valid instrument  $z$  and controls  $x$ :

$$c_{i,t} = \pi z_{i,t} + \delta x_{i,t} + \nu_{i,t} \quad (4)$$

The second step involves plugging the fitted values from Eq.(4),  $\hat{c}_{i,t}$ , into Eq.(3):

$$r_{i,t} = \alpha_i + \beta \hat{c}_{i,t} + \gamma_t + \epsilon_{i,t}$$

Thanks to the first stage,  $\hat{c}$  are now uncorrelated with the error term  $\epsilon_t$ , solving the endogeneity problem.

Among the reviewed papers, Xu et al. (2025) use population density as an instrument for the climate risk index rank variable. In more densely populated areas, climate risk tends to be lower (relevance), and population density should not affect a firm's cost of capital, which is the final dependent variable studied (exogeneity). Malik et al. (2020) employ religiosity as an instrument for corporate social responsibility (CSR) scores: religious environment are often associated with more CSR initiative, but they should not affect firms' returns (the response variable studied).

#### 4.3.8 Difference-in-difference

Difference-in-Difference (DD) is an econometric strategy used to estimate causal effects when firms are exposed to a *discrete* treatment at a specific point in time, such as a policy change, a shock or, in our case, a climate event. The method compares changes in the outcome variable (e.g. returns) for a treated group before and after the event (or any other treatment) to changes for an otherwise similar control group that was not subjected to the change. Since the DD uses changes in variables for different groups, it needs panel data. The classical regression specification for DD reads (Angrist and Pischke, 2009)

$$r_{i,t} = \alpha + \gamma GROUP_s + \lambda d_t + \beta(GROUP_s \cdot d_t) + \varepsilon_{i,t} \quad (5)$$

where  $GROUP_s$  denotes the group to which the firm belongs to (treatment or control), and  $d_t$  is an indicator variable that is one when the event/treatment takes place and zero otherwise.<sup>7</sup> The difference *in* difference lies in comparing the change in the returns from before to after

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<sup>7</sup>The notation used for the indicator of the treatment or event is often *POST* (e.g. Alok et al. (2020)), to stress that it is one during and after the event, and zero before. Notice that the specification can also be augmented with time-fixed effects and additional controls. We refer the reader to Angrist and Pischke (2009) for further details about the practical estimation.

the event *in the treated group* to the change in the control group, captured by the coefficient  $\beta$ . Through a difference of differences, one can effectively tackle the issue of false attribution of treatment effects due to both common trends across groups and pre-existing differences across groups. Other than exogeneity of the treatment, another important assumption of DD is the parallel trend assumption, which means that, in the absence of treatment, treated and control firms would have experienced the same change in returns over time.

Among the papers we review, [Alok et al. \(2020\)](#) studies the differential impact of multiple natural disasters between funds close to their headquarters and those far from them. [Krutli et al. \(2025\)](#) consider hurricanes as separate treatments and firms with zero exposure to the event (due to their location) as a control group.

#### 4.3.9 Time-series econometric models

We refer to “time-series econometric models” to denote the family of econometric approaches to model time-series of data. While an exhaustive presentation of these methods is out of scope, we give a brief explanation of the generalized autoregressive conditional heteroscedasticity (GARCH) model, that is used in several papers among those reviewed. GARCH models ([Bollerslev, 1986, 1990](#)) describe how volatility evolves over time, allowing to capture changes in the risk underlying financial markets. The general form of  $GARCH(p, q)$  model, for each  $t = 1, \dots, T$ , is

$$\begin{aligned} r_t &= \sum_{k=1}^K b_k x_{k,t} + \epsilon_t \\ \sigma_t^2 &= \omega + \sum_{j=1}^p \alpha_j \epsilon_{t-j}^2 + \sum_{l=1}^q \beta_l \sigma_{t-l}^2 \\ \epsilon_t | r_{t-1} &\sim N(0, \sigma_t^2) \end{aligned}$$

where  $x_{k,t}$  denote explanatory variables for  $k = 1, \dots, K$  (which can be replaced by a constant like the mean return if needed),  $\omega$  is the long-run variance,  $\alpha_j$ , for  $j = 1, \dots, p$  captures the moving-average components and  $\beta_l$ , for  $l = 1, \dots, q$  measures the autoregressive components in the variance.<sup>8</sup>

The GARCH model can capture volatility clustering ([Ding et al., 1993](#); [Cont, 2001](#)), which means when highly volatile periods tend to stick together. This phenomenon is pervasive and its effects are large ([Traut and Schadner, 2023](#)). Over time, extensions to the model have

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<sup>8</sup>We have removed the entity index  $i$  for simplicity.

been proposed, for example to capture time-varying correlation structure (dynamic conditional correlation GARCH, [Engle \(2002\)](#)) or shock asymmetries (GJR-GARCH) ([Glosten et al., 1993](#)).

Climate-related hazards, such as hurricanes, may temporarily alter market risk. For instance, [Kreuzer et al. \(2024\)](#) study the returns of various US market indices obtained with GJR-GARCH around hurricanes. Another example is [Montero et al. \(2024\)](#), who estimate a pre- and post-disaster indicator through several GARCH models to evaluate the reaction of return volatility for US insurance companies.

## 5 Empirical evidence: market reactions to physical climate hazards

Despite heterogeneous research designs, a review of 47 studies shows an overall negative impact of physical climate hazards on stock markets, with effects varying widely by event type. Section [5.1](#) reports results by hazard, and Section [5.2](#) confirms and refines these insights using event study analysis.

### 5.1 Market reactions by hazard type

When considering all climate hazards, 25 studies (53%) report overall negative impact. However, 19 studies (40%) document mixed effects, and 3 studies report predominantly positive impacts.<sup>9</sup>

Multiple-hazard studies generally find negative impacts in both the US and the rest of the world. For temperature-related events, extreme heat shows predominantly negative effects, while results for extreme cold are mixed. For wind-related events, there is strong evidence of negative impacts from tropical cyclones and tornadoes, whereas other storms show mixed effects. Wet and dry events are less studied, but floods and droughts generally have negative impacts on the stock market, while wildfires show more mixed results ([Table 4](#)).

[Table 4](#) here

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<sup>9</sup>Positive or negative refers to the perspective of investors holding a stock before a climate hazard occurs. For them, higher returns on held stocks are positive, even though a higher cost of capital is negative for the firm. Negative effects also include increases in illiquidity, volatility, or correlation across stocks and markets, as these raise portfolio concentration for investors. If an article reports multiple results, we give an overall assessment: we classify it as positive (negative) if most results are positive (negative), and as “mixed” if there is no clear majority.

### 5.1.1 Multiple-hazard studies

A body of 14 studies has examined the aggregate impacts of heterogeneous climate-related events, typically relying on large historical disaster databases. In this review, the term ‘mixed events’ refers to studies that analyse several categories of hazards together (e.g., hurricanes, floods, storms, droughts, or wildfires within the same empirical framework), rather than to compound climate events in the climate-science sense. According to this literature, climate hazards exert significant negative effects on the returns and volatility of directly exposed firms, but not necessarily on diversified portfolios. These shocks can propagate along supply chains, and be amplified by investor salience bias associated with geographic proximity. Cross-country analyses suggest that these patterns are not confined to the United States.

A key commonality across these studies is the reliance on specific underlying hazard databases. The international Emergency Disaster Database (EM-DAT) is a global repository that has systematically recorded the occurrence and consequences of disaster events—including associated human losses, economic damages, and event characteristics—since 1900 (Table 1). With more than 26,000 documented events to date, the majority of which are attributable to natural hazards, its extensive temporal and spatial coverage makes it a primary source for cross-country assessments of climate-related physical risks (Malik et al., 2020, 2023; Montero et al., 2024; Li et al., 2024; Pagnottoni et al., 2022). For the United States, the Spatial Hazard Events and Losses Database (SHELDUS) provides county-level information on direct economic losses, crop and property damages, and fatalities associated with natural hazard events since 1960, and is therefore widely used (Barrot and Sauvagnat, 2016; Alok et al., 2020; Ma et al., 2022; Huynh and Xia, 2023).

Mixed climate-related hazards have negative effects on directly and indirectly exposed firms in the United States. Barrot and Sauvagnat (2016) examined the sensitivity of firms to mixed climate-related events via their indirect impacts on supply chain. By systematically identifying firms’ suppliers located in exposed areas, they demonstrate that natural disasters exert significant short-term effects on the sales growth of exposed firms and that these shocks propagate through production networks. When at least one supplier is affected by a natural disaster, client firms experience, on average, a decline of 2 to 3% in post-event sales growth, and these economic losses are associated with a reduction in firms’ equity values of approximately 1%. Malik et al. (2020) provide evidence that these responses also differ among US industries. They find statistically significant negative abnormal returns for firms operating in the paper, mining, financial trading, clothing, aerospace/aircraft, and gold sectors. In contrast, and perhaps more unexpectedly, they also detect significantly positive abnormal returns for firms in the banking, pharmaceutical, and even utilities industries. Davidescu et al. (2025) corroborate this sectoral heterogeneity, finding that insurance and energy firms are particularly sensitive whereas retail companies and some

segments of the industrial sector exhibit more resilience to mixed events.

In order to explain the mechanisms leading to this effects of hazards on the stock market, [Alok et al. \(2020\)](#) adopt the perspective of fund managers. They find that managers located within an affected disaster area tend to reduce their holdings of firms situated in the disaster zone more than managers based in geographically distant regions. Yet, this localized reallocation does not appear to reflect superior information, (the resulting adjustments underperform on average). Instead, the evidence points to a salience bias triggered by geographical proximity to climate-related hazards. Keeping this investor allocation perspective, [Blanco et al. \(2024\)](#) confirm that investors with exposed portfolios divest from affected firms. Interestingly, they also show that due to limited information-processing capacity, exposed investors trade less and incorporate less firm-specific information for the remaining unaffected stocks, reducing price informativeness.

[Ma et al. \(2022\)](#) demonstrate that the effects of climate-related hazards are not limited to abnormal return, but affect the structure of market returns. Specifically, for firms exposed to such hazards, the covariance of individual stock returns with aggregate market returns increases following climate disaster such as hurricanes and floods. [Montero et al. \(2024\)](#) also document that natural disasters systematically modify the conditional volatility dynamics of US insurers, with significant shifts typically manifesting within one month and in some cases persisting for up to three months.

The literature also reveals that the market reaction to mixed events has evolved over time. [Li et al. \(2024\)](#) show that climate-related disasters increasingly affect NASDAQ-100 constituents after 2010, with shocks becoming stronger and more persistent. They observe earlier market anticipation and longer post-event adjustments, replacing the milder, short-lived responses observed in 2000–2009. This recent market anticipation is confirmed in [Panetsidou and Synapis \(2025\)](#), who find that investors respond negatively to ex ante weather alerts, which act as precautionary risk signals.

International evidence confirms that negative, or at least significant market reactions to mixed climate-related hazards are not confined to the United States. Among the pioneers, [Worthington \(2008\)](#) investigates the effects of a mix of storms, floods, cyclones and wildfires on the Australian market. The aggregate results indicate that the market does not systematically react to disaster occurrences, but that disasters are associated with rare and severe downside risks. Using 88 disasters across multiple countries between 1983 and 2013, [Tavor and Teitler-Regev \(2019\)](#) show that natural hazards generate the strongest and most persistent stock-market declines compared to other types of hazards. [Pagnottoni et al. \(2022\)](#) expand the hazard and geographical scope by examining more than 6,700 disasters in 104 countries and their effects on 27 global stock market indices. Their results reveal pronounced heterogeneity: the magnitude and sign of market reactions depend strongly on the type of hazard, with climatological and biological disasters

producing the most severe international market responses. Importantly, they find that global indices react more strongly to shocks originating in European countries. [Xu et al. \(2025\)](#) further deepen the international perspective by linking climate-induced socioeconomic damage to firms' implied cost of equity capital across 38 countries. Extreme climate events trigger a measurable rise in firms' required returns, indicating a repricing of climate risk in capital markets. This effect is amplified for firms with high domestic revenue exposure, firms operating in climate-vulnerable industries, and firms predominantly owned by domestic institutional investors (in line with [Alok et al. \(2020\)](#) and [Blanco et al. \(2024\)](#)).

### 5.1.2 Temperature-related hazards and extreme events

Among the 11 studies analysing temperature-related climate risks, there is robust evidence that extreme heat exerts a negative impact on returns, whereas the effects associated with cold temperatures yield mixed results.

The literature reviewed in this subsection employs heterogeneous temperature-based measures that differ in both temporal horizon and climatic interpretation. Some studies analyse persistent extreme events, such as heatwaves (cold waves), which are typically defined relative to historical local temperature distributions and require unusually high (low) temperatures to persist over several consecutive days. Other studies instead focus on short-term temperature anomalies or temperature shocks, measured as deviations from expected or historical temperature norms at daily, monthly, or annual frequency. Finally, some contributions examine long-run temperature trends constructed from persistent climatic variation. These measures do not identify the same underlying phenomenon: some capture statistically unusual temperature realizations relative to historical distributions, whereas others identify persistent meteorological events requiring sustained deviations over time. These distinctions are important because they can lead to different economic mechanisms and market responses: isolated temperature shocks may primarily affect short-term sentiment or operational conditions, whereas persistent heatwaves or long-run warming trends may convey broader information about productivity losses, adaptation costs, or climate change exposure. Because heatwaves are generally identified only after several consecutive days of abnormal temperatures have occurred, investors may not immediately interpret an isolated hot day as a heatwave-related economic shock, implying that market responses could emerge gradually as the persistence of the event becomes observable.

Using daily temperature observations across several international stock markets between 1960 and 2000, [Cao and Wei \(2005\)](#) document for example a significant negative relationship between stock returns and ambient temperature levels, as well as between returns and short-term temperature deviations from historical norms. These findings are corroborated by [Apergis \(2024\)](#), who studies annual temperature shocks across 20 major stock markets over 1950–2021. The au-

thor documents non-linear effects: increases in average annual temperatures are associated with higher returns at low baseline temperature levels, but reduce returns once temperatures exceed a threshold. Two closely related studies are [Balvers et al. \(2017\)](#) and [Gregory \(2021\)](#), both of which construct a temperature shock factor using mimicking portfolios. In both papers, temperature shocks are extracted from asset returns by regressing temperature variables on a set of base assets and macroeconomic controls. [Balvers et al. \(2017\)](#) constructs a U.S. temperature shock factor by regressing the future twelve-month average U.S. temperature on U.S. size and book-to-market portfolios together with macroeconomic controls. In contrast, [Gregory \(2021\)](#) develops a global temperature shock factor based on monthly global temperature anomalies relative to the 1951–1980 long-run average. Rather than using future annual averages, Gregory employs contemporaneous global temperature anomaly news, arguing that anomalies are more visible to investors and better capture climate-related shocks incorporated into financial markets. Both studies estimate the price of temperature risk using Fama–MacBeth regressions. Despite the methodological similarity, they obtain opposite results: [Balvers et al. \(2017\)](#) find a negative risk premium, consistent with temperature shocks operating primarily through adverse productivity effects, while [Gregory \(2021\)](#) documents a positive risk premium for global temperature shocks, even after controlling for U.S.-specific temperature factors.

While mimicking portfolios have been employed to capture the market’s response to differences in expected or realized temperatures over long horizons, temperature-related acute events—such as heat waves or cold waves—have also been examined using event-study methodologies.

Heatwaves generally depress stock market performance, generating negative abnormal returns, increasing volatility, and reducing market activity. Using the most extreme heatwaves<sup>10</sup> since 1979, [Schuster et al. \(2025\)](#) find statistically negative market reactions in the US and Europe of about -3.0% around the peak day. In the United States, [Griffin et al. \(2019\)](#) match extreme high temperature events to the locations of firms’ headquarters and show that exposed firms lose on average 0.4% over the following month, with smaller, less geographically diversified firms being more affected. [Addoum et al. \(2023\)](#) refine firm-level temperature exposure by combining asset-level geographic data with daily temperature and precipitation. For each firm-quarter, exposure is defined as the number of hours each location experiences different temperature ranges, weighted by its share of firm sales. Instead of using fixed temperature thresholds, they estimate industry- and season-specific non-linear earnings response functions and infer critical temperature thresholds from these. Extreme temperatures significantly affect earnings in many industries, but no contemporaneous stock price response to extreme temperatures is found. This may be evidence for investors not reacting timely to observed temperature shocks; rather, temperature-related information is incorporated into prices around earnings announcements.

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<sup>10</sup>Heat waves are defined using the Heat Wave Magnitude Index daily, which classifies an event as a period of at least three consecutive days during which daily maximum temperatures exceed the local 90th percentile relative to the 1979–2010 period.

This contrasts with earlier studies that find return predictability after weather events, and may stem from [Addoum et al. \(2023\)](#)’s focus on earnings sensitivity-based temperature “extremes” rather than fixed climatological thresholds. Using an derived GARCH model, [Bourdeau-Brien and Kryzanowski \(2017\)](#) show that the impact of heatwaves is not limited to abnormal returns, but also impacts stock return volatility. [Peillex et al. \(2021\)](#) complement these perspectives by examining how extreme heat affects trading activity in France from 1995 to 2019. Using trading volumes for the French CAC40 and SBF250 indices, they find a significant 4–8% decline in volume on days above 30 °C, even after controlling for calendar effects and volatility. The decline is temporary and not offset by later rebounds, indicating that high temperatures directly impede trading behaviour rather than price formation.

On the other side of the thermometer, the impact of cold waves on the stock market are more mixed. [Hamid and Kang \(2024\)](#) measures the impact of a variety of different events included in the NOAA extreme weather databases, including extreme cold (freeze). The latter, however, do not reveal any statistically significant effect on stock returns, in line with the results from [Griffin et al. \(2019\)](#). [Bourdeau-Brien and Kryzanowski \(2017\)](#) find that winter weather has no effect on stock returns. Volatility, instead, clearly increases during both extreme temperatures and severe winter weather episodes.

### 5.1.3 Wind and severe storm hazards: hurricanes, storms, tornadoes, and hail

Wind-related hazards are by far the most extensively examined climate hazards, with 18 studies conducting dedicated analyses of these events. This body of literature initially establish the impact of major tropical cyclones (hurricanes) on the insurance industry. These findings have been further generalized to non-financial firms located within the affected regions, to specific sectors (e.g., the energy sector), and to certain investment styles (e.g., by firm size), while generally indicating the absence of a significant aggregate market reaction. Comparable empirical evidence has been documented in Canada and Australia. Other storm-related hazards, including tornadoes and hail, have received considerably less attention; however, preliminary findings suggest that their financial impacts are relatively limited.

A number of studies examines how tropical cyclones affect US insurance firm stock returns, emphasizing the coexistence of two opposing forces: expected losses from claims payments and potential gains from post-event premium increases. Early event-study analyses exploit major individual hurricanes to identify these channels. [Cagle \(1996\)](#) shows that negative abnormal returns around hurricane Hugo (1989) are concentrated among insurers with substantial claims exposure, while less exposed firms remain largely unaffected. Comparable exposure-driven heterogeneity is documented by [Lamb \(1995\)](#) for hurricane Andrew (1992): only insurers with significant premium exposure in Florida or Louisiana exhibit adverse price reactions. [Angbazo](#)

and Narayanan (1996) refine this evidence by highlighting the dynamic of market responses: although Andrew initially generated negative abnormal returns for insurance stocks, these effects were partially offset by subsequent positive adjustments, consistent with expectations of premium increases. Their results also point to broader contagion effects, as valuation impacts extended beyond directly exposed firms (consistent with Ewing et al. (2006)). Subsequent work generalized these insights across hurricanes. Thomann (2013) shows that major insured hurricanes systematically increase insurance stock volatility and reduce correlations with the market. Feria-Domínguez et al. (2017) analyse the market reaction of insurance companies to seven hurricanes that hit the east coast from 2005 to 2012, finding significant cumulative abnormal returns around landfall for most of them. Schuh and Jaeckle (2023) report consistently negative abnormal returns for insurers after the thirteen costliest hurricanes since 2004, with larger losses for higher-category ones. Wang and Kutan (2013) compare the US and Japanese insurance sectors and find no significant price effects in either market. However, in the United States, tropical cyclones cause a large and statistically significant increase in the conditional volatility of returns; in Japan, cyclones also raise volatility, but the effect is smaller and shorter-lived. Additionally, hurricanes have a weaker impact than earthquakes and tsunamis, suggesting cyclones are treated more as expected, diversified risks.

When the analysis is extended to non-insurance firms, the stock returns of firms with exposure to tropical cyclones are negatively affected. Hamid and Kang (2024) document that landfall hurricanes cause a persistent decline in cumulative abnormal returns for firms in affected areas, lasting 40–60 trading days. In contrast, severe storms generate short-lived positive abnormal returns, and winter storms show a strong, sustained positive post-event drift. Bourdeau-Brien and Kryzanowski (2017) find that firms in disaster areas also experience volatility shocks, with peak effects in the two to three months after disaster. These results on volatility are confirmed by Kruttli et al. (2025): for exposed firms—defined by the share of establishments in hurricane landfall regions—hurricanes lead to large and persistent increases in implied volatility, rising by up to 15–20% and remaining elevated for several months. A post-landfall decline in volatility risk premia indicates that market participants initially underestimate hurricane-related uncertainty. This under reaction, however, diminishes following hurricane Sandy (2012). In the post-Sandy period, the associated increase in idiosyncratic volatility becomes incorporated into expected returns, indicating investor learning and an improvement in market efficiency over time.

Another line of research documents heterogeneous sectoral responses to tropical cyclones, with a focus on the energy sector. Liu et al. (2021) provide evidence that hurricanes generate small but statistically significant stock price reactions within the US energy sector, with strong heterogeneity by carbon intensity: coal companies experience the largest and most persistent negative abnormal returns, whereas oil, gas, nuclear, and particularly renewable energy firms perform better, with renewables exhibiting positive cumulative abnormal in the most recent period. The

authors interpret these patterns as evidence that hurricanes convey climate-change-related information, leading investors to reprice energy firms according to their exposure to carbon transition risk rather than direct physical damage. [Horváth et al. \(2025\)](#) also study US energy firms but use attention for hurricanes (proxied by Google searches) instead of actual hurricane occurrences. This approach directly addresses a key identification issue in earlier work: the financially relevant “event date” is when investors process information, not when the hurricane forms or makes landfall. The study finds that investors do not treat hurricanes mainly as damage shocks for energy firms. Rather, greater attention to hurricanes and storms is associated with higher returns, interpreted as investors pricing in expected supply disruptions, higher energy prices, and short-run demand effects.

Hurricanes also affect certain investment styles but have limited impact on the overall stock market. [Lanfear et al. \(2019\)](#) apply event-studies to 39 US hurricanes between 1990 and 2017. Characteristic-sort portfolios highlight heterogeneity between styles: momentum portfolios experience pronounced losses, whereas value stocks tend to exhibit resilience or even post-event gains. Importantly, controlling for illiquidity and tail risk explains only a minor portion of the total effect, suggesting that hurricanes constitute an unpriced source of physical risk distinct from conventional risk factors. Moreover, no significant changes in alphas and betas between estimation and event window are found, suggesting that abnormal returns cannot be fully explained by either of the two components. [Kreuzer et al. \(2024\)](#) find no consistent overall US stock market reaction when all hurricanes are considered together. Asymmetries appear only when accounting for storm intensity: low-intensity hurricanes are linked to positive effects before landfall, while high-intensity storms cause significant declines before landfall followed by post-event corrections.

Unlike hurricanes, tornadoes are high-frequency, short-lived, localized events which are priced as idiosyncratic shocks affecting specific sectors and firms rather than systematic risks. [Donadelli et al. \(2020\)](#) examine over 50,000 tornadoes and find a modest but negative impact on US stock prices, with highly localized, sector-specific effects. Using geo-granular data, they show tornadoes cause negative abnormal returns mainly in consumer discretionary and telecommunications, while most sectors are unaffected. Regionally, aggregate stock market effects are weak: the Midwest shows slightly positive exposure—attributed to insurance coverage, firm diversification, and adaptation investments—whereas the South and Northeast exhibit negative sectoral effects.

For storms, [Braun et al. \(2025\)](#) focus on exposed US firms, defined as domestic companies whose stock returns are sensitive to aggregate storm losses. Firms with more negative storm-risk betas earn significantly higher subsequent returns, with an excess-return spread above 6% per year between the most and least exposed stocks. This premium is not explained by standard asset-pricing factors, and is concentrated among geographically exposed, historically affected, and institutionally held firms. Extreme weather risk is thus priced in the cross-section of equity

returns, raising the cost of equity for exposed firms.

Some studies examine hurricane and wind-related impacts outside the United States. [U-Din et al. \(2022\)](#) report that hurricanes have a negative, immediate, market-wide impact on Canadian equity prices. In Australia, [Worthington and Valadkhani \(2004\)](#) analyses 42 severe storms, floods, cyclones, earthquakes, and bushfires. Tropical cyclones—along with bushfires and earthquakes—have a statistically significant negative effect on equity returns: the Australian market falls about 1% on the event day, with further declines in subsequent days. In contrast, severe storms (including hailstorms) show no significant effects, either contemporaneous or lagged, which the author attributes to cyclones’ greater severity, spatial concentration, and economic disruption compared with more localized, recurrent storms. Focusing on the 1999 Sydney hailstorm, [Worthington and Valadkhani \(2005\)](#) finds limited, highly sector-specific effects and no broad market response: financial services and most consumer sectors show no significant impact, despite this being the largest insured natural loss in Australian history. The only clear reaction is a positive abnormal return in the materials sector (about +2% in the following days), attributed to higher reconstruction demand. Finally, [Worthington \(2008\)](#) extend the analysis of severe storms and cyclones for the overall Australian market but again find no significant market reaction.

#### **5.1.4 Wet and dry: floods, droughts and wildfires**

There are 11 papers that include floods, droughts and/or wildfires in their analyses. Overall, events related to extreme dry—droughts and wildfires—seem to have a more powerful effects on financial markets compared to floods, with effects that can vary considerably depending on which economic sector is considered.

Droughts have a significant negative effect on the food sector and exposed firms, but a more limited effect on the rest of the stock market. [Hong et al. \(2019\)](#) employ the Palmer Drought Severity index to quantify the effect of droughts for the food sectors of 31 different countries. Building a drought trend at the country level, they find that the food sector of countries with highest drought risk experience 7% lower return compared to countries with the lowest risk. Higher drought risk is also associated with lower future profit growth. Focusing on the US region, [Hamid and Kang \(2024\)](#) carries out event studies for droughts and wildfires, but do not find significant market reactions after droughts. Using US firm-level data from 1990 to 2015, [Huynh and Xia \(2023\)](#) find that drought-exposed firms initially drop in price, but earn positive abnormal returns in the following month, consistent with an overreaction followed by price reversal.

Wildfire risk is inherently multi-dimensional and results from the interaction and compound effects of several climatic drivers, including high temperatures, low humidity, drought conditions,

precipitation deficits, and wind<sup>11</sup>.

Wildfires are widely studied in the financial literature and recognized as significant, but their net impact on markets remains unclear. Early work examines the Australian stock market's response to various climate hazards, including bushfires. [Worthington and Valadkhani \(2004\)](#) report a modest increase in overall Australian market returns on the event day and the next, but this effect disappears when more sophisticated GARCH models are applied ([Worthington, 2008](#)). At the sector level, [Worthington and Valadkhani \(2005\)](#) find that the 2002–2003 Canberra bushfires were followed by a 0.7% decline in the Materials sector. In the Canadian stock market, [U-Din et al. \(2022\)](#) find that wildfires significantly reduce returns the day after the event but increase them on the two following days, with no effect on volatility. [Hamid and Kang \(2024\)](#) document a significant positive reaction to wildfires in the US market, consistent with [Huynh and Xia \(2023\)](#), who attribute this to initial overreaction followed by price reversal. [Tavor \(2024\)](#) analyses 161 wildfires affecting US markets from 2019 to 2022 across nine sectors. The energy sector is significantly negatively affected, as is insurance, though less strongly. The food sector is positively affected, whereas Forestry and real estate show no significant effects. Health companies' returns rise briefly a few days after the fire, then fall, with effects persisting at least 45 days. Transportation reacts mostly positively, but significantly only in a few event windows. Tourism shows negative reactions in shorter windows and positive ones from about 25 to 45 days, indicating reversals; utilities display a similar pattern.

While dry events tend to exhibit significant stock market reactions, the evidence on floods is more mixed. [Worthington and Valadkhani \(2004\)](#) and [Worthington \(2008\)](#) find no significant impact of flood events on equity returns in Australia. Similar null effects are reported for Canada by [U-Din et al. \(2022\)](#). In Europe, [Bauer et al. \(2024\)](#) document a short-lived pattern: equity returns increase in the five days preceding floods, followed by a decline over the subsequent ten days, which dissipates over longer horizons. Evidence for the United States is heterogeneous. [Bourdeau-Brien and Kryzanowski \(2017\)](#) show that floods significantly affect returns in only three out of nine states, with negative effects in Kentucky and Texas and a positive effect in Arizona, while [Hamid and Kang \(2024\)](#) find no significant response at the aggregate U.S. market level. Shifting attention from returns to risk, [Kruttl et al. \(2025\)](#) document a significant increase in stock return volatility following floods, using a difference-in-differences design: volatility rises by about 2% over one week and up to 5% over three months for exposed firms relative to unexposed peers, consistent with the price reversal dynamics highlighted by [Huynh and Xia \(2023\)](#).

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<sup>11</sup>Consistent with the IPCC climatic impact driver classification, this review groups wildfire-related hazards within the broader 'wet and dry' category through the concept of fire weather, which captures weather conditions conducive to wildfire ignition and propagation.

### 5.1.5 The moderated role of corporate social responsibility

Several studies have sought to identify which firm-level characteristics tend to exacerbate or attenuate the price response to physical events. While the geographic location of firms' activities has consistently been shown to be crucial, we find mixed evidence regarding the moderating role of corporate social responsibility. [Huynh and Xia \(2023\)](#) and [Malik et al. \(2023\)](#) document that, when firms are exposed to disaster events, investors exhibit an overreaction by excessively discounting current stock prices. However, firms characterized by a strong environmental profile experience attenuated selling pressure, despite a deterioration in their underlying fundamentals following such disasters. These findings indicate that corporate investments aimed at strengthening environmental performance yield benefits when climate-related risks materialize. [Schuster et al. \(2025\)](#) extend this analysis to temperature (heatwaves) of the Europe region, documenting that, while high environmental performance mitigates losses in the United States, it shows no protective effect in Europe. This finding suggests that the moderating role of environmental performance and CSR may be highly context-dependent across regions and empirical settings, reflecting important institutional and market-specific differences. European firms typically operate under stricter sustainability disclosure requirements and stronger baseline environmental regulation, potentially reducing the informational value of firm-level environmental performance for investors. By contrast, in the United States, where ESG disclosure remains comparatively more heterogeneous and investor preferences regarding climate-related risks are more polarized, strong environmental performance may provide a clearer signal of managerial quality or long-term resilience. Differences in ownership structure, the role of institutional investors, and the salience of climate-related issues in financial markets may further contribute to these heterogeneous findings. More broadly, the wide variation in the definitions and measurement approaches used for CSR, environmental performance, and climate exposure across studies limits comparability and makes it difficult to draw universal conclusions regarding firm-level climate resilience.

## 5.2 Results from event studies

Event studies are the most common research design in the reviewed articles. Because they share a common outcome (abnormal returns), they enable a quantitative meta-analysis. [Table 5](#) shows the distribution of 506 event study results from 20 papers, by hazard type. Results are usually reported in the original papers as cumulative abnormal returns ( $CAR$ ) over an event window. To compare across different event windows, we normalize the  $CAR$  associated with each event-study result by the event window length, which effectively amounts to the average abnormal return at the daily level.<sup>12</sup>

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<sup>12</sup>This corresponds to what we defined above as  $\widetilde{AR}$  for a single test asset, or its cross-sectional average if the article reports directly  $\overline{CAR}$ . To avoid confusion, here we refer to this measure simply as "normalized  $CAR$ ".

[Table 5](#) here

In contrast to the findings presented in the previous subsection, the meta-analysis of event-study results does not indicate a significant overall directional impact, even if mixed events are generally associated with adverse effects in both the United States and global studies. For temperature-related events, the previously documented negative effects of extreme heat are corroborated, whereas results for extreme cold suggest a slightly positive impact. Regarding wind-related events, the strong evidence of negative effects from tropical cyclones is confirmed, while it is more difficult to draw clear conclusions for winter storms and other storm categories given the limited availability of studies. Hydrological extremes (wet and dry events) remain relatively under explored, and no clear pattern emerges. However, estimates for wildfires tend to reinforce the negative effects discussed earlier ([Table 5](#)).

These event-study results confirm strong sectoral heterogeneity in stock market reactions to climate-related hazards, with the insurance and energy sectors being among the most sensitive ([Table 6](#)). The most frequently examined category is the "diversified" sector, encompassing broad stock universes or market indices, and at least one study uses a diversified sample for each hazard type. In contrast, sector-specific analyses typically consider only one or two hazards. Mixed climate events are the only category covered in nearly all sectors. Wildfires also show relatively broad coverage, though evidence comes from a single study ([Tavor, 2024](#)). Hurricanes and wildfires show the most pronounced sectoral effects. Hurricanes are particularly disruptive for insurance, with median abnormal returns near -0.30%, but are associated with positive abnormal returns in gas (0.14%), oil (0.13%), and renewable energy (0.07%), consistent with [Liu et al. \(2021\)](#). Wildfires are linked to large negative effects in energy (-0.33%), moderate losses in tourism (-0.08%), and modest gains in food (0.10%). Some sectoral responses deviate from standard economic intuition: while expectations of reconstruction can support returns in some industries, the immediate damage from extreme events would generally be expected to depress asset prices. Mixed climate events yield especially heterogeneous effects, with positive abnormal returns in some industries (e.g., aerospace and automotives, beer, chemicals, gold and precious metals, telecommunications) and negative in others (e.g., banking, coal, oil).

[Table 6](#) here

We conclude this section by briefly discussing how methodological choices may influence event-study results. Although event studies remain among the most comparable empirical frameworks used in the literature, differences in event-window specification and expected return models can materially affect the estimated magnitude and persistence of abnormal returns.

At the same time, the literature remains highly heterogeneous across hazard types, regions, sample periods, exposure definitions, and empirical specifications, which limits the feasibility of more formal methodological decompositions. In particular, several hazard categories are represented by only a small number of studies and often rely on a single empirical specification. For example, comparisons across return models cannot be meaningfully implemented at the hazard-type level for droughts, snowstorms, or temperature shocks, where only one type of expected-return model is typically employed. At the aggregate level, however, simpler return models tend to produce more negative abnormal returns than richer factor specifications: median normalized CARs amount to approximately -0.011% under the CAPM and 0.001% under the [Fama and French \(1993\)](#) three-factor model, compared with 0.007% when adding momentum and 0.042% under the [Fama and French \(2015\)](#) five-factor model. Model misspecification may therefore cause important differences in estimating the response to physical climate events.<sup>13</sup>

A more informative comparison concerns event-window length, which is sufficiently common across studies to allow for broad categorization. Splitting the sample into short event windows (up to 10 trading days) and long event windows (more than 10 trading days), we find that shorter windows are generally associated with stronger and more negative market reactions, with median normalized CARs of -0.015% compared with practically zero for longer windows. At the same time, long-window specifications are substantially more frequent in the literature (341 estimates versus 165 for short windows). [Table C.1](#) in the Appendix reports a more detailed comparison by hazard category. The largest differences between short and long windows emerge for hurricanes (-0.148% versus -0.006%), storms (-0.1% versus -0.034%), floods (0.022% versus -0.005%), wildfires (-0.027% versus 0.008%), and temperature shocks (0.033% versus 0.007%). For droughts, extreme heat, and snowstorms the available studies rely on one type of event-window specification, preventing meaningful comparisons. Overall, however, the evidence suggests that market reactions to physical climate hazards tend to be stronger in the short run, regardless of whether the estimated effect is positive or negative.

## 6 Discussion and implications for climate finance

The literature examining the relationship between realized climate-related events and the stock market has expanded rapidly in recent years. Nevertheless, several important challenges persist. First, the events and geographical regions analysed remain heavily concentrated on the United States, and the types of events studied are largely constrained by the availability of easily accessible databases, which are not necessarily those in which climate change is expected to exert

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<sup>13</sup>We remind the reader that normalized CARs are abnormal returns at the daily frequency, and that there are fewer event studies for the last two model specifications compared to models with fewer factors, as mentioned in [Section 4.3.5](#).

the greatest impact. Second, the existing studies focus on financial performance, while largely neglecting other dimensions of financial risk. Third, although many statistically significant findings are documented, the underlying transmission mechanisms remain insufficiently specified and lack consistency, particularly with respect to explaining positive abnormal returns. Advancing and consolidating research on realized climate events along these dimensions could substantially contribute to improving the management of future climate-related financial risks.

## 6.1 Coverage of regions and hazard types

From a geographical standpoint, there is a pronounced bias toward the United States (analysed in 34 studies) and, more broadly, toward advanced economies (Europe, Canada, Australia, and Japan). While this historical focus may be partially justified by the concentration of economic and financial activity in these regions, developing countries warrant greater attention in future research for at least three reasons. First, their aggregate economic and financial significance is expanding rapidly. Second, production networks and financial markets are increasingly interconnected, and there is empirical evidence of the propagation of climate shocks across these networks (Barrot and Sauvagnat, 2016; Pagnottoni et al., 2022). Finally, developing regions are among the most exposed to the impacts of climate change on natural hazards (Table 2), particularly in Asia and Africa, where projected changes are compounded by lower adaptive capacity and, consequently, heightened vulnerability to such events.

Regarding the types of hazards considered, we notice a clear bias toward acute events, particularly tropical cyclones (hurricanes). This bias does not arise from the search strategy, which explicitly included keywords related to chronic physical risks, but from the structure of the empirical literature itself. Several reasons might explain this trend. Acute events are more easily matched to precise event dates, locations, and affected firms. They are also supported by relatively accessible disaster databases, especially for the United States, and often generate large observable financial losses (Table 1). Moreover, their short duration makes them especially suitable to empirical designs such as event studies. By contrast, chronic risks have received much more limited attention. The main exception is the literature on temperature variation, which studies how abnormal temperature realizations or longer-term temperature exposure affect equity markets. Yet even this evidence remains less developed than the literature on high-salience disasters, and research on shifts in precipitation regimes, persistent heat exposure, and sea-level rise remains particularly scarce despite their expected materiality under future climate change (Table 2).

Table 7 summarizes the uneven coverage of the literature across regions and hazard types by reporting the number of papers normalized by the number of events over the period 2000-2020 (panel A), and by the associated economic damage (panel B). Panel A thus confirms the limited

scholarly attention devoted to certain regions (notably Africa and Asia), despite their high frequency of hazardous events. When economic damages are taken into account (panel B), this imbalance is mitigated by the lower monetary losses recorded in developing countries. The ratio of papers per tropical cyclone is for example very high in the US, but it "only" corresponds to approximately one publication per 40 billion dollars of damage. These figures should nonetheless be interpreted with caution, as economic loss estimates for disasters remain highly sensitive to data collection constraints. Even so, panel B highlights that certain types of hazards—such as tornadoes and river floods—have attracted relatively limited academic attention despite their substantial economic costs.

[Table 7 here](#)

## 6.2 The positive effect puzzle

A central takeaway from the review is that physical climate hazards are, on average, associated with negative stock market effects from the investor perspective. Yet, there is also a non-negligible set of statistically significant positive effects documented across hazard types, regions, and empirical designs. For instance, [Malik et al. \(2020\)](#) report significantly positive abnormal returns for some sectors (banking, pharmaceutical, and utilities), despite negative effects in many other industries. [Hamid and Kang \(2024\)](#) document positive post-event drifts for winter storms and wildfires in the United States, consistent with short-run gains rather than losses. In the context of hurricanes, [Lanfear et al. \(2019\)](#) show that value portfolios exhibit resilience or post-hurricane gains, even as momentum strategies suffer pronounced losses. Similarly, in the energy sector, [Liu et al. \(2021\)](#) and [Horváth et al. \(2025\)](#) find positive return responses for certain segments—particularly renewables or energy firms benefiting from expected price and supply effects—after hurricanes.

The literature proposes several mechanisms to rationalize these positive effects. A first explanation relies on reconstruction and demand channels. Following destructive events, expectations of rebuilding activity can boost revenues in construction-related sectors or materials industries, as documented in Australian bushfire and hailstorm episodes ([Worthington and Valadkhani, 2005](#)). A second mechanism emphasizes insurance coverage and risk-sharing. In settings where losses are largely insured or diversified, disasters may be perceived as transfers rather than net value destruction, attenuating or even reversing price effects for some firms or regions ([Donadelli et al. \(2020\)](#); [Worthington and Valadkhani \(2004\)](#)). This mechanism is particularly relevant in hurricane-related studies, where insurance and reinsurance structures can partly absorb disaster losses and shape stock market responses, especially for insurers and exposed financial sectors.

A third explanation focuses on pricing power and market structure. In the insurance sector, anticipated post-disaster premium increases can partially or fully offset expected claim losses, generating positive valuation adjustments for less exposed insurers (Angbazo and Narayanan, 1996). In energy markets, hurricanes may signal future supply disruptions or regulatory shifts, leading investors to reprice firms with favourable exposure profiles, such as renewables or low-carbon producers ((Liu et al., 2021); Horváth et al. (2025)). Finally, several studies highlight behavioural channels. Overreaction followed by reversal can mechanically generate short-run negative effects and subsequent positive abnormal returns, as shown for droughts and wildfires by Huynh and Xia (2023) and Hamid and Kang (2024).

A useful way to interpret these mechanisms is through the distinction between cash-flow and discount-rate channels discussed in Section 2.3. Explanations based on reconstruction activity, post-disaster pricing power, insurance premium adjustments, or temporary supply shortages primarily operate through revisions in expected future cash flows. By contrast, mechanisms related to investor attention, salience, overreaction, or changing perceptions of climate-related systematic risk are more naturally interpreted as discount-rate channels. Importantly, however, the existing empirical literature rarely identifies these channels separately. Most studies document realized return responses around climate-related events without being able to disentangle whether abnormal returns reflect revisions in expected profitability, changes in required returns, or temporary deviations from fundamentals.

Despite these proposed explanations, the conditions under which positive effects emerge remain poorly understood. Clarifying when positive market reactions reflect genuine economic gains, temporary pricing distortions, or shifts in risk premia remains an open and important avenue for future research.

An additional dimension that emerges from the literature concerns the timing with which markets incorporate climate-related information. Several studies suggest that the financial effects of physical climate hazards are not absorbed instantaneously, but unfold gradually over time. While some events trigger immediate price reactions, others exhibit delayed adjustment, post-event drift, or reversal patterns. For instance, Huynh and Xia (2023) document contemporaneous declines in the returns of disaster-exposed firms followed by positive future abnormal returns, consistent with an initial market overreaction. Similarly, Addoum et al. (2023) find limited contemporaneous stock-price responses to temperature shocks, even though these shocks are rapidly reflected in firm earnings. Other studies report persistent increases in volatility or prolonged adjustment dynamics following major disasters (Kruttli et al., 2025). Together, these findings suggest that the market absorption of climate-related losses depends not only on the magnitude of the event, but also on the visibility of damages, investor attention, and the speed with which economic consequences become observable. Comprehensively integrating these temporal dimensions into future empirical research could help reconcile some of the heterogeneous findings

documented in the literature.

Relatedly, an open question concerns the extent to which observed market reactions reflect temporary investor sentiment rather than revisions in firms' fundamentals. Some studies document patterns consistent with salience effects, investor attention, or temporary overreaction, including localized responses and post-event return reversals (Alok et al., 2020; Huynh and Xia, 2023; Horváth et al., 2025). At the same time, other evidence points to persistent effects on earnings, volatility, and financing conditions, suggesting that at least part of the market response reflects economically meaningful losses. In addition, several studies highlight that climate shocks may propagate beyond directly exposed firms through supply chains and production networks (Barrot and Sauvagnat, 2016). However, the extent to which these propagation mechanisms may become systemic under more frequent or correlated climate hazards remains insufficiently understood.

### 6.3 The overlooked effects on risk

The existing literature documents extensive evidence on the effects of physical climate events on realized asset returns, but provides a comparatively limited analysis of risk-related outcomes. This emphasis on performance is natural, as returns constitute the most immediate and observable dimension of market reactions and capture the ex-post economic consequences of climate shocks. Yet risk is an equally relevant margin of adjustment, particularly for heterogeneous market participants operating under explicit risk budgets, regulatory constraints, or leverage limits. From this perspective, physical climate risk can be interpreted as a pervasive source of uncertainty that increases asset comovement and strengthens common risk factors.

Despite the common argument that physical climate risk can be diversified away, investors may rationally react to the realization of natural disasters. In a frictionless setting in which all investors hold a fully diversified market portfolio, the idiosyncratic component of disaster risk would indeed be eliminated, implying no systematic price response for disaster-exposed firms (Huynh and Xia, 2023). This reasoning, however, relies on overly strong assumptions. Natural disasters are inherently uncertain in their occurrence, timing, geographic footprint, and intensity, as well as in the magnitude of the associated economic damages. Firms with no prior exposure may still be affected ex post, and historical realizations provide an incomplete guide to future risk. As a result, geographic or sectoral diversification alone is insufficient to fully eliminate physical climate risk. The remaining, partly non-diversifiable component therefore represents a priced source of uncertainty that can affect asset prices, volatility, and market-wide risk dynamics.

The limited empirical evidence available suggests that physical climate hazards affect several dimensions of financial risk simultaneously. Studies focusing on volatility generally document

persistent increases in both realized and implied volatility following major disasters, particularly for hurricanes, floods, and temperature extremes, which can last more than a month (Bourdeau-Brien and Kryzanowski, 2017; Kruttli et al., 2025; Montero et al., 2024). Other contributions show that climate-related disasters increase return comovement and market correlations (Thomann, 2013; Ma et al., 2022; Davidescu et al., 2025), reducing the effective diversification of portfolios during periods of stress and potentially increasing vulnerability to joint downside realizations and extreme portfolio losses (Bagnara and Vaucher, 2025). Evidence on liquidity remains comparatively scarce, but existing results point to lower trading activity and higher frictions following extreme weather events, especially during heatwaves and disaster episodes affecting exposed assets (Lanfear et al., 2019; Peillex et al., 2021).

These dynamics are especially consequential for investors subject to margin requirements, including leveraged investors and derivatives traders, for whom short-lived volatility spikes or increases in asset correlation can trigger margin calls or forced deleveraging. At the same time, the empirical analysis of tail-risk dynamics around short-lived climate events remains challenging, particularly at daily frequencies where the number of observations is limited. The only example to date is Lanfear et al. (2019), who find little evidence that tail risk changes during hurricanes periods. Hence, although physical climate events may increase comovement and weaken diversification benefits, the extent to which these dynamics translate into systematically priced tail-risk effects is not yet understood. This data limitation underscores the value of studies relying on intra-day data, such as Horváth et al. (2025). Beyond tail behaviour, intra-day data can also reveal finer return dynamics, including rapid reversals, temporary liquidity disruptions, or rebounds that are not observable in daily data.

Risk considerations further matter for performance evaluation frameworks that explicitly normalize returns by volatility or downside risk. Overall, while the literature increasingly recognizes that physical climate hazards affect financial markets through multiple risk dimensions beyond average returns, empirical evidence on these channels remains comparatively sparse. This gap is particularly important given the potential implications for portfolio diversification, market liquidity, leverage constraints, and financial stability.

## 6.4 Implications for regulators and practitioners

Despite uneven coverage across hazard types and geographic regions, the empirical literature reviewed in this paper provides robust evidence that climate-related physical hazards have significant effects on stock markets. These effects span returns, volatility, liquidity, and correlations, and are observed across a wide range of empirical designs and data sources. As such, realized empirical evidence constitutes a valuable input for both regulators and market practitioners seeking to manage future climate-related financial risks.

A first implication is that neither hazards nor regions are expected to evolve uniformly. As summarized in IPCC (2023), projected trends differ markedly across hazard categories and regions, both in direction and in the degree of scientific confidence. Some hazards—such as extreme cold events or frost—are expected to decline in frequency or intensity in several regions, while others—such as storms in certain areas—exhibit low or mixed confidence regarding future changes (Table 2). In these cases, where forward-looking projections remain uncertain or ambiguous, understanding the realized market impact of past events is likely one of the most informative ways to anticipate potential future financial effects. Historical evidence provides concrete benchmarks for how markets have processed and priced such shocks when they occurred, even if their future prevalence is unclear.

For other hazards, the scientific consensus points to a clear increase in frequency or intensity, with medium to high confidence. For these hazards, historical realized studies remain of primary importance. Although the climate system is shifting, many of the mechanisms through which they affect firms are likely to remain unchanged. The intensity of some acute risks has already been observed within the historical record, even though their frequency is projected to increase. For example, the damages caused by hurricane Katrina (2005) or the European heatwave of 2003 provide valuable information on how firms and financial markets respond to such shocks. Because the geographical exposure of many firms is structurally determined by fixed assets, supply chains, or natural resource dependencies, those companies most vulnerable to past events are likely to remain vulnerable under future climate conditions. Empirical approaches offer a natural laboratory to quantify how firms, investors, and markets respond to events that are expected to become more salient going forward. In this sense, they can directly inform and refine the damage functions embedded in forward-looking frameworks, such as scenario analysis or stress testing exercises. They can also serve as an external validation tool for bottom-up climate risk scores or internal models developed by financial institutions.

Finally, from a methodological perspective, realized empirical approaches present several advantages for practitioners and regulators. First, physical risks over the short to medium term are largely exogenous to current mitigation choices, due to climate inertia. This strengthens the relevance of historical events as a basis for inference. Second, these approaches are relatively agnostic with respect to the underlying transmission mechanisms. Unlike structural or scenario-based models, they do not require strong assumptions or calibrations regarding the many channels through which physical risks may affect firm value. Third, they are transparent, verifiable, and easy to communicate. Showing the cumulative abnormal return of exposed firms following a well-known event—such as Hurricane Sandy or a recent European heatwave—might be more intuitive for decision-makers than forward-looking scores or model outputs.

These advantages are particularly relevant from an investor perspective, because the literature reviewed in this paper suggests that assessing the financial implications of physical climate risk

requires a broad and granular information set. Beyond the mere occurrence of climate hazards, investors need information on the geographic exposure of firms’ assets and supply chains in order to distinguish between directly and indirectly affected areas; on the sensitivity of sectors and business models to specific hazards, which may generate common vulnerabilities across firms within the same industry; and on the extent to which market adjustments propagate through volatility, correlations, and liquidity conditions. Event studies can help identify which firms, industries, and regions are systematically more vulnerable to particular climate hazards, thereby providing useful inputs for portfolio construction and risk monitoring. Combined with firm-level exposure and resilience measures, this information can support the development of more comprehensive indicators of physical climate risk and help investors determine whether and how such risks should be hedged.

## 7 Conclusion

This review synthesizes the empirical finance literature on realized physical climate hazards and equity markets, with the objective of clarifying whether, how, and under which conditions physical climate risk is reflected in stock prices. Across 47 studies, a consistent message emerges: realized climate-related hazards are economically and statistically relevant for equity markets, even though the sign, magnitude, and persistence of effects vary substantially across hazards, regions, samples, and empirical designs. The evidence is strongest for a set of acute and high-salience hazards—tropical cyclones, tornadoes, and extreme heat—and for dry events such as droughts and wildfires. Importantly, climate hazards affect not only realized returns but also risk-relevant dimensions—volatility, correlations, and, in a smaller subset of papers, liquidity—suggesting that physical climate risk cannot be reduced to a pure “cash-flow shock” narrative.

For practitioners and supervisors, these findings imply that physical climate risk is already priced in financial markets, but in a heterogeneous manner. Forward-looking scenario frameworks remain necessary to assess long-horizon exposures under alternative warming pathways, yet they rest on structural assumptions about transmission mechanisms and calibration choices. Realized empirical approaches provide a complementary and operationally valuable input: they rely on quasi-exogenous shocks, require limited structural modelling, and generate outcomes that are directly observable, auditable, and communicable. We suggest that there is scope for tighter integration between realized evidence and forward-looking tools: event-based estimates can be used to validate scenario-model outputs, discipline damage-function calibration, and benchmark bottom-up risk scores.

At the same time, the literature leaves several open questions that define clear avenues for future

research. First, a structural imbalance emerges between the concentration of existing empirical evidence and the regions and hazard types where climate change is expected to intensify physical risks most strongly. This is particularly true for chronic physical risks. The reviewed literature remains dominated by acute events, with only limited evidence on slower-moving risks such as temperature trends, persistent heat exposure, changing precipitation regimes, and sea-level rise. Addressing this gap should be a priority for future climate-finance research, as chronic risks are likely to affect firms through gradual changes in productivity, operating costs, asset values, adaptation needs, and location decisions, rather than through discrete shocks. Regarding regions, the United States currently dominates the corpus, and hurricanes dominate the event set, partly reflecting the availability of standardized disaster databases and the tractability of short-lived events for event-study designs. Yet the climate science literature suggests that future hazard dynamics are neither uniform nor equally certain across regions and hazard categories. Some hazards exhibit robust projected increases (e.g., hot extremes and coastal flooding driven by sea-level rise), while others display heterogeneous trends and lower confidence (e.g., several wind-driven hazards and storm categories). Expanding geographic coverage—particularly toward Asia and Africa—and developing harmonized event and exposure datasets for these regions is a priority, both because hazard dynamics are expected to shift materially and because financial and supply-chain linkages transmit shocks globally.

Second, the literature reveals that the pricing of physical climate risk can be counter-intuitive. While negative market reactions dominate on average, a non-negligible set of studies documents significant positive abnormal returns across specific hazards and sectors. This “positive effect puzzle” calls for a more structured empirical agenda to disentangle underlying mechanisms: cash-flow gains from reconstruction activity or demand substitution, insurance and public transfer mechanisms, sectoral pricing power and supply disruptions, behavioural overreaction and subsequent reversal, and discount-rate repricing.

Finally, the literature’s focus on realized returns leaves core risk channels insufficiently explored. Physical climate events not only affect expected cash flows but also alter the joint distribution of returns by raising uncertainty, strengthening comovement, and generating short-lived yet material spikes in volatility and market frictions. These dynamics are central for institutions operating under leverage constraints, margin requirements, liquidity risk limits, and capital regulation, where transient stress episodes can translate into binding risk constraints. Systematic empirical evidence on these risk channels therefore remains a priority.

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## Appendix A Final corpus of the literature review

Table A.1: **Final corpus of the literature review**

Papers are presented in chronological order. In the variable column, R denotes abnormal returns, V denotes volatility, C denotes correlation, L denotes liquidity, and O denotes other variables. The sign reported represents a synthesis of the predominant direction of the results from an investor's perspective, with a negative value indicating an adverse impact.

| Reference                                         | Hazard                                | Region | Period    | Method                   | Var. | Sign | Key result (brief)                                                                                                                                                                                                                                 |
|---------------------------------------------------|---------------------------------------|--------|-----------|--------------------------|------|------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <a href="#">Lamb (1995)</a>                       | Hurricanes                            | US     | 1992      | Event study              | R    | –    | Hurricane Andrew triggers significant negative stock price reactions for P&L insurers with direct exposure in FL/LA; no significant reaction for non-exposed insurers.                                                                             |
| <a href="#">Angbazo and Narayanan (1996)</a>      | Hurricanes                            | US     | 1992      | Event study              | R    | –    | Hurricane Andrew produces a large negative price reaction for insurers, partially offset by a smaller positive effect consistent with expectations of future premium increases; industry-wide effects also arise beyond directly exposed firms.    |
| <a href="#">Cagle (1996)</a>                      | Hurricanes                            | US     | 1989      | Event study              | R    | –    | For Andrew, insurer prices decline on average with limited differentiation by exposure; for Hugo, high-exposure insurers exhibit significant negative reactions while low-exposure insurers are largely unaffected.                                |
| <a href="#">Worthington and Valadkhani (2004)</a> | Hurricanes; Wildfires; Floods; Storms | AUS    | 1982–2002 | Time-series model        | R    | +/-  | Some disaster coefficients are significant: bushfires show small positive effects contemporaneously/next day; cyclones and earthquakes show small negative effects on the event day; floods and storms are not significant at conventional levels. |
| <a href="#">Cao and Wei (2005)</a>                | Temperature shocks                    | World  | 1962–2001 | CS reg.; TS reg.; t-test | R    | –    | Higher temperature is associated with lower equity returns in most markets after controlling for inter-market correlations; e.g., for the US, a +1°C day is associated with about -0.21% returns; effects are stronger for cap-weighted indices.   |

*Continued on next page.*

Table A.1 continued.

| Reference                                         | Hazard                                | Region | Period    | Method                   | Var.  | Sign | Key result (brief)                                                                                                                                                                                                                               |
|---------------------------------------------------|---------------------------------------|--------|-----------|--------------------------|-------|------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <a href="#">Worthington and Valadkhani (2005)</a> | Hailstorms; Wildfires                 | AUS    | 1995–2003 | Time-series model        | R     | +/-  | Canberra bushfires are associated with a -0.70% Materials-sector decline in the 10 days following the event, while the Sydney hailstorm produces a +2.32% Materials-sector increase; other sector coefficients are not individually significant. |
| <a href="#">Ewing et al. (2006)</a>               | Hurricanes                            | US     | 1990–2000 | Event study; Time-series | R     | –    | Insurance sector reacts negatively to Floyd and Andrew (CARs of about -2.17% and -2.71% over [-8,+1]); daily responses vary materially with the type of hurricane-related news.                                                                  |
| <a href="#">Worthington (2008)</a>                | Storms; Floods; Hurricanes; Wildfires | AUS    | 1980–2003 | Time-series; t-test      | R     | +/-  | Natural events do not impact daily market returns on average; returns during disasters are slightly positive but display negative skewness and high kurtosis.                                                                                    |
| <a href="#">Thomann (2013)</a>                    | Hurricanes                            | US     | 1988–2006 | Time-series model        | V;C;O | –    | Natural catastrophes increase the volatility of insurance stocks and tend to reduce correlation with the market; additional results reported on catastrophe-related risk measures.                                                               |
| <a href="#">Wang and Kutan (2013)</a>             | Hurricanes                            | JP; US | 1989–2011 | Time-series model        | V;R   | +/-  | Aggregate market returns are not materially affected in the US or Japan, but the insurance sector is: insurance stocks fall in the US and rise in Japan; disaster-related risk increases in all markets except the Japanese aggregate market.    |
| <a href="#">Barrot and Sauvagnat (2016)</a>       | Mixed climate events                  | US     | 1978–2013 | Event study              | R     | –    | Disasters hitting suppliers generate large output losses for customers, especially when inputs are highly specific; these shocks translate into significant market value losses.                                                                 |

Continued on next page.

Table A.1 continued.

| Reference                             | Hazard                                  | Region | Period    | Method                           | Var. | Sign | Key result (brief)                                                                                                                                                                                                                                |
|---------------------------------------|-----------------------------------------|--------|-----------|----------------------------------|------|------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Balvers et al. (2017)                 | Temperature shocks                      | US     | 1953–2015 | Mimicking port.; Factor; CS reg. | R    | –    | Temperature-shock mimicking portfolio carries a significantly negative risk premium (about -2% per month); exposure is more negative for small and value firms and for firms in states with high temperature variability.                         |
| Bourdeau-Brien and Kryzanowski (2017) | Floods; Extreme temp.; Hurricanes; etc. | US     | 1990–2014 | Time-series model                | R;V  | +    | Only a subset of disasters significantly affects returns (localized and persistent); volatility more than doubles following hurricanes, floods, winter storms, and extreme temperature events.                                                    |
| Feria-Domínguez et al. (2017)         | Hurricanes                              | US     | 2005–2012 | Event study                      | R    | –    | Most hurricanes generate significant cumulative abnormal returns for US insurers around landfall; Katrina and Sandy are notable exceptions with no significant abnormal returns.                                                                  |
| Griffin et al. (2019)                 | Extreme heat; Extreme cold              | US     | 2003–2017 | Event study; Panel reg.          | R;V  | –    | Extreme high-temperature events lead to negative cumulative excess returns, particularly for costly and long-duration events and firms in the South/Southeast; equity volatility rises during EHST episodes.                                      |
| Hong et al. (2019)                    | Droughts                                | World  | 1985–2014 | CS reg.; t-test; sort            | R;O  | –    | High drought-risk countries have significantly lower profit growth and earn lower annual returns; a long-short portfolio based on drought-trend ranks earns a significant monthly return/alpha; drought risk predicts lower future profit growth. |
| Lanfear et al. (2019)                 | Hurricanes                              | US     | 1990–2017 | Event study                      | R;L  | –    | Size, Value, and Momentum factors react negatively to hurricanes, with long legs being more illiquid than short legs.                                                                                                                             |

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Table A.1 continued.

| Reference                                      | Hazard               | Region    | Period    | Method                           | Var. | Sign | Key result (brief)                                                                                                                                                                                                         |
|------------------------------------------------|----------------------|-----------|-----------|----------------------------------|------|------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <a href="#">Tavor and Teitler-Regev (2019)</a> | Mixed climate events | World     | 1983–2013 | Descriptive; TS reg.             | R;O  | +/-  | Returns are negative on the event day and the next two days on average; the pessimism index increases returns on the event day and up to two days later; interpretation and some estimates appear internally inconsistent. |
| <a href="#">Alok et al. (2020)</a>             | Mixed climate events | US        | 1995–2016 | Diff-in-Diff                     | R;O  | +    | Post-disaster decrease in disaster-zone holdings is stronger for closed-end funds; underweighted disaster-zone stocks subsequently outperform overweighted ones for salient events, consistent with price pressure.        |
| <a href="#">Donadelli et al. (2020)</a>        | Tornadoes            | US        | 1975–2019 | Panel reg.                       | R    | +/-  | Effects are negative, lagged, and local in aggregate; sector heterogeneity includes negative local effects for consumer discretionary and telecommunications and positive contemporaneous effects for energy.              |
| <a href="#">Malik et al. (2020)</a>            | Mixed climate events | US        | 1960–2015 | Event study                      | R    | +/-  | Industry heterogeneity: significant positive reactions (banking, drugs, utilities) and significant negative reactions (paper, mines, financial trading, apparel, aerospace, gold).                                         |
| <a href="#">Gregory (2021)</a>                 | Temperature shocks   | US; World | 1990–2018 | Mimicking port.; Factor; CS reg. | R    | +/-  | The global temperature shock factor earns a small positive risk premium (about 0.01% per month).                                                                                                                           |
| <a href="#">Liu et al. (2021)</a>              | Hurricanes           | US        | 1992–2012 | Event study                      | R;O  | –    | Hurricane impacts on US energy firms are limited and heterogeneous by carbon intensity; cleaner firms earn higher CARs than coal; Katrina is associated with higher CARs than Hugo/Andrew/Sandy.                           |
| <a href="#">Peillex et al. (2021)</a>          | Extreme heat         | FR        | 1995–2019 | TS reg.; t-test; ES              | L    | –    | Hot days (>30°C) are associated with significantly lower trading volume (about -5%).                                                                                                                                       |

Continued on next page.

Table A.1 continued.

| Reference                                | Hazard                                           | Region | Period    | Method             | Var. | Sign | Key result (brief)                                                                                                                                                                               |
|------------------------------------------|--------------------------------------------------|--------|-----------|--------------------|------|------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <a href="#">Ma et al. (2022)</a>         | Mixed climate events                             | US     | 1980–2016 | Panel reg.; t-test | C    | –    | Disaster months exhibit higher stock–market comovement; most of the increase comes from covariance rather than volatility; institutional and analyst monitoring mitigates the comovement effect. |
| <a href="#">Pagnottoni et al. (2022)</a> | Mixed climate events                             | World  | 2001–2019 | Panel regression   | R    | +/-  | Biological events tend to generate more positive effects on market indexes, while climatological events affect returns more severely in a negative way.                                          |
| <a href="#">U-Din et al. (2022)</a>      | Floods; Hurricanes; Storms; Tornadoes; Wildfires | CA     | 1988–2016 | Panel reg.; t-test | R;V  | –    | All five extreme weather events have a negative effect on stock returns over a 5-day window; volatility effects are also reported.                                                               |
| <a href="#">Acharya et al. (2023)</a>    | Extreme heat; Mixed events                       | US     | 1990–2020 | Panel regression   | R;O  | +/-  | Heat stress increases expected returns mostly after 2015; credit spreads rise, particularly for non-investment-grade bonds.                                                                      |
| <a href="#">Addoum et al. (2023)</a>     | Temperature shocks                               | US     | 1990–2015 | Event study        | R;O  | +/-  | Cumulative abnormal returns do not significantly react to extreme temperature days, but earnings respond significantly in most industries with mixed-direction effects.                          |
| <a href="#">Huynh and Xia (2023)</a>     | Mixed; Hurricanes; Tornadoes; etc.               | US     | 1990–2015 | Panel reg.; Sort   | R;O  | +/-  | Exposed firms have lower contemporaneous stock and bond excess returns but higher future returns (price reversal) and weaker fundamentals (sales growth, spreads, profitability volatility).     |
| <a href="#">Malik et al. (2023)</a>      | Mixed climate events                             | US     | 1995–2015 | ES; Panel reg.; IV | R    | +    | Firms in disaster areas earn positive abnormal returns post-disaster (about +0.4% over (0,+1) up to +3.83% over (0,+30)).                                                                        |

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Table A.1 continued.

| Reference                | Hazard                             | Region | Period    | Method            | Var. | Sign | Key result (brief)                                                                                                                                                                              |
|--------------------------|------------------------------------|--------|-----------|-------------------|------|------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Schuh and Jaeckle (2023) | Hurricanes                         | US     | 2003–2018 | ES + regression   | R    | –    | Hurricanes generate negative abnormal returns for US insurers; more intense and damaging hurricanes imply larger losses, while weaker hurricanes can be associated with positive returns.       |
| Apergis (2024)           | Temperature shocks                 | World  | 1950–2021 | Panel regression  | R;O  | –    | High temperature hurts stock returns if starting temperature is high and boosts returns if starting temperature is low; temperature shocks also relate to assets, investment, and cost of debt. |
| Blanco et al. (2024)     | Mixed climate events               | US     | 1998–2013 | Event study       | R;O  | –    | Institutions with high disaster exposure reduce holdings of affected stocks and lower trading intensity in unaffected stocks, reducing price informativeness.                                   |
| Hamid and Kang (2024)    | Droughts; Floods; Hurricanes; etc. | US     | 1980–2023 | Event study       | R    | +/-  | Average CARs are largely negative but not statistically significant in most days of the event window.                                                                                           |
| Kreuzer et al. (2024)    | Hurricanes                         | US     | 1991–2023 | Time-series model | R    | +/-  | Significant negative reaction to high-strength hurricanes before the event and positive response afterwards (relief); positive reaction before weak hurricanes.                                 |
| Li et al. (2024)         | Mixed climate events               | US     | 2000–2019 | Event study       | R    | +/-  | Extreme weather events have statistically significant effects on NASDAQ returns, with variation by disaster type and evidence of return reversals around event dates.                           |
| Montero et al. (2024)    | Mixed climate events               | US     | 2010–2020 | Time-series model | V    | +/-  | In-sample, insurer volatility decreases one to three months after disasters in many cases; out-of-sample, volatility increases significantly.                                                   |
| Tavor (2024)             | Wildfires                          | US     | 2019–2022 | ES + regression   | R    | –    | Energy sector experiences a persistent post-wildfire CAR decrease, consistent with supply disruptions and safety/environmental concerns.                                                        |

Continued on next page.

Table A.1 continued.

| Reference                                     | Hazard                                                      | Region    | Period        | Method                      | Var.  | Sign | Key result (brief)                                                                                                                                                                                                                  |
|-----------------------------------------------|-------------------------------------------------------------|-----------|---------------|-----------------------------|-------|------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <a href="#">Bauer et al. (2024)</a>           | Floods;<br>Storms                                           | EU        | 2014–<br>2021 | Event<br>study              | R     | –    | Affected firms experience a negative abnormal return of about 99 bps on the event date.                                                                                                                                             |
| <a href="#">Braun et al. (2025)</a>           | Storms                                                      | US        | 1995–<br>2019 | CS reg.;<br>Factor;<br>Sort | R     | –    | Stocks with lower weather beta earn higher returns than those with higher weather beta; a long–short portfolio based on weather sensitivity earns positive abnormal performance.                                                    |
| <a href="#">Davidescu et al. (2025)</a>       | Mixed<br>climate<br>events                                  | US        | 2017–<br>2022 | Time-<br>series<br>model    | R;V;C | +/-  | Insurance and energy are most susceptible with fat-tailed returns; volatility is persistent and returns are positively correlated with market stress; mixed results for autos.                                                      |
| <a href="#">Horváth et al. (2025)</a>         | Weather<br>attention                                        | US        | 2006–<br>2022 | Panel re-<br>gression       | R;V   | +/-  | Intraday volatility falls with attention to weather/hurricanes/storms (but rises for meteo events); intraday and daily returns increase with weather/hurricane/storm attention but decrease with meteo events and major hurricanes. |
| <a href="#">Krutkli et al. (2025)</a>         | Floods;<br>Hurri-<br>canes;<br>Snow<br>storms;<br>Tornadoes | US        | 1996–<br>2019 | Diff-in-<br>Diff            | R;V;O | –    | Implied volatility increases for firms with establishments hit by floods and persists from one week to three months; the design also reports return-related effects around events.                                                  |
| <a href="#">Panetsidou and Synapis (2025)</a> | Weather<br>alerts                                           | UK        | 2015–<br>2023 | Panel<br>reg.; ES           | R     | –    | Firms in vulnerable industries react more negatively to weather alerts, especially red alerts and multi-phenomenon alerts; frequent updates mitigate reactions.                                                                     |
| <a href="#">Schuster et al. (2025)</a>        | Extreme<br>heat                                             | US;<br>EU | 2010–<br>2022 | Event<br>study              | R     | –    | Statistically significant stock-price reactions are reported for US heat waves and for each of the five largest European heat waves.                                                                                                |

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Table A.1 continued.

| Reference                        | Hazard               | Region | Period    | Method                  | Var.  | Sign | Key result (brief)                                                                                                                                                                                                                                     |
|----------------------------------|----------------------|--------|-----------|-------------------------|-------|------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <a href="#">Xu et al. (2025)</a> | Mixed climate events | World  | 2006–2016 | Factor; Panel; IV; Sort | R;L;O | +/-  | High climate-risk portfolios earn significant alpha and predictable year-ahead excess returns; higher climate risk is associated with wider bid–ask spreads, higher implied cost of capital, weaker earnings, higher volatility, and lower valuations. |

## Appendix B Mapping hazard classifications across frameworks

| Category      | FSB            | This paper        | IPCC                                             | EM-DAT                                                      |                                                            |  |
|---------------|----------------|-------------------|--------------------------------------------------|-------------------------------------------------------------|------------------------------------------------------------|--|
| Heat and cold | Chronic        | Air temperature   | Mean air temperature                             |                                                             |                                                            |  |
|               | Acute          | Extreme cold      | Cold spell                                       | Cold wave                                                   |                                                            |  |
|               |                | Frost             | Frost                                            | Severe winter conditions                                    |                                                            |  |
|               |                | Extreme heat      | Extreme heat                                     | Heat wave                                                   |                                                            |  |
| Wind          | Chronic        | Wind speed        | Mean wind speed                                  |                                                             |                                                            |  |
|               | Acute          | Tropical cyclones | Tropical cyclone                                 | Tropical cyclone                                            |                                                            |  |
|               |                | Tornadoes         | Severe wind storm                                | Tornado                                                     |                                                            |  |
|               |                | Winter storms     | Heavy snowfall and ice storm                     | Blizzard/Winter storm                                       |                                                            |  |
|               |                |                   |                                                  | Derecho                                                     |                                                            |  |
|               |                |                   |                                                  | Extra-tropical storm                                        |                                                            |  |
|               |                |                   |                                                  | Hail                                                        |                                                            |  |
|               |                |                   |                                                  | Lightning/Thunderstorms                                     |                                                            |  |
|               |                |                   |                                                  | Sand/Dust storm                                             |                                                            |  |
|               |                |                   |                                                  | Severe weather                                              |                                                            |  |
|               |                |                   |                                                  | Storm (General)                                             |                                                            |  |
|               |                | Other storms      | Hail<br>Sand and dust storm<br>Severe wind storm | Storm surge                                                 |                                                            |  |
| Wet and dry   | Chronic        | Precipitation     | Mean precipitation                               |                                                             |                                                            |  |
|               | Acute          | Flash floods      | Heavy precipitation and pluvial flood            | Flash flood                                                 |                                                            |  |
|               |                |                   |                                                  | Flood (General)                                             |                                                            |  |
|               |                |                   |                                                  | Glacial lake outburst flood                                 |                                                            |  |
|               |                | River floods      | River flood                                      | Ice jam flood                                               |                                                            |  |
|               |                |                   |                                                  | Riverine flood                                              |                                                            |  |
|               |                |                   |                                                  | Avalanche (wet)                                             |                                                            |  |
|               |                |                   |                                                  | Landslide (wet)                                             |                                                            |  |
|               |                |                   |                                                  | Mudslide                                                    |                                                            |  |
|               |                |                   |                                                  | Rockfall (wet)                                              |                                                            |  |
|               |                |                   |                                                  | Sudden Subsidence (wet)                                     |                                                            |  |
|               |                |                   | Landslides                                       | Landslide<br>Agricultural and ecological drought<br>Aridity |                                                            |  |
|               |                |                   | Droughts                                         | Hydrological drought                                        | Drought<br>Forest fire<br>Land fire (Brush, Bush, Pasture) |  |
|               |                |                   | Wildfires                                        | Fire weather                                                | Wildfire (General)                                         |  |
|               |                | Ocean             | Chronic                                          | Ocean level                                                 | Relative sea level                                         |  |
|               |                |                   |                                                  | Ocean acidity                                               | Ocean acidity                                              |  |
| Acute         | Coastal floods |                   | Coastal flood                                    | Coastal flood                                               |                                                            |  |
| Other         | Acute          | Air pollution     | Air pollution weather                            |                                                             |                                                            |  |

Table B.1: **Mapping of Hazard Classifications Across Frameworks**

The table harmonizes the proposed hazard taxonomy with IPCC Climate Impact Drivers and EM-DAT hazard subtypes, aligned with FSB, NGFS and IFRS distinctions between acute and chronic risks.

## Appendix C Additional Results

|                           | Type of Hazard          | Droughts | Extreme cold | Extreme heat | Floods | Hurricanes | Mixed climate events | Snow storms | Storms | Temperature shocks | Wildfires |
|---------------------------|-------------------------|----------|--------------|--------------|--------|------------|----------------------|-------------|--------|--------------------|-----------|
|                           | Event window length     |          |              |              |        |            |                      |             |        |                    |           |
| N. of event studies       | Short ( $\leq 10$ days) | /        | 16           | /            | 1      | 41         | 51                   | /           | 1      | 1                  | 54        |
|                           | Long ( $> 10$ days)     | 1        | 33           | 58           | 3      | 120        | 83                   | 1           | 3      | 3                  | 36        |
| Median normalized CAR (%) | Short ( $\leq 10$ days) | /        | 0.001        | /            | 0.022  | -0.148     | -0.001               | /           | -0.104 | 0.033              | -0.027    |
|                           | Long ( $> 10$ days)     | 0.005    | -0.001       | -0.034       | -0.005 | -0.006     | 0.009                | 0.057       | -0.034 | 0.007              | 0.008     |

Table C.1: **Abnormal Returns by Event Window Length**

This table reports the number of event studies together with the median normalized CAR (percentage points) by event window length, i.e. short (at most 10 days) or long (over 10 days) and type of hazard.

## Tables

| Category     | Hazard / Driver   | AvgEv |                     | Dur<br>(d) | Cost<br>(bn \$) | Aff.<br>(Mn) | NA  | C&SA  | EU    | AF    | AS    | AU  |
|--------------|-------------------|-------|---------------------|------------|-----------------|--------------|-----|-------|-------|-------|-------|-----|
|              |                   | Tot   | (yr <sup>-1</sup> ) |            |                 |              |     |       |       |       |       |     |
| Heat & Cold  | Extreme cold      | 216   | 8.3                 | 19.2       | 0.8             | 0.2          | 4   | 36    | 109   | 9     | 58    | –   |
|              | Frost             | 77    | 3.0                 | 14.6       | 4.0             | 2.1          | 5   | 9     | 41    | –     | 22    | –   |
|              | Extreme heat      | 275   | 10.6                | 55.6       | 1.3             | 0.6          | 13  | 3     | 172   | 8     | 75    | 4   |
| Wind         | Tropical cyclones | 1,405 | 54.0                | 2.2        | 2.3             | 0.5          | 74  | 379   | 7     | 123   | 710   | 112 |
|              | Tornadoes         | 171   | 6.6                 | 1.6        | 1.8             | 0.0          | 110 | 5     | 10    | 6     | 35    | 5   |
|              | Winter storms     | 184   | 7.1                 | 5.7        | 1.2             | 1.5          | 73  | 9     | 36    | 1     | 63    | 2   |
|              | Other storms      | 1,004 | 38.6                | 2.8        | 0.9             | 0.3          | 150 | 72    | 313   | 114   | 322   | 33  |
| Wet & Dry    | Flash floods      | 755   | 29.0                | 7.4        | 0.3             | 0.3          | 26  | 75    | 102   | 153   | 379   | 20  |
|              | River floods      | 3,424 | 131.7               | 12.4       | 1.0             | 0.5          | 129 | 673   | 385   | 842   | 1,320 | 75  |
|              | Landslides        | 490   | 18.8                | 1.6        | 0.1             | 0.0          | 3   | 91    | 18    | 68    | 297   | 13  |
|              | Droughts          | 419   | 16.1                | 213.3      | 2.2             | 5.5          | 16  | 86    | 26    | 177   | 96    | 18  |
|              | Wildfires         | 332   | 12.8                | 15.0       | 1.2             | 0.1          | 99  | 49    | 83    | 28    | 48    | 25  |
| Ocean        | Coastal floods    | 42    | 1.6                 | 9.1        | 1.1             | 0.3          | –   | 6     | 5     | 6     | 17    | 8   |
| <b>TOTAL</b> |                   | 8,794 | 338.2               | 9.4        | 1.4             | 0.7          | 702 | 1,493 | 1,307 | 1,535 | 3,442 | 315 |

Table 1: **Frequency, duration, and economic impacts of climate-related physical hazards (2000–2025)**

Data are obtained from the Emergency Events Database (EM-DAT). Each observation represents a distinct disaster event recorded between 1 January 2000 and 30 September 2025. Hazard types are classified in accordance with our proposed classification (Table B.1). For each hazard, the table reports: the total number of events over the 2000–2025 period; the average annual frequency of events (AvgEv); the mean event duration in days (Dur); the mean economic loss per event, reported in billions of inflation-adjusted (constant 2023) U.S. dollars; the mean number of affected individuals, expressed in millions of persons (Aff.); and the cumulative number of events per region. “People affected” is defined as the sum of individuals reported as injured, displaced or rendered homeless, or otherwise adversely impacted. Regions are: North America (NA), Canada and South America (C&SA), Europe (EU), Africa (AF), Asia (AS) and Australasia (AU).

| Category      | Type    | Hazard/Driver     | NA   |        | C&SA |        | EU   |        | AF   |        | AS   |        | AU   |        |
|---------------|---------|-------------------|------|--------|------|--------|------|--------|------|--------|------|--------|------|--------|
|               |         |                   | Past | Future | Past | Future | Past | Future | Past | Future | Past | Future | Past | Future |
| Heat and Cold | Chronic | Air temperature   | +    | ++     | +    | ++     | +    | ++     | +    | ++     | +    | ++     | +    | ++     |
|               | Acute   | Extreme cold      | -    | -      | -    | -      | -    | -      | -    | -      | -    | -      | -    | -      |
|               |         | Frost             | -    | -      | -    | -      | -    | -      | -    | -      | -    | -      | -    | -      |
|               |         | Extreme heat      | +    | ++     | +    | ++     | +    | ++     | +    | ++     | +    | ++     | +    | ++     |
| Wind          | Chronic | Wind speed        | (-)  | (-)    | -/+  | -      | -    |        | +    | -      | -    |        |      |        |
|               | Acute   | Tropical cyclones |      | +      |      | +      |      |        | +    | +      | +    |        |      |        |
|               |         | Tornadoes         | +    | +      |      | +      |      |        |      |        |      |        |      | +      |
|               |         | Winter storms     |      |        |      |        |      |        |      |        | +    |        |      |        |
|               |         | Other storms      |      | +      |      |        | +    |        |      |        |      |        |      |        |
| Wet and dry   | Chronic | Precipitation     | +    | ++     | +    | +      | +    | -/+    | -    | -      | -/+  | ++     |      | -      |
|               | Acute   | Flash floods      | +    | ++     | +    | +      | +    | ++     | +    | ++     | +    | ++     | +    | +      |
|               |         | River floods      |      | +      | +    | +      | -/+  | -/+    |      | +      |      | +      |      | +      |
|               |         | Landslides        |      | +      |      |        |      |        |      |        |      | +      |      |        |
|               |         | Droughts          | +    | +      | +    | ++     | +    | ++     | +    | ++     |      |        | +    | +      |
|               |         | Wildfires         | +    | ++     | +    | ++     |      | ++     |      | ++     |      | +      | +    | ++     |
| Ocean         | Chronic | Ocean level       | +    | ++     | +    | ++     | +    | ++     | +    | ++     | +    | ++     | +    | ++     |
|               | Acute   | Ocean acidity     | +    | ++     | +    | ++     | +    | ++     | +    | ++     | +    | ++     | +    | ++     |
|               |         | Coastal floods    | +    | ++     | +    | ++     |      | ++     |      | ++     |      | ++     |      | ++     |
| Other         | Acute   | Air pollution     |      |        |      |        |      |        |      |        |      |        |      |        |

Table 2: Observed and projected trends across hazards and climate drivers

Data are drawn from [IPCC \(2021\)](#), Working Group I, in particular the table "Summary of confidence for climatic impact-driver changes" by region. For historical (past) trends, "+" ("-") denotes medium or high confidence in an upward (downward) trend. For projected (future) trends, "+" ("-") indicates medium confidence in an increase (decrease), while "++" ("--") denotes high confidence in an increase (decrease). When trends differ across subregions within a given AR6 reference region, the table reports the dominant trend only. The notation "-/+" indicates opposing trends across subregions within the same region.

| Transmission Block                                  |             |              | Mechanism Description (Financial-Statement Structure)                                                                                                                                                                                                                               |
|-----------------------------------------------------|-------------|--------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Expected (Macro)</b>                             | <b>Cash</b> | <b>Flows</b> |                                                                                                                                                                                                                                                                                     |
| Aggregate productivity and factor-input disruption  |             |              | Climate hazards reduce aggregate labor productivity, alter effective capital utilisation and lower total factor productivity. <i>Income statement</i> : weaker top-line growth, lower operating leverage. <i>Cash flow</i> : reduced operating cash flows and lower free cash flow. |
| Commodity-price and energy-system shifts            |             |              | Water scarcity, heat or drought alter relative prices of key inputs (energy, water, food). <i>Income statement</i> : volatility in COGS. <i>Working capital</i> : higher inventories and hedging needs. <i>Cash flows</i> : higher volatility of free cash flows.                   |
| Macroeconomic demand reallocation                   |             |              | Persistent shifts in household consumption and sectoral demand modify long-run revenue trajectories. <i>Income statement</i> : revisions in sales volumes and pricing power. <i>Valuation</i> : lower terminal growth and residual values.                                          |
| Systemic capital-deepening requirements             |             |              | Adaptation and mitigation needs require economy-wide replacement or hardening of capital. <i>Balance sheet</i> : rising capital intensity. <i>Cash flow</i> : higher maintenance and adaptation capex depress free cash flow.                                                       |
| <b>Expected Cash Flows (Firm-Specific)</b>          |             |              |                                                                                                                                                                                                                                                                                     |
| Asset impairment and accelerated depreciation       |             |              | Physical damages, regulatory obsolescence, or reduced usability alter the useful life of capital. <i>Balance sheet</i> : write-downs. <i>Income statement</i> : accelerated depreciation. <i>Cash flows</i> : lower taxable profits and free cash flow.                             |
| Adaptation, mitigation, and compliance capex        |             |              | Firms invest in protective infrastructure, cooling, abatement, or resilience. <i>Cash flows</i> : structurally higher capex and opex reduce free cash flows to equity and debt.                                                                                                     |
| Supply-chain and market-access disruption           |             |              | Climate events disrupt suppliers, transport routes, and downstream clients. <i>Income statement</i> : lost volumes and higher COGS. <i>Working capital</i> : higher inventories. <i>Cash flows</i> : amplified volatility.                                                          |
| Input-specific productivity losses                  |             |              | Heat stress or water scarcity reduce labour efficiency and resource productivity. <i>Income statement</i> : margin compression. <i>Cash flows</i> : persistent downward revisions of operational cash flows.                                                                        |
| Insurance, financing, and risk-transfer constraints |             |              | Higher climate-exposed default and liquidity risks raise insurance premia and tighten credit conditions. <i>Income statement</i> : higher insurance costs. <i>Financing</i> : higher interest expense and elevated WACC.                                                            |
| Information, disclosure, and expectation updates    |             |              | New information on exposure, vulnerability, or resilience alters analyst expectations. <i>Valuation</i> : revisions to revenues, margins, capex, and discount rates.                                                                                                                |
| <b>Discount Rates</b>                               |             |              |                                                                                                                                                                                                                                                                                     |
| Long-run climate risk (LRR)                         |             |              | Climate affects persistent components of consumption growth. Assets exposed to adverse long-run climate states command risk premia through long-run consumption covariance.                                                                                                         |
| Rare-disaster risk                                  |             |              | Higher perceived probability of climate disasters raises premia for assets sensitive to downside climate states.                                                                                                                                                                    |
| Climate-beta channel                                |             |              | Assets with higher sensitivity to adverse climate shocks must offer higher expected returns.                                                                                                                                                                                        |
| ESG-taste and hedging premia                        |             |              | Green assets earn lower expected returns due to hedging properties and investor preferences.                                                                                                                                                                                        |
| Uncertainty, variance-risk, and volatility feedback |             |              | Extreme events increase conditional volatility and variance-risk premia, raising discount rates.                                                                                                                                                                                    |
| Attention, sentiment, and microstructure dynamics   |             |              | Climate-news salience affects liquidity, spreads, and short-term price discovery.                                                                                                                                                                                                   |

Table 3: **Climate-risk transmission channels to firm financial valuation**

This table synthesises the main pathways through which climate hazards can affect firm value from an investor perspective, distinguishing macro-level from firm-specific mechanisms, and asset-pricing channels.

| Category      | Type    | Hazard / Driver       | US       |             |          | ROW                    |             |           |
|---------------|---------|-----------------------|----------|-------------|----------|------------------------|-------------|-----------|
|               |         |                       | Negative | Not signif. | Positive | Negative               | Not signif. | Positive  |
| Heat and cold | Chronic | Air temperature       | 2        | 1           | 1        | 2 (World)              | 1 (World)   |           |
|               | Acute   | Extreme cold          | 2        |             | 2        |                        |             |           |
|               |         | Frost<br>Extreme heat | 3        | 1           | 1        | 2 (EU,FR)              |             |           |
| Wind          | Chronic | Wind speed            |          |             |          |                        |             |           |
|               | Acute   | Tropical cyclones     | 15       |             | 6        | 2 (AUS, CA)            | 2 (AUS, JP) |           |
|               |         | Tornadoes             | 3        | 1           | 1        | 1 (CA)                 |             |           |
|               |         | Winter storms         | 1        |             | 1        |                        |             |           |
|               |         | Other storms          | 1        | 3           |          | 2 (CA, EU)             | 2 (AUS)     | 1 (AU)    |
| Wet and dry   | Chronic | Precipitation         |          |             |          |                        |             |           |
|               | Acute   | Floods                | 3        | 1           |          | 2 (CA, EU)             | 2 (AUS)     | 1 (EU)    |
|               |         | Landslides            |          |             |          |                        |             |           |
|               |         | Droughts              | 1        | 1           |          | 1 (World)              |             |           |
|               |         | Wildfires             | 2        |             | 2        | 2 (AUS, CA)            | 1 (AUS)     | 1 (AUS)   |
| Ocean         | Chronic | Ocean level           |          |             |          |                        |             |           |
|               |         | Ocean acidity         |          |             |          |                        |             |           |
| Other events  | Acute   | Air pollution         |          |             |          |                        |             |           |
|               |         | Mixed                 | 11       | 1           | 5        | 6 (AUS, CA, UK, World) |             | 2 (World) |
|               |         | Alerts and attention  |          |             | 1        | 1 (UK)                 |             |           |

Table 4: **Distribution of empirical findings by hazard and region**

The table summarizes the direction of stock market responses documented in the literature, classified by hazard category, type (chronic versus acute), and underlying climate driver. Results are reported separately for studies focusing on the United States (US) and the rest of the world (ROW), distinguishing between negative, positive, and statistically insignificant effects. Entries report the number of studies finding at least one statistically significant positive or negative effect for a given hazard–region pair; studies analysing the pair without significant results are classified as not significant (Not signif.).

| Category      | Type of event     | Nb. Res. | Nb. Art. | Mean   | Std.  | Min.   | Median | Max.  |
|---------------|-------------------|----------|----------|--------|-------|--------|--------|-------|
| Heat and cold | Air temperature   | 4        | 1        | 0.014  | 0.013 | 0.005  | 0.008  | 0.033 |
|               | Extreme cold      | 49       | 2        | 0.003  | 0.013 | -0.023 | 0.000  | 0.048 |
|               | Extreme heat      | 58       | 2        | -0.049 | 0.079 | -0.279 | -0.034 | 0.163 |
| Wind          | Tropical cyclones | 161      | 9        | -0.080 | 0.375 | -3.500 | -0.015 | 0.525 |
|               | Winter storms     | 1        | 1        | 0.057  | –     | 0.057  | 0.057  | 0.057 |
|               | Other storms      | 4        | 2        | -0.056 | 0.050 | -0.104 | -0.062 | 0.002 |
| Wet and dry   | Floods            | 4        | 2        | 0.001  | 0.015 | -0.013 | -0.002 | 0.022 |
|               | Droughts          | 1        | 1        | 0.005  | –     | 0.005  | 0.005  | 0.005 |
|               | Wildfires         | 90       | 2        | -0.037 | 0.141 | -0.610 | -0.014 | 0.266 |
| Other events  | Mixed             | 134      | 7        | 0.002  | 0.040 | -0.250 | 0.006  | 0.107 |
| <b>Total</b>  |                   | 506      | 20       | -0.037 | 0.225 | -3.500 | -0.003 | 0.525 |

Table 5: **Distribution of normalized cumulative abnormal returns reported in the event-Study literature**

Nb. Res. denotes the number of individual event-study results found in the literature for a given event type, while Nb. Art. refers to the number of distinct academic articles from which these estimates are drawn. A single article may report multiple results if it computes abnormal returns across different samples, event windows, or model specifications. Reported means correspond to the average of normalized *CAR* (in percentage points) across all results associated with a given event type (e.g., 0.014 corresponds to 0.014%).

| Type of Hazard<br>Sector | Droughts     | Extreme cold | Extreme heat   | Floods        | Hurricanes     | Mixed climate events | Snow storms  | Storms        | Temperature shocks | Wildfires      |
|--------------------------|--------------|--------------|----------------|---------------|----------------|----------------------|--------------|---------------|--------------------|----------------|
| Aero-aircrafts           | -            | -            | -              | -             | -              | 0.033 [2, 1]         | -            | -             | -                  | -              |
| Automotive               | -            | -            | -              | -             | -              | 0.015 [2, 1]         | -            | -             | -                  | -              |
| Banking                  | -            | -            | -              | -             | -              | -0.013 [2, 1]        | -            | -             | -                  | -              |
| Beer                     | -            | -            | -              | -             | -              | 0.019 [1, 1]         | -            | -             | -                  | -              |
| Building Materials       | -            | -            | -              | -             | -              | 0.022 [1, 1]         | -            | -             | -                  | -              |
| Business services        | -            | -            | -              | -             | -              | -0.009 [1, 1]        | -            | -             | -                  | -              |
| Chemicals                | -            | -            | -              | -             | -              | 0.045 [1, 1]         | -            | -             | -                  | -              |
| Coal                     | -            | -            | -              | -             | 0.011 [8, 1]   | -0.041 [1, 1]        | -            | -             | -                  | -              |
| Construction             | -            | -            | -              | -             | -              | 0.001 [1, 1]         | -            | -             | -                  | -              |
| Diversified              | 0.005 [1, 1] | -0.0 [49, 2] | -0.034 [58, 2] | -0.002 [4, 2] | -0.013 [86, 2] | -0.002 [79, 6]       | 0.057 [1, 1] | -0.062 [4, 2] | 0.008 [4, 1]       | 0.019 [1, 1]   |
| Drugs                    | -            | -            | -              | -             | -              | -0.006 [2, 1]        | -            | -             | -                  | -              |
| Electric equipment       | -            | -            | -              | -             | -              | 0.015 [3, 1]         | -            | -             | -                  | -              |
| Energy                   | -            | -            | -              | -             | -              | -                    | -            | -             | -                  | -0.325 [10, 1] |
| Entertainment            | -            | -            | -              | -             | -              | 0.011 [3, 1]         | -            | -             | -                  | -              |
| Fabricated products      | -            | -            | -              | -             | -              | 0.014 [1, 1]         | -            | -             | -                  | -              |
| Financial trading        | -            | -            | -              | -             | -              | -0.005 [1, 1]        | -            | -             | -                  | -              |
| Food                     | -            | -            | -              | -             | -              | -                    | -            | -             | -                  | 0.101 [10, 1]  |
| Forestry                 | -            | -            | -              | -             | -              | -                    | -            | -             | -                  | -0.02 [10, 1]  |
| Gas                      | -            | -            | -              | -             | 0.144 [8, 1]   | -                    | -            | -             | -                  | -              |
| Gold Precious metals     | -            | -            | -              | -             | -              | 0.079 [3, 1]         | -            | -             | -                  | -              |
| Hardware                 | -            | -            | -              | -             | -              | 0.016 [2, 1]         | -            | -             | -                  | -              |
| Healthcare               | -            | -            | -              | -             | -              | 0.018 [1, 1]         | -            | -             | -                  | -0.005 [10, 1] |
| Household consumer       | -            | -            | -              | -             | -              | 0.016 [1, 1]         | -            | -             | -                  | -              |
| Insurance                | -            | -            | -              | -             | -0.272 [35, 6] | -                    | -            | -             | -                  | -0.032 [10, 1] |
| Lab equipment            | -            | -            | -              | -             | -              | 0.014 [3, 1]         | -            | -             | -                  | -              |
| Machinery                | -            | -            | -              | -             | -              | 0.015 [1, 1]         | -            | -             | -                  | -              |
| Meals Hotels             | -            | -            | -              | -             | -              | 0.011 [3, 1]         | -            | -             | -                  | -              |
| Medical equipment        | -            | -            | -              | -             | -              | 0.016 [2, 1]         | -            | -             | -                  | -              |
| Mines                    | -            | -            | -              | -             | -              | 0.016 [1, 1]         | -            | -             | -                  | -              |
| Nuclear                  | -            | -            | -              | -             | -0.021 [8, 1]  | -                    | -            | -             | -                  | -              |
| Oil                      | -            | -            | -              | -             | 0.124 [8, 1]   | -0.04 [1, 1]         | -            | -             | -                  | -              |
| Paper                    | -            | -            | -              | -             | -              | 0.025 [2, 1]         | -            | -             | -                  | -              |
| Real estate              | -            | -            | -              | -             | -              | -                    | -            | -             | -                  | -0.003 [10, 1] |
| Renewable                | -            | -            | -              | -             | 0.069 [8, 1]   | -                    | -            | -             | -                  | -              |
| Retail                   | -            | -            | -              | -             | -              | 0.009 [2, 1]         | -            | -             | -                  | -              |
| Rubber                   | -            | -            | -              | -             | -              | -0.009 [2, 1]        | -            | -             | -                  | -              |
| Smoke                    | -            | -            | -              | -             | -              | 0.05 [2, 1]          | -            | -             | -                  | -              |
| Software                 | -            | -            | -              | -             | -              | 0.012 [1, 1]         | -            | -             | -                  | -              |
| Telecom                  | -            | -            | -              | -             | -              | 0.028 [2, 1]         | -            | -             | -                  | -              |
| Tourism                  | -            | -            | -              | -             | -              | -                    | -            | -             | -                  | -0.084 [10, 1] |
| Toys                     | -            | -            | -              | -             | -              | 0.019 [1, 1]         | -            | -             | -                  | -              |
| Transport                | -            | -            | -              | -             | -              | 0.008 [1, 1]         | -            | -             | -                  | -              |
| Transportation           | -            | -            | -              | -             | -              | -                    | -            | -             | -                  | 0.016 [9, 1]   |
| Utilities                | -            | -            | -              | -             | -              | -0.001 [2, 1]        | -            | -             | -                  | 0.0 [10, 1]    |

Table 6: **Median normalized cumulative abnormal returns reported in the event-study literature per sector**

The table reports the median normalized *CAR* (in percentage points) per hazard type and sector of interest. The first number in the square brackets denotes the number of individual event-study results found in the literature, while the second one refers to the number of distinct academic articles from which these estimates are drawn. A single article may report multiple results if it computes abnormal returns across different samples, event windows, or model specifications.

| Category                                      | Hazard / Driver   | NA    | C.&SA | EU    | AF    | AS    | AU    |
|-----------------------------------------------|-------------------|-------|-------|-------|-------|-------|-------|
| <i>Panel A: Per Event Occurrence</i>          |                   |       |       |       |       |       |       |
| <b>Heat and Cold</b>                          | Extreme cold      | 2.000 | 0.028 | 0.018 | 0.111 | 0.017 |       |
|                                               | Frost             | 0.800 | 0.111 | 0.049 |       | 0.045 |       |
|                                               | Extreme heat      | 0.846 | 0.333 | 0.023 | 0.125 | 0.013 | 0.250 |
| <b>Wind</b>                                   | Tropical cyclones | 0.338 | 0.005 | 0.286 | 0.016 | 0.004 | 0.036 |
|                                               | Tornadoes         | 0.091 | 0.400 | 0.200 | 0.333 | 0.057 | 0.400 |
|                                               | Winter storms     | 0.055 | 0.111 | 0.028 | 1.000 | 0.016 | 0.500 |
|                                               | Other storms      | 0.073 | 0.014 | 0.010 | 0.009 | 0.003 | 0.121 |
| <b>Wet and dry</b>                            | Flash floods      | 0.538 | 0.027 | 0.039 | 0.013 | 0.005 | 0.200 |
|                                               | River floods      | 0.109 | 0.003 | 0.008 | 0.002 | 0.002 | 0.053 |
|                                               | Landslides        | 1.333 | 0.011 | 0.056 | 0.015 | 0.003 | 0.077 |
|                                               | Droughts          | 0.625 | 0.035 | 0.115 | 0.017 | 0.031 | 0.167 |
|                                               | Wildfires         | 0.121 | 0.041 | 0.024 | 0.071 | 0.042 | 0.240 |
| <b>Ocean</b>                                  | Coastal floods    |       | 0.333 | 0.600 | 0.333 | 0.118 | 0.500 |
| <i>Panel B: Per Economic Damages (bn USD)</i> |                   |       |       |       |       |       |       |
| <b>Heat and Cold</b>                          | Extreme cold      | 1.626 |       | 0.266 |       | 0.356 |       |
|                                               | Frost             | 3.620 | 0.743 | 1.285 |       | 0.031 |       |
|                                               | Extreme heat      |       |       | 0.184 |       |       |       |
| <b>Wind</b>                                   | Tropical cyclones | 0.023 | 0.009 |       | 0.300 | 0.007 | 0.169 |
|                                               | Tornadoes         | 0.051 |       |       |       |       |       |
|                                               | Winter storms     | 0.053 |       | 0.437 |       | 0.051 |       |
|                                               | Other storms      | 0.048 | 0.535 | 0.035 | 0.132 | 0.044 | 0.334 |
| <b>Wet and dry</b>                            | Flash floods      | 1.358 | 0.743 | 0.261 | 1.672 | 0.044 | 1.011 |
|                                               | River floods      | 0.142 | 0.040 | 0.014 | 0.101 | 0.004 | 0.116 |
|                                               | Landslides        | 3.476 | 0.657 | 0.932 |       | 0.274 |       |
|                                               | Droughts          | 0.082 | 0.078 | 0.164 | 0.383 | 0.044 | 0.485 |
|                                               | Wildfires         | 0.102 | 0.442 | 0.106 | 1.692 | 0.731 | 0.876 |
| <b>Ocean</b>                                  | Coastal floods    |       |       |       |       | 0.136 |       |

Table 7: **Ratio of academic publications to historical event occurrence and economic damages**

This table reports the number of academic articles normalized by (i) the total number of historical acute events over 2000–2020 (Panel A) and (ii) cumulative economic damages measured in billion USD (Panel B). Panel B is restricted to hazard–region pairs with total damages exceeding USD 1 billion over the sample period. For studies analysing multiple or mixed hazard types, all relevant events recorded in the underlying disaster database are included in the normalization. Air pollution does not appear in the table, as no identified study in the reviewed literature examines this hazard.

## Figures

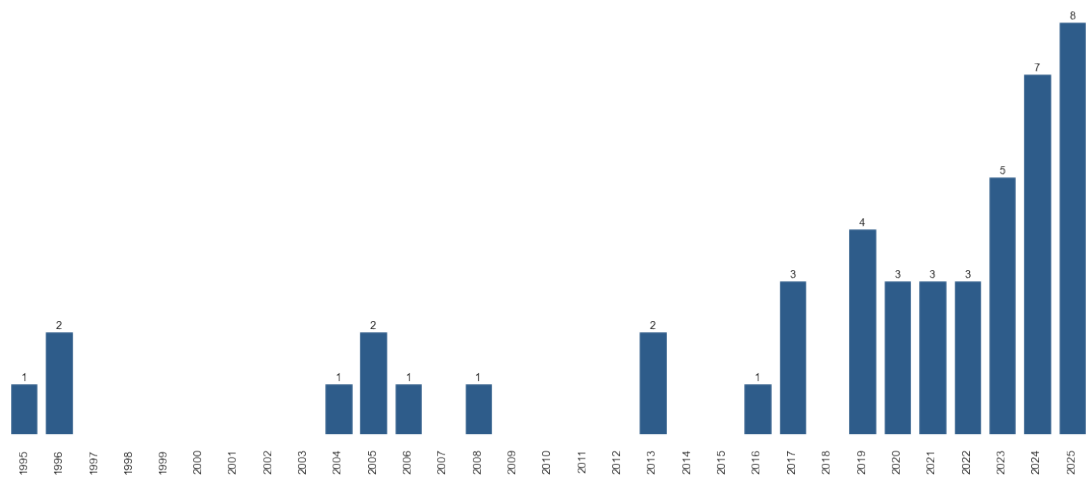


Figure 1: **Publications on the impact of realized climate-related events on stock markets**



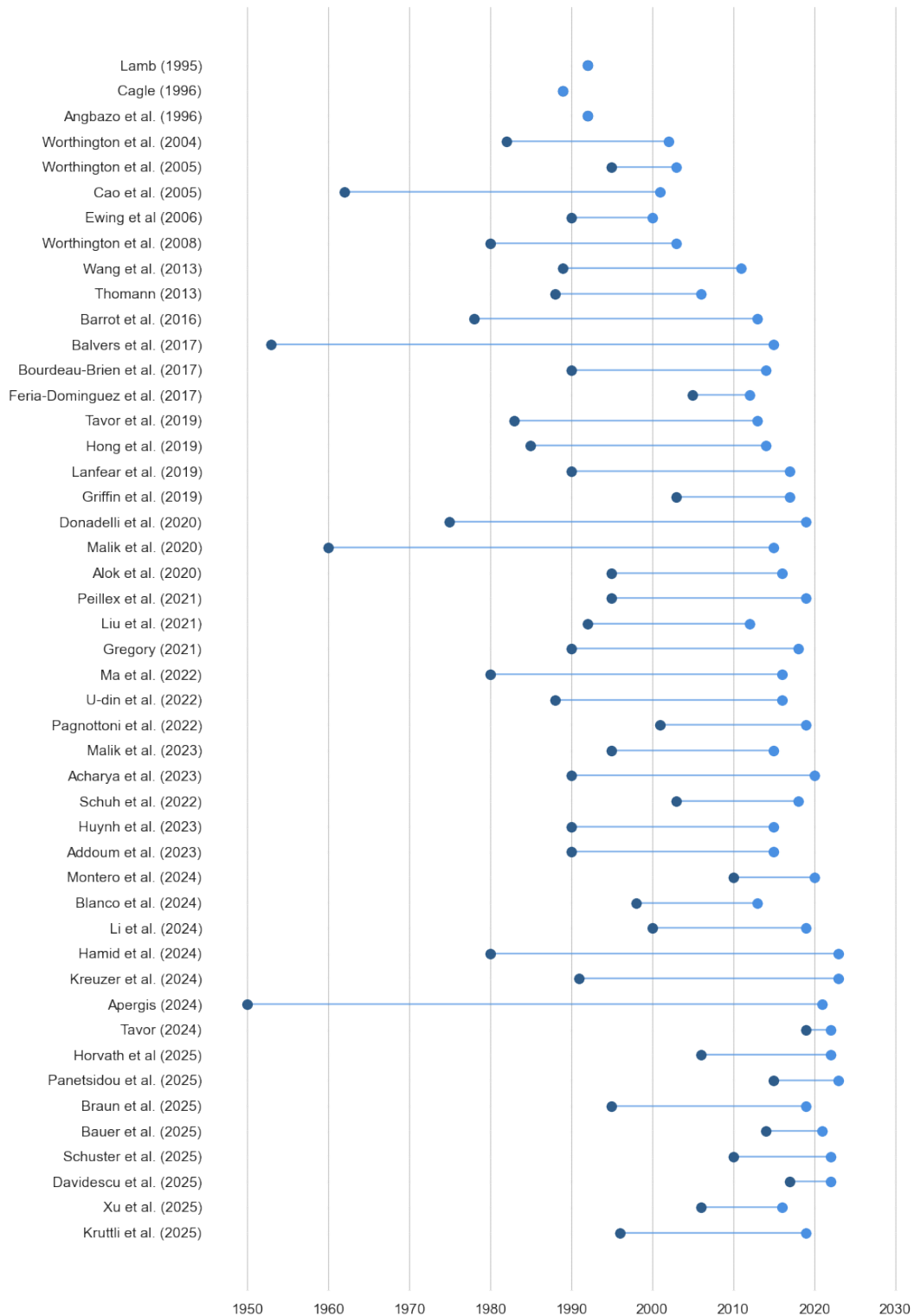


Figure 3: **Temporal coverage of the samples used in the literature**

The figure shows the time span of the sample used in each study in the main analysis. If two analysis within the same paper have different time coverage, we consider the union of the two time periods.

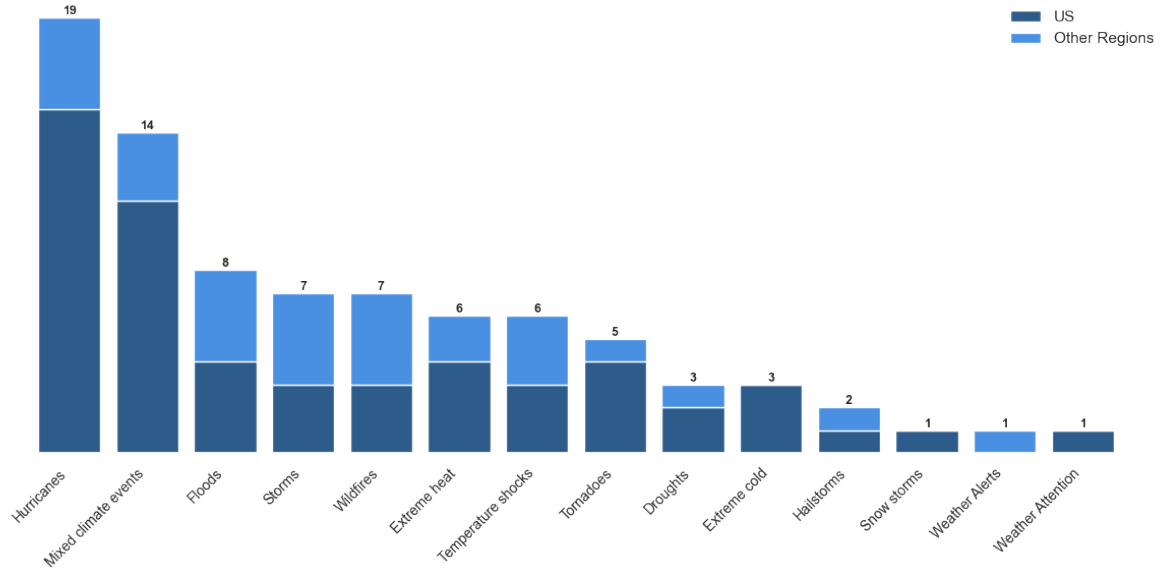


Figure 4: **Climate hazards coverage of the samples used in the literature**

The figure displays, for each hazard category, the number of publications that explicitly focus on that specific type of hazard.