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. Mixed events 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. 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.[1] 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.2).

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

[1] 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 of hazards is highly region-dependent, with areas closer to the equator tending to experience a greater frequency of heat-related events. Second, average duration and frequency differ substantially across hazard types. For example, droughts can persist up to a year, 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.

Category	Hazard / Driver	Tot	AvgEv (yr^{-1})	Dur (d)	Cost (bn $)	Aff. (Mn)	NA	C& SA	EU	AF	AS	AU
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
TOTAL		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.2). 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).

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 has risen steadily. 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).

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	+	++	+	++	+	++	+	++	+	++	+	++
		Ocean acidity	+	++	+	++	+	++	+	++	+	++	+	++
	Acute	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.

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[2] have increased in many regions since the 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 ob-

[2]Droughts are commonly distinguished by the affected component of the Earth system: (i) meteorological drought, defined by persistent precipitation deficits; (ii) agricultural drought, reflecting soil-moisture shortages that constrain crop growth; (iii) ecological drought, capturing water stress affecting natural ecosystems and vegetation functioning; and (iv) hydrological drought, characterized by abnormally low surface or subsurface water availability.

served 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, 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.

Transmission Block	Mechanism Description (Financial-Statement Structure)
Expected Cash Flows (Macro)	
Aggregate productivity and factor-input disruption	Climate hazards reduce aggregate labor productivity, alter effective capital utilisation and lower total factor productivity. *Income statement*: weaker top-line growth, lower operating leverage. *Cash flow*: 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). *Income statement*: volatility in COGS. *Working capital*: higher inventories and hedging needs. *Cash flows*: higher volatility of free cash flows.
Macroeconomic demand reallocation	Persistent shifts in household consumption and sectoral demand modify long-run revenue trajectories. *Income statement*: revisions in sales volumes and pricing power. *Valuation*: lower terminal growth and residual values.
Systemic capital-deepening requirements	Adaptation and mitigation needs require economy-wide replacement or hardening of capital. *Balance sheet*: rising capital intensity. *Cash flow*: higher maintenance and adaptation capex depress free cash flow.
Expected Cash Flows (Firm-Specific)	
Asset impairment and accelerated depreciation	Physical damages, regulatory obsolescence, or reduced usability alter the useful life of capital. *Balance sheet*: write-downs. *Income statement*: accelerated depreciation. *Cash flows*: lower taxable profits and free cash flow.
Adaptation, mitigation, and compliance capex	Firms invest in protective infrastructure, cooling, abatement, or resilience. *Cash flows*: 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. *Income statement*: lost volumes and higher COGS. *Working capital*: higher inventories. *Cash flows*: amplified volatility.
Input-specific productivity losses	Heat stress or water scarcity reduce labour efficiency and resource productivity. *Income statement*: margin compression. *Cash flows*: 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. *Income statement*: higher insurance costs. *Financing*: higher interest expense and elevated WACC.
Information, disclosure, and expectation updates	New information on exposure, vulnerability, or resilience alters analyst expectations. *Valuation*: revisions to revenues, margins, capex, and discount rates.
Discount Rates	
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.

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 final search query returned 357 articles classified under Economics, Econometrics and Finance.[3]

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).

3.2 Extraction and classification of results

Table A.1, which is placed in the Appendix 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

[3]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"))".

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.

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. 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, whereas the most recent contributions date from 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.

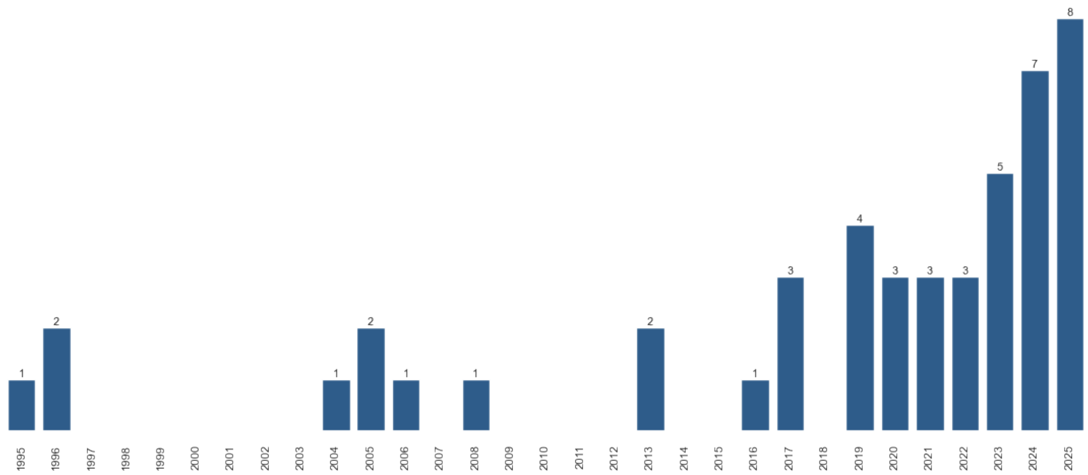

Figure 1: **Publications on the impact of realized climate-related events on stock markets**

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.

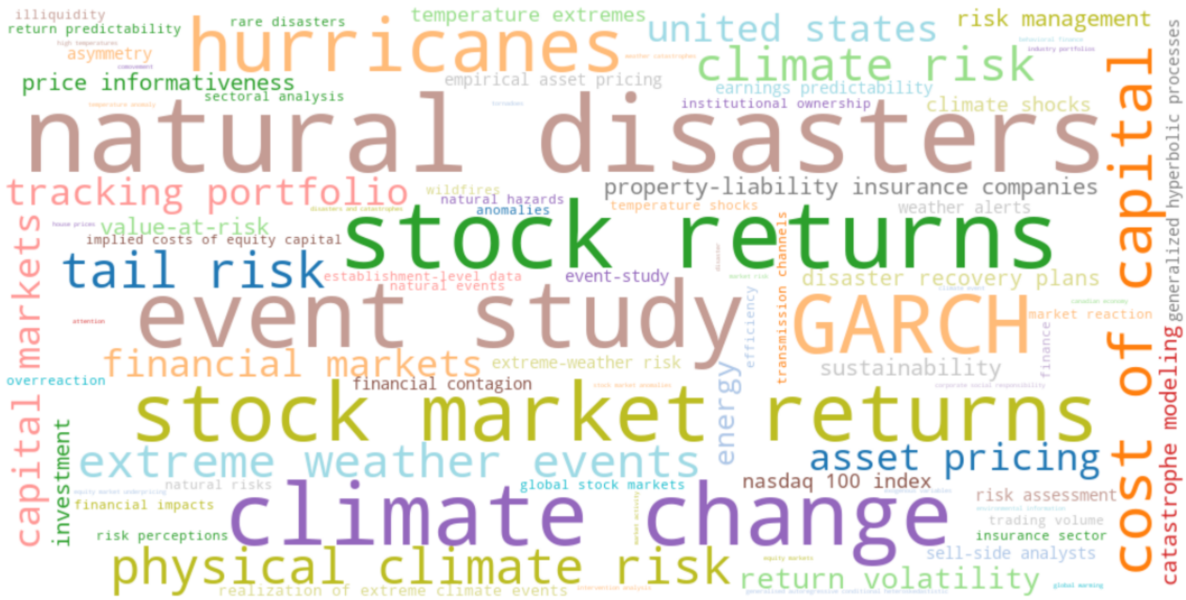

Figure 2: **Keywords by frequency**

The figure shows the distribution of keywords provided by authors, with term size proportional to frequency. For clarity, some keywords were normalized, for example by merging singular and plural forms or unifying different labels for the same method.

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

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. The European region has attracted substantially less attention, with only 4 publications (covering the European Union, France, and the United Kingdom), while Australia is examined in 3 studies. The Asian and African regions are markedly under-represented, with only a single study focusing on Japan. Finally, seven studies adopt a multi-regional approach, comparing different geographical areas.

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).

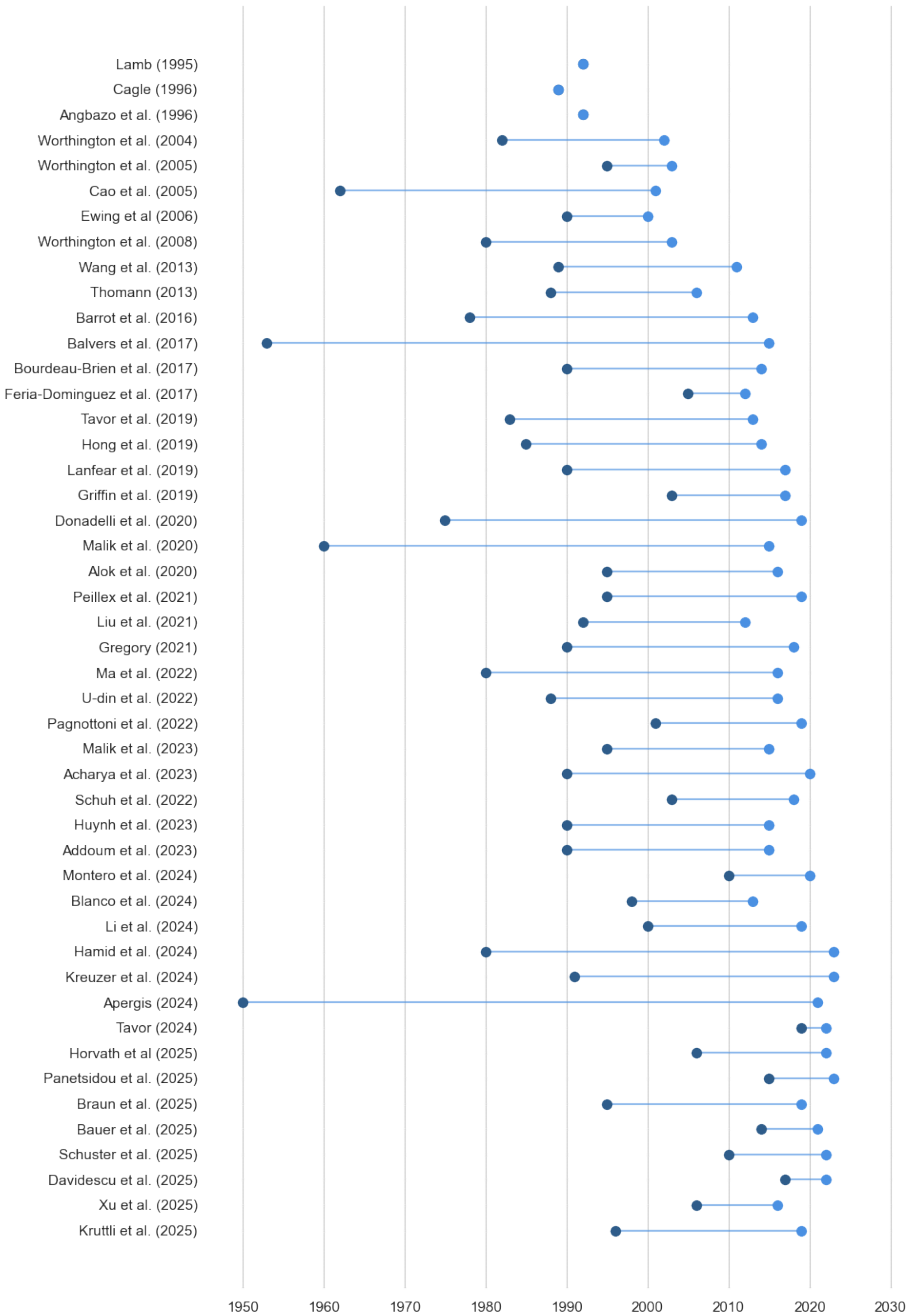

Figure 3: **Temporal coverage of the samples used in the literature**

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.

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 mixed climate events and information signals related to weather alerts or heightened weather attention. Most studies focus either on hurricanes (19 papers) or on mixed climate events (14 papers), 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.

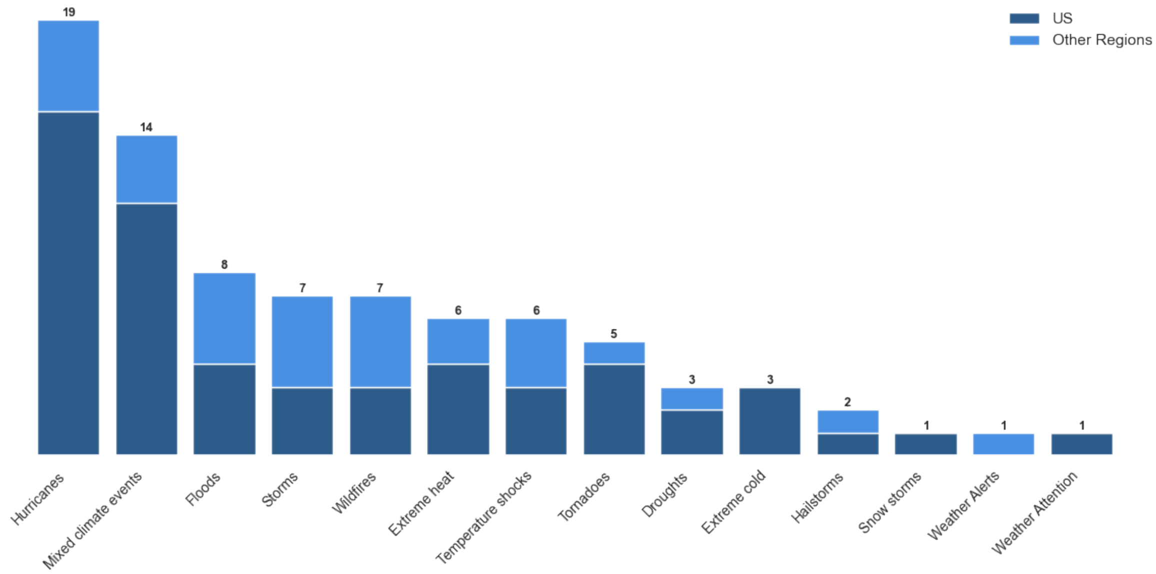

Figure 4: **Climate hazards coverage of the samples used in the literature**

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

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. Breeden 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; Kruttli 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, σ_1^2 (σ_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

Factor models (e.g. Fama and French (1993, 2015)) have the following form:

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

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 $\mathbb{E}[\varepsilon_{i,t}] = \mathbb{E}[\varepsilon_{i,t} f_{k,t}] = 0 \ \forall k = 1, \ldots K$. Finally, α_i represents the "alpha" of the equation, i.e. the systematic mispricing.

Factor models are time-series regressions of a single time series on several factors, and can be estimated with ordinary least squares.[4] In climate-related studies, factor models include climate variables as additional factors to capture exposure to disaster frequency, weather variability, or physical risk (Bolton and Kacperczyk, 2021). For example, Gregory (2021) regresses a global temperature shock factor on Fama and French (2015) plus momentum (Carhart, 1997) factors to test the significance of its alpha, and then evaluates many assets' exposure to the climate factor.

[4] 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.

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 (Breeden 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 τ_1 and ending in τ_2:

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

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)).[5]

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 average abnormal returns, or $CAAR$s, 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

[5]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 ($\overline{AR}$).

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[6]:

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

where $c_{i,t}$ the variable of interest, α_i captures entity-specific effects and γ_t captures time-fixed effects. Further controls can be added to the regression. Panel regressions enable to control for unobserved heterogeneity across entities through α_i and to remove commonalities specific to certain times through γ_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 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:

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

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 ϵ_t, solving the endogoneity problem.

[6] 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).

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)

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

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.[7] The difference *in* difference lies in comparing the change in the returns from before to after the event *in the treated group* to the change in the control group, captured by the coefficient β. 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 mixed natural disasters between funds close to their headquarters and those far from them. Kruttli et al. (2025) consider hurricanes as separate treatments and firms with zero exposure to the event (due to their location) as a control group.

[7]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.

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 $t = 1, \ldots T$, 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 $k = 1, \ldots K$ (which can be replaced by a constant like the mean return if needed), ω is the long-run variance, α_j, for $j = 1, \ldots q$ captures the moving-average components and β_l, for $l = 1, \ldots q$ measures the autoregressive components in the variance.[8]

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 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.

[8] We have removed the entity index i for simplicity.

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.[9]

Mixed events generally have 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).

[9] 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.

Category	Type	Hazard / Driver	US Negative	US Not signif.	US Positive	ROW Negative	ROW Not signif.	ROW Positive
Heat and cold	Chronic	Air temperature	2	1	1	2 (World)	1 (World)	
	Acute	Extreme cold	2		2			
		Frost						
		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.).

5.1.1 Mixed events

A body of 14 studies has examined the aggregate impacts of heterogeneous climate-related events, typically relying on large historical disaster databases. 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 Heat and cold: heatwaves and temperature shocks

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.

Mean temperature changes affect the stock market, especially at high temperatures. An early study, Cao and Wei (2005), finds that stock returns for several developed indices are significantly lower during high-temperature periods from 1960 to 2000. These results have been corroborated more recently by Apergis (2024), who expands the analysis up to 2021. Notably, he documents non-linear effects: high temperatures depress stock returns when initial temperature levels are high, but enhance them when initial temperature levels are low. 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. In Balvers et al. (2017), the tracking regression uses the future twelve-month average U.S. temperature as the dependent variable, while the basis assets consist of U.S. equity portfolios sorted by size and book-to-market, supplemented with industry portfolios and standard macroeconomic variables. Gregory (2021) focuses on global temperature anomalies rather than country-specific measures, motivated by the global exposure of multinational firms. 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 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. 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 sever winter weather episodes.

5.1.3 Wind: 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 wind-related hazards, such as severe storms, 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.

Wildfires are widely studied 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, Kruttli 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).

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.

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.[10]

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
Total		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%).

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

[10] 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".

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).

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 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.

Type of Hazard 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.

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 may be due to two reasons: the relatively high data availability and to the ease of access in the United States, as well as the substantial financial losses associated with such events (Table 1). Moreover, their short duration makes them especially suitable to empirical designs such as event studies. By contrast, chronic risks have received limited attention. Although some studies investigate temperature variation, research on shifts in precipitation regimes and on sea-level rise remains underdeveloped despite important expected changes in the future (Table 2).

Table 7 summarizes this 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.

Category	Hazard / Driver	NA	C.& SA	EU	AF	AS	AU
Panel A: Per Event Occurrence							
Heat and Cold	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
Wind	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
Wet and dry	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
Ocean	Coastal floods		0.333	0.600	0.333	0.118	0.500
Panel B: Per Economic Damages (bn USD)							
Heat and Cold	Extreme cold	1.626		0.266		0.356	
	Frost	3.620	0.743	1.285		0.031	
	Extreme heat			0.184			
Wind	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
Wet and dry	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
Ocean	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.

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)). 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). 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.

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 and returns.

Periods of extreme weather are typically associated with heightened uncertainty, during which correlations across assets and factors tend to rise (Thomann, 2013; Ma et al., 2022; Davidescu et al., 2025). Even portfolios that appear well diversified in normal times may therefore experience higher effective concentration and a greater likelihood of extreme outcomes. Such dynamics are especially consequential for investors subject to margin requirements, including leveraged investors and derivatives traders, for whom short-lived volatility spikes can trigger margin calls or forced deleveraging. Capturing these tail-risk effects around short-lived events is challenging from an empirical standpoint, given the limited number of observations at the daily frequency. This 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 faster reversals 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. Closely related to risk is market illiquidity, a dimension that remains strikingly under explored in the literature (with the exception of Lanfear et al. (2019) and Peillex et al. (2021)), despite its central role in event-driven trading, transaction costs, and price formation during climate-induced disruptions.

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.

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. 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)
Lamb (1995)	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.
Angbazo and Narayanan (1996)	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.
Cagle (1996)	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.
Worthington and Valadkhani (2004)	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.
Cao and Wei (2005)	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)
Worthington and Valadkhani (2005)	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.
Ewing et al. (2006)	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.
Worthington (2008)	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.
Thomann (2013)	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.
Wang and Kutan (2013)	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.
Barrot and Sauvagnat (2016)	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.

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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)
Tavor and Teitler-Regev (2019)	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.
Alok et al. (2020)	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.
Donadelli et al. (2020)	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.
Malik et al. (2020)	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).
Gregory (2021)	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).
Liu et al. (2021)	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.
Peillex et al. (2021)	Extreme heat	FR	1995–2019	TS reg.; t-test; ES	L	–	Hot days (>30°C) are associated with significantly lower trading volume (about -5%).

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Table A.1 continued.

Reference	Hazard	Region	Period	Method	Var.	Sign	Key result (brief)
Ma et al. (2022)	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 co-movement effect.
Pagnottoni et al. (2022)	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.
U-Din et al. (2022)	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.
Acharya et al. (2023)	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.
Addoum et al. (2023)	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.
Huynh and Xia (2023)	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).
Malik et al. (2023)	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.

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Table A.1 continued.

Reference	Hazard	Region	Period	Method	Var.	Sign	Key result (brief)
Bauer et al. (2024)	Floods; Storms	EU	2014–2021	Event study	R	–	Affected firms experience a negative abnormal return of about 99 bps on the event date.
Braun et al. (2025)	Storms	US	1995–2019	CS reg.; Factor; 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.
Davidescu et al. (2025)	Mixed climate events	US	2017–2022	Time-series 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.
Horváth et al. (2025)	Weather attention	US	2006–2022	Panel regression	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.
Kruttli et al. (2025)	Floods; Hurricanes; Snow storms; Tornadoes	US	1996–2019	Diff-in-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.
Panetsidou and Synapis (2025)	Weather alerts	UK	2015–2023	Panel reg.; ES	R	–	Firms in vulnerable industries react more negatively to weather alerts, especially red alerts and multi-phenomenon alerts; frequent updates mitigate reactions.
Schuster et al. (2025)	Extreme heat	US; EU	2010–2022	Event 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)
Xu et al. (2025)	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
		Other storms	Hail Sand and dust storm Severe wind storm	Derecho Extra-tropical storm Hail Lightning/Thunderstorms Sand/Dust storm Severe weather Storm (General) Storm surge
Wet and dry	Chronic	Precipitation	Mean precipitation	
	Acute	Flash floods	Heavy precipitation and pluvial flood	Flash flood
		River floods	River flood	Flood (General) Glacial lake outburst flood Ice jam flood Riverine flood
		Landslides	Landslide	Avalanche (wet) Landslide (wet) Mudslide Rockfall (wet) Sudden Subsidence (wet)
		Droughts	Agricultural and ecological drought Aridity Hydrological drought	Drought
		Wildfires	Fire weather	Forest fire Land fire (Brush, Bush, Pasture) 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.2: **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.