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Impact of bushfires and heatwaves on Australian stock market

Event Study

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ABSTRACT

Australia is geographically exposed to extraordinarily high temperatures every year. Moreover, it is a country well known for frequent bushfires. The aim of this research is to figure out if these events significantly impact the economy. This is carried out by analysing the impact of heatwaves and bushfires on Australian stock market returns. Event study is applied as a statistical method. Neither heatwaves nor bushfires have a statistically significant negative impact on the Australian stock market. Moreover, their effects are positive and statistically significant mainly within certain sectors such as insurance, information technologies, and materials. Additionally, a cross-sectional regression analysis of the drivers of the five-day cumulative abnormal return is conducted. Regarding bushfires, the number of homes destroyed, and the fire-weather conditions have a positive effect on the cumulative abnormal return, while the scope of the damaged area has a negative impact. In the case of heatwaves, the duration of a heatwave has a positive effect, while the heatwave intensity and drought have a negative impact on the cumulative abnormal return.

Keywords: Cross-Sectional Models, Environment, Finance, Event Studies, Financial Economics

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1 Introduction

Significant climate and weather change have been a steady feature around the globe for the last several decades. The main trigger of this change is a gradual global temperature rise, which results in other consequent effects like glaciers' melting or global sea level rise. Subsequently, we can observe more frequent natural disasters such as floods, extreme droughts, and more frequent and stronger storms. According to the World Meteorological Organization, the past two decades included 18 of the 20 warmest years since record-keeping began in 1850 (IPCC, 2018). All these effects, among others, have a serious negative impact on social aspects like poverty and global migration. There is also an economic impact. For instance, economic growth rate and general economic performance are affected. Based on the Global Climate Risk Index, some countries are more exposed to global climate change, while others are less exposed. One of the most vulnerable countries is Australia. Since the bushfires and high temperatures occur regularly every year in Australia, it would be interesting to observe the impact and consequences of these events. Though there is a sufficient number of papers analysing different types of natural disasters and their economic effects, only a limited number of research studies focus on the relationship between the Australian market and bushfires.

Currently available research studies measure the impact of natural disasters like earthquakes, storms, floods, or cyclones, as well as the impact of weather effects like El Niño. Some studies also consider a behavioural finance perspective to measure the impact of the weather, for instance, cloudy or sunny days on financial markets. However, there is only a limited number of studies analysing bushfires in Australia. Studies measuring the impact of heatwaves are available for markets like China or the United States (US). To the best of my knowledge, there is no such paper that focuses specifically on the Australian market by combining more environmentally interconnected natural disasters events like bushfires and heatwaves.

This thesis adds value to the event study literature and raises awareness about climate change trends by filling the aforementioned gap with valuable results and suggestion for further research.

In general, I test a semi-strong form of market efficiency, which states that all new public information is incorporated in asset prices. In relation to this theory, I expect no immediate abnormal return effect on Day 0 as well as no five-day cumulative abnormal return effect from Day 0 to Day 4. These expectations apply for both bushfires and heatwaves.

As the data for abnormal return calculation, I use Australian stock market prices from the Australian stock market index ASX200.

My research hypotheses are stated as follows:

H0: The average abnormal return (AAR_0) of bushfires on the event day is statistically insignificant and close to zero.

H1: The five-day cumulative average abnormal return ($\mathrm{CAAR}_{0,4}$) of bushfires is statistically insignificant and close to zero.

H2: The AAR_0 of heatwaves on the event day is statistically insignificant and close to zero.

H3: The $\mathrm{CAAR}_{0,4}$ of heatwaves is statistically insignificant and close to zero.

If natural disasters occur overnight on the event day, the immediate effect will be visible on Day 1 instead of Day 0. To capture this effect, a calculation of the first-day average abnormal return, AAR_1 was made as well. Consequently, $\mathrm{CAAR}_{0,1}$ has been estimated. This is a complementary analysis that aims to provide a clearer view on the short-term effect of natural disasters. For the rest of the research the primary focus lies on AAR_0 and $\mathrm{CAAR}_{0,4}$.

Some additional hypotheses are stated in the following paragraph:

H4: The average abnormal return (AAR_1) of bushfires is statistically insignificant and close to zero.

H5: The two-day cumulative average abnormal return ($\mathrm{CAAR}_{0,1}$) of bushfires is statistically insignificant and close to zero.

H6: The AAR_1 of heatwaves is statistically insignificant and close to zero.

H7: The $\mathrm{CAAR}_{0,1}$ of heatwaves is statistically insignificant and close to zero.

Moreover, I carry out a control for the sector and the size of companies. To see if there are differences among the sectors, this is performed by checking if some of the sectors are more exposed to the tested bushfires and heatwaves compared to the others. Therefore, I calculated the event day AR_0 and $\mathrm{CAR}_{0,4}$ for different sector indices. The same approach applies also to different company sizes. Therefore, I performed an additional test of the hypothesis as presented in the following paragraph:

H8: The impact of bushfires on the asset value differs with different industries.

H9: The impact of bushfires on the asset value differs with different company sizes.

H10: The impact of heatwaves on the asset value differs with different industries.

H11: The impact of heatwaves on the asset value differs with different company sizes.

While working with the market-adjusted return methodology, the response of AAR_0 to bushfires is positive and statistically significant for the ASX200 index. The response of $\mathrm{CAAR}_{0,4}$ to bushfires is positive and statistically significant for the S&P ASX200 IT index. H8 cannot be rejected. On the other hand, H9 is rejected as there is no significant size effect in relation to bushfires.

The response of AAR_0 to heatwaves is positive and statistically significant for the S&P ASX200 Insurance index. The response of $\mathrm{CAAR}_{0,4}$ to heatwaves is positive and statistically significant for the ASX200 index, the S&P ASX200 IT index, and for the S&P ASX50 Large index. Based on these results, neither H10 nor H11 can be rejected.

Additionally, as part of the event study, I make a cross-sectional regression with the $\mathrm{CAR}_{0,4}$ of bushfires and heatwaves events as a dependent variable and the event characteristics as independent variables. The research is divided into the following chapters: Chapter 2 focuses on the available literature, Chapter 3 describes data, Chapter 4 presents methodology, Chapter 5 provides the results, and Chapter 6 contains the conclusion.

2 Literature

This chapter aims to explore previous research on the topics related to the climate finance, event studies, the impact of climate change and natural disasters on the asset value, firm performance, and other financial and economical metrics.

Literature is divided into several categories. The main important types of research in this regard are provided by papers examining natural disasters in general, research oriented on temperature increase and temperature shocks, and research on the weather impact on the stock market in relation to behavioural finance theory.

2.1 Natural disasters

Substantial amount of studies and research materials is available on the topic of natural disasters and their economic and financial impact.

Cabezon et al. (2019) placed a report at the International Monetary Fund, which quantifies the impact of natural disasters on Pacific Island economies. The authors highlight the interrelation between natural disasters and climate change. By applying vector autoregressive analysis, the outcome of their research suggests that for damage and losses equivalent to one per cent of GDP, growth drops by 0.7 percentage points in the year of the disaster.

In their paper Ferreira and Karali (2015) examine how earthquakes affect the returns and volatility of aggregate stock market indices. According to their results, global financial markets are resilient to shocks caused by earthquakes. They found no systematic effect of earthquakes on the returns of aggregate stock market indices.

Xia et al. (2017) analysed the southeast China region, which is frequently being affected by summer heat waves. Their paper combines meteorological, epidemiological, and economic analyses to investigate the macroeconomic impacts of heat waves on the economy. The study shows economic losses that occur due to the heatwaves. Furthermore, by incorporating industrial interdependencies, the authors calculate indirect economic losses as well. Their research is based on indirect relationships via productivity losses and capacity losses caused by extreme weather.

Wang and Kutan (2013) apply a GARCH model to capture the wealth effects and risk effects of natural disasters on the composite stock market and the insurance sector in Japan and the US, respectively. Their findings suggest that for the US market, no natural disaster has any wealth effects on stock market returns. This means that the market effectively diversifies the impact of natural disasters away. The same applies to the Japanese market. Nevertheless, for both countries there is a significant wealth effect for the insurance sector. For the Japanese market, the researchers' findings indicate 'gaining from the loss hypothesis'. This hypothesis suggests that there is a larger demand for insurance coverage during times of natural disasters to maximize protection. Therefore, there are higher stock returns in this particular sector.

The International Monetary Fund (2015) employed a multi-country framework to analyse the international macroeconomic transmission of El Niño weather shocks. This paper is concerned with 21 country-specific models over the period from 1979Q2 to 2013Q1. It also accounts for indirect effects via third markets. The research contributes to the climate-macroeconomy literature by focusing on weather shocks and their impact on growth, inflation, energy, and non-fuel commodity prices. The Southern Oscillation Index indicates the development and intensity of the El Niño weather event. The authors show that there are considerable heterogeneities in the different countries' responses to El Niño shocks. Countries like Australia, India, or Japan face a short-lived fall in economic activities, while countries like China or the US benefit from this climate event.

Worthington and Valadkhani (2004) use intervention analysis to specify the inclusion of the arrival of natural disasters` related news. The impact of natural disasters on the Australian equity market is examined. They processed 42 storms, floods, cyclones, earthquakes, and bushfires and also considered the minimum insured and total loss criteria. Autoregressive moving average models have been employed in order to model returns. Their study also explains in detail the impact of natural disasters on insurance companies. The most obvious effect is that insurance firms incur large losses because of the payments made to policyholders for the damage caused by such disasters. The other less obvious effect is that natural disasters tend to increase the demand for insurance products. This theory is also in line with the findings made by Wang and Kutan (2013). The net effect varies according to the relative strength of these two opposing forces. For the purposes of my research, the most important results are the ones related to the bushfires. The authors conclude that any small positive impact of bushfires on market returns is restricted to the day of and the day following the event. This theory implies that $\mathrm{CAR}_{0,1}$ should be statistically significant. Later, the hypotheses related to this implication are tested. In general, cyclones, bushfires, and earthquakes have an influence on returns in Australian market. The most significant are those of cyclones and bushfires. Such influences also vary across time. Authors argue that information represented by these events and disasters is relatively incomplete at the time of the event and that it may take some time before a fuller information set is obtained. This opinion, however, implies that $\mathrm{CAR}_{0,4}$ is statistically significant or that the use different long-term period techniques beyond the scope of the event study methodology might be needed. All relevant hypotheses are tested and interpreted.

Fomby, Ikeda, and Loayza (2013) trace the yearly response of gross domestic product (GDP) to natural disasters. Droughts, floods, earthquakes, and storms are taken into consideration. The GDP reaction will be certainly visible with a time delay. Negative effects, however, tend to occur closer to the time of a disaster's occurrence, quite unlike positive effects. Droughts, for instance, have immediate negative effect only on the agricultural sector. Their paper uses vector autoregression in the presence of endogenous variables and exogenous shocks. The result suggests that the effects of the natural disasters manifest stronger on developing countries compared to advanced countries. Some natural disasters can even entail benefits regarding economic growth. This positive effect is caused by reconstruction activities in residential housing or public infrastructure, mostly after earthquakes.

Bourdeau-Brien and Kryzanowski (2017) estimate the impact of natural disasters on stock returns and volatilities by using the event study methodology. In this study the authors use the portfolio of securities as well as individual securities. The impact is spread on a longer event period than the usual five-day event window and is not significant in the days following the peak of a disaster. However, the impact is significant within a 40-day or 60-day event window. The direction of the effect is unclear as approximately half of the intervention variables yield a negative coefficient estimate, while the other half yield a positive coefficient estimate. The intervention variable is used to examine the effects of natural disasters on the returns. These variables are, in fact, dummy variables that equal one when a disaster happens in a state. The results on individual firms and the portfolio of securities are similar. The possible explanation of why some firms gain while at the same time the others lose during natural disasters is not successful in this study. Neither the industry nor the size effect can really explain this specific phenomenon.

In my study, I use the usual five-day event window as a leading methodology for testing the effect of bushfires. This is an approach similar to the one used by Worthington and Valadkhani (2004) in their working paper.

2.2 Temperature increase and temperature shock

Bansal, Ochoa, and Kiku (2016) made a temperature-augmented, long-run risk model accounting for the interaction between temperature, economic growth, and risk. They found out that the long-run impact of temperature on economic growth is significant.

In the same year, the authors also conducted another research, in which they observed the economic impact of global warming and long-run temperature shifts on capital markets. It was presented that an increase in temperature globally lowers equity valuations, including on the US market. The researchers present that even if the effect of rising temperature is deferred into the future, its wealth effect is realized today. The immediate decline in wealth and equity valuation is caused by future global warming uncertainty.

Dell, Jones, and Olken (2012) tested the effect of temperature shocks on economic growth. They examined the historical relationship between temperature fluctuations and economic growth. They found substantial effects of temperature shocks, but only in poor countries. Particularly, 1°C rise in temperature in a given year reduces economic growth by 1.3 percentage points on average. Their paper also presents that this leads to reductions in the industrial output and political stability. Further work is needed to identify precise underlying mechanisms that explain the climate-economy relationship.

Colacito, Hoffman, and Phan (2018) worked on the same line of research focusing on the US economy. However, instead of temperature shocks, they worked with the average summer temperature as an independent variable.

They found that an increase in the average summer temperature has a significant and robust negative effect on economic growth. A 1°F increase in the average summer temperature is associated with reductions in the annual growth rate of the state-level output from 0.15 to 0.25 percentage points.

According to the working paper of Hsiang (2010), temperature increases during the hottest season are associated with the largest reductions in production. The author worked with 20 Caribbean-basin countries and showed the long-term response of the economic output to the changes in seasonal temperatures. Moreover, the study presents that output losses in non-agricultural production exceed those occurring in agricultural production. Here the long-term effect relates to the indirect channels in the economy. A change in the temperature in a given year will indirectly affect the output in the following year through investments, which are negatively affected by the decrease in the output in a given year.

In two separate papers Addoum, Ng, and Ortiz-Bobea (2019) study the impact of temperature shocks. First of these working papers use establishment-level sales and productivity as a dependent variable, while second paper uses industry earnings. The first paper studies the impact of temperature shocks on establishment-level sales and productivity. Establishment-level sales represent sales based on a firm establishment from the geographical perspective. Here the authors are in line with certain literature, thereby confirming almost no relation between temperature and aggregate economic growth in rich countries. Temperature exposure is used as an independent variable. They also find that the effects of temperature shocks are economically small and statistically insignificant. In the second study, the authors measure how extreme temperatures affect company earnings. They conclude that such temperatures impact earnings in over 40% of industries. Additionally, the study discovers that investors do not react to observable intra-quarter temperature shocks right away, but earnings forecasts and stock prices account for temperature effects by the quarter-end. Similarly to Hsiang's (2010) long-term effect, it is also confirmed that the temperature effect is not observable immediately.

The temperature exposure effect is also studied by Pankratz, Bauer, and Derwall (2019). They find that increases in the number of extremely hot days per financial quarter negatively impact, as well as represent negative shocks to revenues and operating income. The negative relation between the number of the days with extremely high temperatures and firm performance is mainly driven by reductions in the asset turnover and by changes in the cost margin.

2.3 Weather effect

Saunders (1993) wrote one of the most important papers examining the effect of the weather on investor behaviour and consequently on the stock prices. This paper tests the null hypothesis that stock prices from New York City exchanges have not been systematically affected by the local weather. The results indicate that both a very sunny weather and a totally cloudy weather influence stock prices. Saunders's findings support the view that the investor's psychology influences asset prices. As the author states, the economic effect produced is surprisingly large, considering that the weather event is such a minor one.

The weather effect has also been studied by Hirshleifer and Shumway (2003), who have examined the psychological aspect of the weather. Their paper measures the relationship between morning sunshine in the city of a country's leading stock exchange and daily market index returns across 26 countries from 1982 to 1997. The findings suggest that sunshine is significantly correlated with daily stock returns. The authors, however, mention that there is no rational explanation of why a day of sunshine near a country's stock exchange should be associated with high return on a market index. They suggest that the investors' awareness of their moods increases in order to avoid mood-based mistakes within trading and decision-making process.

Another study investigating the relation between stock market returns and temperature through psychological effects was published by Cao and Wei (2005). The expected effects suggested by the evidence are that lower temperature can lead to aggression, while higher temperature can lead to both apathy and aggression. It is supposed that aggression results in more risk-taking, while apathy brings the opposite effect. Therefore, it can be expected that lower temperatures will be related to higher stock returns and higher temperatures will be related to higher or lower stock returns, depending on the trade-off between the two competing effects. The authors reveal an overall negative correlation between temperature and stock market returns. Therefore, statistically significant negative correlation takes place across the whole temperature range, suggesting that the impact of apathy dominates over the impact of aggression during the summer months.

Worthington (2009), however, finds absolutely no effect of the weather on market returns in Australia. Australian securities are regressed against precipitation, evaporation, relative humidity, maximum and minimum temperatures, and hours of bright sunshine.

Comprehensive research of literature focused on the climate economy and the weather impact on the economic outcome has been carried out by Dell, Jones, and Olken (2014).

From the literature, it can be concluded that there are various effects of natural disasters on the economic performance, depending mainly on what kind of disaster has taken place and what kind of companies are being exposed to that disaster. The temperature effect is mostly negative with the time delay and therefore not immediately observable. Heatwaves do have a negative effect on the economy via indirect relations and interdependencies. A larger effect might also be expected for some sectors such as agriculture. In general, the majority of the research in this field traces the long-term effects of natural disasters. However, there is some research on event studies. Also, there are other methodologies measuring the short-term effects of such disasters.

I see a room for contribution to the literature by analysing the Australian market from a short-term perspective. From my perspective, there is also not enough studies that use the combination of natural disasters, which can potentially be interconnected, such as bushfires and heatwaves. This research also contributes to event studies and immediate effects' analysis in general.

3 Data

In this chapter, I will show data sources that have been used in this paper along with descriptive statistics. For this study, the main data categories are stock indices, individual stock prices, temperatures, other weather conditions, and the characteristics of bushfires and heatwaves.

3.1 Data sources

For the purposes of this paper, publicly available web sources of data at Investing.com and DataStream have been used for the stock market data and prices. As an Australian market representative, I have introduced the ASX200 index. To make the sector and size-effect analysis, I have used sub-indices. Regarding different Australian sectors, I have used S&P/ASX200 REIT for real estates, S&P/ASX200 Information Technology, S&P/ASX200 Industrials, S&P/ASX200 Financials, and S&P/ASX200 Insurance. For different sizes of Australian companies, I have used S&P/ASX 50 for large companies, S&P/ASX Midcap 50 for mid-sized companies, and ASX Small Ordinaries for small Australian companies. All Australian indices are denominated in the Australian dollar. As a benchmark, the MSCI World Index has been used, denominated in the US dollar. Sub-indices data is available from 20 April 2001, and main ASX200 index data is available from 1 January 1990. To keep comparability, I have analysed the 19-year period from 20 April 2001 until the end of the year 2019. The decision for this period to be used has been done because the S&P/ASX index series and therefore all S&P sub-indices were introduced in 2000. At this point, S&P/ASX200 has replaced the All Ordinaries index as the key institutional benchmark index for the Australian market (S&P Dow Jones Indices, 2019). Later, for a cross-sectional regression of the event characteristics on cumulative abnormal returns, I have worked only with the main ASX200 index in this part of analysis. Therefore, all available data from 1 January 1990 have been used.

For a further analysis of the ASX200 index, I have obtained ASX Composite from DataStream to look at the detailed information about companies, including location and sector.

The Australian Institute for Disaster Resilience provides historical data on natural disasters. Basic statistics and more detailed data from news and reports of such disasters are available. The Australian Institute in cooperation with the Australian government regularly publishes the 'Major Incidents Report' with detailed information about serious events that happened within a certain period. Over the 19-year period covered in my research, I have observed 41 bushfires. In the final event study analysis, I have not counted in all of them as some of those bushfires occurred on the same day or over the course of few days. This is not in line with the correct event study methodology, since it creates a bias in AR calculations. For each bushfire, I looked at some important characteristics of it, such as the location, number of victims, number of homes destroyed, and the damage area. Besides these basic statistics, I also looked at the news and acquired some important information such as what are the circumstances and weather conditions accompanying such event.

In the table below there are the necessary information about the bushfires and their characteristics:

Table 1: Bushfires' characteristics

Date	Victims	State	Damage Area [ha]	Homes Destroyed
11/8/2019	34	New South Wales / Victoria	18 736 070	2 779
2/28/2019	0	Victoria	123 000	29
2/19/2019	0	Western Australia	3 336	0
2/12/2019	0	New South Wales	7 552	18
2/10/2019	0	New South Wales	23 528	14
1/30/2019	0	Western Australia	315 000	0
1/5/2019	0	New South Wales	100	0
1/4/2019	0	Victoria	11 500	0
12/28/2018	0	Tasmania	200 000	0
11/22/2018	1	Queensland	1 400 000	9
11/1/2018	0	Australian Capital Territory	200	0
8/11/2018	1	New South Wales	1 700	0
5/24/2018	0	Western Australia	21 000	1
4/14/2018	0	New South Wales	3 800	0
3/18/2018	0	New South Wales	1 250	65
3/17/2018	0	Victoria	24 254	26
2/18/2017	0	New South Wales	300	11
2/18/2017	0	New South Wales	3 500	0
2/11/2017	0	New South Wales	55 000	35
1/6/2016	2	Western Australia	69 000	181
12/19/2015	0	Victoria	2 500	116
11/25/2015	2	South Australia	82 500	91
1/2/2015	0	South Australia	12 500	27
2/9/2014	0	Victoria	16 000	0

2/8/2014	0	Victoria	130 000	40
1/15/2014	0	Victoria	52 000	0
1/12/2014	1	Western Australia	650	52
1/7/2013	0	New South Wales	131 000	51
1/3/2013	1	Tasmania	36 000	203
11/23/2011	0	Western Australia	58 550	39
8/1/2011	0	South West Queensland	7 000	0
2/5/2011	0	Western Australia	1540	72
2/7/2009	173	Victoria	365 020	2029
12/28/2007	3	Western Australia	39 630	0
12/1/2006	1	Victoria	1 300 000	51
1/1/2006	4	Victoria	160 000	57
1/10/2005	9	South Australia	82 000	79
1/8/2003	4	Australian Capital Territory	160 000	488
1/8/2003	0	Victoria	2 000 000	41
10/9/2002	0	New South Wales	100	10
12/24/2001	0	New South Wales	753 314	109

Source: Australian Institute for Disaster Resilience

The Australian Bureau of Meteorology provides the weather and climate data. By choosing specific meteorological stations, I could obtain a temperature and daily rainfall data. The same data from meteorological stations can be obtained from the National Oceanic and Atmospheric Administration, which provides the global data.

Station data contain daily minimum temperatures, daily maximum temperatures, and daily precipitation. I have also calculated the average daily temperature.

From the ASX Composite, it is observable that 85% of the companies included in the index are based in Sydney, Adelaide, Perth, or Melbourne. For all weather data, I have calculated an average of the stations located in these four cities. These stations are Sydney Observatory Hill, Adelaide Station, Perth Airport, and Melbourne Olympic Park. By using this approach, I was able to get a more representative relationship between weather data and stock returns, and this is especially useful in the analysis of heatwaves.

3.2 Descriptive statistics

Within an event study methodology, I have calculated a return of all stock indices. These returns are calculated as R_t = LN $(\frac{P_t}{P_{t-1}})$. To see a characteristic of these returns, the basic descriptive statistics are also calculated. Descriptive statistics of stock market data for the period from April 2001 until December 2019 are shown in the table below:

Table 2: Stock indices' descriptive statistics

	Mean (%)	Median (%)	Std. dev. (%)	Skewness	Kurtosis
MSCI World	0.02	0.06	0.99	-0.39	8.53
ASX200	0.01	0.05	0.97	-0.48	5.79
ASX200 REIT	0.00	0.03	1.24	-0.79	10.63
ASX200 IT	0.01	0.02	1.54	0.05	4.98
ASX200 Industrial	0.01	0.06	1.05	-0.47	4.12
ASX200 Financials	0.01	0.04	1.12	-0.09	6.07
ASX200 Insurance	-0.01	0.04	1.34	-0.98	11.97
ASX50	0.01	0.05	1	-0.39	5.66
ASX Midcap 50	0.02	0.07	0.97	-0.65	5.05
ASX Small Ordinaries	0.01	0.08	1	-0.89	6.73

Source: Author's calculation

The returns of most of the indices are negatively skewed, which also means that the mean is lower than the median. The IT sector has the largest standard deviation. Kurtosis is higher than 3 for all indices. This means that the distribution of the returns is leptokurtic and thus has a fatter tail.

Descriptive statistics for the characteristics of the events are shown below. They are calculated from the observations used within regression analysis:

Table 3: Events' characteristics

	Mean	Std. Dev.	Median	Minimum	Maximum
Victims	5.75	26.34	0	0	173
Damage Area [ha]	625 286	2 825 672	23 891	100	18 736 070
Homes Destroyed	158	510	26.5	0	2 779
Daily Rainfall [mm]	0.33	0.56	0.12	0	2.68
Duration (days)	3.38	0.82	3	3	7
Intensity (°C)	35.72	1	35	35	38

Source: Author's calculation

On average, there are 6 victims per bushfire. However, it is important to highlight one outlier. The bushfire with 173 victims increases this average. The average damage area is about 630 000 hectares [ha], while on average 158 homes are destroyed per bushfire. During heatwaves, an average of 0.33 mm of daily rainfall occurred. One of the characteristics of heatwaves, ‘intensity’, is expressed as an average maximum temperature during an event. Another characteristic, ‘duration’, is the number of days the heatwave actually lasted.

4 Methodology

The core of the whole research is the event study statistical method. Within this chapter, before I present actual analysis, I will explain some data adjustments. Furthermore, I will show how the abnormal return (AR) and the cumulative abnormal return (CAR) are calculated and what techniques are used. Finally, I will also demonstrate how cross-sectional regression analysis helps to understand CAR better.

4.1 Data adjustments

As it was mentioned in the previous chapter, my main data included those representing stock market prices, bushfires, and heatwaves. Before any analysis could be performed by using statistical and econometric techniques, several adjustments had to be performed as well. From meteorological stations, maximum and minimum daily temperature data along with precipitation data were downloaded. As the headquarters of most of the companies concerned are based in Sydney, Adelaide, Perth, and Melbourne, I have calculated and stated an average of these four stations for all data types. Such a technique ensures that weather conditions are as relevant and representative as possible, so that I can measure their impact on firm performance and stock prices. However, the important fact is that these companies also perform their activities and businesses in other areas and cities all over the Australia and worldwide. To be completely precise, in order to find all areas that are exposed to different weather conditions and could potentially have an effect on the stock prices of these companies, all affiliates, warehouses, business centres, and other interconnected parts of the companies should be tracked. As the biggest and the busiest metropolises were chosen for the purpose of getting weather conditions data, it is highly likely that such data will capture a significant part of the companies' activities and as such these are sufficient representations. It is also likely that if there is any significant effect of high temperatures on the activities performed far from the headquarters (this is typical for mining companies or oil companies) this effect would be observable from the stock market with certain time delay along with a decrease in the quarter revenue or increase in the cost. As I used a statistical technique monitoring mostly the immediate effect of temperature changes, it was sufficient to work with the meteorological stations in the most important cities. Moreover, mostly institutional investors and traders influence stock prices and are also supposed to react to bushfires and heatwaves. Naturally, they are also primarily based in cities like Sydney or Melbourne.

By the Australian Bureau of Meteorology a heatwave is defined as three or more days in a row when both day and night temperatures are unusually high in relation to the local long-term climate. In fact, there is not a single temperature threshold for heatwaves in Australia. For instance, in Adelaide, a heatwave is defined as a temperature of 35 ℃ or above lasting for five consecutive days or a temperature of 40 ℃ or above lasting for three consecutive days (Australian Government, 2010). Additionally, the daily mean temperature above 97th percentile (calculated from the data over the whole studied period) is also considered. In this research, a heatwave is defined as a temperature above 35 ℃ within at least three consecutive days when the mean temperature simultaneously remains above the 97th percentile during the same consecutive days. In this approach, the methodology is in line with the Bureau of Meteorology and at the same time the number of the observations is sufficient for making a proper analysis.

From the downloaded temperature data, the maximum daily temperature is considered to be an important metric. I have also calculated the daily mean temperature. As indicated, both mean and maximum temperatures are averaged from four meteorological stations on a daily basis.

Now, once that three or more days with a maximum temperature above 35 ℃ were compatible with the mean temperature above 97th percentile, I have considered that as an event.

All information about bushfires is publicly available in the aforementioned database. I have considered bushfire news date as a first day of the event.

4.2 Event study

For event study method, my work is compatible with MacKinlay's (1997) paper that focuses specifically on this statistical approach. As the author says, there is a general flow of analysis. Firstly, as already discussed, the events have been defined. The event window is the day of the event plus four consequent days, what creates five-day event window. As mentioned, a two-day event window is also estimated as a complement to the core analysis. By using the longer event window, I am able to examine not only the immediate abnormal return, but also the cumulative abnormal return for a period of interest. Sometimes, the period prior to the event may be of interest as well. Certain price effects could be observable here as a consequence of the acquired insiders' information. For the natural disasters event, this is not the case as it is highly unlikely that traders or any other market participants would be able to predict such an event in advance. In my study, I have included index prices as a metric of interest. Consequently, I worked with individual stock prices within cross-sectional regression.

4.2.1 Abnormal return and cumulative abnormal return

The abnormal return is calculated by subtracting the normal return from the actual return over the event window. The general equation for abnormal return calculation is:

$$AR_{i\tau} = R_{i\tau} - \mathrm{E}(R_{i\tau}|X_{\tau}) \qquad \text{(a)}$$

From the equation, $AR_{i\tau}$, $R_{i\tau}$, and $\mathrm{E}(R_{i\tau}|X_{\tau})$ are the abnormal return, actual return, and normal return, respectively (MacKinlay, 1997). For a normal return modelling, the best method is the market model followed by the constant mean return model. Another simple normal return calculation method is the market-adjusted return model. I have calculated the normal return by using all these methods to compare the results and perform a robustness check. The estimation window for the market model is one year, particularly 253 trading days. For the constant mean return model, I have taken the estimation window of one year and three months. By using a shorter estimation window, the drawback of the overlap of the event window and the estimation window is limited.

The market model is defined as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad \text{(b)}$$

$\mathrm{E}\ (\varepsilon_{it} = 0)$

$\mathrm{var}\ (\varepsilon_{it}) = \sigma_{\varepsilon i}^2$

R_{it} and R_{mt} are the period-t returns on security i and the market portfolio, respectively, and ε_{it} is the zero mean disturbance term. α_i, β_i , and $\sigma_{\varepsilon i}^2$ are the parameters of the market model (MacKinlay, 1997). In my study the MSCI World index is used to represent the market portfolio for both market model and market-adjusted return model. For Australian sub-indices, I could also apply the ASX200 index as a market portfolio. This additional exercise is performed in order to see the difference regarding abnormal returns. Here it is expected to see smaller abnormal returns by using the ASX200 index as a benchmark, which is ideally statistically insignificant. The idea behind it is that the ASX200 index should be impacted by natural disasters in a similar way as its sub-indices, while the MSCI World index should be naturally impacted less.

The constant mean return model is defined as:

$$R_{it} = \mu_i + \xi_{it} \qquad \text{(c)}$$

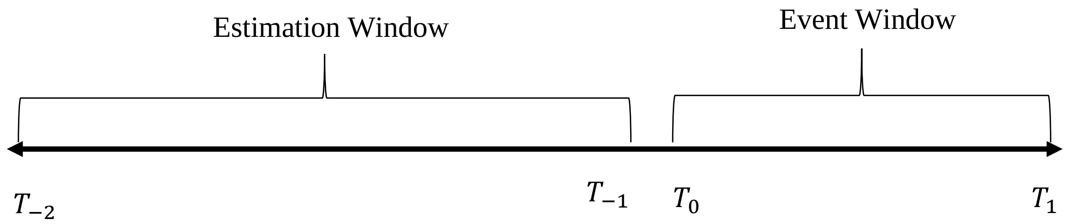
$E(\xi_{it}) = 0$

$Var\ (\xi_{it}) = \sigma^2_{\xi i}$

R_{it} is the period-t return on security i, and ξ_{it} is the time period t disturbance term for security i with an expectation of zero and variance $\sigma^2_{\xi i}$. The model is in line with the data I have worked with, since by using the daily data the model is typically applied to nominal returns (MacKinlay, 1997). I recall that I have calculated a daily nominal return as R_t = LN $(\frac{P_t}{P_{t-1}})$.

The market adjusted-return model is the other statistical model for normal return calculation, which does not require an estimation period to estimate parameters. The abnormal return is simply calculated by subtracting the market portfolio return from the return of the interest, which, in this case, is the Australian stock market return.

For the market model and the constant mean return model, a general timeline looks as follows:



The period between T_{-2} and T_{-1} is an estimation period, which in case of the market model is one year and in case of the constant mean-return model is one year and three months. The period between T_0 and T_1 is the event window from Day 0, which is the day of the event until Day 4. The event window lasted for five days.

By applying the market model, the abnormal return is calculated as follows:

$$AR_{i\tau} = R_{i\tau} - \alpha_i - \beta_i R_{m\tau} \qquad \text{(d)}$$

$AR_{i\tau}$ is the abnormal return of the analysed stock index during the event window, $R_{i\tau}$ is the return of the same index, $R_{m\tau}$ is the return of the market index, and α_i and β_i are parameters calculated from the returns within the estimation window.

By using constant mean return model, the abnormal return calculation is following:

$$AR_{i\tau} = R_{i\tau} - \bar{R}_i \qquad \text{(e)}$$

$\bar{R}_i$ in the equation above is the constant average return of the analysed stock index, which happens to be ASX200. $\bar{R}_i$ is calculated from the estimation window, which, in this case, lasts for one year and three months.

The abnormal return for five consequent days is calculated for each observation. There were 33 bushfires and 19 heatwaves included in the research focused on the 19-year time period. For further analysis, I have worked with the abnormal return for Day 0 which is supposed to capture the immediate reaction of the market to the natural disaster event.

By definition, the abnormal return has to be aggregated through time and through observations. By aggregating through time, for each observation I get a cumulative abnormal return from Day 0 up until Day 4. The most significant cumulative abnormal return is the one obtained by aggregating all the five days and therefore this cumulative abnormal return ($CAR_{0.4}$) is used for further analysis.

In general, the cumulative abnormal return from τ_1 to τ_2 is the sum of the included abnormal returns and the equation is following:

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \qquad \text{(f)}$$

Within an aggregation process through time, it is important that there is no clustering. Therefore, within an event window there is no overlap of the observations and thus no covariance between the abnormal returns. This is the reason why I have worked with only 33 bushfires, even though there were 41 bushfires during the analysed period. This is not the issue in case of heatwaves as these are not as frequent as bushfires.

Under zero hypothesis, on average, the cumulative abnormal return will be zero.

Once all abnormal returns and cumulative abnormal returns were calculated per event, I have made an aggregation of those returns through event observations.

In general, the equation for the average abnormal return is:

$$AAR_\tau = \frac{1}{N}\sum_{i=1}^{N} AR_{i\tau} \qquad \text{(g)}$$

Similarly, the equation for the cumulative average abnormal return is:

$$\text{CAAR}\ (\tau_1,\tau_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(\tau_1,\tau_2) \qquad \text{(h)}$$

All three normal return models were considered and compared. Null hypothesis testing was needed once the average return was calculated. In order to test the null hypothesis, the test statistic of two-sided test calculation must be introduced. It looks as follows:

$$\Theta = \frac{CAAR(\tau_1,\tau_2)}{var\ (CAAR(\tau_1,\tau_2))^{1/2}} * \sqrt{N} \ \text{(i)}$$

It is clear from the aforementioned formula that the standard error of the abnormal return and the cumulative abnormal return needs to be calculated as well. N is the number of the observations.

The distribution of the test statistic is standard normal. Therefore, the null hypothesis about the zero cumulative abnormal return will be rejected if: $\Theta < c\ (\frac{\alpha}{2})$ or $\Theta > c\ (1-\frac{\alpha}{2})$.

I have worked with the common significance levels of 1%, 5%, and 10%. For the 1% significance level, the critical values calculated by using $c\ (\frac{\alpha}{2})$ and $c\ (1-\frac{\alpha}{2})$ are -2.58 and 2.58, respectively. For the 5% level of significance, the critical values are -1.96 and 1.96, respectively. Finally, for the 10% significance level, the critical values are -1.645 and 1.645, respectively.

All calculations as indicated above, were performed for the main Australian stock market index ASX200 as well as for all other sub-indices for different sectors and sizes.

Boehmer, Musumeci and Poulsen (1991) point at event-induced variance. They argue that due to a temporary change in the firm's systematic risk, variance accompanying an event increases. Therefore, it is also important to control for variance changes to obtain appropriate tests of the null hypothesis. They suggest normalizing event-period returns and application of a cross-sectional test to these standardized residuals. This is beyond the scope of my analysis, however the event-induced variance and its dealing methods is a fruitful area for a further research.

4.2.2 Cross-sectional model

Once the cumulative average abnormal return and its statistical significance were calculated, the relationship between the $\text{CAR}_{0.4}$ magnitude and the event characteristics needed to be examined. Five days' cumulative abnormal return is the most statistically significant among all other measured cumulative abnormal returns. By using this regression, I was able to detect the source of $\mathrm{CAR}_{0.4}$. The cumulative abnormal return was regressed on the characteristics of interest. This technique is based on MacKinlay's event study (1997). Owing to the character of the event, which is natural disaster, I was more interested in the cumulative abnormal return than the immediate first-day abnormal return on the market. This way, I can observe the investor's behaviour during a longer time period since natural disasters mostly last longer than one day.

The general regression model equation is:

$$\mathrm{C}AR_{(\tau_1,\tau_2)} = \delta_0 + \delta_1 x_{1j} + \ldots.. + \delta_M x_{Mj} + \eta_j \quad \text{(j)}$$

$E(\eta_j) = 0$

From the equation, x_{Mj} are the M characteristics for the j^{th} observation, δ_M are the M regression coefficients, and η_j is a disturbance term.

In theory, the OLS method can be used for regression estimation. Based on the data structure, panel regression should be run. As I have worked with data on natural disasters, which occur irregularly, during the chosen time period, the pooled cross-section data structure is present. The key feature of panel (longitudinal) data that distinguishes it from the pooled cross-section data is that the same cross-sectional units are followed over a given time period (Wooldridge, 2012). As all cumulative abnormal returns are different, unique events and natural disasters events occur irregularly, I cannot work with longitudinal data. Within a 30-year sample period, there were years when there was no event whatsoever, while in the same period there were also years with several events. Therefore, it is effective to pool cross-sections from different years.

While executing the regression estimation process, I performed a test of standard assumptions underlying the linear regression model. I performed tests of heteroscedasticity and multicollinearity. Omitted variable testing was carried out as well (Brooks, 2019).

The Breusch–Pagan test for heteroscedasticity (1979) is introduced by estimating the F statistic. This test assumes that the errors are normally distributed. The null hypothesis predicts a constant variance.

Variance inflation factor (VIF) is applied to test the model for multicollinearity. For each coefficient, the VIF value is calculated as 1/(1 - R^2). In general, the value 10 is chosen as a cut-off value for multicollinearity. The confirmation of these findings could be the correlation matrix for the introduced variables. Once multicollinearity is detected, all problematic variables might be potentially excluded from regression. In relation to this topic, it is also important to detect if any variable has been omitted from the model. The Ramsey RESET test generally tests whether the relationship between dependent and explanatory variables is linear or not (Brooks, 2019). In STATA, I can use this test to detect if there is any omitted variable based on the F statistic and the null hypothesis, which says that the model has no omitted variables.

I split the index based on the ASX200 Composite information downloaded from DataStream to see all individual firm stocks included in the index. By using this technique, I was able to notice the differences in the effect based on different sectors or different firm locations. In order to do so, I included categorical variables in the regression analysis. The sector split is based on 12 Fama & French industries. These 12 categories are based on Standard Industrial Classification (SIC) codes, which are included within each category. Twelve Fama & French categories are the following:

Table 4: Fama & French industry categories

Number	**Name of the category**
1	Consumer Non-durables: Food, Tobacco, Textiles, Apparel, Leather, Toys
2	Consumer Durables: Cars, TVs, Furniture, Household Appliances
3	Manufacturing: Machinery, Trucks, Planes, Off Furn, Paper, Com Printing
4	Oil, Gas, and Coal Extraction and Products
5	Chemicals and Allied Products
6	Business Equipment: Computers, Software, and Electronic Equipment
7	Telephone and Television Transmission
8	Utilities
9	Wholesale, Retail, and Some Services (Laundries, Repair Shops)
10	Healthcare, Medical Equipment, and Drugs
11	Finance
12	Others: Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment

Source: Kenneth R. French, 2020

The firm location is given by the state where the headquarters are based. Therefore, states introduced within this variable are New South Wales, Victoria, Queensland, South Australia, Tasmania, and Western Australia.

Here the dependent variable is the five-day cumulative abnormal return ($\mathrm{CAR}_{0.4}$). The explanatory variable for bushfires represents the number of victims during the event, the area which has been damaged expressed by the absolute value in hectares, the number of houses destroyed, and fire-weather conditions. All bushfire characteristics and information about windy conditions were obtained from the Australian disasters database and available news. The information about drought was obtained from the Australian Government Bureau of Meteorology's regular monthly drought reports. In order to analyse fire-weather conditions better, I introduced a categorical variable based on different combinations of drought and wind, during a bushfire event. This way, I could observe the effect of specific weather conditions. Categories within this variable were drought, wind, a combination of both and none of those conditions, with the latter meaning that weather conditions driving bushfires did not actually take place.

The explanatory variable for heatwaves was the duration (meaning the number of the days a heatwave lasted), the intensity expressed by the average maximum temperature reached during a heatwave, drought and rainfall. In case of rainfall, expressed in the absolute value in millimetres of precipitation felt during a heatwave, I have calculated an average for all days included in the heatwave event, and consequently, all the analysed meteorological stations in Sydney, Melbourne, Adelaide, and Perth were averaged as well. The reason why I focused especially on these four stations was explained in the data sources part.

5 Results

Since two events were analysed, the section is divided into bushfires and heatwaves details. I looked at the abnormal returns and the cumulative abnormal returns for all the introduced indices. Consequently, I went through with the cross-sectional analysis with all regression tests and model specifications. Finally, I drew a general result conclusion.

5.1 Bushfires' abnormal return

The results for the main ASX200 index and the chosen S&P ASX sub-indices are published below. They are available for the market model, the constant mean return model, and the market-adjusted return model. As a benchmark for the key analysis, the MSCI world index was introduced. In order to perform a comparative analysis, the ASX200 index was also introduced as a benchmark for ASX sub-indices. The comparative analysis results with the ASX200 index as a market portfolio are available in the appendix.

The constant mean return model was calculated by using a one-year estimation window as well as a three-month estimation window. By using a shorter estimation window, the drawback related to the overlap of the event window and the estimation window was limited. Simultaneously with AAR_0 and $\mathrm{CAAR}_{0,4}$ calculation, I performed a comparison analysis of AAR_1 and $\mathrm{CAAR}_{0,1}$. The research hypotheses were also tested simultaneously.

In the following paragraph I present the first set of hypotheses:

H0: The average abnormal return (AAR_0) of bushfires on the event day is statistically insignificant and close to zero.

H4: The AAR_1 of bushfires is statistically insignificant and close to zero.

The results are available in the table below:

Table 5: Bushfires' average abnormal return for Day 0 and Day 1
Sample: 33

Index name	Methodology	AAR (0) (%)	Stdev (0) (%)	t-value (0)	AAR (1) (%)	Stdev (1) (%)	t-value (1)
ASX200	Market model	0.18	0.66	1.57	-0.04	0.62	-0.33
	Constant mean return model (1Yr)	0.14	0.77	1.06	-0.07	0.67	-0.57
	Constant mean return model (3M)	0.15	0.80	1.06	-0.06	0.67	-0.53
	Market-adjusted return model	0.23	0.77	1.67*	-0.21	1.09	-1.09
S&P ASX200 REIT	Market model	-0.12	1.14	-0.60	0.00	1.04	-0.01
	Constant mean return model (1Yr)	-0.14	1.16	-0.68	-0.03	1.00	-0.20
	Constant mean return model (3M)	-0.13	1.19	-0.63	-0.03	1.00	-0.17

	Market-adjusted return model	-0.07	1.38	-0.27	-0.17	1.53	-0.65
S&P ASX200 IT	Market model	0.30	1.23	1.40	0.02	1.03	0.11
	Constant mean return model (1Yr)	0.30	1.25	1.38	0.07	1.15	0.36
	Constant mean return model (3M)	0.29	1.32	1.24	0.06	1.17	0.27
	Market-adjusted return model	0.37	1.32	1.59	-0.07	1.34	-0.31
S&P ASX200 Industry	Market model	0.11	0.73	0.87	-0.01	0.63	-0.09
	Constant mean return model (1Yr)	0.09	0.75	0.67	0.00	0.68	0.00
	Constant mean return model (3M)	0.09	0.76	0.71	0.01	0.67	0.06
	Market-adjusted return model	0.15	0.96	0.92	-0.14	1.10	-0.73
S&P ASX200 Finance	Market model	0.13	0.85	0.85	-0.09	0.79	-0.65
	Constant mean return model (1Yr)	0.10	0.94	0.64	-0.11	0.85	-0.72
	Constant mean return model (3M)	0.11	0.97	0.65	-0.09	0.85	-0.64
	Market-adjusted return model	0.16	0.98	0.93	-0.23	1.27	-1.01
S&P ASX200 Insurance	Market model	0.17	1.20	0.81	-0.06	0.99	-0.34
	Constant mean return model (1Yr)	0.17	1.29	0.74	-0.10	0.98	-0.56
	Constant mean return model (3M)	0.18	1.29	0.82	-0.08	0.98	-0.46
	Market-adjusted return model	0.24	1.50	0.90	-0.25	1.36	-1.06
S&P ASX50 Large	Market model	0.14	0.65	1.21	-0.10	0.61	-0.90
	Constant mean return model (1Yr)	0.12	0.76	0.87	-0.10	0.69	-0.85
	Constant mean return model (3M)	0.12	0.78	0.87	-0.09	0.70	-0.76
	Market-adjusted return model	0.18	0.77	1.37	-0.21	1.13	-1.05
S&P ASX50 Midcap	Market model	0.13	0.78	0.98	-0.01	0.68	-0.05
	Constant mean return model (1Yr)	0.12	0.84	0.82	-0.01	0.72	-0.09
	Constant mean return model (3M)	0.13	0.89	0.82	0.00	0.73	0.00
	Market-adjusted return model	0.20	0.92	1.22	-0.11	1.15	-0.53
S&P ASX Small Ordinaries	Market model	0.20	0.78	1.43	0.02	0.56	0.21
	Constant mean return model (1Yr)	0.18	0.85	1.22	0.02	0.64	0.14
	Constant mean return model (3M)	0.19	0.90	1.24	0.06	0.66	0.51
	Market-adjusted return model	0.25	0.91	1.57	-0.09	1.01	-0.50

Market portfolio: MSCI World
***,**,* Significance at the 1%,5%, and 10% levels, respectively
Source: Author's calculation

Hereby I reject the null hypothesis. All average abnormal returns are statistically insignificant, and therefore efficient market theory cannot be rejected. The exception is the ASX200 index. With the determined value of 0.23%, AAR_0 is positive and statistically significant at the 10% significance level. However, this is the case only for the market-adjusted return model methodology.

In theory, the positive impact on the day of the event is in line with the study of Worthington and Valadkhani (2004). These authors estimate that bushfires are associated with small positive effects on the day of and following an event, namely on Day 0 and Day 1 of the event window.

In their article Skidmore and Toya (2002) investigate the long-run relationship between disasters, capital accumulation, total factor productivity, and economic growth. In their paper, the empirical analysis confirms a positive correlation between climatic disasters and economic growth. Natural disasters are initially felt in the loss of capital and durable goods. The efforts to replace them often increase the economic output. Thus, natural disasters play an important role in macroeconomic activity, but not necessarily in the ways that it might be expected (Skidmore and Toya, 2002). So, the researchers confirm a positive impact, which, however, has a long-term character that is not fully in line with the event day immediate abnormal return results.

In the following paragraph I present the second set of hypotheses:

H1: The five-day cumulative average abnormal return ($\mathrm{CAAR}_{0,4}$) of bushfires is statistically insignificant and close to zero.

H5: The two-day cumulative average abnormal return ($\mathrm{CAAR}_{0,1}$) of bushfires is statistically insignificant and close to zero.

The results are available in the table below:

Table 6: Bushfires' five-day and two-day cumulative average abnormal return
Sample: 33

Index name	Methodology	CAAR (0,4) (%)	Stdev (0,4) (%)	t-value (0,4)	CAAR (0,1) (%)	Stdev (0,1) (%)	t-value (0,1)
ASX200	Market model	0.36	1.54	1.34	0.15	1.03	0.81
	Constant mean return model (1Yr)	0.31	2.20	0.81	0.08	1.11	0.40
	Constant mean return model (3M)	0.33	2.24	0.86	0.09	1.16	0.43
	Market-adjusted return model	-0.10	2.19	-0.27	0.02	1.36	0.08
S&P ASX200 REIT	Market model	0.09	1.88	0.28	-0.12	1.58	-0.44
	Constant mean return model (1Yr)	-0.03	2.11	-0.08	-0.17	1.42	-0.69
	Constant mean return model (3M)	-0.01	2.15	-0.02	-0.16	1.49	-0.62
	Market-adjusted return model	-0.44	2.96	-0.85	-0.24	2.31	-0.60
S&P ASX200 IT	Market model	1.27	3.98	1.83*	0.32	1.40	1.31
	Constant mean return model (1Yr)	1.39	4.37	1.83*	0.37	1.52	1.42
	Constant mean return model (3M)	1.30	4.58	1.63	0.34	1.65	1.18

	Market-adjusted return model	0.95	4.46	1.23	0.30	1.65	1.03
S&P ASX200 Industry	Market model	0.24	1.83	0.75	0.10	0.89	0.66
	Constant mean return model (1Yr)	0.23	2.22	0.61	0.05	0.93	0.33
	Constant mean return model (3M)	0.27	2.35	0.67	0.07	0.95	0.45
	Market-adjusted return model	-0.17	2.62	-0.38	0.02	1.39	0.07
S&P ASX200 Finance	Market model	0.39	1.92	1.17	0.03	1.33	0.11
	Constant mean return model (1Yr)	0.35	2.56	0.79	-0.01	1.44	-0.04
	Constant mean return model (3M)	0.38	2.58	0.85	0.01	1.49	0.05
	Market-adjusted return model	-0.28	2.32	-0.69	-0.11	1.69	-0.37
S&P ASX200 Insurance	Market model	0.38	2.30	0.96	0.11	1.33	0.48
	Constant mean return model (1Yr)	0.39	3.08	0.74	0.07	1.60	0.25
	Constant mean return model (3M)	0.48	3.07	0.90	0.11	1.61	0.38
	Market-adjusted return model	-0.11	2.07	-0.32	-0.01	1.44	-0.06
S&P ASX50 Large	Market model	0.27	1.47	1.05	0.03	0.99	0.17
	Constant mean return model (1Yr)	0.27	2.19	0.70	0.00	1.13	0.01
	Constant mean return model (3M)	0.28	2.21	0.73	0.02	1.17	0.10
	Market-adjusted return model	-0.16	2.13	-0.43	-0.04	1.40	-0.16
S&P ASX50 Midcap	Market model	0.19	1.86	0.58	0.12	1.12	0.61
	Constant mean return model (1Yr)	0.19	2.36	0.47	0.10	1.19	0.49
	Constant mean return model (3M)	0.23	2.46	0.55	0.12	1.27	0.56
	Market-adjusted return model	-0.18	2.62	-0.41	0.08	1.53	0.28
S&P ASX Small Ordinaries	Market model	0.31	1.65	1.09	0.24	0.96	1.41
	Constant mean return model (1Yr)	0.31	2.36	0.76	0.23	1.06	1.23
	Constant mean return model (3M)	0.38	2.39	0.91	0.25	1.14	1.28
	Market-adjusted return model	-0.11	2.39	-0.27	0.15	1.34	0.65

Market portfolio: MSCI World
***,**,* Significance at the 1%, 5% and 10% levels, respectively
Source: Author's calculation

Based on t-statistics, the null hypothesis is rejected. All cumulative average abnormal returns are statistically insignificant, but the exception in this case is the S&P ASXX200 IT sector index. $CAAR_{0,4}$ is statistically significant and reaches 1.27%. In general, information technology is used to predict natural disasters and reduce the potential vulnerability and fatalities caused by disasters. Toya and Skidmore (2015) introduce the cross-country data over a 33-year period and confirm that improvement in the access to information technologies decreases the number of disaster-induced fatalities. This research highlights the role of information technologies in disaster preparation and response, as well as the interaction between information technologies and human capital. For instance, cell phones might save lives, but mainly in countries with higher levels of human capital.

According to Alexander (1991, 1997), information technology plays an important role in monitoring, forecasting, and managing disasters. According to Alexander (1991), particularly technologies like earth recourse satellites, microcomputers, or communication satellites have a potential for natural disaster management. According to Alexander (1997), the information technology revolution will stimulate a wide variety of creative responses to the monitoring, forecasting, and management of disasters. Although these conclusions were made about 25 years ago, it is still an appropriate statement. Nowadays, the development in information technology has progressed rapidly, while the frequency of unexpected events has also increased due to global climate changes. Thus, it will be a crucial approach to work on improving information technologies, which are likely to be a key weapon in the near future.

As a consequence, there is an obvious relationship between a natural disaster such as a bushfire and the information technology sector. Therefore, it is expected to see an increase in performance of this sector with increasing frequency of similar events.

Now, I can make a conclusion about the hypotheses that test if there is any difference in responses in different sectors and different size categories of companies. The hypotheses are stated as follows:

H8: The impact of bushfires on the asset value differs with different industries.

This hypothesis cannot be rejected, since there is statistically significant positive $\mathrm{CAAR}_{0,4}$ of the IT sector on the 10% significance level.

H9: The impact of bushfires on the asset value differs with different company sizes.

This hypothesis is rejected, since there is no significant AAR or CAAR for indices representing different size groups.

5.2 Heatwaves' abnormal return

In relation to the impact of heatwaves, the next set of hypotheses is introduced. Market benchmark portfolios are applied in the same manner as in the bushfires' analysis.

H2: The AAR_0 of heatwaves on the event day is statistically insignificant and close to zero.

H6: The AAR_1 of heatwaves is statistically insignificant and close to zero.

The results are available in the table below:

Table 7: Heatwaves' average abnormal return for Day 0 and Day 1
Sample: 19

Index name	Methodology	AAR (0) (%)	Stdev (0) (%)	t-value (0)	AAR (1) (%)	Stdev (1) (%)	t-value (1)
ASX200	Market model	0.18	0.87	0.89	0.21	0.82	1.13
	Constant mean return model (1Yr)	0.32	1.01	1.38	0.26	0.84	1.35
	Constant mean return model (3M)	0.29	1.02	1.26	0.24	0.86	1.19
	Market-adjusted return model	0.15	1.05	0.61	0.01	1.11	0.02
S&P ASX200 REIT	Market model	-0.05	1.04	-0.20	-0.05	1.01	-0.22
	Constant mean return model (1Yr)	0.02	1.08	0.10	-0.01	0.88	-0.05
	Constant mean return model (3M)	0.02	1.06	0.08	-0.02	0.88	-0.08
	Market-adjusted return model	-0.09	1.48	-0.26	-0.32	1.48	-0.95
S&P ASX200 IT	Market model	0.37	1.12	1.43	-0.16	0.97	-0.73
	Constant mean return model (1Yr)	0.36	1.08	1.44	-0.08	1.13	-0.32
	Constant mean return model (3M)	0.30	1.10	1.18	-0.14	1.16	-0.54
	Market-adjusted return model	0.26	1.49	0.75	-0.38	1.07	-1.56
S&P ASX200 Industry	Market model	0.15	0.91	0.71	-0.04	0.57	-0.31
	Constant mean return model (1Yr)	0.22	1.07	0.90	0.05	0.52	0.44
	Constant mean return model (3M)	0.18	1.08	0.71	0.01	0.56	0.07
	Market-adjusted return model	0.11	1.09	0.43	-0.26	1.12	-1.01
S&P ASX200 Finance	Market model	0.08	1.03	0.36	0.13	0.87	0.64
	Constant mean return model (1Yr)	0.18	1.10	0.72	0.22	0.99	0.99
	Constant mean return model (3M)	0.18	1.12	0.71	0.22	1.07	0.92
	Market-adjusted return model	0.07	1.27	0.26	-0.08	1.06	-0.33
S&P ASX200 Insurance	Market model	0.38	0.84	1.95*	0.04	1.05	0.15
	Constant mean return model (1Yr)	0.50	0.98	2.22**	0.08	1.14	0.32
	Constant mean return model (3M)	0.47	0.96	2.14**	0.06	1.14	0.21
	Market-adjusted return model	0.31	1.11	1.23	-0.19	1.22	-0.67
S&P ASX50 Large	Market model	0.21	0.88	1.03	0.11	0.70	0.70
	Constant mean return model (1Yr)	0.28	1.05	1.18	0.20	0.74	1.17
	Constant mean return model (3M)	0.26	1.06	1.07	0.17	0.78	0.98
	Market-adjusted return model	0.18	1.04	0.76	-0.10	1.01	-0.44
S&P ASX50 Midcap	Market model	0.15	0.99	0.65	-0.04	0.67	-0.26
	Constant mean return model (1Yr)	0.20	1.02	0.84	0.04	0.62	0.29
	Constant mean return model (3M)	0.15	1.03	0.65	0.00	0.63	-0.02
	Market-adjusted return model	0.09	1.30	0.29	-0.27	1.18	-0.98
S&P ASX Small Ordinaries	Market model	0.11	0.87	0.53	0.05	0.68	0.32
	Constant mean return model (1Yr)	0.17	0.86	0.87	0.16	0.71	0.96

	Constant mean return model (3M)	0.13	0.88	0.65	0.12	0.71	0.72
	Market-adjusted return model	0.05	1.29	0.17	-0.16	1.09	-0.65

Market portfolio: MSCI World
***,**,* Significance at the 1%, 5% and 10% levels, respectively
Source: Author's calculation

The rejection of the hypotheses regarding heatwaves is a consequence of the insurance sector response. By testing the impact of heatwaves, I can confirm a positive effect on the insurance sector AAR_0. The effect is 0.38% and significant by using the market model at the 10% significance level and 0.50% by using the constant mean return model at the 5% significance level. Now, I can recall an explanation related to the positive abnormal return in the insurance sector, which has already been mentioned in the literature section. According to Wang and Kutan (2013), 'gaining from loss hypothesis' explains the insurance sector performance well, following the natural disaster event. A larger demand for insurance coverage might occur. This means higher asset returns in this sector.

H3: The $\mathrm{CAAR}_{0,4}$ of heatwaves is statistically insignificant and close to zero.

H7: The $\mathrm{CAAR}_{0,1}$ of heatwaves is statistically insignificant and close to zero.

The outcome is stated in the table below:

Table 8: Heatwaves' five-day and two-day cumulative average abnormal return
Sample: 19

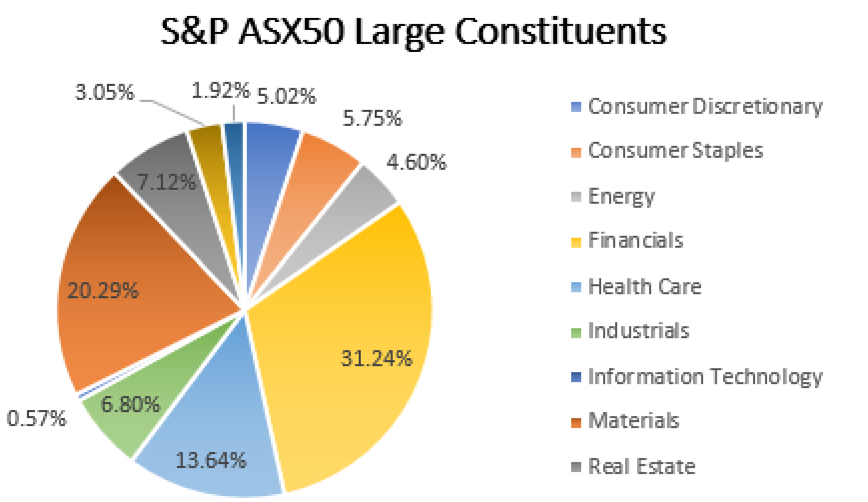
Index name	Methodology	CAAR (0,4) (%)	Stdev (0,4) (%)	t-value (0,4)	CAAR (0,1) (%)	Stdev (0,1) (%)	t-value (0,1)
ASX200	Market model	0.73	1.74	1.83*	0.39	1.13	1.52
	Constant mean return model (1Yr)	0.88	2.09	1.83*	0.58	1.52	1.67*
	Constant mean return model (3M)	0.75	2.17	1.50	0.53	1.56	1.48
	Market-adjusted return model	0.44	1.58	1.22	0.15	1.41	0.47
S&P ASX200 REIT	Market model	0.91	2.45	1.62	-0.10	0.97	-0.44
	Constant mean return model (1Yr)	0.92	2.87	1.39	0.01	1.07	0.06
	Constant mean return model (3M)	0.89	2.80	1.39	0.00	1.04	0.02
	Market-adjusted return model	0.45	2.44	0.81	-0.41	1.96	-0.91
S&P ASX200 IT	Market model	1.20	2.91	1.80*	0.21	1.29	0.70
	Constant mean return model (1Yr)	1.33	3.10	1.87*	0.27	1.50	0.79
	Constant mean return model (3M)	1.04	3.33	1.36	0.15	1.57	0.43
	Market-adjusted return model	0.93	2.71	1.50	-0.13	1.70	-0.32
S&P ASX200 Industry	Market model	0.28	1.48	0.81	0.11	0.93	0.50
	Constant mean return model (1Yr)	0.43	1.87	0.99	0.27	1.28	0.93

	Constant mean return model (3M)	0.21	1.87	0.48	0.19	1.32	0.61
	Market-adjusted return model	-0.05	1.47	-0.14	-0.15	1.59	-0.42
S&P ASX200 Finance	Market model	0.50	2.33	0.94	0.21	1.25	0.74
	Constant mean return model (1Yr)	0.70	2.71	1.12	0.41	1.72	1.03
	Constant mean return model (3M)	0.70	2.97	1.02	0.41	1.83	0.97
	Market-adjusted return model	0.26	2.26	0.50	-0.01	1.47	-0.02
S&P ASX200 Insurance	Market model	0.63	2.12	1.29	0.41	1.46	1.23
	Constant mean return model (1Yr)	0.81	2.51	1.41	0.58	1.90	1.34
	Constant mean return model (3M)	0.67	2.54	1.15	0.53	1.87	1.23
	Market-adjusted return model	0.30	2.10	0.62	0.12	1.69	0.32
S&P ASX50 Large	Market model	0.75	1.70	1.91*	0.32	1.05	1.33
	Constant mean return model (1Yr)	0.91	2.08	1.91*	0.48	1.49	1.42
	Constant mean return model (3M)	0.78	2.17	1.57	0.43	1.53	1.23
	Market-adjusted return model	0.49	1.64	1.32	0.08	1.34	0.26
S&P ASX50 Midcap	Market model	0.38	1.79	0.94	0.11	1.02	0.45
	Constant mean return model (1Yr)	0.53	2.19	1.06	0.24	1.07	0.97
	Constant mean return model (3M)	0.32	2.26	0.62	0.15	1.11	0.59
	Market-adjusted return model	0.09	1.60	0.24	-0.18	1.89	-0.41
S&P ASX Small Ordinaries	Market model	0.60	1.74	1.50	0.16	0.96	0.71
	Constant mean return model (1Yr)	0.77	2.14	1.58	0.33	1.06	1.35
	Constant mean return model (3M)	0.58	2.21	1.14	0.25	1.09	0.99
	Market-adjusted return model	0.27	1.54	0.76	-0.11	1.79	-0.28

Market portfolio: MSCI World
***,**,* Significance at the 1%, 5%, and 10% levels, respectively
Source: Author's calculation

Here H3 is rejected and thus the efficient market hypothesis does not hold for heatwaves. Positive, 0.73% $CAAR_{0,4}$ for ASX200 index is confirmed at the 10% significance level by using the market model methodology. By using the constant mean return model, a positive effect is confirmed for both $CAAR_{0,4}$ and $CAAR_{0,1}$. The IT sector shows 1.20% positive five-day return, which is statistically significant at the 10% significance level. The positive relationship between natural disasters and information technologies is confirmed again. Moreover, large companies also show a positive $CAAR_{0,4}$. A return of 0.75% is confirmed at the 10% significance level. In general, small- and medium-sized companies are more vulnerable to natural disasters compared to large companies. Samantha (2017) introduces the impact of natural disasters on micro, small, and medium enterprises. Her research is particularly focused on flood events in Western Sri Lanka. She mainly concludes that small and medium enterprises need external support to get back to business after being hit by natural disasters. Furthermore, for these firms, it is not possible to pay a high insurance premium. It is suggested that the government should step in and provide protection for these enterprises. Although this might explain why large companies are not significantly affected by natural disasters, it does not explain a positive return. Based on previous explanations, it could be the case that the index consists mainly of insurance, IT, or construction companies (infrastructure, construction, materials etc.), which are empirically proved to gain from disasters. By looking at S&P ASX50 large constituents, the financials and materials sectors are the largest ones in terms of market capitalization. Both these sectors taken together, create 51.53% of the index, as measured by market capitalization. Indeed, financials with insurance companies and insurance business activities included, represent 31.24%, while materials represent 20.29% of the whole market. This sufficiently provides the explanation which is in line with the already introduced literature. Index constituents are visible in the figure below:

Figure 1: S&P ASX50 large constituents



Source: ASX

Finally, we conclude on the hypotheses testing differences within sectors and size categories.

H10: The impact of heatwaves on the asset value differs with different industries.

This hypothesis cannot be rejected as there is statistically significant positive AAR of the insurance sector and statistically significant positive CAAR for the IT sector.

H11: The impact of bushfires on the asset value differs with different company sizes.

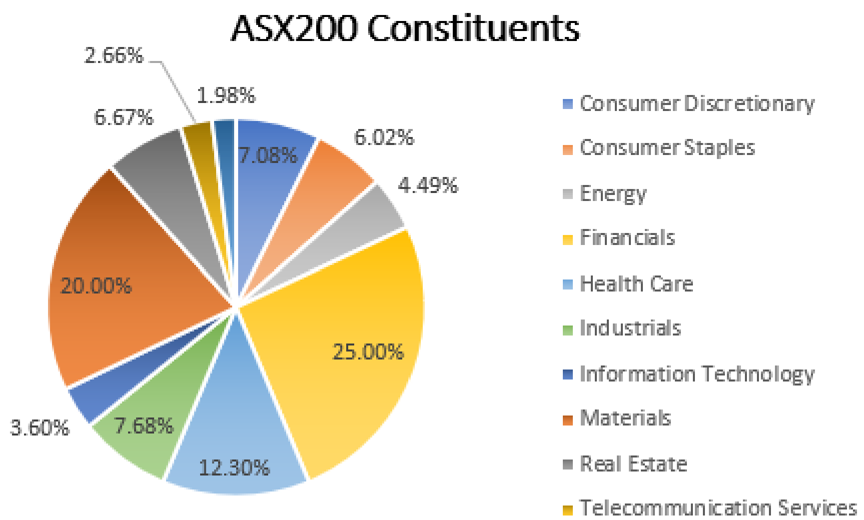
This hypothesis cannot be rejected as there is statistically significant positive $CAAR_{0,4}$ for indices representing large companies.

By summarizing the conclusions above, there is no negative immediate effect of natural disasters on the stock market in Australia. Moreover, in a few cases a positive significant impact is confirmed. Firstly, the Australian market as a whole reacts positively to bushfires immediately on the day of the event. However, this is confirmed only by applying the market-adjusted return model method. In general, the market model is considered to be the most precise because the error term is the smallest.

The Australian market ASX200 index also reacts positively to heatwaves but with a certain time delay, and therefore only the cumulative average abnormal return is statistically significant. In theory, mainly sectors related to replacing the lost capital, as well as the IT and insurance sectors, react positively to natural disasters.

The ASX200 constituents are shown below:

Figure 2: ASX200 constituents



Source: ASX

Financials (insurance including), materials, and industrials indeed create a significant cast within an index.

The IT sector reacts positively to both natural disaster events, as positive $CAAR_{0,4}$ is statistically significant in both cases using precise normal return calculation methods. The insurance sector`s immediate reaction to heatwaves is positive as well as significant. Finally, large companies' $CAAR_{0,4}$ is positive and statistically significant as a consequence of the heatwaves. Index decomposition was needed here in order to see, which types of companies are included in this context, so that a proper explanation could be found.

In general, the Day 1 average abnormal return, AAR_1, and the two-day cumulative average abnormal return, $\mathrm{CAAR}_{0,1}$, are not statistically significant. Therefore, these returns, do not add much value to the research. Both AAR_1 and $\mathrm{CAAR}_{0,1}$ are analysed mainly because the event outbreaks could happen overnight. At this scenario, the abnormal return would not be recorded during the first event window day, which happens to be Day 0. However, it is only natural that heatwaves and bushfires usually do not outbreak overnight. This can be explained by the character of the events. This could be one of the reasons why AAR_1 and $\mathrm{CAAR}_{0,1}$ are statistically insignificant in all cases, except one small positive response of the ASX200 index. The two-day cumulative average abnormal return to heatwaves is significant in this case.

By introducing the comparative analysis with the ASX200 index being applied as a market portfolio for Australian sub-indices, I can confirm the IT sector's positive response to bushfires with a significant $\mathrm{CAAR}_{0,4}$ at the 10% significance level by working with the market model, and at the 5% significance level by working with the market-adjusted return model. Furthermore, the insurance sector's positive response to the heatwaves is confirmed at the 10% significance level for AAR_0.

Once any kind of natural disaster emerges in Australia, the ASX200 index and its sub-indices are likely going to be affected in the similar direction. On the other hand, the MSCI World index should be impacted less, if at all. The logical expectation is to observe lower abnormal returns by using the ASX200 index as a benchmark. Based on the above-described results the prediction is confirmed, and abnormal returns are mostly insignificant. However, the IT sector and the insurance sector still show a positive reaction to events. Detailed results are provided in the appendix.

5.3 Cross-sectional model for bushfires

The first regression model specification incorporates the dependent variable $\mathrm{CAR}_{0,4}$ and independent variables expressing the number of victims, the damage caused by bushfires, and the number of homes destroyed. Additionally, three categorical variables are introduced. The variable 'state' is variable, which is supposed to catch the effect of different firms' locations. The assumption is that firms located closer to bushfires are more affected. The variable 'industry' shows the difference between industries in relation to the impact of a bushfire. Finally, the variable 'conditions' represents different weather conditions during the event.

The first equation looks as follows:

$CAR_{0,4} = \beta_0 + \beta_1$VICTIMS + β_2DAMAGE + β_3HOMES + β_4STATE + β_5CONDITIONS + β_6INDUSTRY + ε

Firstly, I ran a multicollinearity test by using variable inflation factors (VIF). The mean VIF was 3.52, while the VIF of the variable ‘victims’ happened to be 17.39 and the VIF of the variable ‘homes’ was 12.29. This indicates clear multicollinearity between these two variables. By looking at the regression output, the variable ‘victims’ is statistically significant at the 10% significance level, while the variable ‘homes’ is statistically significant at the 1% significance level. Therefore, I excluded victims from the equation.

The next model specification looks as follows:

$CAR_{0,4} = \beta_0 + \beta_1$DAMAGE + β_2HOMES + β_3STATE + β_4CONDITIONS + β_5INDUSTRY + ε

By running the VIF test again, all the VIFs are below 10, with the mean VIF equal to 2.36. Next, I executed the Breusch–Pagan heteroscedasticity test. With the F statistic being 5.91 and its p-value zero, I rejected the null hypothesis about constant variance. Heteroscedasticity is, therefore, confirmed in the current model specification:

Table 9: STATA output: Breusch–Pagan heteroscedasticity test

F (21, 5975)	5.91
Prob > F	0.0000

Source: Author's calculation

One of the mathematical options of how to deal with heteroscedasticity is to take a natural logarithm of the dependent variable and thereby change an original model specification.

The adjusted specification looks as follows:

LN($CAR_{0,4}$) = $\beta_0 + \beta_1$DAMAGE + β_2HOMES + β_3STATE + β_4CONDITIONS + β_5INDUSTRY + ε

Once the logarithmic variable is created, the Breusch–Pagan heteroscedasticity test is introduced again. With the F statistic being 0.71 and its p-value 0.8263, I could not reject the null hypothesis about constant variance:

Table 10: STATA output: Breusch–Pagan heteroscedasticity test

F (21, 3125)	0.71
Prob > F	0.8263

Source: Author's calculation

Consequently, I introduced the Ramsey RESET test in order to figure out if there was any variable omitted from the current specification. With the F statistic being 0.27 and its p-value 0.8492, the null hypothesis could not be rejected, stating that the model has no omitted variable:

Table 11: STATA output: Ramsey RESET test

F (3, 3149)	0.27
Prob > F	0.8492

Source: Author's calculation

Logarithm of the dependent variable eliminates heteroscedasticity to some extent. However, the logarithmic operation ensures mainly the reduction of outliers. Typically, once heteroscedasticity is present, Huber–White robust standard errors should be introduced.
The output from the final model specification is presented in the table below:

Table 12: STATA output: Bushfires regression model

Dependent Variable: LN($CAR_{0,4}$)

Sample: 3 174

Independent Variable	Coef.	Robust Std. Err.	t	P > | t |
Damage	-5.87e-08	1.03e-08	-5.71	0.000***
Homes	.0004	.0001	5.97	0.000***
State				
New South Wales	.0959	.0714	1.34	0.179
Queensland	.0628	.1025	0.61	0.540
Southern Australia	.1862	.1246	1.49	0.135
Tasmania	-.2587	.3981	-0.65	0.516
Western Australia	.1104	.1798	0.61	0.539

Conditions				
Drought	.1529	.0826	1.85	0.064*
Drought + Wind	-.0114	.0886	-0.13	0.897
Wind	.1740	.0895	1.94	0.052*
Industry				
2	-.0307	.2558	-0.12	0.905
3	-.1835	.1416	-1.30	0.195
4	.2836	.1440	1.97	0.049**
5	.1148	.2601	0.44	0.659
6	.3850	.1302	2.96	0.003***
7	-.1319	.1829	-0.72	0.471
8	-.3840	.1637	-2.35	0.019**
9	-.1277	.1390	-0.92	0.358
10	-.1706	.1286	-1.33	0.185
11	.3161	.1078	-2.93	0.003***
12	.0565	.1122	0.50	0.614
_cons	-3.9483	.1377	-28.67	0.000

The number of observations used is 3174. The R-squared value is equal to 0.023. The F-statistic value is equal to 7.37. The values are based on Huber–White robust standard errors.
***,**,* Significance at the 1%, 5%, and 10% levels, respectively
Source: Author's calculation

Both the damaged area and the number of homes are statistically significant at all standard significance levels. After all the adjustments needed, I could discern that the model has a log-linear character. Increasing damage during a bushfire has a negative impact on the stock prices response. $CAR_{0,4}$ is positive during this event and statistically insignificant. However, by increasing the damage area this positivity becomes smaller. On the other hand, by increasing number of destroyed homes during an event, the stock prices return increases. This variable is statistically significant as well.

Next, I observed dummy-categorical variables explaining the effect of different weather conditions, different industries, and different locations.

In fact, 66% of all bushfires included in the sample for the studied period occurred within two states: Victoria and New South West. Simultaneously, roughly 70% of all companies included in the ASX200 index are based in Sydney or Melbourne, the cities that are located in the two aforementioned states. The point here is that it happens to be a geographically demanding task to capture the bushfire impact difference based on location, as only a few companies are actually located out of Victoria and New South West. Indeed, all 'State' dummy variables are statistically insignificant. Moreover, within the scope of this research, I was able to only work with the headquarters of the firms concerned, and therefore in this context those places represent, where the companies are based. Core firm activities, however, might be performed somewhere else, even outside of Australia. The Australian stock market reaction is also significantly driven by institutional investors, who are mainly based in financial centres like Sydney and Melbourne.

Weather conditions are divided into drought, wind, and a combination of these two. From the STATA output, drought and wind have a significant positive impact at the 10% significance level. Again, if the stock market reaction to bushfire is positive, the market reaction is even stronger when these weather conditions are incorporated. The overall negative reaction could be expected. However, due to index constituents including mainly the IT and insurance sectors, the market reaction is positive.

The combination of wind and drought has no additional significant impact. I chose the category 'None' as a base group. This category represents weather conditions when neither wind nor drought is present. The other weather conditions were compared with this base group. In case there is a wind, the firms' stock prices increase by 0.17%. In case of a drought, this value is 0.15%.

Finally, I looked at the sector impact by setting consumer non-durable goods as a base group. At the significance level of 5%, two industry groups are significant. The energy sector with 0.28% positive reaction and the utilities sector with -0.38% negative reaction.

At all significance levels, the business equipment and finance sectors are significant. Business equipment includes computers, software, and electronic equipment. These two sectors represent 0.39 % and 0.32% positive reaction, respectively.

5.4 Cross-sectional model for heatwaves

The first regression model specification incorporates a dependent variable, $\mathrm{CAR}_{0,4}$, and independent variables representing the number of days the heatwave lasted, its intensity, which is the average maximum temperature measured during the heatwave, rainfall, represented by precipitation in millimetres, a dummy variable representing drought conditions based on regular drought reports, and categorical variables representing states and industries.

The first specification looks as follows:

$$CAR_{0,4} = \beta_0 + \beta_1\text{DAYS} + \beta_2\text{INTENSITY} + \beta_3\text{RAINFALL} + \beta_4\text{DROUGHT} + \beta_5\text{CONDITIONS} + \beta_6\text{INDUSTRY} + \varepsilon$$

The multicollinearity test by applying VIF shows no mutual correlation within the explanatory variables, with the mean VIF being equal to 2.12.

The Ramsey RESET test suggests no omitted variable. With the F statistic being 0.61 and its p-value 0.6078, the null hypothesis could not be rejected, which states that the model has no omitted variable:

Table 13: STATA output: Ramsey RESET test

F (3, 3776)	0.61
Prob > F	0.6078

Source: Author's calculation

Now, the Breusch–Pagan heteroscedasticity test with the F statistic of 5.26 and its p-value equal to zero suggests that the null hypothesis about constant variance must be rejected. Heteroscedasticity is confirmed in the current specification:

Table 14: STATA output: Breusch–Pagan heteroscedasticity test

F (20, 3779)	5.26
Prob > F	0.0000

Source: Author's calculation

If a natural logarithm of the dependent variable is taken into consideration and an original model specification is changed, my F statistic and its p-value are following:

Table 15: STATA output: Breusch–Pagan heteroscedasticity test

F (20, 1974)	1.74
Prob > F	0.0220

Source: Author's calculation

By mathematically changing the original model specification, I can partially deal with heteroscedasticity. However, the regression is still not homoscedastic enough.

This means that Huber–White robust standard errors must be introduced again. The output from the final model specification is presented in the table below:

Table 16: STATA output: Heatwaves regression model

Dependent Variable: CAR Sample: 3 800				
Independent Variable	Coef.	Robust Std. Err.	t	P > | t |
Days	.0036	.0018	2.05	0.041**
Intensity	-.0028	.0010	-2.70	0.007***
Rainfall	-.0015	.0016	-0.89	0.372
Drought	-.0038	.0019	-2.03	0.043**
State				
New South Wales	-.0005	.0021	-0.26	0.798
Queensland	-.0045	.0034	-1.31	0.191
Southern Australia	-.0021	.0052	-0.39	0.695
Tasmania	-.0176	.0118	-1.50	0.135
Western Australia	.0095	.0041	2.29	0.022**
Industry				
2	-.0140	.0119	-1.18	0.237
3	-.0098	.0061	-1.61	0.107
4	-.0125	.0070	-1.77	0.076*
5	-.0075	.0074	-1.02	0.309
6	-.0035	.0079	-0.45	0.656
7	-.0120	.0078	-1.54	0.124
8	-.0043	.0061	-0.70	0.483
9	-.0081	.0057	-1.42	0.157
10	-.0122	.0058	-2.08	0.037**
11	-.0039	.0054	-0.72	0.470
12	-.0016	.0054	-0.30	0.763
_cons	.0966	.0343	2.81	0.005

The number of observations used is 3800. The R-squared value is equal to 0.0129. The F-statistic value is equal to 2.24. The values are based on Huber–White robust standard errors.
***,**,* Significance at the 1%, 5%, and 10% levels, respectively
Source: Author's calculation

The variable representing the number of the days a heatwave lasted and the variable representing drought are statistically significant at the 5% significance level. Heatwave intensity is significant at all standard significance levels. The model has the standard lin–lin specification. The variables 'drought' and 'intensity' have a negative impact on $CAR_{0,4}$, while the variable 'days' has a positive impact. Therefore, considering the overall positive reaction of the ASX200 index to heatwaves, only the duration of the heatwave drives this effect. Higher heatwave intensity and drought conditions decrease the final cumulative average abnormal return. Specifically, with each additional day that an event lasts, $CAR_{0,4}$ increases by 0.0036%.

With 1°C higher average maximum temperature during the event, $\mathrm{CAR}_{0,4}$ decreases by 0.0028%. Finally, if drought conditions are confirmed by the Australian Government Bureau of Meteorology, $\mathrm{CAR}_{0,4}$ decreases by 0.0038%. Rainfall does not have a significant impact.

Next, I looked at dummy-categorical variables explaining the effect of different industries and locations.

Again, the headquarters of the companies concerned are disproportionally redistributed. The temperatures data come mainly from the most important Australian cities. Therefore, these data sufficiently represent most of the headquarters. To capture a difference between the firms, which are close to heatwaves and those, which are far away from heatwaves, is a geographically demanding task. Again, all 'State' dummy variables are statistically insignificant. The only exception is Western Australia. Apparently, firms located in this state have a better stock performance compared to those in other states. The coefficient for Western Australia is positive and statistically significant.

Finally, the reaction within different sectors was analysed. Consumer non-durable goods were set as a base group. Energy sector firms' reaction to heatwaves was on average 0.013% lower than the whole index reaction at the 10% significance level. The healthcare sector was statistically significant at the 5% significance level. In this sector, there was about -0.012% negative response to heatwaves. This is in line with the empirical research of Xia et al. (2017) that incorporates health issues within the economic impacts of the analysis of heatwaves. This specific type of natural disaster has obviously a significantly negative impact on health issues which might also bring a pressure on the healthcare sector in general.

The energy sector is a big topic and further research could be carried out beyond the scope of this thesis. Based on my results, it can be observed that if the bushfires occur the performance of firms from the energy sector is better compared to the average performance of the whole index. However, the same performance is worse in the case when the heatwaves occur. The energy sector is hugely impacted by the natural disasters and the direction of this impact is unpredictable.

For instance, natural disasters represent a risk to the energy grid, which is often damaged during these events. Consequently, the energy industry invests a lot in research and simulation to limit this vulnerability. Investments for grid resilience are also made. Another research area is the field of alternative fuels. For instance, natural gas can remain active even during natural disasters due to underground pipelines. Doytch and Yehuda (2017) carried out research on the impact of natural disasters on energy consumption. It is expected for natural disasters to have an immediate negative impact on energy consumption due to infrastructure destruction like energy grids, oil refineries, or energy plants. On the other hand, following natural disasters events, there is a positive impact on renewable energy use, especially in technologically advanced countries. Energy use is related to rebuilding and upgrading as a result of disaster. This was already mentioned several times in this paper. Moreover, in low-income countries the capacity-building in renewable energy sources takes place as a result of wildfires and droughts (Doytch and Yehuda, 2017).

Energy sector and its reaction to natural disasters is a fruitful topic for further research. Of course, the impact should be thoroughly analysed from a long-term perspective and then compared to this short-term event study research.

6 Conclusion

Bologna and Aquino (2020) statistically conclude that the probability that our civilization survives itself is in the most optimistic scenario less than 10%. Calculation incorporates the actual rate of population growth, deforestation rate, and ratio of the technological level. Based on current conditions, the resulting mean-times for a catastrophic outcome to occur is between 2-4 decades.

Many land and ocean ecosystems and some of the services they provide have already changed due to global warming (IPCC, 2018). This has led to changes in the frequency, intensity, spatial extent, duration, and timing of extreme weather and climate events (IPCC, 2012). Among these events, the occurrence of extreme temperatures may increase as well. These extreme temperatures lead to other natural disasters, such as wildfires or floods via hyper-dry soil conditions (Moody & Abel, 2012). This leads to serious climate change effects on the urban infrastructure and economy (Hayhoe, 2010).

The aim of this research is to measure the effects of natural disasters on the Australian market.

The core study question has been mentioned in the following: *What is the impact of bushfires and heatwaves on the Australian stock market?*
A basic logic suggests that there would be a negative impact on the market as there are several negative effects and damages caused by these events.

In fact, our research confirms a positive AAR_0 of the ASX200 index for bushfires, which is on average 0.23% by working with the market-adjusted return model.

Regarding heatwaves, a positive $CAAR_{0,4}$ of the ASX200 index was confirmed, which is on average 0.73%, by working with the market model, and 0.88% by working with the constant mean return model.

Moreover, the IT sector reacts positively to bushfires, with a cumulative average abnormal return of 1.27%. The IT sector also reacts positively to heatwaves, with a cumulative average abnormal return of 1.20%. In the case of heatwaves, the positive reaction was also confirmed for the insurance sector, with a positive average abnormal return of 0.38%. Finally, large companies react positively to heatwaves, with a 0.75% positive cumulative average abnormal return.

All the research hypotheses and the statements accepting or rejecting these hypotheses are available in the table below:

Table 17: Hypothesis testing

Hypothesis	Wording	Statement
H0	The average abnormal return (AAR_0) of bushfires on the event day is statistically insignificant and close to zero.	Rejected
H1	The five-day cumulative average abnormal return ($CAAR_{0,4}$) of bushfires is statistically insignificant and close to zero.	Rejected
H2	The AAR_0 of heatwaves on the event day is statistically insignificant and close to zero.	Rejected
H3	The $CAAR_{0,4}$ of heatwaves is statistically insignificant and close to zero.	Rejected
H4	The average abnormal return (AAR_1) of bushfires is statistically insignificant and close to zero.	Failed to be rejected
H5	The two-day cumulative average abnormal return ($CAAR_{0,1}$) of bushfires is statistically insignificant and close to zero.	Failed to be rejected
H6	The AAR_1 of heatwaves is statistically insignificant and close to zero.	Failed to be rejected
H7	The $CAAR_{0,1}$ of heatwaves is statistically insignificant and close to zero.	Rejected
H8	The impact of bushfires on the asset value differs with different industries.	Failed to be rejected
H9	The impact of bushfires on the asset value differs with different company sizes.	Rejected
H10	The impact of heatwaves on the asset value differs with different industries.	Failed to be rejected

H11	The impact of heatwaves on the asset value differs with different company sizes.	Failed to be rejected

Source: Author's calculation

There are several factors contributing to a positive return. If the bushfire destroys more homes, the market reacts positively. Moreover, fire-weather conditions drought and wind contribute to the positive reaction. However, the combination of these two does not have any significant additional effect. In case of bushfires, the positive reaction is apparently more obvious within the energy, business equipment, and finance sectors. The duration of heatwaves contributes to the ultimate positive reaction. On the other hand, intensity and drought make a negative contribution. In this case, mainly the reaction of the energy and healthcare sectors is lower compared to the other sectors.

Overall, the results suggest that the positive market reaction to natural disasters in Australia is a consequence of Australian market index constituents. A significant part of the index consists of financials, materials, and industrials companies. Based on empirical evidence, these sectors benefit from natural disasters. This explains the overall positive reaction of the market. This is also confirmed by looking at specific sub-indices and by using a categorical variable within the cross-sectional analysis.

The results are compatible with Worthington and Valadkhani (2004), who determine a small positive impact of bushfires on market returns. They suggest working with a longer time window in order to get complete information about the event effect.

Bushfires' impact is also positive in the Wang and Kutan study (2013).

Further research can be done especially on the energy sector. To estimate the effect of natural disasters on the energy sector might be challenging as there are several factors that need to be considered. Some of these factors are among others the energy infrastructure vulnerability, grid resilience, or renewable energy use.

The impact should certainly be more analysed from a long-term perspective and compared to this short-term event study research.

The energy sector and other interesting sectors, as well as their reaction to different types of natural disasters, represent a fruitful area of research, which might add significant value and help to answer important environmental questions.

Finally, focusing on long-term effects might create a much wider research dimension and additional complexity regarding the topic.

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APPENDIX

Table 18: Bushfires' average abnormal return for Day 0 and Day 1
Sample: 33

Index name	Methodology	AAR (0) (%)	Stdev (0) (%)	t-value (0)	AAR (1) (%)	Stdev (1) (%)	t-value (1)
S&P ASX200 REIT	Market model	-0.22	0.97	-1.27	0.02	0.94	0.11
	Market-adjusted return model	-0.25	1.04	-1.40	0.02	0.96	0.14
S&P ASX200 IT	Market model	0.14	1.00	0.81	0.08	1.03	0.43
	Market-adjusted return model	0.18	1.01	1.02	0.13	1.05	0.68
S&P ASX200 Industry	Market model	-0.03	0.53	-0.28	0.05	0.42	0.67
	Market-adjusted return model	-0.03	0.56	-0.33	0.06	0.45	0.72
S&P ASX200 Finance	Market model	-0.04	0.46	-0.44	-0.03	0.40	-0.47
	Market-adjusted return model	-0.03	0.46	-0.38	-0.05	0.40	-0.67
S&P ASX200 Insurance	Market model	0.01	1.22	0.03	0.04	0.81	0.26
	Market-adjusted return model	0.02	1.26	0.08	-0.04	0.73	-0.34
S&P ASX50 Large	Market model	0.00	0.08	-0.13	-0.02	0.08	-1.32
	Market-adjusted return model	-0.01	0.08	-0.42	-0.02	0.09	-1.42
S&P ASX50 Midcap	Market model	-0.01	0.35	-0.12	0.06	0.40	0.91
	Market-adjusted return model	0.01	0.37	0.11	0.08	0.41	1.14
S&P ASX Small Ordinaries	Market model	0.04	0.39	0.63	0.09	0.39	1.31
	Market-adjusted return model	0.06	0.39	0.88	0.10	0.44	1.31

Market portfolio: ASX200
***,**,* Significance at the 1%, 5%, and 10% levels, respectively
Source: Author's calculation

Table 19: Bushfires' five-day and two-day cumulative average abnormal return
Sample: 33

Index name	Methodology	CAAR (0,4) (%)	Stdev (0,4) (%)	t-value (0,4)	CAAR (0,1) (%)	Stdev (0,1) (%)	t-value (0,1)
S&P ASX200 REIT	Market model	-0.12	1.67	-0.41	-0.20	1.40	-0.81
	Market-adjusted return model	-0.28	1.85	-0.88	-0.23	1.51	-0.88
S&P ASX200 IT	Market model	1.07	3.18	1.94*	0.22	1.16	1.08
	Market-adjusted return model	1.11	3.07	2.07**	0.30	1.22	1.43
S&P ASX200 Industry	Market model	0.03	1.17	0.15	0.02	0.58	0.24
	Market-adjusted return model	-0.02	1.19	-0.09	0.03	0.67	0.22
	Market model	0.06	0.99	0.35	-0.07	0.68	-0.57

S&P ASX200 Finance	Market-adjusted return model	0.05	1.02	0.31	-0.05	0.69	-0.43
S&P ASX200 Insurance	Market model	0.09	1.68	0.30	0.04	1.30	0.19
	Market-adjusted return model	0.00	1.59	-0.01	-0.03	1.26	-0.12
S&P ASX50 Large	Market model	-0.01	0.17	-0.30	-0.02	0.10	-1.23
	Market-adjusted return model	0.00	0.17	-0.11	-0.03	0.11	-1.44
S&P ASX50 Midcap	Market model	-0.02	0.86	-0.12	0.06	0.50	0.65
	Market-adjusted return model	-0.03	0.79	-0.22	0.09	0.54	0.95
S&P ASX Small Ordinaries	Market model	0.11	0.87	0.70	0.13	0.49	1.56
	Market-adjusted return model	0.04	0.86	0.28	0.16	0.56	1.64

Market portfolio: ASX200
***,**,* Significance at the 1%, 5%, and 10% levels, respectively
Source: Author's calculation

Table 20: Heatwaves' average abnormal return for Day 0 and Day 1
Sample: 19

Index name	Methodology	AAR (0) (%)	Stdev (0) (%)	t-value (0)	AAR (1) (%)	Stdev (1) (%)	t-value (1)
S&P ASX200 REIT	Market model	-0.22	0.82	-1.17	-0.07	1.02	-0.31
	Market-adjusted return model	-0.24	0.87	-1.21	-0.15	0.99	-0.65
S&P ASX200 IT	Market model	0.20	0.86	1.00	-0.24	0.83	-1.26
	Market-adjusted return model	0.12	0.88	0.57	-0.32	0.85	-1.64
S&P ASX200 Industry	Market model	0.03	0.32	0.35	-0.10	0.31	-1.38
	Market-adjusted return model	-0.02	0.27	-0.32	-0.14	0.38	-1.59
S&P ASX200 Finance	Market model	-0.13	0.50	-1.11	0.02	0.44	0.22
	Market-adjusted return model	-0.10	0.47	-0.97	0.05	0.46	0.45
S&P ASX200 Insurance	Market model	0.29	0.69	1.84*	-0.22	0.65	-1.48
	Market-adjusted return model	0.17	0.43	1.68*	-0.19	0.69	-1.22
S&P ASX50 Large	Market model	0.01	0.09	0.31	0.03	0.08	1.37
	Market-adjusted return model	0.02	0.10	0.70	0.03	0.09	1.46
S&P ASX50 Midcap	Market model	-0.01	0.41	-0.16	-0.13	0.49	-1.16
	Market-adjusted return model	-0.06	0.46	-0.54	-0.16	0.55	-1.27
S&P ASX Small Ordinaries	Market model	-0.01	0.58	-0.10	-0.06	0.38	-0.73
	Market-adjusted return model	-0.08	0.67	-0.51	-0.10	0.40	-1.08

Market portfolio: ASX200
***,**,* Significance at the 1%, 5%, and 10% levels, respectively
Source: Author's calculation

Table 21: Heatwaves' five-day and two-day cumulative average abnormal return
Sample: 19

Index name	Methodology	CAAR (0,4) (%)	Stdev (0,4) (%)	t-value (0,4)	CAAR (0,1) (%)	Stdev (0,1) (%)	t-value (0,1)
S&P ASX200 REIT	Market model	0.38	1.57	1.05	-0.29	1.37	-0.93
	Market-adjusted return model	0.05	1.70	0.12	-0.39	1.42	-1.20
S&P ASX200 IT	Market model	0.67	1.98	1.47	-0.04	1.03	-0.17
	Market-adjusted return model	0.52	2.02	1.12	-0.21	1.12	-0.82
S&P ASX200 Industry	Market model	-0.35	1.05	-1.44	-0.11	0.45	-1.07
	Market-adjusted return model	-0.47	1.26	-1.63	-0.19	0.51	-1.59
S&P ASX200 Finance	Market model	-0.24	0.88	-1.17	-0.10	0.53	-0.85
	Market-adjusted return model	-0.18	0.94	-0.85	-0.06	0.57	-0.44
S&P ASX200 Insurance	Market model	0.13	1.68	0.34	-0.22	0.65	-1.48
	Market-adjusted return model	-0.15	1.20	-0.53	-0.19	0.69	-1.22
S&P ASX50 Large	Market model	0.03	0.15	0.84	0.03	0.13	1.13
	Market-adjusted return model	0.06	0.17	1.59	0.05	0.16	1.33
S&P ASX50 Midcap	Market model	-0.17	0.72	-1.05	-0.14	0.66	-0.95
	Market-adjusted return model	-0.31	0.83	-1.64	-0.22	0.81	-1.16
S&P ASX Small Ordinaries	Market model	0.04	0.92	0.19	-0.08	0.74	-0.45
	Market-adjusted return model	-0.17	1.03	-0.73	-0.18	0.86	-0.90

Market portfolio: ASX200
***,**,* Significance at the 1%, 5%, and 10% levels, respectively
Source: Author's calculation