Haitong Jiang

haitong.jiang@student.reading.ac.uk

ICMA Centre, Henley Business School

University of Reading, UK

August 2, 2025

Dear Professors Flammer and Giglio,

I am writing to express my interest in participating in the PhD Student Workshop on Climate Finance to be held on October 9, 2025, in Cambridge, MA. I am currently a PhD candidate at the ICMA Centre, Henley Business School, University of Reading, UK, and expect to submit my dissertation in September 2025, with full completion anticipated by December 2025.

My current research lies at the intersection of climate finance, machine learning, and asset pricing, with a focus on the financial impact of extreme climate events. One of my ongoing projects examines how extreme heatwave events affect U.S. stock returns. Using event study methods, regression analysis, and neural networks, I analyze firm-level exposure to heatwaves and find evidence of sector-specific vulnerabilities and ESG-driven resilience at the branch level. This project highlights the potential of machine learning to better understand the financial risks posed by climate events.

Broadly, my research interests include climate-related financial risk, derivative markets, and the application of machine learning in pricing and risk forecasting. In the future, I aim to develop financial products and models that help firms hedge climate risks more effectively, contributing to both academic advancements and practical tools for navigating environmental uncertainty.

Professor Emese Lazar (e.lazar@henley.ac.uk) is familiar with my research and would be happy to provide a

reference. I believe this workshop would be an excellent opportunity to receive feedback on my work, engage with leading researchers, and deepen my understanding of climate finance.

Thank you for considering my application. I look forward to the possibility of contributing to and learning from this valuable workshop.

Sincerely,

Haitong Jiang

Haitong Jiang

+447928047438 | haitong.jiang@pgr.reading.ac.uk | ICMA Centre | http://linkedin.com/in/haitong-jiang-145736184

Education

PhD in Finance Sep 2021-Now

ICMA Centre, Henley Business School

- Research area: Option pricing, Asset pricing, Climate finance, Quantitative Finance, Machine Learning.
- Project: Improving Implied Volatility Forecasts for American Options using Neural Networks
  - Enhanced American option pricing models by integrating deep neural networks with Black-Scholes and Heston models; improved implied volatility forecasting using S&P 100 option data from OptionMetrics. Under R&R.
- Project: Using Neural Networks to Forecast Company-Level Implied Volatility under Climate Uncertainty
  - Utilised Python to process over 3000 companies' implied volatility data from OptionMetrics, company establishment information from Orbis and climate data from NOAA; executed comprehensive Deep Learning to estimate and forecast the impact of hurricane locations on company sites.
- Project: Analysing Firms' Stock Performance during Extreme Heatwaves: Regression-based vs. Neural Network Models

  Analyzed the impact of extreme heatwaves on U.S. stock returns; found sector-specific risks and ESG-driven resilience at branch level; neural networks improved prediction of abnormal returns over traditional models.

MSc Financial Engineering Sep 2020-March 2021

ICMA Centre, Henley Business School, University of Reading

- Distinction (Result: 82%).
- Project: Utilised the Monte Carlo Simulation Method in Python to price European, American, and exotic options, employing Black-Scholes, Bachelier, and Heston models.

BSc Mathematics and Applied Mathematic Sep 2016-June 2020

Mathematics and Statistics Department, University of Reading

- First Class Degree (Result: 77%).
- Project: Density Estimation with Maximum Entropy method.

Work And Internship Experience

Lecturer-Contract Oct 2024 - Aug 2025

University of Reading *UK*

- Expertly delivered seminars and workshops in Portfolio Management, Financial Modelling, Market Risk, and Financial Instruments.
- Taught and mentored undergraduate and master's students.

Associate Lecturer-Contract Oct 2023 - Oct 2024

University of Reading *UK*

- Expertly delivered seminars and workshops in Portfolio Management, Market Risk, and Financial Instruments.
- Managed group project allocations and marking criteria, alongside conducting thorough reviews and approvals of exam papers in collaboration with module coordinators.

Teaching Assistant Oct 2021 - Oct 2023

University of Reading *UK*

Student Ambassador Apr 2020 - Jul 2020

University of Reading *UK*

- Successfully completed three advanced modules in data protection, enhancing my understanding of information security and compliance standards.

Technical Proficiencies and Additional Skills

Programming Languages: Proficient in Python, MATLAB, R, high-performance computing cluster and LaTeX, with extensive experience in data analysis, modeling, and simulation.

Financial Data Analysis: Skilled in sourcing and analyzing data from Bloomberg, Thomson Reuters Refinitiv, and WRDS, applying insights to financial research and risk assessment.

Hobbies: Tennis, Dancing and interests in Physics.

Analysing Firms Stock Performance during Extreme Heatwaves: Regression-based vs. Neural Network Models

Michaela Hegglin* Haitong Jiang† Emese Lazar‡ Miriam Marra§
Fuzhen Shen¶

Abstract

This paper investigates the effects of extreme heatwave events on the stock returns of publicly listed U.S. firms by incorporating information on exposure of firms location to the heatwaves within an event study, regression analysis and machine learning techniques. Overall, we find some evidence of negative average CARs around the heatwaves events, especially for sectors like Energy and Materials. Regression analysis reveals that the impact of heatwaves differ depending on whether they affect firm headquarters or branches, with stronger ESG performance enhancing firms' resilience primarily at branches level. Finally, neural networks substantially improve predictive accuracy over traditional linear models, capturing complex, nonlinear relationships between firm attributes, heatwave characteristics, and CARs. Our results underscore the importance of distinguishing between headquarters and branches' locations and their relative exposures to heatwaves and using more advanced modeling techniques to understanding climate-related financial risks.

Keywords: Extreme heatwaves; Climate risk; Cumulative abnormal returns; Neural network.

*University of Reading, Department of Meteorology, and Institute of Climate and Energy Systems (ICE). Email: m.i.hegglin@fz-juelich.de

†ICMA Centre, Henley Business School, University of Reading, Reading, RG6 6BA, UK. Email: haitong.jiang@pgr.reading.ac.uk

‡ICMA Centre, Henley Business School, University of Reading, Reading, RG6 6BA, UK. Email: e.lazar@icmacentre.ac.uk

§ICMA Centre, Henley Business School, University of Reading, Reading, RG6 6BA, UK. Email: m.marra@icmacentre.ac.uk

¶Institute of Climate and Energy Systems (ICE). Email: f.shen@fz-juelich.de]

1. Introduction

Global warming is accelerating at an unprecedented pace, with broad scientific consensus identifying human activity as the primary driver of these changes (Kerr, 2007). Climate has long been recognized as a fundamental influence on the evolution of the global economy (Carleton and Hsiang, 2016), affecting diverse domains including economic productivity, social interactions, and demographic patterns—especially through shifts in temperature. Lau and Nath (2012) project that heatwaves will become significantly more severe in the twenty-first century, with both their duration and intensity increasing substantially across key regions in North America. Recent empirical research has demonstrated that extreme temperatures can significantly impact firm-level financial outcomes. For instance, Carleton and Hsiang (2016) examine the U.S. equity market's response to extreme high surface temperature events by matching the timing of these events with the geographical location of firms' headquarters. Addoum et al. (2023) analyze how extreme temperatures affect corporate profitability across industries and whether sell-side analysts adequately account for these relationships in the U.S. market. Meanwhile, Griffin et al. (2025) extend this line of inquiry to EU and UK firms, investigating the effects of extreme heat spells on key financial performance indicators, including the sales-to-assets ratio, pretax profit margin, and return on assets.

However, most existing studies rely only on the geographical location of firms' headquarters to capture firms' physical exposure to climate events (see, for instance, Schuster et al., 2025; Griffin et al., 2019; Chen, 2021). Data on subsidiaries' and branches' locations and how they may impact the overall firms' responses to heatwaves and high temperature remain largely unexplored in this literature (Huynh and Xia, 2023). In our study, we contribute to the literature by focusing on firms with headquarters located in the United States and covered by the CRSP and Compustat databases. We then collect information on their global branches' and subsidiaries' locations using the Orbis database. As a result, our final dataset encompasses firms' locations worldwide, allowing us to analyze their overall exposure to climate events at a truly global scale.

We begin by conducting an event study to examine the impact of heatwaves on firm-level stock returns. Using the Market Model, the Market Adjusted Model, the Fama-French Three-Factor Model (Fama and French, 1993), and the Fama-French Four-Factor Model (Carhart, 1997). We estimate firms' cumulative abnormal returns (CARs) around heatwave events. We also conduct a sector-level analysis to examine how different sectors react to heatwave events. We then perform regression analyses to assess how specific factors such as heatwave duration, average intensity, cumulative intensity, and firms' Environmental, Social, and Governance (ESG) scores influence the CARs. Finally, we analyse whether the exposure

of headquarters versus branches leads to different impacts from heatwaves.

While most studies in climate finance have used on event study and regression models to examine how firms respond to climate events, these approaches rely on the strong assumption that the relationship between CARs and climate events' exposure, as well as other features, is linear. Modeling and quantifying the potentially more complex and nonlinear impact of climate events on firm performance has not been fully explored. Our contribution in this study is to apply neural network methodologies to investigate the relationships between firms' CARs and both company-level and climate event-level characteristics. Practically, we show an improvement in neural network model fit and predictive ability: R^2s are higher and mean squared errors (MSE) are lower compared to traditional linear models.

Numerous studies have leveraged machine learning methods for asset pricing applications. For example, Gu et al. (2020) perform a comparative analysis of machine learning approaches for estimating asset risk premia. Giglio et al. (2022) review recent methodological advances in applying factor models and machine learning to asset pricing. Chen et al. (2024) introduce deep neural networks to estimate asset pricing models for individual stock returns, exploiting rich conditioning information, maintaining flexible functional forms, and incorporating time variation. Neural networks have gained popularity as advanced tools for modeling in finance (e.g., Hutchinson et al., 1994, Kaastra and Boyd, 1996 and Fallahgoul et al., 2024). Alonso-Robisco et al. (2025) provide a comprehensive review of applications of machine learning in climate finance and note that most climate finance research continues to rely on more traditional statistical techniques. They emphasize that only a small subset of emerging studies harness machine learning to address key questions in this field. Musleh Al-Sartawi et al. (2022) point out that the majority of studies applying machine learning to sustainable finance focus on processing complex data, such as identifying key climate-related terms in news or financial statements, rather than directly modeling the financial impacts of climate events. Our study applies neural networks to model and quantify how extreme heatwave events affect firm CARs. This methodology enables a more flexible and precise investigation of the nonlinear relationships between heatwaves' characteristics and abnormal stock returns.

Our preliminary event-studies results reveal that heatwave events have significant and heterogeneous impacts on firm cumulative abnormal returns (CARs), with effects varying notably across sectors and depending on the model used to estimate abnormal returns. Simpler models, such as the Market and Market-Adjusted Models, show consistent evidence of negative average CARs during heatwaves, particularly concentrated in sectors like Energy, Materials, and Financials, which appear more vulnerable to heat-related disruptions. In contrast, multi-factor asset pricing models, including the two Fama-French specifications, attenuate or even eliminate these average negative effects. Next, our regression analysis

highlights that location and global exposure to heatwaves, whether at a firm's headquarters or branches level, critically shapes its financial sensitivity to the events, with headquarters exposures amplifying the negative effects. In addition, we observe that firms with stronger ESG performance exhibit greater resilience during heatwaves, but this benefit diminishes when heatwaves affect their headquaters. Finally,we show that neural networks substantially outperform traditional linear regressions, enhancing the model explanatory power with over 22 percentage points increse in R^2 and significantly reducing prediction errors. These findings demonstrate that more advanced machine learning techniques can help to accurately assess and forecast the financial consequences of extreme heat events.

The remainder of the paper is structured as follows. Section 2 presents the methodologies used in the paper; Section 3 describes the data sources; Section 4 presents the empirical results, and Section 5 concludes.

2. Methodology

2.1. Event Study and Regression Analysis of Cumulative Abnormal Returns

We start by running a preliminary event study to examine cumulative abnormal returns around heatwaves for affected firms. First, to estimate abnormal returns (ARs), we apply four widely used asset pricing models, each offering a different benchmark for expected returns. Each observation i corresponds to a unique firm-event pairing, defined by company k experiencing heatwave event j. The abnormal return for firm-event observation i on day t is defined generally as

$$\mathrm{AR}_{i,t} = R_{i,t} - E(R_{i,t}),$$

where $R_{i,t}$ is the actual return of firm-event observation i on day t, and $E(R_{i,t})$ is the expected return based on the chosen asset pricing model.

The Market Model is the simplest benchmark we use, assuming that the expected return equals the market return:

$$\mathrm{AR}_{i,t} = R_{i,t} - R_{m,t},$$

where $R_{m,t}$ is the CRSP value-weighted market return on day t.

Next, we estimate the expected returns using using the market model, with the abnormal return calculated as the residual:

$$\mathrm{AR}_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t}),$$

where α_i and β_i are estimated over the estimation window for each firm-event observation i.

We further use the Fama-French Three-Factor Model, which includes two additional factors: size and value premia, to estimate expected returns.

The abnormal return is then given by

$$\mathrm{AR}_{i,t} = R_{i,t} - (\alpha_i + \beta_{1,i} R_{m,t} + \beta_{2,i} \mathrm{SMB}_t + \beta_{3,i} \mathrm{HML}_t).$$

Finally, we use the Fama-French Four-Factor Model as know as Fama-French Three-Factor Model Plus Momentum.

The corresponding abnormal return is calculated as

$$\mathrm{AR}_{i,t} = R_{i,t} - (\alpha_i + \beta_{1,i} R_{m,t} + \beta_{2,i} \mathrm{SMB}_t + \beta_{3,i} \mathrm{HML}_t + \beta_{4,i} \mathrm{MOM}_t).$$

where MOM_t represents the return difference between high- and low-momentum stocks.

We perform an event study following the methodology of Griffin et al. (2019). The estimation window is set to 100 trading days, representing the period used to estimate the expected return and the variance of residuals from each model. A minimum of 70 valid return observations within this window ensures robustness of the return model estimation, avoiding biases from sparse or incomplete data. A 50-day gap separates the end of the estimation window from the start of the event window to mitigate the influence of event-related return variance on model estimation.

The event window is defined as $[-20, +20]$ trading days relative to the onset date of each heatwave, capturing both anticipatory and lagged stock price responses. The cumulative abnormal return (CAR) for observation i is computed as

$$\mathrm{CAR}_i = \sum_{t=-20}^{20} \mathrm{AR}_{i,t},$$

where $\mathrm{AR}_{i,t}$ denotes the abnormal return for firm-event observation i on day t within the event window.

Each firm-event observation i is treated as a distinct data point in our analysis. In total, we obtain $k = 72{,}788$ such observations, each associated with a corresponding cumulative abnormal return CAR_i.

To evaluate the average effect of heatwave exposure across all firm-event observations,

we compute the Mean Cumulative Abnormal Return (MCAR) as follows:

$$\text{MCAR} = \frac{1}{k} \sum_{i=1}^{k} \text{CAR}_i,$$

where $k = 72{,}788$ represents the total number of firm-event observations.

To assess whether the cumulative abnormal returns observed across firm-event pairs are statistically significant, we employ both parametric and non-parametric inference methods.

First, we conduct a two-tailed t-test to assess whether the Mean Cumulative Abnormal Return differs significantly from zero. This test evaluates whether the sample mean CAR is statistically distinguishable from zero under the assumption of approximate normality.

As a robustness check, we also apply the Wilcoxon signed-rank test, a non-parametric alternative that assesses whether the median of the CAR distribution significantly differs from zero. The Wilcoxon test is performed on the signed ranks of CAR values, computing the corresponding test statistic and p-value. This test provides a complementary perspective on the central tendency of abnormal returns when the normality assumption may not hold.

We repeat our analysis of heatwave impacts at industry level. Firms are grouped according to their Global Industry Classification Standard (GICS) 2-digit identifiers. Within each sector, we compute the Mean Cumulative Abnormal Return (MCAR) by averaging the firm-event CARs:

$$\text{MCAR}_{\text{sector}} = \frac{1}{n} \sum_{i=1}^{n} \text{CAR}_{i,j}$$

where n denotes the number of firm-event observations within the sector, and $\text{CAR}_{i,j}$ represents the cumulative abnormal return for firm i during event j.

To assess the statistical significance of sector-level MCARs, we perform both the t-test and the Wilcoxon signed-rank test for each asset pricing model considered.

Next, we perform regression analysis on heatwave-event related CARs. We revise the event window to incorporate the actual duration of each heatwave. Specifically, the event window is redefined as $[-20, \text{duration}_i]$, where duration_i denotes the number of consecutive days that the heatwave persists for firm-event observation i. This modification allows the event study to account for heterogeneity in heatwave lengths across observations, enabling a more precise assessment of firm-level exposure. To investigate the effects of event characteristics and firm attributes on abnormal stock performance, we estimate a set of linear

regression models of the following general form:

$$\begin{aligned}\text{CAR_dur}_{p,i} = {} & \beta_0 + \beta_1 \times \text{Duration}_i + \beta_2 \times \text{Intensity}_i + \beta_3 \times \text{C_intensity}_i + \beta_4 \times \text{HQ}_i \\ & + \beta_5 \times \text{ESG}_i + \beta_6 \times (\text{Duration}_i \times \text{HQ}_i) + \beta_7 \times (\text{Intensity}_i \times \text{HQ}_i) \\ & + \beta_8 \times (\text{C_intensity}_i \times \text{HQ}_i) + \beta_9 \times (\text{ESG}_i \times \text{HQ}_i) + \varepsilon_i, \end{aligned} \tag{1}$$

$$\begin{aligned}\text{CAR_dur}_{p,i} = {} & \beta_0 + \beta_1 \times \text{Duration}_i + \beta_2 \times \text{Intensity}_i + \beta_3 \times \text{C_intensity}_i + \beta_4 \times \text{HQ}_i \\ & + \beta_5 \times \text{ESG}_i + \beta_6 \times (\text{Duration}_i \times \text{HQ}_i) + \beta_7 \times (\text{Intensity}_i \times \text{HQ}_i) \\ & + \beta_8 \times (\text{C_intensity}_i \times \text{HQ}_i) + \beta_9 \times (\text{ESG}_i \times \text{HQ}_i) \\ & + \sum_{s=1}^{S-1} \gamma_s \times D_{s,i}^{\text{Sector}} + \varepsilon_i, \end{aligned} \tag{2}$$

$$\begin{aligned}\text{CAR_dur}_{p,i} = {} & \beta_0 + \beta_1 \times \text{Duration}_i + \beta_2 \times \text{Intensity}_i + \beta_3 \times \text{C_intensity}_i + \beta_4 \times \text{HQ}_i \\ & + \beta_5 \times \text{ESG}_i + \beta_6 \times (\text{Duration}_i \times \text{HQ}_i) + \beta_7 \times (\text{Intensity}_i \times \text{HQ}_i) \\ & + \beta_8 \times (\text{C_intensity}_i \times \text{HQ}_i) + \beta_9 \times (\text{ESG}_i \times \text{HQ}_i) \\ & + \sum_{g=1}^{G-1} \delta_g \times D_{g,i}^{\text{group}} + \varepsilon_i, \end{aligned} \tag{3}$$

$$\begin{aligned}\text{CAR_dur}_{p,i} = {} & \beta_0 + \beta_1 \times \text{Duration}_i + \beta_2 \times \text{Intensity}_i + \beta_3 \times \text{C_intensity}_i + \beta_4 \times \text{HQ}_i \\ & + \beta_5 \times \text{ESG}_i + \beta_6 \times (\text{Duration}_i \times \text{HQ}_i) + \beta_7 \times (\text{Intensity}_i \times \text{HQ}_i) \\ & + \beta_8 \times (\text{C_intensity}_i \times \text{HQ}_i) + \beta_9 \times (\text{ESG}_i \times \text{HQ}_i) \\ & + \sum_{k=1}^{K-1} \theta_k \times D_{k,i}^{\text{industry}} + \varepsilon_i, \end{aligned} \tag{4}$$

$$\begin{aligned}\text{CAR_dur}_{p,i} = {} & \beta_0 + \beta_1 \times \text{Duration}_i + \beta_2 \times \text{Intensity}_i + \beta_3 \times \text{C_intensity}_i + \beta_4 \times \text{HQ}_i \\ & + \beta_5 \times \text{ESG}_i + \beta_6 \times (\text{Duration}_i \times \text{HQ}_i) + \beta_7 \times (\text{Intensity}_i \times \text{HQ}_i) \\ & + \beta_8 \times (\text{C_intensity}_i \times \text{HQ}_i) + \beta_9 \times (\text{ESG}_i \times \text{HQ}_i) \\ & + \sum_{n=1}^{N-1} \phi_n \times D_{n,i}^{\text{NAICS}} + \varepsilon_i, \end{aligned} \tag{5}$$

$$\begin{aligned}\text{CAR_dur}_{p,i} = {} & \beta_0 + \beta_1 \times \text{Duration}_i + \beta_2 \times \text{Intensity}_i + \beta_3 \times \text{C_intensity}_i + \beta_4 \times \text{HQ}_i \\ & + \beta_5 \times \text{ESG}_i + \beta_6 \times (\text{Duration}_i \times \text{HQ}_i) + \beta_7 \times (\text{Intensity}_i \times \text{HQ}_i) \\ & + \beta_8 \times (\text{C_intensity}_i \times \text{HQ}_i) + \beta_9 \times (\text{ESG}_i \times \text{HQ}_i) \\ & + \sum_{f=1}^{F-1} \psi_f \times D_{f,i}^{\text{company}} + \varepsilon_i, \end{aligned} \tag{6}$$

where $\text{CAR_dur}_{p,i}$ denotes the cumulative abnormal return under the variable event window for observation i, estimated under asset pricing model p. Specifically, $p \in \{\text{MA}, \text{MM}, 3\text{F}, 4\text{F}\}$ corresponds to the market-adjusted model, the market model, the Fama-French three-factor model, and the Fama-French Four-factor, respectively.

The variable Duration_i captures the number of days the heatwave event lasts. The variables Intensity_i and C_intensity_i quantify the magnitude of the heatwave; they indicate average intensity and cumulative intensity (i.e., $\text{Duration}_i \times \text{Intensity}_i$). The dummy variable HQ_i indicates whether the observation corresponds to the firm's headquarters (1) or a branch location (0). The variable ESG_i represents the firm's performance or disclosure level in environmental, social, and governance dimensions. The dummy variables $D_{s,i}^{\text{Sector}}$, $D_{g,i}^{\text{group}}$, $D_{k,i}^{\text{industry}}$, $D_{n,i}^{\text{NAICS}}$, and $D_{f,i}^{\text{company}}$ are indicator variables equal to one if observation i belongs to a specific GICS sector, group, industry, NAICS classification, or company, respectively, and zero otherwise. Incorporating fixed effects allows us to control for unobserved heterogeneity across these organizational and industries and firms.

For observations corresponding to branch locations ($\text{HQ}_i = 0$), the marginal effect of each predictor corresponds directly to its main coefficient. For headquarters observations ($\text{HQ}_i = 1$), the total effect equals the sum of the main coefficient and the corresponding interaction term coefficient.

Interaction terms between the main explanatory variables and HQ_i are included to test whether the effects of heatwave characteristics differ between headquarters and branch loca-

tions. For instance, the interaction term $\text{Duration}_i \cdot \text{HQ}_i$ captures whether the relationship between event duration and cumulative abnormal returns varies at headquarters relative to branches.

2.2. Comparing Regression Models with Neural Networks

After running a preliminary analysis of heatwaves impact on firm stock returns using event studies and simple regression models, we turn to compare the model fitting capabilities of neural networks with traditional approaches. First, we estimate a series of slightly more comprehensive linear regressions with fixed effects, which will serve as benchmarks for evaluating the performance of the neural network models.

$$\begin{aligned}\text{CAR_dur}_{p,i} = \beta_0 &+ \beta_1 \cdot \text{duration}_i + \beta_2 \cdot \text{intensity}_i + \beta_3 \cdot \text{C_intensity}_i + \beta_4 \cdot \text{hq}_i \\ &+ \beta_5 \cdot \text{sector_exposure}_i + \beta_6 \cdot \text{high_intensity}_i + \beta_7 \cdot \text{heatwave_exposure_count}_i \\ &+ \beta_8 \cdot \text{EnvironmentalDimension}_i + \beta_9 \cdot \text{SocialDimension}_i \\ &+ \beta_{10} \cdot \text{EconomicGovernanceDimension}_i \\ &+ \sum_{s=1}^{S-1} \gamma_s \cdot D_{s,i}^{\text{Sector}} + \varepsilon_i, \end{aligned} \tag{7}$$

$$\begin{aligned}\text{CAR_dur}_i = \beta_0 &+ \beta_1 \cdot \text{duration}_i + \beta_2 \cdot \text{intensity}_i + \beta_3 \cdot \text{C_intensity}_i + \beta_4 \cdot \text{hq}_i \\ &+ \beta_5 \cdot \text{sector_exposure}_i + \beta_6 \cdot \text{high_intensity}_i + \beta_7 \cdot \text{heatwave_exposure_count}_i \\ &+ \beta_8 \cdot \text{EnvironmentalDimension}_i + \beta_9 \cdot \text{SocialDimension}_i \\ &+ \beta_{10} \cdot \text{EconomicGovernanceDimension}_i \\ &+ \sum_{g=1}^{G-1} \delta_g \cdot D_{g,i}^{\text{Group}} + \varepsilon_i, \end{aligned} \tag{8}$$

$$
\begin{aligned}
\text{CAR_dur}_i = \beta_0 &+ \beta_1 \cdot \text{duration}_i + \beta_2 \cdot \text{intensity}_i + \beta_3 \cdot \text{C_intensity}_i + \beta_4 \cdot \text{hq}_i \\
&+ \beta_5 \cdot \text{sector_exposure}_i + \beta_6 \cdot \text{high_intensity}_i + \beta_7 \cdot \text{heatwave_exposure_count}_i \\
&+ \beta_8 \cdot \text{EnvironmentalDimension}_i + \beta_9 \cdot \text{SocialDimension}_i \\
&+ \beta_{10} \cdot \text{EconomicGovernanceDimension}_i \\
&+ \sum_{k=1}^{K-1} \theta_k \cdot D_{k,i}^{\text{Industry}} + \varepsilon_i, \qquad (9)
\end{aligned}
$$

As before, the variables Duration_i, Intensity_i, C_intensity_i, and HQ_i respectively measure the duration of the heatwave event, its average intensity, the cumulative intensity (calculated as duration multiplied by intensity), and a binary indicator equal to one if the observation corresponds to the firm's headquarters and zero otherwise. The variable high_intensity_i is a binary indicator equal to one if the heatwave intensity for observation i exceeds the sample median, signalling extreme events. The variable sector_exposure_i quantifies each firm's average exposure to heatwaves at the sector level, while $\text{heatwave_exposure_count}_i$ records the total number of heatwave events experienced by the firm. Finally, $\text{EnvironmentalDimension}_i$, SocialDimension_i, and $\text{EconomicGovernanceDimension}_i$ represent the firm's ESG scores across the three corresponding dimensions. The fixed effects terms capture unobserved heterogeneity at the sector, group, or industry level.

Second, we introduce the neural network framework employed to improve model fit and capture potential nonlinear relationships between heatwave characteristics and firm-level cumulative abnormal returns. Neural networks offer flexibility in modeling complex patterns, making them well-suited for analyzing large datasets with multiple interacting features.

For each firm-event observation i, corresponding to company k during heatwave event j, we aim to predict the cumulative abnormal return over the heatwave duration, denoted as $\text{CAR}_{\text{dur}}(p, i)$. Here, the subscript p indicates the asset pricing model used to calculate abnormal returns, where $p \in \{\text{MA}, \text{MM}, \text{3F}, \text{4F}\}$.

The explanatory variables are divided into categorical and numerical features to enable appropriate preprocessing and modeling. The categorical variables include the GICS sector identifier (`gsector`), industry group identifier (`ggroup`), NAICS industry classification code (`naics`), a binary indicator for high-intensity heatwaves (`high_intensity`), which flags whether the heatwave intensity for a given observation exceeds the median intensity across the sample, and the binary indicator (`HQ`) denoting whether the observation corresponds to a company headquarters (1) or branch location (0). The numerical continous variables consist of heatwave duration, average intensity (`Intensity`), the interaction between duration and

intensity (`C_intensity`), sector-level average exposure (`sector_exposure`), the number of heatwave events experienced by each firm (`heatwave_exposure_count`), and the firm's ESG scores across three dimensions—Environmental, Social, and Economic Governance. The variable `sector_exposure` represents the average cumulative abnormal return calculated for each GICS sector, reflecting its specific sensitivity of a sector to heatwaves by averaging CARs across all firms within the same sector. The variable `heatwave_exposure_count` captures the total number of heatwave events experienced by each firm over the sample period, providing a measure of historical exposure frequency that may affect a firm's vulnerability or adaptation to extreme heatwave events.

We define the full feature vector for each observation i as

$$X_i = [H_i,\ D_i]\,,$$

where H_i is the vector of numerical features, given by

$$\begin{aligned} H_i = \Big[&\text{C_intensity}_i,\ \text{duration}_i,\ \text{intensity}_i,\ \text{sector_exposure}_i,\\ &\text{heatwave_exposure_count}_i,\ \text{Environmental Dimension}_i,\\ &\text{Social Dimension}_i,\ \text{Economic Governance Dimension}_i\Big], \end{aligned}$$

and D_i is the vector of one-hot encoded categorical dummy variables, defined as

$$D_i = \left[\{D_{s,i}\}_{s\in S}\,,\ \{D_{g,i}\}_{g\in G}\,,\ \{D_{n,i}\}_{n\in N}\,,\ D_{\text{high_intensity},i}\right],$$

where

- $\{D_{s,i}\}_{s\in S}$ denotes the set of dummy variables for sectors S,
- $\{D_{g,i}\}_{g\in G}$ represents dummies for groups G,
- $\{D_{n,i}\}_{n\in N}$ corresponds to dummies for NAICS industries N,
- $D_{\text{high_intensity},i}$ is the binary dummy for high-intensity events.

To estimate the relationship between cumulative abnormal returns and a set of explanatory variables using a neural network, we model the cumulative abnormal returns as a nonlinear function $f_\theta(\cdot)$, parameterized by weights and biases θ. These parameters are optimized by minimizing the mean squared error loss over the training data:

$$\underset{\theta}{\text{minimize}} \quad \mathcal{L}_{\text{NN}}(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - f_\theta(X_i)\right)^2,$$

where $f_\theta(X_i)$ denotes the neural network's prediction for input features X_i.

The neural network employed in this study consists of an input layer, multiple hidden layers, and an output layer. The model propagates inputs through L hidden layers, where each layer l transforms its input via an affine transformation followed by a nonlinear activation function. The network architecture is defined mathematically as follows:

$$z_0 = X_i,$$

$$z_l = \sigma\left(A_{l-1} z_{l-1} + b_{l-1}\right), \quad \text{for } l = 1, 2, \ldots, L,$$

$$f_\theta(X_i) = A_L z_L + b_L,$$

where X_i denotes the vector of explanatory variables for firm-event observation i, A_{l-1} represents the weight matrix and b_{l-1} the bias vector associated with layer $l-1$, and $\sigma(\cdot)$ denotes the element-wise nonlinear activation function, typically chosen as the rectified linear unit (ReLU) in hidden layers. The output layer produces a scalar prediction of the cumulative abnormal return through a linear transformation of the final hidden layer's output.

Our neural network's function $f_\theta(\cdot)$ is implemented as a fully connected feedforward architecture comprising two hidden layers. The first hidden layer contains 128 neurons, and the second hidden layer contains 64 neurons; both layers use the rectified linear unit (ReLU) activation function to introduce nonlinearity. To mitigate overfitting, dropout regularization is applied after each hidden layer, with dropout rates of 0.3 and 0.2, respectively. The output layer consists of a single neuron with a linear activation function, appropriate for predicting continuous cumulative abnormal returns. The network is trained to minimize the mean squared error loss using the Adam optimization algorithm, with a batch size of 32 and a maximum of 100 epochs. Early stopping with a patience of ten epochs is employed during training to prevent overfitting, with the best-performing model weights automatically restored based on validation loss.

The dataset is randomly split into training and testing subsets, comprising 80% and 20% of the observations, respectively. To evaluate model performance, we calculate the mean squared error (MSE) and coefficient of determination (R^2) on both the training (in-sample) and testing (out-of-sample) data. Specifically, for the training set, the in-sample MSE and R^2 are computed as

$$\mathrm{MSE}_{\mathrm{train}} = \frac{1}{N_{\mathrm{train}}} \sum_{i=1}^{N_{\mathrm{train}}} \left(y_i - \hat{y}_i\right)^2,$$

$$R^2_{\mathrm{train}} = 1 - \frac{\sum_{i=1}^{N_{\mathrm{train}}} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{N_{\mathrm{train}}} \left(y_i - \bar{y}_{\mathrm{train}}\right)^2},$$

and for the testing set, the out-of-sample metrics are defined analogously as

$$\mathrm{MSE}_{\mathrm{test}} = \frac{1}{N_{\mathrm{test}}} \sum_{i=1}^{N_{\mathrm{test}}} (y_i - \hat{y}_i)^2 ,$$

$$R^2_{\mathrm{test}} = 1 - \frac{\sum_{i=1}^{N_{\mathrm{test}}} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N_{\mathrm{test}}} (y_i - \bar{y}_{\mathrm{test}})^2},$$

where $\hat{y}_i$ denotes the model's predicted value for observation i, N_{train} and N_{test} represent the number of observations in the training and testing sets, respectively, and $\bar{y}_{\mathrm{train}}$ and $\bar{y}_{\mathrm{test}}$ are the mean observed responses in the respective datasets.

3. Data

3.1. Heatwave Data Sources and Construction

Daily surface temperature data with a spatial resolution of $0.25° \times 0.25°$, obtained from the hourly observations in the fifth-generation re-analysis (ERA5) dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). Records span from January 1990 to December 2019. ERA5 data are downloaded from the Copernicus Climate Data Store (https://cds.climate.copernicus.eu).

To identify heatwave events, we relied on temperature simulations from the EMAC (ECHAM/MESSy Atmospheric Chemistry) model, which provided global hourly surface temperature data at a coarser resolution of $1.125° \times 1.125°$. EMEMAC outputs were obtained from climate simulations described in Emmerichs et al. (2024) and (... there will be a reference here, it has been accepted, waiting to be published in few weeks.)

To ensure consistency across datasets, ERA5 temperature fields were regridded to match the EMAC spatial resolution prior to analysis.

Following established methodologies, we define a heatwave was defined as a period during which the daily mean temperature exceedes the 95th percentile of the local baseline temperature distribution for at least two consecutive days. The threshold temperature level is calculated separately for each grid cell. Unlike earlier studies that used variable seasonal windows, we apply a fixed definition of hot season, corresponding to December through March in the Southern Hemisphere and May through August in the Northern Hemisphere. Heatwaves are then identified for each grid cell during the hot seasons of 2018 and 2019.

For each identified heatwave event, we compute four indicators characterizing the spatiotemporal structure of extreme temperature phenomena: (i) the total number of heatwave

days per year, defined as the cumulative number of days falling within any heatwave event; (ii) the number of distinct heatwave occurrences per grid cell per year; (iii) the average duration of the heatwave events, measured in days; and (iv) the average heatwave intensity, defined as the mean degrees Celsius above the local threshold across all heatwave days.

3.2. Firm-level Data

We collect the headquarters locations of all publicly listed companies in the United States from the Compustat database. Using the ISIN identifiers of these firms, we retrieve corresponding branches location data from the Orbis database. All firm locations, including headquarters and branches, are geocoded by converting their addresses into latitude and longitude coordinates. These geographic coordinates are then matched with heatwave events to determine firm-level exposure to the heatwaves.

In addition to location data, we obtain ESG scores for each company from S&P Global ESG Scores. These scores are also disaggregated into the three dimensions (Environmental, Social, and Governance) for more granular analysis of firm-level sustainability performance. We also extract industry classification information from Compustat, including the Global Industry Classification Standard (GICS) sector (2-digit), group(4-digit), and industry (6-digit)codes, as well as the North American Industry Classification System (NAICS) codes, to enable sector-level comparisons. Specifically, we identify 11 GICS sectors, 25 GICS groups, 76 GICS industries, and 462 NAICS industry categories.

After matching company locations with heatwave events and excluding firms without available ESG scores, we construct a final sample of 1,804 firms, of which 1,223 have identifiable branch locations. The resulting dataset comprises 3,818,302 firm-location–date observations, where each observation represents a specific corporate location matched to a heatwave event on a given date. Of these, 19,819 observations are associated with headquarters, and 3,798,483 are associated with branch locations.

Figures 1 and 2 display the geographic locations of company headquarters and branches, respectively. As shown, headquarters are concentrated within the United States, while branch locations are distributed globally. This allows us to incorporate both domestic and international heatwaves events and relative firms' exposure. In Figure 1, different colors represent company sectors based on GICS classification. Most headquarters are located in the eastern region in the United States.

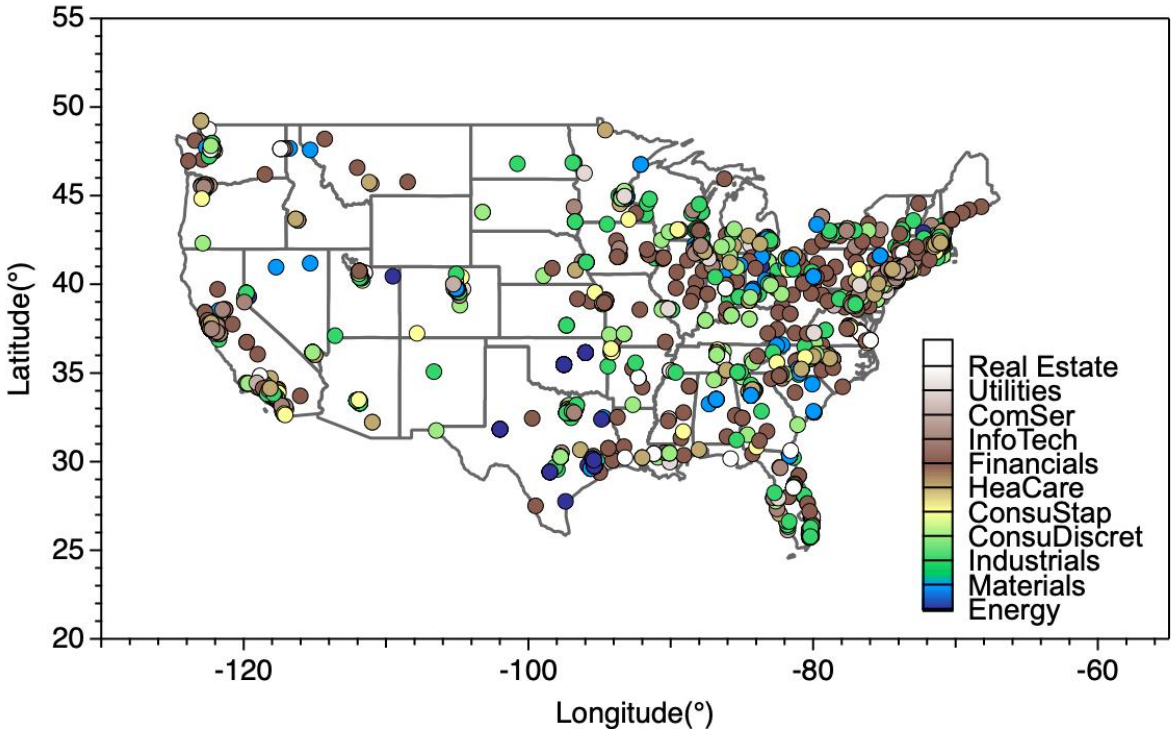


Fig. 1. Geographic distribution of company headquarters across sectors in the United States. Each point represents a firm headquarters, with different color indicating the sector classification based on the Global Industry Classification Standard (GICS). The figure highlights both the geographic concentration and sectoral distribution of firms included in the study sample.

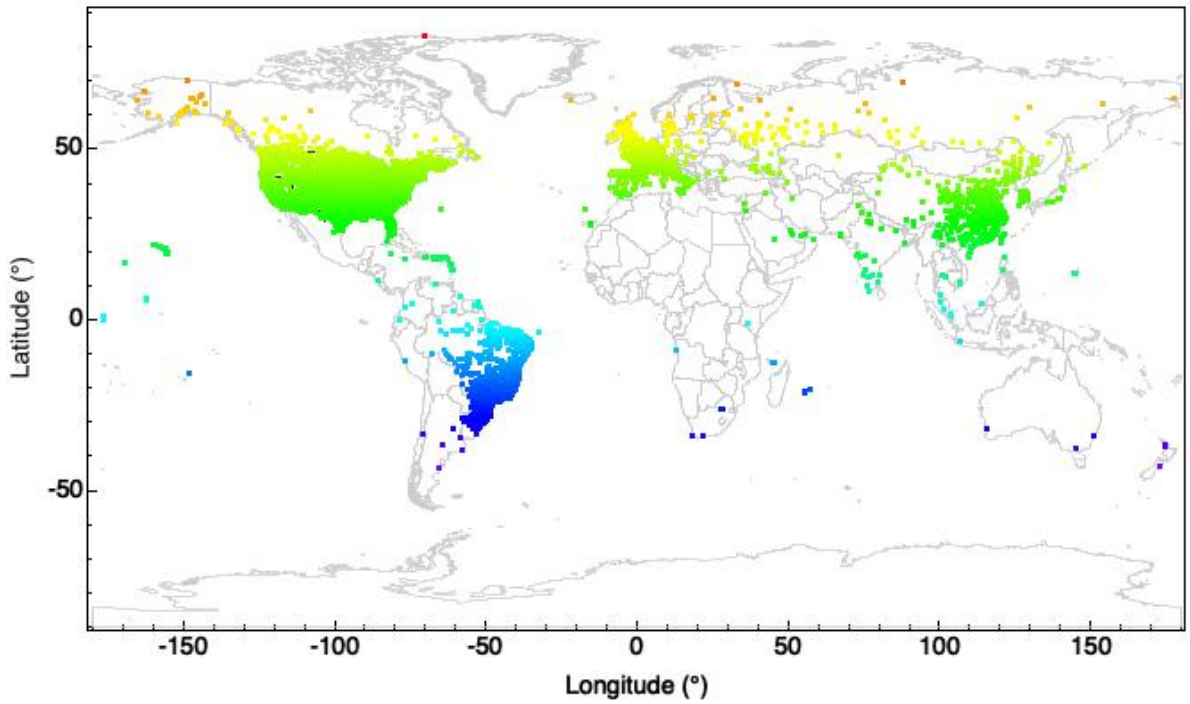


Fig. 2. Geographic distribution of company branch locations. Each point represents the geographic location of a branch associated with firms in the sample.

Figure 3 presents histograms of heatwave intensity and duration. The majority of observed events fall within 1–3°C above the historical baseline and typically last fewer than 5 days. However, both distributions exhibit long right tails, indicating the presence of less frequent but extreme events with significantly higher intensity or extended duration.

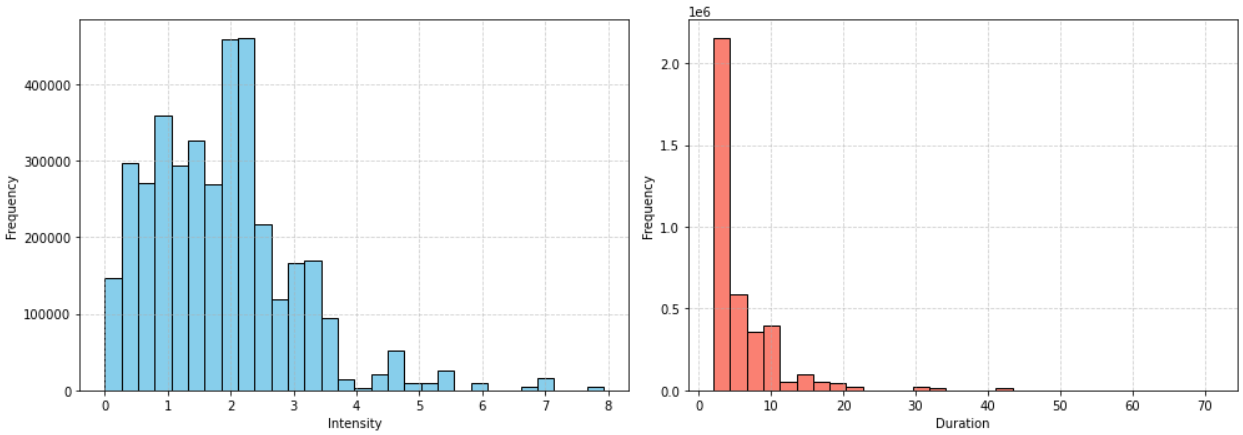


Fig. 3. Histograms of heatwave intensity and duration. The left figure shows the histogram of heatwave intensity (in °C above baseline), and the right figure presents the histogram of heatwave duration (in days). The sample covers the period from January 2018 to December 2019.

4. Empirical Results

4.1. Preliminary event study and sector analysis results

Table 1 presents the mean cumulative abnormal returns (CARs) estimated over the event window spanning from 20 days before to 20 days after the onset of heatwave events, using four asset pricing models. Statistical significance is assessed using both two-tailed t-tests based on mean CAR and non-parametric Wilcoxon signed-rank tests based on comparing the median CAR during the event window with the one calculated over the rest of the observations,

For the Market-Adjusted Model, the mean CAR is -1%, with a highly significant t-statistic of -17.34 ($p < 0.001$) and a Wilcoxon p-value also indicating significance at conventional levels. The Market Model produces similar results, with a mean CAR of -1% and strongly significant t- and Wilcoxon statistics. These findings suggest that, on average, firms experience negative abnormal returns following heatwave events when expected returns are benchmarked against these simpler models.

In contrast, the Fama-French Three-Factor Model yields a mean CAR which is statistically indistinguishable from zero, with a t-statistic of 0.12 and a p-value of 0.91. However, the Wilcoxon signed-rank test still reports a statistically significant differential positive median CAR during the heatwave events, potentially reflecting non-normality in the distribution of CARs or the presence of extreme observations.

The Fama-French Four-Factor Model shows a small positive mean CAR of 0%, yet the t-statistic of 2.92 ($p < 0.01$) suggests this mean is statistically different from zero. As with the other models, the Wilcoxon test reports significant results.

Overall, these results highlight the sensitivity of estimated abnormal returns to the choice of asset pricing benchmark. Simpler models (Market-Adjusted and Market) reveal significant negative average CARs, suggesting that firms systematically underperform during heatwave events relative to basic market expectations. In contrast, multi-factor models (Three- and Four-Factor) attenuate or eliminate the significance of average CARs, underscoring the importance of controlling for additional risk factors when evaluating the impact of extreme weather on stock performance.

Table 1: Mean and significance of cumulative abnormal returns over heatwave event windows from day -20 to +20

Model	Mean CAR	t-stat	p-value	Wilcoxon Stat	Wilcoxon pValue
Market-Adjusted Model	-0.0075	-17.34	0.00	1260233586	0.00
Market Model	-0.0066	-13.26	0.00	1262660504	0.00
Three-Factor Model	0.0001	0.12	0.91	1308118524	0.00
Four-Factor Model	0.0014	2.92	0.00	1302914098	0.00

This table reports the mean cumulative abnormal returns (CAR) and their statistical significance over the event window spanning from 20 days before to 20 days after relative to heatwave onset. Significance is assessed using two tests: (i) the two-tailed t-test, which evaluates whether the mean CAR significantly differs from zero, and (ii) the Wilcoxon signed-rank test, which assesses whether the median CAR significantly differs from zero, providing a non-parametric robustness check. All tests are based on the sample of firm-day observations associated with heatwave events.

We repeat the tests separately for firms in each industry, defined according to the GISC 2-digit classification. are summarized in Tables 2, 3, 4, and 5.

Consistently across models, Energy, Materials, and Financials sectors exhibit significantly negative mean CARs, suggesting heightened vulnerability of these sectors to heatwave events, likely due to their substantial reliance on physical assets, energy-intensive operations, or weather-sensitive financial exposures. For example, in the Market-Adjusted Model (Table 2), the Energy sector shows a mean CAR of -0.07 with a highly significant t-statistic of -25.90 ($p < 0.001$), a result that remains robust when using also the Market Model and the two Fama-French models. Conversely, sectors such as Healthcare, Consumer Staples, and Utilities frequently exhibit positive and significant mean CARs across models, indicating

relative resilience or even overperformance relative to the rest of the stock market during extreme heat conditions, possibly due to increased demand for essential services or healthcare products.

The Industrials and Real Estate sectors display mixed results depending on the model specification. Notably, Industrials demonstrate insignificant or weakly significant CARs calculated from the Market-Adjusted and Market Models but become significantly positive, suggesting that controlling for additional risk factors reveals positive abnormal performance for these sectors. Communication Services and Consumer Discretionary sectors mostly show negative and significant CARs, highlighting their potential exposure to operational disruptions or reduced consumer activity during extreme heat events.

The Wilcoxon signed-rank tests broadly corroborate the findings of the parametric t-tests, with nearly all sectors displaying consistent significance levels across both tests, which strengthens the robustness of the results. This sector-level analysis indicates that the economic and operational characteristics inherent to each sector shape their financial sensitivity to heatwaves.

Table 2: Mean and significance of sector-level CARs over heatwave event windows (day -20 to +20) calculated using the Market-Adjusted Model

Sector	N	Mean CAR	t-stat	p-value	Wilcoxon Stat	Wilcoxon p-value
Energy	3277	-0.07	-25.90	0.00	1362920	0.00
Materials	5128	-0.03	-15.46	0.00	4876744	0.00
Industrials	15441	0.00	-1.73	0.08	58641935	0.08
Consumer Discretionary	12216	-0.01	-10.05	0.00	33512350	0.00
Consumer Staples	4864	0.01	4.55	0.00	5242111	0.00
Health Care	6250	0.01	7.31	0.00	8121706	0.00
Financials	8229	-0.02	-17.91	0.00	13333605	0.00
Information Technology	7980	0.01	4.40	0.00	14759837	0.00
Communication Services	2487	-0.02	-7.71	0.00	1343925	0.00
Utilities	2099	0.01	8.46	0.00	795509	0.00
Real Estate	3743	0.00	-0.88	0.38	3470770	0.62

Note: This table reports the number of observations (N), mean cumulative abnormal returns (CAR), and their statistical significance for each 2-digit GICS sector over the event window from 20 days before to 20 days after the onset of heatwave events. Results are based on the Market-Adjusted Model. Significance is assessed using two tests: (i) a two-tailed t-test evaluating whether the mean CAR significantly differs from zero, and (ii) the Wilcoxon signed-rank test assessing whether the median CAR significantly differs from zero, providing a non-parametric robustness check. All tests are conducted on the sample of firm-day observations corresponding to heatwave exposures.

Table 3: Mean and significance of sector-level CARs over heatwave event windows (day -20 to +20) calculated using the Market Model

Sector	N	Mean CAR	t-stat	p-value	Wilcoxon Stat	Wilcoxon p-value
Energy	3277	-0.05	-18.23	0.00	1727988	0.00
Materials	5128	-0.02	-9.24	0.00	5567080	0.00
Industrials	15441	0.00	-2.00	0.05	59189543	0.45
Consumer Discretionary	12216	-0.02	-11.78	0.00	31585748	0.00
Consumer Staples	4864	0.02	14.81	0.00	4350795	0.00
Health Care	6250	0.02	9.00	0.00	8070434	0.00
Financials	8229	-0.01	-13.54	0.00	14404498	0.00
Information Technology	7980	-0.02	-12.04	0.00	13407129	0.00
Communication Services	2487	-0.02	-7.38	0.00	1344159	0.00
Utilities	2099	0.03	14.79	0.00	620377	0.00
Real Estate	3743	0.01	8.21	0.00	2995079	0.00

Note: This table reports the number of observations (N), mean cumulative abnormal returns (CAR), and their statistical significance for each 2-digit GICS sector over the event window from 20 days before to 20 days after the onset of heatwave events. Results are based on the Market Model. Significance is assessed using two tests: (i) a two-tailed t-test evaluating whether the mean CAR significantly differs from zero, and (ii) the Wilcoxon signed-rank test assessing whether the median CAR significantly differs from zero, providing a non-parametric robustness check. All tests are conducted on the sample of firm-day observations corresponding to heatwave exposures.

Table 4: Mean and significance of sector-level CARs over heatwave event windows (day -20 to +20) calculated using the Fama-French Three-Factor Model

Sector	N	Mean CAR	t-stat	p-value	Wilcoxon Stat	Wilcoxon p-value
Energy	3277	-0.04	-16.14	0.00	1839094	0.00
Materials	5128	-0.01	-5.62	0.00	5982067	0.00
Industrials	15441	0.01	6.20	0.00	55290345	0.00
Consumer Discretionary	12216	0.00	-2.78	0.01	35328657	0.00
Consumer Staples	4864	0.03	16.69	0.00	4196351	0.00
Health Care	6250	0.02	11.90	0.00	7712463	0.00
Financials	8229	-0.01	-7.28	0.00	15723284	0.00
Information Technology	7980	-0.01	-9.38	0.00	14031674	0.00
Communication Services	2487	-0.02	-4.90	0.00	1434669	0.00
Utilities	2099	0.02	11.90	0.00	708866	0.00
Real Estate	3743	0.01	7.84	0.00	3052045	0.00

Note: This table reports the number of observations (N), mean cumulative abnormal returns (CAR), and their statistical significance for each 2-digit GICS sector over the event window from 20 days before to 20 days after the onset of heatwave events. Results are based on the Fama-French Three-Factor Model. Significance is assessed using two tests: (i) a two-tailed t-test evaluating whether the mean CAR significantly differs from zero, and (ii) the Wilcoxon signed-rank test assessing whether the median CAR significantly differs from zero, providing a non-parametric robustness check. All tests are conducted on the sample of firm-day observations corresponding to heatwave exposures.

Table 5: SMean and significance of sector-level CARs over heatwave event windows (day -20 to +20) calculated using the Fama-French Three-Factor Plus Momentum Model

Sector	N	Mean CAR	t-stat	p-value	Wilcoxon Stat	Wilcoxon p-value
Energy	3277	-0.04	-14.11	0.00	1912818	0.00
Materials	5128	0.00	-0.03	0.98	6536681	0.72
Industrials	15441	0.01	13.58	0.00	51228024	0.00
Consumer Discretionary	12216	0.00	-2.34	0.02	35411757	0.00
Consumer Staples	4864	0.01	7.00	0.00	5146744	0.00
Health Care	6250	0.02	7.67	0.00	8464736	0.00
Financials	8229	-0.01	-7.13	0.00	15722441	0.00
Information Technology	7980	0.00	0.85	0.40	15717377	0.32
Communication Services	2487	-0.03	-7.60	0.00	1320072	0.00
Utilities	2099	0.00	2.33	0.02	998448	0.00
Real Estate	3743	0.00	0.46	0.64	3392479	0.09

Note: This table reports the number of observations (N), mean cumulative abnormal returns (CAR), and their statistical significance for each 2-digit GICS sector over the event window from 20 days before to 20 days after the onset of heatwave events. Results are based on the Fama-French Three-Factor Plus Momentum Model. Significance is assessed using two tests: (i) a two-tailed t-test evaluating whether the mean CAR significantly differs from zero, and (ii) the Wilcoxon signed-rank test assessing whether the median CAR significantly differs from zero, providing a non-parametric robustness check. All tests are conducted on the sample of firm-day observations corresponding to heatwave exposures.

Figures 4–7 present the industry-level mean cumulative abnormal returns (CARs) with 95% confidence intervals respectively for the Market-Adjusted Model, Market Model, Fama-French Three-Factor Model, and Fama-French Four-Factor Model. These plots illustrate clear heterogeneity in the effects of heatwave events across industries. Notably, Energy and Communication Services sectors consistently exhibit significantly negative mean CARs across all models, highlighting their pronounced vulnerability to heatwave-induced operational disruptions. In contrast, Utilities, Healthcare, and Consumer Staples demonstrate significantly positive mean CARs, suggesting these sectors may benefit from increased demand or exhibit resilience to heat-related shocks. Sectors such as Industrials and Real Estate display mean CARs near zero with confidence intervals overlapping the null line, indicating limited or insignificant average responses to heatwave exposure. Additionally, while the inclusion of additional factors in the Fama-French models reduces the magnitude of CAR estimates

for certain industries, the overall patterns of sector-specific sensitivity remain robust. These results collectively underscore the importance of sectoral characteristics in shaping firm-level financial reactions to extreme temperature events.

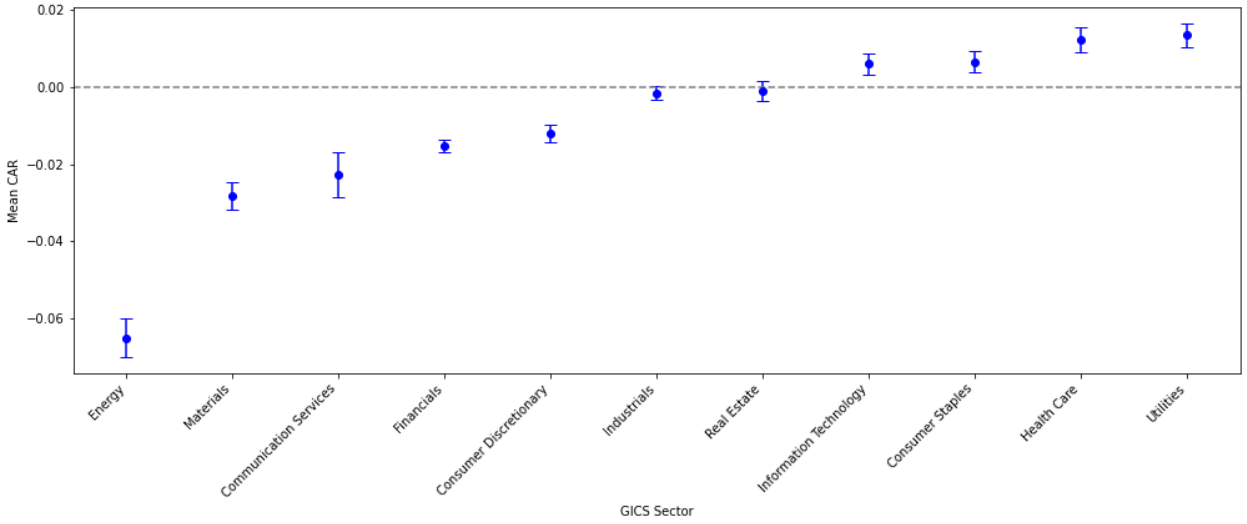


Fig. 4. Mean CARs (with 95% Confidence Intervals) estimated from the Market-Adjusted Model for each industry

Note: This figure shows industry-level mean CARs using the Market-Adjusted Model with 95% confidence intervals.

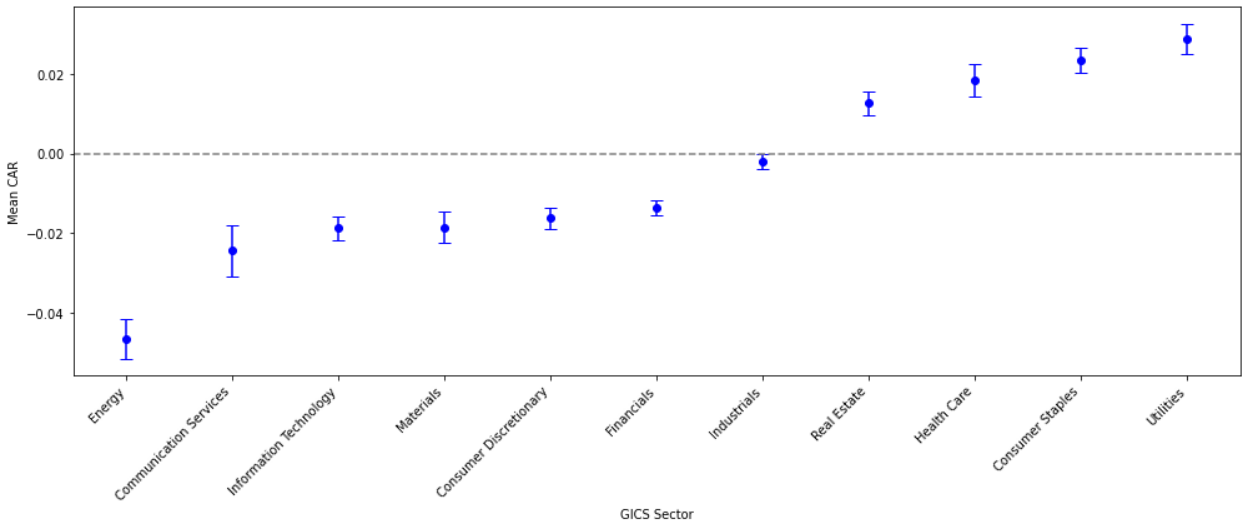


Fig. 5. Mean CARs (with 95% Confidence Intervals) estimated from the Market Model for each industry

Note: This figure displays results from the Market Model, including 95% confidence intervals by industry.

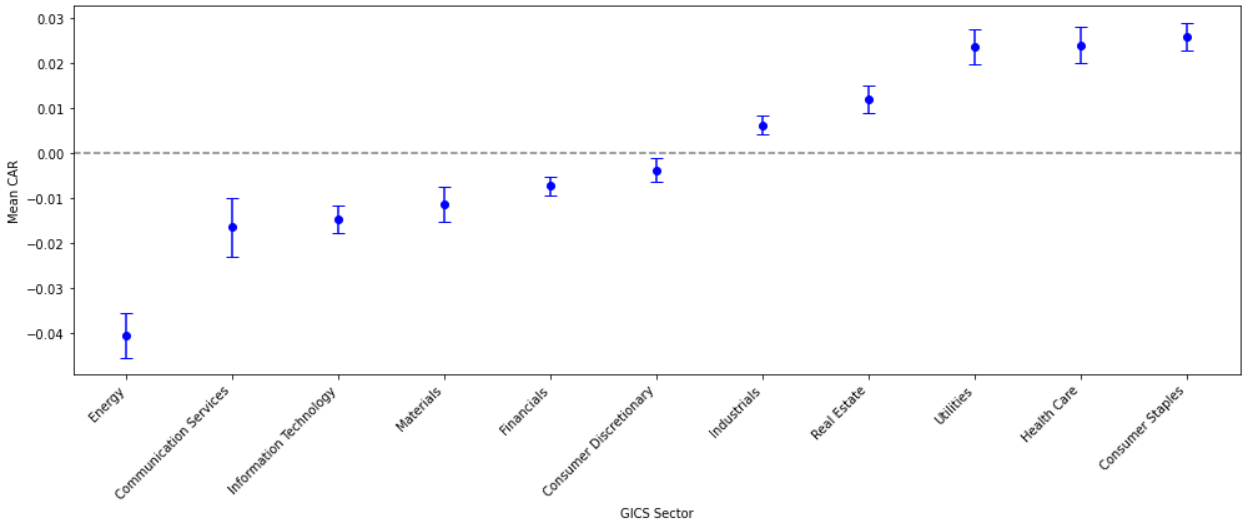


Fig. 6. Mean CARs (with 95% Confidence Intervals) estimated from the Fama-French Three-Factor Model for each industry

Note: This figure displays the sector-level mean CARs estimated using the Fama-French Three-Factor Model, with 95% confidence intervals.

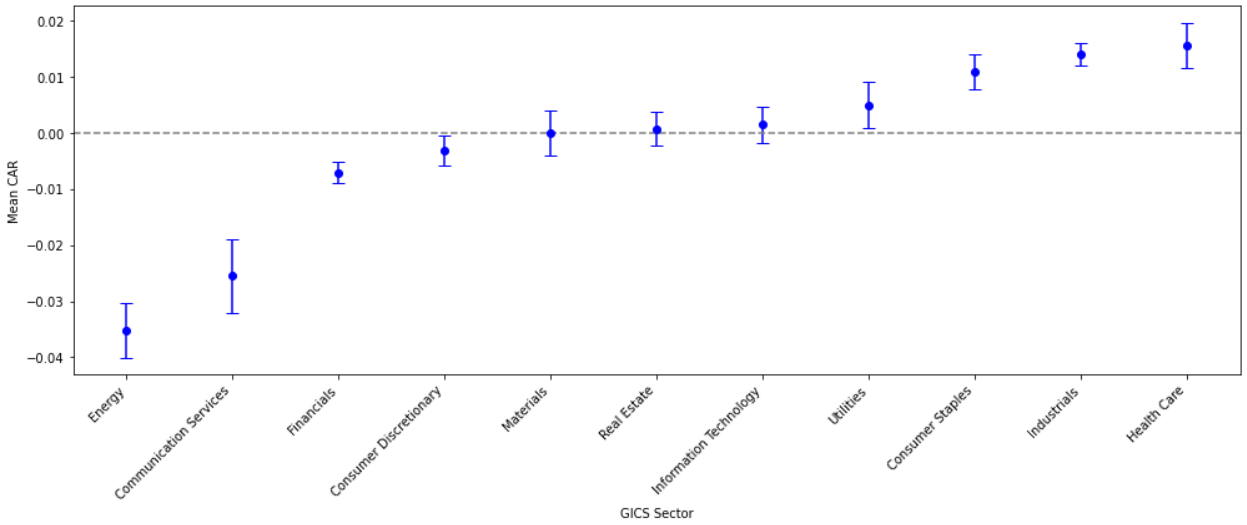


Fig. 7. Sector Effects on Mean CAR (with 95% Confidence Intervals) estimated from the Fama-French Four-Factor Model

Note: This figure presents sectoral CARs under the Fama-French Four-Factor Model, including 95% confidence intervals.

Next, we illustrate the results from six different regression specifications where CARs are regressed on a number of covariates, including the heatwave-related information. Tables 6–9 report the estimated coefficients with CARs estimated from the Market-Model (Panel A), Market Model (Panel B), Fama-French Three-Factor Model (Panel C), and Fama-French

Three-Factor plus Momentum Model (Panel D). Specifications (1) to (6) differ in the use of fixed effects for (sectors, groups, industries, NAICS categories, and firm-level fixed effects) to account for unobserved heterogeneity.

Across all panels and specifications, the estimated coefficients for the heatwave-related variables *Duration*, *Intensity*, and *Cum_Intensity* are consistently positive for *Duration* and *Intensity*, but negative for *Cum_Intensity*, and statistically significant at the 1% level. These results suggest that longer and more intense heatwaves are associated with higher cumulative abnormal returns (CARs), but the cumulative intensity—capturing both duration and magnitude—negatively impacts firm performance, indicating diminishing or adverse effects for prolonged extreme events.

The coefficient on *HQ*, a dummy variable indicating whether the observation corresponds to a firm's headquarters, is positive and highly significant across all models. However, the interaction terms between heatwave variables and *HQ* (Duration · HQ, Intensity · HQ) are negative and significant in most specifications, suggesting that the positive effects of heatwave duration and intensity on CARs are mitigated or even reversed when the event affects a firm's headquarters.

In the specifications with fixed effects (particularly (2)–(6)), the overall fit of the models, as measured by R^2, improves relative to specification (1). For instance, in the Market-Adjusted model (Panel A), R^2 increases from 0.006 in specification (1) to 0.0625 in specification (6) with firm-level fixed effects, indicating that controlling for unobserved firm-specific heterogeneity explains a substantial portion of the variation in CARs. Similar patterns of increasing explanatory power are observed across the other three models, reinforcing the importance of accounting for firm and industry heterogeneity to explain cumulative abnormal returns during extreme heatwave events.

Notably, ESG scores consistently exhibit positive and statistically significant coefficients, implying that firms with better ESG profiles tend to exhibit cumulative higher abnormal returns during heatwave events. This result suggests that firms with stronger ESG performance are more resilient when facing this type of climate-related risks.

Overall, the results highlight the critical role of heatwaves' duration and intensity, the headquarters vs branches location being affected by the events, and ESG factors in shaping firms' abnormal performance during climate extremes. They also underscore the importance of including detailed industry and firm fixed effects to control for confounding factors, which materially improves the models' explanatory power.

CARs from Market-Adjusted Model						
	(1)	(2)	(3)	(4)	(5)	(6)
const	-0.0220***	-0.0270***	-0.0263***	-0.0293***	-0.0280***	-0.0439***
	(0.0002)	(0.0003)	(0.0003)	(0.0010)	(0.0002)	(0.0006)
Duration	0.0018***	0.0018***	0.0018***	0.0018***	0.0019***	0.0019***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intensity	0.0025***	0.0024***	0.0023***	0.0024***	0.0023***	0.0023***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Cum_intensity	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
HQ	0.0210***	0.0180***	0.0178***	0.0182***	0.0230***	0.0130***
	(0.0024)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0000)
ESG	0.0003***	0.0002***	0.0002***	0.0002***	0.0004***	0.0008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Duration·HQ	-0.0020***	-0.0020***	-0.0020***	-0.0020***	-0.0018***	-0.0016***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0000)
Intensity·HQ	-0.0026***	-0.0026***	-0.0024***	-0.0021***	-0.0021***	-0.0022***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0000)
Cum_Intensity·HQ	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0003***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0000)
ESG·HQ	-0.0003***	-0.0003***	-0.0002***	-0.0002***	-0.0003***	-0.0001*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fixed effects						
Sector FE	No	Yes	No	No	No	No
Group FE	No	No	Yes	No	No	No
Industry FE	No	No	No	Yes	No	No
NAICs FE	No	No	No	No	Yes	No
Company FE	No	No	No	No	No	Yes
R^2	0.006	0.01	0.016	0.021	0.0445	0.0625
Observations	3818302	3817210	3817210	3817210	3817210	3817210

Table 6: Regression estimates with standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Market Model						
	(1)	(2)	(3)	(4)	(5)	(6)
const	-0.0216***	-0.0265***	-0.0242***	-0.0173***	-0.0233***	-0.0384***
	(0.0002)	(0.0003)	(0.0003)	(0.0010)	(0.0002)	(0.0006)
Duration	0.0014***	0.0013***	0.0013***	0.0013***	0.0014***	0.0014***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intensity	0.0019***	0.0018***	0.0017***	0.0017***	0.0017***	0.0017***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Cum_Intensity	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
HQ	0.0202***	0.0172***	0.0159***	0.0170***	0.0204***	0.0120***
	(0.0024)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0027)
ESG	0.0003***	0.0002***	0.0002***	0.0002***	0.0004***	0.0008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Duration·HQ	-0.0017***	-0.0017***	-0.0018***	-0.0017***	-0.0015***	-0.0014**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Intensity·HQ	-0.0019	-0.0022**	-0.0021**	-0.0018*	-0.0018*	-0.0021**
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Cum_Intensity·HQ	0.0004**	0.0004**	0.0004***	0.0004**	0.0003*	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
ESG·HQ	-0.0003***	-0.0003***	-0.0002***	-0.0002***	-0.0003***	-0.0001*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fixed effects						
Sector effect	No	Yes	No	No	No	No
Group effect	No	No	Yes	No	No	No
Industry effect	No	No	No	Yes	No	No
NAICs effect	No	No	No	No	Yes	No
Company FE	No	No	No	No	No	Yes
R^2	0.006	0.011	0.017	0.023	0.0395	0.0597
Observations	3818302	3817210	3817210	3817210	3817210	3817210

Table 7: Regression estimates with standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Fama-French Three-Factor Model						
	(1)	(2)	(3)	(4)	(5)	(6)
const	-0.0165***	-0.0234***	-0.0215***	-0.0120***	-0.0200***	-0.0445***
	(0.0002)	(0.0003)	(0.0003)	(0.0010)	(0.0002)	(0.0006)
Duration	0.0017***	0.0017***	0.0017***	0.0017***	0.0017***	0.0017***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intensity	0.0019***	0.0018***	0.0017***	0.0018***	0.0017***	0.0017***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Cum_Intensity	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
HQ	0.0179***	0.0157***	0.0151***	0.0161***	0.0192***	0.0108***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0026)
ESG	0.0002***	0.0002***	0.0001***	0.0001***	0.0003***	0.0010***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Duration·HQ	-0.0018***	-0.0017***	-0.0018***	-0.0017***	-0.0015***	-0.0015***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Intensity·HQ	-0.0018*	-0.0021**	-0.0020**	-0.0017*	-0.0019**	-0.0023**
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Cum_Intensity·HQ	0.0004***	0.0004***	0.0004***	0.0004**	0.0003**	0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
ESG·HQ	-0.0003***	-0.0002***	-0.0002***	-0.0002***	-0.0003***	-0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fixed effects						
Sector FE	No	Yes	No	No	No	No
Group FE	No	No	Yes	No	No	No
Industry FE	No	No	No	Yes	No	No
NAICs FE	No	No	No	No	Yes	No
Company FE	No	No	No	No	No	Yes
R^2	0.005	0.009	0.014	0.020	0.0354	0.0569
Observations	3818302	3817210	3817210	3817210	3817210	3817210

Table 8: Regression estimates with standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Fama-French Three-Factor Plus Momentum Model						
	(1)	(2)	(3)	(4)	(5)	(6)
const	-0.0167***	-0.0214***	-0.0188***	-0.0042***	-0.0176***	-0.0432***
	(0.0002)	(0.0003)	(0.0003)	(0.0010)	(0.0002)	(0.0006)
Duration	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intensity	0.0016***	0.0015***	0.0014***	0.0015***	0.0014***	0.0014***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Cum_Intensity	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
HQ	0.0180***	0.0146***	0.0132***	0.0140***	0.0164***	0.0091***
	(0.0024)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0026)
ESG	0.0003***	0.0002***	0.0001***	0.0001***	0.0003***	0.0010***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Duration·HQ	-0.0014***	-0.0014***	-0.0014***	-0.0013***	-0.0011**	-0.0011**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Intensity·HQ	-0.0012	-0.0014	-0.0013	-0.0010	-0.0012	-0.0015
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Cum_Intensity·HQ	0.0003*	0.0003	0.0003*	0.0003	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
ESG·HQ	-0.0003***	-0.0003***	-0.0002***	-0.0002***	-0.0003***	-0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fixed effects						
Sector FE	No	Yes	No	No	No	No
Group FE	No	No	Yes	No	No	No
Industry FE	No	No	No	Yes	No	No
NAICs effect	No	No	No	No	Yes	No
Company FE	No	No	No	No	No	Yes
R^2	0.005	0.011	0.016	0.022	0.0354	0.0567
Observations	3818302	3817210	3817210	3817210	3817210	3817210

Table 9: Regression estimates with standard errors in parentheses. Statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.2. OLS regressions and Neural network predictions

In this section, we introduce a neural network model to study the impact of heatwaves on firms' stock returns and then compare its empirical results to those obtained from estimating OLS models that incorporate the same event-related information. Specifically, we analyse whether using neural networks improves the model's in-sample and out-of-sample performance metrics, by comparing the coefficients of determination (R^2) and mean squared errors (MSE), of three specifications of the 'benchmark' OLS regressions (defined by Equations (7)–(9)) and the neural network models.

Table 10 summarizes the predictive performance across all models. Panel A presents in-sample results, while Panel B reports out-of-sample results. Each panel shows the performance metrics for the three benchmark fixed-effects regressions—incorporating sector, group, and industry fixed effects, respectively—as well as the neural network models.

Regardless of how CARs are estimated using the Market model, the Market-Adjusted model, the Fama-French Three-Factor model or the Fama-French Three-Factor plus Momentum, the neural network models consistently outperform the benchmark OLS regressions. Specifically, the R^2 values of the benchmark OLS models range between 0.9% and 2.2%, while the neural network models achieve in-sample R^2 between 25.97% and 27.28% and out-of-sample R^2 between 25.97% and 26.90%. This represents an approximate increase in explanatory power of over 1,200% (e.g., from 2.2% to 27.28% corresponds to a relative increase of approximately 1,140%).

In terms of prediction error, the mean squared error (MSE) of the neural network models is reduced by about 20–25% compared to the benchmark regressions across all models (e.g., from 0.67% in OLS models to around 0.49–0.50% in neural networks). These reductions in MSE, combined with the dramatic improvement in R^2, demonstrate that the neural network models capture substantially more variation in abnormal returns and provide superior predictive accuracy relative to the traditional linear benchmarks.

These findings highlight the value of applying neural networks to model complex, nonlinear relationships between heatwave characteristics, firm-specific attributes, and financial market responses, underscoring their potential to significantly improve predictive modeling of asset price dynamics in the context of climate-related events.

Table 10: comparision of predictive performance between benchmark fixed-effects OLS regressions and neural network models

Panel A: In sample								
	(7)		(8)		(9)		Neural Network	
	R^2	MSE	R^2	MSE	R^2	MSE	R^2	MSE
MA	1.22%	0.67%	1.79%	0.67%	2.19%	0.66%	27.02%	0.50%
MM	1.12%	0.67%	1.58%	0.67%	1.83%	0.67%	27.28%	0.50%
3f	1.03%	0.67%	1.49%	0.67%	1.69%	0.67%	26.27%	0.49%
4f	0.95%	0.67%	1.26%	0.67%	1.39%	0.67%	26.80%	0.49%
Panel B: Out of sample								
	(7)		(8)		(9)		Neural Network	
	R^2	MSE	R^2	MSE	R^2	MSE	R^2	MSE
MA	1.22%	0.67%	1.78%	0.66%	2.19%	0.66%	26.74%	0.49%
MM	1.12%	0.67%	1.57%	0.66%	1.82%	0.66%	26.90%	0.50%
3f	1.03%	0.67%	1.48%	0.66%	1.69%	0.66%	25.97%	0.49%
4f	0.94%	0.67%	1.25%	0.67%	1.38%	0.67%	26.49%	0.49%

Note: This table reports in-sample (Panel A) and out-of-sample (Panel B) predictive performance metrics for three benchmark fixed-effects regression models—(7) sector fixed effects (gsector), (8) group fixed effects (ggroup), and (9) industry fixed effects (gind)—alongside neural network models. Performance is evaluated using R^2 (percentage of variance explained) and mean squared error (MSE) for each abnormal return estimation approach: Market-Adjusted (MA), Market Model (MM), Fama-French Three-Factor Model (3f), and Fama-French Three-Factor plus Momentum Model (4f). Higher R^2 and lower MSE indicate better predictive performance.

Figures 8 to 11 present a comparison of the relative importance of predictors across the regression models with different sets of industry fixed effects, as well as the neural network analysis. For the regression analsis, we look at the relative economic significance of the predictors, based on their absolute standardised coefficients. Across the three OLS specifications, heatwave duration and cumulative intensity consistently display the largest absolute standardized coefficients, indicating their central role in explaining cumulative abnormal returns.

In contrast, the significance of the ESG dimensions varies across the OLS specifications. In the models with group and industry fixed effects (Figures 9 and 10), the environmental and governance scores appear more economically significant compared to the sector fixed-effects model (Figure 8).

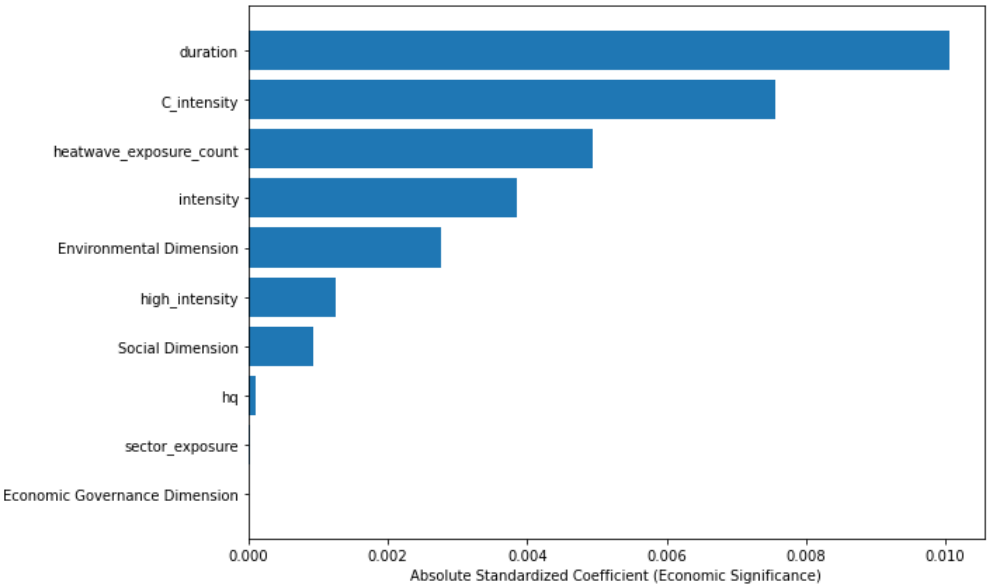
Figure 11 shows a broadly similar ranking of predictors, for the neural network models with duration and cumulative intensity remaining the most important features. However,

the neural network also identifies the firm's industry as a top predictor. Traditional linear specifications do not fully capture the impact of differential industries' exposure to heatwave events.

Furthermore, the neural network assigns greater relative importance to the social and governance scores compared to the OLS regressions.

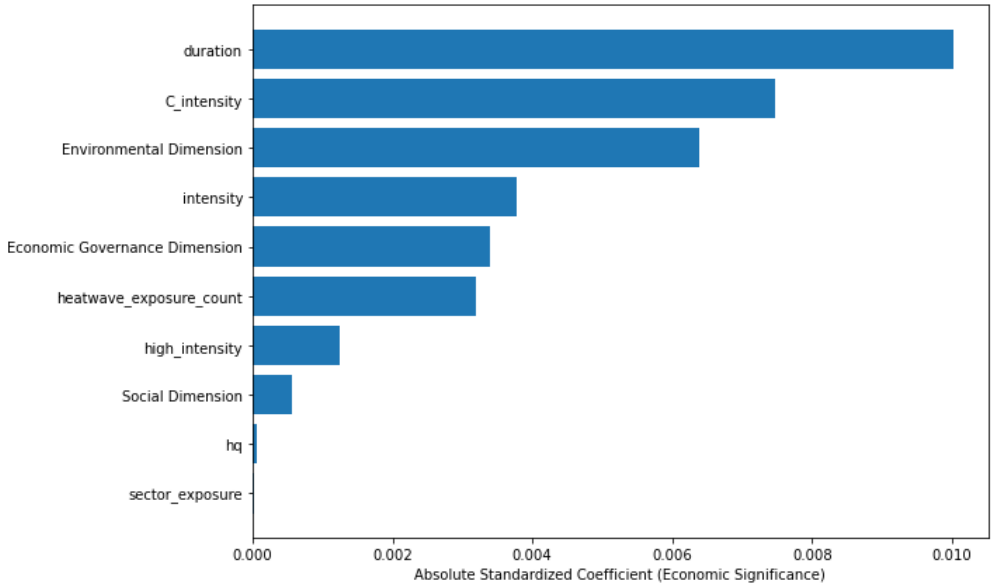
These comparative findings indicate that while both linear and non-linear models identify similar core drivers of cumulative abnormal returns, the neural network uncovers additional nuanced relationships, particularly with regards to industry exposure and ESG scores, reflecting its superior explanator and predictive ability in OLS regression with industry fixed effects (GISC 2-digit classification) for CARs obtained from.

Fig. 8. Economic significance of predictors in the Market-Adjusted model with sector fixed effects.



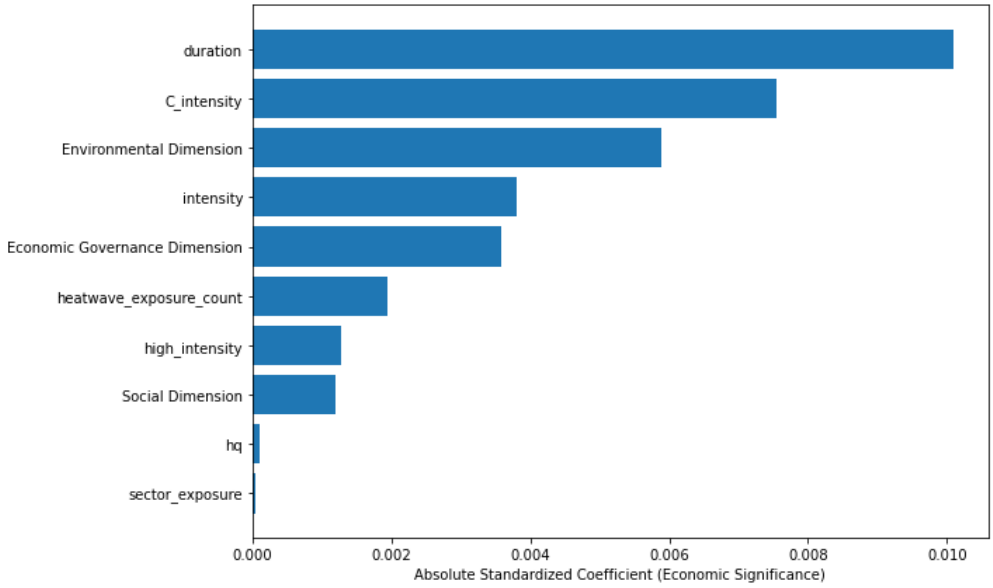
This figure presents absolute standardized coefficients from the Market-Adjusted regression specification that includes sector fixed effects. The coefficients are scaled to allow comparison of the relative importance of predictors.

Fig. 9. Economic significance of predictors in the Market-Adjusted model with group fixed effects.



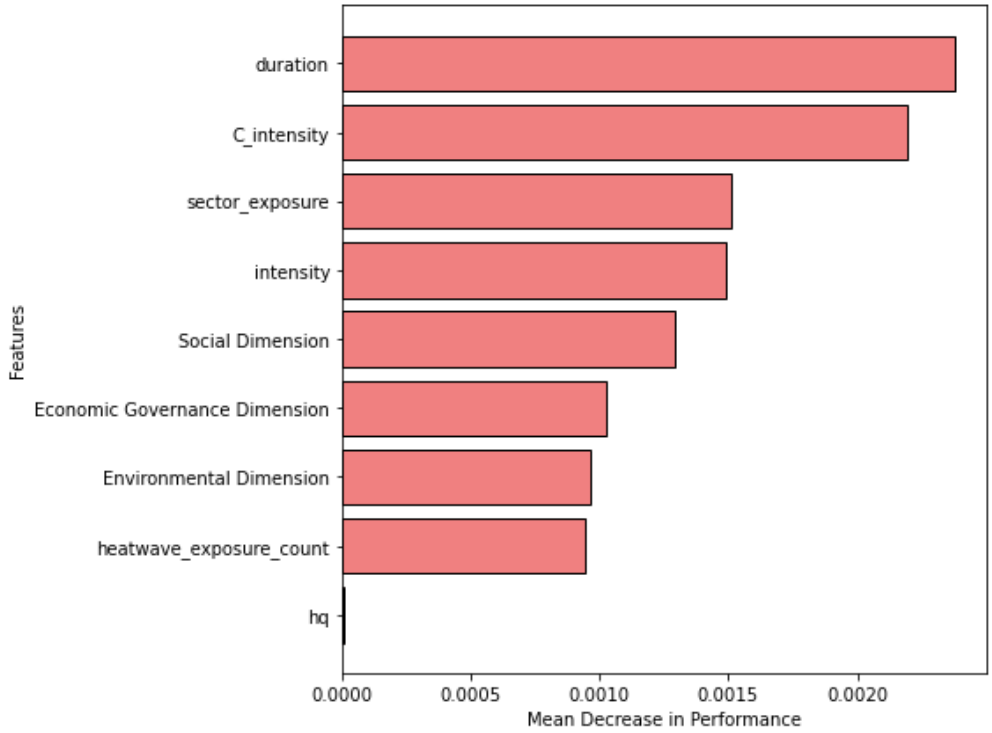
This figure shows absolute standardized coefficients from the Market-Adjusted regression specification with group fixed effects. The figure provides a comparative view of the economic significance of each predictor variable.

Fig. 10. Economic significance of predictors in the Market-Adjusted model with industry fixed effects.



This figure displays absolute standardized coefficients estimated using the OLS regression with industry fixed effects (GISC 2-digit classification) for CARs obtained from the Market-Adjusted model.

Fig. 11. Feature importance of neural network model for the Market-Adjusted Model



This figure shows the top 10 most important features identified by the neural network trained on Market-Adjusted abnormal returns. Importance is measured by mean decrease in performance when each feature is permuted.

5. Conclusion

This study provides novel evidence on how extreme heatwave events influence firm-level financial performance (i.e. stock returns) by combining a comprehensive dataset of U.S. firms' headquarters and global branch locations with their exposure to heatwaves. Firm's stock returns' vulnerability to heatwaves varies depending on the industry where the firm operates, with Energy and Materials sectors exhibiting the most pronounced negative effects, while Healthcare, Consumer Staples, and Utilities showing resilience or even positive abnormal returns.

Our regression results highlight that the proximity to heatwaves exposure matters critically: heatwaves affecting firm headquarters significantly impact on negative abnormal returns more than those affecting their branches, suggesting heightened strategic and operational risks when central decision-making hubs are disrupted. Moreover, firms with stronger ESG scores and greater markets' attention around these event when headquarters are impacted generally experience more favorable outcomes during heatwaves, but resilience dimin-

ishes when events directly impact the headquarters.

Comparing the predictive performances, our neural network models demonstrate markedly superior performance relative to traditional ordinary least squares regressions with industry fixed effects, achieving out-of-sample R^2 values exceeding 25% compared to less than 5% for the OLS linear models, and a relative fixed effects mean squared errors of approximately 25%. These results underscore the importance of modeling complex, nonlinear interactions between firm characteristics, heatwave features, and financial performance. Overall, our findings emphasize that using richer information on exposure of firms' establishments (headquarters and branches) to heatwaves and adopting neural networks can greatly improve the assessment, management, and pricing of climate-related financial risks in equity markets.

References

Addoum, J. M., Ng, D. T., Ortiz-Bobea, A., 2023. Temperature shocks and industry earnings news. Journal of Financial Economics 150, 1–45.

Alonso-Robisco, A., Bas, J., Carbo, J. M., de Juan, A., Marques, J. M., 2025. Where and how machine learning plays a role in climate finance research. Journal of Sustainable Finance & Investment 15, 456–497.

Carhart, M. M., 1997. On persistence in mutual fund performance. The Journal of finance 52, 57–82.

Carleton, T. A., Hsiang, S. M., 2016. Social and economic impacts of climate. Science 353, aad9837.

Chen, D., 2021. Extreme weather and ratings on corporate climate mitigation policies. Business Ethics, the Environment & Responsibility 30, 570–587.

Chen, L., Pelger, M., Zhu, J., 2024. Deep learning in asset pricing. Management Science 70, 714–750.

Emmerichs, T., Shen, F., Gromov, S., Hegglin, M., Wahner, A., Taraborrelli, D., 2024. A storyline of ozone pollution extremes in warmer climates .

Fallahgoul, H., Franstianto, V., Lin, X., 2024. Asset pricing with neural networks: Significance tests. Journal of Econometrics 238, 105574.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of financial economics 33, 3–56.

Giglio, S., Kelly, B., Xiu, D., 2022. Factor models, machine learning, and asset pricing. Annual Review of Financial Economics 14, 337–368.

Griffin, P., Lont, D., Lubberink, M., 2019. Extreme high surface temperature events and equity-related physical climate risk. Weather and Climate Extremes 26, 100220.

Griffin, P. A., Lont, D. H., Lubberink, M. J., 2025. The effects of extreme high temperature spells on financial performance. The British accounting review 57, 101383.

Gu, S., Kelly, B., Xiu, D., 2020. Empirical asset pricing via machine learning. The Review of Financial Studies 33, 2223–2273.

Hutchinson, J. M., Lo, A. W., Poggio, T., 1994. A nonparametric approach to pricing and hedging derivative securities via learning networks. The journal of Finance 49, 851–889.

Huynh, T. D., Xia, Y., 2023. Panic selling when disaster strikes: Evidence in the bond and stock markets. Management Science 69, 7448–7467.

Kaastra, I., Boyd, M., 1996. Designing a neural network for forecasting financial and economic time series. Neurocomputing 10, 215–236.

Kerr, R. A., 2007. Global warming is changing the world. Science 316, 188–190.

Lau, N.-C., Nath, M. J., 2012. A model study of heat waves over north america: Meteorological aspects and projections for the twenty-first century. Journal of Climate 25, 4761–4784.

Musleh Al-Sartawi, A. M., Hussainey, K., Razzaque, A., 2022. The role of artificial intelligence in sustainable finance.

Schuster, M., Krüger, J., Lueg, R., 2025. Physical climate risk: Stock price reactions to the historically most extreme european and united states heat waves since 1979. PloS one 20, e0318166.