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# **The Effect of Natural Catastrophes on the Secondary CAT Bond Market**

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**Abstract**

The impact natural catastrophes have on society has become increasingly costly in recent years. This has led to a higher need for financing, which has historically been provided by (re)insurance companies. However, as these costs are slowly becoming too large for them to bear, insurance-linked securities such as catastrophe (CAT) bonds have been created to spread this risk to capital markets. The study's goal is to facilitate increased market participation needed to achieve efficient levels of risk sharing. Thus, this empirical study is designed to give CAT bond market players a better understanding of what catastrophe types drive secondary market prices and how. As the basis of the empirical work, several OLS regression analyses are conducted to shed light on if/how certain types of catastrophes can statistically explain secondary market returns. Additionally, an event study approach is utilized to examine if/how unrelated catastrophes impact CAT bond returns, this study specifically drawing a conclusion from the US Wind CAT bond market. The time period investigated is from 2010-2019. The study reveals that catastrophe types causing the most damage and occurring most frequently have significant explanatory power, whereas no clear evidence can be established in regard to how CAT bond investors are affected by catastrophic events which are excluded from the bonds' coverage.

**Keywords:** CAT bond, Secondary CAT bond market, Natural catastrophes, CAT bond trading

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## 1 Introduction

This research lays its focus on determining if there are certain types of natural catastrophes that can explain price changes in the secondary catastrophe (CAT) bond market. Shortly after the initialization of this research in the field of CAT bonds, the global pandemic caused by the outbreak of the COVID-19 virus reached Europe. Global catastrophes such as the COVID-19 virus have increasingly severe consequences due to the globalization and internationalization, which have skyrocketed in recent decades and have brought the world closer together from both an economic and humanitarian perspective. However, the recent troubles that we are facing are not an isolated event. Multiple devastating catastrophes have wiped out the livelihoods of millions of people in the last decade, materializing in the form of several severe storms, earthquakes as well as tsunamis. This ultimately resulted in 2017 being the costliest year for the insurance and reinsurance industry since the beginning of records (Bevere, Schwartz, Sharan & Zimmerl, 2018). At the same time, an urge to counteract the phenomenon of general climate change and global warming has been recognized by most citizens as well as governmental authorities. Environmental, Social & Governance (ESG) investment strategies have enjoyed increasing popularity and the field of finance itself is exposed to a ‘green’ revolution.

Especially the last decade, with events such as hurricane ‘Andrew’ and the earthquake triggered tsunami that caused the malfunctioning of the Fukushima power plant in Japan, has demonstrated that there might exist a negative feedback loop between the increase of the overall standard of living of the world’s population and the occurrence of natural catastrophes. Since there has been a higher number of events in recent years, which has resulted in higher losses for the insurance industry compared to the historical average, a need for broader insurance coverage and larger amounts of financing has arisen. This view is supported by several contributors to the literature such as Gürtler, Hibbeln and Winkelvos (2016). Cummins and Weiss (2009) claim that in order to satisfy this financing shortage, multiple alternate financial vehicles have been developed with CAT bonds enjoying particular popularity. CAT bonds, as part of the market for insurance-linked securities, are most frequently used by insurance and reinsurance firms as means to raise capital (Edesess, 2015). Edesess (2015) further shows that CAT bonds are also appealing to the investor-side due to their zero-correlation to other financial instruments, thereby offering a diversification effect. Carayannopoulos and Perez (2015) additionally argue for the importance of the CAT bond stating that due to the significant growth in global catastrophes, insurance and reinsurance companies have almost been forced to search

for innovative strategies to finance the continuously increasing losses. Nguyen and Lindenmeier (2014) conclude that instruments such as CAT bonds are crucial for the sake of a society's continuous development and prosperity as they allow risk to be shared efficiently.

Although CAT bonds have become more popular, the area focusing on the secondary market as well as secondary market trading, called “live cat” bond trading (Patel, 2015, n.p.), still seems rather underserved and has thus far received only little coverage by financial analysts as well as researchers. However, with the emergence of CAT bond market indices, which portray the overall secondary market movements provided by companies such as Swiss Re (Swiss Re, 2014), the secondary CAT bond market has been granted more transparency (Dieckmann, 2019). We thereby reason that the elements of trading, price appreciations/depreciations as well as yield movements in the secondary CAT bond market have been significantly easier to interpret and follow. By incorporating those services, the market seems to have become increasingly popular among several types of investors. This has led to growth in trading levels in anticipation of catastrophes as market players appear to understand its importance (Aon Securities Inc., 2019). Since the secondary market is the medium that displays the effects that trading has on market prices and can thereby incorporate investors' reactions, we deem it a good fit for the basis of our analysis.

Despite the secondary CAT bond market receiving more attention, the majority of previous research focuses on individual CAT bonds and examines questions about the proper pricing and determination of their premiums (see e.g. Galeotti, Gürtler & Winkelvos, 2013). Another thoroughly covered topic relates to investment diversification and deals with the question if CAT bonds actually have limited correlation to other markets and outperform traditional bond markets, which have been among their biggest selling points (Carayannopoulos & Perez, 2015). Moreover, from the perspective of natural catastrophes and how they impact CAT bonds, most of the scholars have focused on how the individual bonds' premiums behave when and after a certain catastrophe occurs, how the premiums are affected by seasonality of catastrophes and how the different perils/insured regions play a role in the initial price of the issuance (see e.g. Gürtler, Hibbeln & Winkelvos, 2016). Building on previous contributions to the field, our work takes a different approach by attempting to establish the link between catastrophes and the secondary market.

As natural catastrophes have become more severe in magnitude and have also occurred more frequently in recent years (EM-DAT, 2020), the purpose of this research is to examine if there are certain types of catastrophes that play a larger role in price changes in the secondary

CAT bond market. We initiate this research by analyzing the historical development of natural catastrophes and by determining how the secondary CAT bond market has reacted in response to this larger number and increased severity of catastrophes. Overall, we include eight catastrophe types in our research; droughts, earthquakes, extreme temperature, floods, landslides, storms, volcanic activities and wildfires. We attempt to fill the identified research gap related to the secondary CAT bond market trading by performing a number of regression analyses. The aim is to determine if any catastrophes have statistically significant power in explaining secondary market returns. Taking those results into account, we then attempt to show how certain catastrophe types affect returns. Additionally, we conduct an event study specific to the catastrophe type ‘storms’ to show if events that originate outside of a market’s coverage have an impact on its prices by testing abnormal returns for their significance. This impact dubbed ‘fear-effect’ is tested to see if investors show a reaction to the occurrence of catastrophes outside of their traditional coverage. Simultaneously, as the secondary CAT bond market in general has not been the focus point of many theoretical and empirical articles so far, we contribute to the existing literature by providing a thoroughly researched compilation of theory that analyzes the link between initial placements and trading. Lastly, we choose a timeframe from 2010-2019 for our empirical work to incorporate the structural changes in the bonds after the financial crisis and to also accommodate the bonds’ development during times of relative economic prosperity with little systematic risk.

Through examining the link between natural catastrophes and price changes in the secondary CAT bond market, we aim to stress the importance of this topic for society. Since (re)insurance firms are starting to crumble under the weight of increased losses, risk needs to be distributed more efficiently. As CAT bonds offer an ideal way to achieve this increased distribution and broader participation, their attributes and mechanics need to find deeper appreciation amongst investors. In order to do so, we also aim to give market players a better understanding on how the market reacts to the occurrence of certain catastrophes in expectation of the event as well as while it is unfolding, Overall, we hope this will be of assistance to investors but also the industry alike by providing them the means to adjust the number/depth of issuances and coverages of certain bonds in light of the current state of the world. Additionally, our discoveries should help individual investors adjust their exposure to certain CAT bonds in the event of catastrophes. As risk needs to be shared more efficiently among the public, this research might also help to attract an even broader investor base to the market.

We find that the link between natural catastrophes and the secondary CAT bond market can be statistically established and validated. For two of the three most damaging event categories, ‘earthquakes’ and ‘storms’, the explanatory power is significant. However, we cannot confirm this relationship for ‘droughts’, which is the remaining one of the three most costly disaster types. Generally, the price reactions attributable to the significant catastrophe types are negative in the short run. Additionally, we are able to identify certain patterns in regard to whether the return of the US Wind CAT Bond index is subject to storms that originate outside the US. Nevertheless, due to possible misspecifications in the established pricing models and a relatively small number of events, we cannot confirm the existence of a ‘fear-effect’ within this particular market.

The subsequent parts of the paper are structured as follows: chapter 2 highlights the previously made literature contributions and aims to link natural catastrophe occurrences to secondary CAT bond market movements eventually leading to the formation of our hypotheses. In Chapter 3 we reveal how we intend to test the hypotheses and discuss which approach, data and variables are utilized. Chapter 4 presents the empirical analysis while a conclusion is drawn in chapter 5.

## 2 Literature Review

In the following section of the paper we investigate previous contributions to the research surrounding CAT bonds and also examine the development of natural catastrophes. The aim of this section is to give a better understanding of the concept of CAT bonds, what determines their pricing and how the secondary market plays an important role for investors and sponsors alike. Also, we take a thorough look at the development of natural catastrophes to identify which categories are most common and how total damage has developed. To sum up, we examine the performance of the CAT bond indices and try to make inference from its development in comparison to the catastrophic events that happened during that time.

### 2.1 History of Natural Catastrophes

In order to analyze the historical progression of natural catastrophes, we utilize the database maintained by the ‘Centre for Research on the Epidemiology of Disasters’ (CRED), called EM-DAT. Thereby, we get a better understanding of aspects such as the development of the total disaster count, the increase in specific catastrophe categories or perils as well as the development of the total monetary damage caused by these events. As can be seen in Figure A1 in the appendix, provided by the EM-DAT database (2020), global natural catastrophes have been increasing steadily since 1990, reaching their peak around 2000 with around 525 disaster, a number which has remained relatively stagnant ever since. The catastrophes that are portrayed in the graph are wide ranged and include devastations in the form of earthquakes, floods, storms, droughts and epidemics. In regard to the development of the separate catastrophe types, EM-DAT (2020) provides a consolidation in Figure A2 (Appendix). Again, it can be observed that the number of each individual type of catastrophe as defined by the database has been increasing, with floods showing the largest proportional increase. Storms were the most common type of natural catastrophes until the number peaked shortly after 1990. In the years after that, floods have been occurring more often. According to Galeotti, Gürtler and Winkelvos (2013), hurricanes and earthquakes are the most dominant categories in the United States, where most of catastrophe coverage takes place. Different peril categories are further investigated in section 2.3.1 CAT Bond Perils.

The total economic damage caused by the catastrophes has also significantly increased since the inception of the database (Figure A3, Appendix). After a gradual increase towards the end of the 1970s, catastrophes in the Americas as well as Asia have been contributing the most

to the monetary damages. The global measurement peaked around 2011 and was subject to another substantial increase in 2017, where losses totaled to be around USD 330 billion. The global peak in 2011 can be mostly attributed to the earthquake off the coast of Japan that triggered a tsunami and ultimately the malfunctioning of the nuclear power plant in Fukushima. In regard to 2017, the US hurricane season played a major role in the loss accumulation. As illustrated in Figure A4 (Appendix), catastrophe types that cause the largest losses tend to be storms including hurricanes as well as earthquakes. Generally, a trend can be observed signaling that even if the number of annual catastrophes has stagnated, the damage incurred keeps rising, although it fluctuates significantly from year to year. In 2011, the year with the largest damage for a single event recorded, the earthquake that triggered the events in Japan amounted to a damage of USD 230 billion. In 2017, out of the above-mentioned total damage of USD 330 billion, storms accounted for almost USD 280 billion, or 85%. Validating the importance of the storm peril, Aon Securities (2019) declare it was the largest driver for catastrophes in 2018. An overview of the costliest natural disasters is presented in the appendix (Figure A5).

Summing up, over the years a clear upward trend of natural catastrophes can be identified. Storms seem to cause the largest losses, closely followed by earthquakes. Additionally, even though the number of catastrophes has stagnated, the damage caused continues to grow leading to an increasing average damage per event.

## **2.2 Development of Insurance-Linked Securities**

The current section discusses the development of the insurance-linked securities (ILS) market including its most important component the CAT bond. Cummins (2008) outlines that the CAT bond market has experienced steady growth over the years. The author considers CAT bonds as financial instruments which help to complete the market. Although the importance of CAT bonds in the reinsurance/insurance market is often highlighted in the literature, Cummins (2008) claims that CAT bonds will not take over the entire reinsurance market, yet should rather be viewed as a complement to the market. Nevertheless, Morana and Sbrana (2019) show that over the last years records in terms of issuance volume of CAT bonds and capital outstanding could be observed. However, the authors claim there is still enormous potential for the insurance-linked securities industry to grow.

Cummins (2008) defines hurricane ‘Andrew’, which occurred in 1992, as the starting point of risk-linked securities since after the catastrophe the need for financing possible future catastrophes arose. Due to hurricane ‘Andrew’, eleven insurance companies were forced to file

for bankruptcy (Morana & Sbrana, 2019). As Laster and Raturi (2001) show, Hannover Re was the first financial firm to successfully issue a CAT bond of USD 85 million in 1994. Cummins (2008) and Cummins and Weiss (2009) further display that in the following years several catastrophe-linked securities were introduced to markets, mostly bringing little success. Cummins and Weiss (2009) assert that particularly following the damages hurricanes caused between 2004 and 2005, the CAT bond market has constantly grown, even though they claim that the market for ILS futures and options was still in its early stages at this point. Additionally, Cummins and Weiss (2009) point out that an increased number of sovereign issues is anticipated to occur in the future. The authors reason this will be mainly due to developing countries searching for ways to fund reconstruction after catastrophic occurrences.

Cummins (2008) shows that the development of the CAT bond market is frequently hindered by how the bonds are treated by the regulators. Furthermore, Edesess (2015) alleges placements of CAT bonds are usually private with no public offerings taking place in the US. Due to regulations, the vast majority of CAT bond issues have been executed offshore (Cummins, 2008). The author reveals that industry experts argue that in offshore jurisdictions such as Bermuda or the Cayman Islands one finds an environment with lots of proficiency as well as low transaction costs making it very attractive for ILS issuances and settlements.

Overall, we can clearly identify the ILS market has experienced extensive developments, some developments becoming urgently necessary after major catastrophes. The regulatory environment seems to shape its development as well, while in general, researchers still find enormous potential for the insurance-linked securities industry to grow.

### **2.3 CAT Bonds**

As Cummins (2008) reveals, insurance-linked securities (ILS) are considered to be crucial financial instruments providing capital during major catastrophic events. He further argues that “the vehicles are especially important because they access capital markets directly, exponentially expanding risk-bearing capacity beyond the limited capital held by insurers and reinsurers” (Cummins, 2008, p. 23). The general consensus among previous contributors to the literature is that the catastrophe bond is the risk-linked security most frequently used. Braun, Müller and Schmeiser (2013, p. 580), for instance, state that "the undoubtedly most successful of these alternative risk transfer measures is the catastrophe (cat) bond, an instrument that allows natural disaster risk to be traded over the counter". Summing up, as the CAT bond market

is becoming more mature, it appears to have turned into a constant part of the landscape for transactions conducted to transfer risk (Cummins & Weiss, 2009).

### 2.3.1 CAT Bond Perils

Dieckmann (2019) reveals that CAT bonds are linked to a wide range of natural catastrophes. In general, researchers (e.g. Edesess, 2015; Lane & Mahul, 2008) appear to agree on the fact that the major peril categories are windstorms and earthquakes. Additionally, Lane and Mahul (2008) define the US, Europe and Japan as the major geographical regions covered by CAT bonds. As outlined in chapter 2.1, these perils are also the disaster types associated with the highest damages and the geographical zones being the most likely areas for catastrophes to occur. Cummins (2008, p. 26) raises one further crucial point and states that CAT bonds are often linked to “high layers of reinsurance protection” as they cover events with a probability of one percent or less that the event happens. That single CAT bonds can be used as insurance for one particular or several perils is shown by Gürtler, Hibbeln and Winkelvos (2016). Banks (2004) discovers there actually is an increase in number of bonds issued which cover several perils.

As already mentioned, the development of different perils appears to be heavily impacted by global warming. Morana and Sbrana (2019) dedicate their research to global warming, their study being the first one to examine how and to what extent climate change impacts the CAT bond mechanisms. The authors claim that the risk of global warming is currently being substantially undervalued in CAT bond markets. Morana and Sbrana (2019) emphasize that it is crucial to examine the ways global warming exerts influence on natural catastrophic risk as they find clear evidence that global warming leads to a higher risk of natural disasters, consequently increasing the risk of CAT bonds.

### 2.3.2 Concept of CAT Bonds

Götze and Gürtler (2020) attempt to explain the concept of CAT bonds and reveal that commonly two parties are involved in a CAT bond agreement, the sponsor and a special purpose vehicle (SPV). Whereas a (re-)insurance company typically is the sponsor of a CAT bond transaction, it is the SPV's responsibility to fund the risk associated with the agreement by offering securities (bonds) to investors. Cummins (2008) outlines that the proceeds of the investments are invested in short-term instruments, which are declared to be safe, for instance bonds issued by governments or highly rated corporates, and are then put into a trust account.

Additionally, the annual report of Aon Securities (2019) illustrates that due to interest rates in the US having stagnated and staying negative in Europe, sponsors and investors have been encouraged to seek collateral investments. Götze and Gürtler (2020) refer to the CAT bond agreement and claim that it incorporates information about the trigger mechanism which serves as a guideline to determine when a catastrophic event occurs. Cummins (2008) defines this part of the CAT bond contract as a call-option feature which is triggered when the pre-specified catastrophe occurs. Edesess (2015) declares if an event occurs with the loss surpassing the threshold, which is outlined in the CAT bond agreement, a default of the bond occurs. There is some disagreement in the literature on how many trigger types exist. Gürtler, Hibbeln and Winkelvos (2016, p. 582) summarize different trigger types and show that indemnity and non-indemnity triggers exist, where the latter “can be further divided into parametric (index) triggers, industry index triggers, modeled loss triggers and hybrid triggers”.

Furthermore, Götze and Gürtler (2020) demonstrate there is a clear procedure to be followed in the event of a catastrophe. Cummins (2008) shows that when the catastrophe occurs, the SPV transfers the proceeds to the insurance company. Moreover, the author argues the insurance company uses the capital to satisfy claims which arose due to the catastrophe. How much capital is released usually depends on the magnitude of the event as Cummins and Weiss (2009) reveal. The investor suffers not only a loss of the principal, yet also no further interest payments are received as Götze and Gürtler (2020) outline. Nevertheless, as this risk is always existent for investors in a CAT bond investment, investors receive compensation via coupon payments incorporating a floating part as well as a risk premium (Götze & Gürtler, 2020). If no catastrophe takes place, the investor receives the full principal at maturity. Additionally, Cummins (2008) points out that frequently an interest rate swap takes place as the fixed interest earned from the investments in the trust fund is most often swapped for a variable rate. He claims this swap is executed to hedge against interest rate risk as well as risk of default.

Edesess (2015) shows the usual maturity of a CAT bond is between one and five years, three years being the most common maturity. A further characteristic of catastrophe bonds is their rating below investment grade (Cummins, 2008). Additionally, Cummins displays that due to the full collateralization of CAT bonds with securities of a high rating, the actual rating is mainly conducted through an analysis of the probability that one of the triggering events will materialize.

Carayannopoulos and Perez (2015) claim that multiple events which occurred during the financial crisis, like Fannie Mae and Freddie Mac's nationalization as well as Lehman Brothers

filing for bankruptcy, shed light on how instable and fragile some parts of the CAT bond structure were. Therefore, the authors show that multiple structural changes were implemented after the crisis with the primary goal to improve the credit quality linked to the asset serving as collateral in the CAT bond agreement.

### 2.3.3 Pricing

To be able to better understand how CAT bond prices and in turn the total market react to natural catastrophes, the question of how individual bonds are priced, arises. Patel (2015) points out that due to the characteristic that CAT bonds are tradeable on the secondary market, multiple features of usual fixed income securities also apply to CAT bonds. Patel (2015) states that although the premium an investor receives from the issuer is set, the spread of a CAT bond is impacted by the bond price and the stream of premium payments. Like with other bonds that carry high risk, the spread of a CAT bond is composed of the risk premium and the expected loss. Patel (2015, n.p.) reveals that the former component, the risk premium, varies based on the “peril zone and modeled expected loss”. Furthermore, as reinsurance is linked to events of greater size and larger infrequency, not only the expected loss yet actually a multiple of it serves as a guideline when setting the price (Lane & Mahul, 2008). In addition to the peril zones, Dieckmann (2019) identifies CAT bond-specific aspects such as the applied trigger mechanism as price determining factors. Moreover, changes in how risk regarding the individual bond is perceived might lead to risk premium variations.

In summary, individual CAT bond pricing highly depends on multiple factors. The major factors are historical loss analysis and characteristics of the bond such as perils and geographic locations.

### 2.3.4 Involved Parties

Morana and Sbrana (2019) investigate the ownership structure of CAT bonds and claim it has experienced some changes over the years. While back in the beginnings of the 2000s mainly reinsurance companies or hedge funds owned CAT bonds, today almost one third of the ownership is composed of institutional investors such as mutual funds or pension funds. Overall, it appears most researchers find that mainly institutional or specialized investors invest in CAT bonds (Cummins, 2008; Dieckmann, 2019; Götze & Görtler, 2020). Kish (2016) reasons that this can be traced back to the SEC 144A regulation which only allows so-called qualified institutional buyers, or short QIB, to execute resales. Hence, only institutional buyers

are qualified to purchase CAT bonds in the first year after issuance. Individual investors, as Kish (2016) argues, can only access the CAT bond market via hedge or mutual funds. However, in Aon Securities' ILS annual report (2019) it is for instance pointed out that pension funds, endowments and family retirement plans are increasingly observing the market for insurance-linked securities and an extended growth from these parts of the economy is anticipated.

Insurance and reinsurance companies are not only on the investor-side, yet also on the sponsor-side. Cummins (2008) shows that during the first years of the 2000s, the vast majority of bond issues was undertaken by insurance or reinsurance companies and only 5% were issued by corporates or sovereigns. The author also reveals that the very first CAT bond issued by a sovereign was placed by the Mexican government in 2006, which was linked to earthquakes. Nowadays, 60% of all ILS are sponsored by either insurers or reinsurers, 20% are sponsored by the government, whereas corporates make up almost 10% (Swiss Re, 2019). Edesess (2015) further highlights that issuers and investors are not the only parties involved in the CAT bond market, yet also structuring agents, index compilers, rating agencies, modeling agents and the media are participants. Swiss Re and Aon Benfield publishing average prices of CAT bonds through their indices, for instance, act as performance index compilers (Edesess, 2015).

#### **2.4 Secondary CAT Bond Market**

Much research has been conducted on the behavior of CAT bond premiums and prices in the primary market in response to changes in the financial and economic climate. However, the area of the importance of the secondary market for this type of insurance-linked security is relatively underserved. In order to determine if certain natural catastrophes have a higher explanatory power in terms of price changes than others, we examine the dynamics and characteristics of the secondary CAT bond market.

Although CAT bonds are usually privately placed, a secondary market provides a platform for transferring CAT bonds between institutional investors (Edesess, 2015). Nevertheless, the private nature of conducting transactions (Finra, 2013) as well as the infrequent trading of CAT bonds hinder the computation of CAT bond returns (Kish, 2016). Thus, so far a thorough quantitative analysis of CAT bonds was rather challenging due to the lack of secondary market data. However, with Swiss Re launching multiple CAT bond indices, the secondary CAT bond market has been granted more transparency (Dieckmann, 2019). The other major provider of secondary CAT bond market data is Aon Benfield, also covering movements of all global CAT bonds. With the secondary CAT bond market coming into sight,

average CAT bond prices can be computed more easily, facilitating the computation of performance indices displaying the return earned over different time periods (Swiss Re, 2014).

#### 2.4.1 Secondary Market Pricing/Trading

This subsequent chapter attempts to shed light on how price movements occur and can be motivated in the secondary CAT bond market. As the volume of transactions conducted in the secondary market is almost equivalent to the one in the primary market (Edesess, 2015), it appears crucial to examine factors encouraging investors to engage in transactions. On one hand, the subsequent part therefore points out multiple motives of investors to conduct transactions in the secondary market. On the other hand, the two main forces driving prices are demonstrated. This discussion builds a fundamental basis for the interpretation of the empirical results of this research.

Although Neuberger Berman (2019) claims that the secondary CAT bond market has limited depth, the author also refers to the fact that the CAT bond instrument is the most liquid of all ILS as it is traded daily. Swiss Re (2019) further shows that investors have recently been presented plentiful investment opportunities in the secondary market and consequently regards the recent trading volume in the secondary market as healthy. Lane and Mahul (2008) support this argument by presenting multiple incentives for investors to trade their CAT bonds on the secondary market. Investors might for instance want to adapt or expand their portfolio with new investments and might therefore wish to sell the insurance-linked securities. This is typically the case after a period with a high level of new CAT bond issuances, which consequently leads to a stimulation of the secondary market trading as new issuances are likely to encourage the rebalancing of the portfolio (Artemis, 2017). According to Artemis (2017), this was validated during 2017 when the issuance level clearly exceeded the CAT bond capital that was maturing, resulting in a higher number of overall capital outstanding, which enabled investors to devote an even bigger amount of capital to CAT bonds. Furthermore, some investors might also want to increase their holding at a later point in time if they were unable to acquire the desired amounts of bonds at their original launch date as Lane and Mahul (2008) point out. Edesess (2015) shows that for instance in 2013 after initial issuance some bonds already traded at a premium of 1-2% above the issue price in secondary market as demand was greater than supply during that year. Neuberger Berman (2019) refers to this idea as tactical trading of new issues into the CAT bond market. The author (Neuberger Berman, 2019) summarizes that depending on the demand after the issue, the bonds can be exchanged, which provides opportunities for

buyers/sellers to buy cheap low demand issues and sell expensive high demand bonds (Neuberger Berman, 2019). Additionally, Patel (2015, n.p.) highlights that investors engage in catastrophe bond trading based on possible catastrophes unfolding and defines it as “live cat” trading. This type of trading allows investors to instantly react to the possible occurrence of a catastrophe by adjusting their coverage. Neuberger Berman (2019) further discusses opportunistic trading and claims it to be the practice of trading bonds subject to an event that has already happened but where the definitive loss is still outstanding. As Neuberger Berman (2019, p. 30) reveals, these types of contracts are called “dead cats”. In 2017, for example, the volume of secondary market transactions expanded after event occurrence as a result of the uncertainty before the publication of the loss estimations (Neuberger Berman, 2019). Overall, it appears that trading and consequently price movements are either triggered by the investors’ desire to adjust their (CAT bond-) portfolios, which can also be of tactical nature, or by trading opportunities arising due to catastrophes occurring.

After having determined why investors engage in CAT bond trading, we subsequently focus on how this translates into price movements. Based on the current literature it appears that price movements are mainly driven by two forces. Firstly, the literature agrees that the cyclicity of event occurrences impacts the price movements in the secondary CAT bond (Galeotti, Gürtler & Winkelvos, 2013). Usually, a soft market, which is, according to the authors, characterized by fairly low prices and an increase in participants in the market, is followed by a hard market with comparably higher pricing levels. Gürtler, Hibbeln and Winkelvos (2016) further find that when analyzing secondary market data for CAT bonds, the problem of seasonality in catastrophe occurrence becomes apparent for all perils except earthquakes. For the remaining part of this section, the US hurricane season (Jun-Nov) is used to further illustrate how seasonality impacts prices.

The Aon Securities’ report (2018) demonstrates that the highest issuance levels are recorded for the first two quarters, while issuances in the third and fourth quarter are usually rather small. This high issuance level during the first half of the year leads to an increased level of supply of CAT bonds in the secondary market, which consequently leads to a price decrease of the outstanding bonds as Artemis quotes fund manager Plenum Investments (Artemis, 2013). In large, this behavior in the CAT bond market appears to explain the seasonality of prices. Based on this theory and *ceteris paribus* demand, prices in the secondary market tend to decrease before the hurricane season and increase during the hurricane season as a lower level of bond issuances, consequently a lower level of supply, can be recorded. This is confirmed by

Lane and Beckwith (2007) and cannot only be witnessed during the US hurricane season, yet also applies to the US typhoon and European windstorm season (Neuberger Berman, 2019).

On a narrower basis, the second force responsible for price movements in the secondary CAT bond market is the occurrence of individual catastrophic events. On the one hand, Neuberger Berman (2019) argues that if the loss caused by an event triggers the CAT bond, a price decrease is the consequence as the investors' right to receive further payments vanishes. On the other hand, prices also move based on the investors' adjustments of their expected loss calculations in context of the occurrence of catastrophes (Patel, 2015). Edesess (2015) points out that even though the expected loss is defined at issuance, this loss estimate is not adjusted during the lifetime of the bond. Hence, Lane and Mahul (2008) argue investors are highly encouraged to keep track of and update the expected loss estimation themselves. Patel (2015) gives an example of how the CAT bond prices can change based on such varying views of the expected loss. He argues that in the middle of major hurricane seasons or when hurricanes are already moving towards the coast, the market might identify an increased likelihood of the loss. This increased loss expectation implies that investors stand a higher risk of losing the right to further payments, which leads to a plunge in the bond price. Contrarily, if the opposite scenario happens and the hurricane diverts back to the ocean, the price is likely to rebound. As mentioned previously, engaging in trading based on possible catastrophes unfolding is defined as "live cat" trading by Patel (2015, n.p.). Nevertheless, as shown in the EM-DAT database (2020), certain catastrophes move in different patterns and vary in length, which might imply that the reaction that investors show may fluctuate significantly in regard to timing. In general, Neuberger Berman (2019) shows that in terms of price changes, the secondary CAT bond market can be very resilient even in light of an approaching event. The author refers to the year 2019 stating that when hurricane 'Dorian' was about to reach land, the market only recorded a decline of 1%, which limited the possibility of managers to trade their CAT bond portfolios opportunistically.

Summing up, price movements in the secondary CAT bond market are caused by differing views of the expected loss as well as supply and demand disproportions (Neuberger Berman, 2019). Nevertheless, one has to be careful when interpreting price movements as several external factors play important roles. It appears that the more perils are covered by one CAT bond, the more complex and the more challenging the interpretation following the occurrence of one trigger event is (Artemis, 2018). Additionally, the accuracy of the investors' loss estimation depends heavily on the information stream which is made available to the

market (Artemis, 2018). Artemis (2018) quotes Rishi Naik, BNP Paribas' head of ILS sales and trading, stating that accessibility and regularity of information as well as improvements in the reporting of losses become inevitable for an efficient secondary market. Otherwise, both points mentioned could adversely lead to high levels of pricing volatility, hindering the ability to properly interpret price movements (Artemis, 2018). As mentioned above, one further challenge related to the interpretability of market reactions is the fact that catastrophe types vary heavily in length (EM-DAT, 2020). Whereas for some catastrophe types the impact might be instantly visible, for others the true effect may only be realized after some time. It is highly likely that this discrepancy impacts investors' reactions in the market. All these aspects are crucial characteristics to consider when determining whether the hypotheses outlined in this research hold or not.

#### 2.4.2 Diversification

Much of the existing literature focuses on determining whether or not the bonds actually offer the diversification benefits they promise. The bonds are supposed to move relatively independent of other financial markets and have therefore enjoyed high levels of popularity (Carayannopoulos & Perez, 2015). Early research has concentrated heavily on determining whether the absence of a link to other capital markets holds and also if it holds in distressed times such as during the financial crisis of 2008. Alongside outperforming regular bonds, the supposed zero-beta characteristic has been the main driver of the CAT bonds' increased popularity, however, arguments that support as well as discredit this theory have been presented by several authors (see e.g. Barrieu & Loubergé, 2009; Cummins, 2008; Dieckmann, 2019). The argument has been tested during multiple timeframes, yet most of the contributions include the financial crisis in their observations, which might yield results that are harder to interpret and question the diversification statement (see e.g. Carayannopoulos & Perez, 2015; Gürtler, Hibbeln & Winkelvos, 2016). Overall, the consensus of the literature finds that the diversification effect mostly holds, at least during relatively calm times.

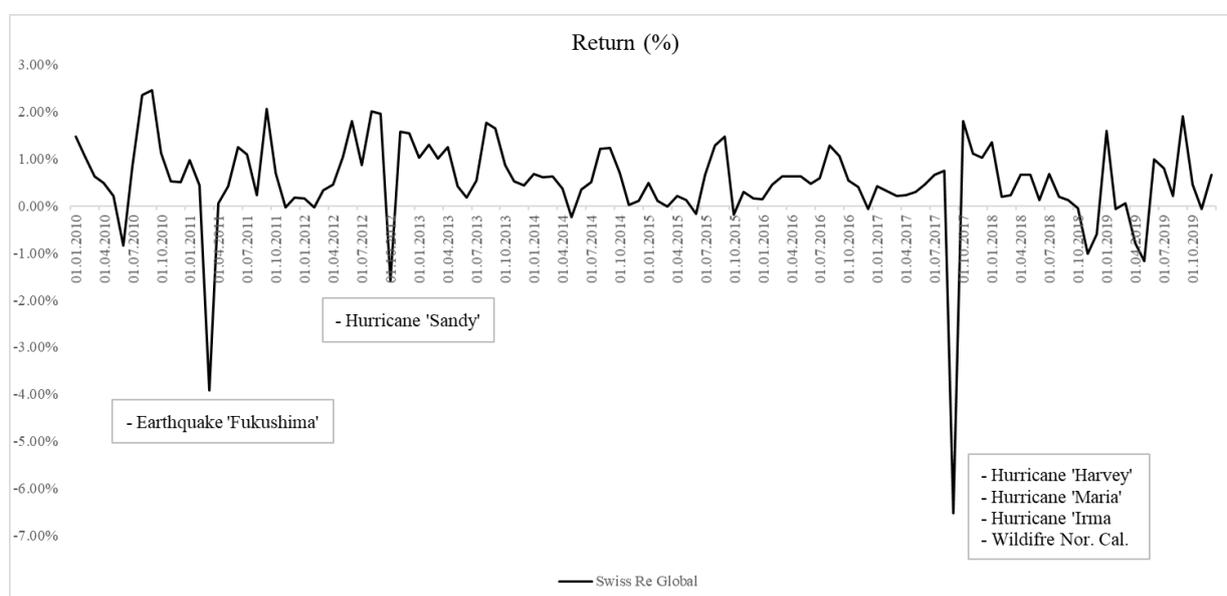
### 2.5 Hypotheses

After analyzing natural catastrophes as well as shedding light on the secondary CAT bond market, we attempt to link the findings of the two aspects to approach our research. As the base understanding for the formulation of our hypotheses is that secondary CAT bond prices are affected by the occurrence of large catastrophes, we attempt to link major return spikes of the

Global CAT Bond Index to natural catastrophes in the chart below. Multiple major negative movements in the returns seem to be attributable to the catastrophes that we list within the figure. 2017 saw an abundance of devastating catastrophes, which highly likely explains the biggest negative change in returns occurring in this year. This graphical validation of our reasoning leads to the formulation of the subsequent hypotheses that we use to test if this relationship can also be statistically confirmed.

**Figure 1:** Impact of Natural Disasters on Swiss Re Global Index

*This figure shows the development of the returns of the Swiss Re Global CAT Bond Index from 2010-2019. Weekly prices are utilized to compute returns and major spikes are linked to several severe natural catastrophes which occurred during this time frame.*



In order to validate our contribution, we establish three hypotheses that aid in determining whether the link between natural catastrophes and secondary CAT bond market prices/returns can be statistically explained and if it can be used to determine how catastrophes affect prices. We reason that the categories causing the largest damages should have the biggest impact on returns as well as enjoy statistically significant explanatory power and use this understanding to formulate our first hypothesis as follows:

H1: Disaster types causing the largest damage should have statistically significant power in explaining secondary CAT bond market returns.

Furthermore, we argue that a catastrophe entails negative news for investors due to the characteristics of a CAT bond, leading to the second hypothesis:

H2: The market shows a short-term negative reaction after the occurrence of a catastrophic event.

Additionally, as storms in the US appear to be the most frequently covered peril in the CAT bond market, we deem it of further interest to analyze how the returns of bonds specific to that category behave in relation to other catastrophes. In other words, we test if catastrophes that are not covered by certain CAT bonds, in this case storms outside of the US, have an impact on the wind CAT bond market in the US. We further aim to determine if a general ‘fear-effect’ exists in the market that causes price changes as a result of basically unrelated events. Consequently, the third hypothesis we test is:

H3: Storms that are not covered by US Wind CAT bonds still have statistically significant power in explaining secondary US Wind CAT bond market returns as a market reaction is triggered due to investors adjusting their portfolios.

### 3 Data and Methodology

In this part of the paper we describe the methodological approaches that are implemented as the basis of the empirical work. Data selection as well as the implementation/creation of the variables that are used in the empirical analysis of the problem are being detailed and we also state the reasoning for why those inputs are chosen.

#### 3.1 Data

Part of the contribution of our research is to provide new insight into the secondary CAT bond market and live CAT bond trading while shedding further light on the behavior of this type of security in a relatively stable market environment. Therefore, the data we use starts from the beginning of 2010 and lasts until the end of 2019. This specification accounts for the structural change in individual CAT bonds that occurred after the subprime mortgage crisis causing a change in the allocation of the collateral away from risky investments and towards risk-free instruments (Carayannopoulos & Perez, 2015).

At the basis of this empirical work financial as well as natural catastrophes data is being used. From the financial perspective, we utilize data featuring the returns of multiple financial instruments. Those instruments include the prices of the Global CAT Bond Index as well as the US Wind CAT Bond Index provided by Swiss Re (further explained below), prices of the S&P 500 equity index, prices of the S&P AAA bond index, prices of the Barclay's High Yield Index, the term spread of the applied time frame as well as the rate for the 1-month LIBOR. Moreover, we use Aon Benfield's All CAT bond index to compare its performance to the one of the Swiss Re index. Alongside the Swiss reinsurer, Aon Benfield is another one of the few CAT bond index data providers. All this data was compiled through Bloomberg. Regarding the data on natural catastrophes, the EM-DAT database, which tracks all global catastrophes and is maintained by the 'Centre for Research on the Epidemiology of Disasters' finds application. As mentioned above, we analyze eight types of natural catastrophes, which include droughts, earthquakes, extreme temperature, floods, landslides, storms, volcanic activities and wildfires. In line with the timeframe for the financial data, we extract information including the start-date, end-date, total damage and geographical region from 2010-2019 from the EM-DAT database. Other information on the catastrophes is available, however, is not of relevance to this research. To adapt the data to our purpose, we implement a threshold in regard to the total damage caused. The threshold is USD 100 million, which leaves 767 catastrophes. Those 767 events can be

further distributed into 37 droughts, 59 earthquakes, 10 periods of extreme temperature, 264 floods, 7 landslides, 342 storms, 42 wildfires and 6 phases of volcanic activity. We believe that this allocation of the total count to the different categories represents the historical average well.

A descriptive summary of the catastrophe types is presented in Table 1. The mean length of the catastrophes varies significantly, ranging from 1 day for earthquakes to a mean length of 338 for droughts. The minimum length of the catastrophe types is either one or two days except for droughts, for which the shortest catastrophe persisted for 31 days. The largest maximum length is recorded for droughts and the shortest maximum length is documented for earthquakes, which also have the highest and lowest standard deviation, respectively. The second lowest standard deviation of length can be observed for storms which also have the second lowest mean length. The highest mean damage can be recorded for earthquakes, followed by droughts and storms. The mean damages of volcanic activity, landslide and extreme temperature are by far the lowest, these types also occur the least often. Most of the minimum total damages are USD 100 million, which can be traced back to the threshold we set. Furthermore, we find that earthquakes have the highest maximum total damage with USD 210 billion, followed by storms with a maximum total damage of USD 95 billion. For these two catastrophe types the standard deviations of total damage are also the highest.

**Table 1: Summary Statistics, Catastrophe Types**

*This table provides a statistical summary of the catastrophe types by examining the number of events, the length as well as the total damage caused, which is illustrated in thousands of USD, for the time period from 2010-2019. For length and total damage, the mean, median, minimum and maximum value as well as the standard deviation are shown.*

	Drought	Earthquake	Extreme Temperature	Flood	Landslide	Storm	Volcanic Activity	Wildfire
<b>Number of Events</b>	37	59	10	264	7	342	6	42
<b>Length</b>								
Mean	338	1	17	17	12	4	9	17
Median	213	1	8	8	2	3	1	9
Min	31	1	2	1	1	1	1	2
Max	1 462	9	62	336	59	60	28	92
St.Dev.	332	1	18	30	21	5	11	19
<b>Total Damage ('000 USD)</b>								
Mean	2 350 432	6 240 242	694 060	1 455 895	479 857	2 137 121	278 667	1 965 591
Median	1 400 000	700 000	340 500	448 500	500 000	600 000	182 500	335 000
Min	100 000	100 000	127 000	100 000	100 000	100 000	103 000	100 000
Max	20 000 000	210 000 000	2 500 000	40 000 000	900 000	95 000 000	600 000	25 000 000
St.Dev.	3 478 643	27 512 861	788 492	3 568 418	317 343	7 962 499	219 645	4 856 039

### 3.1.1 Swiss Re CAT Bond Indices

Swiss Re, the Zurich headquartered global reinsurer, provides a range of CAT bond indices, which are designed to track the performance of the global market. The indices were first launched in 2007 and at that point were the first indices of their kind (Swiss Re, 2014). Since then, the indices have turned into the industry’s key visualization of the returns. Nowadays, they are still the only total return representation that is updated on a weekly and monthly basis (Swiss Re, 2014). Five different indices are included; global, global unhedged, USD CAT bonds, BB CAT bonds and US wind CAT bonds. For each of those indices a representation of the coupon return, price return and the total return is published. We utilize the total return of the Swiss Re Global CAT Bond Performance Index for the first two hypotheses of this empirical work as the Global index “captures bonds denominated in any currency, all rated and unrated cat bonds, outstanding perils, and triggers” (Swiss Re, 2014, p. 3). The US Wind CAT Bond Performance Index “tracks the aggregate performance of USD denominated cat bonds exposed exclusively to US Atlantic hurricane” (Swiss Re, 2014, p.2). As this index does not capture CAT bonds linked to storms outside the US, we apply the total return of this index in the third hypothesis. For both indices, we extract weekly as well as monthly prices, utilizing weekly returns in our empirical models.

**Table 2:** Summary Statistics, Financial Instruments

*This table presents the summary statistics of all financial instruments included in our research. The monthly prices of the Swiss Re Global Index, the Swiss Re US Wind CAT Bond Index, the Aon Benfield Global Index and the Aon Benfield Hurricane Index are utilized to represent CAT bond indices. Moreover, we use monthly prices of the S&P 500, the S&P AAA Bond Index and the Barclay’s High Yield Bond Index which serve as control variables. The mean, standard deviation, minimum and maximum, Sharpe ratio, skewness and kurtosis are shown for the returns of all instruments, while the number of observations and the time period from 2010-2019 remain the same.*

(monthly data)	Swiss Re Global Index	Swiss Re US Wind Index	Aon Benfield Global Index	Aon Benfield Hurricane Index	S&P 500	S&P AAA Bond Index	Barclay’s High Yield Bond Index
Mean	0.48%	0.46%	0.52%	0.52%	0.99%	0.28%	0.44%
St.Dev.	0.97%	1.24%	1.05%	1.43%	3.59%	0.75%	1.24%
Min	-6.33%	-6.30%	-6.11%	-6.21%	-9.18%	-2.17%	-3.03%
Max	2.23%	4.00%	5.00%	9.50%	10.77%	2.45%	3.34%
SR	0.45	0.34	0.45	0.69	0.26	0.32	0.32
Skew	-3.51	-1.19	-1.70	0.84	-0.38	-0.04	-0.13
Kurtosis	22.30	7.83	16.56	18.43	0.65	0.72	-0.07
# Obs.	119	119	119	119	119	119	119
Time Period	10-19	10-19	10-19	10-19	10-19	10-19	10-19

Table 2 shows summary statistics of all financial data we include in our empirical models. The mean return of the S&P 500 is the largest, however, also its standard deviation is highest. Additionally, the mean returns of the CAT bond indices are higher than the mean return of the benchmark high yield bond as well as the mean return of the AAA bond index. The largest

minimum and maximum returns were recorded for the S&P 500, further validating its high volatility. In light of the high volatility of the S&P 500, we also find its Sharpe ratio to be the lowest. We record the highest Sharpe ratios for all CAT bond indices, with Aon Benfield's Hurricane Index having the highest ratio. This fact only further certifies the attractiveness of CAT bonds to investors.

Additionally, we investigate the relative development of CAT bond indices in comparison to all other investments in our time frame by setting all instruments' initial values to 100. We then multiply that figure by the original returns that were computed with the actual individual prices. By doing so, a table is created that offers a representable way to compare the development of all the analyzed instruments. This table is in the appendix and is called Figure A5. When comparing the performance of the other financial instrument indices, it is further validated that the equity markets clearly outperformed bonds during the analyzed period. For example, the S&P 500 returned 201% from the start of 2010 to the end of 2019. When comparing the Global CAT Bond indices provided by Swiss Re as well as Aon Benfield to other similar securities in this space, both CAT bond indices outperform the 'regular' bond indices over the period. While the Swiss Re index and Aon Benfield index return 79% and 83% in total respectively, the high yield index returns 66% and the AAA bond index only 39%. This development adds to the increased popularity of CAT bonds among investors.

As outlined in the literature review, we expect seasonality in the CAT bond returns. In order to investigate this for our sample, we take the average return and compute the volatility of the returns for each month for the time period investigated (Figures 2 and 3). We believe this is of importance as detecting the expected seasonality patterns leads us to deem our data sample as representative. By detecting seasonality as well as choosing a time period that was relatively stable and without any major financial crises, we are able to analyze the behavior of CAT bond returns that are, very likely, only subject to their unsystematic risk. This unsystematic risk hails to a great extent from the movements in weather patterns resulting from the Atlantic hurricane season that typically lasts from June 1<sup>st</sup> to November 30<sup>th</sup> (National Hurricane Center, 2020).

Figure 2 clearly illustrates that an upward movement of returns is already observable before the Atlantic hurricane season starting in June. The average monthly returns peak in August and a downward trend can be recorded for September. However, September is also the month with the highest volatility. For all remaining months the volatility is rather low, the month of March being slightly more volatile than the rest. March is also the month with the lowest average return.

**Figure 2: Average Monthly Return and Volatility of Swiss Re Global Index**

*In this figure the monthly returns of the whole period of the Swiss Re Global CAT Bond Index are averaged and the standard deviation of each month is computed.*

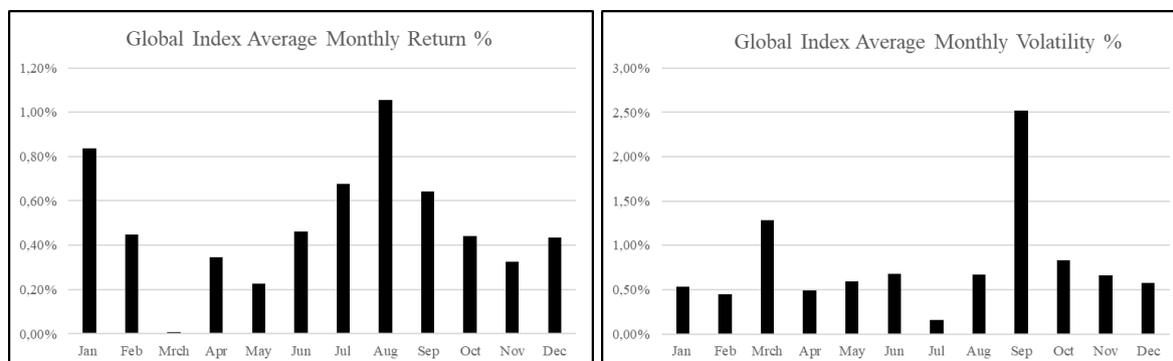
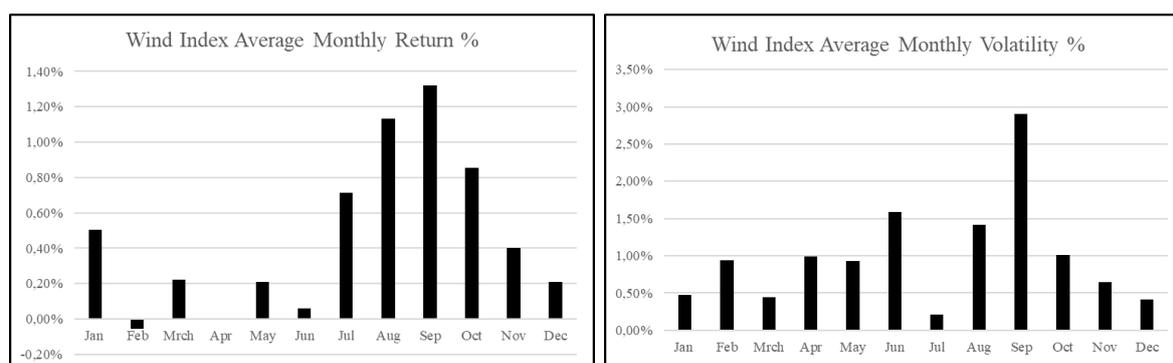


Figure 3 utilizes the US Wind CAT Bond Index, which only covers storms in the US. We expect that the seasonality effect is even more apparent in this figure. This expectation can be evidently validated. One can clearly observe that during the Atlantic hurricane season the average monthly returns gradually rise, peak in September and slowly decrease thereafter. The returns in the first half of the year are rather small. In regard to volatility, the highest volatility is recorded for the month of September and July has, just as before, the lowest volatility.

**Figure 3: Average Monthly Return and Volatility of Swiss Re US Wind Index**

*This figure portrays the monthly returns of the whole period of the Swiss Re US Wind CAT Bond Index as well as the volatility of every month.*



In summary, as claimed in the literature review, seasonality is evident in our dataset suggesting that the probability of a catastrophe occurring significantly increases during certain times. We find evidence that CAT bond prices in our dataset increase before the US hurricane season and decrease thereafter.

## 3.2 Empirical Approach

In order to test the effect that different types of natural catastrophes have on the price changes in the Global CAT Bond market (H1, H2), a linear OLS regression serves as the starting point<sup>1</sup>. We choose to utilize regression analyses as we aim to identify which individual catastrophe types (variables) have an impact on the returns of CAT bonds. This method enables us to make an inference about which types are of highest importance, which catastrophe types can be ignored and how each catastrophe type affects the returns. The dependent variable in the regression equation is comprised of the returns of the market that we derive from the weekly updated prices provided by the Swiss Re Global Index. By using weekly observations, we are able to get a more thorough understanding of the impact the occurrence of the catastrophe has on the returns both in terms of initial expectations as well as while the event is unfolding. In regard to the composition of the explanatory variables, multiple approaches are examined.

### 3.2.1 Transformation of Catastrophe Types

Due to the nature of the data we have on the catastrophes, dummy variables seem to be the best tool to implement catastrophes in our model. Initially, all eight catastrophe types are transformed into dummy variables taking on the value of 1 if an event happens and 0 if not. This leads to the following regression formula

$$R_t = \alpha + \sum_{i=1}^8 \beta_i \times D_{i,t} + \varepsilon_t \quad (1)$$

where  $R_t$  stands for the return of the Global CAT Bond Index at time  $t$ ,  $\beta_i$  is the coefficient estimate of catastrophe category  $i$ ,  $D_{i,t}$  is the dummy variable of each catastrophe category  $i$  taking on the value 1 if the event happens at time  $t$  or 0 if not and  $\alpha$  is the constant.

As we have weekly returns for the CAT bond index and specific start- and end-dates for the catastrophes, attention has to be paid in terms of when to set dummy variables. Due to the fact that our main interest lies in examining the initial market reaction, we choose to use the start-date of the catastrophes as a point of reference. The prices of Swiss Re's CAT bond indices are published every Friday, thus, the start-date of the disaster lies very likely between the publishing dates. Therefore, we choose to set the dummy variables in a manner that they take

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<sup>1</sup> Usage of 'MATLAB' for all estimations.

the value 1 for the whole week after the event occurred. As it is so far still unclear if/when the market reacts to a catastrophe occurrence, we run the regression a second time, this time setting the dummy variables not only during the first week after occurrence, yet also during the second week. Thereby, we aim to gain a more thorough understanding about when and how the market reacts. However, as we already discuss previously, catastrophe types vary significantly in magnitude and length. As ‘plain’ dummy variables do not account for these issues, we introduce interaction variables to our model.

### 3.2.2 Severity of Catastrophes

Since we suspect that the effects of the different dummy variables depend on the length and magnitude of the event (magnitude in terms of total damage), we add interaction variables. We do not consider length separately in the study as we claim it is correlated with total damage. However, we make use of the length-input of each catastrophe type when attempting to interpret the regression results in 4 Empirical Analysis. We introduce the interaction variable in a way that whenever a 1 is set for the dummy variable, either for only the first week after the disaster or for the first two weeks, total damage of this event is included as a further variable. In the case where several events of the same type occur, the total damage of all events is added and the sum is used as input for the total damage of this week and catastrophe type. The following equation shows how to account for the severity of catastrophes, if the only catastrophe type is storms

$$R_t = \alpha + \beta_S \times D_{S,t} + \beta_{TD,S} \times TD_{S,t} \times D_{S,t} + \varepsilon_t \quad (2)$$

where  $R_t$  stands for the return of the Global CAT Bond Index at time  $t$ ,  $\beta_S$  is the coefficient estimate of the stand-alone dummy,  $\beta_{TD,S}$  is the coefficient estimate of the interaction variable,  $D_{S,t}$  is the dummy variable of storm at time  $t$ ,  $TD_{S,t}$  is the total damage of the storm(s) at time  $t$  and  $\alpha$  is the constant. Attention needs to be paid to the fact that total damage is unknown at time  $t$ , yet we assume that the ex-post amount of total damage is correlated with the initial severity of the events. We can therefore use it as a proxy for relative severity of the events at time  $t$ .

Applying this to all catastrophe types results in the following regression equation:

$$R_t = \alpha + \sum_{i=1}^8 \beta_i \times D_{i,t} + \sum_{i=1}^8 \beta_{TD,i} \times TD_{i,t} \times D_{i,t} + \varepsilon_t \quad (3)$$

In order to be able to interpret the regression output including the interaction variables and to analyze how the catastrophes impact the returns, we examine marginal effects. We calculate the marginal effect as the difference between the predicted value at 1 and the predicted value at 0 for each catastrophe type. This provides us the following linear function

$$Y_i = \beta_i + \beta_{TD,i} \times TD_{i,t} \quad (4)$$

where  $Y_i$  is the marginal effect of catastrophe type  $i$ ,  $\beta_i$  is the coefficient estimate of the stand-alone dummy of catastrophe type  $i$  and  $\beta_{TD,i}$  is the coefficient estimate of the interaction variable of catastrophe type  $i$ .

### 3.2.3 Control Variables

Additionally, we include other financial instruments that have previously served as benchmark control variables of CAT bond market returns in the regression. Thereby, we aim to control for the relationship between different parts of the ‘traditional’ financial market and the CAT bond market. The control variables used in the different regression approaches are not the major aspect of interest, however, as we believe that the instruments that were already briefly mentioned above might have an impact on the returns of the CAT bond market, they are included. In order to control for the equity market, we choose to add the S&P 500 equity index. The S&P 500 equity index is considered to be one of the best interpretations of the US stock market and therefore, controls for the relationship between CAT bond returns and equity market returns. We decide to use the S&P 500 equity index instead of a global equity index as most catastrophes as well as catastrophe insurance is centered around the US. As the benchmark bond index, we include Barclay’s High Yield bond index to control for the ‘junk’ bond relationship to the CAT bond market. Additionally, we add the S&P AAA to control for the investment grade bond relationship to the CAT bond market. Apart from the returns of the financial instruments, we incorporate two further explanatory variables to the regression. The term spread, which we compute by subtracting the short-term (US 3-months treasury yield) from the long-term (US 30-years treasury yield) interest rate, controls for the relationship the CAT bond returns have with the interest rate environment. To control for short-term interest rates, we add the 1-month LIBOR rate as previous CAT bond literature identifies this time specification of the rate as most appropriate.

Adding the control variables to the previously specified equation, results in the subsequent final regression equation

$$R_t = \alpha + \sum_{i=1}^8 \beta_i \times D_{i,t} + \sum_{i=1}^8 \beta_{TD,i} \times TD_{i,t} \times D_{i,t} + \sum_{j=1}^5 \gamma_j \times CV_{j,t} + \varepsilon_t \quad (5)$$

where  $\gamma_j$  is the coefficient estimate of the control variable  $j$  (having five control variables in total),  $CV_{j,t}$  is the control variable itself at time  $t$  and all other variables remain as specified above.

Lastly, we attempt to ensure no OLS assumptions are violated by running multiple diagnostic tests. To be more specific, we test for heteroscedasticity and autocorrelation. In order to test for heteroscedasticity, we run the Breusch-Pagan-Godfrey test as well as the White test. The Durbin-Watson test and the Ljung-Box test are implemented to test for autocorrelation.

### 3.2.4 Real Effect versus Fear Effect

The other field of interest of our research is to find out whether or not the occurrence of catastrophes impacts the returns of CAT bonds when these catastrophes are not covered by the bonds in that market. To be more specific, we want to examine if storms happening outside of the US have an impact on the returns of the US Wind CAT Bond Index (H3). Assuming that there is an impact, an additional goal of the study is to determine if a ‘fear-effect’ exists among CAT bond investors, meaning if/how US focused bond holders show a reaction to events occurring in other parts of the world. To test this, an event study approach is utilized where we analyze the 5 biggest storms, in terms of total damage, which occurred outside of the US during our time period. We deem an event study as an appropriate method as we attempt to measure the direct effect certain events have on the US Wind CAT bond market. As we are unable to find prior studies utilizing event studies in this area of research, we determine all event study-features, e.g. the event window, based on our personal judgement. All these specifications are outlined below.

#### *Events of Interest*

We determine the events of interest by filtering for storms outside of the US and sorting by total damage in ascending order. The events in question are the five largest Non-US storms in terms of total damage that occurred between 2010 and 2019 (see Table 3 below). This threshold results in catastrophes that had their origin in Puerto Rico, Japan (2), China as well as the Philippines.

**Table 3:** Events of Interest, Event Study

*This table shows all events tested in the event study including ID event, start- and end date, length, year of occurrence, country, total damage and disaster name. The ID event shows the rank in terms of total damage this event has in the entire catastrophe dataset including other catastrophe types.*

Events of Interest								
ID Event	Start Date	End Date	Length in Days	Year	Country	Total damage ('000 USD)	Disaster name	
3	20-Sep-17	20-Sep-17	1	2017	Puerto Rico	68 000 000	Hurricane 'Maria'	
13	12-Oct-19	17-Oct-19	6	2019	Japan	17 000 000	Tropical cyclone 'Hagibis'	
23	4-Sep-18	5-Sep-18	2	2018	Japan	12 500 000	Typhoon 'Jebi'	
25	10-Aug-19	12-Aug-19	3	2019	China	10 000 000	Tropical cyclone 'Lekima' (Hanna)	
27	8-Nov-13	8-Nov-13	1	2013	The Philippines	10 000 000	Typhoon 'Haiyan' (Yolanda)	

### *Event Window*

When choosing the time period during which we analyze CAT bond returns, we take the nature of our data into consideration. In total, we select five weeks for which we examine returns; one week prior to event, one week capturing the event and then three consecutive weeks after the event. This enables us to test if some effect can already be felt before event start and also allows us to test if and when the possible fear effect becomes apparent. In regard to the observed/actual return, we utilize the US Wind CAT Bond Index since it tracks the movements of all bonds that insure against wind peril related events subject to the United States. As for the first two hypotheses, we choose to use the start-date of the catastrophes as a point of reference. Therefore, the weekly return capturing the event is the first return available after start-date.

### *Estimation Window*

In order to determine parameters for the pricing models, which are subsequently used to compute normal/expected returns, an estimation window must be established. When determining the estimation window, it is of high importance that the estimation window period does not overlap with any of the event windows. We therefore exclude all event windows, 25 weeks in total, when determining the parameters. Generally, when conducting event studies, it is common to use a certain time period before the event of interest as an estimation window. However, as we are including multiple events and assume that the pricing model generally remains stable over time, we opt to utilize the whole period of our sample, excluding the 25 weeks as mentioned above. To measure normal returns used to determine what return would be expected without the occurrence of the event, we apply two different pricing models.

### *The Market Model*

As a first model, we employ the market model and assume a constant relation between the US Wind CAT Bond Index and the Global CAT bond market. As outlined above, we utilize returns from the entire period, from 2010-2019 excluding the event windows, for the OLS regression

to arrive at the  $\alpha$  and  $\beta$  estimates. The following equation illustrates the market model we arrive at

$$E[R_{S,t}|\Omega_{NonUS-S,t}] = \alpha + \beta \times R_{mt} + \varepsilon_t \quad (6)$$

where  $E[R_{S,t}|\Omega_{NonUS-S,t}]$  is the return of the US Wind CAT Bond Index that would be expected if the event did not occur with  $R_{S,t}$  illustrating the return in the event window and  $\Omega_{NonUS-S,t}$  incorporating conditioning information,  $\alpha$  and  $\beta$  are the coefficient estimates of the model and  $R_{mt}$  stands for the return of the overall CAT Bond Index at time  $t$ .

The adjusted market model is a variation of the market model setting the  $\alpha$  coefficient estimate to zero and the  $\beta$  coefficient estimate to 1, assuming the expected normal return is equal to the return of the market, in our model equal to the Global CAT Bond Index. We therefore implement this specification of the market model as well.

#### *The Multivariate Model*

The second model we deploy to determine the normal/expected return is a multivariate model. For this model we utilize a similar approach as for the first two hypotheses. We run an OLS regression with the US Wind CAT Bond Index as the dependent variable and dummy, interaction and control variables as the independent variables. The dummy variables of the regression capture only storms, in- or outside of the United States, yet other catastrophe types are not included. In agreement with the approach which we follow for the first two hypotheses, we vary the manner we set dummy variables. Not only are the dummies turned on during the first week after event occurrence, but we also implement a second model where the dummies are set during the first and second week. Using the estimation window as specified above, this results in the following pricing model equation

$$E[R_{S,t}|\Omega_{NonUS-S,t}] = \alpha + \sum_{i=1}^2 \beta_i \times D_{i,t} + \sum_{i=1}^2 \beta_{TD,i} \times TD_{i,t} \times D_{i,t} + \sum_{j=1}^5 \gamma_j \times CV_{j,t} + \varepsilon_t \quad (7)$$

where  $i$  captures only two categories, namely storms in the US and storms outside of the US, all other variables remain specified as above.

As we outlined in the literature review, a main driver of CAT bond prices is seasonality. To account for that in our pricing model, we modify the estimation window slightly. By only including data from calm periods in the regression, we attain a second pricing model specification. Calm periods include all months but the months where the US hurricane season takes place, hence, data from June to November is excluded. Again, the dummy variables of

this model capture storms in- and outside the US, leading to the same pricing model as specified in the equation above (equation 7). Additionally, we vary the setting of the dummy variables in accordance to previous specifications.

In regard to how normal returns are computed in the event window, some clarification is required in terms of when we set dummy variables. As during the weeks of the event window also other storms, both inside and outside of the US, are very likely to have occurred, we need to account for this when using the multivariate model. In all weeks of the event windows, dummies for US storms are set as noted. Whenever a storm in the US occurs, the value of 1 is set and total damage of this event is included as well. When setting dummy variables for Non-US storms, it is inevitably crucial to exclude the event of interest from the event window. Assuming that besides our event of interest no other storm outside of the US occurred, we simply set the dummy and total damage for Non-US storms during this week to zero. However, if there is another storm outside of the US recorded for the week where the event of interest took place, we in fact set a 1 for the Non-US dummy, however, account for the exclusion of the event of interest when setting total damage. In order to ensure that the storm of interest is excluded from the normal return computation, we only include the total damage of the other Non-US storm which occurred, yet exclude the total damage of the storm of interest in our pricing model.

#### *Winsorizing*

To account for the fact that the result of our event study might be impacted by outliers, we winsorize our data. In order to limit extreme values, we implement a 99% winsorization, thereby setting all data points below the first percentile to the first percentile and all data points larger than the 99<sup>th</sup> percentile to the 99<sup>th</sup> percentile. We choose a level of 99% since we claim our data is by nature very volatile as significant price spikes occur due to large catastrophes. This level ensures that winsorizing does not significantly limit the explanatory power of our data.

#### *Execution of Event Study*

We conduct a separate event study for each pricing model and specification. After calculating expected returns through the pricing models, we subtract the expected return from the actual return to arrive at the abnormal returns. As our specified event window includes five weeks, we get five abnormal returns for each event. These abnormal returns are divided by the standard error of the model, the RMSE, in order to receive t-statistics for the whole event window. In

contrast to other event studies, where emphasis is put on analyzing the cumulative abnormal return, or in short CAR, we attempt to analyze the abnormal return of every week separately and test if any of them are significant. Based on our understanding, we are only able to examine if there is a ‘fear-effect’ in certain weeks in this manner. When making inference about the significance, we test abnormal returns at a 5%- and 10%-level.

### **3.3 Problems and Limitations**

Due to the fact that many of the catastrophes occur simultaneously and that the length is hard to account for, we are limited in setting the dummy variables. For example, a drought might last for multiple weeks, while an earthquake appears swiftly in one day. This problem makes it increasingly hard to interpret the regression results as the market might show different levels of reactions when a certain type of catastrophe occurs and this reaction could be shorter or longer. Furthermore, it is not specified how the EM-DAT database measures/reports catastrophes. Neither are we aware of when the ‘Centre for Research on the Epidemiology of Disasters’, which is in charge of maintaining the database, starts measuring catastrophes, nor do we have any information about how disasters are recorded. Hence, we expect that we may encounter some obstacles regarding the interpretation of market reactions.

## 4 Empirical Analysis

The following chapter presents our empirical results and discusses the various steps we take to arrive at valid conclusions in regard to the outlined hypotheses. Initially, the results for the first two hypotheses are detailed and discussed and eventually the outcomes of the event study used in the final hypothesis are portrayed.

### 4.1 Can Certain Catastrophe Types Explain Secondary CAT Bond Market Returns?

Firstly, we display our attempts to answer hypotheses 1 and 2, show how we arrive at the final regression equations and which variables we include. We then attempt to interpret the results by using the marginal effect every catastrophe type has on the CAT bond return. Additionally, we introduce confidence intervals to gain a better understanding in regard to how valid the results are. To be able to make an inference about what natural catastrophes have significant power in explaining second market price changes, we run several regressions. Equation 5 illustrates the model we exploit, where we include eight different catastrophe types; drought, earthquake, extreme temperature, flood, landslide, storm, volcanic activity and wildfire. After running some diagnostic tests on the preliminary regression, we discover autocorrelation and heteroscedasticity in our model. We account for this by adding the lagged dependent variable as an explanatory variable to the model. Thereby, we can ensure no OLS assumptions are violated and the regression results are unbiased.

Of major interest to us are the interaction variables, to be more specific, their coefficient estimates as well as p-values. Additionally, we attempt to observe how the market reacts to the occurrence of natural catastrophes. As we only have weekly data on the returns, we choose to set the dummy variables in the week after the event, which is equivalent to the first return we observe after the catastrophe. For the first regression, we set the dummy variables only during the first week after event occurrence. The results of this regression are presented on the left side in the table below (Table 4). Since we particularly look at the significance of the interaction variables, we observe that only two interaction variables are significant in this model. The interaction variable earthquake to total damage is significant at a 5%-level and the interaction variable storm to total damage is significant at a 1%-level as their p-values are smaller than 0.05 and 0.01, respectively. All other catastrophe types do not show any significant results. When examining the coefficient estimates on a first glance, we observe that the coefficient estimate of earthquake-total damage is negative, while the coefficient estimate of storm-total

damage is positive. All remaining coefficient estimates of the total damage-interaction term are zero in statistical terms. We further examine the coefficient estimates later utilizing marginal effects and confidence intervals. In regard to control variables, the 1-month LIBOR as well as the term spread are significant at the 5% and 10%-level, respectively. Neither of the other control variables are significant, which leads us to conclude that the price movements in the equity market as well as in debt markets do not have any significant power in explaining price movements in the CAT bond market. The ‘Y-lagged’-variable, which we include to account for the OLS violations, is highly significant, only further validating the importance of its inclusion in the model.

**Table 4:** Regression Results including Interaction Variables, Models 1 and 2

*This table shows the results of the OLS regression analysis as specified in equation 5 when dummies are set during the first week after event occurrence as well as when the dummies are active for two weeks after. The coefficient estimates of all dummy variables, interaction terms and control variables are illustrated along with their standard errors. The interaction variable accounts for the interaction between total damage (TD) and each catastrophe type. The symbols \*, \*\* and \*\*\* show the significance level for 10%, 5% and 1%, respectively.*

Impact of event, 1 & 2 week(s) after (Total Damage in trillion USD)	1 week		2 weeks	
	Estimate	SE	Estimate	SE
(Intercept)	0,0051 **	0,0020	0,0056 ***	0,0022
Y-LAGGED	-0,3889 ***	0,0394	-0,4074 ***	0,0398
DROUGHT	-0,0008	0,0021	-0,0009	0,0015
<b>DR-TD</b>	0,2499	0,3476	0,2377	0,2491
EARTHQUAKE	0,0022 *	0,0012	0,0025 ***	0,0009
<b>EQ-TD</b>	-0,0846 **	0,0383	-0,0923 ***	0,0275
EXTREME TEMP	0,0003	0,0039	0,0007	0,0030
<b>ET-TD</b>	0,3020	0,0039	0,0621	2,5309
FLOOD	-0,0004	0,0008	-0,0016	0,0008
<b>FL-TD</b>	0,1181	0,1398	0,1206	0,0964
LANDSLIDE	0,0000	0,0060	-0,0007	0,0043
<b>LS-TD</b>	3,1874	10,4855	3,9021	7,4945
STORM	-0,0011	0,0007	0,0002	0,0008
<b>ST-TD</b>	0,2919 ***	0,0551	-0,1123 ***	0,0050
VOLCANIC ACT	0,0040	0,0069	0,0015	0,0050
<b>VA-TD</b>	-7,4767	17,7616	-3,2649	12,7148
WILDIFRE	0,0009	0,0014	0,0005	0,0011
<b>WF-TD</b>	0,0941	0,2401	0,1178	0,1738
S&P 500	-0,0119	0,0249	-0,0121	0,0249
High Yield Bond Index	0,0421	0,0662	0,0572	0,0659
AAA Bond Index	-0,0639	0,0941	-0,0923	0,0941
LIBOR 1-month	-0,1836 **	0,0765	-0,1712 **	0,0785
Term Spread	-0,0866 *	0,0515	-0,0877	0,0534
Number of Observations:	521		521	
R-squared:	0,238		0,228	

In our second regression, displayed on the right side of the table above (Table 4), we leave all specifications unchanged yet modify the way we set dummy variables. For this regression we turn on the dummy variables during the first and second week after event occurrence to account for the possibility that the market reactions are not entirely visible during the first week after the start of the event. As outlined for the first regression, we also include the lagged dependent variable in this model. Again, two of the coefficients of the interaction terms are significant. Both, the interaction variable earthquake to total damage and the interaction variable storm to total damage are significant at a 1%-level. The sign of the coefficient estimate ‘Storm-Total Damage’ changes compared to the first regression. While the coefficient estimate is positive in the 1-week model, it becomes negative in the model where dummies are set during the first and second week. As before, the 1-month LIBOR is significant at the 5%, whereas the term spread is not significant anymore. The  $R^2$  of the second regression is slightly lower. Whereas the  $R^2$  is 0.238 in the first regression, it decreases to 0.228 in the second regression. Considering the type of data we utilize, the  $R^2$ s appear quite adequate. We will therefore put no further emphasis on discussing the  $R^2$ s.

Based on the results of the different regression specifications, we are able to draw a conclusion regarding our first hypothesis. As earthquakes have the highest mean total damage and the interaction term is significant, we can accept the hypothesis. Moreover, storms occur most frequently thereby causing the third highest mean total damage. Hence, our expectation that this catastrophe category should be significant in explaining price deviations in the market is met since the interaction term of storms is significant as well. With regard to droughts, which trigger the second largest mean total damage in our dataset, we are, however, unable to support the hypothesis as this catastrophe type does not show any significance in explaining CAT bond returns. We argue this might be justifiable by the fact that droughts are long-lasting and thus, reaching a conclusion about an immediate market reaction appears rather challenging.

## 4.2 Can a Negative Price Reaction Be Recorded after a Catastrophic Event?

To be able to interpret our results more thoroughly and to draw conclusions in regard to H2, we examine the marginal effect every catastrophe type exerts on the CAT bond return. As already stated, for our model the interaction term coefficients are important since the stand-alone dummy coefficients only measure the effect of dummies when the total damage is zero. We therefore expect these stand-alone dummy coefficients to be close to zero. The marginal effects are computed as illustrated in equation 4.

As a means to interpret the marginal effects, we introduce confidence intervals since we are already aware of the fact that the vast majority of interaction variables is not significant. By introducing confidence intervals, we attempt to find out whether we are still able to draw a valid conclusion based on the coefficient estimates, although they might not show any significant results based on the regression. A priori, we neglect the results of extreme temperature, landslide and volcanic activity as we claim the coefficients are not representative due to very low numbers of events occurring and because of the low total damage caused. A presentation of the summary statistics of the catastrophe types can be found in section 3.1 Data. There we show that after implementing our total damage threshold, only 6 volcanic activities, 7 landslides and 10 periods of extreme temperature are included in our sample. Furthermore, these types have the lowest mean total damage. Therefore, we will not further examine these catastrophe types.

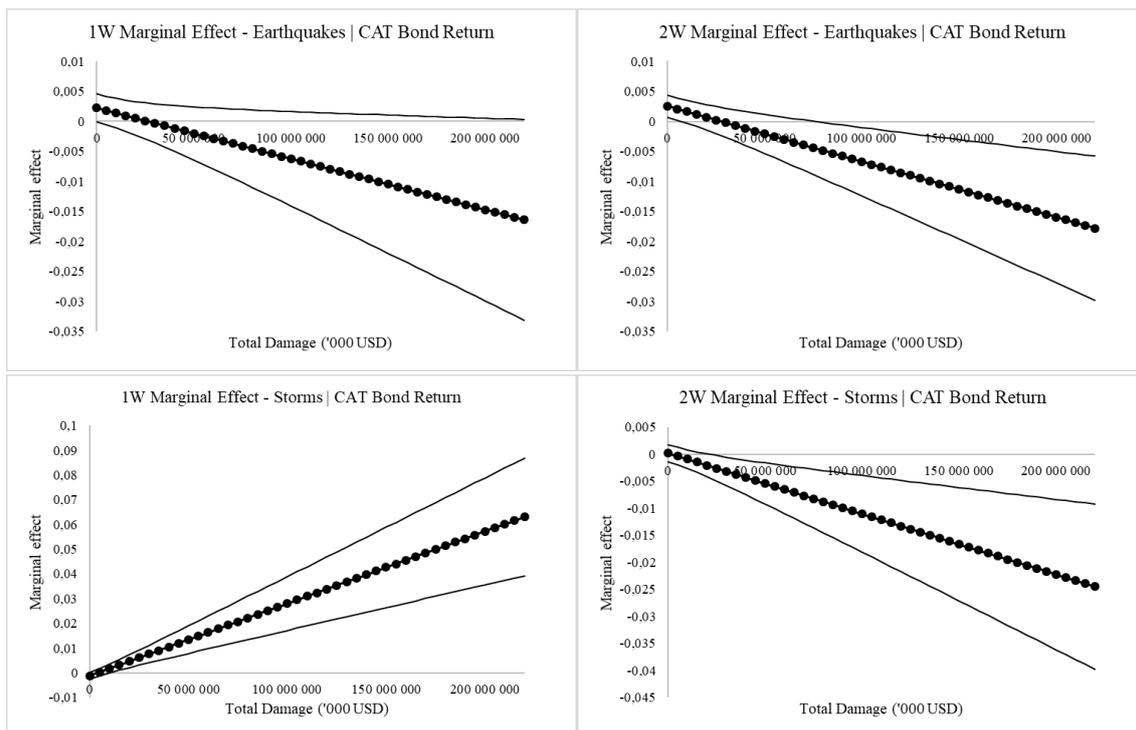
With regard to marginal effects, our models yield different results. For droughts, floods and wildfires the marginal effect is upward sloping in both models, which entails that as total damage increases, the return increases as well. However, none of these interaction variables are significant. In order to identify whether these coefficients are still interpretable, we introduce the confidence intervals. For the estimation of the confidence intervals, we assume that the covariance between the two parameters is zero. Initially, we look at the significant coefficients to see if the results still hold after implementing the confidence intervals. For earthquakes, the marginal effect is, as expected, downward sloping in both models. For storms, however, we get conflicting results in the two different models. Whereas in the 1-week model the slope is positive, we encounter a negative slope in the 2-week model as briefly shown before. For the significant catastrophe types, we show the marginal effects including confidence intervals in the figure below (Figure 4), whereas the figures for the remaining events can be referred to in the appendix (Figure A6).

After implementing confidence intervals, we are provided with further validation that droughts, floods and wildfires have no significant explanatory power to explain CAT bond returns. The illustrations shown in the appendix (Figure A6) show that the confidence interval of all three catastrophe types allows the slope to range from negative to positive. Therefore, no clear interpretation of the coefficient estimates for these interaction variables is possible. In regard to earthquakes and storms, Figure 4 below clearly validates that these catastrophe types have statistically significant power in explaining secondary CAT bond market returns. In the subsequent part, we attempt to interpret the development of the coefficient estimates regarding

the different model specifications and provide clarification on how these catastrophe types impact CAT bond returns.

**Figure 4: Marginal Effects including Confidence Intervals**

The figure illustrates the marginal effects of earthquakes and storms on the CAT bond return with their confidence intervals. The illustration on the left exemplifies data from the first model (1 week), the illustration on the right is based on the results from the second model (2 weeks). The dotted line illustrates the marginal effect based on the coefficients taken from the regression model. The permanent lines demonstrate the confidence intervals for which we assume the covariance between the two parameters to be zero.



We seek to explain the up-/downward sloping effects by linking the slopes to the mean length of the disaster type. Starting with earthquakes (downward sloping), the marginal effect reveals that the CAT bond return decreases in the first and second week after the earthquake. We reason that due to the fact that the mean length of earthquakes is 1 day, the full effect of the earthquake is apparent almost immediately after conclusion of the event and the first as well as the second week capture the return development in the aftermath. We expect a price decrease, among others, after a trigger event, or in general, after a catastrophe. Hence, the downward sloping effect can be justified. In regard to storms, the two models yield conflicting results. When setting the dummy variable only one week after the event, we observe an upward-sloping marginal effect. When setting the dummy variable in the first and second week after the event, the graph is downward-sloping. We view the upward sloping effect as slightly problematic in terms of its interpretability as well as the implication it has on the return. However, we attempt

to explain this difference by again looking at the average length. The average length of storms included in our dataset is 4 days, which implies during the first week after start of the event, the event might still be ongoing, whereas in the second week after the start of the event, the event is, on average, already over and losses and actual severity of the catastrophe are known. The negative slope of the 2-week model can be justified in the same way as for earthquakes. The storm is, on average, already over in the second week after the start date of the event, which explains a price decrease. As mentioned above, for the upward-sloping effect of storm of the 1-week model the explanation is not as straight forward. On the one hand, one might argue that due to the fact that investors try to get more coverage through live CAT bond trading after the start of the hurricane, the demand increases, which consequently leads to a price increase and an increasing slope. On the other hand, one might claim that during the first stage of the hurricane, the market may identify an increased likelihood of the loss, which results in a price decrease, clearly contradicting the upward-sloping effect. However, although the market might identify this increased likelihood of the loss during the first week after start-date, it may as well be the case that the hurricane which moved towards the coast diverts back to the open sea or its severity can be reduced, which leads to a re-estimation of the expected loss, and consequently to a price increase. Nevertheless, it remains unclear to us why the market would underestimate the severity of the hurricane during the first week after it started only to react in the second week when the full magnitude is apparent to investors.

Interpreting marginal effects of more protracted catastrophe types, for instance droughts or floods, is more challenging. In general, we find that the mean length for droughts, floods and wildfires always exceeds the two weeks in which the dummy variables are set. Hence, the catastrophe is still ongoing, on average, after the 2 weeks. Although, the expectations of the loss caused by a catastrophe are incorporated in the price-movements, these expectations are likely to change over time as the severity of the catastrophe may only become apparent after some time or events might only become catastrophic after some time.

To sum up, several steps were taken to arrive at a valid conclusion. After excluding some catastrophe types a priori due to the low number of observations and the low mean damages, marginal effects and consequently, the incorporation of confidence intervals aid in examining how and if the remaining catastrophe types impact returns. We conclude that major negative effects only become noticeable during the second week. Regarding the second hypothesis, we can accept it when using the specification of the second model. All significant catastrophe types indicate that a catastrophe is followed by a downward price-movement in the second model as

the marginal effects of earthquakes and storms are negative. Building on the first model, we are unable to accept the hypothesis, as the marginal effect of storms is positive. Nevertheless, we argue that due to the fact that we are unaware of how the EM-DAT database measures/reports storms as well as the fact that multiple scenarios are possible for each storm, no clear conclusion can be drawn deploying the first model. Overall, we observe a clear pattern; the catastrophe types which we find significant are the ones which evolve fairly quickly, show more deviation in magnitude of damage and occur most frequently.

#### **4.3 Can a ‘Fear-Effect’ Be Validated in the Secondary US Wind CAT Bond Market?**

In this subsequent part we focus on analyzing results related to the third hypothesis, which deals with the question whether storms, which originate outside of the United States and are not covered by the US Wind CAT Bond market, have an effect on the return of this market index. Initially, we validate that Non-US storms have an impact on the US Wind index by running an OLS regression over our whole sample period, which yields the result that the marginal effects of Non-US storms are significant in explaining the returns. The results of this regression are illustrated in the appendix (Table A2). In light of that, we conduct the event study to further examine how market players investing in CAT bonds covering US winds react to major storms occurring outside of the United States. An investor reaction might be justified by the fact that investors fear such storms might also happen in the US or because investors fear the storm which originated outside of the US will eventually also lead to damages in the US. Throughout the analysis we attempt to detect patterns of the results originating from the different pricing model specifications and point out strengths and drawbacks of all specifications. Eventually, we give a suggestion of whether or not we are able to support this ‘fear-effect’ with our data.

In general, we expect that this ‘fear-effect’ is most likely to be observed in the week where the event happens or in the following week. Thus, less importance is placed on the abnormal returns of consecutive weeks. We do not expect any significant abnormal returns during the week before event occurrence as it seems unlikely that investors would already react pre-event occurrence. Furthermore, we expect that it is more likely to observe the ‘fear-effect’ for events of larger severity since we believe investors are more prone to react to events of larger magnitude. Table 3 in chapter 3.2.4 presents the chosen events of interest including their total damages.

### 4.3.1 Market Model

Firstly, we examine the results of the event studies, where we use the market model as a pricing model. As mentioned in the methodology, we develop this pricing model by running an OLS regression utilizing the returns of the Global index as the explanatory variable in regard to the Wind index returns (equation 6). The obtained pricing model has an  $R^2$  of 0.90, showing a very high fit. However, as storm related events have an impact on both, the Wind index as well as Global index, the fit and ultimately the usefulness of this specification stands to question. Additionally, this model limits us in determining what event exactly is responsible for the abnormal returns as no dummy variables are included capturing catastrophe occurrences. Nonetheless, by thoroughly looking through the catastrophe database and determining what and if other storms occurred outside of the US during the period, we can identify weeks where no other event except for the event of interest took place. Thereby, we are confident the market model still offers some insight in whether ‘foreign’ events cause a ‘fear-effect’ and also shows if the effect is even longer lasting. For our interpretation, we only include the first three weeks of the event window as we are mainly interested in analyzing if a ‘fear-effect’ occurs during this time period. Furthermore, as mentioned in chapter 3 Data and Methodology, we winsorize the returns to limit the effect possible outliers have on the results. In the subsequent part, we display (Table 5) and discuss the results of all events of interest.

The first event of interest is Hurricane ‘Maria’ that originated in Puerto Rico in 2017, lasted for one day and caused USD 68 billion of damage. This makes it the third costliest event in our analyzed period and one of the many hurricanes that contributed to the costliest year for the insurance industry. By testing the abnormal returns for their significance in the specified event window, we find that they are significant during all of the first three weeks. We reason this result might be attributed to the year of 2017 as the heaviest losses were recorded for both, the Global as well as the US Wind index. Although smaller in magnitude compared to our event of interest, multiple other storms originated worldwide shortly prior and also in the weeks after hurricane ‘Maria’. Nevertheless, by analyzing the catastrophes which occurred in the event window, we discover that for the week after the event, for which the return is recorded at ‘time 1’ in the table below, no other catastrophes occurred outside the US. Consequently, we reason that this significant abnormal return can be attributed to hurricane ‘Maria’. When examining the expected return of this week compared to the observed return of the US Wind index, we note that our pricing model predicts a negative return of -2.71%, while a positive return of 2.34% was actually recorded. This implies that the pricing model suggests the price of the US

Wind CAT Bond Index should have decreased during this week, which was not the case as the observed return for this week is positive. For all remaining abnormal returns of the event study, we are unable to attribute the abnormal return to only our event of interest.

**Table 5: Market Model-Event Study**

*This table shows the results of the event study conducted for all events of interest. For this event study, the market model was used as a pricing model and the results with winsorized values are presented. The 'Wind Return' illustrates the return of the US Wind CAT Bond Index, while the 'Expected Return' presents the normal return we compute using the market model. The values of time refer to the weeks before/after event, for instance '-1' standing for the week before the event. As we expect to find the 'fear-effect' close to the date of the occurrence, only three weeks of the event window are displayed. The symbols \*, \*\* show the significance level of the abnormal returns for 10% and 5%.*

<b>Event 1</b>	<b>Start Date</b>	<b>End Date</b>	<b>Country</b>	<b>Total Damage ('000 USD)</b>	
Hurricane 'Maria'	20-Sep-17	20-Sep-17	Puerto Rico	68 000 000	
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20170915	-1	5,01%	2,59%	2,43%	**
20170922	0	0,41%	1,20%	-0,79%	*
20170929	1	2,34%	-2,71%	5,05%	**
<b>Event 2</b>	<b>Start Date</b>	<b>End Date</b>	<b>Country</b>	<b>Total Damage ('000 USD)</b>	
Tropical cyclone 'Hagibis'	12-Oct-19	17-Oct-19	Japan	17 000 000	
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20191011	-1	0,31%	-0,05%	0,35%	
20191018	0	0,21%	1,01%	-0,80%	*
20191025	1	-0,03%	-0,86%	0,84%	**
<b>Event 3</b>	<b>Start Date</b>	<b>End Date</b>	<b>Country</b>	<b>Total Damage ('000 USD)</b>	
Typhoon 'Jebi'	4-Sep-18	5-Sep-18	Japan	12 500 000	
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20180831	-1	0,15%	0,15%	0,00%	
20180907	0	0,18%	0,15%	0,03%	
20180914	1	-1,61%	-1,61%	0,00%	
<b>Event 4</b>	<b>Start Date</b>	<b>End Date</b>	<b>Country</b>	<b>Total Damage ('000 USD)</b>	
Tropical cyclone 'Lekima'	10-Aug-19	12-Aug-19	China	10 000 000	
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20190809	-1	0,27%	0,22%	0,06%	
20190816	0	0,46%	0,43%	0,03%	
20190823	1	0,35%	0,39%	-0,04%	
<b>Event 5</b>	<b>Start Date</b>	<b>End Date</b>	<b>Country</b>	<b>Total Damage ('000 USD)</b>	
Typhoon 'Haiyan' (Yolanda)	8-Nov-13	8-Nov-13	The Philippines	10 000 000	
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20131108	-1	-0,04%	0,08%	-0,13%	
20131115	0	0,20%	0,25%	-0,05%	
20131122	1	0,05%	0,03%	0,02%	

The second event, the tropical cyclone ‘Hagibis’, which occurred in 2019 and was focused on the area of Fukushima, lasted for a total of six days. Causing USD 15 billion of total damage puts it on the 13<sup>th</sup> spot in terms of its attributed damage compared to all remaining catastrophes of our dataset. In the analyzed weeks, we find that the abnormal return is significant at the 10% level in the week of occurrence as well as the week after. In the attempt to interpret the original returns, we find that in both significant weeks no other storms originating outside of the US were recorded. We can therefore conclude that this event caused a ‘fear-effect’ among the holders of US Wind CAT bonds. When analyzing the returns in the table above, it can be observed that the expected return is of the same sign as the realized return in both weeks where the abnormal return is significant. Nevertheless, based on the pricing model a larger price change was expected for both weeks as for instance in the event of the event, the pricing model suggests an expected return of 1.01% whereas only a return of 0.21% could be realized. Based on this, one might be inclined to conclude that during the weeks where the abnormal return is significant, the pricing model overestimated the price changes.

For the remaining three events, Typhoon ‘Jebi’, Tropical Cyclone ‘Lekima’ and Typhoon ‘Haiyan’, we are unable to find any significant abnormal returns which suggests no ‘fear-effect’ exists for these events. This is somewhat in line with our expectation as we suggest investors might be more likely to react to storms which are larger in magnitude. Furthermore, we execute the event study deploying the adjusted market model. However, as the market model yields a more precise specification since it explains the relationship between the market and index return instead of only assuming the index return being equal to the market return, we deem the market model as more appropriate. Due to the fact that we are not able to identify any significant results with the adjusted market model and thus, no ‘fear-effect’, we exclude the results from the adjusted market model from further discussion.

Overall, after analyzing the results of the market model, we can conclude that some signs of the ‘fear-effect’ are observable for the first two events of interest, which are of largest total damage, yet not for the remaining three events. Whereas the results from the event study of the first event of interest, hurricane ‘Maria’, are still contradicting, a clear conclusion can be drawn for tropical cyclone ‘Hagibis’. We can evidently observe the ‘fear-effect’ of this event during the week of event occurrence as well as during the week following the tropical cyclone. Nevertheless, we deem it as important to stress that several factors impact the interpretability of our results. Firstly, we are limited in our interpretation as this model does not allow us to pinpoint which event in the event window is responsible for the abnormal return. Secondly, it

is rather problematic to construct the normal returns based on a benchmark that might also be affected by the returns. As the Global CAT Bond Index, whose returns are used as market returns, is impacted by our events of interest, it is questionable whether this market model specification is feasible as a pricing model for our event study. Hence, it is rather challenging to determine whether the abnormal return originates from the US Wind index or the Global index. Lastly, the interpretation of event 1, which occurred in 2017, is challenging as this year was an extreme year in terms of the number and magnitude of storms that manifested worldwide. Therefore, the significant abnormal returns in the event window are influenced heavily by other storms that originated outside of the US.

Nevertheless, we can identify some patterns after conducting the event study using the market model as pricing model. We observe that the smaller the total damage of the event, the less significant the abnormal returns are, which is in line with our expectation. To further illustrate this, it should be noted that hurricane ‘Maria’ and tropical cyclone ‘Hagibis’ are the 3<sup>rd</sup> and 13<sup>th</sup> costliest catastrophes of our dataset in terms of total damage. On the contrary, the remaining events of interest, for which we do not find any significant abnormal returns take the ranks 23, 25, 27, respectively. Furthermore, for the specifications where we find significant results, the abnormal return is significant for the week after the event, supporting our initial expectation that the ‘fear’-effect most likely materializes shortly after event occurrence.

#### 4.3.2 Multivariate Model

To accommodate for the outlined shortcomings of the market model, we also run the event study by using different applications of a multivariate model. By doing so, we aim to arrive at more representable results as this variation allows us to pinpoint if it is our event of interest that is responsible for the abnormal return. Additionally, it enables us to attribute different levels of importance to the respective catastrophes by being able to incorporate the interaction variables that display the magnitude of the events. Initially, we vary the specifications of the multivariate model by applying different estimation windows as well as run multiple OLS regressions to arrive at the parameter estimates. The specifications are outlined in 3.2.4 Real Effect vs. Fear Effect (equation 7). In light of the considerations that are presented in the methodology, we are left with 4 different multivariate pricing model specifications (see Table A3) that find application in the discussion of our events of interest.

Despite our expectation to receive more representable event study results when using the multivariate model, the outcomes are rather contradicting. Therefore, we choose not to discuss

the results in great depth, yet only give a short overview supporting the invalidity of the results. All results are also presented in the appendix (Table A4-A8). The costliest event, hurricane ‘Maria’ shows significant abnormal returns, however, due to 2017 being a turbulent year, we are not able to attribute the effect to only this event. On the other hand, ‘Hagibis’, the second costliest storm, and where we record significant abnormal returns using the market model, shows no significance at all in any of the multivariate specifications. Additionally, the third most damaging event, typhoon ‘Jebi’, where we do not find any interpretable results with the market model, shows significant abnormal returns in at least one week of interest for all multivariate model specifications. The fourth event, tropical cyclone ‘Lekima’, further adds to the inconsistency of the results we receive. Showing no significance using the market model, three of the four multivariate approaches show significant abnormal returns. Nonetheless, in regard to the last event, being the least costly, we are presented with consistent results as we do not record any significant abnormal returns in either specification.

In summary, we are unable to find a multivariate pricing model that allows us to fully explain the impact of regional/foreign storms on the US Wind CAT bond market. This materializes in inconsistent results regarding the ‘fear-effect’ and therefore hinders us from making further inference from the results obtained by using a multivariate model.

#### 4.3.3 Analysis Event Study

As we set out to determine whether or not the US Wind CAT Bond market is subject to a ‘fear-effect’, meaning storms that occur outside of the US trigger a reaction among US bond investors, our first goal was to show that those kinds of storms are statistically significant in explaining the returns of the US Wind index. In light of showing that this is indeed the case, we perform an event study to determine the existence of a ‘fear-effect’ in that market, choosing the five largest storms that occurred outside the US within our sample as the events of interest. Using the market model, which we identify to be limited in its usefulness due to the close relationship between market and security, we find some regularity in the results. Even though we cannot pinpoint if it is our events that are bear sole responsibility for the significant abnormal returns, we recognize a pattern that shows that the larger the total damage caused by the event, the more visible the ‘fear-effect’ investors show. As this expectation is at the basis of H3 and since we record significant abnormal returns only for our first and second costliest events, ‘Maria’ and ‘Hagibis’, we accept H3 on the condition that the magnitude of the event is the

largest driver for the effect. Also, we are additionally careful in generalizing our findings as 5 events are a very small sample to draw such conclusions from.

To validate our findings, we apply different variations of the multivariate model, using a similar approach as for H1 and H2 to arrive at the expected (normal) returns. By being able to attribute the magnitude of total damage to the events, we aim to receive more representative results. After analyzing the results of the event study using the multivariate model, however, we cannot identify a pattern that would indicate a clear existence of the ‘fear-effect’. Whereas for some events of interest we can identify significant abnormal returns, others do not show any significant abnormal returns at all. Furthermore, we detect an inconsistency in terms of when the abnormal returns are significant, meaning when the ‘fear-effect’ materializes, for the events of interest where significant abnormal returns are observed. Additionally, we receive contradicting results in comparison to the market model and also to our expectation being that the more damaging events register a higher chance of causing significant abnormal returns.

In summary, we are confident in accepting that there exists a relationship between storms worldwide and the US wind index as we are able to find that storms that originate outside of the US are statistically significant in explaining the returns of the US Wind CAT Bond index. However, although we are able to identify certain patterns and also record significant abnormal returns attributable to our events, the inconsistency in the results as well as the small number of only 5 events used, leads us to reject the second part of H3. Our understanding remains that the ‘fear-effect’ exists, however, using our model specifications and data we cannot find any empirical guarantee.

## 5 Conclusion

This paper reveals that the occurrence of increased natural catastrophes is not only of high relevance to the society in general, yet it has also led the financial markets to evolve and develop. In light of a rising number of natural catastrophes, the market for insurance-linked securities has gained importance over time with the catastrophe (CAT) bond market enjoying particular popularity. This evolution offers new investment and trading opportunities to an increasingly large number of market participants which strengthens our expectation that the CAT bond market, and in particular the secondary CAT bond market, will see continuous growth in the future. By conducting a literature review, we are able to validate the zero-beta characteristics that CAT bonds offer and can further create a link between the secondary CAT bond market and natural catastrophes. Already in early stages of our research we are able to trace back major price spikes of the secondary CAT bond market to the largest natural catastrophes in our sample. As we claim this area of research is rather underserved at the moment, we aim to shed light on how secondary CAT bond price movements can be motivated to enable investors to make more informed investment decisions.

After a thorough analysis of our catastrophe dataset, we are able to classify ‘earthquakes’ and ‘storms’ as the main catastrophe types in terms of total damage caused and number of occurrences, respectively. After running OLS regressions, we find that these two catastrophe types also show statistical significance in explaining the return of the secondary CAT bond market. We therefore gather enough evidence to conclude that, as claimed in our first hypothesis, catastrophe types which cause the highest total damage are significant in explaining price deviations in the secondary CAT bond market. Nevertheless, when analyzing the catastrophe type causing the second highest total damage on average, namely ‘droughts’, we are not able to draw this conclusion. We justify this by referring to the length of the catastrophe type as droughts are rather protracted, making the interpretation of immediate market reactions challenging. The importance of the length-characteristic of a catastrophe type also becomes apparent when attempting to interpret and answer the second hypothesis, where we aim to examine how the market reacts to the occurrence of natural catastrophes. Therefore, interaction terms representing the total damage of a catastrophe type, and consequently the marginal effects of catastrophe types find application. After excluding multiple catastrophe types a priori due to an insignificant number of event occurrences, we introduce confidence intervals to strengthen the findings’ applicability. As for the first hypothesis, we are again only able to draw a valid conclusion for the catastrophe types ‘storms’ and ‘earthquakes’ since the marginal effects of all

remaining catastrophe types are statistically speaking zero. Both significant catastrophe types indicate that a catastrophe is followed by a downward price-movement as marginal effects of ‘earthquakes’ and ‘storms’ are negative. However, we find that major negative effects only become noticeable during the second week after the catastrophic event. Despite this, we are able to accept our second hypothesis that a natural catastrophe is followed by a negative short-term price movement. Furthermore, we observe a clear pattern concluding that catastrophe types which are significant tend to evolve fairly quickly, show more deviation in magnitude of damage and occur most frequently.

Ultimately, we examine the US Wind CAT bond market in more-depth to determine whether or not this market is subject to a ‘fear-effect’. We thereby aim to find out whether storms which occur outside of the US trigger a reaction among US CAT bond investors. This market is chosen as the catastrophe type ‘storms’ is the peril and the US is the geographical region most frequently covered by CAT bonds. Based on our analysis we are able to prove the existence of a relationship between storms worldwide and the US Wind index. Nevertheless, based on the specification of the event study and the pricing models we deploy, we are unable to empirically prove the existence of a general ‘fear-effect’. This can be traced back to the inconsistency we find in our results as well as the small number of events used.

In summation, we conclude that certain catastrophic events trigger reactions in the secondary CAT bond market and that investors are encouraged to consider this when engaging in secondary CAT bond trading. However, we would like to emphasize that several other factors exist which impact price movements, thereby having made our interpretation more challenging. We therefore stress the importance of considering more complex features such as the peril composition of individual CAT bonds or investors’ revised loss expectations for future research in this area.

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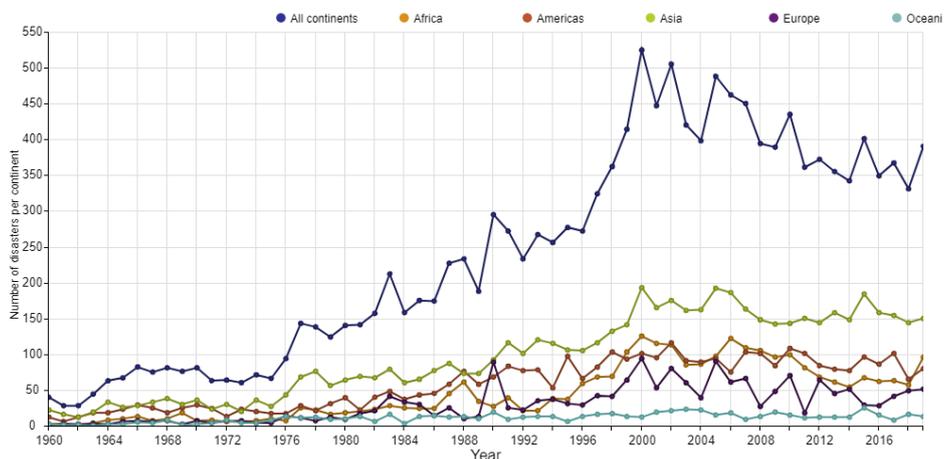
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## Appendix

**Figure A1: Development Global Natural Catastrophes per Continent**

*This figure shows the development of the number of disasters per continent since the inception of the database.*

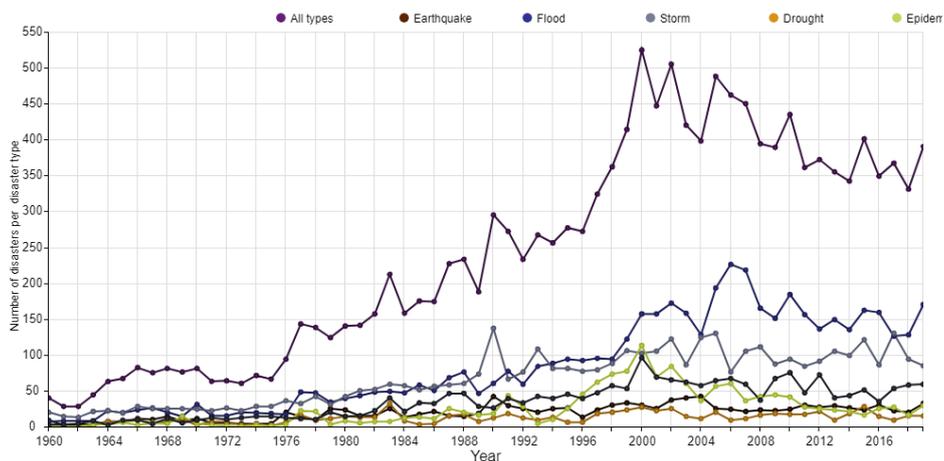


Source: EM-DAT. The Emergency Events Database - Université catholique de Louvain (UCL) - CRED. D. Guha-Sapir - www.emdat.be, Brussels, Belgium

Source: (EM-DAT, 2020)

**Figure A2: Development Global Natural Catastrophes by Category**

*This figure shows the development of the number of disasters per disaster type since the inception of the database.*

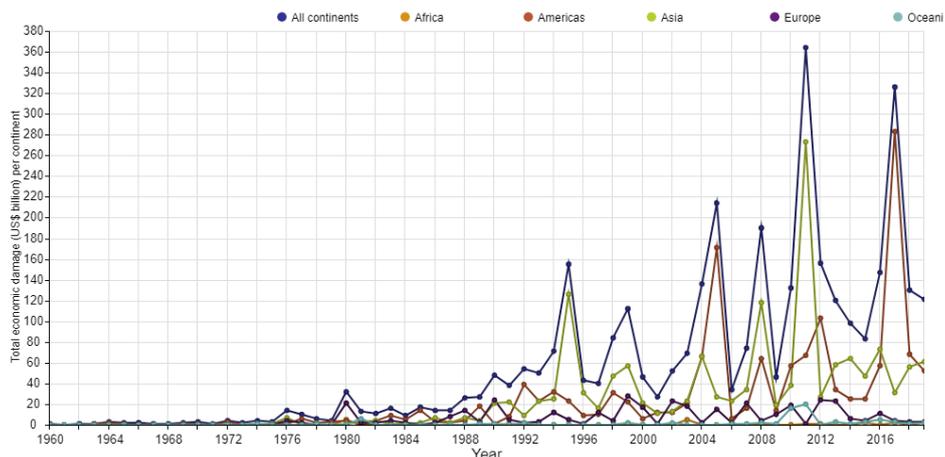


Source: EM-DAT. The Emergency Events Database - Université catholique de Louvain (UCL) - CRED. D. Guha-Sapir - www.emdat.be, Brussels, Belgium

Source: EM-DAT (2020)

**Figure A3: Development Total Damage per Continent**

*This figure shows the development of the total economic damage per continent since the inception of the database.*

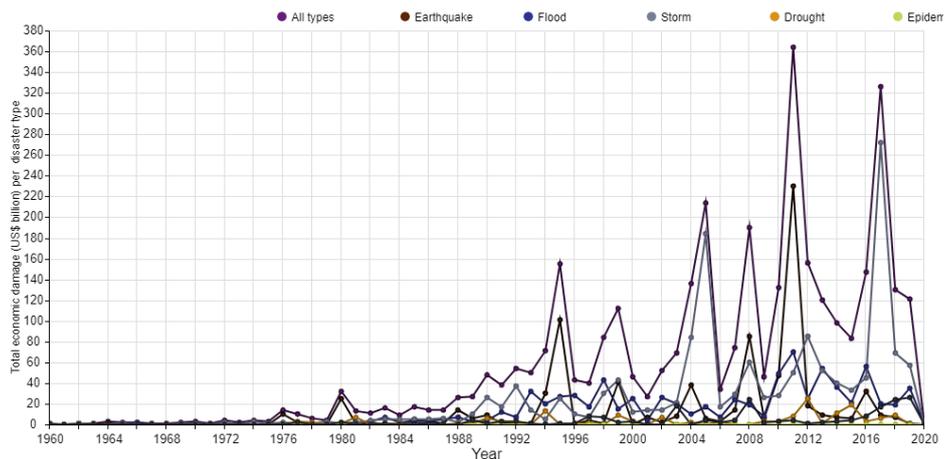


Source: EM-DAT. The Emergency Events Database - Université catholique de Louvain (UCL) - CRED. D. Guha-Sapir - www.emdat.be, Brussels, Belgium

Source: EM-DAT (2020)

**Figure A4: Development Total Damage by Category**

*This figure shows the development of the total economic damage per disaster type since the inception of the database.*

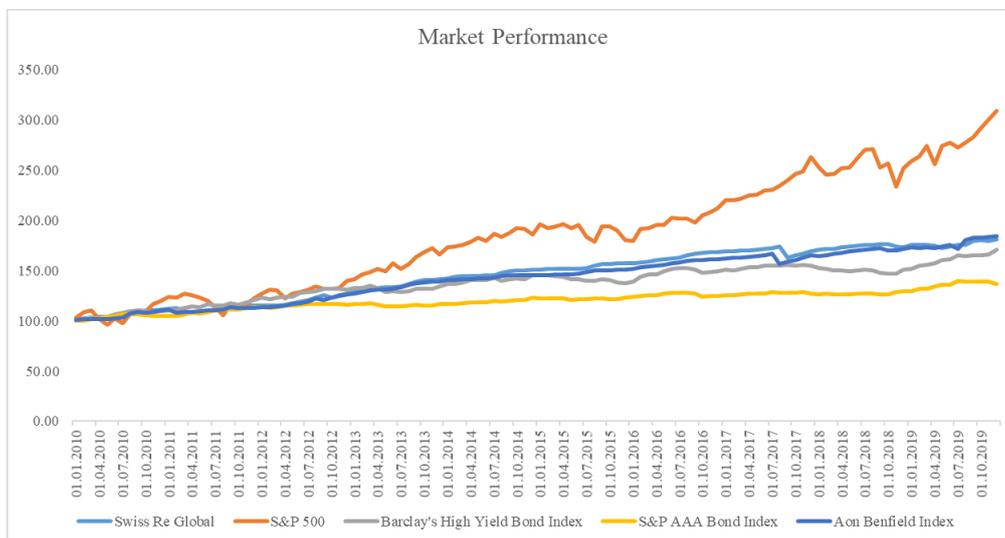


Source: EM-DAT. The Emergency Events Database - Université catholique de Louvain (UCL) - CRED. D. Guha-Sapir - www.emdat.be, Brussels, Belgium

Source: EM-DAT (2020)

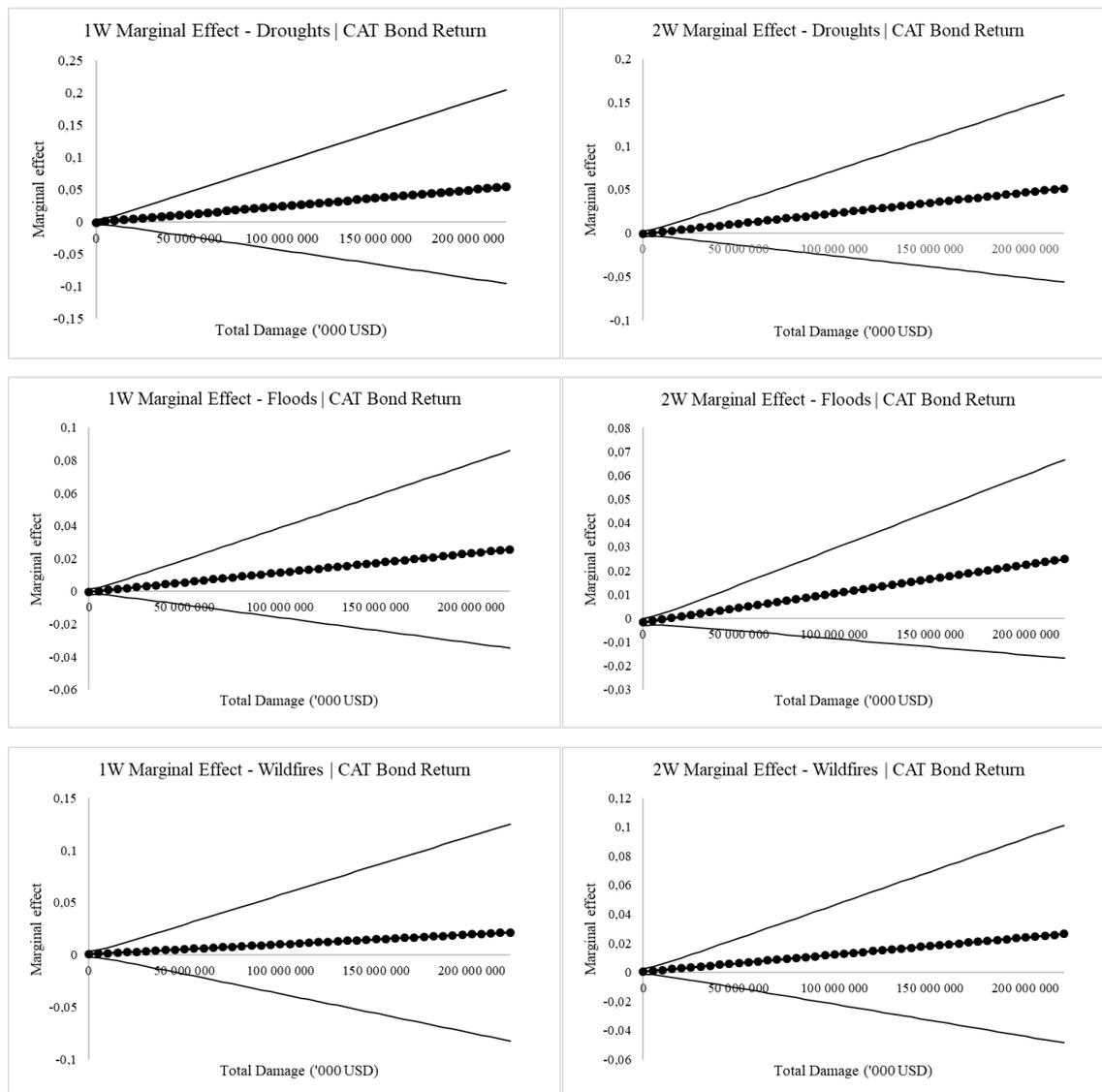
**Figure A5: Comparison Market Performances**

*This figure presents the development of the CAT bond indices in comparison to other relevant financial instruments from 2010-2019.*



**Figure A6: Marginal Effects of Insignificant Catastrophe Types**

The figure illustrates the marginal effects of droughts, floods and wildfires on the CAT bond return with their confidence intervals. The illustration on the left exemplifies data from the first model (1 week), the illustration on the right is based on the results from the second model (2 weeks). The dotted line illustrates the marginal effect based on the coefficients taken from the regression model. The permanent lines demonstrate the confidence intervals for which we assume the covariance between the two parameters to be zero.



**Table A1: Costliest Disasters**

This table shows the costliest disasters since the inception of the database.

Rank	Start date	End date	Length in days	Disaster type	Disaster name	Country	Total damage ('000 US\$)
1	11.03.2011	11.03.2011	1	Earthquake	Fukushima	Japan	210,000,000
2	29.08.2005	19.09.2005	22	Storm	Hurricane 'Katrina'	USA	125,000,000
3	25.08.2017	29.08.2017	5	Storm	Hurricane 'Harvey'	USA	95,000,000
4	12.05.2008	12.05.2008	1	Earthquake	Earthquake 'Sichuan'	China	85,000,000
5	20.09.2017	20.09.2017	1	Storm	Hurricane 'Maria'	Puerto Rico	68,000,000
6	10.09.2017	28.09.2017	19	Storm	Hurricane 'Irma'	USA	57,000,000
7	28.10.2012	28.10.2012	1	Storm	Hurricane 'Sandy'	USA	50,000,000
8	05.08.2011	04.01.2012	153	Flood		Thailand	40,000,000
9	27.02.2010	27.02.2010	1	Earthquake		Chile	30,000,000
10	12.09.2008	16.09.2008	5	Storm	Hurricane 'Ike'	USA	30,000,000

Source: EM-DAT (2020)

**Table A2: Impact of Non-US Storms on US Wind CAT Bond Index**

This table shows the regression output of the OLS regression where we tested if Non-US storms have significant power in explaining returns of the US Wind CAT Bond Index. The coefficient estimates of all dummy variables, interaction terms and control variables are illustrated along with their standard errors. The interaction variable accounts for the interaction between total damage (TD) and each catastrophe type. The symbols \*, \*\* and \*\*\* show the significance level for 10%, 5% and 1%, respectively.

Impact of event 1 week after (Total Damage in trillion USD)	Estimate	SE	Impact of event 2 weeks after (Total Damage in trillion USD)	Estimate	SE
(Intercept)	0,0098	0,0039	(Intercept)	0,0080	0,0043
USA	-0,0003	0,0019	USA	0,0019	0,0017
<b>USA-TD</b>	1,0090 ***	0,1425	<b>USA-TD</b>	-0,4762 ***	0,1086
NotUSA	-0,0023	0,0017	NotUSA	-0,0006	0,0016
<b>NotUSA-TD</b>	0,4670 **	0,2243	<b>NotUSA-TD</b>	0,4959 ***	0,1590
S&P 500	-0,0197	0,0523	S&P 500	-0,0201	0,0539
High Yield Bond Index	0,0591	0,1381	High Yield Bond Index	0,0680	0,1427
AAA Bond Index	-0,1809	0,1900	AAA Bond Index	-0,1560	0,1960
LIBOR 1 month	-0,3751 **	0,1554	LIBOR 1 month	-0,2974 *	0,1627
Term Spread	-0,2289 **	0,1041	Term Spread	-0,1882 *	0,1099
Number of Observations: 521			Number of Observations: 521		
R-squared: 0,115			R-squared: 0,055		

**Table A3: Pricing Model Specification, Multivariate Model**

This table gives an overview of the different specifications we set for the Multivariate Model. For each pricing model specification we show the respective estimation window as well as OLS specification.

Pricing Model #	Description
1	<b>Estimation Window:</b> -25 weeks (all event windows), <b>OLS specification:</b> DV 'on' for 1 week after event
2	<b>Estimation Window:</b> -25 weeks (all event windows), <b>OLS specification:</b> DV 'on' for 2 weeks after event
3	<b>Estimation Window:</b> 'calm' period, <b>OLS specification:</b> DV 'on' for 1 week after event
4	<b>Estimation Window:</b> 'calm' period, <b>OLS specification:</b> DV 'on' for 2 weeks after event

**Table A4: Multivariate Model-Event Study, Event 1**

*This table shows the results of the event study conducted for the first event of interest, hurricane 'Maria', which occurred 2017 in Puerto Rico. For this event study, the multivariate model was used as a pricing model and the results with winsorized values are presented. The 'Wind Return' illustrates the return of the US Wind CAT Bond Index, while the 'Expected Return' presents the normal return we compute using the market model. The values of time refer to the weeks before/after event, for instance '-1' standing for the week before the event. The symbols \*, \*\* show the significance level of the abnormal returns for 10% and 5%.*

<b>Event 1</b>	<b>Start Date</b>	<b>End Date</b>	<b>Country</b>	<b>Total damage ('000 USD)</b>	
Hurricane 'Maria'	20-Sep-17	20-Sep-17	Puerto Rico	68 000 000	
<b>Pricing Model Specification 1</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20170915	-1	5,01%	0,53%	4,48%	**
20170922	0	0,41%	0,02%	0,39%	
20170929	1	2,34%	0,10%	2,23%	**
20171006	2	0,99%	0,08%	0,91%	
20171013	3	1,20%	0,03%	1,16%	*
<b>Pricing Model Specification 2</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20170915	-1	5,01%	-1,13%	6,14%	**
20170922	0	0,41%	-0,56%	0,97%	
20170929	1	2,34%	0,47%	1,86%	**
20171006	2	0,99%	-0,14%	1,13%	*
20171013	3	1,20%	0,00%	1,19%	**
<b>Pricing Model Specification 3</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20170915	-1	5,01%	-0,57%	5,58%	**
20170922	0	0,41%	0,01%	0,40%	
20170929	1	2,34%	0,02%	2,32%	**
20171006	2	0,99%	0,03%	0,97%	**
20171013	3	1,20%	0,05%	1,15%	**
<b>Pricing Model Specification 4</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20170915	-1	5,01%	-0,77%	5,79%	**
20170922	0	0,41%	-0,68%	1,09%	**
20170929	1	2,34%	0,09%	2,24%	**
20171006	2	0,99%	-0,01%	1,00%	**
20171013	3	1,20%	0,07%	1,13%	**

**Table A5: Multivariate Model-Event Study, Event 2**

*This table shows the results of the event study conducted for the second event of interest, the tropical cyclone 'Hagibis', which occurred 2019 in Japan. For this event study, the multivariate model was used as a pricing model and the results with winsorized values are presented. The 'Wind Return' illustrates the return of the US Wind CAT Bond Index, while the 'Expected Return' presents the normal return we compute using the market model. The values of time refer to the weeks before/after event, for instance '-1' standing for the week before the event. The symbols \*, \*\* show the significance level of the abnormal returns for 10% and 5%.*

<b>Event 2</b>	<b>Start Date</b>	<b>End Date</b>	<b>Country</b>	<b>Total damage ('000 USD)</b>	
Tropical cyclone 'Hagibis'	12-Oct-19	17-Oct-19	Japan	17 000 000	
<b>Pricing Model Specification 1</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20191011	-1	0,31%	0,05%	0,26%	
20191018	0	0,21%	0,08%	0,13%	
20191025	1	-0,03%	0,14%	-0,17%	
20191101	2	0,06%	-0,12%	0,18%	
20191108	3	0,11%	0,03%	0,08%	
<b>Pricing Model Specification 2</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20191011	-1	0,31%	0,06%	0,25%	
20191018	0	0,21%	0,10%	0,11%	
20191025	1	-0,03%	0,02%	-0,05%	
20191101	2	0,06%	0,02%	0,03%	
20191108	3	0,11%	-0,03%	0,14%	
<b>Pricing Model Specification 3</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20191011	-1	0,31%	0,06%	0,25%	
20191018	0	0,21%	-0,01%	0,23%	
20191025	1	-0,03%	0,02%	-0,04%	
20191101	2	0,06%	-0,03%	0,08%	
20191108	3	0,11%	-0,03%	0,13%	
<b>Pricing Model Specification 4</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20191011	-1	0,31%	-0,06%	0,36%	
20191018	0	0,21%	-0,03%	0,25%	
20191025	1	-0,03%	-0,01%	-0,02%	
20191101	2	0,06%	0,01%	0,04%	
20191108	3	0,11%	-0,05%	0,16%	

**Table A6: Multivariate Model-Event Study, Event 3**

*This table shows the results of the event studies conducted for the third event of interest, the typhoon 'Jebi', which occurred in Japan in 2018. For this event study, the multivariate model was used as a pricing model and the results with winsorized values are presented. The 'Wind Return' illustrates the return of the US Wind CAT Bond Index, while the 'Expected Return' presents the normal return we compute using the market model. The values of time refer to the weeks before/after event, for instance '-1' standing for the week before the event. The symbols \*, \*\* show the significance level of the abnormal returns for 10% and 5%.*

<b>Event 3</b>	<b>Start Date</b>	<b>End Date</b>	<b>Country</b>	<b>Total damage ('000 USD)</b>	
Typhoon 'Jebi'	4-Sep-18	5-Sep-18	Japan	12 500 000	
<b>Pricing Model Specification 1</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20180831	-1	0,15%	-0,04%	0,19%	
20180907	0	0,18%	-0,02%	0,20%	
20180914	1	-1,61%	-0,02%	-1,59% **	
20180921	2	0,80%	-0,10%	0,90%	
20180928	3	0,48%	-0,14%	0,61%	
<b>Pricing Model Specification 2</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20180831	-1	0,15%	-0,10%	0,25%	
20180907	0	0,18%	-0,07%	0,25%	
20180914	1	-1,61%	-0,26%	-1,35% **	
20180921	2	0,80%	-0,29%	1,09% *	
20180928	3	0,48%	-0,02%	0,50%	
<b>Pricing Model Specification 3</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20180831	-1	0,15%	-0,05%	0,20%	
20180907	0	0,18%	-0,07%	0,25%	
20180914	1	-1,61%	-0,23%	-1,38% **	
20180921	2	0,80%	-0,07%	0,87% **	
20180928	3	0,48%	-0,10%	0,58% **	
<b>Pricing Model Specification 4</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20180831	-1	0,15%	-0,07%	0,22%	
20180907	0	0,18%	-0,09%	0,27%	
20180914	1	-1,61%	-0,22%	-1,39% **	
20180921	2	0,80%	-0,22%	1,02% **	
20180928	3	0,48%	-0,09%	0,56% *	

**Table A7: Multivariate Model-Event Study, Event 4**

This table shows the results of the event studies conducted for the fourth event of interest, the tropical cyclone 'Lekima', which took place in China in 2019. For this event study, the multivariate model was used as a pricing model and the results with winsorized values are presented. The 'Wind Return' illustrates the return of the US Wind CAT Bond Index, while the 'Expected Return' presents the normal return we compute using the market model. The values of time refer to the weeks before/after event, for instance '-1' standing for the week before the event. The symbols \*, \*\* show the significance level of the abnormal returns for 10% and 5%.

<b>Event 4</b>	<b>Start Date</b>	<b>End Date</b>	<b>Country</b>	<b>Total damage ('000 USD)</b>	
Tropical cyclone 'Lekima'	10-Aug-19	12-Aug-19	China	10 000 000	
<b>Pricing Model Specification 1</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20190809	-1	0,27%	-0,08%	0,35%	
20190816	0	0,46%	0,00%	0,46%	
20190823	1	0,35%	0,12%	0,23%	
20190830	2	-1,08%	-0,04%	-1,04% *	
20190906	3	0,35%	0,07%	0,27%	
<b>Pricing Model Specification 2</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20190809	-1	0,27%	-0,09%	0,37%	
20190816	0	0,46%	-0,04%	0,50%	
20190823	1	0,35%	0,05%	0,30%	
20190830	2	-1,08%	-0,10%	-0,98%	
20190906	3	0,35%	0,10%	0,24%	
<b>Pricing Model Specification 3</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20190809	-1	0,27%	-0,06%	0,33%	
20190816	0	0,46%	-0,04%	0,49% *	
20190823	1	0,35%	-0,06%	0,40%	
20190830	2	-1,08%	-0,03%	-1,06% **	
20190906	3	0,35%	0,10%	0,25%	
<b>Pricing Model Specification 4</b>					
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>	
20190809	-1	0,27%	-0,07%	0,35%	
20190816	0	0,46%	-0,07%	0,53% *	
20190823	1	0,35%	-0,09%	0,44%	
20190830	2	-1,08%	-0,06%	-1,03% **	
20190906	3	0,35%	0,01%	0,33%	

**Table A8: Multivariate Model-Event Study, Event 5**

*This table shows the results of the event studies conducted for the last event of interest, typhoon 'Haiyan', which occurred in the Philippines in 2013. For this event study, the multivariate model was used as a pricing model and the results with winsorized values are presented. The 'Wind Return' illustrates the return of the US Wind CAT Bond Index, while the 'Expected Return' presents the normal return we compute using the market model. The values of time refer to the weeks before/after event, for instance '-1' standing for the week before the event. The symbols \*, \*\* show the significance level of the abnormal returns for 10% and 5%.*

<b>Event 5</b>	<b>Start Date</b>	<b>End Date</b>	<b>Country</b>	<b>Total damage ('000 USD)</b>
Typhoon 'Haiyan' (Yolanda)	8-Nov-13	8-Nov-13	The Philippines	10 000 000
<b>Pricing Model Specification 1</b>				
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>
20131108	-1	-0,04%	0,10%	-0,15%
20131115	0	0,20%	0,02%	0,18%
20131122	1	0,05%	0,23%	-0,18%
20131129	2	0,10%	0,07%	0,04%
20131206	3	0,01%	0,24%	-0,23%
<b>Pricing Model Specification 2</b>				
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>
20131108	-1	-0,04%	0,05%	-0,09%
20131115	0	0,20%	0,12%	0,08%
20131122	1	0,05%	0,25%	-0,20%
20131129	2	0,10%	0,27%	-0,16%
20131206	3	0,01%	0,29%	-0,28%
<b>Pricing Model Specification 3</b>				
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>
20131108	-1	-0,04%	0,07%	-0,11%
20131115	0	0,20%	0,06%	0,14%
20131122	1	0,05%	0,11%	-0,06%
20131129	2	0,10%	0,03%	0,07%
20131206	3	0,01%	0,13%	-0,12%
<b>Pricing Model Specification 4</b>				
<b>Date</b>	<b>Time</b>	<b>Wind Return</b>	<b>Expected Return</b>	<b>Abnormal Return</b>
20131108	-1	-0,04%	0,06%	-0,10%
20131115	0	0,20%	0,07%	0,13%
20131122	1	0,05%	0,11%	-0,06%
20131129	2	0,10%	0,11%	-0,01%
20131206	3	0,01%	0,13%	-0,12%