MASTER THESIS

Cross-sectional study on the effect of natural disasters on national industry indices

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Abstract

I test the effect of 263 natural disasters on national industry indices among 23 countries between 2000-2017 with an event study. I find effects that are in line with current literature; I find no robust effect in general, but in the cross-section OECD countries suffer less from natural disasters and the logarithm of fatalities has a negative relation with the CAR. Contrasting to existing literature, Basic Materials industry generates a negative CAR reaction relative to others and the combination of storms and the Consumer Service industry results in a positive reaction compared to other combinations. Additional to literature, unexpected disasters generate more severe CAR reactions. These results can be used as starting point for future research and it can help investors, businesses and governments in their natural disaster impact predictions.

1. Introduction

Over the last 30 years, the total economic costs resulting from natural disasters has an increasing trend and annual losses in only the US are recorded on 306 billion US dollar in 2017 (NOAA, 2018). Part of the increasing costs can be attributed to global climate change which causes certain natural disasters like hurricanes, floods and tornados, while other parts can be attributed to a higher population density in areas which are located in risky areas related to natural disasters (Worthington A. , 2008). The natural disasters I consider include drought/extreme temperatures, wildfires, earthquakes, floods, landslides and storms (Biere & Elliot, 2000) (EM-DAT database). In line with the increasing impact of disasters and the more sophisticated documentation of this, the research concerning the effect of natural disasters has been given more attention last decade. Complementary to the economic analysis of natural disasters, financial analysis focusses on the financial impact of events on businesses, mostly expressed in stock returns, stock prices or indices (for example Anthoniou, Holmes, & Priestley (1998)). The effect of the events studied is limited to the entities that are analyzed. An example is the research relating the Indian Ocean earthquake in December 2004, which is one of the worst natural disasters recorded over history. This earthquake with a magnitude of 9.3 on the scale of Richter resulted in approximately 280.000 fatalities. In line with intuition, damage in the construction sector was enormous due to this disaster (Saatcioglu, Ghobarah, & Nistor, 2006). However, after announcing donations to the area, companies in the U.S. had a significant 5-day positive cumulative abnormal return (Patten, 2008). So interestingly enough, not all companies suffered from the natural disaster.

In order to examine this reaction, I test the effect of 263 natural disasters on the national industry indices among 23 countries between 2000 and 2017. I use the event study methodology in order to calculate cumulative abnormal returns (CAR) per disaster (measured in effect on the indices), followed by a regression to test the effect of various variables on the cumulative abnormal returns. The variables I include are number of fatalities and economic damage resulting from the natural disasters, number of days that the disaster takes place, OECD vs non-OECD country, population density per country, frequency that a country is affected, disasters type (6 types), expected vs unexpected disasters and industry type (10 types). Figure 1 (Appendix I) displays the validity framework for the hypotheses.

In general, I find no significant effect on the CAR due to natural disasters on average, which is in line with existing literature. However, there are significant negative effects in sub-periods when I exclude the first and lasts days of the event period, as there is some positive reversal visible in that period. I find cross-sectional effects in line with current literature; OECD countries suffer less from natural disasters compared to non-OECD countries and the logarithm of fatalities has a negative relation with the CAR. More findings in line with current literature is the fact that the Oil & Gas industry generates one of the most positive (least negative) CAR reactions among industries and when I combine Consumer Goods and floods, the CAR reaction is negative. I also find evidence that contradicts existing literature; Consumer Services and Financial industries generate a positive CAR reaction relative to other industries. Basic Materials industry generates a more negative effect on the CAR relative to other industries, while the opposite is proven in current literature. Another surprising result is the positive effect on the CAR when combining Consumer Goods and storms. Additional to existing literature, I find that unexpected disasters generate a more negative CAR reaction compared to expected disaster types. Other outstanding results are the fact that floods generate the most positive (but still negative) CAR reaction among disaster types while extreme temperatures cause the most negative CAR reaction overall. The Technology industry reacts the most severe to natural disasters among the industries. Above all, another surprise is the combination of Industrials industry and landslides which generates a positive CAR, while the most negative interaction is between extreme temperatures and Basic Materials which results in an average effect on the CAR of -19.6%.

This study adds value to existing literature as it comprises more disasters in one study, using industry indices with the same criteria applied for every country. This makes the result for the different countries comparable. Moreover, in the natural disaster stock market literature, only one or two industries are considered per study, so the fact that I include 10 industries at one time makes the result of this study comparable between different industries. Investors and companies are better able to predict what consequences can be expected following a natural disaster with their specific characteristics. As mentioned in previous research, it can be valuable to know which long and short position can be profitable in the periods of natural disasters and this can differ substantially per industry and disaster type (Koerniadi, Krishnamurti, & Tourarni-Rad, 2016). With this study, there is a profound view on that with multiple industries considered. Moreover, I test all interaction terms between industries and disasters and these reactions are not studied this extensively before. This study also adds value for businesses and governments, because they are better able to assess how to distribute money in case of a natural disaster in order to protect their economy, which is highly relevant with rising costs due to natural disasters lately. Moreover, this research will be a building block for further research into natural disasters and stock markets for other characteristics then the ones I use, or more in-depth research per disaster or industry type.

The remaining part of this paper is divided into 6 parts. In section 2, I elaborate on the hypotheses which are divided into sections for the general effect, the effect of country characteristics, the effect of the disaster type, the severity of the disaster and the effect of the industry type. In section 3, I elaborate on the collected data, followed up by the methodology of the study in section 4. In section 5, I discuss the results in the same order I present the hypothesis before. This leads to a discussion and conclusion in section 6 and finally to limitations and future research in section 7.

2. Hypotheses

2.1 General effect

The costs resulting from natural disasters often contain various components; the tangible effect with market value and the intangible effect without market value. The tangible effect includes the direct costs in the area like damage to infrastructure, constructions and vehicles and indirect costs of production loss, clean-up and emergency response (Bureau of Transport Economics, 2001). The intangible effect includes direct costs from death and injury and destruction of personal and cultural and personal manners, for example the destruction of a touristic attraction; the 'Black Saturday' Bushfires in Australia influenced the tourist interest in the area significant (Walters & Clulow, 2009). The intangible effect also includes indirect costs from stress and inconvenience associated with illness and mortality and social disruption (Bureau of Transport Economics, 2001). For most disasters, the intangible effect results in the highest part of the economic costs (Bureau of Transport Economics, 2001). Stock markets can be damaged by natural disasters in multiple facets; the tangible damage within the industry as well as the intangible stress and expectations in the stock market.

Previous research is done in order to test the relation between natural disasters and stock market reactions, among others Worthington (2008) who examines the impact of natural disasters on the Australian stock market between 1980 and 2003 with daily stock market returns. He specifically studies the effect of recorded storms, floods, cyclones, earthquakes and bushfires. Even though he only includes the most severe disasters, he finds no evidence of an effect on the stock market (Worthington A. , 2008). Moreover, Wang and Kutan (2013) study the effect of natural disasters on stock markets in the US and Japan and they find no wealth effect in their composite stock market portfolio. These portfolios were based on the Japanese Nikkei 225 and the Standard and Poor's 500, which are well-diversified portfolios. These indices can be seen as a measure of the overall performance of the national financial markets because diversifiable risk is eliminated and only systematic risk is left, according to the Capital Asset Pricing Model (CAPM) (Wang & Kutan, 2013). Contrasting with these neutral effects on the stock markets, evidence from the Japan's 2011 earthquake (which was the most powerful known earthquake over time in Japan with a 9.0 on the scale of Richter) resulted in losses in the stock market immediately after the disaster (Hood, Kamesaka, Nofsinger, & Teruyuki, 2013).

To clarify this relation further, Skidmore and Toya (2002) study the difference in short- and long-term effects of natural disasters. They find an increase in economic output on the long run, while on the short term there is an initial loss of capital and durable goods (Skidmore &

Toya, 2002). Obviously, the relationship between natural disasters and their impact on the stock market remains a puzzle. In related literature, terrorism attacks seriously disrupt financial systems, while catastrophes of unintended human origin also have a significant negative influence (Valadkhani & Worthington, 2005). As natural disasters are also unintended and not controlled, the insight could be applied to this field of study. In order to explore the relationship between natural disasters and the stock market, I construct hypothesis one:

H1: The return reaction across all industries in response to natural disasters is negative

Compared to related literature like terrorism, there is mainly a significant effect found in the short run, and only in the long term for the September 11th attacks, which is the one with the highest impact in history. Also, effects of a natural disaster on the stock market is smaller than the effect of a terrorist attack (Brounen & Derwall, 2010) and long term effects of natural disasters could be observed in economic output (Skidmore & Toya, 2002) which is out of the scope of this study. Therefore, my focus is on a short term horizon for the natural disaster effect. I discuss the exact horizon in the methodology and results section.

2.2 Country types

To clarify the relationship between the stock market and natural disasters further, a distinction could be made between different types of countries where the disaster takes place. Noy (2009) finds that the destructional effect of natural disasters is more profound in developing countries compared to developed countries. Moreover, smaller economies are more sensitive to experience a slowdown in production. Countries with higher literacy rate, income per capita, degree of openness to trade, government spending and better institutions are better able to limit the implications on macro-economic level of a natural disaster (Noy, 2009). Also, every 1 USD spend by a country on preparation for disasters lowers the future damage by 15 USD (Healy & Malhotra, 2009). In line with Shughart (2006) who finds that governments are less or equal effective in the situation of a natural disaster compared to normal circumstances, I assume that mostly developed countries spend money on preparation for natural disasters due to sufficient money supply and the established government. According to Kahn (2005), richer countries do not experience less natural disasters, but their economic development provides an 'insurance' against natural disasters effects. Countries with high-quality institutions also suffer from less deaths resulting from natural disasters, due to emergency care to protect the population. Kahn also shows that a 10% increase in GDP results in 5.3% less deaths resulting from natural disasters (Kahn, 2005).

In related research, terrorist attacks have the smallest impact on capital markets in the U.S. compared to other countries, mainly caused by a stable banking/financial sector, that provides sufficient liquidity to stabilize the market and minimize the panic due to an attack (Chen & Siems, 2004). This suggests again that more developed, stable countries suffer less from disasters. In order to capture most of the (non-)developed country variables together, I make the distinction between OECD and non-OECD countries. The 35 OECD countries are the countries with the most advanced economies, but also emerging, growing economies are included into this list. The countries are characterized by a high Human Development Index and most of them have high-income economies (OECD, 2018). This results in the second hypothesis:

H2: The return reaction across all industries in response to natural disasters is more negative in non-OECD countries compared to OECD countries

As mentioned as a reason of the increasing costs of natural disasters damage, a higher population density in disaster-prone states in the U.S. consequently involves higher costs, like Florida and Texas (Worthington A. , 2008). A higher population density results in more infrastructure, constructions and people that can potentially be affected by a disaster. Therefore, the risk of potential mortality increases, same as for damage costs for infrastructure and construction resulting from the natural disaster (Dilley, 2005). Also Kahn (2005) finds that a country with a smaller population most likely suffers from less deaths compared to a country with a higher population density (Kahn, 2005). This results in hypothesis three:

H3: The return reaction across all industries in response to natural disasters is more negative in high population density countries compared to low population density countries

Some countries are affected by natural disasters more often than others. Related research about terrorism events finds that the stock markets of countries that experience often attacks 'normalizes' for the effect of terrorism. This means that the effect is becoming smaller over time or insignificant, due to long-term market confidence (Peleg, Regens, Gunter, & Jaffe, 2011). Applying this insight to natural disasters, this could mean that frequently affected areas have 'immune' stock markets. Moreover, the countries might have sufficient insurance coverage already when a natural disaster strikes again. This results in the following hypothesis:

H4: The return reaction across all industries in response to natural disasters is more negative in countries that are affected less often by natural disasters, compared to countries that are affected in higher frequencies

2.3 Type of disaster and severity

As mentioned before, natural disasters include drought/extreme temperatures, wildfires, earthquakes, floods, landslides and storms. Besides the difference in effect of natural disasters between countries, these disasters are likely to differ a lot in the impact they have on the stock market. There could be an effect of a certain disaster type on all the industries together. In the research of Valadkhani and Worthington (2004), they test the impact of natural disasters in Australia on the equity market with an autoregressive moving average model (ARMA). They find that wildfires and earthquakes have major effects on the stock markets, while the effects of storms and floods are limited. This could be caused by the lower proportion of insured to total loss of 25% for earthquakes in Australia, while this ratio is 35% for the types with limited impact. Moreover, earthquakes are less frequent disaster type in Australia (Valadkhani & Worthington, 2005). This is supported by the finding of a significant negative relation of earthquakes with the overall market return (Koerniadi, Krishnamurti, & Tourarni-Rad, 2016). This results in the hypothesis:

H5: The return reaction across all industries in response to an earthquake is more negative compared to other natural disaster types

Concerning other disaster types, Robinson and Bangwayo-Skeete (2016) show in their working paper the financial impact of hurricanes and storms on stock markets, specifically in the Caribbean between 2001-2015. They find that hurricanes cause stock market losses that can be ten times bigger than the reported losses from damage on property and infrastructure. However, they find no direct impact on the Stock Exchanges in these regions. In their event study methodology, they examine various major hurricanes in the Caribbean (Robinson & Bangwayo-Skeete, 2016). As mentioned before, Valadkhani and Worthinton find that the average insurance coverage of loss is 35% for storms in Australia and it is one of the most frequent disaster types in that country. This results in better preparation in advance of the disaster and smaller losses after the disaster, which result in their finding of the least significant impact on the stock market of storms (Valadkhani & Worthington, 2005). Koernadi et al. (2015) also find a smaller or positive effect of storms (hurricanes and tornadoes) and explain this by the fact that these disasters might not have a substantial impact to influence the market in affected countries. They mention that a large part of their sample is from the US and tornadoes occur almost every year in certain parts of the US. However, not all of the areas are affected often so this cannot explain the effect completely (Koerniadi, Krishnamurti, & Tourarni-Rad, 2016). As a large part of my sample also includes areas that are frequently affected by storms, I formulate the following hypothesis:

H6: The return reaction across all industries in response to a storm is more positive or less negative compared to other disaster types

In existing literature, there are some signals that the degree of expectancy of the disaster influences the impact on financial markets. As Miller and Goidel (2009) mention in their paper, news organizations can gather and transmit information about disasters in order to help the population and companies understand the scope, causes and consequences of the (upcoming) disaster, in their case the Hurricane Katrina. They find that institutional characteristics of news organization do not matter when they report 'breaking news' of natural disasters, implying that citizens will listen to the news anyway (Miller & Goidel, 2009).

In another study about large international military conflicts and stock market reactions, Brune et al. (2015) find that when there is an expected war, there is a decrease in (national) stock market prices when the likelihood of the war increases, but when the war breaks out ultimately, the stock prices increases. However, this differs with the case of unexpected wars; the outbreak of these wars decreases stock prices (Brune, Hens, Rieger, & Wang, 2015). For terrorist attacks the same evidence is found; the unexpected event (at least unexpected for the public and companies) results in a significant negative effect on the stock market of the sectors that are affected, for example the airline industry after bombing on airports (Sascha & Schiereck, 2016). Another study also shows that in the case of the September 11th attack, which was an unanticipated event, the market was concerned about the increased risk of financial distress and for the smaller airlines their stock prices decreased (Carter & Simkins, 2004). Overall, it seems that stock markets perform better when investors know what is coming instead of a surprise. Connecting the dots, I assume that when a natural disaster is expected, news organizations will reach the public and inform them properly about the upcoming disaster. This will likely result in a decrease in stock prices in the days before the disasters and an increase the days after, which could also mean that they stabilize and return to their original stock prices. However, when the disaster is unexpected, the new organizations and therefore the population and companies will not be aware of the disaster either, so this will be a surprise and stock prices will initially decline, while there is no effect in the days prior to the event. Therefore, I expect the effect of an unexpected natural disaster to be more negative compared to expected natural disasters.

My distinction between expected and unexpected disasters is based on the disaster type. Temperature disasters (extreme temperatures, drought, wildfires) are relatively easy to predict. Thereafter, floods are also predictable. For cyclones/storms, this becomes more difficult and earthquakes (including mass movements, landslides) are the most unpredictable, mostly because their 'emergency proportion' is reached acute, instead of in a slow developing pace (Sapir & Lechat, 1986). This results in the following hypothesis:

H7: The return reaction across all industries in response to an unexpected natural disaster more negative compared to expected natural disasters

Relating to the severity of the disaster, the impact on the stock market can differ. Ferreira & Karali (2015) show that disaster specific characteristics mediate the impact on stock markets, among others the number of fatalities. Moreover, in the case of stocks, the equity premium increases substantially when consumption realizes extreme, non-normal outcomes which happens in cases of disasters (Wachter, 2013). Applying this to the stock market of a country, this would mean that extreme returns are realized when there is a 'consumption disaster', which could be caused by a high number of fatalities due to a natural disaster. Moreover, a high number of fatalities could also affect the supply side of production, as many employees could be within the group of fatalities. This results in the hypothesis:

H8: The return reaction across all industries in response to a natural disaster is negatively correlated with the number of fatalities of the disaster

The economic damage or wealth caused by the natural disaster does not influence the return in major financial assets classes like stock, bonds and securities (Froot, 1999). However, Koerniadi et al. (2015) mention that the research on the effect on stock markets is limited, while in related field (terror attacks, wars, nuclear plant accidents, diseases and military disasters) there is a clear relation between economic damage and stock market volatility (Koerniadi, Krishnamurti, & Tourarni-Rad, 2016). In order to investigate this relation further, I test the following hypothesis:

H9: The return reaction across all industries in response to a natural disaster is negatively correlated with the economic damage of that disaster

2.4 Industry types

Besides the difference in effect of natural disasters between countries and disaster characteristics, the effect can differ between the industries types. I elaborate on five industry indices separately in this section.

2.4.1 Oil and Gas industry

The effect of natural disasters on the Oil and Gas industry is only tested in related research about terrorism events. The impact of terrorism on the financial market is tested by Chesney & Reshetar (2011). They find both significant negative and positive return responses to terrorist attacks on global and European level. They observe more often a negative reaction in indices and they explain this by the fear of possible economic slowdown and therefore a decrease in consumer confidence. When there is a lower consumer demand overall (for example in the consumer services industry including tourism), there is a lower demand of e.g. air travel and thereby a lower demand in oil and this could lead to a drop in oil prices (Chesney & Reshetar, 2011). The few positive reactions they find are explained by limits on the supply side of oil; the attack might be in an area that can cause problems for oil production and transportation. Moreover, if the market for oil is tight, an attack in an area that could affect oil production probably will give a positive reaction due to lower oil supply and price increases. Moreover, they mention that the airline industry shows one of the strongest reactions to a disaster compared to other industries like banking and this influences again the oil industry. However, as oil is a commodity, I should be careful with applying these findings to the natural disaster events as such disaster mostly affects only regions and not the global market. Actually, in the same research they find a positive response in commodity markets after terrorist attacks (Chesney & Reshetar, 2011). With these contradicting results and lack of other empirical support, I construct the following hypothesis:

H10a: The Oil & Gas industry index return reaction in response to a natural disaster more negative compared to other industries
H10b: The Oil & Gas industry index return reaction in response to a natural disaster more positive compared to other industries

2.4.2 Basic Materials & Industrials industries

The industries Basic Materials (including Chemicals and Basic Resources like Industrial Metals and Mining) and Industrials (including Construction & Materials and Industrials Goods & Services) have separate indices in Datastream, but due to the common merges in existing literature (Koerniadi, Krishnamurti, & Tourarni-Rad, 2016), I discuss them together. The integrated approach in existing literature is due to the involvement of both in construction activities. Koerniadi et al. (2016) find that construction and material industries react positively to certain disaster type like earthquakes and storms because this increases the demand for their products and services. Especially earthquakes and storms are found to be destructing for properties and infrastructure, which all have to be replace by this industry. Moreover, for 5 out of the 6 natural disaster types that they include in their study, they find a more profound reaction in the construction and materials industry compared to other industries (Koerniadi, Krishnamurti, & Tourarni-Rad, 2016). The more profound reaction in this industry could be due to the fact that there is a clear tangible direct effect, while in the other industries like travel and leisure, the effect is more intangible and it could be harder for investors to exploit the effect of the disaster on the short term. The finding of Koerniadi et al. (2016) is in line with other research that finds an increasing GDP as a result of natural disasters and a higher GDP is expected to enlarge the damaged capital stocks and therefore construction activity (Skidmore & Toya, 2002). Another paper finds a significant return in the materials sectors' capital market due to natural, industrial and terrorist disasters in Australia and this sector is one of the most sensitive ones in the reaction to disasters (Valadkhani & Worthington, 2005). I formulate the hypotheses in order to test the effect:

H11a: The Basic Materials index return reaction in response to a natural disaster more positive compared to other industries
H11b: The Industry index return reaction in response to a natural disaster more positive compared to other industries

2.4.3 Consumer Goods industry

The consumer good industry index includes automobiles, food and beverage, personal and households' goods. An important part for this study is the food, which includes farming. Loayza et al. (2012) find no significant relation between the 10% largest disasters in any sector category and economic growth in all sectors, but they do find the effect of drought and storms that lower agricultural growth (Loayza, Olaberria, Rigolini, & Christiaensen, 2012). In line with this, Hong et al. (2016) find in their working paper that drought causes decline in profitability and stock returns for food companies on country level for their database including 30 countries. They only consider countries with at least 10 food companies during the entire period and they consider long term data from 1975 till 2015. Their result makes sense, because storms and droughts are likely to destruct crops and harvests completely. I expect that this effect is more profound for these types of disasters compared to other ones like earthquakes for example. This results in the following hypotheses:

H12a: The Consumer Good industry index return reaction in response to a storm is more negative compared to the effect of other disaster types in combination with industries
H12b: The Consumer Good industry index return reaction in response to a drought is more negative compared to the effect of other disaster types in combination with industries

Moreover, Loayza et al. (2012) find that floods actually increase growth in the agricultural sector because this fertilizes the soil. However, a flood in the summer of 2007 in England damaged the agricultural sector substantial, with losses for almost all types of farmers in the areas where the flood was located. So at least the short-term effect of the floods was negative (Posthumus, et al., 2009). This contradiction phenomenon results in the following hypotheses:

H13a: The Consumer Good industry index return reaction in response to a flood is positive
H13b: The Consumer Good industry index return reaction in response to a flood is negative

2.4.4 Consumer Services industry

Consumer services includes retail, media and travel & leisure. As mentioned before, the 'Black Saturday' Bushfires in Australia influenced the tourist interest in the area significant negative (Walters & Clulow, 2009). However, this effect on the stock market is not clear. The number of travelers to the area is likely to decrease due to fear of other disaster and a decrease in interest in the area due to the destruction effect of the disaster. Contrastingly, the travelers flying from the affected location is likely to increase because people are evacuated for safety reasons (Koerniadi, Krishnamurti, & Tourarni-Rad, 2016). Specific per disaster type, travel and leisure firms react negatively to earthquakes and storms and the reaction of this industry is one of the most sensitive ones compared to other industries (Koerniadi, Krishnamurti, & Tourarni-Rad, 2016). Research concerning all kinds of events (natural, industrial, terrorists), Valadkhani and Worthington find a strong reaction in the consumer services industry compared to other industries (Valadkhani & Worthington, 2005). Concerning terrorist attacks, these events influence the travel industry significant negatively. An example is Spain; various terrorist attacks has led to a decline of 140.000 tourists monthly after the event. The same paper shows that terrorism affects tourism and not the reverse of tourism that attracts terrorism (Enders & Sandler, 1991). Overall, the Consumer Service industry is very likely to be affected negatively and this leads to the following hypothesis:

H14: The Consumer Services industry index return reaction in response to a natural disaster more negative compared to other industries

2.4.5 Financial industry

The Financial industry includes insurance, real estate, financial services and equity investment instruments. In current literature, there is written about the effect of natural disasters on (the stock market of) the insurance sector. For example, in the same study of Wang and Kutan (2013) in the US and Japan as mentioned earlier, they find a significant effect in the insurance sector. The investors in the US suffered from losses in this sector, while these in Japan gained value (Wang & Kutan, 2013). The relation for the insurance sector is not clear, because two opposing views exist. The first one is based on the fact that the insurance sector experiences losses due to the payments made for damage of insured entities around natural disasters. The second view states that the insurance sector experiences gain due to a higher demand on their products; insurance coverage during times of natural disasters. For both views, empirical evidence is found (Wang & Kutan, 2013) (Valadkhani & Worthington, 2005).

Relating the same industry, research about bank stability is conducted in the US by North and Schuwer (2017) in their working paper. They show that bank stability between 1994-2012 is damaged by natural disasters and this result is robust across time and regions (North & Schuwer, 2017). Moreover, another study shows the negative effect of earthquakes on the real-estate related stock prices and finds a significant negative effect (Shelor, Anderson, & Cross, 1990). Most interestingly, the financial sector is one of the three most sensitive sectors in the study of Valadkhani & Worthington (2005). Therefore, this results in the hypothesis:

H15: The Financial Industry index return reaction in response to natural disasters is more negative compared to other industries

3. Data

3.1 Disaster Data

The Centre for Research on Epidemiology of Disasters (CRED) created the emergency database (EM-DAT). I use this database to obtain detailed natural disaster data including the corresponding country and date between 2000-2017. The natural disasters reported in this database are floods, storms, volcanic activities, epidemics, wildfires, extreme temperatures, drought, landslide, earthquakes and insect infestations. For every type, the amount of fatalities and the total damage in amount of dollars is reported. Sometimes, disasters are followed up by other disasters. Initially, there are 6.568 disasters between 2000-2017. However, some disasters seem to have incomplete information, so I exclude disasters without any fatalities, economic damage or a reported country in order to make sure that I only use the complete documented disasters. This is in line with Kahn (2005), who excludes countries for which the number of fatalities is multiple times zero (Kahn, 2005). Moreover, I exclude disasters with a missing day in the start or end date and the disasters which are followed up by other natural disasters within 40 days, in order to isolate the effect of the specific disaster. Also, the disasters with an overlap time with other disasters in that country are eliminated. Given the fact that the event-study methodology is mainly used in the short-term period in existing literature, disasters that are reported to last over 40 days are also excluded. Eventually, index data from Datastream should be available in order to conduct this study, which lead to a final database of disasters of 263 events. The countries where the disasters take place with the corresponding disaster type are summarized in table 1 below. The number of natural disasters vary from a minimum of 2 disasters in Belgium and Israel to a maximum of 50 disasters in the US. The other variables I include considering disaster characteristics are the number of fatalities, the economic damage the number of days that the disaster takes place and whether or not the disaster was expected, based on the criteria mentioned in section 2.3.

Country	**All natural disasters**	**Earth-quakes**	**Extreme temp. / drought**	**Floods**	**Land-slide**	**Storms**	**Wild-fires**
Australia	13			5		2	6
Belgium	2					2	
Brazil	7			4	1	2	
Canada	6			5		1	
France	5			3		2	
Germany	5			1		4	
Greece	3	1		1			1
Indonesia	21	7		10	4		
India	24	4		15	1	4	
Israel	2					1	1
Italy	9	3		6			
Japan	12	2				10	
Mexico	10	2	1	2		5	
New Zealand	4	1		2		1	
Philippines	34	3		10	1	20	
Pakistan	9	3		5	1		
South Africa	10	1		6		2	1
Spain	6	1		3			2
Switzerland	3			2	1		
Taiwan	11	2		2		7	
Thailand	15	1		14			
United Kingdom	4			4			
US.	50			13	1	24	12
Total	263	31	1	113	10	87	23

Table 1: Natural disaster type per country

3.2 Index data

In order to assess the impact on various industries, I collect index data from Datastream of all countries where disasters are reported. The focus is on the level 2 industry index level data, which divides all companies in a country into ten industry categories; Oil & Gas, Basic Materials (including Chemicals and Basic Resources like Industrial Metals and Mining), Industrials (including Construction & Materials and Industrials Goods & Services), Consumer Goods, Health Care, Consumer Services (including Retail, Media and Travel & Leisure), Telecommunications, Utilities (including Electricity, Gas, Water & Multi utilities), Financials (including Banks, Insurance, Real Estate, Financial Services) and Technology. Using the level 2 industry index data from Datastream is consistent with previous research in natural disaster event studies (Degiannakis, Filis, & Floros, 2013) (Mohan & Faff, 2008). Datastream industry indices have the major strength that it applies the same criteria for defining industries across countries, which makes them comparable and it minimizes the risk of misclassification of firms (Stulz & Griffin, 2001). I collect this data from 1999 until 2017 (which is one additional year used for the estimation period for events in the beginning of 2000). The total return index in Datastream includes the stock price and dividends, so I use this index in order to calculate the return per day per index using the following formula:

$$R_{it} = (CloseIndex_t - CloseIndex_{t-1}) / CloseIndex_{t-1} \quad (1)$$

CloseIndex is the index value on which the index closed that day. I only consider the industries with enough observations per index, which is in line with the approach of Hong et al. (2016). This comprises dropping indices with less than 51 observations in the event period [-10;+40] and with less than 90 observations in the estimation period. I checked the data for outliers, which resulted in the replacement of any index day data point above the return of +100% or below -100% (which happened 5 times) by the average of the return of the day before and after.

Furthermore, I use daily MSCI world data which I collected from Datastream and I use daily risk-free rate based on data available on the Data Library of Kenneth French. Not all days match between the Kenneth French database and the Datastream available days, but when there is a missing value for the risk-free rate, I use the average of the days before and after. Moreover, I include country type (OECD vs non-OECD), population density per squared km in the country in 2016 and the frequency that a country is affected by a disaster. Table 2 provides the descriptive statistics of the categorical variables.

Variable	Observations
Expectancy of disaster	
• Expected	192.742
• Not expected	177.513
Country type	
• OECD	187.384
• Non-OECD	182.871

Table 2: Descriptive statistics of categorical variables

Table 3 provides the descriptive statistics of the numerical variables. Most variables are skewed, so in order to keep them consistent, all natural logarithms are taken to normalize the values. However, a logarithm of zero has no value so I add one for every observation in order to correct this error. The final continuous variables descriptive are shown in table 4 below. Moreover, table 5 in Appendix II provides an overview of the various data sources of the collected data.

Variable	Obs	Mean	Median	Min	Max	Skewness	Kurtosis
Index return daily	370,225	0.0001915	0	-0.37	0.93	0.77	40.81
World return daily	370,225	0.0001881	0.0002396	-0.09	0.12	-0.03	11.72
Total fatalities	370,225	484.7	6	1	73,338	13.79	205.08
Total damage (USD)	370,225	968.7	100,000	30	50,000,000	9.19	107.98
Duration of disaster in days	370,225	4.7	2	1	30	1.94	6.59
Population density per squared km in country	370,225	174.26	144	3	445	0.54	1.88
Frequency affected per country	370,225	203.12	130	8	419	0.32	1.59

Table 3: Descriptive statistics of numerical variables

Variable	Obs	Mean	Median	Min	Max	Skewness	Kurtosis
Index return	370,225	0.0001915	0	-0.37	0.93	0.77	40.81
World return	370,225	0.0001881	0.0002396	-0.09	0.12	-0.03	11.72
Total fatalities (ln)	370,225	3.25	2.79	1	12.2	1.48	6.47
Total damage (USD) (ln)	370,225	12.14	12.51	4.4	18.72	-0.17	2.72
Duration of disaster in days (ln)	370,225	2	1.69	1	4.4	0.56	1.96
Population density per squared km in country (ln)	370,225	5.56	5.97	2.09	7.09	-1	3.51
Frequency affected per country (ln)	370,225	5.99	5.88	3.08	7.04	-0.50	2.44

Table 4: Descriptive statistics of numerical variables after taking natural logs

4. Method

Following the approach of Robinson and Bagwayo-Skeete (2016) and based on Schweitzer (1989), I test the return reaction of natural disasters on industry indices using the event study methodology. This methodology can be used to isolate the effect of a certain event, taking other known factors of influence into account. The event study methodology is widely used in the literature concerning natural disasters and stock markets, however Worthington & Valadkhani (2004) use an autoregressive moving average analysis (Worthington & Valadkhani, 2004). This model is useful stationary time series for a very short time period of 2 till 5 days, but the information of the events might take longer to be absorbed by the market participants. Therefore, most authors choose to use the event study methodology, as this method is able to capture the consequences over a longer time span (Koerniadi, Krishnamurti, & Tourarni-Rad, 2016). This methodology has the underlying assumption that the capital market is semi-strong form efficient, meaning that the asset prices comprise all publicly available information which is relevant for the formation of the price. For every natural disaster, I consider corresponding total return indices (this includes capital and dividend returns) of ten industries of the country in that period in time.

4.1 Expected return and abnormal return

In order to perform the event study, I need an estimation of the expected returns in the event period. First, I calculate the expected normal return of these industries using the CAPM (Womack & Zhang, 2003). This is the most classical finance model explaining stock returns. I run a time series regression of the model on the industry indices with daily returns per industry as follows:

$$R_{it} - R_{Ft} = \alpha_I + b_i (R_{Mt} - R_{Ft}) + e_{it} \quad (2)$$

With $E[e_{i,t}]= 0$ and $VAR[e_{i,t}]= \sigma^2_{ei}$, where R_{it} is the return on the index for day i, R_{ft} is the risk-free rate return and R_{Mt} is the return on the value-weighted market portfolio, estimated with the MSCI world index. The exposure to the market portfolio factor is captured in b_i, which is calculated with an estimation period of 90 days in total (period of trading days before the event date, dependent on specific event window). This the smallest estimation period using daily stock returns without a decrease in explanatory power of the model (Corrado & Zivney, 1992). Moreover, this estimation period is most frequently used in the event studies concerning natural disasters (Brounen & Derwall, 2010) (Cao, Xu, & Guo, 2015). Resulting from equation (2), the **first expected excess return** per industry index per day is:

$$E(R_{it}) = \alpha_I + b_i (R_{Mt} - R_{Ft}) + R_{Ft} \tag{3}$$

In order to test the robustness of the results, I calculate the **second expected return** using a simple market model:

$$E(R_{it}) = R_{Mt} \tag{4}$$

Where R_{it} is the return on the index for day i and R_{Mt} is the return on the value-weighted market portfolio, estimated with the MSCI world index. The assumed that the beta has a value of 1 in this model. For the third and final model I follow the approach of related research in which the expected return is calculated as the mean-adjusted-returns (Chen & Siems, 2004). The **third expected return** per industry index per day is calculated as:

$$E(R_{it}) = 1/90 \sum_{t=\text{ start event window}-91)}^{\text{start event window}-1} R_{it} \tag{5}$$

Where R_{it} is the return on the index for day i. In other words, the expected return for every day in the event period is the average return over the estimation period for the index.

4.2 Abnormal return and cumulative abnormal return

After calculating the expected returns for the three models, I calculate the abnormal return over the event window in order to find out the change in stock return due to the event. Multiple start dates of events take place during weekends. The indices data only comprises trading-day data, so the disasters in the weekend are matched to the closest next trading day, which is in line with previous research (Wang & Kutan, 2013). I calculate the abnormal returns with the following formula, for all 3 models as discussed in section 4.1:

$$AR_{it} = R_{it} - E(R_{it}) \tag{6}$$

Where AR_{ij} is the abnormal return per day i per country disaster in combination with an industry index j. R_{ij} is the actual return per day i per country industry index j. Over the event window that I choose, the total effect of the natural disaster per country industry index in the entire event window can be calculated by the cumulative abnormal return formula:

$$CAR_i(T_1, T_2) = \sum_{t=T1}^{T2} AR_{i,t} \tag{7}$$

Where (T_2 – T_1) is the event window. I determine the event window after analyzing the cumulative average abnormal return (CAAR) around the event date. I calculate the CAAR according to the formula:

$$CAAR_{(T1,T2)} = 1/N \sum_{i=1}^{N} CAR_{i(T1,T2)} \tag{8}$$

I analyze the CAAR in a graph in order to see the movements over time. Given the fact that the distribution of the CARS is non-normal, I test the persistency of the effect of the CAR with the non-parametric Wilcoxon signed-rank test (Corrado & Zivney, 1992). This tests whether the distribution of the CAR is the same as the value or variable I choose, which is zero in this case. When the distribution is significantly different, this means that there is a CAR reaction that is significantly different from zero. In order to check the result of the Wilcoxon signed-rank test with other tests, I perform a t-test on the equality of means. It makes sense to use the t-test because this is the test statistic used for significance in the hypothesis testing in the next sections (even though this test assumes a normal distribution of the CAR). To correct for non-normality, I use the Johnson-test, which adjusts the variable for skewness in the distribution (Johnson, 1978). Finally, I use the generalized sign-test in order to make the sign test and t-test results more comparable as they both assume normal distribution. I use the following formula to conduct the generalized sign-test (Cowan, 1992):

$$T_{GS} = \frac{P_0^+ - P_{Est}^+}{\sqrt{P_{Est}^+(1-P_{Est}^+)/N}} \tag{9}$$

This is a test to check whether the ratio of positive CARs in the event window (P_0^+) does not deviate systematically from the ratio of positive CARs in the estimation window(P^+_{Est}). N is the number of observations. Again, this results in testing whether the CAR is significantly different from zero. When these tests result in a significant CAR (which is significantly different from zero), this means that there is a CAR in the event window on average across all industries and events that is significantly different from zero.

4.3 Hypothesis testing with OLS regression

In order to test the cross-sectional effects of the CAR, I run an OLS regression with the CAR as dependent variables and the other variables as independent variables:

$$CAR_i = \alpha_I + b1 * DT_i + b2 * C_i + b3 * FT_i + b4 * ED_i + b5 * ID_i + b6 * DU_i + b7 * PD_i + b8 * FR_i + b9 * EX_i + b10 * DD_i + e_i \quad (10)$$

Where CAR_i is the cumulative abnormal return per disaster and industry j, DT is the disaster type as dummy variable, C is the dummy variable for OECD and non-OECD countries, FT is the natural logarithm of the number of fatalities for the specific event as continuous variable, ED is natural logarithm of the economic damage for the event in dollar as continuous variable, ID is the industry dummy variable of the index, DU is natural logarithm of the duration of the event as continuous variable, PD is the natural logarithm of the population density of the country as continuous variable, FR is the natural logarithm frequency a country is affected by natural disaster in 2000 till 2017 as continuous variable, EX is a dummy variable for expected and unexpected and DD is the dummy variable for disaster type. Moreover, I use interaction dummies in order to test a hypothesis that includes two independent, categorical variables like industry and disaster types. In this phase, I also test for multicollinearity for certain variables and I exclude them from the same regression model if necessary. For example, population density and number of fatalities could be highly correlated because when there are more people in an area, it is more likely that people are affected.

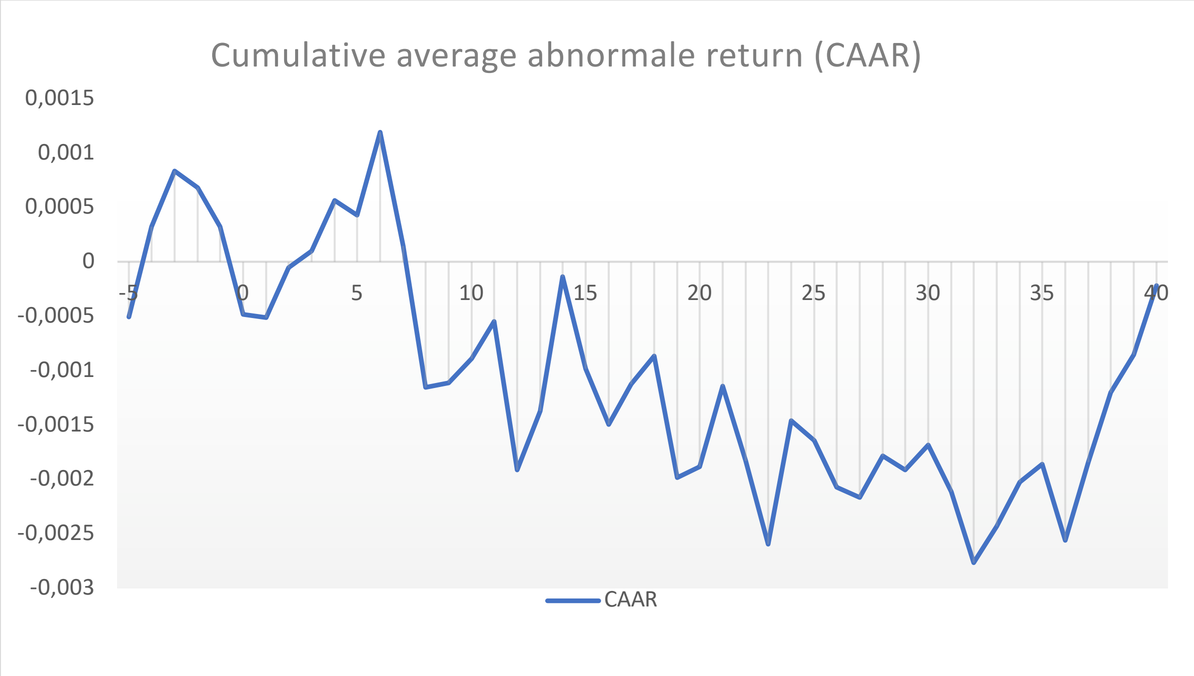
In summary, I apply the event methodology for the natural disasters over an event window, using total return industry indices per country. Thereafter, I perform a hypothesis test with an OLS regression of the variables. In Appendix I, the validity framework is attached.

5. Results

In this chapter, I start with discussing the general return reaction of industry indices on natural disasters and the persistency of the effect. Afterwards, I discuss the results of the variables that are relevant for the hypothesis and I mention results of control variables when they are outstanding. In all cases, I first conduct a univariate OLS regression in which I assume that there are no effects of other variables, which I consequently check with a multiple OLS regression where I control for the effect of all other factors. The main focus is on the CAPM model in equation (3), while I check the results of the simple market model in equation (4) and the average estimation model in equation (5) as a robustness test. These robustness test results are attached in Appendix V and VI and I discuss them in section 5.6.

5.1 General effect

In order to perform the event study, I determine the event window in this section. To capture the widest spread of all the cumulative average abnormal return (CAAR) movements, I initially use the event window of [-5, 40]. The start date of the disasters is [0] in the event window. The event windows' maximum is 40 because events that are in sequence of each other within 40 days are removed, so enlarging the event window could mean that there is a bias of other events within the event period. I examine the cumulative average abnormal return (CAAR) in order to study the magnitude of the CAAR over the days in Graph 1 below. As the graph shows, the CAAR is positive between -4 and -1, but it has a negative value between 0 and +2. Between +3 and +7, the CAAR is positive again and from +8 until +40 the CAAR is negative. It seems like the market is reacting when the natural disaster starts at [0], but tries to recover right after. One week after the start of the natural disaster, the impact on the industries increases and remains negative until at least +40, but there is a small recovery around +13 and +14 and a recovery of greater magnitude from +37 on. Moreover, there might be some noise in [-4;-1] as the natural disaster did not start yet. Therefore, it is interesting to continue to analyze the event window [-5;+40] in further analysis, as well as [-5; +14], [-1;+14], [-5;+36] and [-1;+36]. In this way, I am able to understand the CAR over time and I can determine which event windows provide CARs that are significant different from zero.



Graph 1: The cumulative abnormal return resulting from the CAPM abnormal returns in the event window [-5;40] where [0] is the start date of the natural disaster. Values are based on an estimation window of 90 days before the event window. Scale: 1=100%

With these event windows, I perform the CAR calculation based on equation (7) as discussed in section 4. The descriptive statistics of the CARs are shown in Table 6 below. For every event window, the estimation window is adjusted to 90 days prior to the exact event window. This makes the CAR estimations most reliable but this also means that the CAR estimation can differ slightly per day among the CARs, because there are some differences within the estimation period (for example, this is why there is a different maximum value for the first, fourth and fifth CAR, while the event window of the last CAR is part of the first one). Analyzing the results, the mean value of the CAR in [-5;+40] is -0.0001197, meaning that the average CAR is -0.01197% over all events. The CAR remains negative over the other event windows and actually increases in magnitude. For the CAR [-5;+14], the average CAR is -0.04082% over all events, while this becomes more negative for the [-1;+14] CAR, which is on average -0.1133% over all events. The CAR reaction is more negative for [-5;+36], which is -0.35561% on average. Finally, the greatest magnitude I find is for the [-1;+36] event window with a CAR reaction of -0.3947% on average, so this is the event window without the positive reaction before the event date and without the reversal from +37 on. This means that in these 38 days in the event window, on average a total negative return of almost -0.4% is resulting from the natural disasters.

Variable	Obs	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
CAR [-5;+40]	370,225	-0.0001197	0	0.1347	-1.0967	0.7997	-0.4075	10.1310
CAR [-5;+14]	370,225	-0.0004082	0	0.7351	-0.4104	0.5292	0.4918	7.2828
CAR [-1;+14]	370,225	-0.001133	0	0.0648	-0.2546	0.5547	0.4814	7.4257
CAR [-5;+36]	370,225	-0.0035561	0	0.1222	-1.0739	0.8174	-0.9101	14.0418
CAR [-1;+36]	370,225	-0.003947	0	0.1189	-1.0315	0.8432	-0.8487	13.1846

Table 6: Descriptive statistics of CAR

In order to determine which CARs are significantly different from zero, I perform different tests as discussed in section 4. As the descriptive statistics show, the distribution of the CARs is non-normal due to high kurtosis values. Therefore, I test the persistency of the CAR with the non-parametric Wilcoxon signed-rank test (Corrado & Zivney, 1992). For this test, the null hypothesis is as follows: CAR median = zero. Table 7 below shows the results. The z-value should be large enough in order to obtain a significant probability to reject the null hypothesis. As the result shows, the z-value for the greatest event window of [-5;+40] is not significant different from 0 as it generates a probability to reject the null hypothesis above 89.74%. However, all the other CARs are highly significant different from zero as the z-values magnitudes and corresponding probabilities are sufficient. This means for the other 4 CARs that the median of the CAR is significantly different from zero.

Variable	Obs positive	Obs negative	Obs zero	Adjusted variance	z-value	Pr. H0: CAR=0
CAR [-5;+40]	1.8e+05	1.8e+05	16920	4.229e+15	-0.129	0.8974
CAR [-5;+14]	1.7e+05	1.8e+05	15369	4.230e+15	-21.955	0.0000
CAR [-1;+14]	1.7e+05	1.8e+05	15792	4.230e+15	-21.889	0.0000
CAR [-5;+36]	1.8e+05	1.8e+05	15228	4.230e+15	-12.072	0.0000
CAR [-1;+36]	1.8e+05	1.8e+05	15228	4.230e+15	-6.120	0.0000

Table 7: Wilcoxon signed-rank test. H0: CAR median = 0

In order to check the persistency of the CARs and to keep the statistics consistent, I perform the t-test, as I also use this test statistic for the hypothesis testing in the next paragraphs. The results are shown in table 8. The null hypothesis is as follows: CAR mean = zero. These results also show that the broadest event window does not generate a CAR that is significantly different from zero, as I can reject the null hypothesis above 58.87% confidence level. Concerning the other CARs, the null hypothesis can be rejected with a high significant level, which means that these CARs' means are significantly different from zero.

Variable	Obs	Mean	Std. Dev.	95% conf. Interval	t-value	Pr. H0: mean CAR=0, Ha: Mean!=0
CAR [-5;+40]	370.225	-0.0001197	0.1347	-0.0005537; 0.0003142	-0.5407	0.5887
CAR [-5;+14]	370.225	-0.0004082	0.7351	0.000645; -0.0001714	-3.3784	0.0007
CAR [-1;+14]	370.225	-0.001133	0.0648	-0.001342; -0.000924	-10.6253	0.0000
CAR [-5;+36]	370.225	-0.0035561	0.1222	-0.00395; -0.0031623	-17.6968	0.0000
CAR [-1;+36]	370.225	-0.003947	0.1189	-0.0043301;-0.0035639	-20.1921	0.0000

Table 8: T-test. H0: Cumulative abnormal return =0

Moreover, I perform the Johnson t-test adjusts for skewness but given the fact that the CARs are not skewed, this test results in the same values as the normal t-test gives. As mentioned before, the Wilcoxon signed-rank test does not assume normal distribution, while the t-test does. In order to compare the t-test with a normal distributed sign-test, I also perform the generalized sign test with equation (9). The null hypothesis is as follows: CAR mean = zero. The results in table 9 are consistent with the previous tests, suggesting that CAR [-5;+40] does not significantly differ from zero because the test-statistic of -0.115 is not within the 95-confidence level. This test-statistic means I can reject the null hypothesis above 11.5% probability. The 4 other CARs do differ significantly from zero as their test statistics are within the 95-confidence level.

Variable	Test-statistic
CAR [-5;+40]	-0,1156573
CAR [-5;+14]	-0,0152047
CAR [-1;+14]	-0,0172139
CAR [-5;+36]	-0,005426
CAR [-1;+36]	-0,0075559

Table 9: Generalized signed-test. H0: Cumulative abnormal return =0

To conclude, the return reaction across all industries in response to natural disasters is not significant different from zero over the event period of [-5;+40], but in the 4 sub-periods there is a significant effect found. The insignificant effect is mainly due to positive effect in the first and last days in the event period, because when they are excluded, a significant negative effect is found. Given the fact that there is not a significant negative effect within the broadest event period does also not mean that there is no significant effect in the cross section. Therefore, I proceed to test the other hypotheses with the OLS regression over the event period of [-5;+40], as this period contains the most information. The robustness check for this result is included in Appendix V and I discuss this in section 5.6 together with the other robustness checks.

5.2 Results of general variables

Before conducting the OLS regressions in order to test the hypotheses, I check the correlation among the variables. The correlation matrix in Table 10 below shows that the highest correlation is -0.6134 between Expectancy and Duration of the disaster. This correlation is still acceptable for the OLS regression, so no variables have to be excluded from the same regression. However, since the variable Expectancy is a composition from the categorical variable of the disaster types, this variable is omitted in a multiple regression with all categories of disasters.

Variable	CAR	LNduration	LNpopdens	LNfrequencyaffected	LNtotal economic damage	LNtotalfatalities	OECD	Expected
CAR	1.0000							
LNduration	-0.0084	1.0000						
	0.0000							
LNpopdens	-0.0035	-0.2248	1.0000					
	0.0000	*0.0000*						
LNfrequencyaffected	-0.0023	-0.0228	0.0911	1.0000				
	0.0000	*0.0000*	*0.0000*					
LNtotal economic damage	0.0152	0.1640	-0.1090	-0.0838	1.0000			
	0.0000	*0.0000*	*0.0000*	*0.0000*				
LNtotalfatalities	-0.0680	0.0536	0.3862	0.1687	0.2774	1.0000		
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*			
OECD	-0.0438	-0.0371	0.5040	0.1496	-0.3389	0.4260	1.0000	
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*		
Expected	-0.0237	-0.6134	0.1854	0.1123	0.0015	0.0459	0.0109	1.0000
	0.0000	*0.0000*	*0.0000*	*0.3572*	*0.0000*	*0.0000*	*0.0000*	

Table 10: Correlation Matrix

Table 11 shows the results of the general variables in the univariate and the multiple OLS regressions. First of all, as discussed in the previous section, the general effect of a natural disaster on the stock market of industries during the event period gives a CAR reaction of -0.01197%, but this effect is not significant. Other non-observable or insignificant results are the effect of the percentage increase in frequency affected of a country and the CAR and for population density. However, when looking at the multiple regression where I control for other factors, these factors become significant with a reaction on the CAR of +0.3% for the percentage increase in frequency affected and +0.5% for the percentage increase in population density.

I find consistent results for the other variables; 1% increase in the total economic damage due to the natural disaster results in a positive reaction in the CAR of +0.1% and this effect increases slightly to +0.2% in the multiple regression. The variable expectancy of the disaster gives a CAR reaction is +0.6% compared to when the disaster is unexpected and this becomes the variable with the greatest magnitude in the multiple regression of +1.3% on the CAR compared to unexpected natural disasters. The difference between a natural disaster in an OECD country compared to a non-OECD country is +1.2%, meaning that the CAR in OECD countries is higher, but this effect decreases to a difference of +0.4% in favor of the OECD countries in the multiple regression. I find a negative relation for 1% increase in the total amount of fatalities, which results in a significant CAR reaction of -0.7% when controlling for other variables.

Variable	**Reg1**	**Reg2**	**Reg3**	**Reg4**	**Reg5**	**Reg6**	**Reg7**	**Reg8**	**Reg9**
LNfrequency affected		0.000							0.003***
LNtotaldamage			0.001***						0.002***
LNfatalities				-0.005***					-0.007***
Expectancy, (expected= 1)					0.006***				0.013***
LNduration						-0.001***			-0.004***
LNpopdens							0.000*		0.005***
OECD, (OECD = 1)								0.012***	0.004***
Constant	-0.0001197	0.002	-0.010***	0.016***	-0.003***	0.002***	0.002	-0.006***	-0.053***
N	370255	370255	370255	370255	370255	370255	370255	370255	370255
R^2	0.000	0.000	0.000	0.005	0.001	0.000	0.000	0.002	0.009
Adjusted R^2	0.000	0.000	0.000	0.005	0.001	0.000	0.000	0.002	0.009

Table 11: CAR reaction based on regression with estimation window of 90 days previous to event window

*legend: * p<0.05; ** p<0.01; *** p<0.001*

5.3 Results of disaster types

Table 12 shows the CAR reactions in the different disaster type cases in the univariate and multiple OLS regression. Extreme temperature is the omitted variable in the multiple regression, so the reported values of the other types are relative to extreme temperatures (which is the reported constant value). Starting with the univariate regression, the effect of an earthquake is significant with -0.9%, meaning that when a natural disaster occurs, the CAR is 0.9% lower when it is an earthquake compared to all other disaster types. This results in a total CAR of -0.8% when taking the constant into account. Analyzing the results further, the total effect of earthquakes after controlling for the other disaster types and general variables results in a CAR reaction of -5.4%. Storms generate +0.2% CAR compared to non-storms, resulting in a total CAR of +0.1% for storms which is also significant. However, when controller for other factors, the total reaction becomes -5.2% on the CAR, so the positive and negative effects contrast each other here.

Concerning the other disaster types, I find the strongest significant effects for extreme temperatures (most negative effect of -8.5% CAR) and floods (which is the least negative with -3.4% CAR) compared to the other types.

Variable	Reg10	Reg11	Reg12	Reg13	Reg14	Reg15	Reg16
Earthquake	-0.009***						0.031***
Extreme temperature		-0.028***					(omitted)
Flood			0.015***				0.051***
Landslide				-0.033***			0.018***
Storm					0.002***		0.033***
Wildfire						-0.024***	0.012**
LNfreq.aff.							0.004***
LNtotaldamage							0.002***
LNfatalities							-0.006***
LNduration							-0.003***
LNpopdens							0.003***
OECD, (OECD = 1)							0.009***
Constant	0.001***	0.000	-0.006***	0.001***	-0.001***	0.002***	-0.085***
N	370255	370255	370255	370255	370255	370255	370255
R^2	0.000	0.000	0.003	0.002	0.000	0.003	0.015
Adjusted R^2	0.000	0.000	0.003	0.002	0.000	0.003	0.015

Table 12: CAR reaction based on regression with estimation window of 90 days previous to event window, per disaster type

*legend: * p<0.05; ** p<0.01; *** p<0.001*

5.4 Results of industry types

Table 13 shows the results of the industry type regressions in univariate and multiple OLS regressions. In the multiple regression, the Basis Material industry is omitted so the reported values for the industry types are relative to this industry. The Basic Material industry CAR reacts significantly with -0.5% compared to other industries. This means that when a natural disaster takes place, the CAR in this industry is 0.5% lower compared to the other industries. The total reaction when controlling for other variables is -5.7% on the CAR, so the magnitude increases. Moreover, I find the most negative CAR reaction in the Technology sector with a significant effect of -0.8% on the CAR compared to the other industries, which results into a total CAR reaction of -6% in the multiple regression.

I find inconsistent results for the Consumer Services, which CAR reacts significant to natural disasters with +0.8% compared to other industries and taking into account the constant, the CAR of consumer services is still positive with +0.7%, which is the most positive reaction I find. However, when controlling for other factors, this total reaction becomes negative instead of positive with -4.6% on the CAR, but it is still least negative reaction I find. The Industrials Industry shows a small and insignificant effect of -0.1% effect on the CAR, but this becomes a significant -5.4% on the CAR in total when controlling for other factors. Also for the Oil & Gas industry, the univariate and multiple regressions are not consistent. In the univariate regression, the Oil & Gas industry generates +0.2% on the CAR compared to other industries and in total, which is significant with a p-value of 0.01, meaning that this result is certain with a 99% probability. In the multiple regression this becomes -5.1% in total on the CAR. The financial industry shows a slightly positive but significant CAR reaction of +0.4% compared to non-financials in the univariate regression, resulting in a total CAR reaction of +0.3% but this also becomes highly negative (-4.9%) in the multiple regression.

Variable	Reg17	Reg18	Reg19	Reg20	Reg21	Reg22	Reg23	Reg24	Reg25	Reg26	Reg 27
BM	-0.005***										(omitted)
CG		-0.005***									-0.001
CS			0.008***								0.011***
FN				0.004***							0.008***
G1					-0.008***						-0.003***
H1						-0.003***					0.001
ID							-0.001				0.003**
O1								0.002**			0.006***
T1									0.004***		0.008***
Ut1										0.004***	0.008***
LNfreq. Aff.											0.003***
LNtot.dam.											0.002***
LNfatalities											-0.007***
Expectancy, (expected= 1)											0.013***
LNduration											
LNpopdens											-0.004***
OECD, (OECD = 1)											
Constant	0.000	0.000	-0.001***	-0.001*	0.001**	0.000	0.000	0.000	-0.001*	-0.001*	-0.057***
N	370255	370255	370255	370255	370255	370255	370255	370255	370255	370255	370255
R^2	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.010
Adjusted R^2	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.010

Table 13: CAR reaction based on regression with estimation window of 90 days previous to event window, per industry index

*legend: * p<0.05; ** p<0.01; *** p<0.001*
BM= Basic materials
CG= Consumer goods
CS= Consumer services
FN= Financials
G1= Technology
H1= Health care
ID= Industrials
O1= Oil & gas
T1= Telecommunication
U1= Utilities

5.5 Results of interaction effect

Table 14 shows the interaction effects of industries and natural disaster types. The values are the effects of the specific combination of disaster type and industry, compared to all other combinations. I find that the CAR reaction to a natural disaster in the case of extreme temperatures and the consumer goods industry is significant +2.8% with a p-value of 0.05%, meaning that this result is certain within the 95-confidence level, but the significance of the reaction disappears in the multiple regression where I control for other factors. For flood in combination with consumer goods, there is a highly significant CAR reaction of -0.8%, so this means that the combination results into -0.8% CAR compared to other combinations. When controlling for other factors, the reactions' magnitude increases to -1.1%. Concerning storms in combination with consumer goods, there is a positive CAR reaction of +0.9% and after controlling for other factors this increases to +1%.

Variable	Reg28		Reg29		Reg30	
Extreme temp * Consumer goods	0.028*	0.013				
Flood * Consumer goods			-0.008***	-0.011***		
Storm * Consumer goods					0.009***	0.010***
LNfrequencyaffected		0.003***		0.003***		0.003***
LNtotaldamage		0.002***		0.002***		0.002***
LNfatalities		-0.007***		-0.007***		-0.007***
Expectancy, (expected= 1)		-0.013***		-0.014***		-0.014***
LNduration		-0.004***		-0.004***		-0.004***
LNpopdens		0.005***		0.005***		0.005***
OECD, (OECD = 1)		-0.004***		-0.004***		-0.004***
Constant	0.000	-0.005	0.000	-0.003	0.000	-0.004
N	370255	370255	370255	370255	370255	370255
R^2	0.000	0.009	0.001	0.009	0.000	0.009
Adjusted R^2	0.000	0.009	0.001	0.009	0.000	0.009

Table 14: CAR reaction based on regression with estimation window of 90 days previous to event window, interaction effects

*legend: * $p<0.05$; ** $p<0.01$; *** $p<0.001$*

The extended results of the interactions are attached in Appendix III including all industry and natural disaster combinations. The most outstanding results include the strongest positive, significant CAR reaction for landslides in combination with the industrials industry of +3.8% (+0.2% after controlling for other factors) and the strongest negative, significant CAR reaction of -12.7% for extreme temperatures in combination with the basic material sector (-19.6% after controlling for other factors). Another strong effect is the combination of extreme temperatures and the Industrials industry which results in a CAR effect of -8.9% (-15.8% after controlling for other factors). The multiple regression with these three specific interaction effects are included in Appendix IV.

5.6 Control checks and robustness of results

In order to check the results based on the CAPM model, I perform robustness checks with equation (4) which is the simple market model and equation (5) which is the average estimation model. The results are attached in Appendix V and VI, which I discuss briefly in this section. Concerning the general effects of natural disasters on the industry indices, the other models confirm the inconsistency of the relation over the [-5;+40] event window, as these models report slightly positive relations but these are not significant over all persistency tests.

For the other variables, I only report results that are robust in all three models. In the general variables category, I find that the variables percentage increase of total fatalities, the percentage increase of duration, the expectancy of a disaster and the OECD variable generate robust results. For the disaster types, I find robust results for extreme temperatures and floods, in the sense that flood it always generates the least negative reaction. Concerning the industry types, I find robust results for Technology as this always generates the lowest CAR and the Basic Materials is the second most negative one. The Financial industry, Oil & Gas industry, as well as the Consumer Services industry always belong to the most positive CAR reaction among industries (the top 50%). The flood and storm interaction effects with Consumer Goods are robust in the sense that their direction of the effects compared to other interactions is stable over all models.

6. Discussion and conclusion

6.1 Discussion

In this section, I discuss all hypothesis with the evidence from section 5. For the first hypothesis concerning the general effect across all industries in response to natural disaster, I find an effect but this is not significant (-0.01197% on the CAR). However, the sub-periods generate a significant negative reaction due to the different event windows when the most positive periods of [-4;-1] and [-37;+40] are left out. When checking the results with the robustness models, they show that there is not a negative reaction in total overall in the broadest event period. This result could also be due to positive periods within the event window. Because of the inconsistent results I find overall, there is insufficient evidence to support or contradict hypothesis 1.

Continuing with the hypothesis relating to the country type (hypothesis 2- hypothesis 4), I find significant, robust support that OECD countries suffer less from natural disasters compared to non-OECD countries, so I find evidence in favor of hypothesis 2 and in line with previous literature. This means OECD countries probably have more resources to prepare for disasters and they can limit the implications better due to their economic growth. However, I find no evidence for the correlation between high population density countries and a more negative CAR as mentioned in hypothesis 3, because the evidence I find is inconsistent. Countries affected more often by natural disasters also generates inconsistent results, so due to lack of evidence also I find no sufficient evidence to support or contradict hypothesis 4.

Hypothesis 5 until hypothesis 9 concern the disaster type and severity. The CAR reaction I find in response to earthquakes compared to the other types is inconsistent among the models and regressions, so I find insufficient evidence to support or contradict of hypothesis 5. I also do not find significant, robust evidence for storms having a positive effect on the CAR (hypothesis 6). However, in line with hypothesis 7, the CAR reaction is more positive for expected natural disasters, while this is negative for unexpected disasters. Therefore, I find evidence in favor of hypothesis 7. This is an addition to existing literature as this relation is not tested yet in the natural disaster event studies. This means that stock markets perform better when they know about an upcoming natural disaster instead of an unanticipated natural disaster. This is probably due to preparation time in order to minimize the effect of the disaster. To continue with the other hypotheses, the natural logarithm of fatalities has a negative relation with the CAR which is robust, so I find evidence to support of hypothesis 8. This means the higher the percentage increase of fatalities due to a natural disaster, the more severe the implications for the country are on both the supply and demand side of consumption, which translates into stock prices. However, for hypothesis 9 about the economic damage due to the natural disaster I only have inconsistent effects in the regressions. In addition to the hypotheses, the higher the logarithm of the duration of a disaster, the more negative the CAR reaction is. This means that the longer the natural disaster lasts, the more negative the reaction of the industries' stock market is. As another addition to the hypotheses testing, floods generate the least negative return across all models and extreme temperatures generate the most negative return effect compared to other disaster types. These findings are new to the natural disaster literature in the sense that they have not been combined all together in an analysis.

Finally, I test the hypothesis concerning the industry types and interaction effects (H10-H15). Hypothesis 10a and hypothesis 10b about the Oil & Gas indicate that there is inconsistency in the current literature; there is no evidence concerning natural disasters cases yet, but there is in related field. Actually, my results consistently show that the Oil & Gas industry CAR belongs to the 50% most positive results among industries, so I do find sufficient evidence to support hypothesis 10b. This means that investors are not as concerned as about the Oil & Gas industry compared to other industries. They do not fear economic slowdown compared to other industries (which would lead to lower demand for oil in the affected areas). It could be that affected areas produce/distribute oil, which means that oil becomes more scarce in affected areas. The Basic Material industry generates a more negative CAR compared to most other industries (except the Technology industry), so I find evidence against hypothesis 11a which points in the other direction based on existing literature. It could be that production is expected to stop for and therefore the expected return of stocks decreases. However, existing literature finds that the Basic Material industry is one of the most sensitive industries in their stock market reaction and I find support for that. For hypothesis 11b which applies to the Industrial industry, I find inconsistent results which are not robust so I do not find evidence in favor or against hypothesis 11b.

Concerning the Consumer Good industry, the results of the combination of Consumer Goods with storms show a robust positive reaction compared to other combinations, so I find evidence contradicting hypothesis 12a. A possible explanation is that stores that are devastated by disasters need to be replenished, which increases the demand for products. However, with this explanation I assume that the positive effects in cities is larger than the negative effect in agriculture (crops that are devastated), or at least investors expect this which translates into the stock prices. I find insignificant results in the interaction effects between extreme temperatures and consumer goods, so I do not find sufficient evidence to support or contradict hypothesis 12b. However, I find robust, significant evidence in favor of hypothesis 13b (and against hypothesis 13a), because the effect when combining Consumer Goods and floods is negative. Floods are good for fertilizing the soil in agriculture, but apparently this effect is not recognized on the short term which is in line with previous literature. Additional to the hypotheses concerning the other interaction effects, landslides in combination with the Industrials industry generates the most positive CAR overall and extreme temperatures in the Basic Material sector generates the most negative CAR overall. The reasons for this remain unclear at this point. Interactions are not studied extensively before with the amount of natural disasters I use, so these findings are extending current empirical findings in literature.

Continuing with other industries, the Consumer Services industry generates one of the most positive CAR among all models so I find evidence that contradicts hypothesis 14 which states the opposite. This means that this is contrasting with current literature which says that there is a negative reaction. A possible explanation is that current literature focusses on the tourism sector, which is a part of the Consumer Services industry. However, the Consumer Services industry also comprises retail among others, which might be stimulated due to natural disasters. Given the fact that there is no research done in the field of retail and natural disasters yet, I am not able rule out this possibility. However, current literature also finds that the Consumer Services industry is among the most sensitive industries in their reaction, so I do find support for that, even though it is in the opposite direction. Concerning the final hypothesis about the Financial Industry predicting a more negative reaction compared to the other industries, I find evidence against this hypothesis as the Financial industry belongs in all models in the least negative reaction 50%. A possible explanation is given in current literature; the insurance sector experiences gains due to a higher demand on their products (Wang & Kutan, 2013). Moreover, the real estate market might benefit from the destructing effect of natural disasters as the demand of their products also increases. However, this is contrasting to what is found in literature before, so the exact cause remains unclear. Other notable results include the reaction of the Technology industry, which generates the most severe CAR reaction across all models. Also in this case, the reason behind this remains unclear as there is no literature in this field relating natural disasters.

6.2 Conclusion

Overall concerning the hypotheses test, I find relations which are in line with current literature, as well as results that contradict or extend current literature. In line with current literature is the lack of evidence for a negative relation between natural disasters and the stock market across industries overall. Moreover, I find that OECD countries suffer less from natural disasters compared to non-OECD countries. A percentage increase in the fatalities caused by a natural disaster leads to a negative CAR reaction. Also in line with current literature is the finding that the Oil & Gas industry CAR reaction belongs to the most positive reaction among industries and another finding is the negative effect on the CAR when combining Consumer Goods and floods.

Contrasting with existing literature is the Basic Materials industry that generates one of the most negative CAR reaction in response to a natural disaster. Other surprising results are the combination of Consumer Goods with storms which results into a positive reaction compared to other combinations and the Consumer Services and the Financial industry generating one of the most positive CAR reactions. As an addition to existing literature, the cumulative abnormal return reaction is more positive in the case of expected natural disasters compared to unexpected natural disasters.

The outstanding results from the control variables include the finding that the longer a natural disaster lasts, the more negative return reactions become. Floods generate the least negative return and extreme temperatures generate the most negative return effect compared to other disaster types. Landslides in combination with the Industrials industry generates the most positive CAR overall and extreme temperatures in the Basic Material sector generates the most negative CAR overall. For all these results, the reasons are unclear as the existing literature is limited in these specific fields.

7. Limitations and future research

The collected data contains some limitations. One limitation is the EMDAT database with the natural disaster information. Many disasters from the original dataset did not have complete information and as this is the only available database with detailed information, I was not able to check the reliability. Moreover, due to time constraints, I use the level 2 industry indices data from Datastream. However, in every index there are many industries included, so when I find a negative effect of the overall industry, this could still mean that there is a positive effect in the sub-industries.

The methodology is based on an event window of [-5;+40], however, results are likely to be different when this time window changes. I exclude many disasters from the database because they occurred within each other's' event window, which makes the return analysis biased. When the event window is shorter, more natural disasters could be included. Furthermore, I exclude disasters that lasts more than 40 days due to the event window, but these disasters could actually result in interesting insights as the magnitude of their impact might be greater than the disasters I included. Nevertheless, I could not include disasters that last over 40 days because in that cause, I would not capture the entire effect of the disaster in my event period.

Further research could focus on the more detailed level of the Datastream industry indices. The results are surprisingly concerning the Oil & Gas, Financial, Consumer Services and Technology industry, so more in dept research could be done to clarify this effect. Also, the interaction effects show some interesting relations which could be the starting point for future research. Specific sub-sector could be analyzed in order to find the causes these return reactions. Moreover, industry characteristics could be taken into account in the analysis, for example dependency on foreign countries, average profitability margins and industry volatility.

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Appendix I

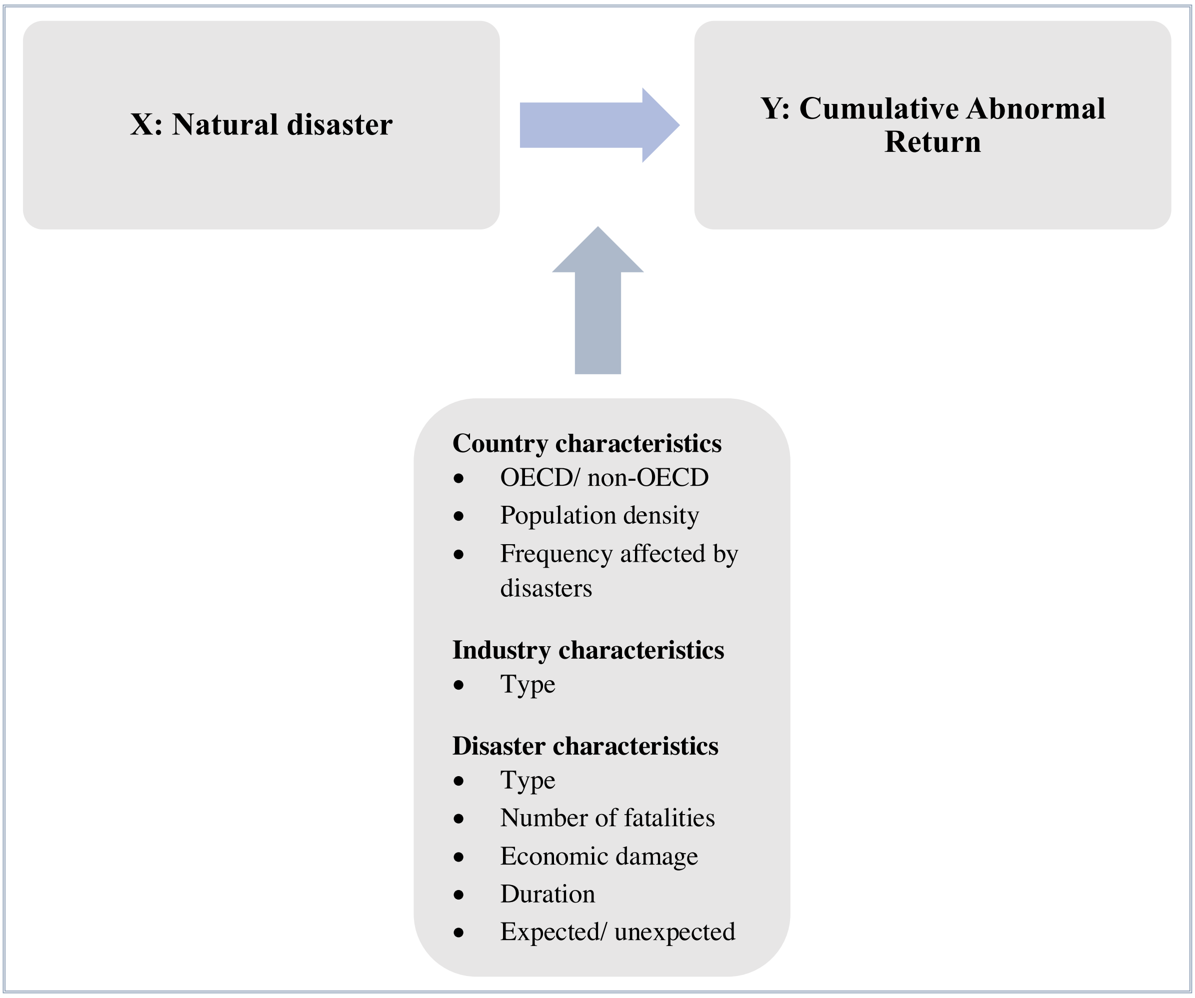

Figure 1: Validity framework

Appendix II

Database	Data	Level	Interval/date
EMDAT	Disasters, fatalities, economic damage, frequency affected, duration of disaster	Country	Daily
Kenneth French	Risk free rate	N.A.	Daily
Datastream	Industry indices level 2	Industry- Country	Daily
Datastream	MSCI World index	World	Daily
Worldbank Data	Population density/km^2	Country	2016
OECD.org	OECD vs non-OECD	Country	2017

Table 5: Data sources

Appendix III

Results of CAPM model (4) in univariate regression of interaction terms.

Variable	Model31	Model32	Model33	Model34	Model35	Model36	Model37	Model38	Model39	Model40
E*BM	0.010***									
E*CG		0.011***								
E*CS			0.016***							
E*G1				-0.008***						
E*FN					-0.032***					
E*H1						-0.019***				
E*ID							-0.019***			
E*O1								-0.003		
E*T1									-0.020***	
E*U1										-0.019***
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	370255	370255	370255	370255	370255	370255	370255	370255	370255	370255
R^2	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000

Table 15: CAR reaction based on regression with estimation window of 90 days previous to event window, interaction of earthquakes with all industries

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Variable	Model41	Model42	Model43	Model44	Model45	Model46	Model47	Model48	Model49	Model50
Ex*BM	**-0.127*** **									
Ex*CG		0.028*								
Ex*CS			-0.029*							
Ex*FN				-0.013						
Ex*G1					0.000					
Ex*H1						0.000				
Ex*ID							-0.089***			
Ex*O1								0.000		
Ex*T1									-0.047***	
Ex*U1										0.000
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	370255	370255	370255	370255	370255	370255	370255	370255	370255	370255
R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 16: CAR reaction based on regression with estimation window of 90 days previous to event window, interaction of extreme temperatures with all industries

*legend: * p<0.05; ** p<0.01; *** p<0.001*
BM= Basic materials
CG= Consumer goods
CS= Consumer services
FN= Financials
G1= Technology
H1= Health care
ID= Industrials
O1= Oil & gas
T1= Telecommunication

U1= Utilities

Variable	Model51	Model52	Model53	Model54	Model55	Model56	Model57	Model58	Model59	Model60
Fl*BM	0.006***									
Fl*CG		-0.008***								
Fl*CS			0.017***							
Fl*FN				0.014***						
Fl*G1					0.012***					
Fl*H1						0.012***				
Fl*ID							-0.004***			
Fl*O1								0.013***		
Fl*T1									0.006***	
Fl*U1										0.021***
Constant	0.000	0.000	-0.001***	-0.001**	-0.001**	-0.001**	0.000	-0.001**	0.000	-0.001***
N	370255	370255	370255	370255	370255	370255	370255	370255	370255	370255
R^2	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 17: CAR reaction based on regression with estimation window of 90 days previous to event window, interaction of floods with all industries

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Variable	Model61	Model62	Model63	Model64	Model65	Model66	Model67	Model68	Model69	Model70
L*BM	-0.046***									
L*CG		-0.105***								
L*CS			-0.021***							
L*FN				0.001						
L*G1					-0.007*					
L*H1						-0.068***				
L*ID							**0.038*****			
L*O1								-0.026***		
L*T1									0.022***	
L*U1										-0.104***
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	370255	370255	370255	370255	370255	370255	370255	370255	370255	370255
R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.000
Adjusted R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.000

Table 18: CAR reaction based on regression with estimation window of 90 days previous to event window, interaction of landslide with all industries

*legend: * p<0.05; ** p<0.01; *** p<0.001*
BM= Basic materials
CG= Consumer goods
CS= Consumer services
FN= Financials
G1= Technology
H1= Health care
ID= Industrials
O1= Oil & gas
T1= Telecommunication
U1= Utilities

Variable	Model71	Model72	Model73	Model74	Model75	Model76	Model77	Model78	Model79	Model80
St*BM	-0.003*									
St*CG		0.009***								
St*CS			0.000							
St*FN				0.004**						
St*G1					-0.016***					
St*H1						-0.002				
St*ID							0.007***			
St*O1								0.004**		
St*T1									0.014***	
St*U1										0.000
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.001**	0.000
N	370255	370255	370255	370255	370255	370255	370255	370255	370255	370255
R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Adjusted R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000

Table 19: CAR reaction based on regression with estimation window of 90 days previous to event window, interaction of storms with all industries

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Variable	Model81	Model82	Model83	Model84	Model85	Model86	Model87	Model88	Model89	Model90
W*BM	-0.051***									
W*CG		-0.017***								
W*CS			-0.010***							
W*FN				-0.023***						
W*G1					-0.045***					
W*H1						-0.025***				
W*ID							-0.010***			
W*O1								-0.039***		
W*T1									-0.016***	
W*U1										0.015***
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	370255	370255	370255	370255	370255	370255	370255	370255	370255	370255
R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Adjusted R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001

Table 20: CAR reaction based on regression with estimation window of 90 days previous to event window, interaction of wildfires with all industries

*legend: * p<0.05; ** p<0.01; *** p<0.001*
BM= Basic materials
CG= Consumer goods
CS= Consumer services
FN= Financials
G1= Technology
H1= Health care
ID= Industrials
O1= Oil & gas
T1= Telecommunication
U1= Utilities

Appendix IV

Results of the CAPM model (3) in multiple regression of interaction terms.

Variable	Model91	Model92	Model93
LNfrequencyaffected	0.003***	0.003***	0.003***
LNtotaldamage	0.003***	0.002***	0.002***
LNfatalities	-0.007***	-0.007***	-0.007***
Expectancy, (expected= 1)	0.014***	0.013***	0.013***
LNduration	-0.004***	-0.004***	-0.004***
LNpopdens	0.005***	0.005***	0.005***
OECD, (OECD = 1)	0.004***	0.004***	0.004***
Landslide * Industrials	0.057***		
Extr. Temp * BM		-0.142***	
Extr. Temp * Industrials			-0.104***
Constant	-0.055***	-0.054***	-0.054***
N	370255	370255	370255
R^2	0.009	0.009	0.009
Adjusted R^2	0.009	0.009	0.009

Table 21: CAR reaction based on regression with estimation window of 90 days previous to event window, multiple regression of interaction effects

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Appendix V

Results of the simple market model (4): Simple Market Model (SMM) and model (5): Average Estimation Model (AEM) from section 4.

Variable	Obs	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
CAR SMM [-5;+40]	370,225	0.002947	-0.0002	0.1071	-0.7885	0.7192	-0.1739	10.1727
CAR AEM [-5;+40]	370,225	0.0006781	0	0.1461	-1.1329	0.9075	-0.3553	8.7414

Table 22: Descriptive statistics of simple CAR (based on equation (5)).

Variable	Obs positive	Obs negative	Obs zero	Adjusted variance	z-value	Pr. H0: CAR=0
CAR SMM [-5;+40]	1.8e+05	1.9e+05	0	4.230e+15	11.400	0.0000
CAR AEM [-5;+40]	16e+05	16e+05	53438	4217e+15	8.392	0.0000

Table 23: Wilcoxon signed-rank test. H0: CAR median = 0

Variable	Obs	Mean	Std. Dev.	95% conf. Interval	t-value	Pr. H0: mean CAR=0, Ha: Mean!=0
CAR SMM [-5;+40]	370.225	0.002947	0.1071	0.0026019;0.0032919	16.7409	0.0000
CAR AEM [-5;+40]	370.225	0.0006781	0.1461113	0.0002074;0.0011487	2.8238	0.0047

Table 24: T-test. H0: Cumulative abnormal return =0

Variable	Test statistic
CAR SMM [-5;+40]	-0,009104
CAR AEM [-5;+40]	0,01271355

Table 25: Generalized signed-test. H0: Cumulative abnormal return =0

Appendix VI

Results of the simple market model (4): Simple Market Model (SMM) and model (5): Average Estimation Model (AEM) from section 4.

Variable	Model 94: SMM	Model 95: AEM
LNfrequencyaffected	0.000	0.005***
LNtotaldamage	-0.002***	0.000
LNfatalities	-0.001***	-0.008***
Expectancy, (expected= 1)	0.010***	0.010***
LNduration	-0.001***	0.006***
LNpopdens	-0.002***	0.007***
OECD, (OECD = 1)	0.007***	0.009***
Constant	0.024***	-0.067***
N	370255	370255
R^2	0.004	0.014
Adjusted R^2	0.004	0.014

Table 26: CAR reaction based on model (4): Simple Market Model (SMM) and model (5): Average Estimation Model (AEM), general variables

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Variable	Model 96: SMM	Model 97: AEM
LNfrequencyaffected	0.001**	0.006***
LNtotaldamage	-0.001***	0.000
LNfatalities	0.000***	-0.008***
LNduration	-0.002***	0.006***
LNpopdens	-0.002***	0.006***
OECD, (OECD = 1)	0.010***	0.012***
Earthquake	0.024***	0.069***
Extreme temperature	(omitted)	(omitted)
Flood	0.044***	0.083***
Landslide	0.054***	0.052***
Storm	0.027***	0.071***
Wildfire	0.022***	0.055***
Constant	-0.010**	-0.136***
N	370255	370255
R^2	0.009	0.018
Adjusted R^2	0.009	0.018

Table 27: CAR reaction based on model (4): Simple Market Model (SMM) and model (5): Average Estimation Model (AEM), disaster types

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Variable	Model 98: SMM	Model 99: AEM
BM	(omitted)	(omitted)
CG	0.003***	-0.001
CS	0.006***	0.010***
FN	0.012***	0.006***
G1	-0.006***	-0.002
H1	0.012***	0.001
ID	0.011***	0.002
O1	0.010***	0.007***
T1	0.007***	0.007***
Ut1	0.017***	0.010***
LNfrequencyaffected	0.000	0.005***
LNfatalities	-0.002***	0.000
LNtotaldeaths	0.001***	-0.008***
Expectancy, (expected= 1)	0.010***	0.010***
LNduration	-0.001***	0.006***
LNpopdens	-0.002***	0.007***
OECD, (OECD = 1)	0.007***	0.009***
Constant	0.017***	-0.071***
N	370255	370255
R^2	0.007	0.015
Adjusted R^2	0.007	0.015

Table 28: CAR reaction based on model (4): Simpel Market Model (SMM) and model (5): Average Estimation Model (AEM), industry types

*legend: * p<0.05; ** p<0.01; *** p<0.001*
BM= Basic materials
CG= Consumer goods
CS= Consumer services
FN= Financials
G1= Technology
H1= Health care
ID= Industrials
O1= Oil & gas
T1= Telecommunication
U1= Utilities

Variable	Model 100: SMM	Model 101: AEM
LNfrequencyaffected	0.000	0.005***
LNtotaldamage	-0.002***	0.000
LNfatalities	0.001***	-0.008***
Expectancy, (expected= 1)	0.010***	0.010***
LNduration	-0.001***	0.006***
LNpopdens	-0.002***	0.007***
OECD, (OECD = 1)	0.007***	0.009***
Extreme temp * Consumer goods	-0.009	-0.033**
Constant	0.024***	-0.067***
N	370255	370255
R^2	0.004	0.014
Adjusted R^2	0.004	0.014

Table 29: CAR reaction based on model (4): Simpel Market Model (SMM) and model (5): Average Estimation Model (AEM), general variables and interaction effect

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Variable	Model 102: SMM	Model 103: AEM
LNfrequencyaffected	0.000	0.005***
LNtotaldamage	-0.002***	0.000*
LNfatalities	0.001***	-0.008***
Expectancy, (expected= 1)	0.010***	0.011***
LNduration	-0.001***	0.006***
LNpopdens	-0.002***	0.007***
OECD, (OECD = 1)	0.007***	0.009***
Flood * Consumer goods	-0.032***	-0.014***
Constant	0.024***	-0.067***
N	370255	370255
R^2	0.004	0.014
Adjusted R^2	0.004	0.014

Table 30: CAR reaction based on model (4): Simple Market Model (SMM) and model (5): Average Estimation Model (AEM), general variables and interaction effect

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Variable	Model 104: SMM	Model 105: AEM
LNfrequencyaffected	0.000	0.005***
LNtotaldamage	-0.002***	0.000*
LNfatalities	0.001***	-0.008***
Expectancy, (expected= 1)	0.010***	0.011***
LNduration	-0.001***	0.006***
LNpopdens	-0.002***	0.007***
OECD, (OECD = 1)	0.007***	0.009***
Storm * Consumer goods	0.003*	0.013***
Constant	0.024***	-0.068***
N	370255	370255
R^2	0.004	0.014
Adjusted R^2	0.004	0.014

Table 31: CAR reaction based on model (4): Simple Market Model (SMM) and model (5): Average Estimation Model (AEM), general variables and interaction effect

*legend: * p<0.05; ** p<0.01; *** p<0.001*