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Measuring the Impact of Extreme Climate-Related Events on the Portuguese Stock Market

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Master in Economics

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PhD Luís Filipe Farias de Sousa Martins, Associate Professor,
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October, 2024

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Acknowledgments

First, I would like to express my gratitude to my thesis supervisor, professor Luís Martins, for all your expertise, support, and guidance during the entire development of this thesis.

I would also like to thank my friends for your encouragement and camaraderie, which kept me motivated until the end of this journey.

I am also grateful to my girlfriend for all the emotional support, for listening to all my worries, and always reassuring me that everything was okay.

Additionally, this endeavor would not have been possible without my cat, Jorginho. Thank you for always keeping me company at home.

Finally, I want to thank my family, particularly my brother, whose work ethic and dedication inspire me every day, and my mother and father, thank you for your endless love and support, and for giving me all the tools I could ever need to do anything I could ever want. My achievements are as much yours as they are mine.

Resumo

Esta tese analisa o impacto de eventos climáticos extremos nos retornos diários e na volatilidade do mercado de ações português durante o período 2000-2023. A frequência e a gravidade dos eventos climáticos extremos estão a aumentar na Europa. Portugal já sofreu um impacto estimado de 15.042 milhões de euros em perdas económicas causadas por riscos climáticos extremos entre 1980 e 2022.

É realizado um estudo de eventos, para o qual são utilizados modelos do tipo GARCH para captar os impactos nos retornos e na volatilidade. Dois conjuntos de eventos climáticos extremos são incorporados como variáveis dummy, um representando desastres naturais e o outro, anomalias meteorológicas extremas. A análise é efetuada para cada tipo de evento e para as categorias de eventos agregados, nomeadamente desastres naturais e anomalias meteorológicas extremas.

Os resultados indicam que os desastres naturais não têm impacto global nos retornos do mercado quando considerados em conjunto, enquanto as anomalias meteorológicas extremas têm um efeito negativo. Relativamente a cada tipo de evento, observa-se um efeito global negativo associado às anomalias de precipitação extremamente elevadas e aos desastres por temperaturas extremas, enquanto as tempestades têm um impacto positivo, e as restantes variáveis não apresentam um efeito global estatisticamente significativo. Os resultados também indicam que nenhum tipo de evento tem um impacto significativo na volatilidade. Estas conclusões sugerem que, embora certos tipos de eventos climáticos extremos influenciem os retornos financeiros, a maioria não tem um efeito não diversificável nos retornos do mercado de ações português, e nenhum afeta a sua volatilidade.

Palavras-chave: Estudo de eventos; Retornos do Mercado de Ações; Volatilidade dos Retornos; Modelos GARCH; Eventos Climáticos Extremos; PSI

Sistema de Classificação JEL: C22; Q54

Abstract

This thesis examines the impact of extreme climate-related events on daily returns and volatility in the Portuguese stock market over the period 2000–2023. The frequency and severity of extreme climate-related events are rising in Europe. Portugal has already suffered an estimated impact of 15.042 million EUR in economic losses caused by extreme climate-related hazards between 1980 and 2022.

An event study is conducted, for which GARCH-type models are employed to capture the impacts on returns and volatility. Two sets of extreme climate-related events are incorporated as dummy variables, one representing natural disasters and the other extreme weather anomalies. The analysis is conducted for each event type and the aggregated event categories, namely natural disasters and extreme weather anomalies.

The results indicate that natural disasters have no overall impact on market returns when considered as an aggregate, while extreme weather anomalies have a negative effect. As for each event type, a negative overall effect associated with extremely high-precipitation anomalies and extreme temperature disasters is observed, while storms have a positive impact, and the remaining variables show no statistically significant overall effect. The results also indicate that no event type significantly impacts volatility. These findings suggest that while certain types of extreme climate events influence financial returns, most do not have a non-diversifiable effect on the Portuguese stock market's returns, and none affect its volatility.

Keywords: Event Study; Stock Market Returns; Return Volatility; GARCH Models; Extreme Climate events; PSI

JEL Classification System: C22; Q54

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List of Abbreviations

Abbreviation	Meaning
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
AOI	All Ordinaries Index
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive Moving Average
ASX	Australian Stock Exchange
CAPM	Capital Asset Pricing Model
CRED	Centre for Research on the Epidemiology of Disasters
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
EHPA	Extremely High-Precipitation Anomalies
EHST	Extreme High Surface Temperatures
EHTA	Extremely High-Temperature Anomalies
ELPA	Extremely Low-Precipitation Anomalies
ELTA	Extremely Low-Temperature Anomalies
EMA	Emergency Management Australia
EM-DAT	Emergency Events Database
ESG	Environmental, Social, and Governance
ETF	Exchange Traded Fund
EUR	Euro
EWA	Extreme Weather Anomaly
Extreme Temp.	Extreme Temperature
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GARCH-M	GARCH-in-Mean
GDP	Gross Domestic Product
Ged	Generalized error distribution
IPCC	Intergovernmental Panel on Climate Change
IPMA	Instituto Português do Mar e da Atmosfera
JB	Jarque-Bera
LM-test	Lagrange Multiplier test
MA	Moving Average

MLE	Maximum Likelihood Estimation
NASDAQ	National Association of Security Dealers Automated Quotations
ND	Natural Disasters
Norm	Normal
NYSE	New York Stock Exchange
PSI	Portuguese Stock Index
PT10A	Portugal 10-Year Government Bond Yield
s.d.	Standard Deviation
Sged	Skewed generalized error distribution
Snorm	Skewed normal
Sstd	Skewed student’s t distribution
Std	Student’s t distribution
TGARCH	Threshold Generalized Autoregressive Conditional Heteroskedasticity
US	United States
USD	United States Dollar
WHO	World Health Organization

CHAPTER 1

Introduction

In recent years, the connection between climate risk factors, particularly extreme climate-related events, and financial markets has gained significant attention. Climate change has been strongly linked with a rise in the frequency and severity of natural disasters in numerous regions (Field et al., 2012; Van Aalst, 2006), with the European Environment Agency stating, in a 2024 Climate Risk assessment, that “Europe is the fastest-warming continent in the world” and that climate-related extremes, such as extreme heat, catastrophic floods resulting from heavy precipitation, and severe droughts, are becoming more frequent in many regions, as well as increasing in severity. (EEA, 2024).

This can lead to profound impacts on many economic and financial systems, with Dietz et al. (2016) estimating that “the impact of twenty-first-century climate change on the present market value of global financial assets” is represented by a Climate Value-at-Risk[1] of 1,8%, or 2,5 trillion USD, along a business-as-usual carbon emissions path. Regarding the past impacts of these disasters, a 2023 report by the European Environment Agency estimated that Portugal had suffered 15.042 million EUR in economic losses from climate-related hazards, namely meteorological, hydrological, and climatological hazards, for the period between 1980 and 2022 (EEA, 2023)

Extreme climate-related events can have various effects on the economy, including impacts on companies, such as asset losses and damage to infrastructures, resulting in disrupted operations or production delays, and effects on individuals through, for example, damages to their homes. These disruptions are often then reflected in financial markets, either through the devaluation of affected companies or shifts in market expectations, possibly impacting stock market returns, as well as its volatility (Zhou et al., 2023).

This rise in the frequency and severity of extreme climate-related events, together with the economic losses recorded in the past as a consequence of these events, as well as projected possible impacts from climate change on present assets, highlights the importance of studies that attempt to measure these impacts and investigate if they are reflected in the financial

[1] Value-at-Risk (VaR) measures the potential loss in a portfolio of assets over a specified time period.

markets, as well as understand how each type of extreme climate-related event affects the financial markets.

Yet, in contrast with the many recorded negative impacts of extreme climate-related events on the economy, empirical findings from the current literature studying whether the occurrence of these types of events is reflected in financial markets are mixed. The results obtained by the authors tend to vary depending on different factors, namely the type of event, period, region studied, and methodology used. Seminal studies focusing on the Australian stock market have found contrasting results, with Worthington and Valadkhani (2004) finding positive and statistically significant impacts caused by bushfires, negative effects from cyclones, and mixed impacts from earthquakes, while Worthington (2008), using a different econometric model, find that natural disasters do not influence Australian stock market returns. Other studies outside of Australia see the same mixed results, with many finding negative impacts from these types of events on stock market returns, others finding no effect, and some finding positive impacts associated with specific event types.

Despite the growing number of studies on the impacts of climate risks in financial markets, little research has been done on the relationship between climate risk variables and the Portuguese stock market. Zanatto et al. (2023) explore the impact of climate risk on the Portuguese stock market using a news-based index, while Silva & Almeida (2011) analyze the influence of weather variables on the Portuguese stock market index. Moreover, there is a total gap in research focusing on the impact of extreme climate events on the Portuguese stock market´s returns and volatility, which this study attempts to fill.

This study examines the effect of extreme climate-related events on the Portuguese stock market returns, aiming to better understand whether extreme climate-related events are important in explaining stock market returns in Portugal. To do this, the study follows an event study approach that uses an AR-EGARCH framework to model the returns of the Portuguese Stock Index as a function of explanatory variables, including control variables and extreme climate events, introduced in the model as dummy variables, with the coefficients associated to these variables measuring their average effect on returns across the sample period.

Another objective is to analyze the influence of extreme climate events on the volatility of the PSI index. Using a GARCH-based model allows for analyzing how independent variables, in this case, the extreme climate dummy variables, affect the volatility associated with the returns.

Finally, this study attempts to understand if the impact of climate events on returns and volatility differs across event types. For this, two separate empirical analyses are conducted, one which aggregates the events into two main categories, natural disasters and extreme weather anomalies, and another disaggregated analysis, where every event type is analyzed on its own by creating a dummy variable for each event type. In particular, by dividing the extreme weather anomalies into extremely high-temperature anomalies, extremely low-temperature anomalies, and extremely high-precipitation anomalies, and the natural disasters into four separate dummies: extreme temperatures, storms, floods, and wildfires.

The total gap in research focusing on the relationship between extreme climate-related events and the Portuguese stock market, combined with the mixed results reported in the current literature, which can vary significantly across regions, highlights the need for localized research on the effects of extreme climate events on specific markets. This study contributes to filling this gap, providing insights into the unique risks and vulnerabilities of the Portuguese stock market, as understanding these impacts is crucial for investors and policymakers in designing adaptive strategies to mitigate risks associated with extreme climate events, which, for investors can mean creating disaster-based trading strategies, and, for policymakers can involve developing policy responses to counter potential recessionary impacts (Bonato et al., 2022), as well as including stock market effects when assessing the impacts of extreme climate-related events on the economy.

This thesis is structured as follows. After this chapter, there is the Literature Review, which goes in-depth into the theoretical framework of the subject and examines the empirical work in the current literature, focusing on the similarities and differences found in the literature and showing how different approaches, types of events, periods and regions of study influence the results and conclusions arrived by the authors. The following section defines the methodology used for the empirical analysis, explaining the econometric approach taken and defining and describing the data used to create each variable. In the 4th chapter, Results and Discussion, the process to determine the model specification is first described, after which the results are displayed and interpreted. The final chapter pertains to the conclusion, which summarizes the findings from the study, identifies its limitations, and offers suggestions for possible future research.

CHAPTER 2

Literature Review

This literature review aims to identify existing research on the impact of climate risks on financial markets by examining the key findings and methodologies used in previous studies, focusing mainly on the effects of extreme climate events on financial markets. The review begins by exploring how climate risk is defined in the literature and its impact on the economy, especially financial markets. The diverse methodologies employed across the literature are then described, followed by a deep dive into the main empirical findings by region of study and where this impact is measured, namely stock market returns and volatility. Finally, the review focuses on the Portuguese context, highlighting the research explicitly conducted for Portugal.

Climate risks are divided into three main categories: physical risks, transition risks, and liability risks, though there is not much research done to date regarding the latter (Carney, 2015). Physical risks address the direct impact of climate and weather-related events on financial assets, being differentiated between chronic risks, related to the gradual effect of climate change, for instance, temperature rises, increases in the sea level, and changes in precipitation patterns (Venturini, 2022), and acute risks related to the impact of extreme climate-related events, such as floods, extreme temperatures, earthquakes, storms, hurricanes, droughts, or wildfires. Transition risks pertain to the effect that changes towards a greener, lower-carbon economy could have on companies, as well as the adjustments companies would have to allow for these changes (Carney, 2015). Finally, liability risks refer to the potential consequences that may occur if those who have experienced losses or damages due to climate change demand compensation from whom they consider to be liable for these consequences (Carney, 2015).

The impact of these risks on the economy can take many different forms. In the case of transition risks, mitigation policies put in place by governments to encourage a transition to a greener economy and achieve specific climate change scenarios, such as the IPCC's 2º C temperature rise, could result in higher costs for companies, as could also technological changes that would force companies to adapt their processes and operations (Carney, 2015; Field et al., 2012). Physical risks can have a direct and an indirect economic effect. Direct effects from extreme climate events include asset losses and damage to companies' infrastructures, as well as monetary losses for individuals, which in turn could lead to indirect effects, such as the disruption of companies' operations and production, or at the household level, deposit withdrawals, and diminished investment (Zhou et al., 2023). All these economic impacts can then be reflected in the financial markets, be it through the devaluation of companies affected by the climate events or through changes in the market's expectations, which Zhou et al. (2023) refer to as the "changes in disaster risk perception and uncertainty about future profitability and investment returns caused by a disaster occurrence", both subsequently impacting the financial markets. Additionally, climate-related events can also increase stock price volatility (Van Aalst, 2006).

Many methodologies have been used across the literature to measure the impact of extreme climate-related events in financial markets, the most widely used one being an event study methodology. An event study has the objective of testing whether there is a presence of abnormal returns due to the occurrence of a specific event or multiple events, that is if the actual returns are affected by said event/events (Antoniuk & Leirvik, 2024; Ferreira & Karali, 2015).

Ferreira & Karali (2015) define two different event study methods. The first approach consists of estimating a forecasting market model, where a company/market's returns are regressed against the returns of one or multiple market indices to measure the company/market's expected returns before the event, thus estimating the model's parameters. This model is then used to forecast the company/market's abnormal returns during the event occurrences by comparing these expected returns calculated by the model with the actual observed returns during the event windows.

An example of the use of this methodology in the literature is in the paper "Market anomalies and disaster risk: Evidence from extreme weather events", which assesses if extreme weather disasters, in this case, hurricanes, affect stock market returns and anomalies, namely "size, value, momentum, return-on-equity (ROE) and investment-to-assets (I/A)." (Lanfear et al., 2019). The authors use a single-factor capital asset pricing model (CAPM), performing parametric and non-parametric tests to determine if there are abnormal returns. Another example is in the work of Griffin et al. (2019), where, for their study on how extreme high surface temperature events in the United States affect the stock market, the authors also use the same base approach by employing three different models that calculate the excess (or abnormal) returns, where the first one uses only a market-weighted index to measure the firms' excess return, the second is a market model that also takes into consideration a risk-free rate, and the third one measures the abnormal returns by subtracting from the daily equity returns an expected return forecasted using a three-factor model (one overall market factor and two factors related to firm size and book-to-market equity) from Fama & French (1993). One disadvantage of this approach is that by using this method, in the case that different factors cause overlapping events, that is, events from different types that occur during the same period, for example, a heatwave and a drought, the abnormal returns calculated for that period cannot be differentiated between the two event types.

The second approach defined by Ferreira & Karali (2015) uses the climate variables as dummies instead. These dummies assume the value of one during the period in which the events occurred and 0 on every other observation in the sample, using an econometric model to regress the asset's returns while using the dummy variables as independent regressors, thereby capturing the abnormal returns resulting from the event by the regressors' coefficients. Just as different models can be used for the first approach, the same is true for this second approach.

Regarding the use of this approach, one of the most foundational works in the literature is the paper "Measuring the impact of natural disasters on capital markets: an empirical application using intervention analysis", in which Worthington & Valadkhani (2004) use an intervention analysis framework, that involves estimating autoregressive moving average (ARMA) models to evaluate the effect of abnormal events, modeling the market's returns and calculating if these are impacted by the natural disasters included in the form of exogenous explanatory dummy variables. One issue that can arise from simply using an ARMA model is that this model assumes that the conditional volatility is constant over time, which is typically not the case when dealing with high-frequency financial data. Therefore, there are also many examples of studies that use the same approach but with different models that can capture the possible changing volatility. A later, very influential paper from one of the same authors, Worthington, expands on his earlier research by applying an ARCH-type model to capture the time-varying volatility observed in the returns by modeling the variance as a function of past squared error terms, in turn capturing the changing of the variance. The authors employ a GARCH-M model due to the GARCH model being able to measure both long and short-term memory in returns, as well as being better suited to capture volatility clustering, where "large changes in returns are often followed by other large changes, and small changes in returns are often followed by yet more small changes" (Worthington, 2008). There are various examples in the literature of studies that use the second approach defined by Ferreira & Karali (2015) by building on the research done by these two papers, namely, the paper "The Impact of Natural Disasters on Stock Markets: Evidence from Japan and the US", which also uses a GARCH model, where Wang & Kutan (2013) test TGARCH and EGARCH specifications, both of which incorporate an asymmetric term into the variance equation of the models, allowing negative shocks (bad news) and positive shocks (good news) to have different impacts on volatility (Enders, 2008), with the authors having selected an EGARCH(1,1) model for the study. This paper also builds upon the work that came before in two major ways: first by including control variables, that are absent in previous studies, such as the exchange rate and the interest rate, and second by choosing to also analyze the impact of the natural disasters in the variance equation of the model, as opposed to only introducing these dummy variables in the mean equation, to measure what the authors define as the "risk effect" (Wang & Kutan, 2013). Another example is the paper "The impact of natural disasters on the stock returns and volatilities of local firms", which, just like the study by Wang & Kutan (2013), also uses an EGARCH model, but the authors combine this model with the intervention analysis framework from (Worthington, 2008) by adding autoregressive and moving average terms to the mean equation of the model, resulting in an ARMA-EGARCH specification (Bourdeau-Brien & Kryzanowski, 2017).

Regarding the main empirical findings in the literature, grouping the papers by the region of the study, it is possible to see that it is not easy to find a consensus on if extreme weather-related events have an impact on stock markets and what that impact is, particularly since the types of events studied vary a great deal across the literature.

In the case of Australia, both Worthington & Valadkhani (2004) and Worthington (2008), which are quite similar papers, use the Australian Stock Exchange (ASX) All Ordinaries index (AOI), a market-weighted index, and also the same natural disasters database in order to construct their extreme climate events dummy variables, the Emergency Management Australia (EMA), which identifies five categories of events: severe storms, floods, tropical cyclones, wildfires, and earthquakes. The studies were also conducted over nearly identical periods, specifically from 1982 to 2002 and from 1980 to 2003, respectively. However, the findings from the two papers are, in some respects, contradictory. In the first paper, Worthington and Valadkhani (2004) find that bushfires have a statistically significant positive effect on market returns, cyclones negatively affect the market, and earthquakes, although having a mixed impact, negative at first but positive five days after the event, are also statistically found to be significant, which contrasts to the findings in the second paper, where the authors, by using a GARCH model, find that "natural events and disasters in Australia exert no systematic influence on market returns." (Worthington, 2008). The differences in results might be due to using different models, as a cross-country paper by Ferreira & Karali (2015), mentioned before, that focuses solely on the impact of major worldwide earthquakes, domestic or otherwise, in the stock markets of 35 countries, also uses a GARCH model, unlike Worthington and Valadkhani (2004), and finds that major earthquakes have no impact on the Australian Stock Market.

A substantial body of research on the impact of extreme climate events on financial markets has focused on the United States of America, notably, these studies often differ in how the authors define and represent extreme climate events. Most authors study the impact of natural disasters, but within the category of natural disasters, there is still a divergence in what disasters the authors consider. Wang & Kutan (2013) use a natural disasters dataset provided by The National Geophysical Data Center that has records of three kinds of natural disasters: earthquakes, tsunamis, and volcano eruptions. Bourdeau-Brien & Kryzanowski (2017) use two different natural disaster databases, one from The Federal Emergency Management Agency and another from the National Climatic Data Center, combining them and ending up with five natural disaster sub-categories, all different from the previous paper; these are storms, floods, extreme temperature, winter weather, and fires. Another, less common way to represent natural disasters is through a textual factor, with Faccini et al. (2023) using a natural disasters textual factor that reflects global news about natural disasters, such as extreme weather, rainfall, drought, wildfires, and extreme pollution, to measure if climate risks are reflected in stock prices, with this textual factor capturing the investors' concerns that the frequency of global natural disasters may indicate worsening climate conditions, potentially leading to more frequent and disruptive events in the U.S.. This method was popularized by Engle et al. (2020), where the authors conducted a textual analysis of newspapers based on climate change news as a way to hedge climate change risk. Some authors consider variables other than natural disasters. For example, Griffin et al. (2019) study only extreme temperatures, mainly focusing on extreme high surface temperatures (EHST) and, to a smaller extent, extreme cold events, and Lanfear et al. (2019) use landfall hurricanes as their variables for extreme weather events.

In contrast to the earlier studies on the Australian stock market, the research focusing on the United States analyzes more recent periods, with all the mentioned studies using a sample period that ends after 2010, and only Wang & Kutan (2013) having a period of analysis that starts before 1990.

Concerning the conclusions reached with respect to the impact of extreme climate events on the U.S. market's returns, certain authors find specific types of events to be statistically significant. Wang & Kutan (2013) center their research on the impacts of these events on both Japanese and the U.S. stock markets, particularly on their composite markets, represented, respectively by the Nikkei 225 and S&P 500, and insurance sectors, represented by the Japan TOPIX Insurance Index and the S&P 500 Insurance Composite. Using an EGARCH model, they find that there is a significant negative impact of volcanic eruptions in insurance stocks three trading days after the start of the volcanic eruption, more concretely, a 0,76% daily drop in stock returns. Using the CAPM model on portfolios of NYSE, NYSE MKT, and NASDAQ stocks, Lanfear et al. (2019) find that hurricanes have a "substantial negative impact on the stock market". Griffin et al. (2019) analyze the effect of the extreme high surface temperature events by matching the firms' locations with the location of the events and then calculating the abnormal returns over a period counting from the day of the event until 20 days after. Using the first approach described in this literature review, the authors also find a negative effect of the events on the firms' returns, as the cumulative mean excess return reacts negatively to EHST events. It is worth noting that while most studies cover a sample period of at least 20 years, Griffin et al. (2019) utilize a shorter period, spanning from 2003 to 2017. Moreover, Bourdeau-Brien & Kryzanowski (2017), who measure the impact on U.S. firms' returns by grouping the firms at the state level and using an ARMA-EGARCH model, also find that some of the natural disasters have a significant impact on some states, namely storms are significant in three out of 21 states, floods are significant in three out of nine, and extreme temperatures in only one state, though the authors struggle to identify the effects of the events, as in some states the effect is positive and in other negative. Nevertheless, some findings indicate that there is no effect of extreme climate events on the markets' returns. Wang & Kutan (2013) find that neither tsunamis, volcano eruptions, nor earthquakes have any effect on the U.S. composite stock returns, reaching the same conclusion as Ferreira & Karali (2015), who, in their study on the impact of earthquakes in stock markets, found that that "financial markets are resilient to earthquake shocks". Griffin et al. (2019) conclude that extremely cold events have no impact on returns, and finally, Faccini et al. (2023), through their textual analysis on all U.S. common stocks traded at NYSE, NYSE MKT and NASDAQ, reports that the natural disasters are statistically insignificant.

Regarding the impact on return volatility, there is less literature available, as most studies primarily focus on the effects of extreme climate-related events only on returns. However, among the papers that do examine the impact of extreme weather-related events on the volatility of the financial returns in the US, the findings tend to align more closely, with authors generally finding either no impact on financial return volatility or, when a statistically significant effect is observed, it is a positive impact, indicating an increase in the market's volatility following the extreme weather-related events. Wang & Kutan (2013) find a significant increase in volatility of the composite stock market's returns only after tropical cyclones and in the insurance sector's volatility following volcanic eruptions. Bourdeau-Brien & Kryzanowski (2017) find more conclusive results stating that "conditional volatility clearly increases following hurricanes, floods, episodes of extreme temperature and severe winter weather." (Bourdeau-Brien & Kryzanowski, 2017).

With respect to studies focusing on countries other than Australia and the US, the findings also echo these mixed results for the impact on the returns and more consensual findings for the impact on volatility. Some authors also conclude that specific extreme events, such as floods, wildfires, tornados, hurricanes, storms, tsunamis, and extreme temperatures, have a significant effect on the financial markets under study. U-Din et al. (2022) study the impact of various extreme climate events on the Canadian stock market, measured by the TSX Composite, for the period between 1988 and 2016. The authors find both positive impacts, resulting from fires, and negative impacts, from hurricanes, storms, and tornados, on the Canadian stock market's returns, as well as increases in its volatility. Robinson & Bangwayo-Skeete (2016), in their study on the influence of hurricanes and tropical storms on Caribbean stock markets, determine a negative impact on the returns, but only in Jamaica (the authors also tested for impacts in the Bahamas and Eastern Caribbean), and Kang et al. (2010) conclude that extreme weather (extremely low and extremely high temperatures) influences the returns and volatility of the Shanghai stock market. While for Wang & Kutan (2013) there is a positive impact of tropical cyclones on the Japanese insurance sector, but no statistically significant impact on the Japanese stock market's returns volatility, for Galido & Khanser (2013) the events have an insignificant effect on the market returns in Japan and the Philippines, respectively. Ferreira & Karali (2015), despite arriving at the same conclusion as Wang & Kutan (2013) regarding the market's returns, report increased volatility in the Japanese market due to earthquakes.

Apart from Wang & Kutan (2013), who focus part of their research on the insurance sectors, a limited number of studies measure the effects of extreme climate events specifically on the various sectors that make up the economy, as opposed to the entirety of the financial market. U-Din et al. (2022) find that "the highest effect of extreme weather events is observed in the information technology sector, which lost about 65% of returns during the event period.". Antoniuk & Leirvik (2024), who focus part of their study on climate change events in the impact of the Fukushima nuclear accident on ETFs representing different sectors, determine that the event positively affected fossil fuels and clean energy stocks, and had a negative impact on the energy-intensive and utilities sectors. Finally, Sun et al. (2020) conduct a study on the impact of several climate risk indexes on the mining sector in China and find that the financial performance of this sector is very sensitive to these types of risks, having both positive and negative effects on the companies assessed.

Noticeably, research conducted for Portugal about the climate risks on the Portuguese stock market, specifically extreme climate-related events, is very limited. Ferreira & Karali (2015), discussed before, conducted their event study for thirty-five countries, one of them Portugal, and, regarding the country, the authors find that while the major worldwide earthquakes included in the study (none of which occurred in Portugal) have no effects on financial returns in Portugal, the variable representing the number of deaths caused by the earthquakes is statistically significant, having a negative effect on the financial returns.

Outside of the literature on extreme climate events, Zanatto et al. (2023) attempt to measure climate risk on the Portuguese stock market through a news index, similar to the method applied by Faccini et al. (2023), but instead of building the index based on news reflecting natural disasters such as extreme weather, rainfall, drought, wildfires, and extreme pollution, the authors create a news index based on Environmental, social, and governance (ESG) news, therefore capturing not only news related to environmental issues, but also social and governance issues. There is also evidence of research on the effect of weather variables on the Portuguese stock market, as Silva & Almeida (2011) investigate the relationship between weather variables and the Portuguese stock market index between 2000 and 2009, though the focus of the study is not on extreme weather, but rather on “good” and “bad” weather days. The authors divide each weather variable into three bins each, according to their distribution, creating, for example, for the variable of temperature, a bin with low temperatures, another with “medium” temperatures, and one with high temperatures, then measuring the effect of each of these bins on the market’s returns through an OLS regression. This is a fundamentally different study as it does not focus solely on extreme values in the sample or transforms the values based on their seasonality. Additionally, the authors use an OLS regression, instead of a GARCH-type model.

In conclusion, from this analysis, it is possible to state that the literature reveals mixed findings regarding the impact of extreme events on financial markets, with more consistent findings regarding volatility, as most authors find either no impact or increased volatility in the returns due to the extreme weather-related events, but mixed results regarding the financial markets returns. Some authors report a negative impact, others find positive effects, and many observe no significant effect, suggesting that the financial impact of these events may vary significantly depending on factors such as the type of event, location, the sector investigated, and the methodology adopted. As for methodologies, event study methodologies are the most widely used, with authors choosing between two main ways of calculating the abnormal returns associated with the events, each having their strengths and limitations. Another point of divergence in the literature is the choice of variables representing extreme climate-related events. While most authors focus solely on natural disasters, some extend their analyses to include extreme temperatures. Concerning the Portuguese context, it becomes clear that there is a significant gap in research on the impact of extreme climate events on the stock market, which, combined with the mixed results from other studies across the literature, changing in part based on the location of the market analyzed, highlights the need for localized research for Portugal in order to better understand the unique risks and vulnerabilities that can be associated with the country and provide valuable insights into how extreme weather-related events specifically impact the Portuguese stock market.

CHAPTER 3

Methodology and Data

The methodology and data employed in the study are outlined in this section. Initially, the event-study approach taken is defined, and the several models tested in the analysis are explained. Then, a comprehensive account of all utilized data is provided, including the transformations made to each variable and their descriptive statistics.

3.1. Event-study methodology

An event study is conducted for the empirical analysis, which, as discussed in the literature review, can be approached in two main ways. The first approach measures abnormal returns by calculating the difference between the observed returns and the expected returns forecasted by a model such as the Capital Asset Pricing Model. The second approach instead models the returns as a function of explanatory variables, introducing the extreme events as dummy variables, with the impact of these events determined by their coefficients (Ferreira & Karali, 2015). This research employs the latter approach due to many different factors. First, it makes it possible to conduct a more detailed analysis by allowing the inclusion of different types of extreme climate as dummy variables, thus providing a direct measure of the impact associated with each type of climate-related event. It also enables the study of this impact during the whole sample period, as, by using a single dummy variable for each event type, equaling one for all the periods during which the event type occurs, the coefficient of this dummy variable represents the average abnormal return across all event periods, all the rest in the model remaining constant. Additionally, this approach allows for the testing of delayed effects of the events by including lagged dummy variables in the model, as well as enabling the measurement of event impacts not only on financial returns but also on the volatility of those returns by using GARCH-type models.

The event study methodology employs various Generalized Autoregressive Conditional Heteroskedasticity (GARCH) based models. GARCH models are statistical models typically used to analyze and predict financial time series data, especially the volatility (or conditional variance) of returns over time, which allows for time-varying volatility, making them particularly well suited for modeling high-frequency financial data due to the variance of this type of data usually not being constant over time, therefore exhibiting ARCH effects. In this case, this data corresponds to daily stock market returns. The GARCH model was first developed by Bollerslev (1986), who, by introducing a more flexible structure for modeling volatility that incorporates not only past squared error terms but also past conditional variances, built on the work of Engle (1982) that established the ARCH model. The addition of the past conditional variances allows the model to capture all previous shocks, quantifying “both long and short-term memory in returns” (Worthington, 2008), in turn capturing an essential characteristic of asset returns: volatility clustering, where significant variations in returns tend to be followed by other large variations, and small changes are similarly followed by minor changes, such that a volatility shock today can affect expectations of volatility far into the future (Worthington, 2008).

With regards to the selection of the type of GARCH model, various options are presented in the literature, as different authors choose to focus on different models, with no clear consensus on what the most well-suited model for this form of analysis is, as the choice often also depends on the specific data being analyzed. Consequently, this study tests a range of GARCH-based models, including a standard GARCH, a GARCH-M, a TGARCH, and an EGARCH.

The standard GARCH model, previously defined, can be considered the simplest, as all other models include the terms present in the GARCH specification with additional components. Nonetheless, this model may offer the most suitable specification for our data, as some authors, such as Ferreira & Karali (2015) found in their studies.

The GARCH-M (GARCH-in-Mean) is a variant of the standard GARCH model that incorporates the conditional variance in the mean equation, thus being better at capturing the relationship between expected returns and their volatility when this relationship is present (Engle et al., 1987). Examples of the use of this model are the foundational paper by Worthington (2008) and Galido & Khanser (2013).

Finally, the TGARCH and EGARCH models both build on the GARCH structure by adding an asymmetric term to the volatility equation, which tests if good news and bad news (negative and positive returns shocks, respectively) have different effects on volatility (Enders, 2008), in turn capturing the leverage effect, a common and well-documented phenomenon in financial time series where a price drop tends to increase volatility more than a comparable price increase does (Bollerslev et al., 2006; Engle & Ng, 1993; Wu & Xiao, 2002). The main difference between the two models is that, unlike the TGARCH, the EGARCH uses an exponential function to model the conditional variance (Lim & Sek, 2013). The EGARCH model is the most widely used in similar studies across the literature (Bourdeau-Brien & Kryzanowski, 2017; U-Din et al., 2022; Wang & Kutan, 2013), and Wang & Kutan (2013) also consider using the TGARCH model, though the authors find the EGARCH better suited to their data.

Following Bourdeau-Brien & Kryzanowski (2017), the GARCH-based models are combined with the ARMA models used by Worthington & Valadkhani (2004) for the authors' intervention analysis framework. Including the autoregressive and moving average terms to the mean equation of the GARCH models can improve the performance of the models and provide a more accurate representation of the underlying data by capturing both serial correlations, where past errors influence future values, and mean reversions, where the series tends to return to its average level (Bourdeau-Brien & Kryzanowski, 2017).

The remaining variables incorporated into the models consist of two sets, described comprehensively in the subchapter ahead. A set of control variables, containing several variables considered important determinants of stock market returns, is included in the mean equation of the models, helping to isolate the effect of the extreme climate-related event variables, which is the focus of this study. The second set of variables are the dummy variables themselves, constructed to represent extreme climate-related events, which take the value of one during the period when the events happened and zero otherwise. The events are classified into two primary categories: natural disasters and extreme weather anomalies, with each category further subdivided into specific event types, detailed in the following section. Unlike the control variables, the dummy variables are incorporated into both models' mean and variance equations, as this study aims to examine the impact of extreme climate-related events on both stock market returns and volatility. Furthermore, the first lag of each dummy variable is also included in the models, to capture possible delayed or dynamic effects of the extreme events on the returns and the volatility[2].

To estimate the GARCH-type models, the Maximum Likelihood Estimation (MLE) was used, with different error distributions being considered to account for potential heavy tails and skewness in the stock market returns. The Akaike Information Criterion (AIC) was used to select the error distribution, as well as the optimal specification for the final models, due to its ability to balance goodness of fit and model complexity, penalizing models with more parameters as a way to avoid overfitting (Sakamoto et al., 1986).

[2] The addition of further lags in the models was tested, however, the ML estimator fails to converge to a solution.

The equations for both the mean and the volatility equations of the final chosen models are presented in the Results and Discussion chapter.

3.2. Data

3.2.1. Stock returns

Daily returns of the Portuguese Stock Market Index from January 2000 to December 2023 are used as the dependent variable in the models. The PSI is the benchmark stock market index that tracks the performance of the largest companies traded on Euronext Lisbon, serving as the most widely referenced indicator of the Portuguese stock market (Euronext, 2024). The PSI dates back to December 31, 1992, then named PSI-20, and was created to track the twenty largest companies traded on Euronext Lisbon. In 2022, the index slightly changed its methodology and name, no longer focusing on the top twenty companies but instead tracking those with a market capitalization of over 100 million euros (Leonor Mateus Ferreira, 2021). The data for the daily closing prices of the PSI was sourced from the Bloomberg terminal, and daily percentage changes in the PSI were calculated to represent daily returns.

3.2.2. Extreme climate-related events

To capture extreme climate-related events, two distinct datasets are employed to create separate measures of events. The first dataset represents natural disasters, while the second focuses on extreme weather anomalies.

3.2.2.1. Natural Disasters

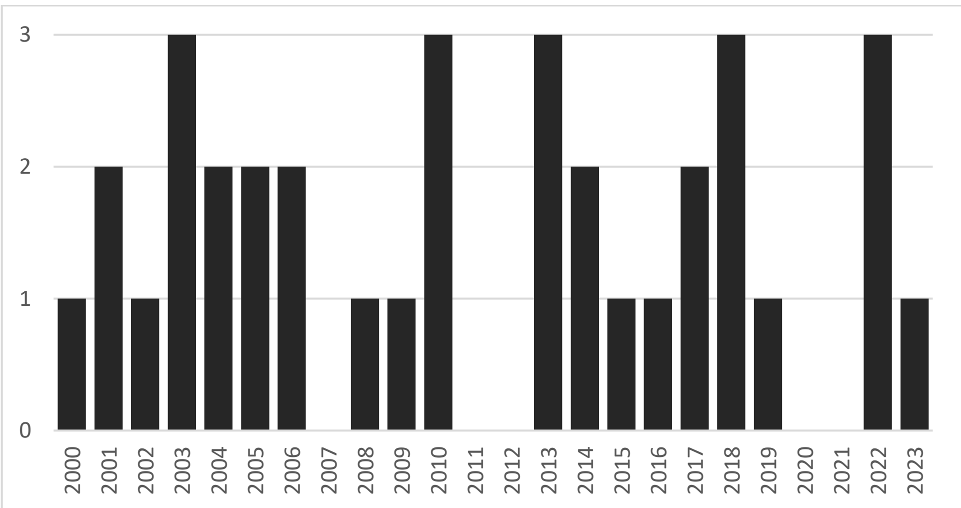
The natural disasters were obtained through the Emergency Events Database (EM-DAT), a popular database that has been utilized in similar studies, including Pagnottoni et al. (2022) and Galido & Khanser (2013). The Emergency Events Database (EM-DAT) was created in 1988 by the Centre for Research on the Epidemiology of Disasters (CRED), with the support of the World Health Organization (WHO) and the Belgian Government. Since 1990, the Bureau for Humanitarian Assistance has provided support for the database (CRED, 2023). The database tracks disasters and their human and economic impacts at the country level, categorized by hazard type. It defines disasters as events involving unexpected and significantly detrimental effects on individuals (Delforge et al., 2023), and records both natural hazard-triggered disasters and technological disasters. The human impact is measured through the following variables: the total number of fatalities associated with the disaster plus the number of people whose whereabouts since the disaster are unknown and so they are presumed dead, the number of people injured as a result of the disaster, the number of affected people (through impacts on their houses for example), the number of homeless, calculated via the number of houses that the events have completely destroyed, and finally the total number of affected people. As for the economic impact variables, there are three main statistics, these are: reconstruction costs, associated with both the purchasing costs of destroyed goods and mitigation costs intended to minimize future disaster damage; the insured damage, reported by insurance companies; and the total damages (Delforge et al., 2023).

For this study, only natural disasters are considered. The EM-DAT categorizes these into six main subgroups: biological disasters, climatological disasters, extraterrestrial disasters, which involve impacts on the planet, geophysical disasters such as earthquakes and volcanic activity, hydrological disasters, and, finally, meteorological disasters.

According to Delforge et al. (2023), data for events before the year 2000 is particularly subject to reporting bias, therefore, this study only includes data starting from the year 2000.

From the start of the year 2000 until the end of 2023, 35 natural disasters attributed to Portugal were recorded in the database, 13 of which were climatological disasters, specifically 11 wildfires and 2 droughts. 7 are classified as hydrological disasters, all associated with floods, and 15 are meteorological disasters, represented by 8 storms and 7 extreme temperature events, with the latter being defined as a period of abnormally hot/cold weather that typically lasts two or more days. Figure 3.1 shows the distribution of the events over time.

Figure 3.1: Number of Natural Disasters in Portugal per year



These events are transformed into dummy variables for each event type, in which, for the days inside each event window, the dummy variable takes the value of 1, and everywhere else, it assumes the value of 0. The event windows are defined by the start and end dates provided by the database for each event. Though not every event has an identified starting or ending date, more specifically, there are some events for which the database only reports the starting and ending months, and one event with only its ending year reported. To account for these limitations, the following criteria were established. For events where only the start and end months are provided, the entire period between the first day of the starting month and the last day of the ending month was considered as the event window, with the dummy assuming a value of 1. Also, when a disaster begins or ends on a non-trading day, for example, during the weekend, as is likely to happen, those dates are attributed to the next available trading day after the disaster. Finally, events that lasted for more than half a year were excluded from the sample, as the presence of highly prolonged events could difficult the isolation of the impact of that specific event type on the stock market, especially since the analysis is conducted for daily data. This resulted in the exclusion of three events, namely two droughts and one wildfire. Due to the low number of events registered for Portugal, a combined natural disasters dummy variable has also been created, aggregating the events across all event types.

3.2.2.2. Extreme Weather Anomalies

Extreme weather anomaly (EWA) dummy variables are introduced to enhance the analysis by providing an additional method for measuring extreme weather events, distinct from the methodology used by the natural disasters database. For this, two meteorological variables were selected. The first is temperature, which allows the identification of events related to extremely high and low-temperature anomalies, as is done by Griffin et al. (2019), and it adds temperature-related measures different from the records of extreme temperature events from the EM-DAT, which according to Delforge et al. (2023) may be prone to missing some extreme weather events, due to the thresholds defined by the database for what is considered a natural disaster, leaving events considered by the database as “lower-impact events” unaccounted for. The second variable is precipitation, which allows the identification of extreme precipitation anomalies, complementing the data from the natural disasters database by adding another measure related to heavy rainfall, apart from the limited number of floods registered by the EM-DAT, providing a higher representation of heavy rainfall in the sample.

The IPMA (Instituto Português do Mar e da Atmosfera) supplied the data for the creation of these dummy variables, providing daily values for maximum and minimum temperatures and precipitation for both Lisbon and Porto. The two cities were chosen due to their geographical and economic importance, as these are the two largest cities in Portugal and serve as major economic centers, as well as the fact that their weather data is more readily available.

From the raw data, daily average temperatures are calculated by taking a simple average of the maximum and minimum daily temperatures for each city, which are combined to obtain a single daily temperature value. The exact same process is applied to estimate the daily precipitation values. After calculating the daily average temperature and precipitation, to remove the seasonal factor, these are converted into daily anomalies. For this, as is done by the IPMA for its measurement of monthly temperature and precipitation anomalies, the daily values are compared against the average monthly values for the period between 1971 and 2000 by subtracting from the daily values this historical mean of their corresponding month. Anomalies are used instead of absolute daily weather values because anomalies allow for the control of seasonality, accounting for the expected seasonal variations in temperature and precipitation throughout the year. Finally, to study only the effect of extreme values on the stock markets' returns and volatility, as is done by Kang et al. (2010), the daily anomalies are transformed into dummy variables, each representing extremely high or low-temperature/precipitation anomalies. The dummy variables are generated according to the following criteria:

- Extremely High-Temperature Anomalies (EHTA):

$$EHTA_t = 1 \text{ if } Temp.Anom_t > Avg.Temp.Anom + 2 \cdot s.d., \ else\ EHTA_t = 0 \quad (1)$$

- Extremely Low-Temperature Anomalies (ELTA):

$$ELTA_t = 1 \text{ if } Temp.Anom_t < Avg.Temp.Anom - 2 \cdot s.d., \text{ else } ELTA_t = 0 \quad (2)$$

- Extremely High-Precipitation Anomalies (EHPA):

$$EHPA_t = 1 \text{ if } Prec.Anom_t > Avg.Prec.Anom + 2 \cdot s.d., \text{ else } EHPA_t = 0 \quad (3)$$

- Extremely Low-Precipitation Anomalies (ELPA):

$$ELPA_t = 1 \text{ if } Prec.Anom_t < Avg.Prec.Anom - 2 \cdot s.d., \text{ else } ELPA_t = 0 \quad (4)$$

So, the dummy variables take the value of 1 in two scenarios. First, when the extreme weather anomaly is greater than the average weather anomaly plus 2 standard deviations ($s.d.$)[3] of the distribution of weather anomalies, representing an extremely high weather anomaly. And second, in the cases where the extreme weather anomaly is less than the average weather anomaly minus 2 standard deviations, corresponding to extremely low weather anomalies.

[3] The standard deviation measures of dispersion of the values of a variable relative to its mean.

3.2.3. Control variables

Adding control variables to the models is essential, as these account for other factors that might influence the dependent variable, other than the extreme climate-related events, thereby helping to isolate the specific impact of the main variables of interest of this study on the financial returns and volatility, as well as increasing the explanatory power of the models.

Not every author chooses to include control variables in their analyses, in fact, many studies do not, as is the case with Ferreira & Karali (2015), Worthington & Valadkhani (2004), and Bourdeau-Brien & Kryzanowski (2017), for example. Focusing on the studies that include control variables, both Wang & Kutan (2013) and U-Din et al. (2022) introduce controls as independent variables into their models in the form of interest rates and exchange rates, as the authors consider these to be "two major determinants of the stock exchange performance" (U-Din et al., 2022). Thus, these two variables are included in this study. The EUR-USD exchange rate represents the exchange rate variable, and the interest rates are represented by two variables. The first one is government bonds, captured through the Portugal 10-Year Government Bond Yield, as 10-year government bond yields have been widely associated with stock market returns (Alam & Uddin, 2009a; Al-Sharkas, 2004; Kvietkauskienė & Plakys, 2017), though the studies show mixed results on whether the impact is positive or negative. The other interest rate variable is the 3-month EURIBOR rate, which captures the effects of a shorter-term interest rate.

Outside of the literature on the impact of extreme climate-related events on financial markets, there is extensive literature on the determinants of stock market returns, with authors focusing on several variables. For this study, to complement the two control variables mentioned before, only variables with a daily frequency were considered as possible control variables, as this ensures that the control variables match the frequency of the dependent variable, avoiding data interpolation issues that can arise when transforming lower-frequency data, into a different, higher frequency. This led to the exclusion of some variables shown in the literature to impact financial returns, such as GDP (Çagli et al., 2010; Osisanwo & Atanda, 2012) and unemployment rates (Boyd et al., 2005; Pilinkus, 2010), for which the highest frequencies available are quarterly and monthly, respectively.

Thus, two more control variables are added to the models, besides the interest rate and exchange rates variables. Oil prices, represented by Brent Crude Oil futures, are added as a commodity market indicator, as according to Gasparėnienė et al. (2021), oil prices are "the most influential factors on the stock market" among commodity market indicators. And gold prices, measured by the gold spot rate, which are found by Mota et al. (2023), in their study of the impact of macroeconomic factors, specifically on the Portuguese stock market, to have a negative effect on the PSI. The authors also find that both the EUR-USD exchange rate and oil prices impact the Portuguese financial market, impacting it negatively and positively, respectively. All the data for the control variables was extracted from the Bloomberg terminal, apart from the Portugal 10-Year Government Bond Yield, which was obtained from the global financial portal Investing.com.

3.3. Descriptive statistics

Building the dataset for the models involved combining all variables according to the PSI dates. This process led to a few days (less than 0.7% of the sample size) with missing values for some control variables. To address this issue, values from the previous day in the sample were assigned to the current day(s) with missing observations, avoiding removing those days from the sample.

The Augmented Dickey-Fuller (ADF) test, which determines whether a time series has a unit root, indicating non-stationarity (Banerjee et al., 1993), was applied to the variables. This test uses a regression that incorporates a constant and a linear trend. To avoid the presence of non-stationarity in the variables, confirmed by the results of the ADF test, shown in Table 3.1, the variables were transformed accordingly. Percentage variations were calculated for the oil and gold prices, as well as for the EUR-USD exchange rate. Even though the interest rates and government bonds represent a rate of return, the results of the ADF test still indicate that they are not stationary. Consequently, their first differences were taken. After these transformations, all the variables used are stationary, as indicated by the results of the ADF test in Table A.1 in Appendix A.

Table 3.1: Stationarity tests before variable transformations

Variable	ADF Stat.	ADF p-value
PSI	-2,57	0,34
EURIBOR	-0,07	0,99
Oil	-2,32	0,44
Gold	-2,10	0,54
EURUSD	-2,03	0,56
PT10A	-1,45	0,81

The final sample used in this study contains daily data from January 2000 to December 2023, which after applying these transformations, includes 6.119 observations.

Table 3.2 presents the descriptive statistics for the dependent and control variables added to the models. Most variables have a mean very close to zero, with only oil and gold price variations having a more significant positive mean, suggesting a slight upward trend in the oil and gold prices. Oil price variations have the highest standard deviation, with a value of over 2, indicating significant oil price fluctuations, also evidenced by the high maximum and low minimum values of over 20% in absolute terms. In contrast, the first differences of the EURIBOR rates and government bonds have the lowest volatility, with values closer to 0 (0,015 for the EURIBOR), reflecting relatively stable 3-month EURIBOR rates and government bond yields over the sample period. A strong negative skewness exists for the interest rate, indicating that significant drops in the 3-month EURIBOR rate are more common than rises. Other variables, namely the PSI stock market returns, oil price variations, and government bonds, also display negative skewness, though with much lower values, around -0,2. As for the kurtosis of the variables, the 3-month EURIBOR rates and government bond yields exhibit by far the highest values, indicating that there are periods when these variables undergo substantial variations, having heavy tails compared to the normal distribution. Finally, the Jarque-Bera test result for stock market returns shows a p-value of 0, meaning that the null hypothesis of normality is rejected, indicating that the variable does not follow a normal distribution, which is common for financial data.

Table 3.2: Descriptive Statistics

Variable	**Mean**	**Max**	**Min**	**Std. Dev.**	**Skewness**	**Kurtosis**	**JB p-value**
PSI	-0,003	10,734	-9,859	1,166	-0,242	9,92	0
EURIBOR	0,000	0,159	-0,358	0,015	-2,628	84,16	0
Oil	0,049	21,019	-24,404	2,268	-0,244	11,89	0
Gold	0,036	9,291	-8,571	0,999	0,109	10,06	0
EURUSD	0,003	3,511	-2,490	0,595	0,100	4,66	0
PT10A	0,000	6,142	-6,470	0,264	-0,282	375,87	0

Table 3.3 presents the percentage of days in the sample where the dummy variables take the value of one for each of the extreme weather anomalies (EWA) and natural disasters event types, as well as their aggregated variables. Analyzing the aggregated variables, EWA has the highest percentage of ones, with 10,770%. In comparison, the aggregated variable for natural disasters has 6,390%, or 391 days of the 6.119 days of the sample pertaining to a natural disaster. These percentages are lower than the sum of the percentages for each event type, as there are days when multiple types of events occur. Regarding the disaggregated variables, it is

possible to see how each type of event is represented in the aggregated categories. For the extreme weather anomaly variables, the methodology used to create these variables results in 5,2% extremely high-temperature anomalies (EHTA), 0,6% extremely low-temperature anomalies (ELTA), 5% extremely high-precipitation anomalies (EHPA), and 0% extremely low-precipitation anomalies (ELPA), as there are 0 extremely low-precipitation anomaly events. This is to be expected due to the nature of the data for the daily precipitation, which is characterized by a large concentration of days with no precipitation and a few with much precipitation, resulting in a distribution of anomalies that has a mean close to zero, with very high positive anomalies, associated with heavy-rainfall days (see Figure A.1 in Appendix B) Because of this, the ELPA variable is excluded from the study. As for the ELTA, with only 0,6% of occurrences, it has very low variability, which can make it hard for the models to discern any meaningful pattern or relationship between this dummy variable and the dependent variable. Nonetheless, the impact of this variable is tested in this study. As for the natural disasters, extreme temperatures have the highest percentage, 3,60%, followed by wildfires with 2,76%, with a significant drop off in representation of storms and floods in the sample, with a percentage of ones of 0,23% and 0,41% each, which show the same low-variability present in the ELTA, illustrating the need to combine the four variables into the aggregated one, so that the natural disasters have a higher representation, while still including all types of disasters in the analysis.

Table 3.3: Percentages of ones for each dummy variable

Variable	Percentage of ones
EHTA	5,164
ELTA	0,605
EHPA	5,034
ELTA	0,00
EWA	10,770
Natural Disasters	6,390
Extreme temperatures	3,595
Storms	0,229
Floods	0,409
Wildfires	2,762

From the Correlation Matrix (%) below, the highest Pearson correlation values are, as expected, between the disaggregated dummy variables and their corresponding aggregated variable, more significant for the ones with the highest representation in the aggregated variable. This is evidenced in the extreme weather anomalies dummies by the 67% Pearson correlation between EHTA and EWA, and 66% between EHPA and EWA, as well as in the natural disasters dummies by the 74% and 65% between extreme temperatures and natural disasters and between wildfires and natural disasters, respectively. Consequently, to avoid the issue of multicollinearity, the study divides the aggregated and disaggregated dummies into separate models. One model includes the extreme weather anomalies and the natural disasters dummies, and another the EHTA, ELTA, and EHPA, plus the four types of natural disasters dummies: extreme temperatures, storms, floods, and wildfires. Noticeably, both the extreme temperature anomalies and extreme precipitation anomalies have a low correlation between themselves and the extreme temperature and the floods natural disasters, respectively.

Table 3.4: Correlation Matrix (%)

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1. PSI	-													
2. EURIBOR	-1	-												
3. Oil	24	3	-											
4. Gold	-4	1	12	-										
5. EURUSD	10	-3	14	-18	-									
6. PT10A	-7	0	-1	0	-2	-								
7. EHTA	0	1	0	-1	0	0	-							
8. ELTA	3	-2	1	0	-2	-1	-2	-						
9. EHPA	-1	-1	1	0	0	2	-5	0	-					
10. EWA	0	0	1	-1	0	1	67	22	66	-				
11. Natural Disasters	1	-1	1	2	-2	0	7	2	1	6	-			
12. Extreme Temp.	0	2	1	1	-3	0	8	4	-2	5	74	-		
13. Storms	3	-1	0	1	1	-1	-1	0	8	5	18	-1	-	
14. Floods	1	1	1	0	1	0	0	0	6	4	25	-1	0	-
15. Wildfires	0	-4	1	1	0	0	6	-1	-2	3	65	22	-1	-1

CHAPTER 4

Results and Discussion

4.1. Model Specification

The following steps are taken to ensure the correct model specification. Firstly, to have a baseline configuration of the models that can be used to test which GARCH-type model fits the data the best, the ARMA terms that will be added to the mean equation of the models are defined, then the ARCH (p) and GARCH (q) terms are identified, and finally the distribution of the error terms of the model is identified. After this, the GARCH-type models are compared, and the best one is chosen for the analysis.

4.1.1. ARMA and GARCH terms

To select the number of AR and MA terms that will be included in the final model, several autoregressive and moving average models were constructed for the PSI returns, without any covariates. The complete results for each model can be found in Table A.2-A.6 in Appendix B.

Firstly, an AR (1) model was estimated, showing the AR term to be statistically significant. Then, an AR (2) model was tested, but only the first AR term remained significant. A similar process was applied to the moving average terms, yielding the same conclusions. Since both AR (1) and MA (1) indicate the statistical significance of their respective terms, an ARMA (1,1) model was tested. However, in this model, both terms became statistically insignificant. Thus, to decide which term to include in the GARCH models, the information criteria of the models, namely the AIC, were compared, and the AR (1) model, with the lowest AIC, was selected. Consequently, one autoregressive term was incorporated into the mean equation of the GARCH models.

The ARCH LM-test for the (squared) residuals of the AR (1) model also confirms the assumption that the PSI returns exhibit ARCH effects, presenting a p-value of under 2,20E-16, supporting the need to model these errors using a specification that can capture the ARCH-type effects.

With regards to the p and q terms, it has been shown in the literature that a simple GARCH (1,1) performs no worse than models with more p and q terms added to it, as Hansen & Lunde (2005), in their comparison of more than 300 ARCH-type models, found that "a model with $p = q = 2$ rarely performs better (out-of-sample) than the same model with fewer lags"

(Hansen & Lunde, 2005). Thus, a *p* and *q* of 1 for each is assumed for the GARCH-based models employed in this study.

4.1.2. Distribution of the Conditional Error Term

For the distribution of the errors of the models, the GARCH process by Bollerslev (1986) assumes a normal distribution, though, as shown before in the descriptive statistics, the PSI returns do not follow a normal distribution (JB p-value=0). Also, the returns exhibit a slight left skew of -0,242 and a considerable level of kurtosis of 9,92. Consequently, several distributions were tested against the normal distribution for the models' errors, namely a skewed normal distribution, a student's t and a skewed student's t distribution, a generalized error distribution, and a skewed generalized error distribution. To test which distribution fits the data the best, a GARCH (1,1) model was estimated for each with the respective distribution used for the errors of the model. Ultimately, skewed student's t distribution was chosen as its corresponding model presented the lowest AIC value, as seen in Table 4.1 below.

Table 4.1: AIC of each model

Distribution	**AIC**
Norm	2,84817
Snorm	2,84178
Std	2,81927
Sstd	2,81550
Sed	2,82165
Sged	2,81782

4.1.3. Selection of GARCH-type Model

Based on the results of the two previous sections, the four potential models, GARCH, GARCH-M, EGARCH, and TGARCH, are all tested with one AR term in the mean equation, (1,1) specification for the *p* and *q* terms, and with a skewed student's t distribution for the error term of the models. Besides these terms, the control variables identified in the methodology chapter and the dummy variables are included in the models. As the analysis will be divided into two parts, one focusing on the impact of the aggregated dummy variables, namely extreme weather anomalies and natural disasters, and the second part of the analysis focusing on the impact of each type inside of these, the four GARCH-type models are then tested and compared for each of the two analyses.

As before, the best specification was chosen based on its Akaike Information Criteria. As the results in Table 4.2 show, it is concluded that the EGARCH model best suits the data. This aligns with what has been found in the literature, as the EGARCH is the most used GARCH-type model in similar studies (Bourdeau-Brien & Kryzanowski, 2017; U-Din et al., 2022; Wang & Kutan, 2013). Hence, the AR(1)-EGARCH(1,1) model is selected for both aggregated and disaggregated cases.

Table 4.2: AIC of each model, by type of analysis

Model	**AIC**	
	Aggregated	*Disaggregated*
AR(1)-GARCH(1,1)	2,7918	2,7973
AR(1)-GARCH-M(1,1)	2,7921	2,7976
AR(1)-EGARCH(1,1)	2,7722	2,7758
AR(1)-TGARCH(1,1)	2,7752	2,7801

4.1.4. Model Characteristics

The results from the AR(1)-EGARCH(1,1) model, incorporating all control variables for both the aggregated and disaggregated dummy analysis, indicate that not all control variables are statistically significant (see Table A.7 and A.8 in Appendix C for the results of the aggregated and disaggregated models). Specifically, the EUR-USD exchange rate and the 3-month EURIBOR show p-values near one in both cases (0,94 and 0,93 for the EURIBOR in the aggregated and disaggregated models, respectively). Thus, these were first re-estimated without the EURIBOR variable, as it has the highest p-values, and then without both the EURIBOR and the exchange rate variables. As shown in Table 4.3 below, for both types of analysis, the models excluding only the EURIBOR variable yielded the lowest AIC. Consequently, the final models are the AR(1)-EGARCH(1,1) models without the 3-month EURIBOR variable, but still retaining an interest rate measure, specifically the Portugal 10-Year Government Bond Yield. As for the EUR-USD exchange rate variation, despite not being statistically significant (with p-values of 0,25 and 0,16 in the aggregated and disaggregated models, respectively), it belongs to the model with the smallest AIC and it has been included in other similar studies (U-Din et al., 2022; Wang & Kutan, 2013), and may, therefore, remain useful as a control variable in this analysis.

Table 4.3: EGARCH Model Comparison Based on AIC Values

Model	**AIC**	
	Aggregated	*Disaggregated*
AR(1)-EGARCH(1,1)	2,7722	2,7758
AR(1)-EGARCH(1,1), without EURIBOR	2,7719	2,7755

AR(1)-EGARCH(1,1), without EURIBOR and EURUSD	2,7720	2,7756

Hence, the final empirical models employed are formulated as follows:

$$R_t = \mu + \alpha R_{(t-1)} + \sum_{i=1}^{4} \beta_i C_{i,t} + \sum_{m=1}^{M} \delta_m EWA_{m,t} + \sum_{m=1}^{M} \theta_m EWA_{m,t-1} + \sum_{n=1}^{N} \gamma_j ND_{j,t} + \sum_{n=1}^{N} \varphi_j ND_{j,t-1} + \varepsilon_t \tag{5}$$

Where, R_t is the stock market returns at time t, μ is the constant (mean) term, α is the autoregressive coefficient, $\beta_1, \beta_2, \beta_3, \beta_4$ represent the coefficients of the control variables, namely oil, gold, exchange rate, and Interest rate, δ_1,...,δ_M represent the extreme weather anomalies dummies' coefficients, with *M*=1 in the aggregated analysis, as there is only the aggregated extreme weather anomalies variable, and *M*=3 in the disaggregated analysis, θ_1 ,...,θ_M represent the coefficients for the first lag of the EWA variables, $\gamma_1, \ldots, \gamma_N$ represent the natural disasters dummies coefficients, for which *N* is equal to 1 in the aggregated analysis and equal to 4 in the disaggregated analysis, $\varphi_1, \ldots, \varphi_N$ represent coefficients of the lagged natural disasters dummies, and finally, ε_t is the error term, which follows the skewed student's t distribution.

The variance equation of the model is as follows:

$$\ln(h_t) = \omega + \alpha \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma \left(\left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| - E \left[\left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| \right] \right) + \beta \ln(h_{t-1}) + \sum_{m=1}^{M} \theta_i EWA_{i,t} + \sum_{m=1}^{M} \delta_i EWA_{i,t-1} + \sum_{n=7}^{N} \psi_j ND_{j,t} + \sum_{n=7}^{N} \sigma_j ND_{j,t-1} \tag{6}$$

Where, h_t is the conditional variance at time t, ω is the unconditional variance, α represents the coefficient associated with the ARCH term, γ measures the asymmetric response, capturing the leverage effect, β is the coefficient associated with the GARCH term, capturing the persistency in the conditional volatility of returns. The remaining terms, relative to the extreme climate-related events' dummies, are equal to the ones described in the mean equation, although in this case, its coefficients represent the impact of the variables on the conditional variance.

4.1.5. Model Diagnostic tests

The Ljung-Box tests on standardized residuals and squared residuals were performed on the models, the results of which indicate no significant serial correlation (none at lag 1), suggesting that the model adequately captures the autocorrelation in the data. From the ARCH LM test, which checks for remaining ARCH effects, the results indicate that there are no ARCH effects, indicating that the EGARCH model successfully captures the time-varying volatility.

4.2. Empirical Results

This section aims to evaluate the impact of extreme climate-related events and the control variables on stock market returns and volatility. This analysis is conducted in two main ways. First, through the estimation of a model that aggregates all variables based on their primary event category, namely extreme weather anomalies and natural disasters. Secondly, by decomposing each variable and assessing the impact of each specific event type, as well as how the results compare with those from the aggregated analysis and the existing literature.

4.2.1. Aggregated Analysis

This first part of the study focuses on the aggregated analysis. Table 4.4 shows the results from the model estimation, displaying the impact of the extreme weather anomalies and natural disasters variables, along with their lagged variables, on both the stock market returns (mean equation) and its volatility (variance equation), measured by the estimated coefficients and their associated p-values.

Table 4.4: Extreme Climate-related events and PSI returns- Aggregated analysis

Variable	Estimate	Std. Error	t-value	Pr(>|t|)
Panel A: Mean equation				
mu	0,0122	0,0069	1,7602	0,0784
AR(1)	0,0670	0,0113	5,9441	0,0000
Oil	0,0618	0,0073	8,4510	0,0000
Gold	-0,0356	0,0161	-2,2091	0,0272
EURUSD	0,0322	0,0280	1,1524	0,2492
PT10A	-0,1640	0,0750	-2,1879	0,0287
EWA	-0,0154	0,0055	-2,7896	0,0053
EWA_lag1	0,0136	0,0278	0,4893	0,6247
ND	0,1716	0,0508	3,3755	0,0007
ND_lag1	-0,1822	0,0474	-3,8477	0,0001
Panel B: Variance equation				
omega	-0,0007	0,0030	-0,2334	0,8155
alpha	-0,0877	0,0106	-8,2360	0,0000

beta	0,9726	0,0044	220,6546	0,0000
gamma	0,1685	0,0160	10,5048	0,0000
EWA	-0,0836	0,0701	-1,1933	0,2327
EWA_lag1	0,0838	0,0698	1,1997	0,2303
ND	-0,0461	0,1376	-0,3352	0,7375
ND_Lag1	0,0183	0,1366	0,1338	0,8936
skew	0,9400	0,0180	52,3338	0,0000
shape	9,7751	1,2383	7,8939	0,0000

4.2.1.1. Wealth effects

The mean equation examines the impact of the variables on stock market returns, referred to as the wealth effect (Wang & Kutan, 2013). The displayed results allow many conclusions to be drawn.

Beginning with the autoregressive term, the results indicate that it is highly significant ($p<0,0001$), with an estimate of 0,0670, aligning with the results from the previous analysis of the ARMA model and reinforcing the need to include it in the model.

The p-values associated with the control variables indicate that all variables are statistically significant at the 5% level, except for the EUR-USD exchange rate returns, which have a p-value of 0,2492, suggesting no strong relationship between exchange rate fluctuations and stock market returns. This contrasts slightly with the findings from U-Din et al. (2022) and Wang & Kutan (2013), which found statistical significance for the exchange rates used, namely the USD-Canadian dollar and the USD-Japanese yen exchange rates, respectively. However, U-Din et al. (2022) only found significance at the 10% level, and Wang & Kutan (2013), which studied the United States and Japanese stock markets, also found significance only at the 10% level for the United States and found no significance for the Japanese case. Furthermore, both studies considered exchange rates different from the one used in this thesis, the EUR-USD exchange rate. Therefore, the results obtained for the EUR-USD exchange rate returns are unique and not directly comparable.

Oil price variations are positively associated with Portuguese Stock market returns, with an estimate of 0,0618, meaning that a one percent increase in oil prices leads to a 0,0618% increase in returns, all the rest remaining constant. In contrast, the negative coefficients associated with gold and government bonds demonstrate that both variables have an inverse relationship with the returns, implying that a one percent increase in the percentage variation of the gold spot rate, as well as an increase of one unit in the first differences of the Portugal 10-year

Government Bond Yield, lead to a decrease in the stock market returns of 0,0356% and a 0,164%, respectively.

The positive relationship between oil price variations and stock market returns reflects the mixed results found in the literature, aligning with the conclusions of some authors (Shaeri & Katircioğlu, 2018) but contrasting with the findings from others (Alamgir & Amin, 2021; Zhu et al., 2016). The negative relationship exhibited by gold price variations matches the findings by Mota et al. (2023) in their study on the Portuguese stock market. Finally, the conclusions for the government bonds variable also match the consensus in the literature that increases in interest rates, such as treasury bills and government bonds, slow down economic growth, leading to decreases in stock returns (Alam & Uddin, 2009b; Shaeri & Katircioğlu, 2018).

As for the impact of the extreme climate-related events' variables, the results are mixed, though it appears that three out of the four variables included are statistically significant.

For the extreme weather anomalies, its current dummy variable has a p-value of 0,0053, indicating that it is statistically significant, and it shows a negative coefficient of -0,0154, meaning that when such an event occurs, there is a 1,54% decrease in stock market returns. However, the variable representing its first lag is not statistically significant, with a high p-value of 0,6247, evidencing no strong relationship between stock market returns and past extreme weather anomalies. This suggests that extreme weather anomalies, when studied as an aggregate of extreme temperature anomalies and extreme precipitation anomalies, cause a slight negative reaction in investors, possibly due to the perceived risk and potential impact of these events on economic activity, but it also suggests that this effect is mostly contemporaneous, with investors reacting immediately to the occurring events.

Concerning the natural disasters dummies, the takeaways are slightly different, as both the natural disasters dummy and its lagged variable are statistically significant, with very low p-values (0,0007 and 0,0001, respectively). The natural disasters dummy shows an estimate of 0,1716, indicating a 17% average increase in the market's returns during natural disasters over the sample period. Still, its lagged variable exhibits a negative coefficient of -0,1822, suggesting that even though there might be an initial positive reaction, it is completely corrected when shifting the event window by one period, with the negative coefficient of the lagged variable surpassing the positive estimate for the current natural disasters variable. To further investigate the overall impact of the aggregated natural disasters on returns, a Wald test was conducted to test if the sum of the coefficients of the two variables, natural disasters, and its lagged variable, differs from zero. The p-value associated with the Wald test statistic is 0,7719. Therefore, the null hypothesis that the final overall impact is zero cannot be rejected, which implies that the opposing signs of the two coefficients cancel each other out, and their combined impact on the dependent variable is statistically insignificant. The disaggregated analysis of the impact of each type of natural disaster, presented below, can provide more context to the results and how these relate to the findings in the literature, as much of the literature focuses on the impact of individual climate-related types.

4.2.1.2. Risk Effects

The variance equation of the model illustrates the impact of the dummy variables on the volatility of Portuguese stock market returns, as well as the statistical significance for the EGARCH model specification parameters. This measures the risk effects (Wang & Kutan, 2013).

Regarding the parameters associated with the GARCH-based models, the results indicate that both alpha and beta are highly significant, with p-values of 0 associated with both, once more confirming the presence of ARCH effects, that is, volatility clustering in the dependent variable. The same conclusion can be drawn for the EGARCH-specific parameter, gamma, suggesting that there is an asymmetry in response to shocks, confirming the presence of the leverage effect, where negative shocks increase volatility more than positive ones.

As for the impact of the extreme climate-related events dummies on the volatility of returns, neither the current nor the lagged extreme anomaly variables are statistically significant in the variance equation, with p-values of 0,2327 and 0,2303, respectively. The same is true for the natural disasters dummy and its lagged variable, which show even higher p-values of 0,7375 and 0,8936. This suggests that, even though some of these variables are shown to impact returns, they do not induce heightened uncertainty in the stock market in a way that influences the volatility of its returns.

4.2.2. Disaggregated Analysis

Aggregating the individual dummy variables for each event type into two broader categories of extreme events is helpful for the analysis, as it increases the percentage of occurrences in the sample, addressing the issue of low variability caused by the lower occurrence of certain types of events, which can make it difficult for the models to discern any meaningful patterns or relationships between these dummy variables and the dependent variable. Nevertheless, aggregating the variables can also hide the distinct effects of each type of event. Therefore, this section focuses on examining the impact of each type of extreme weather anomaly, namely extremely high-temperature anomalies, extremely low-temperature anomalies, and extremely high-precipitation anomalies, as well as the different types of natural disasters, including extreme temperatures, storms, floods, and wildfires, along with their lagged variables. Table 4.5 shows the results of this estimation.

Table 4.5: Extreme Climate-related events and PSI returns- Disaggregated analysis

Variable	Estimate	Std. Error	t-value	Pr(>|t|)
Panel A: Mean equation				
mu	0,0121	0,0096	1,2604	0,2075
AR(1)	0,0668	0,0120	5,5572	0,0000
Oil	0,0618	0,0058	10,6436	0,0000
Gold	-0,0362	0,0105	-3,4620	0,0005
EURUSD	0,0324	0,0235	1,3785	0,1681
PT10A	-0,1603	0,0805	-1,9919	0,0464
EHPA	-0,0426	0,0149	-2,8518	0,0043
EHPA_lag1	-0,0106	0,1115	-0,0954	0,9240
EHTA	0,0025	0,0501	0,0493	0,9607
EHTA_lag1	0,0045	0,0428	0,1052	0,9162
ELTA	0,1178	0,1820	0,6474	0,5174
ELTA_lag1	0,0836	0,1296	0,6451	0,5188
Extreme Temperatures	0,1927	0,1213	1,5887	0,1121
Extreme Temperatures_lag1	-0,2396	0,1173	-2,0423	0,0411
Storms	0,5529	0,2035	2,7172	0,0066
Storms_lag1	-0,0055	0,2513	-0,0218	0,9826
Floods	0,1761	0,0338	5,2116	0,0000
Floods_lag1	-0,1149	0,0383	-2,9968	0,0027
Wildfires	0,0081	0,2079	0,0388	0,9691
Wildfires_lag1	-0,0004	0,2042	-0,0017	0,9986
Panel B: Variance equation				
omega	-0,0010	0,0031	-0,3361	0,7368
alpha	-0,0896	0,0108	-8,2775	0,0000
beta	0,9716	0,0046	211,9923	0,0000
gamma	0,1667	0,0163	10,2334	0,0000
EHPA	-0,1529	0,1017	-1,5032	0,1328
EHPA_lag1	0,1476	0,1048	1,4080	0,1591

EHTA	-0,0879	0,1000	-0,8790	0,3794
EHTA_lag1	0,0985	0,1003	0,9815	0,3263
ELTA	0,2525	0,2851	0,8856	0,3758
ELTA_lag1	-0,2601	0,2684	-0,9693	0,3324
Extreme Temperatures	-0,1236	0,1937	-0,6379	0,5235
Extreme Temperatures_lag1	0,1050	0,1937	0,5421	0,5878
Storms	-0,3369	0,2917	-1,1551	0,2481
Storms_lag1	0,4144	0,3036	1,3652	0,1722
Floods	0,1316	0,4796	0,2743	0,7838
Floods_lag1	-0,2700	0,4903	-0,5507	0,5818
Wildfires	-0,0222	0,2006	-0,1105	0,9120
Wildfires_lag1	-0,0066	0,1931	-0,0343	0,9726
skew	0,9379	0,0179	52,2792	0,0000
shape	10,0431	1,3096	7,6687	0,0000

4.2.2.1. Wealth effects

Comparing the results regarding the variables present in both models, it is possible to see that most of the conclusions remain the same regardless of whether the additional variables, in this case, the extreme climate-related events dummies, are added as each event type on its own or aggregated into extreme weather anomalies and natural disasters. This is true for the control variables, where every variable exhibits close to the exact estimates in this and the previous model, with oil price variations showing a positive and highly significant coefficient of 0,0618 and both the percentage variations of the gold spot price and the first differences of the Portugal 10-Year Government Bond Yield presenting negative and statistically significant (at the 5% level for the latter) estimates. Finally, the EUR-USD exchange rate remains not statistically significant, although showing a smaller p-value of 0,1681 in this instance, compared to the 0,2492 from the previous model.

As for the extreme weather anomaly variables, the results are consistent with the findings from the aggregated analysis, where the non-lagged variable was shown to be statistically significant with a negative estimate, and the results for its lagged variable were not. Delving into the types of extreme weather anomalies studied with this model, all temperature-related variables are shown to be statistically insignificant, with both extremely high-temperature anomalies and its lagged variable having p-values close to 1 (0,9607 and 0,9162, respectively), as well as the extremely low-temperature anomalies and its lagged variable, that while having lower p-values, still are not close to being statistically significant (0,5174 and 0,5188 respectively). The extremely high-precipitation anomalies variable displays a highly significant (p-value=0,0043) negative estimate of -0,0426, so days in which there is an amount of precipitation that deviates highly from the corresponding monthly historical mean are associated with an average 4,26% decrease in stock returns. In contrast, its lagged variable shows a statistically insignificant estimate. This suggests that the statistical significance found for the extreme weather anomalies variable in the aggregate model comes from EHPA events.

Regarding the natural disasters variables, namely extreme temperatures, storms, floods, and wildfires, the results are the following.

Extreme temperatures, while not showing a statistically significant estimate for the current lag, the results reveal that its lagged variable has a negative estimate of -0,2396 which is statistically significant at the 5% level, implying that past extreme temperature events have a slightly delayed negative impact on returns.

For storms, the results display the opposite, with the lagged variable having a statistically insignificant estimate (p-value= 0,9826) but the contemporaneous variable showing a statistically significant (p-value=0,0066) positive estimate of 0,5529. This result might seem counterintuitive, as some research points to a negative impact on stock market returns caused by storms (U-Din et al., 2022), but it could indicate that markets perceive storms as opportunities for certain sectors, such as the construction or insurance sectors, as Wang & Kutan (2013) found a positive and statistically significant estimate for tropical cyclones (a type of storm) associated with their impact on the Japanese insurance sector, and Bourdeau-Brien & Kryzanowski (2017), in their study on the impact of natural disasters on state-based portfolio returns in the U.S., also found storms to have a statistically significant positive impact on 3 three states, namely Tennessee, Oklahoma, and Missouri.

The floods variable has a statistically significant estimate of 0,1761. However, its lagged variable’s effect is negative (-0,1149) and statistically significant, indicating that, while the immediate effect might be positive, this effect is countered when shifting the observation window by one period. The total effect, inferred through the Wald test on the statistical significance of the sum of both impacts, is null, as the p-value associated with the Wald statistic is 0,5104, meaning that the null hypothesis that the sum of both variables' impacts is zero cannot be rejected. These mixed suggestions are also observed across the literature, with some studies finding no overall effect on stock market returns attributable to floods (U-Din et al., 2022; Worthington, 2008) and others finding positive and negative impacts depending on the studied markets (Bourdeau-Brien & Kryzanowski, 2017).

Lastly, none of the wildfire-related variables were found to be statistically significant, as both wildfires and its lagged variable exhibited extremely high p-values of 0,9691 and 0,9986, respectively. Comparing the results for wildfires is more challenging, as this specific type of natural disaster has been the focus of relatively few studies, with mixed results from ones that included them in their analyses, as U-Din et al. (2022) found positive and negative estimates depending on the lag of the variable that was analyzed, and Bourdeau-Brien & Kryzanowski (2017) found no impact from the variable “fire” in the few U.S. states considered.

The results associated with both the extreme weather anomalies and the natural disasters variables are consistent with the results from the aggregated analysis model. For the extreme weather anomaly variables, in both analyses only its lagged variable is statistically significant, with a negative coefficient, reflected in the disaggregated analysis by the first lag of the EHPA variable. As for the natural disasters variables, while in the two analyses both lags have statistically significant variables, the Wald test for the combination of both lags, in this case, storms and floods combined with the first lags of extreme temperatures and floods, has an associated p-value of 0,1678, revealing a null overall impact on the dependent variable from the natural disasters events, just as the aggregated analysis suggested.

Another helpful comparison is between the results for the extreme weather anomalies, divided into extreme precipitation and temperature anomalies, and the results from the floods and extreme temperature types of natural disasters, from which several conclusions can be taken. Firstly, both measures of heavy rainfall are statistically significant, with both EHPA and the first lagged floods variable displaying a negative estimate, although the non-lagged floods variable exhibits a positive coefficient. Secondly, the results from the variables related to extreme temperatures align with each other in the fact that the current non-lagged variables are shown to be statistically insignificant in both models, though the extreme temperatures variable shows a much smaller p-value when compared to the EHTA and ELTA variables (0,1121 versus 0,9607 and 0,5173), but they also contrast in the sense that whereas the lagged variable of both EHTA and ELTA is not statistically significant, the lagged variable of extreme temperatures is. This could be due to the different methodologies used to identify the events, as for extreme temperature events to be identified by the EM-DAT as a natural disaster, these have to meet a certain threshold based on the events’ consequences on human beings, and the extreme temperature anomaly events are simply based on the recorded value’s deviation from its monthly historical mean, and not its impact and the consequences caused by it.

4.2.2.2. Risk Effects

Regarding the variance equation of the model with the individual types of events for both extreme weather anomalies and natural disasters, the results mirror the ones from the previous analysis. The equation terms associated with the EGARCH specification, namely alpha, beta, and gamma, are all shown to be highly significant. As for the coefficients associated with the extreme weather anomaly variables and those linked to the natural disaster variables, the results suggest that though some variables exhibit a positive coefficient, such as lagged EHPA, lagged EHTA, ELTA, lagged extreme temperatures, lagged storms and floods, and the others a negative coefficient, none of these variables are statistically significant, even at the 10% level.

As mentioned in the Literature Review chapter, the literature on the effects of extreme climate-related events on the volatility of financial returns is not as comprehensive. Still, comparing the results obtained with the existing literature, it is possible to see similarities and contrasts in these results. Bourdeau-Brien & Kryzanowski (2017) also found storms not to have a statistically significant impact on the volatility of stock market returns in any of the event periods tested, while U-Din et al. (2022) found only the first lag of the storms dummy variable to have a significant increase in the volatility of the Canadian stock market, and Wang & Kutan (2013) also found a positive impact on the volatility of the U.S. stock market's returns associated with the first lag of storms, but none for the Japanese stock market. Regarding floods, Bourdeau-Brien & Kryzanowski (2017) arrived at the same conclusion of no increased volatility found from the occurrence of these types of events, while U-Din et al. (2022) found that the conditional volatility noticeably increases following floods. For extreme temperatures, the results obtained differ from the small existing literature, as both Griffin et al. (2019) and Bourdeau-Brien & Kryzanowski (2017) find that stock price volatility increases after the occurrence of extreme temperature events. Finally, the impact of wildfires in the literature is the less studied of the mentioned, but U-Din et al. (2022) finds, like this study, that fires have no statistically significant impact on market volatility.

CHAPTER 5

Conclusion

This study presents an analysis of the relationship between extreme climate-related events and the Portuguese Stock Index, representing the Portuguese stock market. For this, an empirical approach is taken, which uses GARCH-based models to evaluate the impact of various extreme climate-related event variables on stock market returns and volatility. The data employed consists of the daily stock returns of the PSI over the period between January of 2000 and December of 2023, along with two more sets of data, one concerning the control variables used in the models, namely, interest rates, oil and gold prices, and the exchange rate, and the extreme climate variables dataset, divided between extreme weather anomalies and natural disasters.

As seen in the literature, despite the multitude of reports on how these events negatively impact the economy, with European Environment Agency (2023) reporting that Portugal has suffered 15.042 million euros in economic losses from climate-related hazards for the period between 1980 and 2022, the findings on if there is a significant impact on financial markets and what this impact is, are mixed, ranging from authors finding negative effects of extreme climate events on the stock market, positive effects, and even no statistically significant effects at all.

The empirical analysis conducted attempts to investigate the impact of each extreme climate-related event type on stock market returns and its volatility, as well as measure this impact by aggregating different event types by their main categories. Regarding the effect on the returns, several conclusions can be taken from both the aggregated and disaggregated analyses.

For the aggregated analysis, the findings indicate different conclusions for extreme weather anomalies and natural disasters. The extreme weather anomalies dummy is shown to have a negative contemporaneous impact on stock market returns, not corrected by its lagged variable, suggesting an overall negative effect on market returns. On the other hand, the results for natural disasters show that while there is contemporaneous positive reaction from the market , this is then corrected by the lagged variable, leading to no overall impact, and so, it is possible to conclude that natural disasters, when measured as an aggregate of extreme temperatures, storms, floods and wildfires, do not have an undiversifiable effect on the Portuguese stock market.

When examining the specific event types, it is evident that this contemporaneous negative impact from EWA is caused by extremely high-precipitation anomalies, while both extreme temperature anomalies have no impact on the PSI returns. Among the natural disasters, storms and floods result in the contemporaneous positive impact observed, while the negative lagged impact comes from extreme temperatures and floods, with the joint impact of all significant variables suggesting, again, that the overall impact is null. The results also reveal that while the natural disasters variables are shown to have no overall impact, the conclusions for its specific event types are not all the same. Extreme temperatures are shown to have an overall negative impact on returns and storms a positive one. This positive impact from storms, although counterintuitive, has been found by other authors (Bourdeau-Brien & Kryzanowski, 2017; Wang & Kutan, 2013) , with the latter suggesting that this could be due to a 'gaining from loss hypothesis' (Wang & Kutan, 2013), associated with cyclones.

From the different results across the measures of temperature present in both EWA and Natural Disasters, it is also possible to conclude that, regarding stock market returns, the consequences generated by the extreme temperature events matter more than significant deviations from the monthly historical mean, measured by the extreme weather anomalies. This is reasonable, as the temperature-related economic impacts described by the European Environment Agency (2024) , namely, damages to ecosystems, food production, health, and infrastructure, which are then reflected negatively in the economy, including financial markets, result from extreme temperature events, such as heatwaves, where days exhibit temperatures above 35°C.

While overall, the findings from the disaggregated analysis match the ones from the aggregated analysis, as there is a contemporaneous negative effect from EWA dummies and no overall impact from the natural disasters dummy variable, this analysis highlights the importance of distinguishing between extreme climate events, as it revealed nuanced effects and enabled more precise conclusions about which events lead to significant impacts within each category.

Another objective of this dissertation was to study the impact of the events on the volatility of the Portuguese Stock Index. In this case, the findings are evident, the results for the types of events investigated, both when analyzed as an aggregate and when each event type is analyzed separately, show that none of the extreme climate events significantly affect market risk. These findings could lead to the conclusion that extreme climate-related events do not translate into economic uncertainty and changes in investor sentiment, which have been shown in the literature to impact stock market volatility (Schwert, 1989; Y. Wang & Deng, 2018), or perhaps that the PSI volatility is more sensitive to other commonly associated factors such as macroeconomic factors like output growth and inflation (Schwert, 1989).

While this thesis provides valuable insights, it is important to acknowledge its limitations. The main limitation arises from the relatively low frequency of extreme climate events in Portugal when compared to some of the more frequently researched countries, such as the U.S., Australia, and Japan. This, combined with the fact that the analysis is conducted for a daily frequency, can limit the robustness of the findings from the models, especially from the disaggregated analysis, which contains some specific event types that have a percentage of observations taking the value of below one percent, namely as storms and floods. The paper addresses this in two ways. First, by conducting an aggregated and a disaggregated analysis, which allows for a higher representation of natural events in the aggregated model. Secondly, by adding a second measure of extreme climate-related events, the extreme weather anomalies, which, due to the different methodology used, based on the weather variables' values instead of its consequences, generate a higher frequency of events, raising the representation of extreme climate events in the sample. There are also limitations associated with the natural disasters database used. Despite the EM-DAT being the only comprehensive disaster loss database with free access and adequate global coverage (Mazhin et al., 2021) it still has some limitations due to the limited number of sources and how effectively natural disasters are reported around the world, which can lead to biases in the data and, in turn, a database that is never entirely accurate, with the CRED reporting that data for events which occurred before the year 2000 is particularly subject to reporting biases, limiting the research of this thesis to events that happened from the year 2000 onwards.

There is a very significant gap in the current literature for research on the Portuguese context, and while this thesis has focused on addressing this gap, there is still plenty of opportunity for further research on the topic to be made. As mentioned, two main event study approaches are used across the literature. This study focuses on the second one, determining abnormal returns by the coefficients associated with the dummy variables of extreme climate-related events. One potential avenue for future research is to employ a different event study methodology to measure the abnormal returns associated with extreme climate-related events, namely one that calculates abnormal returns by measuring the difference between the observed returns and the forecasted expected returns of the market during the events' windows. Future research could also focus on more localized analyses, centering on the impact of specific climate-related events, or event types, on different regions of the country and investigating their impact on local firms.

The reported impact of extreme climate events on the Portuguese economy during the last 30 years, combined with the rising frequency and severity of climate-related events due to climate change, means that understanding their impact on financial market dynamics will be crucial for both investors and policymakers when it comes to creating resilient financial strategies. This thesis contributes to the growing body of literature on the relationship between extreme climate-related events and financial markets, specifically within the under-researched context of the Portuguese stock market.

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Appendix

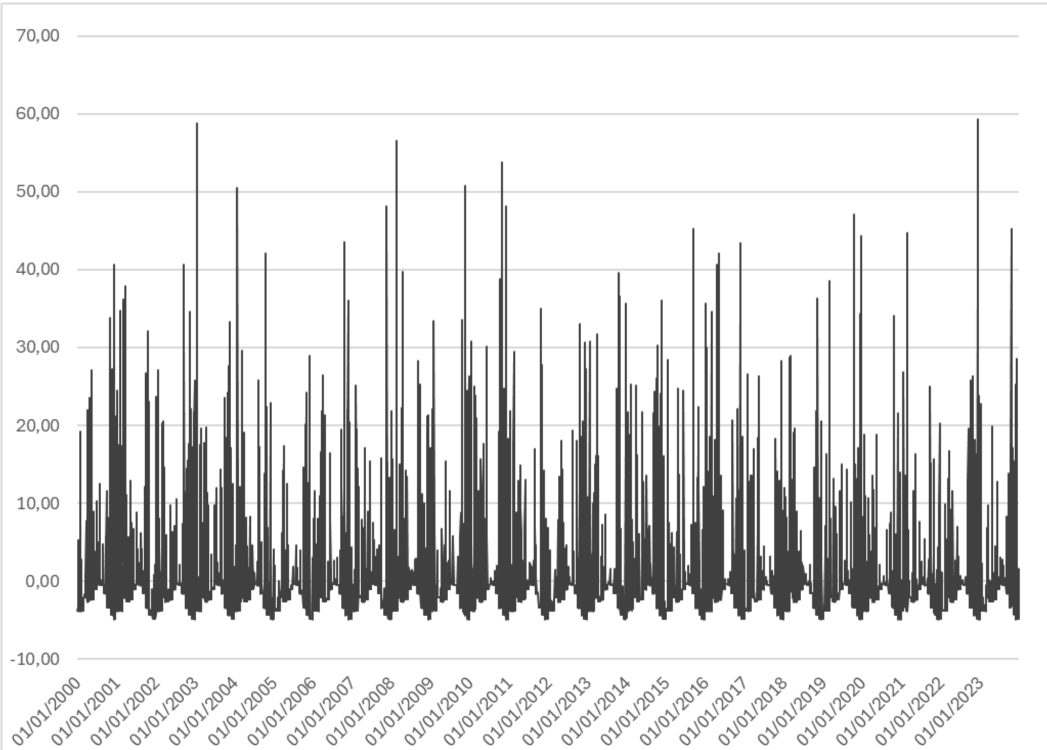
Appendix A- Supporting tables for the Methodology and Data

Table A.1: Stationarity tests after variable transformations

Variable	ADF Stat.	ADF p-value
PSI	-17,27	0,01
EURIBOR	-9,86	0,01
Oil	-16,75	0,01
Gold	-18,47	0,01
EURUSD	-17,27	0,01
PT10A	-20,15	0,01

Appendix B- Supporting figures for the Methodology and Data

Figure A.1: Precipitation Anomalies over time



Appendix C- Supporting tables for the Model Specification

Table A.2: AR (1) Results

Variable	Estimate	Std. Error	t-value	Pr(>|t|)
ar1	0,07589	0,012733	5,96	2,52E-09

intercept	-0,00231	0,014848	-0,155	0,877
		AIC = 19205,94		

Table A.3: AR (2) Results

Variable	Estimate	Std. Error	t-value	Pr(>|t|)
ar1	0,074887	0,012777	5,861	4,60E-09
ar2	-0,004365	0,012764	-0,342	0,732
intercept	-0,001882	0,014843	-0,127	0,899
		AIC = 19203,59		

Table A.4: MA (1) Results

Variable	Estimate	Std. Error	t-value	Pr(>|t|)
ma1	0,07477	0,012758	5,861	4,61E-09
intercept	-0,002566	0,01596	-0,161	0,872
		AIC = 19207,15		

Table A.5: MA (2) Results

Variable	Estimate	Std. Error	t-value	Pr(>|t|)
ma1	0,0759193	0,0127729	5,944	2,79E-09
ma2	0,0009446	0,0128767	0,073	0,942
intercept	-0,0020688	0,0159822	-0,129	0,897
		AIC = 19202,7		

Table A.6: ARMA (1,1) Results

Variable	Estimate	Std. Error	t-value	Pr(>|t|)
ar1	0,178171	0,12269	1,452	0,146
ma1	-0,104264	0,125258	-0,832	0,405
intercept	-0,002045	0,013306	-0,154	0,878
		AIC = 19207,29		

Table A.7: Extreme Climate-related events and PSI returns- Aggregated analysis (with EURIBOR)

Variable	Estimate	Std. Error	t-value	Pr(>|t|)
Panel A: Mean equation				

mu	0,0122	0,0061	2,0161	0,0438
AR(1)	0,0669	0,0100	6,6956	0,0000
EURIBOR	0,0876	1,0899	0,0804	0,9359
Oil	0,0617	0,0069	8,9140	0,0000
Gold	-0,0357	0,0143	-2,4951	0,0126
EURUSD	0,0322	0,0285	1,1277	0,2594
PT10A	-0,1639	0,0757	-2,1640	0,0305
EWA	-0,0156	0,0054	-2,9020	0,0037
EWA_lag1	0,0137	0,0282	0,4851	0,6276
ND	0,1714	0,0522	3,2842	0,0010
ND_lag1	-0,1822	0,0484	-3,7624	0,0002
Panel B: Variance equation				
omega	-0,0007	0,0030	-0,2311	0,8173
alpha	-0,0877	0,0106	-8,2532	0,0000
beta	0,9726	0,0044	220,8650	0,0000
gamma	0,1686	0,0161	10,4759	0,0000
EWA	-0,0837	0,0701	-1,1939	0,2325
EWA_lag1	0,0838	0,0698	1,2003	0,2300
ND	-0,0459	0,1375	-0,3341	0,7383
ND_Lag1	0,0181	0,1365	0,1322	0,8948
skew	0,9400	0,0180	52,2329	0,0000
shape	9,7729	1,2366	7,9032	0,0000

Table A.8: Extreme Climate-related events and PSI returns- Disaggregated analysis (with EURIBOR)

Variable	**Estimate**	**Std. Error**	**t-value**	**Pr(>|t|)**
Panel A: Mean equation				
mu	0,0121	0,0073	1,6540	0,0981
AR(1)	0,0667	0,0127	5,2468	0,0000
EURIBOR	0,1023	1,0861	0,0942	0,9250
Oil	0,0618	0,0057	10,8933	0,0000
Gold	-0,0362	0,0126	-2,8758	0,0040

EURUSD	0,0324	0,0182	1,7871	0,0739
PT10A	-0,1600	0,0785	-2,0383	0,0415
EHPA	-0,0428	0,0098	-4,3808	0,0000
EHPA_lag1	-0,0106	0,0270	-0,3950	0,6928
EHTA	0,0024	0,0498	0,0488	0,9611
EHTA_lag1	0,0047	0,0433	0,1080	0,9140
ELTA	0,1170	0,1825	0,6408	0,5216
ELTA_lag1	0,0835	0,1282	0,6510	0,5150
Extreme Temperatures	0,1915	0,0519	3,6900	0,0002
Extreme Temperatures_lag1	-0,2391	0,0426	-5,6099	0,0000
Storms	0,5532	0,2034	2,7206	0,0065
Storms_lag1	-0,0073	0,2484	-0,0295	0,9765
Floods	0,1760	0,0384	4,5880	0,0000
Floods_lag1	-0,1150	0,0388	-2,9644	0,0030
Wildfires	0,0082	0,1416	0,0580	0,9537
Wildfires_lag1	-0,0002	0,1506	-0,0015	0,9988
Panel B: Variance equation				
omega	-0,0010	0,0031	-0,3380	0,7353
alpha	-0,0896	0,0109	-8,2051	0,0000
beta	0,9716	0,0046	210,3515	0,0000
gamma	0,1669	0,0164	10,1651	0,0000
EHPA	-0,0875	0,1000	-0,8753	0,3814
EHPA_lag1	0,0981	0,1003	0,9781	0,3280
EHTA	0,2504	0,2849	0,8789	0,3794
EHTA_lag1	-0,2582	0,2683	-0,9621	0,3360
ELTA	-0,1532	0,1015	-1,5095	0,1312
ELTA_lag1	0,1477	0,1030	1,4340	0,1516
Extreme Temperatures	-0,1233	0,1926	-0,6404	0,5219
Extreme Temperatures_lag1	0,1048	0,1932	0,5424	0,5875
Storms	-0,3355	0,2853	-1,1759	0,2396
Storms_lag1	0,4132	0,2997	1,3785	0,1680
Floods	0,1331	0,4792	0,2777	0,7813
Floods_lag1	-0,2715	0,4900	-0,5541	0,5795

Wildfires	-0,0218	0,2012	-0,1083	0,9138
Wildfires_lag1	-0,0070	0,1934	-0,0362	0,9711
skew	0,9381	0,0182	51,6387	0,0000
shape	10,0320	1,3076	7,6723	0,0000