Climatological Disasters and the US Stock Market: An Event Study on the S&P500 and Industry Dynamics

Katharina Leonie Plock

Dissertation written under the supervision of Professor Zoë Venter

Dissertation submitted in partial fulfillment of requirements for the MSc in Finance, at the Universidade Católica Portuguesa, 20.12.2024.

Author: Katharina Leonie Plock
Topic: Climatological Disasters and the US Stock Market: An Event Study on the S&P500 and Industry Dynamics

Abstract

This study examines the impact of climatological disasters on the stock performance of companies listed in the S&P500. Using the event study methodology, the cumulative abnormal returns (CARs) for 58 U.S. climatological events were analyzed over 21 years. The expected returns were calculated using the CAPM and the Fama-French five-factor model. Overall, the results demonstrate a significant negative impact of climatological events on the stock market for the event windows [-2;2] and [-5;5]. Furthermore, the results of various regressions demonstrate that company size appears to be the most relevant driver for investor behavior, with consistently significant positive coefficients observed. However, the industry dummy, which categorizes companies based on their climate sensitivity, also provided positive significant results for the event window [-5;5]. This effect is mainly observed within the primary model (CAPM) and reduces with the five-factor model. Lastly, the study underscores the increasing importance of natural disasters to financial markets and provides the foundation for future research examining various factors that influence investment behavior in response to such events, including political dynamics and industries.

Keywords: Event Study, Climatological Disasters, Industry Dynamics, US Stock market

Autor: Katharina Leonie Plock
Título: Catástrofes climatológicas e o mercado de acções dos EUA: Um estudo de eventos sobre o S&P500 e a dinâmica do sector

Resumo

Este estudo examina o impacto das catástrofes climatológicas no desempenho das acções das empresas cotadas no S&P500. Utilizando a metodologia de estudo de eventos, foram analisadas as rendibilidades anormais acumuladas (CAR) de 58 eventos climatológicos nos EUA durante um período de 21 anos. Os retornos esperados foram calculados com base no CAPM e no modelo de cinco factores de Fama-French. Em geral, os resultados demonstram um impacto negativo significativo dos fenómenos climatológicos no mercado bolsista para as janelas de eventos [-2;2] e [-5;5]. Além disso, os resultados de várias regressões demonstram que a dimensão da empresa parece ser o fator mais relevante para o comportamento dos investidores, com coeficientes positivos consistentemente significativos. No entanto, a dummy do sector, que categoriza as empresas com base na sua sensibilidade ao clima, também apresentou resultados positivos significativos para a janela de eventos [-5;5]. Este efeito é especialmente observado no modelo primário (CAPM) e reduz-se com o modelo de cinco factores. Por último, o estudo sublinha a importância crescente das catástrofes naturais para os mercados financeiros e fornece a base para futuras investigações que examinem vários factores que influenciam o comportamento de investimento em resposta a tais acontecimentos, incluindo a dinâmica política e as indústrias.

Palavras-chave: Estudo de Eventos, Catástrofes Climatológicas, Dinâmica da Indústria, Mercado Acionista dos EUA

Table of Contents

Table of Abbreviations

α	Intercept
β_i	Beta coefficient for security *i*
ϵ_i	Error term for security *i*
R_{ft}	Risk-free rate at time *t*
R_{it}	Return of Asset *i* at time *t*
R_{Mt}	Market Return at time *t*
CAPM	Capital Asset Pricing Model
CAR	Cumulative Abnormal Return
Leverage	Total Debt to Total Capital
Performance	Return on Assets (ROA)
RCAR	Cumulative Abnormal Returns of the Robustness Model
Size	Market Capitalization
5FF	Fama & French Five-Factor Model

1 Introduction

Every year, the number of natural disasters increases rapidly worldwide. The U.S., in particular, is severely affected, as society and financial markets are confronted with increasing challenges every year. According to the National Center for Environmental Information and a study by BCG, in the past 15 years alone, climate change and weather-related events have resulted in more than 7,000 deaths and costs of over $1.6 billion in the U.S. (Zuzek-Arden et al., 2024). Extreme weather events, especially droughts, are a major cost factor with an average cost of 9.4 billion dollars per event. This makes them the second most expensive natural disaster after hurricanes (Birdsey and Walker, 2023). However, many authorities in the U.S., from local to national level, are just starting to realize the scale of challenges that they are confronted with (Zuzek-Arden et al., 2024). Focusing on droughts specifically, forecasts indicate that by 2050, the likelihood of severe droughts will be up to three times higher, and in some regions, even 20 times higher, due to increasing global temperatures (Birdsey and Walker, 2023). To illustrate this, Figure 1 shows the annual probabilities of severe droughts in 1971-2000 on the left side and 2021-2050 on the right side.

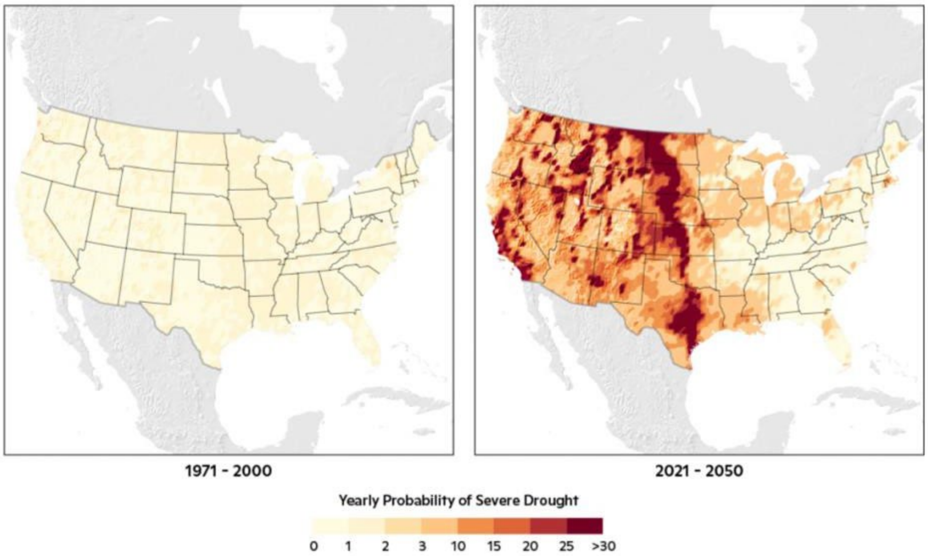

Figure 1:" Yearly Probabilities (%) of a Severe Drought in 1971-2000 and 2021-2050. A severe drought is defined as a 6-month average of extreme drought" (Source: Birdsey and Walker, 2023).

Furthermore, periods of drought lead to dry soils, making them highly flammable and creating conditions for more extensive and intense wildfires. As a result, and due to rising temperatures and changing precipitation patterns, the fire season in the U.S. is lengthening and intensifying, putting existing ecosystems under severe strain.

This has led to the average area burned in the U.S. doubling between 2000 and 2019 compared to 1980 and 1999 (Birdsey and Walker, 2023). The following study examines the consequences of droughts and wildfires on companies headquartered in the U.S..

In general, the risks associated with climate change at a corporate level can be divided into physical[1] and transitional risks[2]. Both risks represent severe challenges for companies through their operations and financial performance. Nevertheless, these risks affect certain companies more than others, depending on the industry they operate in. Therefore, this study focuses on the differences in investment behavior based on whether companies operate in climate-sensitive industries or not.

In the past, droughts and wildfires have not been studied for their corporate implications as frequently as other natural disasters. However, according to Venturini (2022), extreme droughts and wildfires are classified as extreme weather events due to their acute nature. This classification makes them suitable for analysis as their identifiable timeframes provide a clear basis for the applied event study.

For this reason, this study examines the impact of such so-called climatological disasters on the stock performance of companies listed on the S&P500 index. In this study, the focus is firstly on determining if there is a significant market reaction to climatological events and secondly on whether investors factor the industry into their decision-making. The analysis covers 21 years (2002 to 2023) and examines 58 disasters in 24 U.S. states. Furthermore, as a supplementary analysis, the president/party in office during each event is examined using dummy variables to reflect political relevance.

The study is structured as follows: First, an overview of the literature on investment behavior following a natural disaster is provided, along with examining previous studies on market reactions to climatological events specifically. This is followed by a presentation of the two underlying hypotheses. Chapters 3 and 4 outline the data used and describe the methodology applied, including the event study approach and the subsequent regressions. The empirical results are then presented and critically analyzed in the existing literature. Lastly, the study concludes with a summary of the findings, a discussion of their limitations, and implications for future research.

[1] Physical risk adresses the harmful effects of climate- and weather-related events on corporate operations, communities and supply chains (Tankov & Tantet, 2019).

[2] Transitional risk addresses all potential scenarios associated with the transition to a low-carbon economy (Curtin et al., 2019), as well as corporate reputation and technological change (Semieniuk et al., 2021).

2 Literature Review

2.1 Investor Behavior during Natural Disasters

Understanding investor behavior during natural disasters is crucial for analyzing market dynamics and the broader economic impact of such events. Two fundamental behavioral theories provide valuable insights into how investors react under these extreme conditions: the salience theory of choice under risk and the risk-as-feelings theory. These theories help explain deviations from rational decision-making models by emphasizing the role of attention, emotions, and perception in financial decisions. According to the salience theory of choice under risk by Bordalo et al. (2012), people frequently focus on the most conspicuous or salient parts of information and neglect other aspects. In other words, they give disproportional weight to salient information in the decision-making process (Bordalo et al., 2012). By doing so, investors overestimate the probability of a rare adverse event if it is particularly salient or present. As a result, they may be overly risk-averse to assets exposed to such rare events (Alok et al., 2019).

In particular, the study by Bernile et al. (2017) shows that natural disasters highly influence the risk attitude of fund managers. Their results suggest that fund managers exposed to disaster zones irrationally reduce their portfolio volatility as they become more risk-averse than fund managers who have not experienced a disaster. The effect decreases as managers repeatedly face risk (Berlie et al., 2017).

This aligns with the findings of Alok et al. (2019), who found that companies located in a disaster area do not appear to underperform. In their study, the authors analyzed the performance of companies using the proxies Return on Assets (ROA) and Sales Growth. They found no statistically significant changes in a firm's performance post-disaster period. Similarly, Malik et al. (2020) conclude that industries show a short-term, immediate response to climate disasters, with the most robust significant responses to climatological events (the events of interest in this study) occurring within the first week. However, considerable responses vary for other types of natural disasters, with some delayed effects observed up to the 30-day mark (Malik et al., 2020).

Like the salience theory, the risk-as-feelings theory concerns individual behavior in decision-making processes such as investment behavior. The theoretical framework designed by Loewenstein et al. (2001) assumes that emotions play a certain role in influencing immediate responses to a risky situation. This theory is frequently cited to explain the connection between emotions and the tendency to engage in risk-taking behavior. Bourdeau-Brien and

Kryzanowski (2020) provide empirical evidence for this theory, which examines the impact of natural disasters on investors' risk aversion in the U.S. municipal bond market. Their study concludes that natural disasters cause a significant but temporary increase in risk aversion among investors, especially in the regions directly affected. This increased risk aversion is primarily driven by emotional reactions such as fear, which influence investors' decision-making processes and cause them to reduce their exposure to riskier assets. Over time, as the emotional impact of the disaster subsides, risk aversion returns to normal, suggesting that the initial reactions were driven by immediate feelings rather than long-term rational assessments. Similarly, Kong et al. (2021) examine how natural disasters affect financial analysts' earnings forecasts. They find that analysts become more pessimistic in their forecasts for firms' performance located near the disaster's epicenter, even though there is no significant negative impact on firms' actual performance. This pessimism is due to psychological shocks and heuristic biases influenced by emotional reactions to the disaster. Media coverage amplifies these effects by increasing the availability of high-profile information, causing analysts to overestimate risks. Finally, the authors reach the same conclusion as Bourdeau-Brien and Kryzanowski (2020), stating that over time, analysts adjust their forecasts as the emotional influence diminishes, which is consistent with the predictions of the risk-as-feelings theory.

Based on the theories and empirical results presented, it can be concluded that investors exhibit significant but temporary deviations from rational decision-making processes after natural disasters. As a result, this study can be expected to show short-term market reactions that normalize over time once the emotional influences subside.

2.2 Climatological Disasters and Financial Market Reactions

As exogenous shocks, natural disasters have an ever-greater impact on the stock market and investor behavior (Akter et al., 2023). Especially in the light of the intensification of climate change, investigating these phenomena has become crucial. The Centre for Research on the Epidemiology of Disasters (CRED) characterizes natural disasters as physical phenomena that occur naturally and are triggered by different events. These include the following five events: meteorological events, such as extreme temperatures, hurricanes, and storm surges; hydrological events, such as avalanches and floods; climatological events, such as droughts and wildfires; geophysical phenomena, such as earthquakes, landslides, tsunamis and volcanic activity and biological events such as disease epidemics.

When looking at the immediate impact of natural disasters on the stock market, it is noteworthy that modern forecasting systems have made it possible to predict hurricanes, extreme heat, droughts, and similar events several days in advance with reasonable accuracy since the launch of the first NASA weather satellite in 1960 (Malik et al., 2020). However, wildfires, a subcategory of climatological disasters, remain challenging to predict. This uncertainty may stem from human activity and natural triggers such as lightning, which are the leading causes of wildfire outbreaks (Pickell et al., 2017; Malik et al., 2020).

When analyzing the results of various studies, different findings emerge regarding the impact of climatological events on the stock market. Research suggests that climatological events, including wildfires and droughts, have among the most extreme impacts on financial markets compared to other types of natural disasters (Pagnottoni et al., 2022). However, studies show significant effects in opposite directions, indicating heterogeneity in the results. On the one hand, according to Pagnottoni et al. (2022), climatological events tend to have a significantly more negative impact on stock returns than other types of disasters, particularly in regions that are more frequently affected by these events, as can be seen in the Australian S&P ASX 200 Index, for instance. Similar findings are observed in studies concerning the impact of droughts on firm performance, stock prices, and cost of equity, as highlighted by Hong et al. (2019), Huynh et al. (2020), and Kim et al. (2024).

On the other hand, the study of Malik et al. (2020) describes climatological events as a "blessing in disguise" for several industries. Their analysis shows that climatological disasters can positively impact several industries, including insurance, gold, medical devices, construction materials, aerospace, etc. (Malik et al., 2020).

2.3 Formulation of Hypotheses

The literature indicates that investors frequently show significant but temporary deviations from rational decision-making after natural disasters occurred due to increased risk perception and emotions (Bordalo et al., 2012; Loewenstein et al., 2001). Empirical studies have observed immediate market reactions to such events, which tend to normalize once the emotional influences subside (Bernile et al., 2017; Bourdeau-Brien and Kryzanowski, 2020; Kong et al., 2021). Therefore, the first hypothesis is:

H_1: Climatological disasters have a significant impact on the stock performance of S&P500 companies.

In addition, companies in climate-sensitive sectors may face a more significant impact from climatological events. Previous research suggests that investors and analysts react differently to natural disasters depending on the companies' industry (Malik et al., 2020; Pagnottoni et al., 2022). Some industries may experience adverse market reactions due to their vulnerability to climate risks, while others may benefit. This leads to the second hypothesis:

H_2: Companies operating in climate-sensitive industries with high dependency on natural resources and significant CO_2 intensity experience negative market reactions to climatological events.

3 Data

I employed three primary data sources for this analysis: the Economic Policy Uncertainty (EPU) website, Datastream, and the Kenneth R. French Data Library.

The Economic Policy Uncertainty (EPU) website is an online database containing extensive data and indices on uncertainty in macroeconomic policies, making it a valuable resource for empirical research purposes. Through this database, I was able to determine the exact date of climatological events and the associated states.

Refinitiv Workspace (Datastream) is a comprehensive data platform that provides access to time series data on firm-specific information such as stock price returns and other metrics. Through Datastream, I have collected data on the firm-specific returns of S&P 500 companies over 21 years, along with industry data, company locations, and annual control variables.

The Kenneth R. French Data Library is an online database that provides comprehensive data on investment returns, financial factors, and other relevant financial ratios for empirical research purposes, including various Fama and French financial models. I extracted the market return data from this library for my series and obtained the necessary information for my robustness test using the Fama-French Five-Factor model.

3.1 Overview of the Dataset

In this empirical study, I analyze the impact of 58 climatological events—specifically wildfires and droughts—that occurred in 24 U.S. states between 02.11.2002 and 07.31.2023 on 226 companies listed in the S&P 500 Index. The selection of companies within the S&P500 is based on the criterion of exclusively including companies headquartered in states affected by climatological disasters during the time.

To examine market participants' short-term and isolated reactions, I have selected two event windows: [−2;2] and [−5;5], where the numbers represent trading days relative to the event date. These windows capture immediate market responses surrounding the climatological events. Using two financial models - the Capital Asset Pricing Model (CAPM) as the primary model and the Fama-French Five-Factor (FF5) model as a robustness check, I identify four dependent variables of interest. These variables are based on the Cumulative Abnormal Returns (CAR), of which the calculation is explained in more detail in the Methodology section. The CAPM yields CAR[−2;2] and CAR[−5;5] as dependent variables, while the FF5 model provides RCAR[−2;2] and RCAR[−5;5] serving as robustness-adjusted counterparts. For the explanatory variables, I used *industry_affected*, a dummy variable indicating whether the event's impact on a firm depends on the industry it is operating in, and *ESG_Scores* as a robustness measure. Accordingly, I ran five regression models, each estimated twice: once with *industry_affected* as the explanatory variable and once with *ESG_Scores*. In addition to these variables, I include control variables for size, performance, and leverage. Each of the variables mentioned were taken from Refinitiv Workspace (Datastream).

Furthermore, as an additional analysis, I tested whether the impact of the events on stock performance was influenced by the incumbent U.S. president at the time of the event. The corresponding correlation matrix and summary statistics are in the appendix (table 6 and table 7). I will discuss these independent variables in more detail in the following three subsections.

3.2 Explanatory Variable of Primary Interest

This study introduces the binary dummy variable *industry_affected* as a key explanatory factor, categorizing firms based on whether they operate in industries directly impacted by climatological events due to resource dependency and CO_2 intensity, leading to significant property damage, operational disruptions, and potential negative market reactions. Specifically, the variable takes on the value 1 if a company belongs to the industries: basic materials, energy, industrial, real estate, utilities, financial or consumer staples, and the value 0 otherwise. The selection of these industries as "affected" is justified by their increased exposure to climate-related risks. More details on the individual reasons are provided below. The basic materials industry includes companies operating in food processing and secondary agriculture, which are significantly affected by water shortages and droughts. In contrast, the energy industry faces increased regulatory pressure due to climate change. Traditional energy infrastructure, such as oil rigs and pipelines, as well as renewable energy facilities, such as solar and wind farms, are additionally particularly vulnerable to extreme weather conditions. The industrial industry is affected by its dependence on commodity-intensive processes and complex supply chains that climate events can disrupt. Disruptions to transportation infrastructure caused by wildfires and droughts can contribute to supply chain challenges. However, the extent of these disruptions can vary depending on the specific circumstances and regions affected. The real estate industry is highly exposed to the physical risks of climate disasters, leading to higher insurance premiums and possible devaluation of properties. The utilities industry, meanwhile, is heavily affected as it is highly dependent on natural resources such as water, which can become scarce during periods of drought. The financial industry, which includes insurance companies, is heavily impacted by climate-related disasters as claims increase and insurance premiums rise. In addition, banks and other financial institutions may be exposed to credit risks if climate events impact customers. Finally, the consumer staples industry sources its raw materials, such as grains, fruits, and vegetables, directly from agriculture, which is greatly impacted by droughts and wildfires.

As mentioned in the previous chapter, I performed regressions with ESG scores to check robustness. This is because companies in the affected industries are likely to have lower ESG scores due to the environmental challenges associated with their operations. Including this variable helps control the possibility that lower ESG performance, rather than direct exposure to climate disasters, may influence the results. It adds depth to the analysis and improves the credibility of the results by considering additional factors that could impact the relationship between industry exposure to climate disasters and company performance. However, it should be noted that the relationship between the dummy variable *industry_affected* and *ESG_scores* is not one-to-one, as ESG scores, on the one hand, also include social and governance factors, and on the other hand, companies may have strong sustainability initiatives that mitigate their environmental impact.

3.3 Control Variables

A series of regressions are performed with the dependent variables of interest and various independent variables to ensure a comprehensive analysis. These models aim to identify the relationships between the (R)CARs at time t and various company attributes in the corresponding period. Hence, the variables size, leverage, and performance are gradually added.

The regression proxies the variable size by the company's market capitalization. This metric measures the total value of all company outstanding shares and indicates its size. Larger companies often have more stable returns and are less volatile than smaller companies. Therefore, the size of a company can has a significant influence on how a company can manage unexpected events and potential losses.

Next, the variable leverage is proxied by the Total Debt to Total Capital ratio. The leverage ratio measures the proportion of borrowed capital to total capital and provides information about a company's financial structure. Accordingly, companies with a high leverage ratio can react more sensitively to events, as they are less flexible, have a higher perception of risk, and their creditworthiness or liquidity can be strongly influenced.

Lastly, the performance variable is proxied by the Return on Assets (ROA). The ROA measures the profitability of a company relative to its total assets. This captures how efficiently a company uses its resources to generate profits. Therefore, the variable indicates the profitability and health of a company, which can be very relevant in the case of an unexpected event.

3.4 Presidential Variable

As a supplementary analysis to the event study, binary dummy variables were introduced for corresponding U.S. presidents. This additional analysis aims to examine the impact of political leadership changes on investment behavior in the context of climate disasters. During the period analyzed, four presidents were in office, two of whom were Republicans: George W. Bush (2001-2009) and Donald Trump (2017-2021), and two Democrats: Barack Obama (2009-2017) and Joe Biden (2021-2025). The two political camps have conflicting approaches and views, especially when it comes to climate change. Republican presidents tend to favor less stringent environmental regulations and promote more business-friendly policies, while Democratic presidents are more inclined to push for initiatives to combat climate change. As a result, investors may value companies differently depending on the political leader, as the political objectives create different expectations for regulatory guidance and action to combat climate change. On the one hand, companies can be expected to be less affected by climate disasters under Republican presidents due to the limited regulatory requirements. On the other hand, investors may consider current environmental regulations as too weak and therefore undervalue companies in terms of climate change development and long-term damage.

4 Methodology

4.1 Event Study Approach

This empirical study employs the statistical approach of an event study, a methodology originating from Ball and Brown (1968) and Fama et al. (1969). Event studies analyze how specific events, such as mergers, earnings announcements, or macroeconomic news, impact stock prices by examining price reactions (Corrado, 2011). The objective is to identify deviations in actual stock returns from expected returns attributable to events which may indicate unusual market reactions.

The basic methodology of an event study involves estimating the expected return of a stock based on historical data and comparing it to the actual return on the event day as well as its surrounding days. The expected return can be calculated using different financial models, such as the market model or different factor models, which incorporate typical market movements. The difference between the expected and actual returns is called the abnormal return. Abnormal returns are crucial, as they provide insights into how the event affects the company's value during the event period. For this, specific observation periods are defined around the event day, including pre-and post-event windows, to capture the full impact of the event. Abnormal returns are then cumulated over these periods, creating cumulative abnormal returns (CARs) to measure the aggregate effect of the event. A t-test or similar statistical test is typically used to determine whether the event has led to significant changes in stock price.

This study analyzes the impact of multiple climatological disasters (wildfires, droughts) on the U.S. stock market. To accomplish this, companies from the S&P500 were chosen and organized based on the location of their headquarters within U.S. states, allowing for an analysis whether climate disasters directly impact companies. The United States are particularly affected by climate disasters and as previously mentioned, have a well-developed network of meteorologists and early warning systems that can alert the public in advance of climate disasters. Therefore, the time windows [-2;2] and [-5;5] offer the possibility of recognizing the effects before the natural disasters occur, when information about the impending event has already been published or anticipated by the market, as well as reactions after the natural disaster, when the market adjusts to the new information. If an event occurred on a non-trading day, the next trading day is set as event day (0). After the time window was set, the expected returns were calculated using the Capital Asset Pricing Model (CAPM), introduced by Sharpe (1964) and Lintner (1965). This model considers market risk as the primary factor influencing stock returns and is illustrated in equation (1):

(1) $R_{it} - R_{ft} = \alpha + \beta_M(R_{Mt} - R_{ft}) + \varepsilon_t$

Where R_M is the return to the market portfolio, R_{ft} is a risk-free rate, and β_M measures the sensitivity of the asset i to the market. The realized abnormal returns for each observation within the event window were calculated to analyze any excess returns in the event window. To ensure the robustness of the results, the Fama-French Five-Factor model (FF5) introduced by Fama and French (2015) is used to reassess the expected returns. The robustness test is necessary to evaluate whether additional factors significantly affect returns and provide a more comprehensive view than the CAPM alone. More precisely, the FF5 model incorporates the additional factors—size (Small Minus Big), value (High Minus Low), profitability (Robust Minus Weak), and investment (Conservative Minus Aggressive)—alongside the market risk factor used in the CAPM. Each factor is multiplied by its corresponding beta (β), representing the sensitivity of the asset's returns to that factor, indicating how much each characteristic influences performance. The FF5 is illustrated in the following formula (2):

(2) $E(R_{it}) = \alpha_i + \beta_{iM} R_{mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iRMW} RMW_t + \beta_{iCMA} CMA_t$

Once the expected returns had been calculated, the abnormal returns were measured by applying the following formula (3):

(3) $AR_{it} = R_{it} - E(R_{it})$

Where AR_{it} is the abnormal return of security *i* at time *t*, R_{it} is the actual return of security *i* at time *t,* and $E(R_{it})$ is the expected return of security *i* at time *t*. Lastly, to fully capture the impact of an event, the abnormal returns are aggregated over the event window to get a more comprehensive view of the potential effect on the different stocks/companies. This cumulative sum of abnormal returns over the event window is called the cumulative abnormal return (CAR) and is calculated as follows (4):

(4) $CAR_{i(t_1,t_2)} = \sum_{t=t_1}^{t2} AR_{it}$

where $CAR_{i(t_1,t_2)}$ is the cumulative abnormal return for security *i* from time t_1 to t_2, AR_{it} is the abnormal return of security *i* at time *t,* and t_1 is the start of the event window, while t_2 is the end of the event window.

To examine whether climate disasters cause a significant reaction in stock prices, a one-sample t-test is performed on the cumulative abnormal returns (CARs) for the CAPM and the 5FF. The test assesses whether the average CARs significantly differ from zero across all observations. This approach quantifies the market reaction over different time windows and assesses the significance of the observed deviations.

4.2 Regression Analysis

The regression analysis is conducted after calculating the cumulative abnormal returns and performing the t-test. In this analysis, the regression models gradually introduce the independent variables to assess their impact on the dependent variable.

However, several diagnostic tests were conducted before running the regressions to ensure the appropriateness and validity of the models. A Hausman test was conducted to determine whether a fixed-effects or random-effects model should be used. Tests for heteroscedasticity

(Breusch-Pagan test) and serial correlation (Wooldridge test) were also performed. If necessary, adjustments were made to ensure the robustness of the regression results. Next, the explanatory variables were inserted gradually to analyze the individual effects on the independent variables. The first regression of the analysis focuses exclusively on the relationship between the industry dummy/ESG score and the dependent variable of interest (R)CAR and proceeds as follows:

$$(5a)\quad (R)CAR_i = \alpha + \beta_1 \text{industry\_affected}_i + \epsilon_i$$

$$(5b)\quad (R)CAR_i = \alpha + \beta_1 \text{ESG\_Score}_i + \epsilon_i$$

Next, in each regression, an additional explanatory variable is added to adjust for company-specific characteristics, resulting the following three regressions:

$$(6a)\quad (R)CAR_i = \alpha + \beta_1 \text{Industry\_affected}_i + \beta_2 Size_i + \epsilon_i$$

$$(6b)\quad (R)CAR_i = \alpha + \beta_1 \text{ESG\_Score}_i + \beta_2 Size_i + \epsilon_i$$

$$(7a)\quad (R)CAR_i = \alpha + \beta_1 \text{Industry\_affected}_i + \beta_2 Size_i + \beta_3 Leverage_i + \epsilon_i$$

$$(7b)\quad (R)CAR_i = \alpha + \beta_1 \text{ESG\_Score}_i + \beta_2 Size_i + \beta_3 Leverage_i + \epsilon_i$$

$$(8a)\quad (R)CAR_i = \alpha + \beta_1 \text{Industry\_affected}_i + \beta_2 Size_i + \beta_3 Leverage_i + \beta_3 Performance_i + \epsilon_i$$

$$(8b)\quad (R)CAR_i = \alpha + \beta_1 \text{ESG\_Score}_i + \beta_2 Size_i + \beta_3 Leverage_i + \beta_3 Performance_i + \epsilon_i$$

Furthermore, the dummy variables for the presidents Bush, Obama, and Trump are inserted for the supplementary analysis on how the president's election influences the market reaction. The dummy for President Biden was omitted to avoid perfect multicollinearity.

$$(9a)\quad (R)CAR_i = \alpha + \beta_1 \text{Industry\_affected}_i + \beta_2 Size_i + \beta_3 Leverage_i + \beta_3 Performance_i + \beta_4\, Bush_i + \beta_5 Obama_i + \beta_6 Trump_i + \epsilon_i$$

$$(9b)\quad (R)CAR_i = \alpha + \beta_1 \text{ESG\_Score}_i + \beta_2 Size_i + \beta_3 Leverage_i + \beta_3 Performance_i + \beta_4\, Bush_i + \beta_5 Obama_i + \beta_6 Trump_i + \epsilon_i$$

Lastly, after running the regression, the model's effectiveness is evaluated using the R^2 value, a statistical measure that indicates how well the regression line fits the observed data.

5 Empirical Results and Discussion

In the following subchapters, I present and discuss the results of the analyses. First, I begin with the first hypothesis as to whether climatological events significantly influence the stock performance of companies in the S&P500. I examine the results of the t-test for the event windows [-2;2] and [-5;5] for the CAPM (CAR) and 5FF (RCAR), respectively. This is followed by a more detailed analysis of the regressions and the individual variables. This subchapter focuses on the second hypothesis, whether the defined industry variable is a relevant factor. The event windows [-2;2] and [-5;5] for the CAPM (CAR) and 5FF (RCAR) are likewise examined here.

5.1 T-Test Results

To test the first hypothesis, whether climatological disasters have a significant impact on the stock performance of S&P500 companies, I conducted a one-sample t-test on the cumulative abnormal returns (CARs) for the CAPM and the 5FF model over the event windows [-2;2] and [-5;5]. The results in table 1 show a statistically significant response of the stock market, with all CARs significantly different from zero at a 99% confidence interval. In particular, the t-values show negative results, indicating a consistent negative market reaction to the climatological disasters across both models and event windows. This negative response suggests that investors adjust their valuations of companies in anticipation of the potential negative impact of these disasters on company performance. Such results are consistent with the salience theory of choice under risk and the risk-as-feelings theory, which state that investors and analysts react strongly to salient information when unexpected negative events occur as well as that emotions such as fear can influence investment behavior instead of rational decision-making (Bordalo et al., 2012; Loewenstein et al., 2001). This does not necessarily mean the event actually harms the company economically or physically.

	obs	Mean	St Err	t value
CAR22	2827	-0.003	0.001	-3.603
CAR55	2827	-0.005	0.002	-4.003
RCAR22	2827	-0.007	0.001	-6.675
RCAR55	2827	-0.011	0.002	-8.085

Table 1: One sample t-test

Looking into the results of the t-tests more closely, the medium-large event window [-5;5] causes stronger, more significant negative market reactions than the short window [-2;2]. Precisely, the average CAR for the event window [-5;5] results in -0.005 (CAPM) and -0.011 (5FF), compared to -0.003 (CAPM) and -0.007 (5FF) for the shorter time frame [-2;2].

This indicates that, in contrast to some previous studies, the effects of climatological disasters extend beyond the immediate days following the event and require a more extended adjustment period on the market. One possible reason for this could be that droughts and wildfires are often long-lasting events whose full extent is only recognized after several days. In addition, the active involvement of authorities and news, which provide ongoing information on the losses and the expected magnitude of the disaster, ensures that investors receive a comprehensive stream of information over several days, which can amplify the market's response over a more extended period. These results align with the findings of Malik et al. (2020), who observed the most significant response to climatological disasters within the first week.

In addition, comparing the CAPM and the 5FF model results reveals interesting differences in capturing market reactions. For both event windows, the cumulated abnormal returns calculated with the 5FF model are consistently more negative and show a more substantial statistical significance than the results of the CAPM. These differences appear to be due to the additional explanatory factors of the Five-Factor model, such as size, value, profitability and investment, which enable a more differentiated explanation of investment behavior. The more significant results of the 5FF indicate that company-specific characteristics play an essential role in how investors and analysts assess the impact of climatological disasters on companies. This leads to the conclusion that the mere consideration of systematic risk according to the CAPM is insufficient in explaining investment behavior in the event of climatological disasters fully. To allow a more accurate interpretation, the next chapter presents the results of various regressions in which company-specific variables such as size, leverage, and performance are gradually introduced.

5.2 Regression Results

Before running the regressions, several diagnostic tests were performed to ensure the validity of the regression analysis. I used the Hausman test to distinguish between fixed and random effects. A p-value of 0.0624 was obtained for the event window [-2;2] and a p-value of 0.1025 for the event window [-5;5]. Accordingly, I decided to use random effects in the regressions. The results of the Wooldridge and Breusch-Pagan tests indicated autocorrelation and heteroscedasticity. Therefore, the regressions were adjusted accordingly, and robustness checks were performed.

The following sections analyze the results obtained with the CAPM initially, followed by those of the Fama-French Five-Factor model. The analysis covers the two defined event windows, starting with window [-2;2] followed by [-5;5], and concludes with a collective interpretation of the results.

5.2.1 CAPM

5.2.1.1 Short-Term Event Window

The CAPM provided significant results in the previous analysis. The model assumes that deviations from the expected return are exclusively due to systematic risks, and generally, an efficient market prevails. By introducing various independent variables, I examine the extent to which the cumulative abnormal returns can be explained. The corresponding regressions for the event window [-2;2] can be seen in table 2.

Variables	(1) CAR22	(2) CAR22	(3) CAR22	(4) CAR22	(5) CAR22
dummy_industry	-0.001	-0.000	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Market_Capitalization		0.003***	0.003***	0.002***	0.002**
		(0.001)	(0.001)	(0.001)	(0.001)
Total_Debt_Total_Capital			-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)
Return_on_Assets				0.000	0.000
				(0.000)	(0.000)
Bush_Dummy					-0.003
					(0.003)
Obama_Dummy					0.002
					(0.003)
Trump_Dummy					-0.003
					(0.003)
_cons	-0.003***	-0.045***	-0.042***	-0.040***	-0.036**
	(0.001)	(0.011)	(0.010)	(0.011)	(0.015)
Observations	2827	2827	2783	2778	2778
R^2	0.0000	0.0074	0.0121	0.0123	0.0142

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 2: Regression results CAPM [-2;2] with industry dummy

Starting from the first regression performed, the previously defined industry dummy was introduced and ran against the CARs for the event window [-2;2]. The insignificant results of the industry dummy in all five regressions show that, in contrast to previous empirical studies, the company's industry does not appear to play a decisive role for investors in their investment decisions in the event of a climatological disaster.

However, the introduction of the size variable (market capitalization) leads to highly significant positive results ($p<0.01$), indicating that larger companies tend to have a more stable stock performance in climatological disasters compared to smaller companies. This is in line with the findings of Balvers et al. (2017), which show that smaller companies are significantly more sensitive to temperature shocks than larger companies. This is attributed to the limited resources of smaller companies, which restrict their ability to adapt to such shocks. In contrast, larger companies benefit from their geographical diversification, allowing them to better mitigate extreme temperature events' physical and operational risks (Hugon and Law, 2019). Therefore, investors might rate company size as a key factor, considering larger companies more resilient to such events.

In contrast, the non-significant results for the control variables leverage and profitability suggest that these firm-specific characteristics do not significantly influence market reactions. Large companies, however, are often intuitively perceived as less volatile and better positioned to absorb external shocks. As a result, investors, who frequently react emotionally and impulsively to negative events, may place more value on size and less attention on more complex indicators such as leverage or profitability. In addition, the similarly insignificant coefficients of the presidential dummies suggest that the political conditions during the events have no immediate demonstrable influence on returns. These results could indicate that short-term market reactions are characterized more by direct disasters and less by political factors. Although the results for the dummies are insignificant, slight differences in the signs of the coefficients can be identified. Accordingly, a positive reaction can be observed under Obama and negative ones under Bush and Trump. However, these observations are purely speculative and should not be overinterpreted, as there is no statistical significance.

Finally, the R^2 values emphasize the explanatory power of the independent variables used to explain the cumulative abnormal returns. The results suggest that although introducing company-specific variables increase the explanatory power, other factors are more critical in examining the market reaction.

Replacing the industry dummy with *ESG_score* as the primary explanatory variable demonstrates similar results (the corresponding table is in the appendix: table 8). This underlines the conclusion that the rating of companies in terms of their sustainability and impact on the environment does not play a decisive role in the short-term valuation by investors. The company-specific variables and the presidential dummy yielded results similar to those in the previous regressions.

5.2.1.2 Medium-Term Event Window

Otherwise, looking at the larger time window [-5;5], one can see interesting differences, especially within the industry dummy. The corresponding regressions can be seen in table 3.

	(1) CAR55	(2) CAR55	(3) CAR55	(4) CAR55	(5) CAR55
dummy_industry	0.005*	0.006**	0.008***	0.008***	0.007***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Market_Capitalization		0.004***	0.004***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Total_Debt_Total_Capital			-0.000**	-0.000*	-0.000**
			(0.000)	(0.000)	(0.000)
Return_on_Assets				0.000*	0.000*
				(0.000)	(0.000)
Bush_Dummy					-0.010**
					(0.004)
Obama_Dummy					-0.001
					(0.003)
Trump_Dummy					-0.013***
					(0.004)
_cons	-0.007***	-0.071***	-0.065***	-0.058***	-0.045**
	(0.001)	(0.016)	(0.015)	(0.014)	(0.019)
Observations	2827	2827	2783	2778	2778
R^2	0.0000	0.0050	0.0109	0.0109	0.0139

Robust standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 3: Regression results CAPM [-5;5] with industry dummy

The industry dummy shows significance in all models with increasing magnitude across the regressions (models 3,4, and 5 results in p<0.01), in contrast to the observations for the event window [-2;2]. Surprisingly, however, the corresponding coefficient is positive, indicating that companies operating in climate-sensitive industries react positively to the event. One possible explanation could be that investors assume that companies operating in these sectors have already adjusted to the physical risks associated with natural disasters. However, future research could benefit from looking more closely at specific sectors to uncover the underlying causes.

The coefficients of the size variable continue to show strongly positive significant results, indicating that investors likewise consider large companies to be exceptionally resilient to the events. However, something has changed in the case of the leverage variable, which was insignificant in the shorter time window. For the event window [-5;5], the results show consistently negative significant coefficients, indicating that investors perceive companies with a higher debt ratio as riskier regarding climatological events. Furthermore, there has been a change in the profitability variable as well. Although the results point to a just slightly positive significant coefficient ($p<0.1$), it can be concluded that investors price in this metric and perceive profitable companies as more stable and resilient in the longer time frame.

Finally, by analyzing the presidential variables, interesting developments can be seen. The results show, in both cases of the republican presidents Bush and Trump, negative significant coefficients. As the republic parties and the connected presidents are known for a business-friendly policy instead of focusing on climate protection, Investors might negatively assess the long-term risks of their inadequate and inefficient climate actions.

The R^2 results of the regressions run by the event window [-5;5] indicate similar findings as the previous analysis, suggesting that various additional factors explain the development of the stock performance more precisely than solely the Industry, Size, Leverage, Profitability, and president in office.

Replacing the industry dummy variable with *ESG_score* as the primary explanatory variable provides different results (the corresponding table is in the appendix: table 9). Firstly, the variable *ESG_score* leads to positively significant results within the first regression. This could mean that investors consider companies with a high sustainability performance more resistant to climatological disasters. However, this effect is diminished after the explanatory variables are introduced. In later regressions, the coefficients for the variable no longer show any significant results, making it difficult to interpret the findings. The more significant results of the industry dummy could be attributed to having a variable that includes exclusively climate-sensitive companies. In contrast, ESG scores include other factors in addition to environmental exposure.

Secondly, this regression analysis confirms that the company's size represents a decisive role for investors, with consistently positive significant results. However, interestingly, in comparison to the previous analysis, no significant results can be found for the variables of leverage and profitability. The presidential dummy demonstrates another significant negative result under Trump. This may indicate that investors assess long-term risks more strongly due to a lack of climate policy. However, no concrete assumption can be made as this effect cannot be attributed exclusively to Trump's climate policy.

Finally, the R^2 remains at a similar value, meaning that additional vital factors determine the performance of the stocks.

By comparing the two estimation windows, the immediate reaction to climatological events is possibly characterized by uncertainty and emotions, as investors primarily base their behavior solely on the company's size (based on the variables examined). However, if one extends beyond the initial shock, industry-specific and financial variables become more relevant. This is consistent with the assumption that investors receive new information daily during a climatological disaster to help them assess the event and make an investment decision.

5.2.2 Five-Factor Model

5.2.2.1 Short-Term Event Window

The Five-Factor model likewise conducted significantly negative results in the previous t-test analysis. The model assumes that, in addition to systematic risk, company-specific characteristics such as size, value, profitability, and investment should be considered when calculating the expected return. The corresponding table for the regressions can be seen in table 4.

Variables	(1) RCAR22	(2) RCAR22	(3) RCAR22	(4) RCAR22	(5) RCAR22
dummy_industry	-0.001	-0.000	0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Market_Capitalization		0.004***	0.004***	0.004***	0.002***
		(0.001)	(0.001)	(0.001)	(0.001)
Total_Debt_Total_Capital			-0.000	-0.000	-0.000**
			(0.000)	(0.000)	(0.000)
Return_on_Assets				0.000	0.000
				(0.000)	(0.000)
Bush_Dummy					-0.013***
					(0.003)
Obama_Dummy					0.004
					(0.003)
Trump_Dummy					0.002
					(0.003)
_cons	-0.006***	-0.068***	-0.065***	-0.064***	-0.038**
	(0.001)	(0.012)	(0.011)	(0.012)	(0.015)
Observations	2827	2827	2783	2778	2778
R^2	0.0000	0.0136	0.0169	0.0167	0.0329

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 4: Regression results 5FF [-2;2] with industry dummy

Running all five regressions with the industry dummy as the primary explanatory variable leads to an ambiguous result. Looking at the dummy specifically, the sign of the coefficients varies across the regressions, while the variable itself is insignificant. This suggests that in the more complex Five-Factor model, the industry does not seem to affect the immediate reaction of market participants either. The results of the control variables are similar to those of the CAPM. The size variable shows positively significant results across all regressions, indicating that company size appears relevant in the immediate response. The leverage variable also shows significant results in the last model despite a low value for the coefficient, which shows that companies with a high level of debt react negatively to the disaster. The profitability still does not seem to be an important factor in the immediate reaction to the event. The presidential dummies reveal a significant negative result for Bush's term of office in the short time window of the Five-Factor model. This demonstrates further that, especially during Republican administrations, investors expect companies to perform worse after natural disasters. However, it is important to note that the result cannot be attributed purely to the president or his party and that this is only one possible explanation.

The R^2 results are slightly higher than in the CAPM comparison table. However, these results reflect that additional factors to the three company-specific metrics, the industry and the president, have an important effect on the investment behavior of investors.

When replacing the industry dummy with the variable *ESG_score*, only one significant result for the primary explanatory variable is found for the last regression (see table 10 in the appendix). The coefficient is statistically significant and negative. This indicates that companies with a high ESG score are expected to respond negatively to natural disasters, which contradicts the assumption that investors perceive sustainable companies as more resilient. Moreover, companies with a high market capitalization are seen as significantly robust to climatological events. The remaining company-specific variables show insignificant results similar to the CAPM findings.

Interestingly, the dummy variables for the Bush and Obama presidencies show significant results in this financial model (regression 5). The Bush coefficient shows a negative result, and the Obama coefficient is a positive one. This underlines the assumption that investors could possibly assume that companies would deal better with environmental disasters under a Democratic president than under a Republican president.

The results of the R^2 demonstrate that there are further aspects that must be considered for the interpretation of investment behavior on climatological events.

5.2.2.2 Medium-Term Event Window

In this last subchapter of the Empirical results and discussion chapter, I present and interpret the results of the Five-Factor model for the time window [-5;5]. The results of the regressions can be found in table 5.

	(1) RCAR55	(2) RCAR55	(3) RCAR55	(4) RCAR55	(5) RCAR55
dummy_industry	0.004	0.005*	0.005*	0.005*	0.003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Market_Capitalization		0.005***	0.005***	0.004***	0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Total_Debt_Total_Capital			0.000	0.000	-0.000*
			(0.000)	(0.000)	(0.000)
Return_on_Assets				0.000	0.000
				(0.000)	(0.000)
Bush_Dummy					-0.036***
					(0.005)
Obama_Dummy					0.002
					(0.004)
Trump_Dummy					0.003
					(0.004)
_cons	-0.013***	-0.089***	-0.089***	-0.088***	-0.013
	(0.002)	(0.016)	(0.016)	(0.016)	(0.017)
Observations	2827	2827	2783	2778	2778
R^2	0.0000	0.0180	0.0175	0.0174	0.0540

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 5: Regression results 5FF [-5;5] with industry dummy

Similar to the CAPM model for the event window [-5;5], the regressions for the primary explanatory dummy variable *Industry_affected* show slightly positive significant results in three regressions. This underlines the previous findings that companies operating in industries that are more likely to be sensitive to climate disasters are perceived by investors as reacting positively to the event. In addition, the variable for company size continues to be a robust indicator that investors expect large companies to react positively to climatological disasters. The result of the control variable for leverage likewise produces significant results and demonstrates that companies with a high level of leverage are more likely to expect negative results following a climatological catastrophe. The control variable for probability remains insignificant. However, the dummy variable for the Bush presidency again shows negative significant results similar to the CAPM model for the same estimation window [-5;5].

Replacing the industry dummy with the variable for the ESG score results in a weakly positive and significant coefficient in the first regression (the corresponding table can be seen in the appendix: table 11). However, when control variables are introduced, the sign of the coefficient changes to negative and becomes strongly significant. This change could be attributed to the fact that the control variables isolate the actual effect of the ESG scores by considering previous correlations with other factors.

Furthermore, the size variable shows positively significant coefficients in most variables. This is consistent with the results observed to date. When introducing the presidential variables, we again see a negative significant effect of the Bush dummy and a positive significant effect of the Obama dummy. This is consistent with the previous results. Interestingly, however, the 5th regression shows a positively significant coefficient for Trump's dummy variable.

The R^2 results indicate that additional explanatory factors exist that influence the investment behavior of investors and are not yet considered in this model.

Comparing the two estimation windows [-2;2] and [-5;5] of the Five-Factor model shows similar effects. It appears that investors price the same company-specific indicators in their behavior immediately after the event as they do a few days later. Interestingly, however, the primary explanatory variable (industry) gains importance in the larger time window, even if marginally, resulting in the industry being considered in investment behavior.

Comparing the results of the two price models shows that the Five-Factor model offers slightly better explanatory power (slightly higher R^2) than the CAPM. This is the case since the Five-Factor model includes additional company-specific factors and offers a more detailed analysis. Furthermore, the control variable for size remains the most robust factor in both models, displaying consistently strong positive effects, suggesting that this is very likely the main factor influencing the investment decision based on the variables analyzed. Looking specifically at the industry dummy and the variable for the ESG score, one can see that the industry dummy shows consistently positive and significant results in both models for the time window [-5;5]. Nevertheless, the significance of the coefficient is lower in the more complex five-factor model. The results of the ESG scores were, however, inconsistent. In the CAPM, the variable for the ESG score is weakly positively significant in the simple model (model 1). Similar findings can be observed for the results of the five-factor model. However, a weak positive significance can be seen in the simpler models, which turns into a negative significance in the more comprehensive models. The resulting contrary positive coefficients of the industry dummy and the negative coefficients of the ESG score variable generally match, although the variables cannot be directly compared.

The results of the presidential dummies are consistent in both models. The analyses show negative significant effects under Republican administrations (Bush and Trump) and positive effects under Democratic President Obama in more complex regressions. These results illustrate the perceived influence of the political context on market reactions.

Overall, the Five-Factor model confirms the robustness of the main CAPM results while providing additional insights into the role of company-specific factors.

6 Conclusion

Previous studies have examined the effect of natural disasters on company performance. Despite studies and science demonstrating that climatological events have a significant impact on financial markets and are among the most expensive natural disasters (Pagnottoni et al., 2022; Woodwell Climate Research Center, 2023), only a few companies have specialized in this area. In an attempt to understand this, studies have analyzed investment behaviors and frequently found irrational decision-making in response to natural disasters. Additionally, further studies have shown that stock performance varies by industry, however, only a few have examined consistent patterns in these differences. This study aims to build on the existing literature and investigates whether investors react differently to companies in climate-sensitive industries compared to those that are not.

The event windows [-2;2] and [-5;5] were selected for the analysis, as investors generally react most strongly to climatological events in the first week after the outbreak (Malik et al., 2020). Furthermore, the CAPM was selected as the primary financial model and tested for robustness using the five-factor model by Fama and French. As a supplementary analysis, dummy variables were introduced for presidents to test whether political decisions have an impact on investment behavior.

The results for the first hypothesis (whether investors react significantly to climatological events) reveal significant negative results at a 99% confidence interval. The results increase in significance with the more complex financial model of Fama and French and stronger effects can be seen with the slightly larger event window [-5;5] compared to [-2;2].

This indicates that systematic risk alone is not sufficient to explain investment behavior and that investors need a few days to assess the magnitude of the event. In addition, media coverage of natural disasters provides new information daily, which must then be priced in. The results of the regression analysis show further interesting findings. In this analysis, independent variables were introduced gradually, starting with the main explanatory variable for the industry, continuing with three company-specific industries and finally adding the dummy variables for the presidents. The results indicate that in the short estimation window [-2;2] the industry does not influence the investment behavior, but rather the size of the company. However, when the estimation window is extended to [-5;5], other factors have a significant impact. In particular, the industry dummy surprisingly shows positive significant results in the

CAPM as well as slightly less significant but also positive results in the 5FF. In addition, the size of the company continues to play an important role and shows that investors consider larger companies to be more robust against these events. The variables for leverage and performance further show significant results in some cases. However, the variables do not yield consistent results across the various regressions and should therefore not be overinterpreted. Moreover, it is interesting to note that ESG scores show little significance for investment behavior. Finally, the dummy variables for the presidents highlight that the companies' stock performed better during the presidency of a Democratic president than under a Republican one. However, these results are not consistent for the individual presidents across all regressions and should therefore be interpreted with caution.

The R^2 displays positive values for all regressions, yet also highlights that additional factors are relevant to investment behavior and have not yet been captured. Overall, the study emphasizes that the most relevant factor (out of the provided ones) for investors is the size of the company, yet the industry seems to be a somewhat relevant indicator for investors beyond the immediate response.

The limitations of the study should, however, also be emphasized when interpreting the above results. First of all, the study examined the influence of wildfires and droughts as natural disasters. Although these events are considered acute, they occur over a longer time period and can change in intensity. Accordingly, the defined event windows [-2;2] and [-5;5] may not cover the overall reaction, but rather the initial one. Secondly, the categorization of companies as climate-sensitive was conducted by me and is not based on a standardized grouping. Lastly, the use of presidential dummies for political influences simplifies the actual political and regulatory influences on market reactions.

Nevertheless, the results of this study provide an interesting insight into investor behavior. Future studies could take a closer look at why climate-sensitive companies are perceived by investors as more resilient to climatological events compared to non-climate-sensitive companies. In addition, larger time windows could be examined to see how investment behavior changes over time. Finally, the results suggest that political leaders can influence investment behavior to some extent in response to such events. Future research could examine more closely the specific factors and the extent of their impact.

7 References

Akter, M., Cumming, D., & Ji, S. (2023). Natural disasters and market manipulation. *Journal of Banking & Finance*, *153*, 106883.Alok, S., Kumar, N., & Wermers, R. (n.d.). *Do Fund Managers Misestimate Climatic Disaster Risk?* Last retrieved: 12.12.2024 https://www.sciencedirect.com/science/article/pii/S0378426623001073

Ball, R., & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*, *6*(2), 159–178. Last retrieved: 12.12.2024 https://doi.org/10.2307/2490232

Balvers, R., Du, D., & Zhao, X. (2017). Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *Journal of Banking & Finance*, *77*, 18-34. Last retrieved: 12.12.2024 https://www.sciencedirect.com/science/article/pii/S0378426616302631?casa_token D1Y2feWtfeIAAAAA:6BEBtE3BecnQdYAjMVFpsy0ANDukJfa3wdpxBl5kXgOZ WV72IaI4dBncHdX6U-e2xgrKI1K0jg

Bernile, G., Bhagwat, V., Kecskés, A., & Nguyen, P. A. (2021). Are the risk attitudes of professional investors affected by personal catastrophic experiences?. *Financial management*, *50*(2), 455-486. Last retrieved: 12.12.2024 https://onlinelibrary.wiley.com/doi/pdf/10.1111/fima.12328?casa_token=xdo4Nm7du U4AAAAA%3AoALaHlE487iSrq90b-auSSDgC7QOENhsL44MITL4NiOxrPrZA0uFP5pfkArX9HtBpJWPs2e22ImSqBE

Birdsey, R., & Walker, W. (2023). *Principles and Safeguards for Natural Climate Solutions*. Woodwell Climate Research Center. Last retrieved: 12.12.2024 https://assets-woodwell.s3.us-east-2.amazonaws.com/wp-content/uploads/2023/10/10214518/Principles_and_Safeguards_for_Natural_Climate_Solutions_Oct2023.pdf

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience theory of choice under risk. *The Quarterly journal of economics*, *127*(3), 1243-1285. Last retrieved: 12.12.2024 https://academic.oup.com/qje/article-abstract/127/3/1243/1922202?redirectedFrom=PDF&casa_token=0zuzxK0ZpPsAAAAA:wU5Cx3o71FSpFGsMSBftUrl3a8U3tCjBAbatGco9qQTA-Z8nfjc9cmlBC29eeZ1h91pXfc9Lnw_3tg#no-access-message

Bourdeau-Brien, M., & Kryzanowski, L. (2020). Natural disasters and risk aversion. *Journal of Economic Behavior & Organization*, *177*, 818-835. Last retrieved: 12.12.2024 https://www.sciencedirect.com/science/article/pii/S0167268120302298?casa_token=tfOH3VaNxSgAAAAA:80-NkNz46ZkEo-dAw9AvNJi8aV-OSaYCjMTYo9S88FhzOce4aavhPALnK5aXPMZYAK2VQVHh0g

Corrado, C. J. (2011). Event studies: A methodology review. *Accounting & Finance*, *51*(1), 207-234. Last retrieved: 12.12.2024 https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-629X.2010.00375.x?casa_token=F7mE6U63gpsAAAAA:FjDbSwA46P4ZKkmoSM52b4cex29zkjrLF6hq2lYcFb84EvVLaQtTh6jq_EzZfmL2F6nJlIqdNyHJs7E

Curtin, J., McInerney, C., Gallachóir, B. Ó., Hickey, C., Deane, P., & Deeney, P. (2019). Quantifying stranding risk for fossil fuel assets and implications for renewable energy investment: A review of the literature. *Renewable and Sustainable Energy Reviews*, *116*, 109402. Last retrieved: 12.12.2024 https://www.sciencedirect.com/science/article/pii/S1364032119306100?casa_token=Dpr7wnqclo8AAAAA:zI1yCNcda45CD2kif_xWRo9NAzU3XFwDUTnbbhNIy5USQO3wOXRnQ5nrCfY9NCcScGN_yYGuzA

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. *International economic review*, *10*(1), 1-21. Last retrieved: 12.12.2024 https://www.jstor.org/stable/pdf/2525569.pdf?casa_token=FZCC7XaeEOYAAAAA:c1bjkVf5w9GeJesqH0EiGCJ21Nf4DOC1srubbq3q_IQon4Kyk7J9rD_yxBWCorE7IasXr-6sE9vBNzemUWgv_b6Al0Iny3djH5rubeDcYfWSMqusNw0

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, *116*(1), 1-22. Last retrieved: 12.12.2024 https://www.sciencedirect.com/science/article/pii/S0304405X14002323?casa_token=_yr-g9C9wqAAAAAA:xcz4qrTh-_ybXFv1xrRyByzTJNntcUC0bbYL0y0qj09XAuib2-Ixqcom4A1ol7O6ZExBrgbGXA

French, K. R. (n.d.). *Data library*. Dartmouth College. Last retrieved: 12.12.2024 https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Hong, H., Li, F. W., & Xu, J. (2019). Climate risks and market efficiency. *Journal of econometrics*, *208*(1), 265-281. Last retrieved: 12.12.2024 https://www.sciencedirect.com/science/article/pii/S0304407618301817?casa_token=f5tLrqwNEs0AAAAA:b9STFWGhLkKn9D8nPsVURrRbde1N0Ai2L5Zc9z3gmYWnPGur9KjPFTXh0A5wIpDcbtFrpukBuw

Hugon, A., & Law, K. (2019). Impact of climate change on firm earnings: Evidence from temperature anomalies. *Available at SSRN 3271386*. Last retrieved: 12.12.2024 https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3271386

Huynh, T. D., Nguyen, T. H., & Truong, C. (2020). Climate risk: The price of drought. *Journal of Corporate Finance*, *65*, 101750. Last retrieved: 12.12.2024 https://www.sciencedirect.com/science/article/pii/S0929119920301942?casa_token=n0XLjDvpz8MAAAAA:DrThzzQxwU-MrdpvG3dA8o5A-LLRUBCeEX73ozgeEOJAoDxwNpN7iJeCijLtkinQzpIjkhzE-Q

Kim, S., Jeon, J., & Kim, H. (2024). Drought and energy stock markets in the United States. *Environmental Research Letters*, *19*(9), 094012. Last retrieved: 12.12.2024 https://doi.org/10.1088/1748-9326/ad61ff

Kong, D., Lin, Z., Wang, Y., & Xiang, J. (2021). Natural disasters and analysts' earnings forecasts. *Journal of Corporate Finance*, *66*, 101860. Last retrieved: 12.12.2024 https://doi.org/10.1016/j.jcorpfin.2020.101860

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, *47*(1), 13–37. Last retrieved: 12.12.2024 http://finance.martinsewell.com/capm/Lintner1965a.pdf

Malik, I. A., Faff, R. W., & Chan, K. F. (2020). Market response of U.S. equities to domestic natural disasters: industry-based evidence. *Accounting & Finance*, *60*(4), 3875-3904. Last retrieved: 12.12.2024 https://onlinelibrary.wiley.com/doi/pdf/10.1111/acfi.12484?casa_token=L1fUtU0G46MAAAAA:rpCegofAlPbqYu4G7RQlxv2P1atAoRc_o6U1OwohJ16jIye933yMFTKJtsycVlP6GszHn8SQjvAqvqw

Pagnottoni, P., Spelta, A., Flori, A., & Pammolli, F. (2022). Climate change and financial stability: Natural disaster impacts on global stock markets. *Physica A: Statistical Mechanics and Its Applications*, *599*, 127514. Last retrieved: 12.12.2024 https://www.sciencedirect.com/science/article/pii/S037843712200365X?casa_token=XmEQoM8tvxYAAAAA:zNhcLtPMQ9g1CTvCIU1XNwvpiYCPMMfwrbyW5aef7xk6bkBSOCDdJQo8YmcWeazLiLB4Rum_ow

Pickell, P. D., Coops, N. C., Ferster, C. J., Bater, C. W., Blouin, K. D., Flannigan, M. D., & Zhang, J. (2017). An early warning system to forecast the close of the spring burning window from satellite-observed greenness. *Scientific Reports*, *7*(1), 14190. Last retrieved: 12.12.2024 https://doi.org/10.1038/s41598-017-14730-0

PolicyUncertainty.com. (n.d.). *Climate uncertainty index*. Last retrieved: 12.12.2024 https://www.policyuncertainty.com/climate_uncertainty.html

Refinitiv Workspace. (2024). *Financial data and analytics platform*. Refinitiv.

Semieniuk, G., Campiglio, E., Mercure, J. F., Volz, U., & Edwards, N. R. (2021). Low-carbon transition risks for finance. *Wiley Interdisciplinary Reviews: Climate Change*, *12*(1), Last retrieved: 12.12.2024 https://wires.onlinelibrary.wiley.com/doi/pdfdirect/10.1002/wcc.678

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19*(3), 425-442. Last retrieved: 12.12.2024 https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1964.tb02865.x

Tankov, P., & Tantet, A. (2019). Climate data for physical risk assessment in finance. *Available at SSRN 3480156*. Last retrieved: 12.12.2024 https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3480156

Venturini, A. (2022). Climate change, risk factors and stock returns: A review of the literature. *International Review of Financial Analysis*, *79*, 101934. Last retrieved: 12.12.2024 https://www.sciencedirect.com/science/article/pii/S1057521921002568?casa_token=F6whWdym4ycAAAAA:2E4dloGQoNGZG6Y7QUu8ltcp2UVuzT5O677WBIG-41s7mRuPI4FLcZJON_DgRTjKkR-gtLrnNg

Zuzek-Arden, T., Gibbs, R., Zawadzki, A., & Caines, C. (2024). *It's Time for the U.S. to Invest in Weather Resilience*. Buston Consulting Group. Last retrieved: 12.12.2024 https://web-assets-pdf.bcg.com/prod/its-time-for-the-us-to-invest-in-weather-resilience.pdf

8 Appendix

Table 6: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) CAR22	1.000												
(2) CAR55	-	1.000											
(3) RCAR22	-	-	1.000										
(4) RCAR55	-	-	-	1.000									
(5) Bush_Dummy	-0.028	-0.019	-0.141	-0.245	1.000								
(6) Obama_Dummy	0.035	0.044	0.076	0.111	-0.401	1.000							
(7) Trump_Dummy	-0.029	-0.063	0.049	0.099	-0.311	-0.465	1.000						
(8) Biden_Dummy	0.020	0.040	-0.002	0.007	-0.216	-0.324	-0.251	1.000					
(9) industry_affected	-0.015	0.023	-0.030	0.023	-0.079	0.083	-0.019	0.002	1.000				
(10) ESG_Score	0.009	0.037	0.025	0.049	-0.346	-0.060	0.200	0.231	-0.009	1.000			
(11) Market_Capitalization	0.077	0.076	0.100	0.094	-0.181	-0.137	0.124	0.240	-0.076	0.427	1.000		
(12) Return_on_Assets	0.025	0.032	0.024	0.025	-0.012	-0.113	0.025	0.137	-0.139	0.097	0.287	1.000	
(13) Total_Debt_To_Capital	-0.019	-0.035	-0.010	0.023	-0.214	-0.001	0.108	0.113	0.219	0.198	-0.065	-0.273	1.000

Table 7: Summary Statistics

Variables	Mean	Median	p25	p75	SD	se(Mean)	Min	Max	N
CAR22	-0.003	-0.002	-0.022	0.018	0.045	0.001	-0.443	0.323	2827
CAR55	-0.005	-0.002	-0.033	0.028	0.068	0.001	-0.833	0.634	2827
RCAR22	-0.007	-0.003	-0.028	0.018	0.052	0.001	-0.547	0.367	2827
RCAR55	-0.011	-0.004	-0.036	0.023	0.074	0.001	-0.833	0.347	2827
ESG_Score	3.885	4.013	3.644	4.270	0.514	0.011	0.900	4.553	2344
Market_Capitalization	16.792	16.757	15.788	17.848	1.683	0.032	10.361	21.820	2827
Return_on_Assets	8.270	7.900	3.640	13.670	11.476	0.218	-105.780	70.610	2781
Total_Debt_To_Capital	32.997	29.840	8.600	50.060	29.002	0.550	0.000	256.060	2783
Bush_Dummy	0.273	0.000	0.000	1.000	0.446	0.008	0.000	1.000	2827
Obama_Dummy	0.333	0.000	0.000	1.000	0.471	0.009	0.000	1.000	2827
Trump_Dummy	0.220	0.000	0.000	0.000	0.415	0.008	0.000	1.000	2827
Biden_Dummy	0.173	0.000	0.000	0.000	0.378	0.007	0.000	1.000	2827
industry_affected	0.347	0.000	0.000	1.000	0.476	0.009	0.000	1.000	2827

Table 8: Regression results CAPM [-2;2] with ESG Scores

Variables	(1) CAR22	(2) CAR22	(3) CAR22	(4) CAR22	(5) CAR22
ESG_Score	0.001	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Market_Capitalization		0.003***	0.003***	0.002***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Total_Debt_Tota_Capital			-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)
Return_on_Assets				0.000	0.000
				(0.000)	(0.000)
Bush_Dummy					-0.002
					(0.004)
Obama_Dummy					0.002
					(0.003)
Trump_Dummy					-0.003
					(0.003)
_cons	-0.005	-0.037***	-0.036***	-0.036***	-0.036**
	(0.006)	(0.010)	(0.010)	(0.011)	(0.015)
Observations	2344	2344	2316	2313	2313
R^2	0.0013	0.0031	0.0028	0.0028	0.0048

Robust standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 9: Regression results CAPM [-5;5] with ESG Scores

	(1)	(2)	(3)	(4)	(5)
Variables	CAR55	CAR55	CAR55	CAR55	CAR55
ESG_Score	0.004*	0.001	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Market_Capitalization		0.003***	0.003***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Total_Debt_Total_Capital			-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)
Return_on_Assets				0.000	0.000
				(0.000)	(0.000)
Bush_Dummy					-0.004
					(0.005)
Obama_Dummy					0.001
					(0.004)
Trump_Dummy					-0.010***
					(0.004)
_cons	-0.022**	-0.061***	-0.059***	-0.058***	-0.060***
	(0.010)	(0.016)	(0.017)	(0.017)	(0.021)
Observations	2344	2344	2316	2313	2313
R^2	0.0011	0.0020	0.0029	0.0030	0.0074

Robust standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 10: Regression results 5FF [-2;2] with ESG Scores

Variables	(1) RCAR22	(2) RCAR22	(3) RCAR22	(4) RCAR22	(5) RCAR22
ESG_Score	0.002	-0.002	-0.002	-0.002	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Market_Capitalization		0.003***	0.004***	0.004***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)
Total_Debt_Total_Capital			0.000	0.000	-0.000
			(0.000)	(0.000)	(0.000)
Return_on_Assets				-0.000	-0.000
				(0.000)	(0.000)
Bush_Dummy					-0.012***
					(0.004)
Obama_Dummy					0.007**
					(0.003)
Trump_Dummy					0.005
					(0.003)
_cons	-0.015**	-0.058***	-0.059***	-0.060***	-0.046***
	(0.006)	(0.011)	(0.011)	(0.011)	(0.014)
Observations	2344	2344	2316	2313	2313
R^2	0.0030	0.0099	0.0098	0.0099	0.0313

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 11: Regression results 5FF [-5;5] with ESG Scores

	(1) RCAR55	(2) RCAR55	(3) RCAR55	(4) RCAR55	(5) RCAR55
ESG_Score	0.007*	0.002	0.000	0.000	-0.009***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Market_Capitalization		0.004***	0.005***	0.005***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)
Total_Debt_Total_Capital			0.000	0.000	-0.000
			(0.000)	(0.000)	(0.000)
Return_on_Assets				0.000	0.000
				(0.000)	(0.000)
Bush_Dummy					-0.035***
					(0.005)
Obama_Dummy					0.010**
					(0.005)
Trump_Dummy					0.012**
					(0.005)
_cons	-0.037**	-0.090***	-0.095***	-0.094***	-0.045**
	(0.015)	(0.020)	(0.021)	(0.020)	(0.020)
Observations	2344	2344	2316	2313	2313
R^2	0.0030	0.0099	0.0098	0.0099	0.0313

Robust standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*