Journal of Multinational Financial Management 77 (2025) 100887

Contents lists available at ScienceDirect

Journal of Multinational Financial Management

journal homepage: www.elsevier.com/locate/mulfin

Stock market returns and climate risk in the U.S.

Yiyang Chen [a], Rogemar Mamon [a,d,*], Fabio Spagnolo [b,f], Nicola Spagnolo [b,c,e]

[a] *Department of Statistical and Actuarial Sciences, The University of Western Ontario, London, Ontario, Canada*
[b] *Department of Economics and Finance, Brunel University of London, UK*
[c] *Centre for Applied Macroeconomic Analysis (CAMA), National Australian University, Canberra, Australia*
[d] *Division of Physical Sciences and Mathematics, University of the Philippines Visayas, Miagao, Iloilo, Philippines*
[e] *Dipartimento di Economia, Università degli Studi della Campania, Luigi Vanvitelli, Italy*
[f] *Department of Economics, University of Messina, Italy*

ARTICLE INFO

JEL classification:
D24
O13
O47
Q40

Keywords:
Hidden Markov models
Event study
Climate change risk
Systematic risk

ABSTRACT

Using a data set for all companies forming the S&P 500 index, we investigate the stock price responses to acute physical risks, chronic physical risks, and transition risks. Our findings reveal that certain sectors are more vulnerable to climate risks, whereas others appear to be relatively unaffected. In addition, our results show that listed firms with poor environmental performance scores are more exposed to climate risk, as indicated by their stock returns being negatively affected, compared to firms with higher environmental performance scores. This suggests that improving environmental performance may help companies to better cope with climate risks and improve their financial performances. Our analysis provides evidence that the short-term systematic risk is more vulnerable to the climate risk events, whereas effects on long-term systematic risk do not appear to be statistically significant. These findings indicate that investors and firms should pay a particular attention to short-term systematic risk when considering the potential impact of climate risk on stock market performances.

1. Introduction

Climate change has been causing serious adverse effects on the earth's ecosystem. According to the report "Drought in numbers" by the United Nations Convention to Combat Desertification (UNCCD) (UNCCD, 2022), droughts have become more severe, frequent, and persistent in many regions worldwide. Based on the fourth national climate assessment by Wuebbles et al. (2017), rising sea levels increase the likelihood of extreme rainfall leading to severe floods. Additionally, the intensity and frequency of storms increase as the Earth's temperature rises, as stated in the same report.[1] The instability of climate conditions poses a wide range of financial and non-financial risks to individuals, organisations, and the whole society. Understanding the impacts of climate-related risks is, therefore, a crucial element for organisations aiming at financial stability in an era of fast-changing climate dynamics.

This paper focuses on investigating the dynamics of stock return and market risk responses to various types of climate risks. The primary objectives are twofold. Firstly, to analyse how stock returns in different sectors respond to diverse climate risks, identifying sector-specific behaviours and susceptibilities. Secondly, to explore the relationship between a stock's environmental performance and its reaction to climate risks, to determine if and how environmental performance influences stock. According to the Basel Committee (on Banking Supervision, 2021), there are two distinct drivers of physical risk, acute and chronic physical hazards. The

* Correspondence to: Department of Statistical and Actuarial Sciences, The University of Western Ontario, 1151 Richmond Street, London, Ontario, Canada N6A 5B7.

E-mail address: rmamon@uwo.ca (R. Mamon).

[1] Please see Muluneh (2021) for an up-to-date scientific review on the impact of climate conditions on global bio-diversity.

https://doi.org/10.1016/j.mulfin.2024.100887
Received 3 February 2024; Received in revised form 8 November 2024; Accepted 18 November 2024

Available online 28 November 2024

acute risk drivers refer to the economic impact of short-lasting events, e.g., cyclones, wildlife, heatwaves, and landslide, whereas the chronic risk drivers are associated to the gradual shifts of climate, e.g., rising sea levels, rising global mean temperature, and desertification. Transition risks are associated with the risks faced by the economic and social environment whilst converting to a low-carbon emission production.

Most of the recent literature has mainly focused on the transition risk, especially on the effects of climate-related regulatory announcements (i.e., transition risk) on the stock market. However, the effects of unexpected physical risks, which can also potentially have significant impacts on the stock markets, have comparatively attracted less attention. In particular, only a relatively small number of studies have focused on the impact of physical risk on stock markets. Hong et al. (2019) investigate the effect of droughts on the prices of food stocks and Kruttli et al. (2019) conduct a study to examine the impact of uncertainty resulting from hurricanes on the stock market. These studies, generally, have proxied physical risks with sea level, temperature, and the level of precipitations but have not explicitly differentiated this risk from acute risk, which drivers are sudden, short-lived events. Indeed, the effects of the two drivers can vary given their distinct different nature. Therefore, this paper seeks to investigate drivers of transition risk, acute physical risk, and chronic physical risk.

We gather major regulatory announcements related to green policy in the U.S. as indicators of transition risk. Additionally, we collect data on major natural disasters in the U.S. to serve as indicators of acute physical risks. For chronic risks, we propose to use a hidden Markov model (HMM) to construct a chronic risk indicator based on the following three climate-related variables: temperature anomaly, level of precipitation, and Google Trends Intensity Index. The latter is based on a string of physical risk-related keywords. Our model assumes two possible regimes: a normal and an abnormal climate regime. Days in which shifts from the former to the latter occurred are used to construct a physical risk indicator. We employ an event study methodology to analyse the impact of three types of risks on the immediate and cumulative five-day post-event stock returns of S&P 500 companies. To the best of our knowledge, this is the first attempt to investigate the impact of the two types of risks on the stock market. To understand sector-specific responses, we categorise these stocks into 11 sectors using the Global Industry Classification Standard (GICS), allowing for a detailed examination of sector behaviour. Additionally, we divide the stocks into four groups based on their Environmental Scores (ES) obtained from Bloomberg. This classification is designed to analyse the varied responses of stocks with different ES to climate-related risks. Furthermore, we test for the effect on stock's systematic risk, performing a risk analysis as suggested by Ramiah et al. (2013) and Pham et al. (2019a).

The event study analysis reveals that chronic physical risk and transition risk significantly impact stock prices negatively, more so 5 days after the event than immediately. In contrast, acute physical risk shows a more immediate negative effect on stocks, but this impact is short-lived compared to the other two risks. Additionally, sectoral reactions to these risks vary; some sectors are largely resilient, whereas others, such as real estate and utilities, demonstrate more significant reactions. These findings suggest that policymakers might need to develop targeted regulations and support to cater to the unique vulnerabilities and strengths of each sector. Further analysis, classifying firms into four environmental sustainability (ES) groups based on performance, reveals that the group with the poorest environmental record suffers the most from all three climate risks. This could prompt policymakers to enforce stricter environmental standards, pushing companies towards better environmental performance and reduced climate risk vulnerability. The results of our risk analysis suggest that whilst climate risk events influence short-term systematic risk, they do not show a statistically significant effect on long-term systematic risk. This stability in long-term systematic risk may imply overall market resilience to climate-related events, potentially bolstering investor confidence in the market's enduring stability.

The layout of the paper is the following: Section 2 provides a review of the relevant literature; Section 3 presents the data, which includes S&P 500 stocks, climate-related series, natural disaster events, climate change policies, and Google Trends intensity. Section 4 introduces the methodology, whereas the event study analyses are discussed in Section 5. The risk analyses are reported in Section 6; Section 7 offers some concluding remarks.

2. Literature review

A fast-growing body of literature examines the impact of climate risks on financial market instruments. It is not obvious to say in advance whether and to what extent climate risks are priced. Some institutional investors may not consider climate risks important, whereas other may find them difficult to price and hedge (Krueger et al., 2020). Green investors (Heinkel et al. 2001) and trading constraints to decarbonising portfolios (Bessembinder, 2017) are factors to be considered. Another potential aspect is the introduction of legislations including climate risks which may have effect on the profitability of firms (Ramadorai and Zeni, 2021; Bartram et al. 2022), and consequently on stock valuations. Pastor et al. (2022) document that stocks of green firms outperform those of brown firms. Oestreich and Tsiakas (2015), Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2022), Faccini et al. (2023) and Hsu et al. (2023) find that climate risk are priced, when proxied by carbon emissions, whereas Gorgen et al. (2019) find opposite results, when using a composite measure of carbon emissions and environmental firm rating.

Aslan et al. (2022) studied air pollution's effect on banks' lending decisions in Turkey, whilst Javadi and Masum (2021) analysed the impact of climate risk on bank loan costs. Nguyen et al. (2020a,b) investigated the effect of sea level rise on mortgage interest rates. Painter (2020) and Goldsmith-Pinkham et al. (2019) looked at the relationship between climate risk and municipal bond prices. Auh et al. (2022) explored the effect of natural disasters on U.S. municipal bond returns. Huynh and Xia (2021) examined the impact of climate change news risk on corporate bond returns. Antoniuk and Leirvik (2021a) studied the effect of transition climate risk on green bond indices. Lastly, Bernstein et al. (2019), Giglio et al. (2021a), and Baldauf et al. (2020) analysed the impact of climate risk on real estate prices.

A strand of the literature has been looking at the relationship between climate risks and the pricing of equities. Some empirical studies have focused on the effects of physical risk on stock pricing; for example, Bansal et al. (2017) found that temperature shocks harm equity returns. Similarly, Balvers et al. (2017) tracked portfolios formed from basic assets to find that the temperature shocks factor has a negative risk premium. Several empirical studies have investigated the effects of the transition risk on equity pricing; typically, climate change-related political news is used to represent transition risk. A typical representative of the transition risk is climate change-related political news. Ramiah et al. (2013) analysed the Australian stock market's reaction to 19 announcements of changes in environmental regulation and found mixed results. Pham et al. (2019b) used an event study to investigate the impact of the Paris Agreement on the German stock market and found that announcements pertaining to the Paris Agreement have negative consequences for polluting industries. Antoniuk and Leirvik (2021b), employing a similar methodology based on event studies, show that the impacts of four unexpected political events on different sectors of stocks in the US market; their findings indicated each industry has a specific climate risk sensitivity. The effect of the climate change policy announcements on the European stock market was examined in Birindelli and Chiappini (2021). The authors confirmed that the impact of the climate policy announcements has a sector-by-sector difference and that the announcements negatively affect the average stock returns of all the sectors. Bua et al. (2021) used text analysis to construct risk indicators and examined their impact on euro area equity markets. They discovered that the risk premia for both physical and transition climate risks have increased since the Paris Agreement. More comprehensive reviews of the relation between climate risks and stock and other assets can be found in Venturini (2022) and Giglio et al. (2021b). In addition to directly investigating the impact of physical and transition risk indicators, Choi et al. (2020) employed Google search volume on global warming as a measure of people's awareness of climate change and analysed its influence on global stock markets. Their findings revealed that the stocks of low carbon-intensive firms outperform the high carbon-intensive firms during abnormally warm weather conditions. Recently, Albanese et al. (2024), using a balanced panel VAR model for 48 countries, find a positive impact of transition risk on stock returns and a negative one of physical risk, especially in the short term.

In recent years, climate reporting has emerged as a critical component of corporate sustainability practices and financial market analysis. Another significant area of study has focused specifically on firm-specific climate reporting measures. Matsumura et al. (2014) studied the relationship between carbon emissions, carbon disclosures, and firm value using data from S&P 500 firms between 2006 and 2008. They found the capital markets penalise firms for their carbon emissions and further penalise those that choose not to disclose this information. Busch et al. (2016) reviews how sustainable development, including climate reporting, affects financial market performance, emphasising the importance of comprehensive climate disclosures in improving firm performance and investor confidence. Krueger et al. (2020) found that institutional investors largely recognise climate risks as having significant financial impacts on their portfolios, with particular concern for regulatory risks that have already begun to manifest. Ilhan et al. (2023) explored institutional investors' preferences for climate risk disclosures and discovered that investors value high-quality climate risk information and are influenced by both disclosure costs and benefits. A method was developed by Sautner et al. (2023a) to assess climate change exposures, which reflects the attention paid by market participants in earnings calls to firm's climate-related risks and opportunities. In a related study, Sautner et al. (2023b) estimated the risk premium for firm-level climate change exposure amongst S&P 500 stocks and its time-series evolution. By employing textual analysis of earnings call transcripts, Li et al. (2024) quantified firm-level climate risk and found that unexpected climate risks lead firms to increase investments but reduce employment growth.

3. Data description

3.1. S&P 500 index

Our data set is retrieved from Bloomberg and includes daily observations for all the 503 stocks comprised in the S&P 500 ETF for the period January 02, 2014, to December 29, 2020. This specific time frame is chosen as that one of the goals of our paper is to analyse the impacts of the three climate risks on firms with different environmental performance. To achieve this, we rely on ESG metrics, which provide a comprehensive view of companies' environmental performance. ESG data became more comprehensive and widely available after 2020, covering a larger portion of companies in Bloomberg. Before 2020, the ESG data coverage was limited, which made it challenging to conduct a thorough analysis. Using this period allowed us to utilise the most reliable ESG data available for our study.

The S&P 500 index is employed as a proxy for global market returns whereas the 10-year Treasury Rate is utilised to proxy the risk-free rate. A specific focus in this research is to investigate the impacts of chronic climate risk, which can potentially have a long-term impact on stock returns. The 10-year Treasury rate reflects long-term investor expectations and is therefore suitable for analysing such impacts. To ensure comparability across different types of climate risks analysed in our study, we consistently used the 10-year Treasury rate. Additionally, Ramiah et al. (2013) and Pham et al. (2019) used the 10-year U.S. Treasury rate as the proxy for the risk-free rate in their event study to investigate the impacts of climate change related policies.

The summary statistics of the S&P 500 stock returns are reported in Table 1. Panel A in Table 1 shows the relevant statistics of the average daily returns of the S&P 500 stocks.

First, we cluster the S&P 500 stocks into 11 sectors based on the Global Industry Classification Standard (GICS) to assess how each sector reacts to the three types of risks. The statistics of the average returns in each sector are reported in Table 1 Panel B. It is worth noticing that all sectors have positive average daily returns, with the only exception of the energy sector, which is also the most volatile. The information technology sector has the best performance in terms of the average daily return whilst the consumer staples sector has the lowest variation in the daily return. We also observe that returns in all sectors are negatively skewed and have fat tails, with the consumer discretionary, real estate, and energy sectors being particularly highly skewed.

Table 1
Summary statistics of S&P 500 stock returns.

	Mean (%)	SD (%)	Skewness	Kurtosis	Min (%)	Q1 (%)	Median (%)	Q3 (%)	Max (%)
Panel A									
S&P500 Index	0.047	108.124	−1.071	25.718	−12.765	−0.313	0.069	0.515	8.968
Panel B: Average returns by sector									
Consumer Discretionary	0.051	137.255	−1.397	39.128	−17.918	−0.462	0.103	0.677	15.105
Financials	0.043	144.238	−0.985	24.204	−16.243	−0.512	0.099	0.66	12.253
Real Estate	0.018	133.187	−2.104	40.599	−20.45	−0.488	0.078	0.603	8.633
Communication	0.055	119.07	−0.917	14.052	−10.569	−0.43	0.099	0.652	7.914
Information.Technology	0.084	137.601	−0.897	18.129	−14.696	−0.485	0.153	0.77	11.103
Industrials	0.052	126.956	−0.775	18.847	−11.778	−0.461	0.101	0.647	12.016
Consumer Staples	0.033	92.767	−0.57	16.74	−9.591	−0.378	0.071	0.494	7.407
Utilities	0.029	120.351	−0.566	24.804	−13.374	−0.489	0.101	0.613	11.687
Energy	−0.023	211.856	−2.135	44.867	−34.405	−0.838	0.009	0.903	15.035
Materials	0.031	135.068	−0.992	17.13	−13.491	−0.537	0.078	0.66	10.429
Panel C: Average returns by ES group									
$< Q_1$	0.076	1.188	−1.396	27.382	−14.83	−0.395	0.142	0.645	10.826
$[Q_1, Q_2)$	0.048	1.129	−1.383	28.718	−14.006	−0.356	0.096	0.551	10.034
$[Q_2, Q_3)$	0.037	1.154	−1.217	27.115	−13.336	−0.386	0.069	0.535	10.81
$\geq Q_3$	0.039	1.119	−1.238	25.434	−11.969	−0.364	0.073	0.527	10.188

Note: S&P 500 stock returns for the period 2015–2020.

Secondly, we examine whether companies with varying levels of environmental performance exhibit differing responses when faced with the three climate risks. For this purpose, the ES for each company listed in the S&P 500 is gathered for the period of 2015–2020 from the Bloomberg Environmental, Social & Governance dataset. The ES is a data-driven corporate environmental and social performance metric and is based on indicators such as air quality, climate exposure, ecological impact, energy management, greenhouse gas emissions management, and water management. The ES data provided by Bloomberg is disclosure-oriented data, which is collected from companies' annual reports or sustainability reports. The ES ranges from 0 to 10, where a higher score indicates better company sustainability. We proceed by clustering the S&P 500 companies' environmental performance into four groups according to the 25%, 50%, and 75% percentiles of Bloomberg's ES. The panel C in Table 1 displays the statistics of the stock returns for the four ES groups. Accordingly, firms with ES lower than the first quartile (25th percentile) are placed in the group $< Q_1$, and firms with ES higher than the third quartile (75th percentile) are put in the group $\geq Q_3$. Lastly, firms with ES values between the first quartile and second quartile are grouped in the category $[Q_1, Q_2)$ and firms with ES values between the second quartile and third quartile are put into the group $[Q_2, Q_3)$.

In Table 2 (Panel C), we provide ES summary statistics for the S&P 500 index, the 11 sectors, and the 4 ES groups. It can be observed that the group with the lowest ES has the highest daily returns, whereas the average daily returns decrease whilst the group's environmental score increases. The standard deviations of the returns for the four groups are very close. Notice that some firms' ES are unavailable on Bloomberg; the number of firms with missing scores is reported in the last column. Four sectors display an average ES larger than 3 (material, energy, utility, and consumer staples) whilst two sectors (consumer and financial) exhibit an average ES below 2, with the remaining sectors scoring between 2 and 3. We also notice that the ES increment of the four groups is around 1.50; the lowest average ES is 0.380, and the highest average ES is 4.877. Finally, whilst the ES variations in $< Q_1$, $[Q_1, Q_2)$, and $[Q_2, Q_3)$ groups are similar, the amount of variation in ES is twice as big in $\geq Q_3$ group compared to the other three groups.

3.2. Climate risk indicators

Compared to systematic risks, climate risks and systematic risks can both lead to increased market volatility. Investors may react to sudden changes, whether due to climate-related events such as an earthquake or economic events like interest rate changes. Furthermore, both types of risks introduce uncertainty into the market, affecting investor confidence and decision-making. This may result in more cautious investment behaviour and possible market declines. On the other hand, climate risks often have more localised or sector-specific impacts. For instance, a hurricane may devastate coastal areas but have limited direct impact on inland regions, and droughts can severely affect agriculture whilst having less immediate impact on the technology sector. In contrast, systematic risks typically have broader impacts on the market.

It is important to highlight the distinct impacts of the three types of climate risks on financial markets. Acute climate risks, chronic climate risks, and transition climate risks all introduce uncertainty, affecting investor confidence. Also, each type of climate risk can have sector-specific impact. However, acute climate risks often cause immediate and seveWe appreciate your suggestion to consider the impact of international policies and agreements on US firms.

As illustrated in the table of events considered for policy impacts, we include several key milestones related to the Paris Climate Agreement, which is a significant international policy with potential implications for U.S. firms. Financial markets typically respond quickly to such events, with immediate effects on the stock prices of affected companies and sectors. As rebuild undertakes, recovery from acute events generally happens over the short to medium term. In contrast, chronic climate risks have more widespread impacts,

Table 2
Summary statistics of ES score.

	Mean	SD	Min	Q1	Median	Q3	Max	Count	Missing
Panel A: full sample									
S&P 500	2.580	1.743	0.000	1.141	2.583	3.808	8.017	418	85
Panel B: ES by sectors									
Consumer Discretionary	1.910	1.521	0.000	0.490	1.663	2.967	5.687	53	5
Financials	1.943	1.655	0.000	0.961	1.718	2.459	5.045	7	59
Real Estate	2.043	0.900	0.548	1.478	2.050	2.472	4.140	29	2
Communication	2.186	1.683	0.000	0.954	2.058	3.243	5.175	26	0
Health Care	2.300	2.351	0.000	0.000	1.803	3.648	8.017	58	6
Information Technology	2.348	1.911	0.000	0.689	1.839	3.885	6.358	76	0
Industrials	2.588	1.625	0.000	1.133	2.733	3.637	6.290	65	6
Consumer Staples	3.358	1.401	0.880	2.018	3.390	4.530	5.755	31	2
Utilities	3.533	1.038	0.030	3.061	3.558	4.008	5.483	27	2
Energy	3.608	1.065	1.752	2.965	3.687	4.362	5.318	21	0
Materials	3.678	1.028	1.625	3.177	3.720	4.412	5.687	25	3
Panel C: ES by groups									
$< Q_1$	0.380	0.374	0.000	0.000	0.303	0.667	1.140	105	0
$[Q_1, Q_2)$	1.879	0.379	1.145	1.608	1.909	2.195	2.548	104	0
$[Q_2, Q_3)$	3.180	0.337	2.617	2.913	3.175	3.497	3.800	104	0
$\geq Q_3$	4.877	0.847	3.810	4.310	4.698	5.318	8.017	105	0

Note: Q_1, Q_2, and Q_3 are the first quartile, the second quartile, and the third quartile of the ES scores.

Table 3
Natural disaster events.

Number	Date	Natural disaster
1	August 29, 2015	Tropical Cyclone ERIKA-15
2	August 31, 2017	Tropical Cyclone HARVEY-17
3	May 28, 2018	Volcanic eruption for Kilauea
4	October 12, 2018	Tropical Cyclone MICHAEL-18
5	July 6, 2019	M7.1 Earthquake
6	September 9, 2019	Tropical Cyclone DORIAN-19
7	July 26, 2020	Tropical Cyclone HANNA-20
8	August 5, 2020	Tropical Cyclone ISAIAS-20
9	October 10, 2020	Tropical Cyclone DELTA-20
10	November 13, 2020	Tropical Cyclone ETA-20

Note: Data were collected from Global Disaster Alert and Coordination System.

affecting broader sectors over extended periods. Financial markets may adjust more gradually to chronic risks as their impacts become apparent over time. Similarly, transition risks can also have systemic impacts, affecting the entire economy through policy and market sentiment changes. Financial markets are sensitive to policy announcements and regulatory changes related to climate action.

In this study, we selected 10 natural disasters, 10 climate change policy announcements, and 9 events identified by a hidden Markov model as proxies for acute, transition, and chronic climate risk indicators, respectively. The selection was guided by several principles to ensure the relevance and comparability of the events. We focused on the most severe events for each indicator to capture their significant impacts on stock returns, as these events are more likely to cause substantial economic disruptions, making them crucial for analysing the influence of climate risks on stock markets. Additionally, we aimed to have a similar number of events for each category to facilitate a direct comparison between the three types of risks, helping to clearly identify how each type of risk affects stock returns. Our selection criteria also align with previous literature, which emphasises the most severe events (e.g., Ramiah et al., 2013, Antoniuk and Leirvik, 2021b, Birindelli and Chiappini, 2021), ensuring that our research is comparable with existing studies.

3.3. Physical risk indicators

As previously mentioned, we categorise physical risks into two types: acute and chronic. For the former, we use the information on natural disasters of orange level,[2] and above, which took place in the United States from 2015 to 2020, obtained from the Global Disaster Alert and Coordination System (GDACS) website. These natural disasters, presented in Table 3 will be used as acute physical risk indicators.

[2] These are disasters classified as major.

Table 4
Summary statistics of climate change indicators.

	Mean	Median	SD	Kurtosis	Skewness	Minimum	Maximum	Count
Temperature	1.317	1.288	0.787	0.664	0.066	−2.509	3.800	2190
Precipitation	0.014	0.009	0.257	−0.095	0.102	−0.836	0.888	2190
G-trends	0.201	0.189	0.078	19.449	3.333	0.100	1.000	2190

Note: Temperature, precipitation, and G-trends data was collected from Berkeley Earth, National Oceanic and Atmospheric Administration, and Google trends, respectively.

For the second type of risk, a multivariate hidden Markov model will be considered to construct chronic physical risk indicators. The model, which utilises time series of climate variables as inputs, generates the corresponding climate conditions (i.e., normal and abnormal climate conditions) for all time periods as outputs. As inputs to the model, we use the information on temperature anomaly, precipitation anomaly, and Google Trends on climate risk topics to capture the physical climate risk.[3]

The three climate-related time series used in this study are daily data ranging from January 01, 2015 to December 29, 2020. For the temperatures, the global daily average land-surface temperature anomaly was collected from Berkeley Earth, whereas for precipitations we retrieved Climate Prediction Center (CPC) global daily precipitation data from the National Oceanic and Atmospheric Administration (NOAA). The prediction data set contains the daily precipitation gauge from over 30,000 stations installed around the global land areas. To obtain the daily precipitation anomaly per station, each daily precipitation was subtracted from the average precipitation on that day. Then, the average anomaly of the stations was computed to obtain the global daily average precipitation anomaly.[4] We also use Google Trends (GT), a publicly available platform by Google, to collect internet searches on the following eight climate risk-related keywords: "drought", "flood", "storm", "wildfire", "extreme weather", "landslide", "cold wave", and "heat wave". These keywords are used by World Meteorological Organisation (WMO) to characterise climate disasters. Google Trends normalises the returned values between 0 and 100.

The values of keywords at each date were summed up and scaled down by 100 to create our Google Trends index. Note that, the final Google Trends index ranges from 0 and 1, with low values indicating less awareness of climate-related risks and a high value indicating strong high awareness. As the eight keywords focus on climate-related natural disasters, the final Google Trends index only captures the public attention to the physical climate risk. The summary statistics of the tree time series are provided in Table 4.

The dynamics of climate-related variables can be modelled by stochastic models. Under different climate conditions such as normal and abnormal conditions, the dynamics of climate variables may distinct different behaviour. The physical climate risk raises when the climate condition turns from normal into abnormal. We build our chronic risk indicator from the implied climate conditions. Therefore, a hidden Markov Model (HMM) is employed to capture the climate conditions from the three climate-related time series. HMMs have been widely applied in the areas of economics, finance, and engineering for the purpose of detecting unobservable information. Furthermore, the HMM has been successfully incorporated in stochastic models to allow for time-dependent dynamics in many literatures. An HMM-driven Ornstein–Uhlenbeck (OU) process with added Poisson jump component was utilised to model the spot electricity price in Erlwein et al. (2010); this extended the framework and the filtering estimation of Erlwein and Mamon (2009). Xiong and Mamon (2018) employed a HMM-driven OU process to fit the dynamics of the daily average temperature. When the HMM is made to depend not only on one but more prior time steps, this leads to the concept of a higher-order HMM that captures state memory; see Xiong and Mamon (2016) and Xiong and Mamon (2019). Furthermore, the univariate model setting can be extended to a multivariate model setting. Gu et al. (2021) propose an automated indices-processing scheme under a term multivariate modelling framework to classify market liquidity regimes. A multivariate model is featured to provide an accurate and efficient price modelling of precious metals in Mamplata et al. (2022). This study extends the multivariate modelling framework in Tenyakov et al. (2016) by allowing one of the three processes to have the dynamics specification of the OU process with added Poisson jump component. The multivariate Hidden Markov setting applied in this study consists of two OU processes and one OU process with a Poisson jump component (OU-PJ). Appendices 1, 2 and 4 provide a description of the multivariate HMM setting, the parameter estimation procedures and the estimated parameters, respectively.

HMMs' filtered probabilities, for the period 2015–2021, are presented in Figure A.1. The normal climate regime dominates the high probabilities most of the time. The probabilities of abnormal climate regimes occasionally surge. The filtered probabilities are subsequently converted into zeros and ones depending on whether the probabilities are smaller or larger than 0.5, respectively. A value of 0 will then indicate a normal climate risk period and 1 an abnormal climate risk period. Our proposed multivariate hidden Markov model setting identifies a total of 9 abnormal climate periods. We interpret the first day of transitioning from normal to abnormal climate conditions as the chronic physical risk indicators. The plot of the three climate time series and filters indicated climate risk periods are displayed in Fig. 1. The temperature and precipitation fluctuate around some levels, with gradual change over time. Both series display some cluster effects, with large values generally followed by large changes, whereas small values change tends to be followed by small changes. The Google Trends index usually stays between 0.2 and 0.4, with some spikes

[3] In the recent literature, both temperature and precipitation are commonly used as proxies for the physical climate risk, see Venturini (2022) amongst others. Google Trends on climate change topic has also been utilised as a proxy for climate risk to study its impact on mutual fund performance in Ho (2022).

[4] To avoid the extreme precipitation values from the Antarctic and Circle Arctic Circle, only gauging stations within 60°N and 60°S were included in our data set.

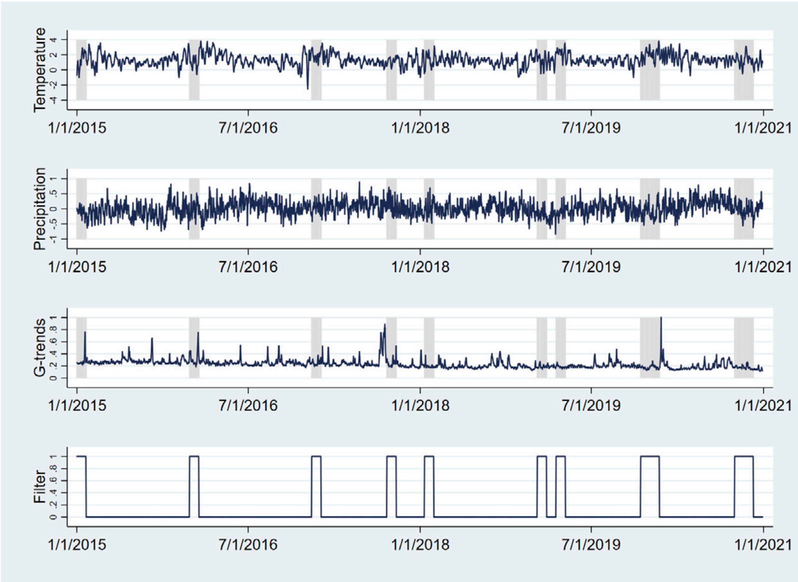

Fig. 1. Climate risk indicators and HHM regimes.

Table 5
Climate change policy announcements.

Number	Date	Description
1	August 3, 2015	Obama announced the finalisation of America's Clean Power Plan.
2	December 12, 2015	The Paris Agreement was reached by 196 parties at COP 21 in Paris.
3	February 9, 2016	The US Supreme Court blocked Obama's Clean Power Plan.
4	September 3, 2016	The US formally ratified the Paris Agreement.
5	November 4, 2016	The Pairs Agreement enters into force.
6	March 28, 2017	Trump signed an executive order unwinding Obama's climate policies.
7	June 1, 2017	Trump announced his intention to withdraw the US from the Paris Agreement.
8	Oct 10, 2017	EPA proposed Repeal of the Clean Power Plan.
9	November 23, 2018	Fourth National Climate Assessment was released.
10	November 4, 2019	US administration gave a formal notice of intention to withdraw, which takes 12 months to take effect.

Note: List of climate change policy announcements for the U.S.

from time to time. The bottom plot represents the estimated regimes, with the grey shade areas in the top three plots denoting the periods of abnormal climate risk. The estimated filters pick up the periods where at least one of the three climate series has abnormal behaviours.

3.4. Transition risk indicator

To investigate the impact of transition climate risk, we selected ten US green policy announcements from 2015 to 2020, reported in Table 5. These ten policies are employed as the transition risk indicators. The Obama administration launched several programs to address the global climate crisis, whereas the Trump administration had a different view stating that the actions to reduce carbon emissions harmed American businesses and rolled back major climate policies to boost industrial productivity. The ten selected events are the national-level climate-related policies during 2015–2020. We choose national-level policies because these policies can affect a broader range of firms in the US stock market.

In summary, there are similarities and differences between the impacts of climate risks and systematic risks on financial markets. The three types of climate risks introduced in this paper could be compared. Overall, both climate risks and systematic risks could lead to increased market volatility and investment uncertainty. However, the scope differs: climate risks are often localised or sector-specific, whilst systematic risks are broader. Acute climate risks usually cause immediate, severe, and localised impacts leading to short-term disruptions. In contrast, chronic climate risks result in gradual, persistent, and widespread impacts that require long-term adaptation. Transition climate risks, driven by policy and market changes, and cause systemic economic impacts.

4. Methodology

4.1. Event study

The event study analysis, widely used in finance, aims to measure the effectiveness of an event (e.g., firms' earnings announcements, issues of new debt, macroeconomic news, mergers, and acquisitions) on the financial performance of a security. The impact of an event is normally measured by the stock's abnormal return (AR). The abnormal return is calculated by subtracting the observed return from the expected return:

$$AR_{i,t} = R_{i,t} - \hat{R}_{i,t},$$

where $R_{i,t}$ indicates the observed return for stock i on the time t and $\hat{R}_{i,t}$ represents the expected return for stock i on the time t. We denote $t = 0$ as the event date. Different return models can be adopted to estimate the expected return $\hat{R}_{i,t}$, in this paper, we utilise a different version of the standard capital asset pricing model (CAPM):

$$R_{i,t} = R_{f,t} + \beta_i(R_{mt,t} - R_{f,t}) + \epsilon_{i,t}, \tag{1}$$

where in Eq. (1), $R_{mt,t}$ denotes the return on the market portfolio, $R_{f,t}$ represents the risk-free rate, and $\epsilon_{i,t}$ is the error term with zero mean and finite variance. The $AR_{i,t}$ for the market model is given by

$$AR_{i,t} = R_{i,t} - R_{f,t} - \beta_i R_{mt,t}.$$

We also consider the cumulative abnormal return (CAR), which quantifies the impact of an event over a period of time:

$$CAR_{i,[t:t+k]} = \sum_{l=t}^{t+k} AR_{i,l},$$

where $CAR_{i,[t:t+k]}$ denotes the CAR from time t to $t+k$ for stock i.

Alternatively, the impact of an event on a group of stocks (e.g., stocks from either the same sector or with similar characteristics) can be examined by means of average abnormal returns (AAR) and cumulative average abnormal returns (CAAR):

$$\begin{aligned} AAR_t &= \frac{\sum_{i=1}^{N} AR_{i,t}}{N} \\ \text{and } CAAR_{[t:t+k]} &= \frac{\sum_{i=1}^{N} CAR_{i,[t:t+k]}}{N}. \end{aligned} \tag{2}$$

In Eq. (2), AAR_t represents the average abnormal returns in the group for time t, and $CAAR_{[t:t+k]}$ represents the average cumulative abnormal return in the group from time t and $t+k$. The estimation procedure for AAR and CAAR starts with creating an estimation window and event window from the data sample. The estimation window refers to the sample before the event date. The coefficients of the model in Eq. (1) are estimated using the data from the estimation window. To ensure that abnormal returns (ARs) can be compared across different firms, stock returns were standardised before conducting the event study.[5]

To test if the estimated AAR and CAAR are statistically different from zero, we perform the following tests: a standard cross-sectional T-test; the t statistics described in Patell (1976); and, finally, the standardised cross-sectional testing method (i.e., BMP-t test) introduced by Boehmer et al. (1991). The advantage of the BMP-t statistic over the Patell (1976) t-statistic is that it can account for potential heteroscedasticity (time-varying variance) in the data, which may be present in event study data.

4.2. Risk analysis

In this paper, we apply a risk analysis approach similar to that used by Ramiah et al. (2013) and Pham et al. (2019b), who suggested that the adoption of new climate policies may lead firms to alter their operations, potentially impacting systematic risk. Specifically, to examine the change in systematic risk following the ten climate change policy announcements (outlined in previous sections), we employ three modified versions of the Capital Asset Pricing Model (CAPM), estimated using ordinary least squares regression. For comparative purposes, the same risk analysis is also conducted on the physical and sentiment risk indicators discussed in Section 3. The use of the ordinary least-squares regression here is motivated by having results that are comparable to those of previous studies which employed the same functional form. The first risk model has the following form:

$$R_{s,t} - R_{f,t} = \beta_s^0 + \beta_s^1(R_{mt,t} - R_{f,t}) + \beta_s^2(R_{mt,t} - R_{f,t}) * AD_t + \beta_s^3 AD_t + \epsilon_{s,t}, \tag{3}$$

where $R_{s,t}$ represents a sector's return at time t; AD_t is the aggregate dummy variable, which takes value of 1 on the event dates and 0 on the other dates; β_s^0 is the intercept term; β_s^3 indicates the change in β_s^0; β_s^1 measures the short-term systematic risk for the sector s; β_s^2 describes the change in the short-term systematic risk for the sector s.

A potential drawback associated to the risk model in Eq. (3) is that the different events may have opposite effects on a sector and cancel each other. Therefore, instead of including the aggregate dummy variable, an individual dummy (ID) variables can be

[5] This is a common practice (e.g., Antoniuk and Leirvik, 2021b when analysing a portfolio of stocks, so that the ARs can be compared in a meaningful way despite any differences in the volatility and expected returns of the individual stocks.

incorporated into the risk model. Thus, the changes in the systematic risk, caused by different events, can be individually tested. Accordingly, the second risk model is formulated as:

$$R_{s,t} - R_{f,t} = \beta_s^0 + \beta_s^1(R_{mt,t} - R_{f,t}) + \sum_{l=0}^{p} \beta_s^{l+1}(R_{mt,t} - R_{f,t}) * ID_l + \epsilon_{s,t}, \tag{4}$$

where β_s^{l+1} represents the short-term changes in the systematic risk caused by the event l. The individual dummy variables $ID_{l,t}$ take value 1 on the date the event l happened and 0 otherwise. By replacing the individual dummy variable $ID_{l,t}$ by the long-term individual dummy variables LID, which takes value 0 before the date the event l happened and 1 after, the third risk model is written as:

$$R_{s,t} - R_{f,t} = \beta_s^0 + \beta_s^1(R_{mt,t} - R_{f,t}) + \sum_{l=0}^{p} \tilde{\beta}_s^{l+1}(R_{mt,t} - R_{f,t}) * LID_l + \epsilon_{s,t}, \tag{5}$$

where $\tilde{\beta}_s^{l+1}$ represents the long-term changes in the systematic risk caused by the event l.[6]

The results of Eq. (3) are reported in Tables A.9 and A.10. For Eqs. (4) and (5), we display the results in Figs. 5–8, as they are also better visualised graphically.

5. Event study analysis

To exclude firm-specific events, we eliminated firms that had such events within five days before and after our event days. Examples of firm-specific events include annual meetings, industry conferences, and other significant company occurrences. The purpose of this exclusion is to ensure that our analysis remains focused on the impact of climate risk events, without being confounded by these firm-specific occurrences, which could otherwise skew our results. We compute $AR_{i,0}$ and $CAAR_{i,[0:5]}$ for each individual stock. The $AR_{i,0}$ indicates the stock i immediate reaction to the occurrence of the abnormal climate risk. The $CAAR_{i,[0:5]}$ describes the total impact on stock i's return five days after the occurrence of the abnormal climate risk. Then, the AAR and CAAR for each of the groups are computed. Our estimation window spanned 252 trading days, with the latest day being 20 days prior to the event day. It is worth noticing that since our estimation window partially includes the COVID-19 pandemic period, any impact of the pandemic on the returns will be already incorporated into our analysis. Therefore, we do not anticipate the pandemic to have a significant impact on our estimation results.

Concerning the pre-estimation window, when the events of interest are infrequent and have long-term impacts, a longer window helps capture the normal performance of stocks across various market conditions. Given that climate risk events are both infrequent and can significantly impact financial markets, using a longer estimation window ensures a more comprehensive and stable baseline for assessing these effects. It is suggested that estimation windows longer than 100 days can provide sufficient estimation for parameters. For instance, Birindelli and Chiappini (2021), who also investigated the impact of transition climate risks, utilised an event study with a pre-estimation window of 260 trading days, starting from 20 trading days before the event day. This demonstrates that extended pre-estimation windows are a recognised approach in event studies examining climate risks.

Our analysis is structured as it follows. First, we consider S&P 500 stocks as one group and investigate the impacts of the three climate risks for a general view. Second, the S&P 500 firms are grouped into 11 sectors according to GICS in order to explore the effects of the three risks on the 11 sectors. Third, we cluster the S&P 500 firms into four groups as discussed in Section 3. We compare the impact of the three climate risks on companies with different environmental performances.

5.1. Impact on S&P 500 index

We calculated the AARs and 5-day CAARs for the S&P 500 stocks on the event day with respect to the three risk indicators. The statistical significance is then examined by means of three popular statistical tests, namely, cross-sectional test, Patell, and BMP test. The AARs, CAARs, and p-values of the corresponding tests are shown in Table A.2, reported in Appendix 6. Table 6 provides a summary of Table A.2 and records the number of events causing positive and negative significant AARs and CAARs for each of the three climate risk indicators. Note that since we conducted three significance tests, an event will be classified as having a significant impact if at least two of the p-values, from each test, are less than the 5 percent significance level. A significant event is identified as having a positive effect if its AAR or CAAR is positive, and as having a negative effect if its associated AAR or CAAR is negative.

From Table 6, the S&P 500 index returns were predominantly negatively affected by the three climate risks both on the event day and five days later. Our analysis revealed that the acute risk had the greatest negative impact on S&P 500 returns on the event day, although some of the negative effects subsided five days after the events occurred. Conversely, whilst the negative effect of the transition risk was relatively mild on the event day, it was found to have a significant negative impact on returns five days after the events. The chronic risk, on the other hand, showed a similar pattern to the transition risk, with a relatively mild negative impact on returns on the event day and a more significant negative impact five days after the events.

[6] To overcome multi-collinearity issues caused by the dummy variables in Eqs. (4) and (5), estimations will be obtained by means of ridge regression methods.

Table 6
Number of significant events - S&P 500 Index.

	AAR		5-days CAAR	
	Positive effect	Negative effect	Positive effect	Negative effect
Acute risk (10)	2	6	3	3
Chronic risk (9)	1	3	2	5
Transition risk (10)	2	3	1	6

Note: The numbers in parentheses refer to the total number of statistically significant events associated to acute, chronic and transition risks.

Table 7
Number of significant events by sector.

	Sector	AAR		5-days CAAR	
		Positive effect	Negative effect	Positive effect	Negative effect
Acute risk (10)	Consumer Discretionary	3	1	3	1
	Financials	0	3	0	2
	Real Estate	3	4	4	3
	Communication	2	1	2	0
	Health Care	1	3	2	4
	Information Technology	3	4	2	2
	Industrial	2	3	3	3
	Consumer Staples	1	1	1	1
	Utilities	1	7	1	4
	Energy	5	3	6	3
	Materials	1	4	3	4
Chronic risk (9)	Consumer Discretionary	2	6	1	2
	Financials	1	1	1	1
	Real Estate	7	0	4	2
	Communication	0	3	0	4
	Health Care	0	2	4	4
	Information Technology	2	2	0	3
	Industrial	2	3	2	5
	Consumer Staples	3	1	2	2
	Utilities	4	2	5	3
	Energy	3	3	3	2
	Materials	2	3	2	4
Transition risk (10)	Consumer Discretionary	3	1	1	1
	Financials	0	1	0	1
	Real Estate	4	2	3	3
	Communication	0	0	1	2
	Health Care	4	4	1	2
	Information Technology	1	5	1	5
	Industrial	3	2	1	4
	Consumer Staples	5	3	2	3
	Utilities	6	2	3	4
	Energy	3	3	2	3
	Materials	1	1	0	3

Note: The numbers in parentheses refer to the total number of statistically significant events associated to acute, chronic and transition risks.

5.2. Impact on firms clustered by sector

In order to account for the sectors' specific characteristics, we examine their distinct responses to climate risks. Therefore, we will conduct a sector-by-sector event study analysis of the three climate risks to determine if and to what extent each sector is impacted. Table A.3–A.5 (in Appendix 6) report the results of the event study analysis performed on acute, chronic and transition risk event dates for each of the 11 sectors. The results of the non-parametric Corrado ranking test are also presented for reference. A summary of the number of significant effects events for the three climate risks is provided in Table 7.[7]

5.2.1. Acute climate risk

As discussed in Section 3, we consider 10 acute risk events. On the event day, we observed that the majority of sectors (i.e., financial, real estate, health care, information technology, industrial, utilities, and materials) experienced a greater number of negative effect events compared to positive effect events. We also noted that three sectors (consumer discretionary, communication, and energy) had more positive effect events than negative effect events. However, an examination of the five days following the

[7] Note that sectors are arranged in Table 7 based on their average ES, from the lowest to the highest value.

event dates, reveals that the sectors of real estate, information technology, and industrial no longer experienced more negative effect events than positive effect events. Nonetheless, the three sectors with more positive effect events (compared to negative) remained unchanged.

Regardless of the direction of the significant events, the energy, utilities, information technology, and real estate sectors are the most responsive on the event day. Additionally, both the energy and real estate sectors carry over their effects into the five-day period following the events. This responsiveness can be attributed to several factors. In the energy sector, prices can be highly volatile and sensitive to disruptions in supply caused by acute climate events, leading to both positive and negative abnormal returns depending on the nature of the event. For the utilities sector, whilst damage to infrastructure can result in negative returns, the sector can also experience positive returns during the recovery phase as demand for rebuilding and repairing infrastructure increases. In the information technology sector, acute climate events can disrupt supply chains, data centres, and manufacturing facilities, leading to significant financial impacts. Lastly, in the real estate sector, properties are highly susceptible to physical damage from acute climate events, resulting in significant financial losses and negative abnormal returns.

In contrast, the consumer staples, communication, and financial sectors were the least responsive, with three or fewer significant events on the event day and in the five days following. This limited responsiveness can be attributed to several factors. The consumer staples sector provides essential products such as food, beverages, and household goods, ensuring constant demand regardless of climate events. This stability makes the sector less sensitive to short-term disruptions. The communication sector offers crucial services during and after disasters, maintaining high demand and enabling quick recovery, thereby minimising financial impact. The financial sector benefits from diversified portfolios and a focus on financial assets rather than physical ones, which reduces direct damage and helps maintain operational stability. It is also worth to notice that the utilities sector experienced seven significant negative events and only one positive event on the relevant dates, indicating that the sector was primarily impacted by adverse effects; results are qualitatively similar five days after the acute risks had passed. Similarly, the materials sector was also mainly negative effected by the risks on the event day.

5.2.2. Chronic climate risk

Chronic risk indicators are constructed via the estimated filters, obtained by our multivariate HMM which utilise chronic climate variables as input (to reflect overall climate conditions); our proposed approach identified 9 chronic risk events. Table 7 shows both positive and negative reactions of different sectors to abnormal climate conditions, indicating that the impact of chronic risk on stock returns is not uniform.

During the event dates, the real estate sector stood out with seven positive impact events and zero negative impact events. Similarly, the consumer staples and utilities sectors also experienced a higher number of positive impact events compared to negative ones. In the five days following the events, the real estate, utilities, and materials sectors also experienced a high number of significant impacts on the event day. The predominance of positive significant impacts from chronic climate risks in these sectors suggests that the market views long-term climate changes as opportunities. Real estate companies may be adapting their practices and designs to be more sustainable and climate-resilient, which investors perceive favourably. In the consumer staples sector, changes in climate might drive demand for certain staple products, and companies that adapt their offerings accordingly could benefit. Utilities transitioning to renewable energy sources might also be viewed positively by the market as they adapt to chronic climate risks and regulatory changes.

Concurrently, the consumer discretionary, communication, health care, industrial, and materials sectors experienced a higher number of negative effect events during the same period. The count of sectors that experienced more positive or negative effects during the five days after the event dates has not changed. Amongst all sectors, the consumer discretionary experienced the most significant impact events on the event day, with 8 out of 9 events affecting it. However, chronic risk events had a decreasing impact on the consumer discretionary sector. Within 5 days after the events, the number of negative effect events decreased from 6 to 2, whilst positive effect events dropped from 2 to 1. The results for chronic risk in these sectors, showing a majority of negative impacts, suggest that these sectors may face particular challenges in adapting to long-term climate changes. For example, in the consumer discretionary sector, persistent climate changes may alter consumer behaviour, reducing demand for certain discretionary products; in the communication sector, long-term climate changes might require significant investment in adapting existing infrastructure, which can be costly; in the health care sector, climate changes may lead to a rise in certain health issues, straining healthcare systems and affecting profitability; in the industrial and materials sectors, changes in climate can impact the availability of natural resources, leading to increased costs or supply shortages for some companies. In contrast to these sectors, the financial sector was the least responsive both on the event day and five days later. This may imply that financial institutions often have diversified portfolios, which can mitigate the risks associated with long-term climate change by spreading them across various assets and geographies.

5.2.3. Transition climate risk

Ten climate-related policies, announced in the US between 2015–2020 and discussed in Section 3, were used as transition climate risk indicators. On the days announcements were recorded, five sectors experienced a higher number of positive impact events than negative ones: consumer discretionary, real estate, industrial, consumer staples, and utilities. This may imply that companies in these sectors that can innovate and adapt quickly to new regulations or market trends driven by climate policies may benefit positively from these events. Conversely, the information technology sector experienced more negative effect events than positive ones, which may due to new climate-related regulations could require IT companies to make costly operational changes.

Remarkably, turning our focus to the five days following the event date, it is observed that none of the sectors exhibited more positive than negative effect. Turning to the individual sectors, on the event day, the health care, consumer staples, and utilities

Table 8
Number of significant events by quartile.

	Group	AAR		5-days CAAR	
		Positive effect	Negative effect	Positive effect	Negative effect
Acute risk (10)	$< Q_1$	2	4	1	1
	$[Q_1, Q_2)$	2	2	1	2
	$[Q_2, Q_3)$	1	3	2	3
	$\geq Q_3$	1	3	1	2
Chronic risk (9)	$< Q_1$	0	4	1	4
	$[Q_1, Q_2)$	2	1	2	3
	$[Q_2, Q_3)$	1	1	1	1
	$\geq Q_3$	1	1	0	1
Transition risk (10)	$< Q_1$	2	6	1	5
	$[Q_1, Q_2)$	2	1	0	3
	$[Q_2, Q_3)$	1	1	0	4
	$\geq Q_3$	0	2	1	4

Note: The numbers in parentheses denote the total number of events associated to different risks.

sectors showed the highest number of significant events. In contrast, the communication, financial, and materials sectors were the least responsive to transition risks, both on the event day and five days after. Notice also that in most sectors, the positive effects of the significant events tended to diminish after five days. For instance, the consumer staples sector experienced five positive effect events initially, but this number decreased to only two positive events after the five-day period. Sectors with similar behaviour include the utilise, health care, industrial, and consumer discretionary.

Overall, sector behaviour can differ in relation to various climate risks, with some sectors maintaining consistent responses to all three risks. For instance, the financial and communication sectors were largely unaffected by these risks, whilst the real estate and utilities sectors exhibited the most pronounced reactions compared to other sectors. The present results do not seem to indicate how a sector's environmental performance influences climate risks, as there are mixed findings across sectors with different ES. One possible explanation is that there are significant discrepancies in the ES scores of firms within the same sectors, as evidenced by the standard deviations of the sectors' ES scores in Table 2 panel B. In fact, the minimum ES stand deviation of the 11 sectors is 0.90 (real estate), whilst the average ES for the S&P 500 firms is only around 2.58. This finding underscores the significance of categorising firms into distinct ES groups, which will be the next focus of our study.

5.3. Firms clustered by ES

In order to delve deeper into the potential impact of environmental performance on firms' stock prices during the three climate risks, we conducted an identical event study analysis on four distinct groups. These groups were determined based on ES scores and included firms with ES scores that fell below the first quartile ($< Q_1$), as well as firms with scores in the $[Q_1, Q_2)$, $[Q_2, Q_3)$, and $\geq Q_3$ ranges, with the number of firms increasing in each subsequent category. We again assessed the effect of climate risks on both the event day and the cumulative effect over the 5 days following the events. The outcomes are reported in Tables A.6–A.8, Appendix 6. Additionally, the Corrado ranking test results, which are non-parametric, are included for reference. A summary of the number of significant impact events is presented in Table 8.

5.3.1. Acute climate risk

On the event day, the groups categorised as $< Q_1$, $[Q_2, Q_3)$, and $\geq Q_3$ experienced more negative effect events than positive effect events, whereas the group $[Q_1, Q_2)$ experienced an equal number of positive and negative effect events. The $< Q_1$ group had the highest number of negative effect events amongst the four groups and had a total of 6 significant events on the event day, which is the most compared to the other three groups, each of which had 4 significant events on the event day. The reasons for these results are due to several factors. Companies with poor environmental practices are often less prepared to handle acute climate events, which can lead to greater operational disruptions, higher repair and maintenance costs, and longer recovery periods when the natural disasters happen. Additionally, low environmental performance often correlates with inadequate infrastructure and poor risk management practices, making these companies more likely to suffer severe physical damage during acute climate events, resulting in significant financial losses. Furthermore, investors are increasingly factoring in ESG criteria when making investment decisions. Companies with low environmental ratings are perceived as higher risk, leading to negative investor sentiment. During acute climate events, this perception can result in more pronounced stock price declines and higher volatility. After 5 days, the acute risks' effects decreased for the three groups, except for the $[Q_2, Q_3)$ group. The $< Q_1$ group experienced the most significant reduction in the impacts of acute risks, with only 2 significant events after 5 days.

To better assess the change in the effects of each acute event from the event day to 5 days later, the following heat maps are constructed. Each of the four heat maps (one for each ES group), presented in Fig. 2, are a three by three matrix that provides a visual representation of the change in the effects of acute events over time. The columns P0, N0, and I0 represent the number of acute events with positive, negative, or insignificant effects on the event day, respectively. The rows P5, N5, and I5 represent the number of acute events with positive, negative, or insignificant effects 5 days following the event day. For example, a cell located

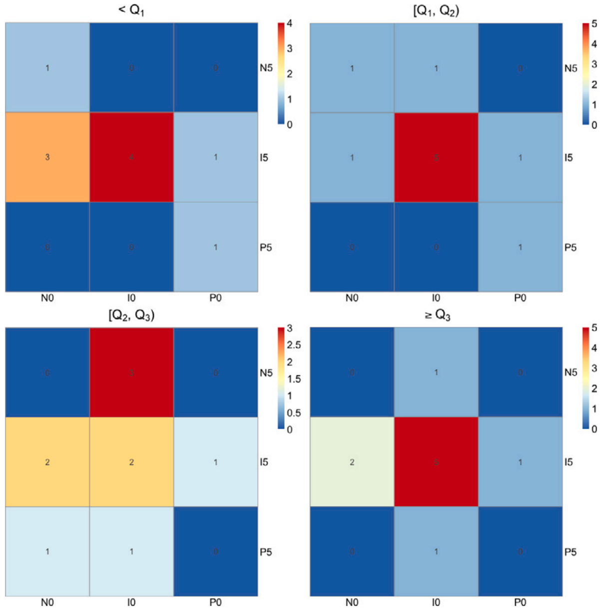

Fig. 2. Acute climate risk heat map - group-by-group analysis.

at the intersection of the column P0 and the row P5 indicates the number of events that had positive effects on the event day and still had positive effects 5 days later. By examining the patterns of cells across the heat map, we will be able to identify: (i) which types of acute events had persistent effects or were more likely to dissipate over time and (ii) how these patterns varied across the four ES groups. In the heat map, colours closer to red indicate higher numbers, whilst colours closer to black indicate lower numbers. An interesting insight, looking at the heat map, is that for most of the groups, an acute event that initially did not cause a significant effect was more likely to remain insignificant 5 days later. Furthermore, in many cases, significant effect events did not persist beyond the event day. For example, in the $< Q_1$ group, four events had a negative effect on the event day, but three of these events became insignificant 5 days later. Similar patterns were observed for positive and negative events in the $[Q_2, Q_3)$ and $\geq Q_3$ groups.

5.3.2. *Chronic climate risk*

Similarly, the $< Q_1$ group experiences significant and persistent negative impacts from chronic climate risks. This can be caused by several reasons. First, chronic climate risks, such as rising temperatures, sea-level rise, and changing precipitation patterns, exacerbate the vulnerabilities of these companies over time. Their inadequate infrastructure and poor risk management practices become even more detrimental as these gradual changes continually strain their operations and financial health. Second, companies with low environmental performance often lag in adopting sustainable practices and technologies that can mitigate the long-term effects of climate change. This lag places them at a competitive disadvantage compared to companies that proactively address environmental challenges. In contrast, the two groups with higher average ES reacted inactively to the chronic risk, with at most two significant effect events on both the event day and 5 days later. As before, heat maps displayed in Fig. 3 are used to visualise the results for the chronic risk analysis. For the two higher ES groups, the events that are insignificant on the event day are most likely to stay insignificant 5-days following the event day. Similar to the results of the acute risk analysis, significant events on the event day appeared to be transient, with many of them becoming insignificant 5 days later.

5.3.3. *Transition climate risk*

Turning to the transition climate risk analysis, we noticed that amongst the four groups, the three higher ES groups ($[Q_1, Q_2)$, $[Q_2, Q_3)$, and $\geq Q_3$) did not exhibit significant reactions to transition risks on the event day. On the other hand, the $< Q_1$ group showed a strong reaction to transition risks, with 6 negative effect events and 2 positive effect events on the event day. The impacts of the transition risks persisted 5 days later, with the $< Q_1$ group continuing to experience mostly negative effects. Moreover, there was an increase in the number of significant events during the 5 days after the event day for the other three groups, with the three groups experiencing more negative effect events on day five compared to the event day. This may be because companies with low environmental performance are more vulnerable to regulatory changes and technological advancements aimed at promoting sustainability. They may face higher compliance costs and a need for significant capital investment to meet new standards. These companies are often slower to adapt to new regulations and market trends. Transition risks persistently impact these companies as they struggle to meet evolving environmental policies and market expectations, leading to ongoing financial challenges and increased volatility. Fig. 4 displays the changes in each group's response to transition risk from the event day to 5 days later. The

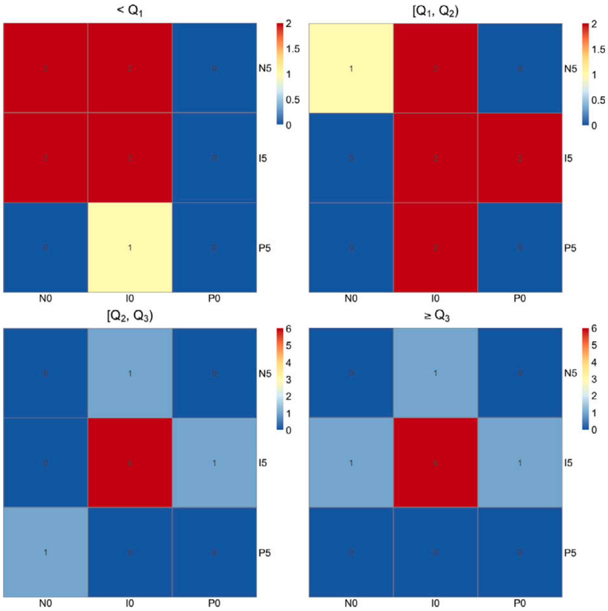

Fig. 3. Chronic risk heat map - group-by-group analysis.

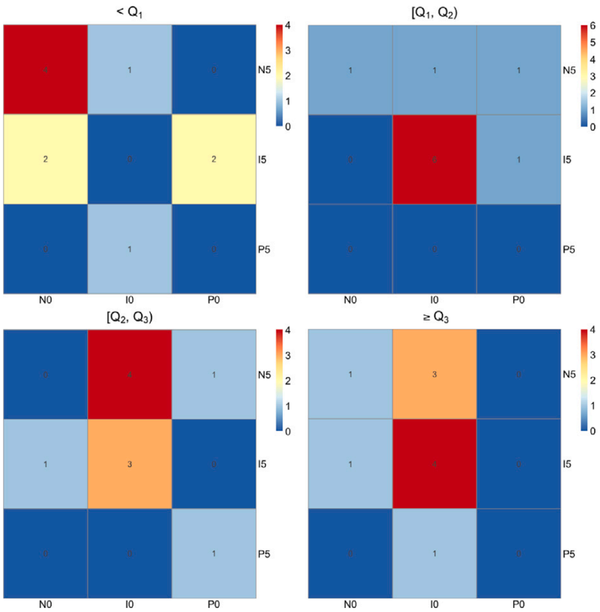

Fig. 4. Transition climate risk heat map - group-by-group analysis.

$< Q_1$ group continued to be negatively affected by transition risk during this time, with most events still causing negative effects 5 days later. Additionally, some events in the group $[Q_2, Q_3)$ and $\geq Q_3$ that were initially insignificant became negative effect events after 5 days.

Compared to the results of the sector-by-sector analysis, we observed a lower number of significant events in the group-by-group analysis. This could be attributed to the fact that firms within the same sector tend to react similarly to climate risks due to shared characteristics. However, when firms are grouped by ES, a group may contain firms from various sectors, leading to a cancellation of the effects of climate risks on these firms. When comparing the two physical risks to the transition risk, we found that the effects of the physical risks were more short-live, whilst the transition risk had a more long-lasting impact on the four groups. The low number of significant events for the two physical risks after the event day, in contrast to the higher number of significant events for the transition risk, provides evidence for the lasting impact of the transition risk. Lastly, our analysis reveals that the group

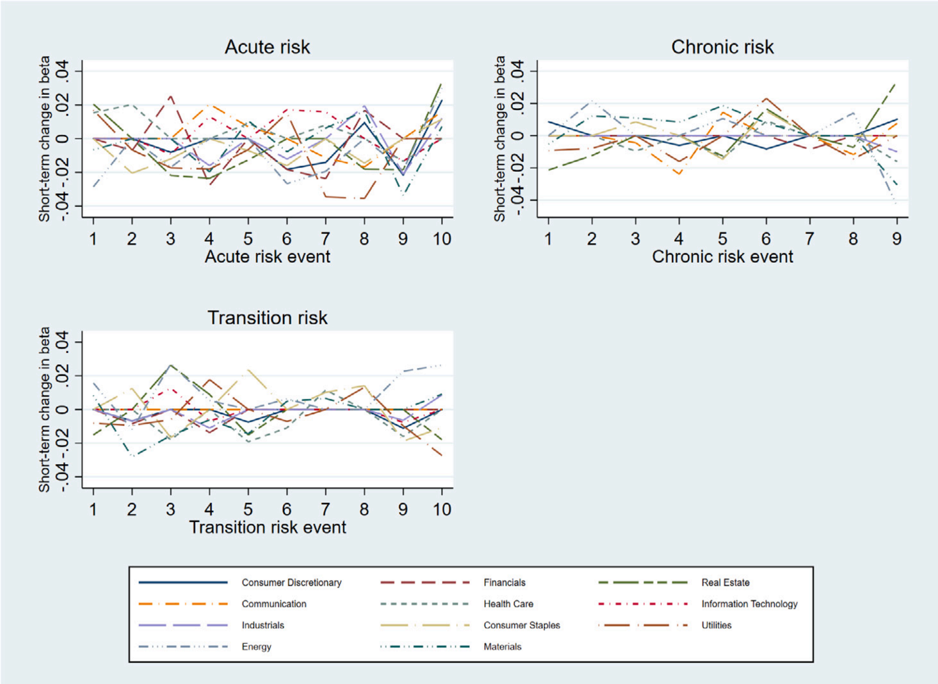

Fig. 5. Individual short-term changes in systematic risk with dummy variables associated to the three climate risks indicators.

with poor environmental performance was hit harder by the negative AAR and CAAR than the groups with higher ES, which were relatively more resilient.

5.3.4. Comparative insights: climate risks in global stock markets

Similar to our approach, numerous studies have utilised event study analyses to assess the impact of climate risks on stock markets around the world. This section aims to concisely review these global findings, particularly focusing on outcomes from the Australian, German, and European markets. Most of these studies primarily examined the transition risks through regulatory announcements affecting stock returns.

Ramiah et al. (2013) focused on the Australian stock market, analysing the impact of 19 environmental regulation announcements on equities listed on the Australian Stock Exchange from 2005 to 2011. They used event study methods to assess how these announcements affected stock returns across 1770 stocks in 35 industries. Their findings show a varied impact: 14 industries had no significant change in stock returns, 10 experienced negative abnormal returns, 7 reported positive abnormal returns, and 4 industries displayed a mix of positive and negative returns. In the German market, Pham et al. (2019b) analysed 20 announcements related to the Paris Climate Agreement and their impact on 17 industries. They found that 5 industries had purely positive abnormal returns, 3 had purely negative returns, and 3 showed mixed results. Two industries with mixed results, consumer discretionary and industrial, align with our findings. Additionally, the telecommunication sector in Germany, like in our study, showed no reaction to the announcements. Birindelli and Chiappini (2021) investigated the impact of eight EU climate policy announcements on the Euro stock market from 2013 to 2018. Grouping stocks based on GICS, they observed most sectors experiencing mixed positive and negative abnormal returns to these announcements, a pattern also evident in our analysis.

Although the above-mentioned literature focuses on different markets, climate policies, sector classifications, and methodologies, there are still some commonalities in the results. Our observations reveal that stock reactions to climate risks can vary significantly across different sectors and markets. This variability likely stems from differences in sector classifications, specific policy announcements, and methodologies considered in various studies. A consistent finding across global markets is that distinct sectors or industries exhibit unique behaviours in response to transition risks. Therefore, it is crucial to develop sector-specific policies or guidelines tailored to the unique characteristics of each sector, helping them effectively navigate and mitigate transition risks. By acknowledging these sector-specific behaviours, policymakers and businesses can create more effective strategies to address the diverse impacts of climate risks.

6. Risk analysis results

To explore the impacts of the acute, chronic and transition risk event on the short-term and long-term systematic risks, Eqs. (3)–(5) are estimated. The risk analysis is first performed on the 11 sectors; subsequently, it is extended to the four ES groups.

6.1. Risk analysis by sector

The risk model in Eq. (3) provides estimates of β_s^1 (i.e., beta) coefficients for three climate risks, which are reported in Table A.9, Appendix 6. The β_s^2 (i.e., changes in these beta estimates), also shown in Table A.9, indicate how each climate risk affects the overall risk level of a given sector in the short term. The change in beta coefficient estimates for all 11 sectors shows no statistically significant change from zero in terms of acute, chronic, and transition risks, which implies that the overall short-term systematic risks in all sectors do not change following the occurrence of the three climate risks. The findings reveal that all acute, chronic and transition risks do not produce changes in the short-term systematic risk.[8]

For Eq. (4), which captures the effect of the individual event on the short-term systematic risk, critical values were calculated by means of bootstrapping, with 1000 replications. To provide a better understanding of how individual climate events affect short-term systematic risk, we plotted the beta change coefficients (β_s^{l+1}) in Eq. (4) for the three climate risks. Plots in Fig. 5 show parameters found to be statistically significant; for convenience, insignificant estimates are labelled with 0s. In our model, the β_s^{l+1} parameter reveals the impact of climate events on the beta parameter, which reflects the level of system risk. For instance, when the U.S. Supreme Court blocked Obama's Clean Power Plan (i.e., event 3 of the transition risk), the system risk beta increased by 0.027 in the energy sector. Over the short term, the acute, chronic, and transition climate risks had both positive and negative statistically significant impacts on the systematic risk, but these effects were generally mild in magnitude with ranges of −0.034 to 0.034, −0.045 to 0.035, and −0.025 to 0.025, respectively. All 11 sectors showed a response to acute risks, with each sector experiencing at least five acute risk events. Whilst all sectors were impacted by the three types of risks, a couple of sectors were not affected by specific risks. For instance, the information technology sector did not show a significant response to chronic risks, and the communication sector was not impacted by the transition risk. The materials sector was notably impacted by all three types of risks. The varying results observed can be attributed to each sector's unique vulnerabilities to different types of climate risks. Additionally, the magnitude and timing of climate events vary, leading to diverse impacts across sectors. The market also reacts differently to various climate events based on their perceived severity and potential long-term implications. However, the relatively small magnitude of these impacts can be explained by market efficiency, robust risk management practices, and the diversified nature of investments, which help absorb and mitigate the immediate effects of climate risks in the short term.

Replacing the short-term dummy variable in Eq. (4) with the long-term dummy variable, will result in Eq. (5), which is used to detect changes in the long-term systematic risk. Plots of the beta change coefficients of the three climate risks, presented in Fig. 6, show the estimates of Eq. (5) with the three risks serving as the dummy variable. Note that, in some sectors, the results were reversed in the long term. For example, the materials sector was the most vulnerable to all three risks in the short term; its vulnerability, however, decreased significantly in the long term.

On the other hand, whilst the financial sector appeared to be less vulnerable to the three climate risks in the short term, its vulnerability increased significantly in the long term. Moreover, it is worth noting that certain risks can have a relatively high impact on systematic risk in the long term. For instance, Event 4, which involved the formal ratification of the Paris Agreement by the United States, increased the beta by 0.6 in the long run. The effects of the acute, chronic, and transition risks vary in magnitude, with ranges of −0.25 to 0.4, −0.2 to 0.45, and −0.4 to 0.6, respectively. The occurrence of several diamond shapes in the three risks suggests that certain events from these risks led to changes to the long-term systematic risk in different directions. We compared the impacts of systematic risk changes between the short term and long term by examining Figs. 5 and 6. One notable finding is the significant difference in the number of events that have a statistically significant impact on systematic risk. In the short term, every event influences the systematic risk of at least one sector. However, in the long term, several events show no significant impact, meaning none of the sectors are affected. This suggests that whilst some events have an immediate effect, their influence diminishes over time. This phenomenon could be explained by the fact that short-term market reactions often reflect immediate uncertainties and adjustments, causing sectors to respond quickly to events. Over time, however, markets tend to adapt and absorb information related to climate risk events, particularly acute, chronic, and transition risks. Initial reactions to these risks may be significant, but as companies and investors adjust their strategies and practices, the long-term impact on systematic risk often diminishes. This finding is consistent with the work of Zivin and Neidell (2014), where the effect of climate risks may differ across different industries. Hence, we performed our empirical investigation by industry. Zivin and Neidell (2014) also showed that temperature increases at the higher end of the distribution reducing hours worked in industries with high exposure to climate and reducing time allocated to outdoor leisure for the non-employed, with this time reallocated to indoor leisure.

6.2. Risk analysis by ES clusters

Table A.10 (Appendix 6) displays estimates of Eq. (3) for the acute, chronic, and transition risks, respectively. No change in beta estimate is statistically significant from zero, suggesting that the three risks do not affect the short-term systematic risk at the aggregate level. The results are consistent with the results from the sector analysis. The change in beta coefficients estimates of Eq. (4) for the three risks are plotted in Fig. 7.

The results of the group-by-group analysis in the short term are similar to those of the sector-by-sector, with very small effects from the three climate risks. The largest effect was observed in the acute risk category, specifically event 6 with a value of 0.18. The chronic risks had almost no effect on the four ES groups, except for a slight increase in systematic risk in the $[Q_2, Q_3)$ group

[8] Note that Ramiah et al. (2013) argued that Eq. (3) can generate an improper result, as the positive and negative effects from the events might cancel out.

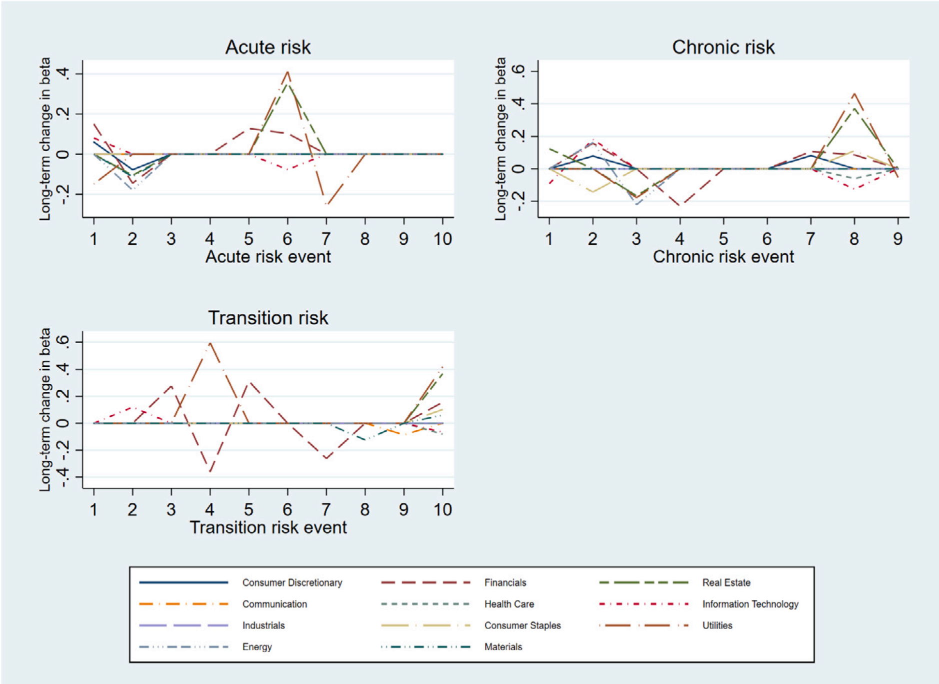

Fig. 6. Individual long-term changes in systematic risk with three climate risks as the dummy variable in sector-by-sector analysis.

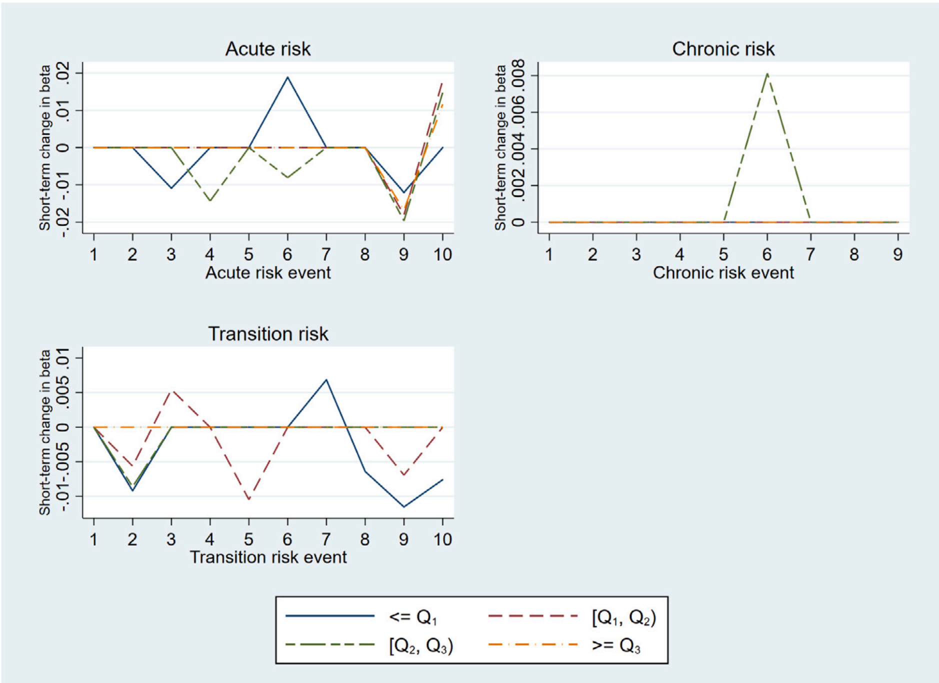

Fig. 7. Individual short-term changes in systematic risk with three climate risks as the dummy variable in group-by-group analysis.

resulting from event 6. When comparing the number of events that create significant effects among the four ES groups, it becomes apparent that the highest ES group, $\geq Q_3$, is consistently less affected by the three risks. These companies with high environmental performance typically have advanced risk management strategies to mitigate the impact of climate risks. Also, investors perceive

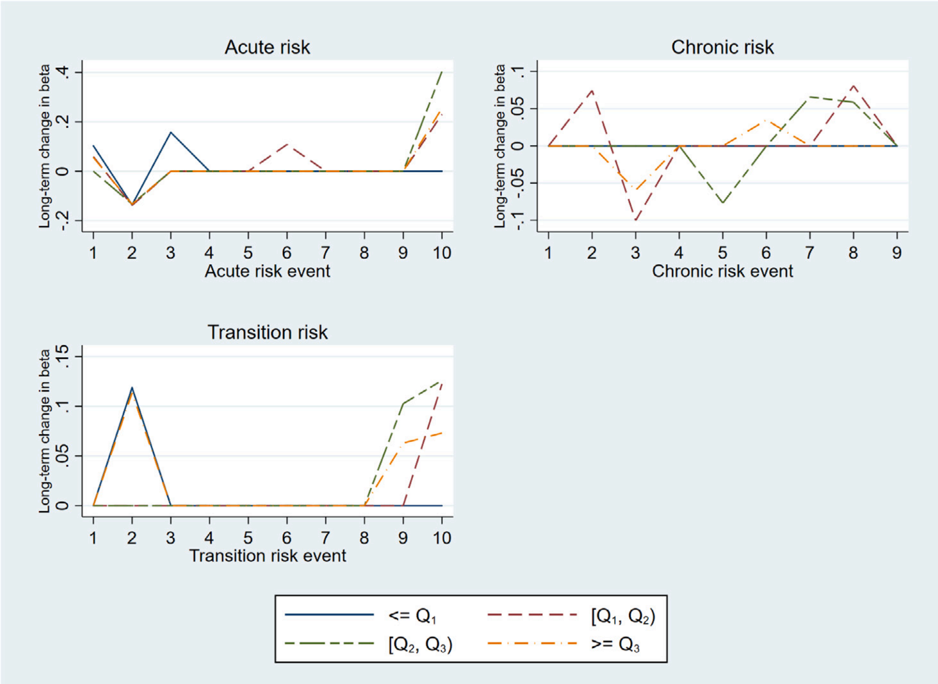

Fig. 8. Individual long-term changes in systematic risk with three climate risks as the dummy variable in group-by-group analysis.

these companies as lower-risk investments. This confidence results in stable stock prices even during climate events, as investors believe these companies are better equipped to handle environmental challenges, leading to low volatilities.

Replacing the short-term dummy variables, in Eq. (4), with the long-term dummy variables produce the results presented in Fig. 8. The impacts of the three types of risks are more noticeable in the long term than in the short term. Four acute risk events had significant effects on the systematic risk of four ES groups, with three of the events increasing the systematic risks. The long-term effects of chronic risks became increasingly apparent as the number of significant events grew for the $[Q_1, Q_2)$, $[Q_2, Q_3)$, and $\geq Q_3$ groups. This can be the result of the cumulative effects of chronic climate risks become more pronounced. These gradual changes lead to sustained financial impacts, which are less evident in the short term. In addition, the transition risks caused the systematic risk to rise for all ES groups. The regulation changes can impact all companies, regardless of their environmental performance. Compliance with new regulations often requires substantial investments and operational adjustments, increasing the overall risk for all ES groups. Overall, the effects of the three risks on the four ES groups are relatively moderate compared to some of the effects on certain sectors. This could be due to the fact that firms within the same sector tend to experience similar effects, which amplifies the impact on the sector as a whole.

Lastly, the short-term systematic risk is more vulnerable to climate risk events whereas long-term systematic risk is not. This finding is consistent with the work of Zivin and Neidell (2014), where the effect of climate risks may differ across different industries. Hence, we performed our empirical investigation by industry. Graff Zivin and Neidell (2014) also showed that temperature increases at the higher end of the distribution reducing hours worked in industries with high exposure to climate and reducing time allocated to outdoor leisure for the non-employed, with this time reallocated to indoor leisure.

7. Conclusion

The broad discussion surrounding the impact of climate change on economies and financial systems has garnered significant attention in recent years, driven by the increasingly urgent and threatening climate conditions we face globally. This heightened focus reflects a growing awareness that the risks posed by climate change are not just environmental, but also have profound economic and financial implications. Central to this discourse is the impact of climate-induced risks, which have become a focal point of research and analysis. These risks, stemming from both the direct physical effects of climate change and the transitional challenges associated with moving towards a low-carbon economy, are reshaping how investors, businesses, and policymakers evaluate financial stability and growth prospects.

Previously, research into the impact of climate risks on economic and financial systems typically specialised in examining either physical risks—such as extreme weather events and rising sea levels—or transition risks stemming from regulatory changes in the shift towards a low-carbon economy. Our study simultaneously explores both physical and transition risks, offering a more comprehensive understanding of the multifaceted climate risks. Specifically, this paper investigates how acute, chronic, and transition-related climate risks affect stock returns and their associated systematic risks in the U.S. market. To measure acute risk indicators, we collected data on ten natural disaster events that occurred in the U.S. between 2015 and 2020. For chronic risk, we proposed the use of a multivariate hidden Markov model that takes into account temperature and precipitation anomalies, as well as Google Trends data on climate change-related keywords. Using a change-of-measure-based filtering technique, we estimated the probabilities of normal and abnormal climate conditions, as well as the regime-switching parameters, based on daily data ranging from January 1, 2015 to December 29, 2020. Our proposed model detected nine abnormal climate periods during this period, which we used as a proxy for physical climate risk. As for transition risk, we collected data on ten climate change policy announcements made in the U.S., during the same period of time, and used them as a proxy for this type of risk. By considering all three types of risk, we aimed to gain a more comprehensive understanding of their impact on stock returns and systematic risks.

An event study methodology was employed to assess the impacts of the three climate risks on stocks' returns. For this purpose, we categorised the S&P 500 stocks into 11 sectors and analyse the impacts of the three risks on those sectors. We calculated the average abnormal returns, which describes the immediate impact of the climate risk on the stock prices and compared them with the 5-day cumulative abnormal returns, which depicts the impact of the climate risk five days after the risk occurred. To measure the environmental performance of the firms, Bloomberg ES for the S&P 500 firms were obtained. We computed the average ES for each sector and explored whether the sector's environmental performance affects the stock prices differently during the occurrence of the three climate risks. Furthermore, we studied the impacts of the three climate risks on the systematic risks of the 11 sectors. The three climate risks were converted into dummy variables and incorporated into the CAPM model to investigate the influences of the systematic risk parameter beta.

Several important conclusions can be drawn from our empirical results. First, we found that whilst certain sectors exhibit different behaviours in response to various climate risks, some sectors maintain consistent exposure to all three risks. Notably, the financial and communication sectors appeared to be largely unaffected by these risks, whereas the real estate and utilities sectors showed the most pronounced reactions compared to other sectors. These findings suggest that some sectors may be more susceptible to climate risks than others, and therefore that investors and policymakers should take these differences into account when making decisions. Secondly, by clustering firms into four ES groups, based on their environmental performance, we found that the group with the lowest performance suffered the most significant negative impact on stock returns from the three climate risks. In contrast, the groups with higher environmental performance were less severely affected by these risks. These results indicate that companies with a weak environmental performance may face greater challenges in tackling climate risks and may experience more significant financial losses. Our risk analysis results suggest that climate risk events have an impact on short-term systematic risk whereas no statistically significant evidence was found on long-run systematic risk.

To justify the results showing different patterns across sectors in the U.S., we rely on the arguments by Kamiar et al. (2023). The degree of adaptation and mitigation towards climate change differs across industries. In particular, (i) adaptation efforts might be concentrated in certain sectors; (ii) in others adaptation is not keeping pace with climate change; (iii) the effects of adaptation might have been offset by structural changes to the US economy; (iv) firms underestimating the severity of future weather extreme events, may not adapt sufficiently; and finally (v), firms tend to underinvest in adaptation owing to its high cost (Deryugina and Hsiang, 2014). We do not observe firm-specific characteristics wherefore drawing firm conclusions about results across sectors is not possible and will be left to further studies.

Our paper provides an extensive analysis on the consequences of different measures of climate risk (physical and transition) on listed US firms. Furthermore, the latter are clustered by industry and firms' propensity, proxied by ESG scores, towards green transition. Our findings provide evidence to investors and policymakers to make informed decisions during the on-going green transition. It should be acknowledged that the present study has some limitations arising from the focus on the US only; however, the methodology we developed remains invariant in respect to any other geographical location. As per future works, the use of data from different countries is a consideration for follow-up studies along with the use of various ARCH-type models as suggested by Pham et al. (2019).

CRediT authorship contribution statement

Yiyang Chen: Writing – original draft, Visualization, Validation, Investigation, Data curation. **Rogemar Mamon:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition. **Fabio Spagnolo:** Writing – review & editing, Validation, Investigation, Formal analysis. **Nicola Spagnolo:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Fabio Spagnolo acknowledges the financial support provided for the project ‘‘ESCAPE - Economic and Social Consequences of Altered Planet Environment’’, CUP: J43C24000400006, Project Code: PE00000018 GRINS, funded under the NextGeneration program - European Union. Yiyang Chen and Rogemar Mamon acknowledge the support of the Natural Sciences and Engineering Research Council of Canada (NSERC) through a Discovery Grant (RGPIN-2017-04235). We would like to thank the Editor and two anonymous referees for very useful comments and suggestions. All errors are our own.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.mulfin.2024.100887.

References

Albanese, M., Caporale, G.M., Colella, I., Spagnolo, N., 2024. The effects of physical and transition climate risk on stock markets: Some multi-country evidence. Int. Econ. 100571.
Antoniuk, Y., Leirvik, T., 2021a. Climate transition risk and the impact on green bonds. J. Risk Financial Manag. 14 (12), 597.
Antoniuk, Y., Leirvik, T., 2021b. Climate change events and stock market returns. J. Sustaina. Finance & Investment 14 (1), 42–67.
Aslan, C., Bulut, E., Cepni, O., Yilmaz, M., 2022. Does climate change affect bank lending behavior? Econom. Lett. 220, 110859.
Auh, J., Choi, J., Deryugina, T., Park, T., 2022. Natural Disasters and Municipal Bonds (No. W30280). National Bureau of Economic Research.
Baldauf, M., Garlappi, L., Yannelis, C., 2020. Does climate change affect real estate prices? Only if you believe in it. Rev. Financ. Stud. 33 (3), 1256–1295.
Balvers, R., Du, D., Zhao, X., 2017. Temperature shocks and the cost of equity capital: Implications for climate change perceptions. J. Bank. Financ. 77, 18–34.
on Banking Supervision, Basel Committee, 2021. Climate-related risk drivers and their transmission channels. Retrieved February 9 2023, from https://www.bis.org/bcbs/publ/d517.htm.
Bansal, R., Ochoa, M., Kiku, D., 2017. Climate Change and Growth Risks: The Role of Uncertainty and Risk. NBER Working Paper 23009.
Bernstein, A., Gustafson, M.T., Lewis, R., 2019. Disaster on the horizon: The price effect of sea level rise. J. Financ. Econ. 134 (2), 253–272.
Birindelli, G., Chiappini, H., 2021. Climate change policies: Good news or bad news for firms in the European union? Corpor. Soc. Responsibil. Environ. Manag. 28 (2), 831–848.
Boehmer, E., Masumeci, J., Poulsen, A., 1991. Event-study methodology under conditions of event-induced variance. J. Financ. Econ. 30 (2), 253–272.
Bolton, P., Kacperczyk, M., 2021. Do investors care about carbon risk? J. Financial Econon. 142 (2), 517–549.
Bolton, P., Kacperczyk, M., 2022. Global pricing of carbon-transition risk. J. Finance 78 (6), 3677–3754.
Bua, G., Kapp, D., Ramella, F., Rognone, L., 2021. Transition versus physical climate risk pricing in euro area financial markets: A text-based approach. ECB Working Paper No. 2677, http://dx.doi.org/10.2866/583769, Retrieved February 8 2023, from.
Busch, T., Bauer, R., Orlitzky, M., 2016. Sustainable development and financial markets: Old paths and new avenues. Bus. Soc. 55 (3), 303–329.
Choi, D., Gao, Z., Jiang, W., 2020. Attention to global warming. Rev. Financ. Stud. 33 (3), 1112–1145.
Deryugina, T., Hsiang, S.M., 2014. Does the Environment Still Matter? Daily Temperature and Income in the United States. NBER Working Paper No. 20750.
Erlwein, C., Benth, F.E., Mamon, R., 2010. HMM filtering and parameter estimation of an electricity spot price model. Energy Econ. 32 (5), 1034–1043.
Erlwein, C., Mamon, R., 2009. An online estimation scheme for a Hull–White model with HMM-driven parameters. Stat. Methods Appl. 18 (1), 87–107.
Faccini, R., Matin, R., Skiadopoulos, G. and, 2023. Dissecting climate risks: Are they reflected in stock prices? J. Bank. Financ. 155, 106948.
Giglio, S., Kelly, B., Stroebel, J., 2021b. Climate finance. Annu. Rev. Finan. Econ. 13, 15–36.
Giglio, S., Maggiori, M., Rao, K., Stroebel, J., Weber, A., 2021a. Climate change and long-run discount rates: Evidence from real estate. Rev. Financ. Stud. 34 (8), 3527–3571.
Goldsmith-Pinkham, P., Gustafson, M., Lewis, R., Schwert, M., 2019. Sea Level Rise and Municipal Bond Yields. Rodney L. White Center for Financial Research.
Gorgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., Wilkens, M., 2019. Carbon Risk. Working Paper, University of Augsburg, Germany.
Gu, X., Mamon, R., Davison, M., Yu, H., 2021. An automated financial indices-processing scheme for classifying market liquidity regimes. Internat. J. Control 94 (3), 735–756.
Ho, T., 2022. Climate change news sensitivity and mutual fund performance. Int. Rev. Financ. Anal. 83, 102331.
Hong, H., Li, F.W., Xu, J., 2019. Climate risks and market efficiency. J. Econometrics 208 (1), 265–281.
Huynh, T., Xia, Y., 2021. Climate change news risk and corporate bond returns. J. Financ. Quant. Anal. 56 (6), 1985–2009.
Ilhan, E., Krueger, P., Sautner, Z., Starks, L., 2023. Climate risk disclosure and institutional investors. Rev. Financ. Stud. 36 (7), 2617–2650.
Javadi, S., Masum, A., 2021. The impact of climate change on the cost of bank loans. J. Corpor. Finance 69, 102019.
Kamiar, M., Ng, R., Pesaran, H., Raissi, N., J., Yang, 2023. Climate change and economic activity: Evidence from US states. Oxford Open Econ. 00, 1–11. http://dx.doi.org/10.1093/ooec/odac010.
Krueger, P., Sautner, Z., Starks, L.T., 2020. The importance of climate risks for institutional investors. Rev. Financ. Stud. 33 (3), 1067–1111.
Kruttli, M., Tran, B., Watugala, S., 2019. Pricing Posei- Don: Extreme Weather Uncertainty and Firm Return Dynamics, Finance and Economics Discussion Series 2019-054. Board of Governors of the Federal Reserve System, Washington, http://dx.doi.org/10.17016/FEDS.2019.054.
Li, Q., Shan, H., Tang, Y., Yao, V., 2024. Corporate climate risk: Measurements and responses. Rev. Financ. Stud. 37 (6), 1778–1830.
Mamplata, J., Mamon, R., David, G., 2022. Modelling and filtering for dynamic investment in the precious-metals market. Int. J. Comput. Math. 99 (12), 2382–2409.
Matsumura, E., Prakash, R., Vera-Munoz, S., 2014. Firm-value effects of carbon emissions and carbon disclosures. Account. Rev. 89 (2), 695–724.
Muluneh, M., 2021. Impact of climate change on biodiversity and food security: A global perspective—a review article. Agric. Food Secur. 10 (1), 1–25.
Nguyen, D., Ongena, S., Qi, S., Sila, V., 2020a. Climate change risk and the cost of mortgage credit. Swiss Finance Institute Research Paper No. 20-97, pp. 1509–1549.
Nguyen, V., Pham, H., Ramiah, V., Moosa, I., 2020b. The effects of environmental regulation on the stock market: the french experience. Account. Finance 60 (4), 3279–3304.
Oestreich, A., Tsiakas, I., 2015. Carbon emissions and stock returns: Evidence from the EU emissions trading scheme. J. Bank. Financ. 58, 294–308.
Painter, M., 2020. An inconvenient cost: The effects of climate change on municipal bonds. J. Financ. Econ. 135 (2), 468–482.
Pastor, L., Stambaugh, R., Taylor, L., 2022. Dissecting green returns. J. Financ. Econ. 146 (2), 403–424.
Patell, J., 1976. Corporate forecasts of earnings per share and stock price behavior: Empirical test. J. Account. Res. 14 (2), 246–276.
Pham, H., Nguyen, V., Ramiah, V., Mudalige, P., Moosa, I., 2019a. The effects of environmental regulation on the Singapore stock market. J. Risk Financial Manag. 12 (4), 175.
Pham, H., Nguyen, V., Ramiah, V., Saleem, K., Moosa, I., 2019b. The effects of the Paris climate agreement on stock markets: evidence from the german stock market. Appl. Econ. 51 (57), 6068–6075.
Ramiah, V., Martin, B., Moosa, I., 2013. How does the stock market react to the announcement of green policies? J. Bank. Financ. 37 (5), 1747–1758.
Sautner, Z., van Lent, L., Vilkov, G., Zhang, R., 2023a. Firm-level climate change exposure. J. Finance 78 (3), 1449–1498.
Sautner, Z., van Lent, L., Vilkov, G., Zhang, R., 2023b. Pricing climate change exposure. Manage. Sci. 69 (12), 7540–7561.
Tenyakov, A., Mamon, R., Davison, M., 2016. Filtering of a discrete-time HMM-driven multivariate Ornstein–Uhlenbeck model with application to forecasting market liquidity regimes. IEEE J. Sel. Top. Sign. Proces. 10 (6), 994–1005.
UNCCD, 2022. Drought in Numbers. UNCCD, Bonn Germany, Retrieved February 8 2023, from https://www.unccd.int/resources/publications/drought-numbers.
Venturini, A., 2022. Climate change, risk factors and stock returns: A review of the literature. Int. Rev. Financ. Anal. 79, 101934.
Wuebbles, D., Fahey, D., Hibbard, K., 2017. Climate Science Special Report: Fourth National Climate Assessment, Volume II. p. 440.
Xiong, H., Mamon, R., 2016. A self-updating model driven by a higher-order hidden Markov chain for temperature dynamics. J. Comput. Sci. 17 (1), 47–61.
Xiong, H., Mamon, R., 2018. Putting a price tag on temperature. Comput. Manag. Sci. 15 (2), 259–296.
Xiong, H., Mamon, R., 2019. A higher-order Markov chain-modulated model for electricity spot-price dynamics. Appl. Energy 233–234, 495–515.
Zivin, G., Neidell, M., 2014. Temperature and the allocation of time: Implications for climate change. J. Labour Econ. 32 (1), 1–26.