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The Impact of Financial Crises and Natural Disasters on the US Catastrophe Bond Market

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Abstract

Catastrophe (CAT) bonds bring the needs of (re)insurance companies and investors together: They insure against natural disasters by transferring risk to the capital market while at the same time promising high returns and a certain detachment from financial markets. Being an alternative investment class that has been on the rise only in recent years, academic research on CAT bonds is comparatively limited. The thesis aims to fill a research gap by exploring new angles and taking upon previous research and extending its temporal scope. The thesis' goal is to shed light on financial market- and disaster-related patterns that shape the US-American CAT bond market. Several analyses (GARCH-BEKK model, OLS regression models and diversification ratio) are conducted on the one hand to explore the impact financial crises have on the CAT bond market and on the other hand to assess the indirect impact of the cyclical weather patterns El Niño-Southern Oscillation (ENSO) on the performance of CAT bonds. The analyses of the two research questions of interest cover either the period from 2002 until 2022 or from 2005 until 2019. The thesis reveals that CAT bonds are a sound diversifying instrument, also in times of financial crisis. Moreover, it uncovers a geophysical dependence of Atlantic hurricanes on the ENSO, but at the same time a rather weak link between Atlantic hurricanes and the performance of CAT bonds.

Keywords: Catastrophe Bond, Atlantic Hurricanes, Natural Disasters, Financial Crisis

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1 Introduction

In times of climate change, the importance of financial protection against natural catastrophes is increasing and insuring against physical risks becomes paramount. At the same time, investors seek assets that limit financial market risks attached to their portfolios, especially during global economic turmoils like the COVID-19 pandemic. Taking upon these needs, catastrophe (CAT) bonds are an alternative investment class that transfers insurance risks to the capital market and that is commonly known for its overall dissociation from financial market developments. They bring together characteristics of both conventional bonds and insurances by – in simplified terms – paying a coupon and entailing a principal payback mechanism that is conditional on the occurrence of a predefined natural disaster.

CAT bonds have become increasingly popular among (re)insurance companies and investors around the world. Being an asset class that can be used not only to yield profit but also to cope with natural disaster repercussions, it is important for participants of the CAT bond market to have a profound understanding of the elements that determine their bonds' performance. The thesis aims at contributing to this and at shedding light on some financial market- and disaster-related patterns that shape the US-American CAT bond market. We develop two research questions that are analyzed independently from each other due to their rather uncorrelated nature. However, even though they take on different angles, both questions are relevant to the risk perception and supply and demand pattern of CAT bonds.

The first research question is: *What impact do financial crises have on the Swiss Re USD Total Return Index?* The observed time period spans from January 2002 until January 2022. The Swiss Re USD Total Return Index tracks the aggregate performance of USD denominated catastrophe bonds (Swiss Re, 2014). The question is based on the common perception that CAT bonds are an attractive diversifying financial instrument due to their long-term weak correlation with broader financial markets. We prove this notion by computing diversification ratios (based on a weighted average and portfolio volatilities) in a portfolio setting. Then, we turn towards the supposition that in the short-term, financial crises might change the extent of correlation and the consequential diversification benefit. This assumption roots in analyses amongst others by Carayonnopoulos and Perez (2015) who detect an effect of the financial crisis of 2008 on the CAT bond market. The thesis at hand takes up this finding and analyzes further financially unstable times, including the COVID-19 pandemic. It does so by means of several methods, including a GARCH-BEKK model and an OLS regression. The methods require the determination of periods of financial crisis. To avoid taking over definitions of secondary sources, we determine the periods of financial crises by implementing the Mahalanobis Distance measure which was first introduced by Kritzman and Li (2010).

The second research question is: *What impact does the El Niño-Southern Oscillation have on the Swiss Re US Wind Total Return Index?* Due to data limitations, the observed time period is shorter than in the first research question and spans from January 2005 until December 2019. The El Niño-Southern Oscillation (ENSO) is a cyclical weather pattern that influences the likelihood of the formation of Atlantic hurricanes. The Swiss Re US Wind Total Return Index tracks the aggregate performance of USD denominated CAT bonds exposed exclusively to US Atlantic hurricanes (Swiss Re, 2014). The question is based on the assumption that risk-enhancing weather phenomena have an impact on CAT bond returns – especially on the CAT bonds that cover the peril of hurricanes. The question is approached by deploying an OLS regression. The question takes on a novel angle by not directly relating CAT bond returns with its CAT bond-triggering events like Atlantic hurricanes, but by shifting the focus to a cyclical weather phenomenon ENSO that favors the formation of Atlantic hurricanes. Hence, the relationship between ENSO and CAT bond returns is of a rather indirect nature.

The thesis is limited in terms of geography. We focus on the USA since its CAT bond market is comparatively developed. It covers the greatest share of country-specific CAT bonds, namely more than half of all CAT bonds outstanding (Artemis, 2022b). The high coverage of US-American perils makes us assume that different US-related data that is used in the empirical analyses is likely to have a considerable impact on global CAT bond indices. Moreover, a developed CAT bond market suggests that price mechanisms are in place, which facilitates the interpretation of the empirical analyses' output. Regarding the second question, a focus on the USA is inherent in the Swiss Re index that displays the peril US-American Atlantic hurricanes.

As mentioned above, the research questions can be analyzed quite independently from each other. However, the findings related to the two questions can have important joint implications for the risk assessment of the participants in the CAT bond market (see chapter 5).

The thesis is structured as follows: To ensure an understanding of the CAT bond market and introduce previous research, we review relevant literature (chapter 2). Then, we display the data and methodologies used to answer the two research questions (chapter 3). Subsequently, we present the empirical analysis (Chapter 4) and draw a conclusion (chapter 5).

2 Literature Review

In this chapter, we review previous literature on CAT bonds. First, we provide a general overview essential to understanding how CAT bonds work: Subchapter 2.1 introduces the basic mechanisms of CAT bonds, subchapter 2.2 displays the development of the CAT bond markets, and subchapter 2.3 discusses the pricing mechanisms of CAT bonds. The following two subchapters illustrate previous research that is directly related to the research questions. Subchapter 2.4 displays research on the diversification effect of CAT bonds. Lastly, subchapter 2.5 focuses on US-American CAT bonds that cover the peril of Atlantic hurricanes and explains the impact the ENSO has on the formation of Atlantic hurricanes.

2.1 Basic Mechanisms of Catastrophe Bonds

CAT bonds resemble conventional bonds in the sense that they pay a coupon (consisting of a risk premium and a money market return) and a principal. However, the payments are carried out conditional on the occurrence of a predefined natural disaster or a metric related to this (Swiss Re, 2011; Holliger, 2019).

The setup of a CAT bond requires three main parties, namely a Special Purpose Vehicle (SPV) (a separate legal entity that isolates financial risks), a sponsor and investors. The SPV enters into a reinsurance agreement with a sponsor. It then issues the CAT bond to investors and receives the principal. The principal is deposited in a trust account and is invested in highly rated and liquid collateral securities whose yields correspond to market interest rates (e.g., LIBOR). The return that the principal gains is forwarded to the investors as an interest. Therefore, the investors receive a coupon composed of the floating interest rate and of the premium the sponsor pays to the SPV. In case a predefined trigger event occurs, the SPV (and subsequently the sponsor) are indemnified by receiving all or part of the principal. Otherwise, the principal is returned to the investors upon maturity (Braun and Kousky, 2021; Götze and Gürtler, 2020). The CAT bond structure is illustrated in Figure 1 (based on Braun and Kousky, 2021).

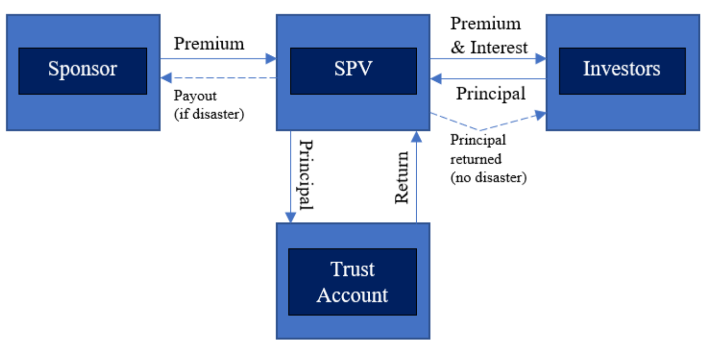

Figure 1: Typical Structure of a Catastrophe Bond (own depiction, based on Braun and Kousky, 2021)

Specialized modeling firms are entrusted with assessing the financial loss distribution (Götze and Gürtler, 2020). They determine the risk premium by estimating the probability of the triggering event to occur and by determining the expected loss for investors. Their models account for scientific aspects, policies, and data on insured properties. Nonetheless, they cannot be freed from uncertainties (Braun and Kousky, 2021).

Between 1997 and 2017, sponsors of CAT bonds have by large parts (85 percent) been insurance or reinsurance companies (Polacek, 2018). They are attracted by the transfer of risk to the capital market and hence, diversify the risk attached to the underwritten policies, while investors, most often institutional investors, are promised to benefit from (alleged) characteristics like a weak or neglectable correlation with broader financial markets and mostly superior risk-adjusted returns (between 2002 and 2020 the annualized return was 7 percent) (Swiss Re, 2011; Patel, 2015; Holliger, 2019; DiFiore et al., 2021).

CAT bonds fall into the category of insurance-linked securities (ILS) which comprise all sorts of instruments whose value is affected by an insured loss event (Braun and Kousky, 2021). A major difference with traditional reinsurances and other ILS instruments is the tradability of CAT bonds on the secondary market. On average, 15 million USD of securities are traded every day, with liquidity increasing with total market size and average deal size (DiFiore et al., 2021). CAT bonds' terms on average last around three years, however, a typical maximum term is five years (Papachristou, 2011).

CAT bonds are activated by predefined triggers, meaning that before the occurrence of the triggering events, the specific event, region, and line of business must be agreed on. The trigger types have different characteristics and induce different mechanisms. They in particular differ when it comes to transparency for investors and basis risk to the sponsor. The former refers to information asymmetries regarding incurred losses that emerge from moral hazard: (Re)insurers and upstream parties involved in assessing actual losses can retain information which makes it hard for investors to verify the reported losses. The length of the payout process depends on the information flow regarding incurred losses and hence, can differ substantially between trigger types. The basis risk to the sponsor comprises the incongruence of incurred losses and the actual payout (Polacek, 2018; RMS, 2012). The most popular trigger is the indemnity trigger which made up 70 percent of outstanding capital in March 2021 (Braun and Kousky, 2021). It captures the actual losses sustained by the sponsor (RMS, 2012). One-fifth of outstanding CAT bond capital (March 2021) is triggered by an industry loss index. It has rather aggregated characteristics: A respective CAT bond's payment streams are only triggered if the aggregate loss of the industry exceeds a predefined threshold. Therefore, in the case of idiosyncratic above-industry-average realized losses, there is no guarantee that the bond issuer's CAT bond is triggered. Once having been a popular trigger type, nowadays modeled loss triggers make up only six percent of issuances. Its underlying logic is comparable to the indemnity trigger, but it relies on expected, hence projected, losses and not actual losses. Even less popular than the modeled loss trigger is the parametric trigger: Solely about 3 percent of outstanding capital is covered by a parametric index (March 2021) (Braun and Kousky, 2021) for example the magnitude of an earthquake. Even though trigger types are distinguishable in theory, in reality, CAT bonds are highly customized by for example combining multiple triggers. Hence, the design of the trigger mechanism can vary substantially (Braun and Kousky, 2021). Also, the composition of implemented trigger types constantly changes: The two most popular triggers, the indemnity and industry loss index trigger, made up nearly 85 percent of all CAT bonds in 2021, whereas they made up only around 40 percent in 2002 (Artemis, 2022c).

2.2 Development of ILS and Catastrophe Bond Markets

The ILS market started developing in the mid-1990s (Cummins, 2008) after the landfall of Hurricane Andrew in 1992. It caused devastating damages which forced eleven insurance companies to go bankrupt (Morana and Sbrana, 2019). Turned out to be the costliest natural disaster in the United State, only Hurricane Katrina in 2005 surpassed Hurricane Andrew's destructive power (Braun and Kousky, 2021). These events initiated the financial market to become a medium to transfer natural disaster risks to the market and to directly insure and finance the incurred losses of disasters.

In 1994, the first successful CAT bond worth 85 million USD was issued by the reinsurance firm Hannover Re (Swiss Re, 2011). However, in the following years, most of the introduced catastrophe-linked securities were unsuccessful and were withdrawn (Cummins, 2008; Cummins and Weiss, 2009). After initial difficulties in establishing itself as a well-performing and demanded security, the catastrophe bond market has expanded significantly throughout the last decade (see Figure A1 in the appendix, adapted from Artemis, 2022a). Despite a range of natural disasters and a breakdown in returns in 2017 due to an exceptionally destructive hurricane season, catastrophe bonds and ILS risk capital outstanding have more than doubled in size over the last ten years. After the financial crisis of 2008, more and more institutional investors became interested in CAT bonds, which made levels of demand rise in the mid-term (Munich Re, 2010; Munich Re, 2011). In 2021, the CAT bond market reached a record of 35.886 billion USD worth in value (see Figure A1 in the appendix, adapted from Artemis, 2022a). Since the end of 2011, the compound annual growth rate has amounted to 9.9 percent and – assuming this rate continues – could lead to a market worth 50 billion USD by the end of 2025 (Swiss Re, 2021).

The USA is the country that covers most of the country-specific CAT bonds. Spread over different covered perils, it accounts for around 43 percent of outstanding bonds and an additional around 12 percent of outstanding bonds cover US-state specific perils. The peril of US-American storms and hurricanes amounts to around 6 percent of globally outstanding CAT bonds (Artemis, 2022b).

2.3 Pricing of Catastrophe Bonds

Getting an understanding of the pricing of CAT bonds is crucial to explaining the output of the empirical analyses. Therefore, this subchapter is dedicated to outlining previous research on the drivers of CAT bond coupons.

The coupon that investors receive from the SPV generally consists of the spread and the risk-free rate which often corresponds to the LIBOR or the US-American Treasury Bill Rate (Patel, 2015). The spread is composed of the modeled annual average expected losses and an additional risk premium. Figure A2 in the appendix depicts the components of a CAT bond coupon. The risk premium is connected to the modeled expected losses and uncertainties related to the estimation of expected losses and other determinants (Patel, 2015). The interrelation between expected losses and the risk premium is positive, but not linear, amongst others due to a minimum risk premium that investors require independent of the expected losses (Papachristou, 2011). It is broadly acknowledged, however, that expected losses are the most important driver of the CAT bond risk premium (Braun, 2016). From 2009 until 2021, there has been the tendency of a decreasing multiple of the spread at issuance to expected loss: It decreased from around 5 to around 2, meaning that the expected loss has had the tendency to make up an increasing share of the spread. However, between 2016 and 2020 the long-term declining trend reversed in the medium-term (Swiss Re, 2021). The rising additional (actual or perceived) risk might have been sustained by the strong hurricane season of 2017. In accordance with this assumption, Papachristou (2011) explains a high-risk premium by determinants that are not closely tied to the expected losses like potential lower liquidity of the CAT bond market, uncertainty in natural hazard models, and cost of capital. Nowadays, more than half of outstanding CAT bonds pay a coupon (composed of expected loss, risk premium and a risk-free component) between 2 and 6 percent, and around the same share of CAT bonds yield expected losses of up to 2 percent (Artemis, 2022d). U.S.-American spreads on average outperform CAT bond spreads in other countries, even though the average expected loss tends to be lower (Braun, 2016).

Previous research that analyzes the drivers of risk premiums weighs the importance of determinants other than expected loss differently depending on the model, data, and the temporal and geographical focus. Gürtler et al. (2016) and Braun (2016) note that there is little research on the broad secondary market and a large part of previous research has caveats like small sample size, inconsistent standard errors, or selection bias, which provides leeway for further research. Gürtler et al. (2016) investigate secondary market CAT bond premiums between 2002 and 2012 by means of fixed effects models. They assert that investors require higher risk premiums when exposed to multiple peril types or multiple peril regions within a single CAT bond. (Braun et al., 2019) analyze 57 ILS funds between January 2001 and December 2015 by means of several factor models and have a similar finding. They come to the conclusion that multi-peril CAT bonds have a higher return than U.S. hurricane and earthquake bonds. This is also in line with the findings of

Braun (2016). Moreover, investors demand higher risk premiums for CAT bonds with lower ratings, implying that CAT bond ratings are decisive when making investment decisions (Gürtler et al., 2016). Also, Gürtler et al. (2016) determine a positive correlation between traditional reinsurance premiums and CAT bond premiums. Götze and Gürtler (2020) detect different patterns at different points of time within the reinsurance cycle – which according to Papachristou (2011) reflects the loss experience, changes of perception of risk over time, and availability of capital: During "soft" markets prices are low and CAT bonds trade at a premium. During "hard" markets prices are high and CAT bonds trade at a discount. Furthermore, (Gürtler et al., 2016) do not find evidence for investors demanding a higher risk premium for CAT bonds with longer maturity periods and lower issue volumes. However, the impact of the fund's size is not uniformly agreed on. According to Braun et al. (2019), previous research has discovered an inverse relation between the size and abnormal returns. They, on the contrary, detect a positive relationship. They acknowledge that both findings might be reasonable, arguing that both, enhanced agility in the first case and economies of scale and highly qualified employees in the second case, might lead to high returns.

2.4 Catastrophe Bonds as a Diversifier

CAT bonds are popular among investors due to their diversifying properties. The alleged phenomenon of zero or low beta stems from the construction of CAT bond returns that are commonly determined by natural disasters rather than by financial market-related risks and developments (Drobetz et al., 2020). The precise extent of correlation with wider financial markets, however, has been up to discussion. Braun et al. (2019), on the one hand, do not recognize a large correlation. Statistical analyses, on the other hand, do not find zero-betas. Drobetz et al. (2020) investigate weekly returns from 2002 until 2018 by means of Engle's DCC model and find that overall, CAT bonds are not insensitive to changes in systemic risks, wherefore the zero-beta hypothesis is refuted. They consider CAT bonds to be a safe haven only during the post-2008 period. Safe havens are characterized by the fact that they retain or even increase in value during times of severe market turbulence which would result in no or negative correlation during times of crisis. Their assessment suggests that overall, CAT bonds have a weak positive correlation with other assets, which makes CAT bonds an effective diversifier that smoothes out risks among the assets of a multi-asset portfolio.

Carayonnopoulos and Perez (2015) apply a dynamic multivariate GARCH model to the Swiss Re BB Cat Bond Performance Index and three asset classes from the period January 2002 and October 2013. Overall, they find that before the financial crisis of 2008, the S&P 500 index and corporate bonds were not significantly correlated with CAT bond index returns. During the crisis, however, the correlation increased. US treasury bonds' correlation with the CAT bond index returns was insignificant during the crisis. They trace the overall strong effect of the subprime financial crisis on correlations back to a weak composition of the assets used as collateral in the trust account[1]. This caused distress in the CAT bond market which made investors sell their bonds and prices decreased. Similarly, DiFiore et al. (2021) find that the short-term enhanced correlation is rooted in the default of Lehman Brothers, which put pressure on investors to sell off liquid assets, among other CAT bonds. According to Carayonnopoulos and Perez (2015), after the financial crisis and up until 2011, the correlations went back to their pre-crisis levels which are found to be insignificant. They also underline that in addition to financial crises, simultaneously occurring major catastrophic events can influence the correlation, even though only in the short-term. Carayonnopoulos and Perez (2015) and DiFiore et al. (2021) assume that this was the case when Hurricane Ike made landfall in September 2008. However, Hurricane Katrina in 2005 has not driven correlation significantly.

Cummins and Weiss (2009) create time-invariant correlation matrices of CAT bond returns with several other indices and yield rates. Similar to Carayonnopoulos and Perez (2015), they ascertain that in the absence of abnormal economic conditions, CAT bonds' correlation with stock and bond returns is close to zero. During the financial crisis of 2008, however, CAT bond returns were significantly correlated with stocks and bonds. With respect to the long-term perspective, a common conclusion of the displayed studies is that even though the zero-beta hypothesis is not accepted, CAT bonds still function as a diversifier.

2.5 Atlantic Hurricane CAT Bonds, Seasonality and El Niño-Southern Oscillation

Atlantic Hurricane CAT Bonds

Between 2005 and 2019 (the period of time of interest regarding the second research question), CAT bonds that cover US-American Atlantic hurricanes have experienced a long-term upward trend in returns. However, during that time two major natural disasters/disaster periods took place. Hurricane Katrina in 2005 did not impact CAT bond returns despite depleted reinsurance capital and rising reinsurance prices (Polacek, 2018). This is because only one CAT bond issued by Kamp Re was triggered (Dieckmann, 2008), and in the aftermath huge amounts of capital were attracted, resulting in a (until that point of time) record issuance of CAT bonds in 2006 and 2007 (Polacek, 2018). On the contrary, the Atlantic hurricane season of 2017 induced a short-term breakdown in returns. The three consecutive hurricanes Harvey, Irma, and Maria made landfall in US territories in August and September (Munich Re, 2018; AON Benfield, 2022) and triggered 19 CAT bonds (DiFiore et al., 2021). That year, losses amounted to 215 billion USD (mainly in the USA). Even though the economic impact of the storms was devastating, prices (and hence supply

[1] Back then, Lehman Brothers was the counterparty of four CAT bonds. Its collapse and the overall crisis made new issuance slow down (Polacek, 2018). Prior to the crisis, credit risks were elevated due to collateralization with securities that – contrary to common collateralization nowadays – were not low-risk money market funds or government-backed securities. After the financial crisis, the restructuring of CAT bonds initiated a detachment of CAT bond risk from the capital market and counterparty risks, leading to more-secure counterparty and trust account structures (Munich Re, 2010) (Polacek, 2018).

and in particular also demand) recovered noteworthily quickly and coupon returns even kept growing during these turbulent weeks (see Swiss Re US Wind Coupon Return Index, Bloomberg ticker: SRUSWCPN). Correspondingly, risk premiums and expected losses rose a bit in the second half of 2017 (Willis Tower Watson, 2019), which in parts must have contributed to the quick recovery of the total return index. In the mid-term, CAT bond market participants' behavior seems to have been rather detached from the rising risk and uncertainty brought along by the Atlantic hurricane season of 2017. The "flight to liquidity" and "flight to quality" in times of imminent disaster risk (Brookes and Daoud, 2012) failed to appear. This roots in untypical developments regarding the supply of and demand for CAT bonds: Even during, but also after the hurricane season of 2017 the value of outstanding CAT bonds increased. The constant growth of the US-wind CAT bond market and the overall stability of Atlantic hurricane CAT bond total returns suggest that the demand side keeps up with supply. Artemis suggests that demand can be stabilized and grow due to a continuous influx of capital (e.g., due to a widening and risk-friendly investor base that is attracted by higher expected coupons) and due to a softening of the broader reinsurance market (meaning that premiums are relatively low and capital is abundant) (Artemis, 2014). Also, low-interest levels in the capital market make CAT bonds an attractive investment for investors (Munich Re, 2011).

CAT bonds that cover the peril of Atlantic hurricanes have not only been impacted by the Atlantic hurricane season of 2017 but also slightly by the financial crisis of 2008. However, similar to the overall CAT bond market, also the sub-group of hurricane CAT bonds benefitted from a quick recovery of the trust of investors (Munich Re, 2010; Polacek, 2018) and rising demand and supply after 2009.

Seasonality

The US Atlantic hurricane season typically stretches from 1st June until 30th November. This seasonality has an impact on prices and coupons. DiFiore et al. (2021) find that trading volumes decrease when risk increases, in particular, during the hurricane season or when natural disasters have recently occurred are expected to occur. AON Benfield (2018) reports that the issuance of CAT bonds was decisively higher during the first half of the year compared to the second half of the year, which leads to decreasing prices in the secondary market. Conversely, during the hurricane season in the second half of the year, prices tend to go up. Patel (2015) also points out that changes in expected losses determine prices during the hurricane season: Prices can break down due to increased risk of losses and hence default whenever there is a major hurricane season and hurricanes threaten to make landfall. Correspondingly, Herrmann and Hibbeln (2021) find that spreads fluctuate over time with the hurricane season – up to 47 percent of market fluctuations in the yield spreads on single-peril hurricane CAT bonds stem from seasonality: Starting high at the beginning of the season, they decline throughout the season assuming that the CAT bond was not triggered. The effect is supported by higher expected losses and an approaching maturity of the bond.

El Niño-Southern Oscillation

There are recurring weather phenomena that favor the formation of hurricanes, which in turn supposedly are linked to US hurricane-related CAT bonds. The most influential climate pattern is the El Niño-Southern Oscillation (ENSO) which affects the ocean and the atmospheric circulation (NOAA, 2016). El Niño swings back and forth every two to seven years on average and typically lasts between nine and twelve months. It is caused by weakening trade winds that push warm water towards the Pacific (west coast of the Americas). Amongst others, this makes the Pacific jet stream move south (NOAA, n.d. a). The shift in average location and strength of this mid-latitude jet stream influences weather patterns around the globe in different ways (NOAA, 2016). The opposite phenomenon, La Niña, makes the Pacific jet stream move north, strengthens surface winds across the Pacific and near the equator and on average cools down the water. During La Niña, the southern tier of Alaska and the U.S. Pacific Northwest tends to be colder and wetter than the average, whereas the U.S. southern tier of the state tends to be warmer and drier than average (NOAA, n.d. a).

Lacking CAT bond-related academic research, at this point we can only establish a link between ENSO and the occurrence of Atlantic hurricanes. The latter are more likely to form during La Niña and even more likely during neutral phases of ENSO (hereinafter referred to as "neutral phase"), hence when neither El Niño nor La Niña prevails. For example, the disastrous hurricanes Andrew (1992) and Katrina (2005) happened during neutral phases (National Weather Service, n.d.). Conversely, in 2016 when a strong El Niño phase in the North Atlantic prevailed, the number of hurricanes (4) fell short of the 1995-2016 average (7.6) (Munich Re, 2016). This underlines the moderating impact of El Niño. According to AON Benfield (2022), since 1990, on average ENSO has not increasingly favored the formation of storms. However, the intensity has increased due to the warmer atmosphere and oceans allowing "more opportunity for rapid intensification and maintaining storm intensity for a longer period. This enhances the potential for greater risk and loss potential to coastal and inland assets." (AON Benfield, 2022). Therefore, hurricane risks attached to ENSO (to be more specific, La Niña and neutral phases) have increased over time.

3 Data and Methodology

This chapter presents the data and the methodology used to develop the two research questions. It is divided into three major subchapters: Subchapter 3.1 presents the data used to answer both research questions, subchapter 3.2 illustrates the methodology deployed for the first question (in particular, 3.2.1 Diversification Ratio, 3.2.2 Mahalanobis Distance, 3.2.3 GARCH-BEKK model, and 3.2.4 OLS Regression) and subchapter 3.3 focuses on the methodology of the second question.

3.1 Data

Swiss Re CAT Bond Indices

Swiss Re is a major global reinsurance company that provides different CAT bond indices. The indices were launched in 2007 and were the first total return indices provided to the CAT bond sector. Their indices date back to 2002 and are set to the value of 100 on 4th January 2002. Five different indices are made available amongst others on Bloomberg: Global, Global Unhedged, USD CAT bonds, BB CAT bonds, and US Wind CAT bonds. Since the thesis focuses on the USA, solely the Swiss Re USD Total Return Index and the Swiss Re US Wind Total Return Index are used as the dependent or main variables in the empirical analyses. For each of those indices, Swiss Re tracks the coupon return, price return, and total return. The total return is composed of price returns and coupon returns weighted by the contribution of each bond to the overall index (Swiss Re, 2014). Besides the Swiss Re CAT bond indices, there are no CAT bond indices that span such a long period of time and that are updated on a weekly and monthly basis. Therefore, the Swiss Re CAT bond indices are the industry's most comprehensive key point of reference.

The Swiss Re USD Cat Bond Index Total Return (Bloomberg ticker: SRCATTRR) "tracks the aggregate performance of USD denominated catastrophe bonds offered under Rule 144A" (Swiss Re, 2014). Rule 144A of the Securities Act of 1933 limits the scope of the Swiss Re Index to rather liquid CAT bonds on the secondary market. The index captures "all rated and unrated cat bonds, outstanding perils, and triggers and seeks to capture the overall universe of USD-denominated cat bonds" (Swiss Re, 2014). The Swiss Re US Wind Cat Bond Index Total Return (Bloomberg ticker: SRUSWTRR) "tracks the aggregate performance of USD denominated CAT bonds exposed exclusively to US Atlantic hurricanes" (Swiss Re, 2014). In the following, we refer to the Swiss Re USD Cat Bond Index Total Return as Swiss Re USD Total Return Index and the Swiss Re US Wind Cat Bond Index Total Return as Swiss Re US Wind Total Return Index, respectively. Figure 2 shows the development of the two indices over time.

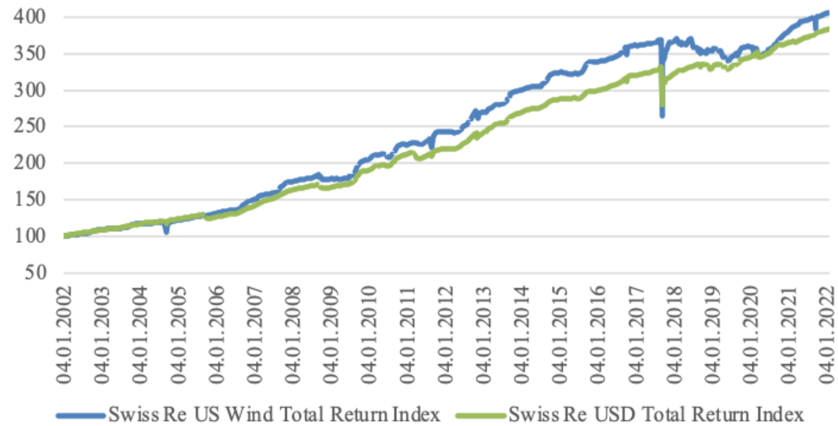

Figure 2: Development of the Swiss Re US Wind Total Return Index and the Swiss Re USD Total Return Index

For the analysis of both research questions, weekly data is used. To approach the first research question, Swiss Re USD Total Return Index data is retrieved from January 2002 to January 2022 (1048 observations). To approach the second research question, Swiss Re US Wind Total Return Index data is retrieved from January 2005 until December 2019 (782 observations). We consider a shorter period of time due to data limitations concerning the deployed control variables. Since major hurricanes like Hurricane Katrina in 2005 and the destructive Atlantic hurricane season in 2017 are still included in this dataset, this limitation is bearable. Table 1 displays the descriptive statistics of the two CAT bond indices.

Table 1: Descriptive Statistics: Swiss Re Indices

WEEKLY	***Swiss Re USD Total Return***	***Swiss Re US Wind***
	From Jan 2002 to Jan 2022	**From Jan 2005 to Dec 2019**
Mean	230,07	256,09
Standard Error	2,74	2,95
Median	219,17	250,63
Standard Deviation	88,64	82,54
Kurtosis	-1,43	-1,45
Skewness	0,09	-0,10
Minimum	100,00	122,24
Maximum	383,65	371,06
Observations	1048	782

Financial Market

Financial market indices are required in particular to approach the first research question. However, some of the indices are also incorporated in the OLS regression concerning the second research question.

Six representatives of four major asset classes, namely equities, fixed income, real estate, and commodities are considered over the course of the thesis. The data is retrieved from Bloomberg on a weekly basis.

As proxies for the asset class equity, we use the S&P 500 (Bloomberg ticker: SPX) which captures about 80 percent of available market capitalization and is the benchmark index in the US stock market. As a proxy for fixed income, we use the Bloomberg US Aggregate Bond Index (Bloomberg ticker: LBUSTRUU). It comprises the investment grade, US dollar-denominated, fixed-rate taxable bond market, meaning that it captures amongst other treasuries, government-related and corporate securities. The Bloomberg US Corporate High Yield Total Return Index Value Unhedged USD (Bloomberg ticker: LF98TRUU) is used as a representative of corporate bonds and the 10-year US Government Bond Index (Bloomberg ticker: USGG10YR) captures the performance of government bonds. For real estate, we use the FTSE EPRA/NAREIT United States Index (Bloomberg index: UNUS) which contains publicly quoted real estate companies that meet the EPRA Ground Rules and is the representative benchmark for real estate. These indices reflect developments in the US-American market. This is desirable due to the geographical focus of the thesis. Lastly, commodities reflect a major alternative investment class. We use the Bloomberg Commodity Index Total Return (Bloomberg ticker: BCOMTR) which is composed of futures contracts and reflects the returns on a fully collateralized investment in the BCOM. Since commodity markets are global in character, we believe that this index is appropriate to account for US-American commodity market developments.

Moreover, the US-American Consumer Price Index (CPI) is required to approach both research questions. Its monthly data is retrieved from the OECD database and is a "measure of inflation, or the changes in average retail prices of a fixed basket of goods and services representing household consumption" (OECD, 2022). Since the Swiss Re indices are incorporated into the empirical models on a weekly basis, the CPI is set constant for each week of a respective month. The 1-month London Interbank Offered Rate (LIBOR) is required to approach both research questions as well. It is one of the main benchmarks for borrowing costs between banks and short-term interest rates. It also is a proxy for the risk-free component of the coupon (which in turn is a decisive driver of returns). Financial market indices' data, except for CPI, is retrieved from Bloomberg from January 2002 to January 2022 (1048 observations). Table 2 displays the descriptive statistics of these variables.

Table 2: Descriptive Statistics: Financial Indices

WEEKLY	*Real Estate Index*	*Fixed Income Index*	*Commodity Index*	*S&P 500*	*Government Bond*	*Corporate Bond*	*CPI*	*LIBOR*
	From Jan 2002 to Jan 2022							
Mean	2321,76	1687,07	239,27	1830,24	2,98	1345,54	2,18	1,44
Standard Error	20,11	12,34	2,06	27,85	0,04	17,46	0,04	0,05
Median	2377,01	1769,44	242,63	1431,90	2,82	1290,49	2,05	0,82
Standard Deviation	651,17	399,50	66,68	901,46	1,18	565,29	1,45	1,58
Kurtosis	-0,76	-1,19	-0,11	1,06	-1,02	-1,19	1,52	0,62
Skewness	-0,23	0,02	0,58	1,28	0,09	0,25	0,48	1,29
Minimum	728,84	1006,82	128,50	683,38	0,53	491,02	-2,10	0,07
Maximum	3896,38	2399,26	473,92	4766,18	5,40	2461,43	7,48	5,82
Observations	1048	1048	1048	1048	1048	1048	1048	1048

Natural Disasters

Data concerning natural disasters is required in particular to approach the second research question. One exception is total damages (in billions of USD, adjusted for inflation) which serve as a control variable in the first research question. Its data (January 2002 to January 2022, 1048 observations) is retrieved from the EM-DAT database, an international disaster database provided by the Center for Research on the Epidemiology of Disasters of the Université Catholique de Louvain (UCLouvain, 2022). Adjusted total damages cover different types of natural disasters: Drought, earthquakes, storms, floods, wildfire, extreme temperature, landslide, and volcanic activity.

Data regarding hurricane damage (in billions of USD) (January 2005 to December 2019, 782 observations) is collected manually by the authors. The database is based on a compilation of US hurricanes provided by Wikipedia (2022) and on interlaced articles on the individual hurricanes of interest. According to the Saffir-Simpson Hurricane Wind Scale (a wind speed scale), the hurricanes of interest cover the categories 1 to 4 out of 5 categories (with 5 being the most forceful category). Based on hurricane damages, a dummy variable on the occurrence of hurricanes that made landfall in the USA and caused damages in the respective week is created. Hurricanes that formed above the Atlantic Ocean but did not make landfall are not captured by the variable.

The main variable of interest regarding the second research question, ENSO, refers to the weather phenomenon itself and manifests itself in El Niño, La Niña and neutral phases. The Southern Oscillation Index (SOI) refers to an index that quantifies the intensity of the ENSO. The SOI gives standardized information on the pressure differences between Tahiti and Darwin. The US-American National Oceanic and Atmospheric Administration (NOAA) provides data on SOI (NOAA, 2022a) and assigns La Niña to values above 0.5, neutral phases to values between -0.5 and 0.5, and to values below -0.5 stand for El Niño. The forecast of SOI, instead, indicates the probability of one of the phases to occur. The corresponding data is retrieved from the National Weather Service/NOAA (2022). Please refer to A1 in the appendix for a more detailed description of how the ENSO forecast was calculated.

ACE accounts for the accumulated cyclone energy in week t by displaying the sum of squares of the estimated 6-hourly maximum sustained wind speed (National Weather Service/NOAA, 2002). The data is published by NOAA (2022b) and collected by Phil Klotzbach from Colorado State University. ACE and ENSO-related data are published on a monthly basis. To adjust it to the weekly character of the analysis, we set it equal for each week of the respective month.

Another dummy variable accounts for the seasonality of Atlantic hurricanes. It is set to 1 during the typical Atlantic hurricane season between 1st June and 30th November (and set to 0 between 1st December and 31st May) (NOAA, n.d. b).

Table 3 displays the descriptive statistics of numerical variables related to natural disasters. Dummy variables are not included, since their descriptive statistics would not provide valuable insights.

Table 3: Descriptive Statistics: Natural Disaster Indices

WEEKLY	*Total Damages (USD bn)*	*SOI*	*Forecast*	*Hurricane Damages (USD bn)*	*ACE*
	From Jan 2002 to Jan 2022	**From Jan 2005 to Dec 2019**			
Mean	2,21	0,23	0,68	2,49	10,32
Standard Error	0,38	0,03	0,01	0,51	0,79
Median	0,09	0,20	0,72	0,00	0,40
Standard Deviation	12,34	0,97	0,20	14,25	22,22
Kurtosis	147,40	0,58	-0,17	50,36	19,63
Skewness	11,48	0,15	-0,73	6,92	3,78
Minimum	0,00	-3,10	0,12	0,00	0,00
Maximum	173,44	2,90	0,97	125,00	174,10
Observations	1048	782	782	782	782

3.2 Question 1: What Impact Do Financial Crises Have on the Swiss Re USD Total Return Index?

The chapter is divided into four subchapters that jointly aim at answering the research question *"What impact do financial crises have on the Swiss Re USD Total Return Index?*".

Before approaching this question, we step back to verify the common notion that the inclusion of Swiss Re USD Total Return Index-replicated CAT bonds in a portfolio on average serves as a diversification instrument throughout the observed period of time. We do so by computing diversification ratios (chapter 3.2.1.). In order to run the further empirical models that specifically examine times of financial crisis, we introduce the Mahalanobis Distance measure (chapter 3.2.2.). The detected periods of financial crisis are deployed in the subsequent GARCH-BEKK and OLS models (chapter 3.2.3. and chapter 3.2.4.). The former enables us to detect patterns in the multivariate time-varying correlation between the

Swiss Re USD Total Return Index and several financial market indices. Finally, the OLS regression which directly accounts for periods of financial crises by means of a dummy variable is introduced. It supports the findings of the GARCH-BEKK model and provides nuanced insights by including control variables.

3.2.1 Diversification Ratio

Following Choueifaty and Coignard (2008), the diversification ratio gives insights into the diversification effect of the inclusion of the Swiss Re USD Total Return Index in a portfolio. The diversification ratio is the ratio of the weighted average of volatilities divided by the portfolio volatility:

$$DR(P) = \frac{P' \times \Sigma}{\sqrt{P'VP}}$$

With P being the portfolio composed of several assets, $\sum$ being the 1 x N vector of asset volatilities and V being the covariance matrix of the assets. When computing the ratio, two constraints are implemented: Weights are positive (which prevents short selling) and the sum of weights is 1.

The diversification ratio is computed eight times: The maximized diversification ratio, called Most-Diversified Portfolio (MDP), is run four times and the diversification effect with equal weights is computed four times as well. Two of the MDP and the equally weighted version, respectively, comprise the three asset classes that are later used for running the GA1RCH-BEKK model (S&P 500 (as a representative of equity), corporate bonds and government bonds) and the Swiss Re USD Total Return Index. In order to get the diversification effect of a broader portfolio, we also run two of the MDP and of the equally weighted versions, respectively, with two additional assets (Real Estate Index and Commodity Index).

3.2.2 Mahalanobis Distance

In order to determine times of unusualness in financial market data, hereinafter classified as financial crisis, we apply the Mahalanobis Distance method, a multivariate distance metric. It measures the distance between a point and a distribution. The method "show[s] how to use a statistically derived measure of financial turbulence to measure and manage risk and to improve investment performance" (Kritzman and Li, 2010).

The Mahalanobis Distance accounts for the correlation between the analyzed assets and for joint movements of asset returns (Stöckl and Hanke, 2014). According to Stöckl and Hanke (2014), the Mahalanobis Distance "condenses the information on unusual behavior across all assets into a single number". The location parameter μ and scatter matrix $\sum$ determine the distance. A period t can be labeled turbulent if returns move in opposite directions even though the assets are positively correlated. The method is easily applicable given that the measure is scalable without distorting the informative value of the asset returns (Stöckl and Hanke, 2014). Moreover, the method does not only account for the magnitude of asset returns, but also for interactions among the assets (Kritzman and Li, 2010).

Chow et al. (1999) were the first to apply the Mahalanobis Distance to financial markets making use of historical multivariate distributions in their approach:

$$d_t = \sqrt{(y_t - \mu)\Sigma^{-1}(y_t - \mu)'}$$

Where d_t displays a "turbulence index", the Mahalanobis distance of the sample average in period t, y_t is the 1 x N vector of asset returns for period t, μ is the sample average 1 x N vector of historical returns and Σ is the N x N sample covariance matrix of historical returns (Kritzman and Li, 2010). Multiplying the distance of the vector from the mean $(y_t - \mu)$ by the inverse of the covariance matrix Σ^{-1} implies that the covariances increase with the correlation. Therefore, strongly correlated variables reduce the distance.

In order to classify time periods as turbulent or as "normal", a threshold is established. Whenever the Mahalanobis distance exceeds this threshold, the corresponding period of time is denoted as a financial crisis. In order to establish a threshold, the three median absolute deviation (MAD) rule is applied. It determines an upper limit by taking the sum of the sample median and three times the median of the absolute differences between Mahalanobis Distances and the sample's median. The three MAD rule requires normally distributed data. To approximate normally distributed data, asset returns (y_t) are log-linearized.

$$Threshold = MEDIAN(d_t) + 3 * MEDIAN(|(d_t) - MEDIAN(d_t)|)$$

To assure that the Mahalanobis distance defines outliers that correspond to the findings of a reliable second source, we compare the results with the distribution of the Federal Reserve's St. Louis Fed Financial Stress Index (Federal Reserve Bank of St. Louis, 2022). If the two measures more or less match each other, the Mahalanobis Distance measure is credible. The Federal Reserve's index takes into account 18 data series capturing interest rates, yield spreads, and other indicators and it sets the average of the index (starting in 1993) to zero. This average represents normal financial market conditions, wherefore positive values indicate above-average financial distress (Federal Reserve Bank of St. Louis, 2022).

3.2.3 GARCH - BEKK Model

The conditional variance of selected financial market indices and their time-varying correlation with the Swiss Re USD Total Return Index over time are analyzed. The financial market indices are representatives of the equity and bond market. The three selected indices are the S&P 500 index, the Bloomberg US Corporate High Yield Total Return Index Value Unhedged USD (as representative of corporate bond), and the 10-year US Government Bond Index (as representative of government bond).

A Multivariate Generalized Autoregressive Conditional Heteroskedastic (MGARCH) model is implemented. An MGARCH model allows the conditional-on-past-history covariance matrix of the dependent variables to follow a flexible dynamic structure. Thereby, it helps to identify the co-volatility between several indices. There are different specifications of MGARCH models. The specification that is applied in the thesis at hand is the Baba-Engle-Kraft-Kroner (BEKK) model. It was proposed by Engle and Kroner (1995) and makes use of parameterization in order to guarantee the positivity of the conditional variance matrix. The BEKK model is preferred over the VEC model, given that the latter entails limitations due to the high dimensionality of its parameters: The number of parameters required to solve the model increases rapidly which makes it difficult to solve non-bivariate cases (Bauwens et al., 2006). To reduce the number of parameters in the variance and covariance equation, Bollerslev, Engle and Wooldridge (1988) developed a simplified model called diagonal VEC (DVEC) whose matrices are diagonal. However, DVEC imposes strong restrictions on the parameters to ensure a positive-definite covariance matrix (Bauwens et al., 2006). The BEKK model, which is a further development of the VEC model, applies a new parameterization to the conditional variance matrix H_t that guarantees its positive definiteness:

$$H_t = C'C + A'\eta_{t-1}\eta'_{t-1}A + B'H_{t-1}B$$

where C is N x N upper triangular with $\frac{N(N+1)}{2}$ parameters, and A and B are N x N matrices. The restrictions imposed on the model guarantee covariance stationary.

In particular, this empirical analysis deploys the diagonal BEKK model in which A and B are diagonal matrices. To implement the diagonal BEKK (1,1) model, the log-returns and residuals of the respective price index are calculated: Consider $ln(r_t) = \mu + \eta_t$ as a N x 1 vector of log-returns at time t and $\eta_t|\Omega_{t-1} \sim N(0, H_t)$. Lagged squared residuals, lagged variances, and covariances, displayed by the following formulas, are used to build the variance-covariance matrix.

$$\sigma_{11,t} = c_{11}^2 + \alpha_{11}^2\eta_{1,t-1}^2 + \beta_{11}^2\sigma_{11,t-1}$$
$$\sigma_{22,t} = c_{12}^2 + c_{22}^2 + \alpha_{22}^2\eta_{2,t-1}^2 + \beta_{22}^2\sigma_{22,t-1}$$
$$\sigma_{12,t} = c_{11}c_{12} + \alpha_{11}\alpha_{22}\eta_{1,t-1}\eta_{2,t-1} + \beta_{11}\beta_{22}\sigma_{12,t-1}$$

The restrictions imposed are 1. α_{11}, β_{11} and the diagonal elements of C must be positive to ensure a unique solution and 2. $\alpha_{11}^2 + \beta_{11}^2$ <1 and $\alpha_{22}^2 + \beta_{22}^2$ <1. Also, to obtain the time-varying correlation, the covariance at time t is divided by the square root of the product of the two variances at time t. After estimating the required variables, we apply the Maximum Likelihood method whose log-likelihood function is given by:

$$ln\, L_t(\theta) = -ln(2\pi) - ln(\sqrt{\sigma_{11,t}}) - ln(\sqrt{\sigma_{22,t}}) - \frac{1}{2} ln(1-\rho_t^2) - \frac{1}{2(1-\rho_t^2)}(\frac{\eta_{1,t}^2}{\sigma_{11,t}} + \frac{\eta_{2,t}^2}{\sigma_{22,t}} - 2\rho_t \frac{\eta_{1,t}\eta_{2,t}}{\sqrt{\sigma_{11,t}\sigma_{22,t}}})$$

3.2.4 OLS Regression

An OLS regression gives insight into the impact of financial crises on the Swiss Re USD Total Return Index.

$$ln(R_t) = \alpha + \beta_{FC} \times D_{FC,t} + \sum_{j=1}^{4} \gamma_t \times CV_{j,t} + \varepsilon_t$$

where $\sum_{j=1}^{4} \gamma_t \times CV_{j,t} = \beta_{CPI} \times CPI_t + \beta_{SP500} \times SP500_t + \beta_{LIBOR} \times LIBOR_t + \beta_{TD} \times TD_t$

Where R_t stands for the Swiss Re USD Total Return Index at time t (however, we log-linearize it in order to make it more suitable for a linear regression), α is the constant, β_{FC} is the coefficient estimate of the stand-alone dummy, $D_{FC,t}$ is the dummy variable of a financial crisis at time t, γ_j is the coefficient estimate of the control variable j, $CV_{j,t}$ displays the control variable j at time t and ε_t is the error term at time t.

The OLS regression is run five times. First, no control variable is deployed which corresponds to Model 1 in the analysis of the output. Afterward, the four control variables are grouped into three groups of control variables. Model 2 comprises the US-American Consumer Price Index (CPI_t). Being a measure of inflation, the CPI is expected to affect attractiveness of CAT bonds. Model 3 includes the second group of control variables and comprises S&P 500 ($SP500_t$) and 1-month LIBOR ($LIBOR_t$). They are grouped together since both of them are a benchmark, one for the stock market and other one for the short-term money market interest rate. LIBOR accounts for the risk-free component of the spread while the S&P 500 was found to have the highest correlation with CAT bonds compared to government and corporate bonds (Carayannopoulos and Perez, 2015) and therefore is the most likely index that has an impact on the Swiss Re USD Total Return Index. Model 4 accounts for adjusted total damages (TD_t) since part of the damages are likely to be covered by CAT bonds and hence, are the most likely variable to trigger CAT bonds. Therefore, total damages are expected to have a negative impact on returns. Finally, Model 5 considers all control variables.

We consider incorporating the Bloomberg US Corporate High Yield Total Return Index Value Unhedged USD and the 10-year US Government Bonds Index as well. However, their Variance Inflation Factors exceed the critical threshold of 10 which implies multicollinearity. Due to data limitations, we cannot control for the most decisive driver of the coupon, namely expected losses.

The regression at hand accounts for financial crises in a different way than previous research: Instead of dividing the time series into periods of crisis and non-crisis (see e.g., Carayannopoulos and Perez, 2015) or pre- and post-crisis (see e.g., Drobetz et al., 2020), we account for financial crises by means of the dummy variable. This is more feasible, since times of crisis and of non-crisis alternate quickly, especially according to the Mahalanobis Distance measure, which would require a division of the time series in a large number of quite small fractions. The dummy variable at hand is more nuanced and is able to capture short-term reactions of the Swiss Re USD Total Return Index.

In order to assure that the OLS regressions comply with their underlying assumptions, we run several diagnostic tests. The White test and Breusch-Pagan-Godfrey test detect heteroscedasticity and the Ljung-Box test detects autocorrelation in the data at hand. To account for this, we use robust heteroskedasticity and autocorrelation consistent covariance estimators.

3.3 Question 2: What Impact Does the El Niño-Southern Oscillation Have on the Swiss Re US Wind Total Return Index?

Given that the majority of US hurricane-related CAT bonds are triggered by losses that were caused by hurricanes[2] and supply- and demand patterns change with the rising likelihood of Atlantic hurricanes (see chapter 2.5), it is essential for CAT bond investors to understand how the formation dynamics of Atlantic hurricanes influence CAT bond returns. Therefore, an OLS regression addresses the second research question: *What impact does the El Niño-Southern Oscillation have on the Swiss Re US Wind Total Return Index?*

We run four versions of the regression, each of them having a different ENSO-related main variable of interest. The first two versions take into account two dummies that reflect, respectively, whether or not i) La Niña or a neutral phase was actually observed (ex-post approach)[3] ($D_{LaNiña_t}$ and $D_{Neutral_t}$) and ii) La Niña or a neutral phase was expected to occur (ex-ante approach)[4] ($D_{Prob(LaNiña)_t}$ and $D_{Prob(Neutral)_t}$).

[2] Since there are only a few CAT bonds that are triggered by a parametric trigger (see subchapter 2.1).

[3] The dummy variables are set to 1 when La Niña or a neutral phase, respectively, was observed and to 0 when El Niño was observed.

[4] The dummy variables are set to 1 when La Niña or a neutral phase, respectively, were expected to occur. Therefore, when the dummy variable of La Niña takes on the value of 1, the development of La Niña was more likely than the development of El Niño or a neutral phase (in relative terms, e.g., it takes on the value of 1 if the probability of La Niña is 40 percent and of the other two phenomena 30 percent, respectively). Similarly, when the dummy variable of

The regressions i) and ii) are comparable with each other since the variables of interest contain information solely on the question *if* La Niña or a neutral phase, respectively, have occurred or were expected to occur. The regressions models are:

i) $$ln(R_t) = \alpha + \beta_{LaNiña} \times D_{LaNiña_t} + \beta_{Neutral} \times D_{Neutral_t} + \sum_{j=1}^{7} \gamma_j \times CV_{j,t} + \varepsilon_t$$

ii) $$ln(R_t) = \alpha + \beta_{Prob(LaNiña)} \times D_{Prob(LaNiña)_t} + \beta_{Prob(Neutral)} \times D_{Prob(Neutral)_t} + \sum_{j=1}^{7} \gamma_j \times CV_{j,t} + \varepsilon_t$$

R_t stands for the Swiss Re US Wind Total Return Index at time t, however, we log-linearize it in order to make it suitable for a linear regression.

The other two versions combine the dummies from i) and ii) with a variable concerning the intensity and expected probability, respectively, by means of an interaction term: Version iii) reflects the SOI index, hence the intensity of La Niña or the neutral phase, respectively[5] ($D_{LaNiña_t} \times LaNiña_t$ and $D_{Neutral_t} \times Neutral_t$), and version iv) reflects the probability of La Niña or a neutral phase, respectively ($D_{Prob(LaNiña)_t} \times Prob(LaNiña)_t$ and $D_{Prob(Neutral)_t} \times Prob(Neutral)_t$), to occur[6]. Running these third and fourth versions of the regression enables us to draw a more nuanced picture of the interrelation between the ENSO and log-linearized Swiss Re US Wind Total Return Index. However, since the ENSO-related variables in the versions iii) and iv) display different information (intensity on the one hand and probability on the other hand), the outcome is not as easily comparable as the outcome of versions i) and ii).

Due to data limitations compared to the first chapter, we analyze a shorter period of time from January 2005 until December 2019. Since major hurricanes like Hurricane Katrina in 2005 and the destructive Atlantic hurricane season in 2017 are still included in this dataset, this caveat is bearable.

The regressions models are:

iii) $$ln(R_t) = \alpha + \beta_{LaNiña} \times D_{LaNiña_t} \times LaNiña_t + \beta_{Neutral} \times D_{Neutral_t} \times Neutral_t + \sum_{j=1}^{7} \gamma_j \times CV_{j,t} + \varepsilon_t$$

iv) $$ln(R_t) = \alpha + \beta_{Prob(LaNiña)} \times D_{Prob(LaNiña)_t} \times Prob(LaNiña)_t + \beta_{Prob(Neutral)} \times D_{Prob(Neutral)_t} \times Prob(Neutral)_t + \sum_{j=1}^{7} \gamma_j \times CV_{j,t} + \varepsilon_t$$

a neutral phase takes on the value of 1, the development of a neutral phase was more likely than the development of the El Niño or La Niña (in relative terms).

[5] Hence, the interaction term is 0 when El Niño has occurred and takes on actual SOI values that range between 0.5 and 2.9 (the highest peak reached in December 2010) when La Niña occurred and between -0.5 and 0.5 when a neutral phase has occurred.

[6] Hence, the interaction term is 0 when El Niño is expected to occur and takes on the probability of La Niña or a neutral phase, respectively.

where $\sum_{j=1}^{7} \gamma_j \times CV_{j,t} = \beta_H \times D_{H,t} + \beta_{HD} \times HD_t \times D_{H,t} + \beta_{ACE} \times ACE_t + \beta_{Seasonality} \times$

$$\times D_{Seasonality,t} + \beta_{CPI} \times CPI_t + \beta_{SP500} \times SP500_t + \beta_{LIBOR} \times LIBOR_t$$

The regressions are run four times. First, the versions i) - iv) are run without control variables, hence without the term $\sum_{j=1}^{7} \gamma_j \times CV_{j,t}$ (Model 1). Then, two groups of control variables are added separately (Model 2 and Model 3). Lastly, all control variables are integrated into the same model (Model 4).

The first group contains information on natural disasters and comprises the first four control variables. The interaction term $HD_t \times D_{H,t}$ accounts for the severity of hurricane damages in week t by combining the damages of the hurricane that made landfall in the USA and the dummy variable for a hurricane which is set to 1 when the recorded damage is greater than zero (and set to 0 when there is no recorded damage). Hence, the dummy variable $D_{H,t}$ accounts for hurricanes that caused damage in week t. The dummy variable $D_{Seasonality,t}$ accounts for the seasonality of Atlantic hurricanes and ACE_t accounts for the accumulated cyclone energy in week t. The first group of control variables is decisive since natural disaster-related factors are expected to have quite a huge impact on Swiss Re US Wind Index returns and could, thus, distort the ENSO-related coefficients if they are not accounted for in the regressions. When analyzing ENSO, it must be kept in mind that ENSO solely is an upstream phenomenon that arouses hurricanes which influence variables like the number of hurricanes that made landfall, hurricane damages, and ACE. Hence, even though the ENSO and the control variables do not show critical multicollinearity, the main variables of interest are likely to favor the severity of some control variables.

The second group contains information on the broader economy and the risk-free component of CAT bond spreads and comprises the last three control variables previously used in chapter 3.2.4, namely CPI_t, $SP500_t$ and $LIBOR_t$. Regarding the second group, we have also considered including 10-year US government bonds and corporate bonds, however, the model would suffer from multicollinearity. Parallel to the OLS regression in chapter 3.2.4, financial market variables are used as control variables given their potential influence on the return of CAT bonds.

In order to assure that the OLS regressions comply with their underlying assumptions, we run several diagnostic tests. The White test and Breusch-Pagan-Godfrey test detect heteroscedasticity and the Ljung-Box test detects autocorrelation in the data at hand. To account for this, we use robust heteroskedasticity and autocorrelation consistent covariance estimators.

4 Empirical Results

This chapter presents the results of the empirical analyses. It is divided into two major subchapters according to the two research questions.

4.1 Question 1: What Impact Do Financial Crises Have on the Swiss Re USD Total Return Index?

The outcome of the empirical models is presented in the same order as in chapter 3.2. A final conclusion that connects the sub-analyses concerning the first research question can be found in chapter 5.

4.1.1 Diversification Ratio

The diversification ratios resulting from the combination of different setups like maximized (MDP) or equal weights, excluding or including the Swiss Re USD Total Return Index and the number of assets are displayed in Tables A1, A2, A3, and A4 in the appendix. The smaller the denominator is, the higher the diversification ratio.

Including the Swiss Re USD Total Return Index lowers portfolio risk by between around 15 and 50 percent. Similarly, the weighted standard deviation declines by between around 20 and 40 percent. It is the lowest for the setup with maximized weights and including the Swiss Re USD Total Return Index, S&P 500, corporate bonds and government bonds. A comparison between the setups with equal weights shows that the diversification ratios become greater in absolute terms when incorporating the Swiss Re index and when adding more assets (from three to five assets case). The same comparison between the setups with maximized weights (MDP), which puts weights of around 60 percent on the Swiss Re index in the three and five assets case, shows that the diversification ratios become even greater in absolute terms. In relative terms, the three-asset case that includes the Swiss Re index with maximized weights shows the greatest increase in its ratio compared to the case that excludes the Swiss Re index (+21 percent). However, the MDP versions are likely to not correspond to most investors' strategies since they tend to put high weights on the Swiss Re index and low weights on the S&P 500. This notion is summed up in the compilation of the diversification effects (see Table 4). These insights support the hypothesis that the inclusion of CAT bonds in a portfolio serves as a diversifier, in this case in particular over the analyzed time period from January 2002 until January 2022.

Table 4: Comparison of Diversification Ratios

Assets	Weights	Diversification Ratio: Without Swiss Re USD Total Return Index	Diversification Ratio: With Swiss Re USD Total Return Index
S&P 500, Corporate Bond, Government Bond	MDP	1,359062	1,639834
	Equal Weights	1,274421	1,363592
S&P 500, Corporate Bond, Government Bond, Real Estate Index, Commodity Index	MDP	1,510495	1,765269
	Equal Weights	1,447325	1,508294

4.1.2 Mahalanobis Distance

All points in the graph exceeding the threshold set by the three MAD rule can be classified as outliers and hence as a financial crisis. The threshold for financial crises is 2.881. Therefore, a dummy variable of the value "1" is assigned to these points of time that exceed the value of 2.881 (see Figure A3 in the appendix).

The outliers correspond with breakdowns of most financial market indices. According to the Mahalanobis Distance measure, the economy recouped from the financial crisis of 2008 in March 2010. Between 2010 and the beginning of 2020, some outliers are sporadically detected. The measure indicates that the tension was high at the beginning of 2020 due to the outbreak of the COVID-19 pandemic. However, the crisis was not persistent over time, since, according to the measure at hand, the US-American economy recovered quite quickly.

To assure that the Mahalanobis Distance measure defines outliers similar to those that secondary sources have identified, we compare the obtained results with the distribution of the Federal Reserve's St. Louis Fed Financial Stress Index (Federal Reserve Bank of St. Louis, 2022). The Mahalanobis Distance measure and the FED's index deviate regarding the length of financial crises: Overall, the Federal Reserve index' dummy variable is set to 1 more frequently than the Mahalanobis Distance measure's dummy (see Figure A3 and A4 in the appendix). Since overall, the distributions resemble each other, we accept the Mahalanobis Distance measure outliers and hereinafter incorporate only the outliers detected by the Mahalanobis Distance measure in the empirical analysis.

4.1.3 GARCH-BEKK Model

Table A5 in the appendix shows the value of the parameters after the maximization of the sum of the log-likelihood function (see chapter 3.2.3) in the estimation of the multivariate GARCH – diagonal BEKK specification. The model is run three times and considers the relation between log-returns of the Swiss Re USD Total Return Index and the log-returns of the S&P 500, corporate bonds, and government bonds, respectively. The outcomes of the parameters are relatively similar in all three analyses.

The time-varying correlations between the Swiss Re USD Total Return Index and the S&P 500 index and the chosen representatives of corporate and government bonds, respectively, that result from these parameters are the main element of interest.

Swiss Re USD Total Return Index and S&P 500

The conditional variances of both indices are close to zero. However, the Swiss Re USD Total Return Index exhibits only one spike during the strong hurricane season in 2017, whereas the S&P 500 shows greater volatility (see Figure A5 and A6 in the appendix). The correlation between the indices shows that the indices are positively but weakly linked, which is in line with previous research (see chapter 2.4). However, over time the level of correlation oscillates. The lowest value of around 0.033 was reached in October 2008 and also at the beginning of 2020, the correlation rapidly declined in the short-term (see Figure 3). Therefore, contrary to previous research, the correlation became weaker at the beginning of financial crises. The highest correlation value of 0.28 was reached in November 2017 (see Figure 3).

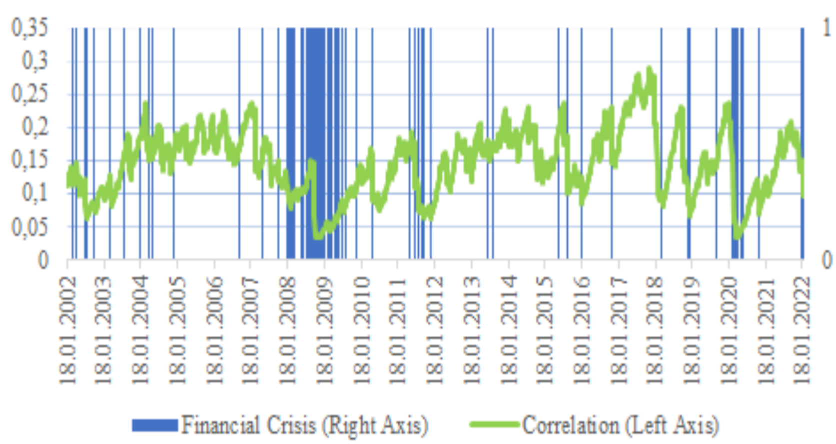

Figure 3: Correlation between Swiss Re USD Total Return Index and S&P 500 Index

Swiss Re USD Total Return Index and Corporate Bonds

Corporate bonds show a similar pattern and level of conditional variance compared to the conditional variance of the S&P 500 index – for example, the two major spikes occurred between 2008 and 2009 and between 2020 and 2021 (see Figure A6 and A8 in the appendix). The Swiss Re USD Total Return Index and corporate bonds are weakly positively correlated, however at lower levels than the correlation between the Swiss Re Index and the S&P 500 index. The correlation fluctuates between 0.0023 and 0.037. Similar to the S&P 500-related correlation, financial crises seem to lower the correlation (see Figure 4).

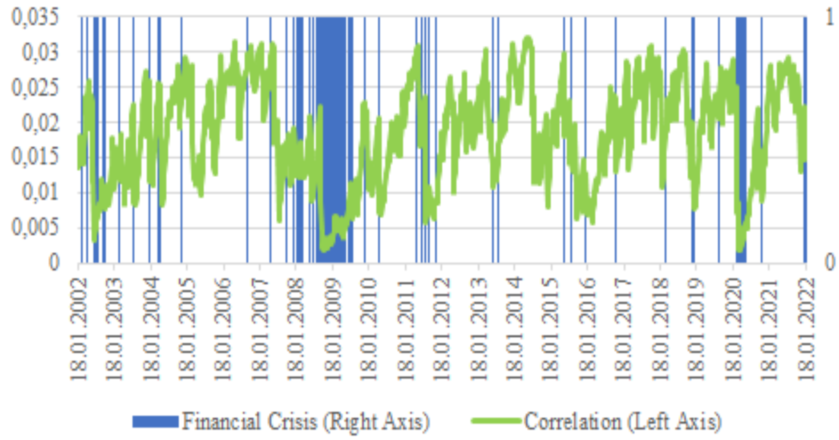

Figure 4: Correlation between Swiss Re USD Total Return Index and Corporate Bonds

Swiss Re USD Total Return Index and Government Bonds

The government bonds show a different pattern than the S&P 500 and corporate bonds: The conditional variance peaks only between 2020 and 2021, however at comparatively higher levels (see Figure A10 in the appendix). The time-varying correlation ranges between 0.0015 and 0.017. This is lower than in the case of the corporate bonds and decisively lower than in the S&P 500 case. Similar to the first two cases, the correlation weakens during financial crises (see Figure 5).

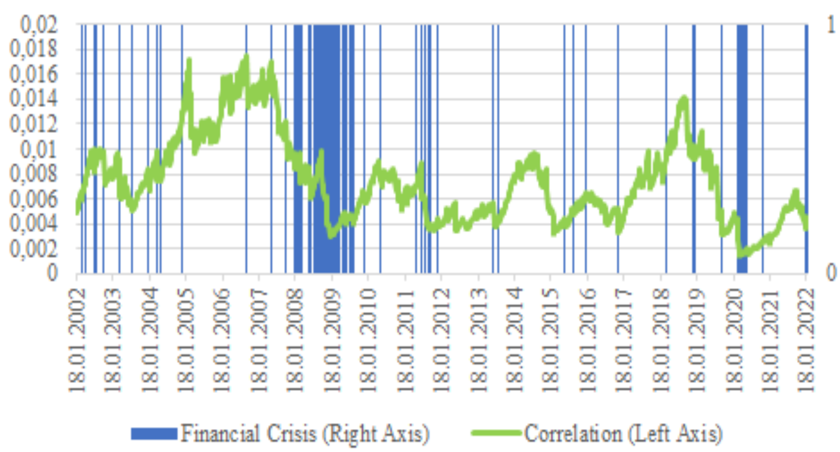

Figure 5: Correlation between Swiss Re USD Total Return Index and Government Bonds

Interpretation

The time-varying correlations according to the GARCH-BEKK model correspond with findings of previous research that correlation is low, especially regarding CAT bonds and government and corporate bonds, respectively (see chapter 2.4). However, contrary to what previous research implies, during periods of financial crises that span over several weeks, correlations seem to decline. All three scenarios present similar trends in how the correlation evolves. For example, the respective correlation patterns overall increase until 2007, subsequently decline (even before the occurrence of financial crises), and reach a minimum at the end of 2008, hence during the financial crisis of 2008. Over the years, this parabolic pattern repeats and alternates, showing moments of lowest correlation value at times of financial crisis, in particular at the beginning of 2020 at the breakout of the global COVID-19 pandemic. After financial crises, correlation levels recover quickly to pre-crisis levels (except for the government bond-case).

The analysis at hand implies that the major factor that links CAT bonds to financial markets, namely the trust accounts that invest the bonds' principals in the capital market, does not have an effect as pronounced as assumed. We assume that the elevated risk attached to CAT bonds during financial market movements did not affect the whole index, but rather individual CAT bonds – especially for example having in mind that in 2008 only four CAT bonds were at risk due to the Lehman brother bankruptcy (see chapter 2.4). This assumption is supported by the time-varying evolution of the Swiss Re USD Total Return Index and the S&P 500. In non-crisis times, both follow a long-term upward trend with little volatility. During the financial turmoils in 2008 and 2020, however, the S&P 500 showed a temporal breakdown, whereas the Swiss Re index continued its long-term upward trend. Therefore, occasional peaks in volatility (during financial crises, but also during "normal" financial market conditions) do not occur at the same time (Figure A5 and A6 in the appendix) and seem to occur quite independently of each other.

When analyzing correlations against the background of financial market crises, one should not leave unmentioned a possible case that results in a higher correlation but that roots in two independent external developments: For example, natural disasters can have a decisive impact on the Swiss Re USD Total Return Index and at the same time, financial markets experience turbulence due to a cause that is unrelated to natural disasters. Moreover, natural disasters can impact both the Swiss Re Index and financial markets at the same time. According to a study by S&P Global Ratings, 15 percent of companies that are displayed by the S&P 500 index report that their earnings have been impacted by weather events. The study, however, suffers from low disclosure rates (Whieldon, 2018), which makes a higher dimension of the impact probable. Since the respective conditional variances do not peak at the same time, in the analysis at hand we do not have to be cautious about these possible skewed correlations.

Overall, the detected correlations imply that the Swiss Re Index has offered a diversification benefit in the long term. This effect has been higher for corporate bonds and government bonds than for S&P 500.

Moreover, correlations dropped during financial crises, in particular in 2008 and in 2020 with the outbreak of the COVID-19 pandemic, which has strengthened the CAT bonds' diversifying qualities.

4.1.4 OLS Regression

The OLS regression is run by means of financial crisis dummies that stem from the Mahalanobis Distance measure. To validate the dummies, we also run the regression by means of financial crisis dummies that stem from the FED indicator. Since the output of the two versions resembles each other, we only display the version that is based on the Mahalanobis Distance measure.

One caveat related to the interpretation of the outcome must be kept in mind: The outliers of the Mahalanobis Distance measure are more nuanced than most other measures. However, the subsequent dispersion of the outliers makes the financial crisis dummies change their values frequently. Investors are unlikely to change their risk assessment and behavior at the same pace. Therefore, financial crises do not necessarily show immediate repercussions in CAT bond returns and are more likely to manifest over financial crises that span several weeks.

Table 5 shows that the level of significance of the financial crisis dummy depends on the control variables that are applied. Model 5 accounts for all control variables and displays an insignificant coefficient of the financial crisis dummy. Therefore, on average and ceteris paribus, there is no significant impact of financial crises on the log-linearized Swiss Re USD Total Return Index.

Table 5: Results of OLS Regressions Using Mahalanobis Distance

Mahalanobis	***Model 1***	***Model 2***	***Model 3***	***Model 4***	***Model 5***
Financial Crisis	-0,1126**	-0,1220***	0,0089	-0,1130**	0,0011
	(0,0650)	(0,0023)	(0,0020)	(0,0733)	(0,0313)
CPI		-0,0320***			-0,0570***
		(0,0020)			(0,0129)
S&P 500			0,0003***		0,0004***
			(0)		(0)
LIBOR			-0,0832***		-0,0617***
			(0,0006)		(0,0084)
Total Damages				-0,0005	0,0001
				(0)	(0)
Constant	5,3659***	5,4366***	4,8482***	5,3671***	4,8912***
	(0,0406)	(0,0079)	(0,0099)	(0,0580)	(0,0515)
Adjusted R-Squared	0,0048	0,0162	0,7510	0,0041	0,7820
Observations	1048	1048	1048	1048	1048

Standard errors in parentheses

* 10% significance level, **5% significance level, ***1% significance level

The estimated coefficient of the dummy variable for financial crisis effects without accounting for control variables (Model 1) is -0.1065[7] and is significant at the 5% significance level. This implies that the actual occurrence of the financial crisis has a small, but significant negative effect on the Swiss Re Index. When controlling for the US-American CPI (Model 2), the adjusted coefficient of the financial crisis dummy variable decreases only a little to -0.1149 at the 1% significance level. The respective adjusted R^2 rises a bit but remains low.

When controlling for the second group of control variables, 1-Month LIBOR and S&P 500, the adjusted R^2 increases decisively to 0.75. This suggests the S&P 500 and the 1-Month LIBOR explain most of the variation of the log-linearized Swiss Re index. Furthermore, both control variables stand out: They are significant at the 1% significance level and the adjusted LIBOR coefficient of -0.0868[8] is comparatively high in absolute terms. The dummy variable for the financial crisis is now insignificant. This might in part be due to the correlation between S&P 500 and the log-returns of the Swiss Re USD Total Return Index detected by the GARCH-BEKK model in chapter 4.1.3: The positive S&P 500 adjusted coefficient of 0.0004 in the analysis at hand might capture the effect of the positive and low overall correlation. Following this thought, the dummy for financial crisis does not absorb the effect of the low correlation in times of crisis anymore, which deprives the variable of the channel through which the financial crisis-effect in parts is expected to take effect. Moreover, in absolute terms, LIBOR has a decisively greater impact on the log-linearized Swiss Re USD Total Return Index than S&P 500 and therefore, is likely to induce large parts of the change in the coefficient of the dummy variable of financial crisis. Assuming that the money market LIBOR rate on average has been the most decisive reference rate for CAT bonds' trust account returns (chapter 2.1), the great influence makes sense. However, the negative sign is unexpected and is assessed further in the analysis of the second research question (chapter 4.2.2) since its OLS regression shows similar results.

When controlling for total damages (Model 4), the coefficient estimate of the control variable is insignificant at any standard level. The adjusted coefficient of the dummy variable for the financial crisis is -0.1068 and is significant at the 5% significance level. The adjusted R^2 decreases decisively to 0.0041. Therefore, out of all control variable groups, the second group has the most decisive impact on the log-

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[7] The interpretation after applying a common adjustment to facilitate the interpretation of dummy variables ($e^{\hat{\beta}} - 1$) is: The presence of a financial crisis decreases the Swiss Re USD Total Return Index by 0.1065 percent (ceteris paribus and on average) compared to the absence of a financial crisis.

[8] The interpretation after applying a common adjustment to facilitate the interpretation of log-linear models ($e^{\hat{\beta}} - 1$) is: an increase of 1 unit in LIBOR will decrease the Swiss Re USD Total Return Index by 0.0868 percent (ceteris paribus and on average).

linearized Swiss Re USD Total Return index and their model fit is the best. The reverse case applies to the third group. This finding is unexpected and is assessed further in the analysis of the second research question (chapter 4.2.2), since its OLS regression shows similar results.

Ultimately, we account for all control variables (Model 5). Similar to Model 3, the coefficient of the dummy of the financial crisis is not significant at any significance level, while except for total damages, the control variables are significant at the 1% significance level.

To conclude, accounting for all control variables (Model 5), the occurrence of financial crises does not have an impact on the log-linearized Swiss Re USD Total Return Index, however, when not accounting for S&P 500 and LIBOR (Model 1, Model 2 and Model 4) the impact is negative and significant at the 5% significance level.

4.2 Question 2: What Impact Does the El Niño-Southern Oscillation Have on the Swiss Re US Wind Total Return Index?

First, the output of the OLS regressions is analyzed (chapter 4.2.1). Since some coefficients and patterns are striking, they require further explanation (chapter 4.2.2).

4.2.1 Analysis

The respective "Model 1" in Table 6 and 7 (which correspond to the regression versions i), ii), iii) and iv)) display the ENSO-related effects without accounting for control variables. They are significant at the 1%- or 5% significance level. The negative signs suggest that neutral phases and La Niña have an adverse impact on Atlantic hurricane CAT bonds' returns. The dummy-related versions i)'s adjusted coefficients are -0.068 and -0.1093 for the neutral phase dummy variable and the La Niña dummy variable, respectively. The dummy-related versions ii)'s adjusted coefficients are -0.2099 and -0.2293 for the neutral phase dummy variable and the La Niña dummy variable, respectively. The outcomes suggest the forecast of the neutral phase has a more pivotal negative impact on the index than the actual observed neutral phase.

The intensity-related versions iii)'s adjusted coefficient is -0.1582 and -0.0723 for the neutral variable and La Niña variable, respectively. The probability-related versions iv)'s adjusted coefficients are -0.3857 and -0.3564 for the neutral phase variable and La Niña variable, respectively. All the coefficients are significant at the 1% level. Versions iii) and iv) support the finding of the preceding two versions, namely a more pivotal negative impact of the forecast. However, the comparison is more skewed since the coefficients of versions iii) and iv) measure different factors (intensity and probability). However, the comparison of version ii) and version iv) suggests that the probability of the neutral phase or La Niña to occur (version iv) has a greater impact on the log-linearized Swiss Re US Wind Total Return Index than the information if the neutral phase or La Niña generally are expected to occur (version ii). The low adjusted R^2s in all versions indicate that the ENSO-related variables cannot explain a large proportion of the variance of the Swiss Re Index.

Adjusted R^2 does not rise decisively when controlling for the first group of control variables (Model 2). Therefore, the ENSO-related variables in Model 2 do not seem to have absorbed much further disaster-related information. Moreover, natural disaster-related control variables are not significant in most versions. Between Model 2 and Model 3, the adjusted R^2s increase decisively to between 0.93 and 0.94. This suggests that financial market variables capture the variation in returns well. The change of signs and significance (some coefficients in particular with regard to neutral phases become insignificant) of the ENSO-related variables is striking. We refrain from displaying the ENSO-related adjusted coefficients of Model 2 and Model 3 in a detailed manner, since ultimately, the coefficients of Model 4 are the least unadulterated and hence, are of greatest importance. In all versions of Model 3, the adjusted coefficients of 1-month LIBOR stick out: They amount to between -0.1001 and -0.1029 in the four versions and are significant at the 1% significance level.

Table 6: Results of OLS Regressions i) and ii)

Version i) Dummy SOI	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Dummy Neutral	-0,0699**	-0,0735**	0,01309	0,0139*
	(0,0900)	(0,0885)	(0,0176)	(0,0174)
Dummy La Niña	-0,1157***	-0,1133***	0,0446***	0,0466***
	(0,1131)	(0,1126)	(0,0310)	(0,0311)
Dummy Hurricanes		0,0071		-0,0434**
		(0,1009)		(0,0175)
Hurricane Damages (HD)		0,0019		0,0006**
		(0,0016)		(0,0004)
ACE		-0,0010		-0,0005**
		(0,0011)		(0,0003)
Dummy Seasonality		0,03206		0,02444***
		(0,0532)		(0,0169)
S&P 500			0,0004***	0,0004***
			(0)	(0)
CPI			-0,0078***	-0,0059**
			(0,0134)	(0,0125)
LIBOR			-0,1063***	-0,1066***
			(0,0125)	(0,0120)
Constant	5,5537***	5,5436***	4,8852***	4,8729***
	(0,1081)	(0,1090)	(0,0583)	(0,0637)
Adjusted R-Squared	0,0131	0,0145	0,9340	0,9360
Observations	782	782	782	782
Version ii) Dummy FORECAST	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Dummy Neutral	-0,2357***	-0,2281***	0,0594***	0,0630***
	(0,1172)	(0,1206)	(0,0348)	(0,0338)
Dummy La Niña	-0,2604***	-0,2643***	0,0008	-0,0005
	(0,1009)	(0,0799)	(0,0137)	(0,0140)
Dummy Hurricanes		0,0179		-0,0437***
		(0,0958)		(0,0194)
Hurricane Damages (HD)		0,0022**		0,0007**
		(0,0017)		(0,0004)
ACE		-0,0006		-0,0005***
		(0,0010)		(0,0002)
Dummy Seasonality		0,0387		0,0284***
		(0,0547)		(0,165)
S&P 500			0,0004***	0,0004***
			(0)	(0)
CPI			-0,0039	-0,0017
			(0,0112)	(0,0103)
LIBOR			-0,1087***	-0,1090***
			(0,0116)	(0,0112)
Constant	5,6784***	5,6623***	4,8972***	4,8844***
	(0,0831)	(0,0724)	(0,0547)	(0,0585)
Adjusted R-Squared	0,0989	0,1020	0,9352	0,9370
Observations	782	782	782	782

Standard errors in parentheses

* 10% significance level, **5% significance level, ***1% significance level

Table 7: Results of OLS Regressions iii) and iv)

Version iii) Observed SOI	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Neutral	-0,1722***	-0,1766***	0,0174	0,0221
	(0,1451)	(0,1457)	(0,0345)	(0,0314)
La Niña	-0,0756***	-0,0726***	0,0189***	0,0213***
	(0,0468)	(0,0499)		(0,0190)
Dummy Hurricanes		-0,0144		-0,0417**
		(0,1024)		(0,0199)
Hurricane Damages (HD)		0,0020*		0,0006**
		(0,0017)		(0,0003)
ACE		-0,0008		-0,0005***
		(0,0010)		(0,0002)
Dummy Seasonality		0,0153***		0,0275***
		(0,0485)		(0,0190)
S&P 500			0,0004***	0,0004***
			(0)	(0)
CPI			-0,0063**	-0,0046
			(0,0125)	(0,0117)
LIBOR			-0,1068***	-0,1069***
			(0,0127)	(0,0124)
Constant	5,5227***	5,5177***	4,8936***	4,8787***
	(0,0846)	(0,0981)	(0,0609)	(0,0673)
Adjusted R-Squared	0,0279	0,0347	0,9330	0,9350
Observations	782	782	782	782
Version iv) FORECAST	***Model 1***	***Model 2***	***Model 3***	***Model 4***
Neutral	-0,4873***	-0,4924***	-0,0163	-0,0189
	(0,1981)	(0,1618)	(0,0353)	(0,0363)
La Niña	-0,4407***	-0,4261***	0,0904***	0,0963***
	(0,1981)	(0,2232)	(0,0557)	(0,0546)
Dummy Hurricanes		-0,0182		-0,0449***
		(0,0918)		(0,0203)
Hurricane Damages (HD)		0,0022**		0,0007**
		(0,0016)		(0,0004)
ACE		-0,0006		-0,0005***
		(0,0010)		(0,0002)
Dummy Seasonality		0,0389		0,0283***
		(0,0558)		(0,0170)
S&P 500			0,0004***	0,0004***
			(0)	(0)
CPI			-0,0030	-0,0008
			(0,0104)	(0,0096)
LIBOR			-0,1084***	-0,1088***
			(0,0118)	(0,0113)
Constant	5,6841***	5,6677***	4,9057***	4,8931***
	(0,0936)	(0,0751)	(0,0512)	(0,0545)
Adjusted R-Squared	0,1150	0,1180	0,9350	0,9360
Observations	782	782	782	782

Standard errors in parentheses

* 10% significance level, **5% significance level, ***1% significance level

The ultimate Model 4 which displays the most “pure” ENSO-related effects by accounting for both groups of control variables shows similar results to Model 3 (apart from occasional differences in significance levels) concerning the ENSO-related variables’ coefficients, the second control group’s coefficients and the adjusted R^2. The significant adjusted coefficients of the neutral phase in version i) are 0.01399 at the 10% significance level and in version ii) 0.065 at the 1% significance level. The observed intensity of the neutral phase (version iii) and the level of probability of the neutral phase (version iv) are not statistically significant. The significant adjusted coefficients of La Niña in version i) are 0.0477, in version iii) 0.02153 and in version iv) 0.1011, all at the 1% significance level. The probability of La Niña (version iv) has a higher effect on the log-linearized Swiss Re US Wind Total Return Index than the other versions. Overall, except for version ii), La Niña has a higher impact on the Swiss Re US Wind Total Return Index than the neutral phase.

To conclude, when accounting for all control variables, the significant ENSO-variables have a positive, but small impact on the log-linearized Swiss Re US Wind Total Return Index of up to around or below 0.1 percent. Other factors like the LIBOR have a stronger impact (in absolute terms).

4.2.2 Interpretation

To come to an understanding of the mechanisms and market developments that explain the regression output, the main reference are the four versions of Model 4 (given that they capture the most unadulterated effect of the ENSO-related variables).

Before discussing the “pure” ENSO-related coefficients of Model 4, they are assessed against the background of the two groups of control variables. This is important due to the direct links between the ENSO-related variables and the control variables.

4.2.2.1 ENSO-related Variables and Natural Disaster-related Control Variables

According to the dataset at hand, as expected all Atlantic hurricanes have occurred during either a neutral phase or La Niña. Therefore, there is a direct relation between ENSO and Atlantic hurricanes, that ultimately have the power to trigger CAT bonds. On that basis, two main indirect mechanisms link the neutral phase and La Niña with the Swiss Re US Wind Total Return Index: On the one hand, prices can break down due to a supply- and demand imbalance in the wake of increasing hurricane risk and hence, default risk (see chapter 2.5), which is expected to influence price returns negatively. On the other hand, as an antagonist, both risk premiums and the expected loss estimate of newly issued CAT bonds can rise which would result in increased spreads and coupon returns (see chapter 2.3). The variables that proxy the enhanced risk attached to the occurrence or likely occurrence of Atlantic hurricanes are captured by the natural disaster-related control variables.

The low jump in adjusted R^2s from Model 1 to Model 2 indicates that little variation in the Swiss Re is captured by natural disaster-related control variables. Nonetheless, as expected most of the control variables show a significant impact on the Swiss Re US Wind Total Return Index in Model 4.

In all versions, as expected the occurrence of hurricanes on average has a negative impact on CAT bond returns. Since hurricanes are only predictable in the very short-term (Huang et al., 2021; AON Benfield, 2022), the variable rather captures the short-term behavior of investors and sponsors which manifests itself in changing supply and demand patterns, which in turn has a short-term impact on price returns. The occurrence of hurricanes does not imply in a deterministic manner that CAT bonds are triggered – the variable only entails the information that a hurricane has made landfall in some part of the USA. Hence, the coefficient estimates of the occurrence of hurricanes are likely to be weakly related to the direct risk that specific CAT bonds are triggered, but rather reflect an increase in the overall level of risk and uncertainty.

The coefficients of the related variable of hurricane damages, however, are low. This is likely to stem from the fact that only a fraction of outstanding CAT bonds has actually been triggered by hurricanes: In order for hurricanes to actually trigger Atlantic hurricane CAT bonds, they must be covered by the terms and conditions previously agreed on in the reinsurance contract. This has rarely been the case. Hurricane Katrina (2005) caused one of the two major peaks in hurricane damage during the observed period of time, but only one CAT bond was triggered (Dieckmann, 2008). The situation was different at the beginning of the hurricane season in 2017 when the Swiss Re US Wind Total Return Index showed a short-term breakdown in returns: 19 CAT bond tranches encompassing 1.4 billion USD were triggered (Polacek, 2018). However, returns recovered even while further hurricanes occurred. Hence, even the triggering of CAT bonds did not cause a lasting breakdown of the Swiss Re US Wind Total Return Index (see Figure A11 in the appendix). This quick recovery even during the hurricane season could justify the positive coefficients of hurricane damages. Overall, there seems to be a rather weak link between CAT bonds' performance and Atlantic hurricanes. Further research that includes lagged hurricane damages is required. Hurricanes damages are reported with a temporal lag due to lengthy loss assessment procedures which makes it difficult for investors to adjust their trading behavior at the time the respective hurricane causes destruction.

The accumulated cyclone energy (ACE) does not have a great impact on the log-linearized return index either. Similar to hurricane damages, this might be due to a pronounced link to the occurrence of hurricanes, but it is a weak link to an actual trigger of CAT bonds. However, as expected and different from hurricane damages, the respective coefficients are negative.

While the occurrence of hurricanes has the greatest negative impact on the Swiss Re US Wind Total Return Index, seasonality has the greatest positive impact and is significant at the 1% significance level in all versions. Therefore, the anticipation of higher hurricane risks (see chapter 2.5) is decisive and since the coefficient estimates are positive, seasonality seems to express itself through the channel of rising spreads (and possibly also rising prices by the end of the hurricane season).

4.2.2.2 ENSO-related Variables and Financial Market-related Variables

The adjusted R^2s change decisively between Model 1 and Model 3. Depending on the version, in Model 3 which accounts for the financial market-related control variables, it amounts to between 0.93 and 0.94. This is mainly due to the inclusion of the 1-Month LIBOR, the representative of the risk-free component of CAT bond coupons. The inclusion of financial market-related variables causes the change in signs of ENSO-related variables from Model 1 and 2 to Model 3 and 4. This, too, is in large part likely to be due to the inclusion of the 1-Month LIBOR.

It is striking that contrary to the coefficients' implication, basic intuition would rather suggest a positive impact on returns (Patel, 2015), especially since the coupon return makes up the major share of total return over the observed period of time[9]. Since the LIBOR is decisively more volatile than the log-linearized Swiss Re US Wind Total Return Index, an average overall negative coefficient is not unreasonable from a statistical point of view. However, the spreads must have shown a more or less inverse development to LIBOR (at least until 2017) to facilitate a quite constant upward trend in coupon returns (see Swiss Re US Wind Coupon Return Index, Bloomberg ticker: SRUSWCPN). We do not have comprehensive data concerning spreads at our disposal. Therefore, analyzing and verifying this matter is up to further research. Moreover, one must keep in mind that LIBOR solely is used as a proxy for the average risk-free part of the coupon of the Swiss Re hurricane-exposed CAT bonds. Since the share of CAT bonds that have followed the LIBOR rate is inconclusive (e.g., some CAT bonds follow the rates of the US-American Treasury Bill instead and some CAT bonds' trust accounts paid capital market returns instead of risk-free returns), the control variable's informative value might be skewed.

The S&P 500 has a low, but positive impact on the Swiss Re US Wind Total Return Index. This goes hand in hand with the insights of chapter 4.1.3 (that however refers to the Swiss Re USD Total Return Index) which point towards a low positive correlation between Wind CAT bonds and the S&P 500. The US-American Consumer Price Index does not determine the development of the Swiss Re US Wind Total Return Index.

[9] This is an assessment that is based on the comparison of the Swiss Re US Wind Total Return Index and Swiss Re US Wind Coupon Return Index: The latter follows total returns quite closely, especially until 2017.

4.2.2.3 ENSO-related Variables

The most “pure” ENSO-related coefficients of Model 4 are expected to be insignificant since the ENSO does not directly impact the returns of CAT bonds, but does so indirectly through the described channels of the control variables. Therefore, if one would account for all determinants of the return in separate control variables, the ENSO-related variables should be neglectable.

The regressions at hand cannot do so – for example, expected losses which are a decisive determinant of the coupon apart from the LIBOR (see chapter 2.3) are not accounted for due to lack of data. Therefore, the ENSO-related variables are likely to absorb the (probably positive) effect of expected losses. It is left for further research to single out the effect of expected losses. Further elements that potentially influence the risk premium and supply-demand patterns (see chapter 2.3) are not accounted for in the model but might on average influence CAT bond returns as well. Risk premiums might in particular be reflected by the forecasts of the ENSO-related variables (which would go hand in hand with the relatively high estimated coefficients of the neutral phase in version ii) and of La Niña in version iv). The prospect of especially a neutral phase, but also of La Niña, raises the likelihood of the formation of Atlantic hurricanes and can thereby influence not only expected losses but also risk premiums (see chapter 2.3). Since the forecast is available up to nine months in advance, sponsors and investors can adjust their expectations regarding an overall enhanced risk of hurricanes to occur (not regarding the specific trajectory and force of a particular hurricane) and their behavior in the mid-term. With rising spreads, the coupon return is positively influenced. Against the background of coupon returns’ significant impact on total returns, the positivity of the ENSO-related variables makes sense. This hypothesis must, however, be verified by further research. However, it is uncertain to what extent ENSO actually influences the estimates of expected losses and risk premiums on the index level, since, for example, the expected loss estimate most often is not adjusted during the term of the CAT bond (Edesess, 2015). Since we do not have a comparison of newly issued CAT bonds vs. “old” outstanding CAT bonds during hurricane seasons at our disposal, we cannot make a nuanced statement regarding the developments of coupon returns.

Moreover, elements that are related to risk premiums and expected losses and that are likely to be absorbed by the significant forecast coefficients of ENSO-related variables are not necessarily linked to ENSO (not even indirectly). For example, coupons seem to have risen constantly regardless of the state of the ENSO cycle (see Swiss Re US Wind Coupon Return Index, Bloomberg ticker: SRUSWCPN), risk premiums do not linearly depend on expected losses (see chapter 2.3) and spreads do not correlate with the peaks in hurricane damages.

Furthermore, according to the constructed datasets at hand hurricanes made landfall during La Niña or neutral phases which supports the finding of geophysical dependence of Atlantic hurricanes on the ENSO (see chapter 2.5). However, La Niña or a neutral phase solely increase the likelihood of hurricanes but are not deterministic. Hence, the points of time prevail in which La Niña or a neutral phase have occurred, but no hurricane has made landfall and the CAT bond market has not shown any striking development. This makes it hard to find a causal relationship between the dependent and independent variables of interest. Consequently, it is not feasible to draw provable conclusions from the statistically significant ENSO-related coefficients at hand. Moreover, the coefficient estimates and the significance level of La Niña or a neutral phase change depend on the version. Therefore, even though hurricane risk generally is higher during neutral phases, it cannot identify any corresponding pattern in the coefficient estimates.

5 Conclusion

To investigate the impact financial crises have on the Swiss Re USD Total Return Index, we deployed several methods. By computing diversification ratios, we have taken a step back to confirm the common notion that CAT bonds are a well-suited instrument for diversification in a portfolio. Then we have turned towards the impact of financial crises on the performance of CAT bonds. For this, the Mahalanobis Distance measure has defined periods of financial crisis. Its outliers indicate that financial crises that span over several weeks occurred in 2008 and – for several weeks – also in 2020 when the COVID-19 pandemic broke out.

The main channels that connect the CAT bond market with financial markets are the bonds' trust account and their principal that is invested in the capital market. However, according to the GARCH-BEKK model, this channel has not shown strikingly pronounced repercussions on CAT bond returns. The correlation between CAT bonds and equity and bonds has even dropped (from mostly already low levels) in times of financial market turmoil in 2008 and 2020. This has made CAT bonds a well-suited diversifying instrument in times of crisis. The OLS regression underlines that in particular after controlling for the S&P 500 and LIBOR (hence the two main financial market indices that are likely to influence the trust accounts' return and therefore the coupon), financial crises on average do not have a significant impact on CAT bond returns (compared to "normal" market conditions). Therefore, over the observed period of time, the short-term decline in correlation and the overall low correlation are likely to not have been decisive factors that have influenced the long-term quite stable total returns. As discussed in chapter 2, total returns are determined by other elements apart from the trust accounts' returns as well, for example by spreads and price returns.

To investigate the impact the ENSO has on the Swiss Re US Wind Total Return Index, we deployed an OLS model. The ENSO cycle was expected to impact Atlantic hurricane CAT bonds' returns indirectly via several channels of the control variables. Hence, the ENSO-related coefficients were expected to absorb effects that we could not account for by means of control variables. Therefore, significant positive variables, which appear especially regarding the ENSO forecast variables, indicate that elements like expected loss and risk premiums are absorbed by ENSO-related coefficients. Since these effects are not verifiable without further investigation and a direct relation between the ENSO and CAT bond returns is not likely, the statistically significant coefficients cannot provide further insights into the mechanisms of CAT bonds. However, insignificant coefficients suggest that natural disaster-related control variables explain the link between ENSO, the trigger of CAT bonds (incurred losses), and CAT bond returns. In particular, the occurrence of hurricanes and seasonality influence the Swiss Re US Wind Total Return Index in negative and positive ways, respectively. We cannot deduce whether the neutral phase or La Niña determine the log-linearized Swiss Re US Wind Total Return Index more. It is left to further research to investigate the second research question with more comprehensive data (e.g., expected loss and risk premiums) and more sophisticated models.

Bringing the findings of the two research questions in line is tedious because they refer to two different Swiss Re CAT bond indices. However, since the US Wind Total Return Index follows the overall trend of the USD Total Return Index – despite being a bit more volatile and yielding higher average returns over time (see Figure 2) – we attempt to draw a general conclusion. However, one must consider that the research questions refer to historical data. Therefore, they only give an indication of future developments under the strong assumption that underlying factors like the structure of CAT bonds, determinants of price and coupon returns, and natural disaster-related physical dynamics do not change decisively. Despite these caveats, one can infer that the *simultaneous* occurrence of a neutral phase or La Niña and of a financial crisis can have indirect repercussions on the CAT bond market. In a scenario where CAT bond-triggering Atlantic hurricanes (that are induced by the ENSO) make landfall and at the same time a financial crisis occurs, according to our analysis, the financial crisis does not work as a catalyst of enhanced risk. On the contrary, in times of crisis, the correlation between the log-returns of the Swiss Re USD Total Return Index and the three selected asset classes has decreased, which has detached CAT bond returns from financial market risks. Moreover, natural disasters seem to have a rather small impact on CAT bond returns and affect individual CAT bonds rather than the whole CAT bond market. Therefore, in particular CAT bonds whose predefined trigger mechanisms make them as little exposed to natural disaster risks as possible can on average be considered a rather "safe" asset – both from a financial market perspective and from a natural disaster perspective. Next to the analyzed correlation and the occurrence of natural disasters, factors like the LIBOR are most decisive for CAT bond returns. However, despite good fits of the models, none of the analyzed variables shows a high estimated coefficient. Therefore, on the index level CAT bonds promise stable long-term returns while being decoupled from the development of major risk categories.

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7 Appendix

A1: Explanation of Modeling Expected ENSO:

The Columbia Climate School's International Research Institute for Climate and Society (a cooperation partner of the NOAA's Climate Program Office) publishes an ENSO forecast which is updated on the second Thursday of every month. It estimates the probabilities of El Niño, neutral phases and La Niña for three months periods (e.g., January-February-March, February-March-April, …) and includes forecasts until 9 or 10 months ahead. In order to obtain three-month forecasts, we take the average for each forecasted three-month period of the values published in each month of a respective year, which gives us the average forecast of a three-month period of a year (e.g., to obtain the average of the three-month period January-February-March of 2015, we take the average of all forecasts of this time period that were published in 2015). In order to then obtain monthly average values, we again take the average of the three-month periods which includes the respective month (e.g., to obtain the forecast of January 2015, we calculate the average of the three-month periods November 2014 - December 2014 - January 2015, December 2014 - January 2015 - February 2015, and January 2015 - February 2015 - March 2015) (National Weather Service/NOAA, 2022).

Figure A1: Catastrophe Bonds & ILS Risk Capital Issued & Outstanding by Year (Artemis, 2022a)

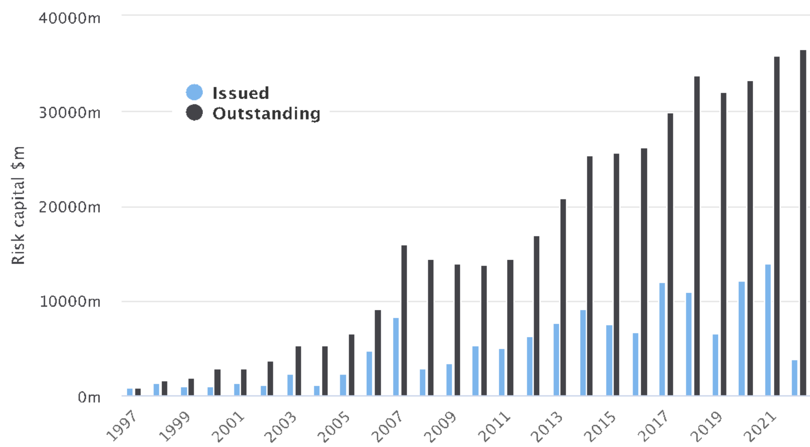


Figure A2: Components of CAT Bond Coupon (Own Depiction)

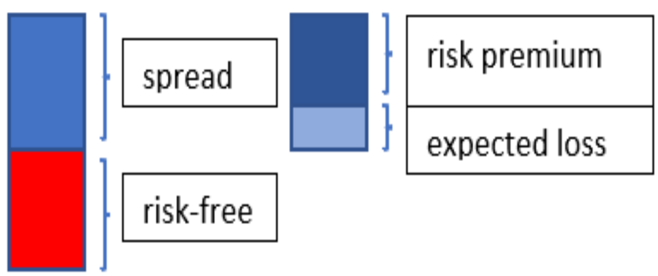


Figure A3: Mahalanobis Distance Measure Distribution with a Threshold of 2.881

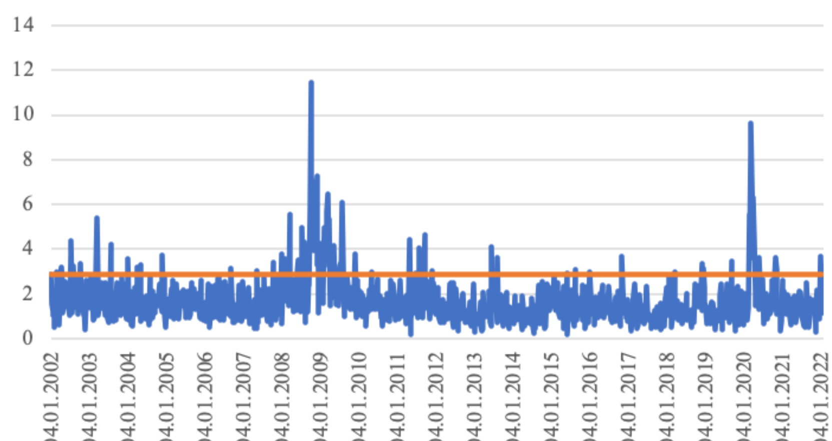
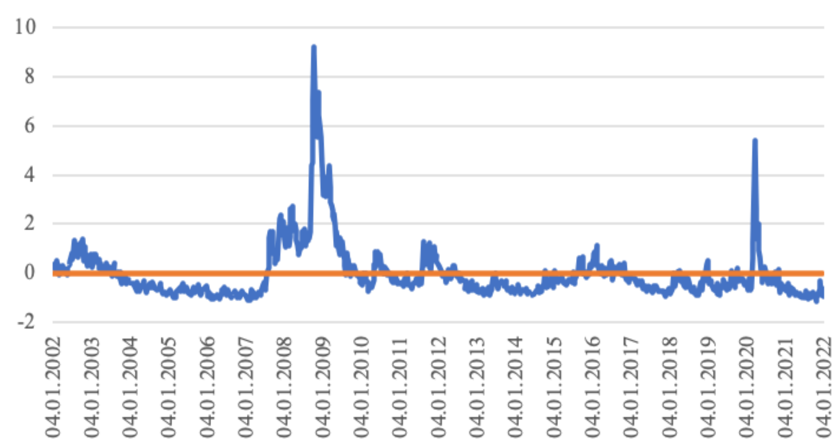


Figure A4: Federal Reserve's St. Louis Fed Financial Stress Index Distribution with a Threshold of 0



GARCH-BEKK: Swiss Re USD Total Return Index and S&P 500

Figure A5: Conditional Variance of Swiss Re USD Total Return Index (Sigma 11)

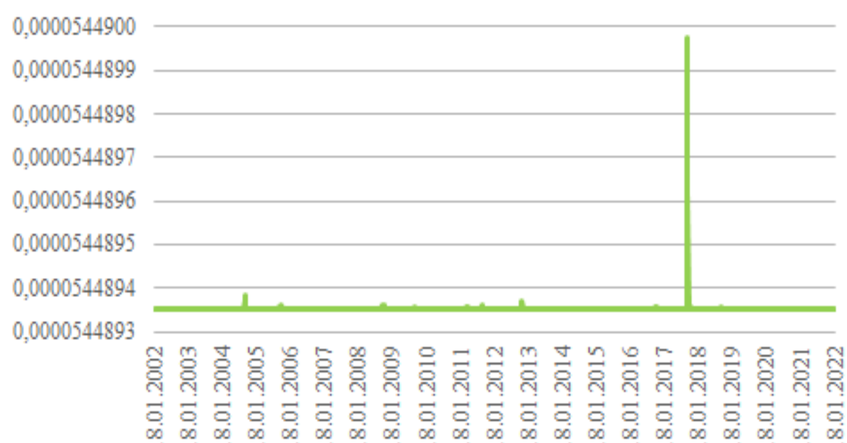
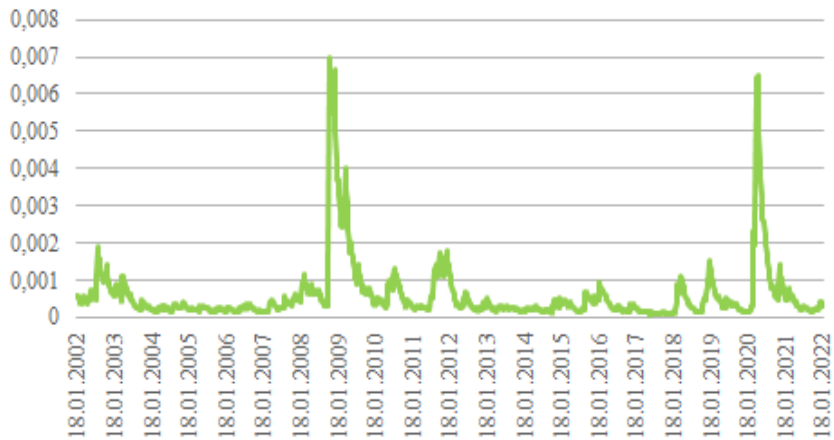


Figure A6: Conditional Variance of S&P 500 Index (Sigma 22)



GARCH-BEKK: Swiss Re USD Total Return Index and Corporate Bonds

Figure A7: Conditional Variance of Swiss Re USD Total Return Index (Sigma 11)

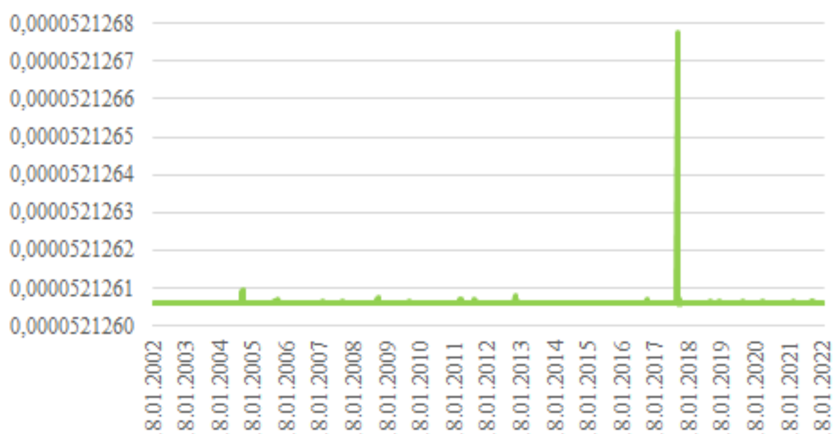
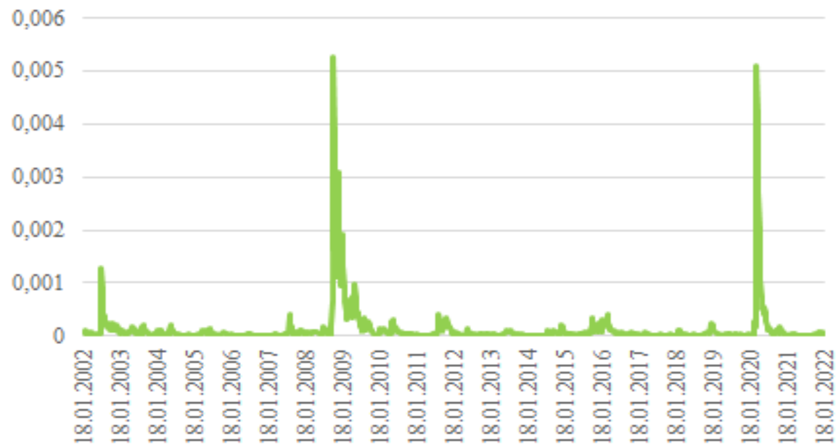


Figure A8: Conditional Variance of Corporate Bonds (Sigma 22)



GARCH-BEKK: Swiss Re USD Total Return Index and Government Bonds

Figure A9: Conditional Variance of Swiss Re USD Total Return Index (Sigma 11)

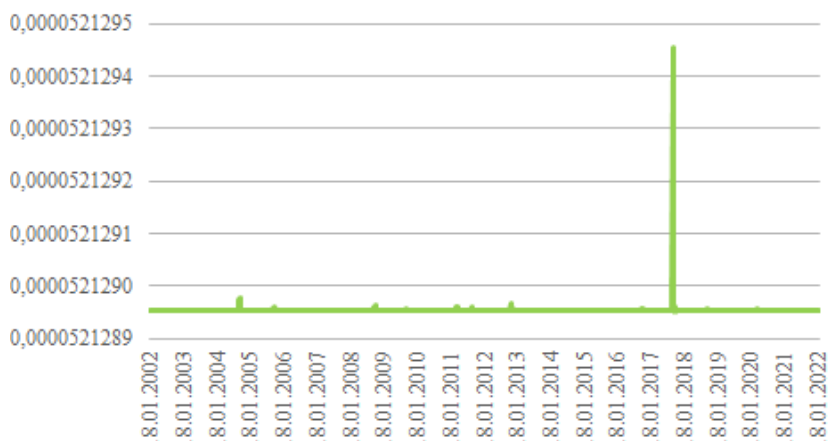


Figure A10: Conditional Variance of Government Bonds (Sigma 22)

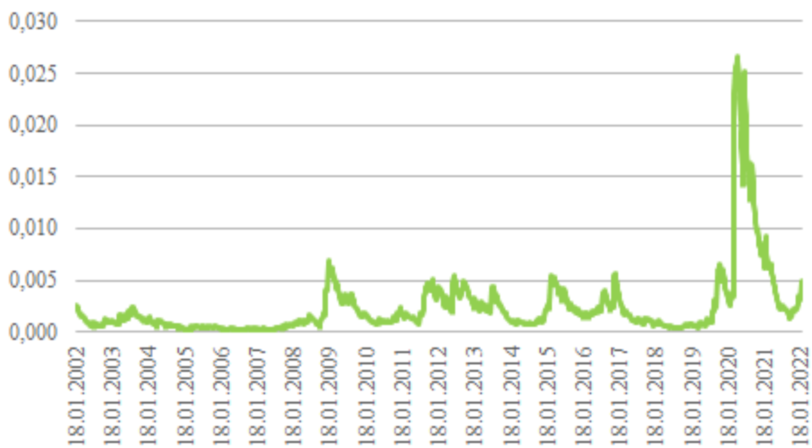


Figure A11: Swiss Re US Wind Total Return Index and Hurricane Damages

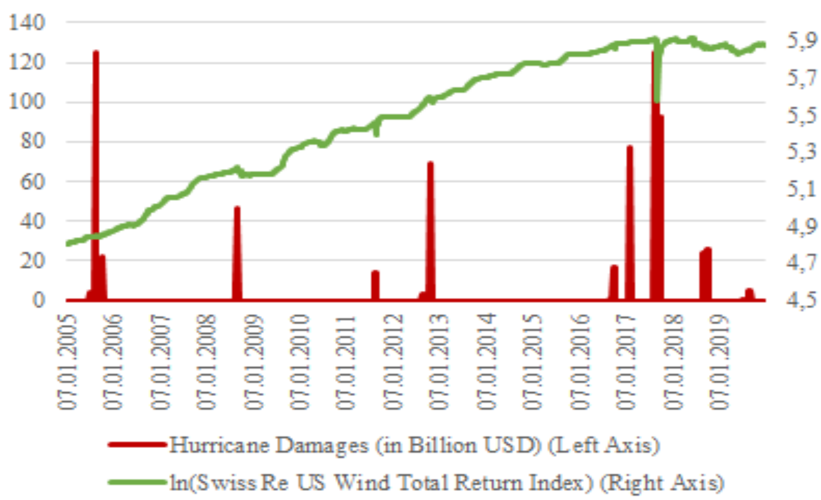


Table A1: Diversification Ratio Composed of Three Assets Excluding Swiss Re USD Total Return Index (January 2002– January 2022)

Without Swiss Re USD Total Return Index			
MDP	**Corporate Bond**	**Government Bond**	**S&P 500**
Annualized Standard Deviation	0,077415	0,373345	0,173824
Weights	0,704825	0,164992	0,130183
Portfolio Risk		0,102123	
Weighted Standard Deviation		0,138792	
Diversification Ratio		1,359062	
Equal Weights	**Corporate Bond**	**Government Bond**	**S&P 500**
Annualized Standard Deviation	0,077415	0,373345	0,173824
Weights	0,333333	0,333333	0,333333
Portfolio Risk		0,163364	
Weighted Standard Deviation		0,208195	
Diversification Ratio		1,274421	

Table A2: Diversification Ratio Composed of Three Assets Including Swiss Re USD Total Return Index (January 2002 – January 2022)

With Swiss Re USD Total Return Index				
MDP	**Corporate Bond**	**Government Bond**	**S&P 500**	**Swiss Re USD Total Return Index**
Annualized Standard Deviation	0,077415	0,373345	0,173824	0,05057
Weights	0,281084	0,069598	0,05688	0,592438
Portfolio Risk			0,053415	
Weighted Standard Deviation			0,087591	
Diversification Effect			1,639834	
Equal Weights	**Corporate Bond**	**Government Bond**	**S&P 500**	**Swiss Re USD Total Return Index**
Annualized Standard Deviation	0,077415	0,373345	0,173824	0,05057
Weights	0,25	0,25	0,25	0,25
Portfolio Risk			0,123782	
Weighted Standard Deviation			0,168788	
Diversification Effect			1,363592	

Table A3: Diversification Ratio Composed of Five Assets Excluding Swiss Re USD Total Return Index (January 2002 – January 2022)

Without Swiss Re USD Total Return Index					
MDP	**Corporate Bond**	**Government Bond**	**S&P 500**	**Real Estate Index**	**Commodity Index**
Annualized Standard Deviation	0,077415	0,373345	0,173824	0,260457	0,160651
Weights	0,429943	0,160119	0	0,144809	0,265129
Portfolio Risk			0,114779		
Weighted Standard Deviation			0,173373		
Diversification Effect			1,510495		
Equal Weights	**Corporate Bond**	**Government Bond**	**S&P 500**	**Real Estate Index**	**Commodity Index**
Annualized Standard Deviation	0,077415	0,373345	0,173824	0,260457	0,160651
Weights	0,2	0,2	0,2	0,2	0,2
Portfolio Risk			0,1445		
Weighted Standard Deviation			0,209138		
Diversification Effect			1,447325		

Table A4: Diversification Ratio Composed of Five Assets Including Swiss Re USD Total Return Index (January 2002 – January 2022)

With Swiss Re USD Total Return Index						
MDP	**Corporate Bond**	**Government Bond**	**S&P 500**	**Real Estate Index**	**Commodity Index**	**Swiss Re USD Total Return Index**
Annualized Standard Deviation	0,077415	0,373345	0,173824	0,260457	0,160651	0,05057
Weights	0,16066	0,067618	0	0,065886	0,10942	0,596417
Portfolio Risk				0,058111		
Weighted Standard Deviation				0,102582		
Diversification Effect				1,765269		
Equal Weights	**Corporate Bond**	**Government Bond**	**S&P 500**	**Real Estate Index**	**Commodity Index**	**Swiss Re USD Total Return Index**
Annualized Standard Deviation	0,077415	0,373345	0,173824	0,260457	0,160651	0,05057
Weights	0,166667	0,166667	0,166667	0,166667	0,166667	0,166667
Portfolio Risk				0,121137		
Weighted Standard Deviation				0,18271		
Diversification Effect				1,508294		

Table A5: Parameters of GARCH-BEKK Model

Parameter	μ_1	μ_2	c_{11}	c_{12}	c_{22}	α_{11}	α_{22}	β_{11}	β_{22}	Sum ln L_t
S&P500	0,00124	0,00068	0,00738	0,00271	0,00035	0,00015	0,3679	0,0001	0,9245	8155,06
Corporate Bond	0,0013	0,00183	0,00722	0,00014	0,00205	0,00016	0,5627	0,000103	0,8206	9270,00
Government Bond	0,001303	0,00013	0,00722	0,00025	0,00013	0,00013	0,3021	0,0001	0,948	7415,18