The impact of climate change on total returns in the property insurance industry

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Abstract

There is undeniable consensus on climate change and its negative impact on global ecosystems. Natural disasters are an important part of the global weather and are influenced by imperfections caused by climate change. Besides the loss of life, loss of opportunity and loss of development, disasters cause tremendous amounts of economic damage each year, continuing an unfavorable trend. Insurers and reinsurers play a key role in partially absorbing risks associated with disasters. The insurance business provided investors with steady total returns due to the solidity of the business model. Using a forecasting algorithm that employs natural disasters as random shocks based on key meteorological indicators, we forecast the effects on asset returns for a selected list of 9 property and casualty re-/insurers in a lower-bound and upper-bound setup which differ in the probability of shock and amplification of adverse returns. First, we find that, for a majority of underwriters, there are adverse returns in the aftermath of natural disasters. This effect on average is -0.188% for insurers and -0.065% for our index control group. Furthermore, the effect gets weaker if we extend the period to measure the adverse returns (14 days). The effect is strongest for a 7-day period (-0.308%) and does not excessively fluctuate thereafter. Second, our forecast suggests that the current path of climate change has a negative impact on asset prices only in an upper-bound scenario. This implies, on average, that there would be no significant negative effect on stock returns for investors. Analyzing the real effects, a similar pattern is identified. Although there is a negative link between disaster-related expenses and net income, it does not affect the dividend payout policy of the company due to sufficient capital reserves. Hence, the total return to investors is not at risk concerning natural disasters in the context of climate change.

Contents

List of abbreviations

AOML	Atlantic Oceanographic and Meteorological Laboratory
CRED	Center for Research on the Epidemiology of Disasters
EM-DAT	Emergency Events Database
ENSO	El Niño Southern-Oscillation
ETCCDI	Expert Team on Climate Change Detection and Indices
GDP	Gross Domestic Product
GFSR	Global Financial Stability Report
GWP	Gross Written Premiums
iii	Insurance Information Institute
IPCC	Intergovernmental Panel on Climate Change
NAIC	National Association of Insurance Commissioners
NCEI	National Centers for Environmental Information
NHC	National Hurricane Center
NOAA	National Oceanic and Atmospheric Administration
OHC	Ocean Heat Content
PCI	Property and Casualty Insurance/Insurers
SES	Simple exponential smoothing
SST	Sea Surface Temperature
WMO	World Meteorological Organization

ALL	Allstate Corporation
ALV.DE	Allianz SE
CS.PA	Axa Group
FCHI	CAC 40 Index
GDAXI	Dax Performance Index
GSPC	SP500 Index
HNR1.DE	Hannover Re
MUV2.DE	Munich Re
SREN.SW	Swiss Re
TRV	Travelers Companies
VIG.VI	Vienna Insurance Group
ZURN.SW	Zurich Insurance Group

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1 Introduction

Although the undeniable beauty of natural events, some carry risks beyond the imaginative capabilities of most individuals. Natural disasters are as old as planet earth itself and lie outside the control of humanity. Due to global warming, some of these events pose a more serious threat than ever before. The Intergovernmental Panel on Climate Change (Langsdorf et al., 2022) has recently released its newest synthesis report on climate change. They state that "Global warming, reaching 1.5°C in the near-term, would cause unavoidable increases in multiple climate hazards and present multiple risks to ecosystems and humans (high confidence)" (Langsdorf et al., 2022). Furthermore, there is a direct threat from extreme weather events as near-term economic contraction and displacements in all regions are directly attributable with high confidence (Langsdorf et al., 2022). Amongst the destructive leaders are tropical cyclones (Douris et al., 2021)(Appendix A&B). Though, how strong the linkage between climate change and increase in disaster frequency and intensity is, is a wild debate among scientists. In 2005, Kerry Emanuel concluded that "net hurricane power dissipation is highly correlated with tropical sea surface temperature, reflecting well-documented climate signals, including multi-decadal oscillations in the north Atlantic and north Pacific, and global warming" (Emanuel, 2005). As the coastal population increases, this leads to an accumulation of risk and an increase in possible economic damage in certain regions (Emanuel, 2005). However, his colleagues argue that these conclusions are premature and not founded on a solid scientific basis (C. W. Landsea, 2005). Later research, based on the IPCC AR4 simulations report, found a reduction in frequency but an increase in intensity (Manuel et al., 2008). While the debate over the exact causal relationship is still keeping scientists on the edge, there is a consensus on the link between climate change and economic damage through natural disasters - as stated above in the most recent IPCC AR6 report (2022) and many other sources (Cummins & Mahul, 2009; Holzheu et al., 2021; Kunreuther & Michel-Kerjan, 2009).

On the linkage between natural disasters and insurance stocks, the Cambridge Center of Risk Studies has released a report on climate change sentiments and investment impact. They find that unquantified climate risks could lead to unexpected economic shocks (Kelly et al., 2015) and that "[...] the perception of climate change represents an aggregate risk driver." (Kelly et al., 2015). Due to the natural resilience of the insurance business (Born & Viscusi, 2006), these assets are widely used to generate long-term continuous returns with low risk. With climate change posing a new and not fully understood risk to underwriting companies, adverse returns could cause a variety of new challenges for market participants holding insurance assets (Dlugolecki, 2008). Changing weather patterns and environmental conditions will have an impact on the insurers' clients and their operations – not only stemming from disasters themselves but also from indirect sources such as policies to reduce emissions (Dlugolecki, 2008). Dlugolecki also finds that catastrophe models are wrongly calibrated and thus not suitable to adequately forecast the risk (Dlugolecki, 2008). This would ultimately harm the insurers' profit and bear the risk of investors' exiting their positions in insurance assets as either returns fade or risk increases without additional compensation. Thomman (2013) has already found a negative effect on the volatility of insurance stocks given disaster events (Thomann, 2013). He states that "[...] natural catastrophes increase the volatility of insurance stocks" (Thomann, 2013). (Ammar et al., 2018) used statistical methods to, among other, quantify the relationship between natural disaster events and short-term returns. They found that there is a significant, negative real effect of natural disasters on insurance stocks' return on equity through the real disaster losses (Ammar et al., 2018). However, asset price movements in the short-term aftermath of explicitly disasters remain unclear, although they used a dummy variable to include the catastrophe effect. The effect turns insignificant after including other dummies (Ammar et al., 2018). The model introduced in this paper is adapting the findings of Ben Ammar et al. and the idea that exogenous shocks cause short-term adverse returns due to market inefficiencies and fear-induced irrational behavior – similarly to monetary policy changes or sentimental shocks (Charest, 1978; Rigobon & Sack, 2004).

The proposed idea is that (1), given the relationship observed by Ben Ammar et al., insurance stock prices would react negatively to information entering the market regarding natural disasters since an expected increase in the loss-ratio would increase the combined ratio and pressurize the profitability of the affected corporation. (2) The realfinancial effects may force insurers to reduce their dividend payments to investors due to equity position shortages. Furthermore, the real effects may have lagged effects on the asset prices if no countermeasures are performed.

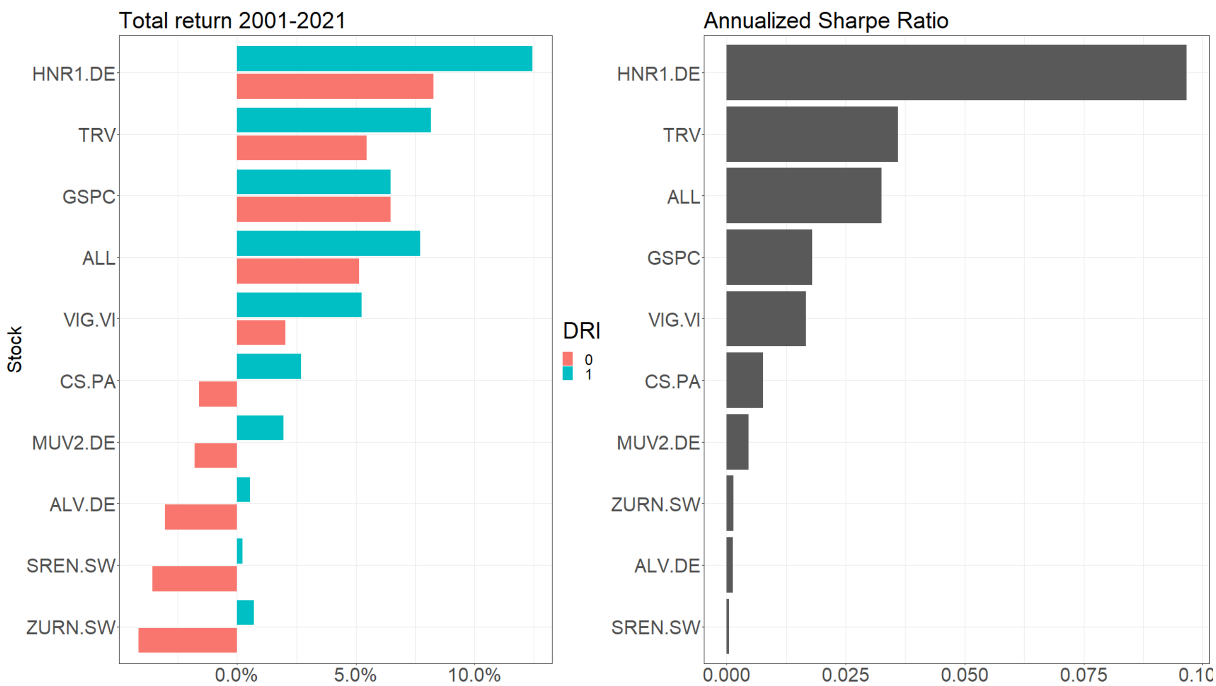
Using a model to forecast stock returns (prices) based on climatic indicators and historic events, we estimate the possible impact of climate change on primary insurers' and reinsurers' asset returns. Additionally, we analyze the real effect using a simple relationship between the combined ratio and the net income.

2 About Insurance

2.1 Asset performance

The insurance industry is not particularly famous for its excessive stock returns but rather for its steady dividend payments. The nature of the insurance business does not allow for extensive growth as it is limited by the individual's capacity to pay for insurance, which is determined by the economic growth in a country (Fu, 2012). Simultaneously, insurance is a driving force of economic growth (Bacani et al., 2015; Outreville, 2013). This cycle webs the industry into the global economy and has made it more resilient than others in the past (Holzheu et al., 2019). Figure 1 LHS plots the total returns for the relevant insurance stocks compared to the SP500 (GSPC) on the left side. The returns have been calculated assuming all dividends have been reinvested (blue) and simple capital gains (red). Only two out of the nine assets have managed to outperform the SP500. Even when incorporating the volatility, only three out of nine offered a better return than the SP500 for the past two decades (Figure 1 RHS).

Figure 1: Asset performance of selected stocks



Note: The left figure shows the total and stock return of the selected stocks compared to the SP500 (GSPC). The blue bars indicate total returns (capital gains + dividends reinvested). The red bars indicate simple asset performance. The right figure plots the annualized sharpe-ratio for the selected companies in comparison to the SP500 (GSPC). The sharpe ratio is calculated incorporating dividend reinvestments.
Source: Own graphic. Data: see bibliography extension.

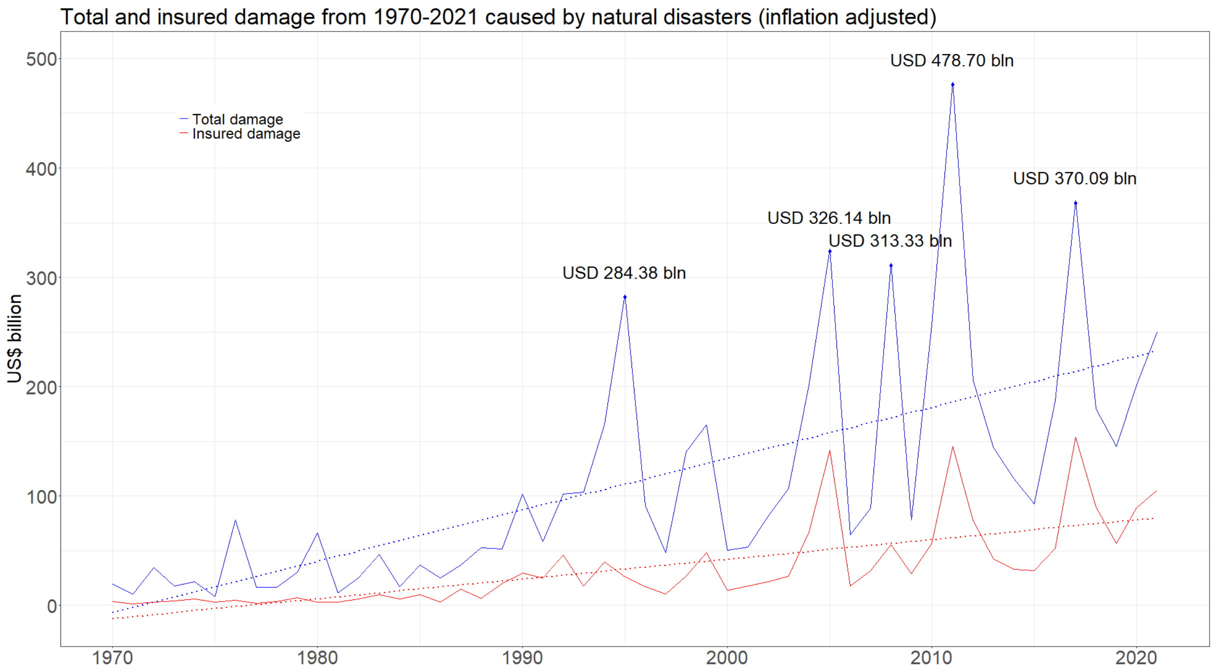
2.2 Types of Insurance

Insurance is broadly split into three segments; (1) Property and Casualty Insurance, (2) Life Insurance and Annuities, (3) Private Health Insurance of which the latter two are often combined which then simplifies to life (2+3) and non-life (1) insurance. Each of these categories is split into further subcategories. For this paper, we focus on Property and Casualty Insurance (PCI). PCI can be further divided into several subcategories following the definition of the National Association of Insurance Commissioners (NAIC) in accordance with the Insurance Information Institute (iii) and holds for residential and commercial agreements. Namely; (I) Motor insurance, (II) Flood insurance, and (III) Homeowners' insurance (of Insurance Commissioners, 2022). As insurance terms are not standardized globally, the above-mentioned definition, which is the US-Standard, is used as an approximate representation of global standards. Flood and homeowner insurance covers all major damage caused by fire, windstorms, hail, and floods. Geophysical insurance is specific to the affected country/region as well as event and is not naturally covered by regular insurance contracts, except for earthquakes (Holzheu et al., 2015; iii, 2022). This classification covers all common types of natural disaster-related insurance claims.

2.3 Market Summary

Total global insurance premiums written have grown from USD 500 billion in 1980 to USD 6.3 trillion in 2020 (of Insurance Supervisors (IAIS), 2021). With life insurance having the bigger share of total premiums written until 2013, non-life insurance now accounts for over 55% of total premiums written – continuing the trend of shifting from life to non-life insurance (Casanova et al., 2021). In the non-life insurance division, PCI accounts for USD 1.8 trillion at the end of 2020 (Holzheu et al., 2021). Relevant to this paper is the share of property insurance, which is estimated at USD 450 billion of direct premiums written at the end of 2020 (Holzheu et al., 2021).Insurance penetration is highest in advanced markets with 9.9% of total GDP of which 5.7% are attributed to non-life and 4.2% to life insurance. In emerging markets, insurance penetration is at 3.4% of GDP of which 1.6% are attributed to non-life and 1.8% to life insurance (OECD, 2022). Total insured damage is estimated at USD 1.76 trillion during the period from 1970 to 2021. This implies that, about 28% of economic damage caused by natural disasters is insured (2020). Total damage, as well as insured damage, has continuously increased over the past centuries as can be seen in Figure 2 shown by the red and blue trend lines. Increased damage peaks can be attributed to stronger natural disasters as well as economic development (Bevere & Remondi, 2021).

Figure 2: Total and insured damage 1970-2021



Note: This figure plots the total and insured damage over a time horizon of 50 years. The blue lines indicate the annual total damage and the trend. The red lines indicate the insured damage and the trend. The annotations quantify five damage peaks in USD billion.
Source: Own graphic. Data: EM-DAT by CRED, retrieved at: https://www.emdat.be/

2.4 The insurance protection gap and underinsurance

The (property) insurance protection gap is defined as "[...] the uninsured portion of losses resulting from an event, meaning the difference between total economic and insured losses" (Holzheu et al., 2015). Underinsurance is defined as "[...] the difference between the amount of insurance that is economically beneficial [...] and the amount actually purchased" (Holzheu et al., 2015). Holzheu and Turner have identified numerous reasons causing underinsurance such as affordability, limitations of supply, degree of development in the financial sector, weak rule of law, underestimation of low-probability events and financial literacy (Holzheu & Turner, 2018).

3 About natural disasters and coverage

3.1 Classification

Disasters are broadly split into two categories following the CRED definition (Debarati et al., 2022)(Appendix G); (1) Natural and (2) Technological. Natural disasters summarize (I) Geophysical, (II) Meteorological, (III) Hydrological, (IV) Climatological, (V) Biological and (VI) Extraterrestrial events. Technological disasters summarize industrial accidents, transport accidents and miscellaneous accidents. The international Disaster Database (EM-DAT) captures and classifies all disasters accordingly. An entry to the EM-DAT database is recognized as a disaster if one of the following criteria apply; (1) 10 or more human casualties, (2) 100 or more people affected/injured/homeless or (3) the affected country has declared the state of emergency and/or applied for international assistance(Debarati et al., 2022). Damage reports to this database consist exclusively of directly attributable damage.

This paper focuses exclusively on natural disasters related to global warming. More specifically on (II), (III) and (IV). In regular terms, these will be events such as extreme temperatures (II), storms (II), floods (III), droughts (IV) and wildfires (IV) (Appendix G). Geophysical, Biological and Extraterrestrial events are not proven to be directly linked to climate change, which is why they are not relevant to this paper. Literature usually uses the terms "primary peril" and "secondary peril". These categorize natural disasters based on their frequency and severity. Primary perils subsume events that occur less frequently but are more severe (Tropical Cyclones, Earthquakes, European winter storms), whereas secondary perils describe events that happened more often but typically generate low to medium-sized losses (Severe convective storms, drought, wildfire, snow, flash floods and landslides) (Bevere & Remondi, 2021; Bevere & Weigel, 2021).

3.2 Occurrence

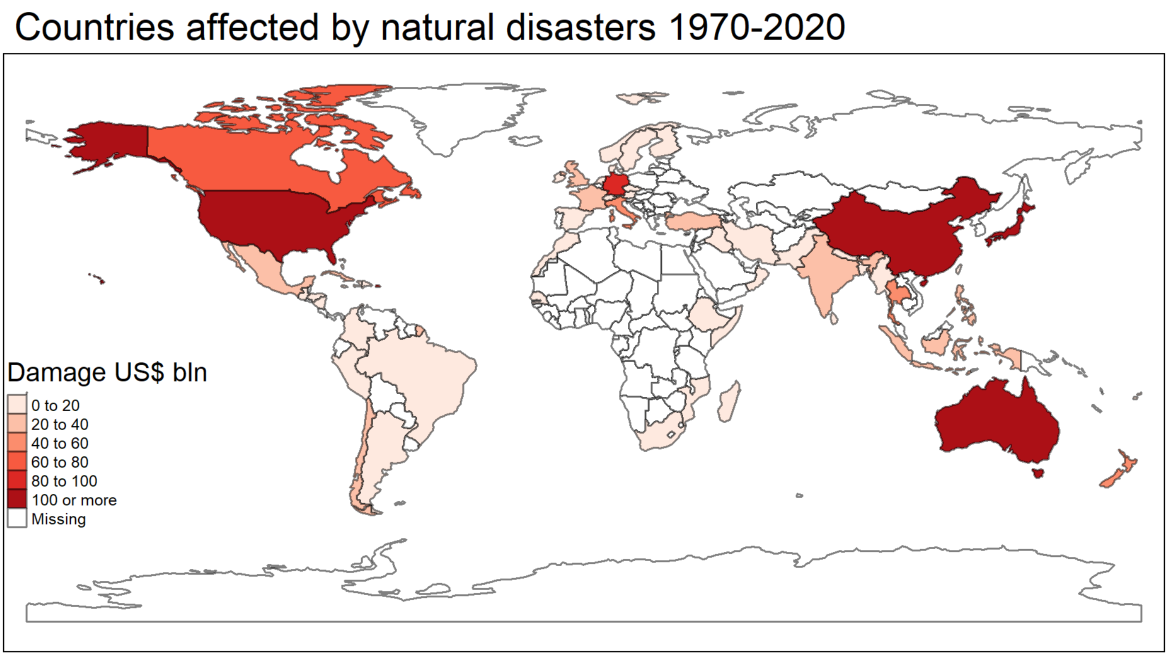
Historically, natural disasters occurred as pseudo-random events as they are deterministic but were impossible to reliably predict due to an almost infinite number of input factors. With continuous research and highly sophisticated meteorological models, we are now able to measure the anthropological impact on natural disasters and their related consequences.

"Human-induced climate change, including more frequent and intense extreme events, has caused widespread adverse impacts and related losses and damages to nature and people, beyond natural climate variability" (Langsdorf et al., 2022). With high confidence, the IPCC furthermore states that "the rise in weather and climate extremes has led to some irreversible impacts as natural and human systems are pushed beyond their ability to adapt" (Langsdorf et al., 2022). The WMO analyzed global natural hazard data from 1970 to 2019 focusing on total economic losses and hazard composition. Storms (tropical cyclones) account for 54% (38%) of total economic losses, followed by floods (riverine floods) with 31% (20%). The total losses from natural hazards are estimated at USD 3.6 trillion over the stated time series (Douris et al., 2021).

3.3 Impact

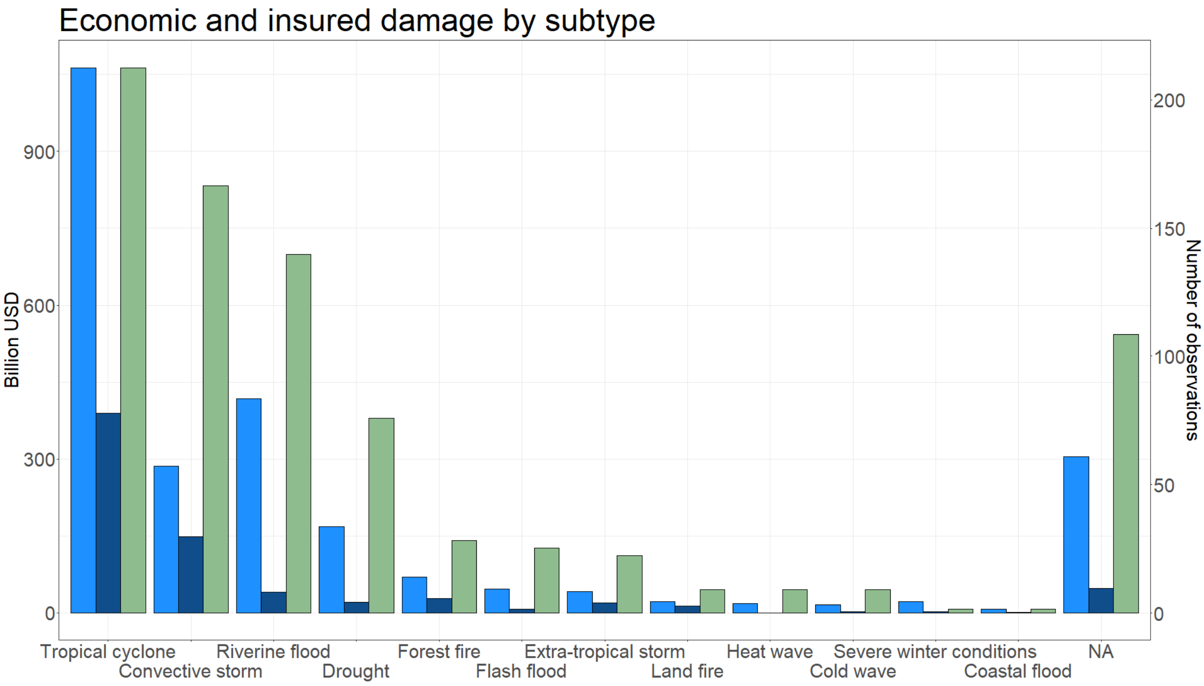
The severity can be measured in three categories; (1) physical disaster magnitude and scale which describes the covered area in case of floods, droughts or wild fires, the Richter scale for earthquakes or the sustained wind speed in case of storms. (2) Anthropologic damage measured in the number of human casualties, missing and people affected. (3) Economic damage measured in units of currency (USD) (Debarati et al., 2022). For this paper, only the directly attributable economic damage matters since the focus lies on analyzing the expected financial impact for investors, although it is heavily driven by the physical disaster magnitude and scale. Additionally, this paper only focuses on major events which have caused more than USD 1 billion in economic damage. This breaks down the total number of reported disasters from 11072 to 544, whereas these 544 account for USD 2.484 trillion (81%) in economic damage (Douris et al., 2021). While some countries are hardly ever hit by natural disasters, others are engaging in a continuous battle. Figure 3 shows which countries have been hit the hardest during the period from 1970 to 2020. Global damage leaders are the United States with an amount of USD 1258 billion. Followed by Japan with a total of USD 860 billion and China in third place with USD 374 billion (Appendix B1). Damage is not only caused by severity, but also by frequency. While there are events that cause a tremendous amount of damage in one sitting, other countries are frequently hit by the same type of disaster (Appendix B2). Figure 4 captures the severity and number of occurrences by type. Due to their nature, hurricanes happen every year with certainty and are thus by far the most frequent events which, connected with their strength, adds up in damage dealt, especially in the United 9 States (Appendix B1). On the other hand, in Asia, earthquakes and tsunamis take the lead due to geographic circumstances. The so-called "ring of fire" and the subduction zones lie exactly on the coastal lines of Japan, Thailand, the Philippines and many more. Damage is especially severe in developed countries such as Japan with notable earthquakes in 1995 and 2011. Note that damage was also caused by the tsunami and radioactive fallout in 2011. Even though the damage was at over USD 300 billion, insured losses were comparatively low at USD 35 billion due to a high protection gap in Japan (Daigaku, 2018).

Figure 3: Countries affected by natural disaster 1970-2020



Note: This figure shows the summed-up damage per country for the past 50 years. All kinds of natural disasters are included here.
Source: Own graphic. Data: Swiss Re World Insurance Series, retrieved at: https://www.swissre.com/institute/research/sigma-research/World-insurance-series.html, EM-DAT by CRED, retrieved at: https://www.emdat.be

Figure 4: Economic and insured damage by subtype



Note: The left figure shows the direct, measurable economic damage caused by natural disasters by disaster subtype. The light blue bar shows the total direct economic damage caused (LHS). The dark blue bar shows the total insured damage measured in claims paid (LHS). The light green bars show the number of occurrences (RHS). The "NA" subtype is due to damage not directly attributable to a certain event. Yet it is still classified under disaster type.

Source: Own graphic. Data: EM-DAT by CRED, retrieved at: https://www.emdat.be/

4 Empirics

4.1 Data sources and preparation

Several datasets and sources were used in this paper of which some were created explicitly for this case. All data handling and analysis is done using the statistical program R. All datasets can be either found in the appendix or directly at the original source (link provided).

1. Stock prices and dividend data are retrieved from Yahoo finance (https://finance.yahoo.com/) for a period of 2001-01-01 to 2021-31-12. Dividend data has additionally been checked for correctness with Bloomberg and the companies' individual statements. The individual datasets consist of 5335 observations. The number of observations may slightly deviate due to missing values. We do not use any correction metric such as interpolation as these missing values are not of significant manner. The daily returns are calculated using the simple return metric from R based on the closing prices. For performance analytics incorporating dividends, we create a portfolio for each stock and match it with dividend payments to apply an algorithm reinvesting these dividends on the day after they have been paid.

2. Natural disaster data is retrieved from several sources.

   (a) Data for the period 1970-2021 from the EM-DAT public database (https://public.emdat.be/). The EM-DAT database is maintained by the Center for Research on the Epidemiology of Disasters (CRED) and is compiled from a variety of reliable sources such as the UN, NGOs and sector-related companies. This database contains information about the Year, Period, Classification, Location, Total affected, Total costs, Total insured costs and more. The database has 11814 observations based on the entry criteria provided in the introduction. For the model, this dataset is split into five subsets based on the decades (yearclass variable).

      i. 1970-1979; 711 observations, yearclass=1.

      ii. 1980-1989; 1410 observations, yearclass=2.

      iii. 1990-1999; 2247 observations, yearclass=3.

iv. 2000-2009; 3498 observations, yearclass=4.

v. 2010-2019; 3948 observations, yearclass=5.

vi. 2020-2029; forecasted dataset, yearclass=6.

(b) Data for the period 1970-2021 from the sigma-explorer webpage is provided by the Swiss Re institute's annual and quarterly Sigma reports (Swiss Re, 2022). The World Insurance Series (Sigma reports) contains information about disasters and their economic damage caused as well as insured losses. Furthermore, it provides information about the insurance gap, premium growth and other macroeconomic variables on a global basis and discusses relevant topics on a quarterly basis (https://www.swissre.com/institute/research/sigma-research/World-insurance-series.html).

(c) Tropical Cyclone data is verified by the National Hurricane Center (NHC) under NOAA. The NHC provides annual summary reports providing detailed information about all Atlantic and Central Pacific hurricanes as well as a hurricane database (NOAA/AOML - Hurricane Research Division, 2014; NOAA/NHC, 2022).

(d) Our World in Data keeps an updated time-series and cross-country database for macro data on all natural disasters which was used to further verify the correctness of the used data. (https://ourworldindata.org/natural-disasters).

3. Climate data is retrieved from the National Oceanic and Atmospheric Administration (NOAA) and its National Center for Environmental Information (NCEI).

(a) Ocean heat content is provided by NCEI/NOAA and contains the annual value of stored heat in the ocean measured in Zettajoule from 1970 to 2020. It provides data for the world, northern and southern hemispheres individually. World data was used in this paper (NASA, 2022).

(b) Ocean and land surface temperature anomaly datasets are provided by NCEI/NOAA and contain the annual temperature anomaly measured in 13 degrees Celsius from 1970 to 2020 (NOAA National Centers for Environmental information, 2022).

4. Company data is retrieved from the companies' annual reports for the period of 2000-

2021 and collected in an own dataset (Appendix C & extension to bibliography).

4.2 Working Process

Section 1 discusses the selection of relevant companies which are used in the analysis and forecasting process. Section 2 describes which natural disasters were used in the model. Section 3 focuses on the climatic indicators to explain the development of natural disasters. In section 4, the model is presented and in section 5, the results are discussed.

4.2.1 Section 1: Selecting the companies

Primary insurers are selected based on three inclusive criteria. (1) 20% of revenue has to be from disaster-related insurance premia. That is, GWP of PCI minus all non-disaster related insurance, mainly motor insurance, which often accounts for the majority of PCI. (2) The company needs to be listed on an exchange and have a price history of at least 21 years (2000-2021) as well as a dividend history of the same period. (3) Underwriting activity has to be focused on disaster-affected geographic regions. Reinsurers are chosen based on their risk-taking relationship with the above-mentioned companies. The selection is based on the year 2020 under the assumption that the company's history in operating activity remained unchanged. Table 1 provides an overview of the selected companies. Exposure describes the share of relevant PCI premium of total GWP. Relevant PCI premium is calculated as the total of PCI premiums written for perils such as fire, flood, wind, storm and hail. If not stated explicitly by the company, homeowners' insurance was taken as an approximate as it also covers the majority of damages caused by these events (hurricane damage, tornado damage). RI is an indicator of reinsurance activity. Note that "Exposure" may deviate slightly from the true value due to indistinguishability between certain contract specifications.

Table 1: List of selected companies

Company	Symbol	Exposure	RI
Allianz SE	ALV.DE	27.81%	0
AXA Group	CS.PA	29.60%	0
Zurich Insurance	ZURN.SW	20.25%	0
Vienna Insurance Group	VIG.VI	20.25%	0
Allstate Corporation	ALL	30.34%	0
Travelers Companies Inc.	TRV	36.89%	0
Swiss Re	SREN.SW	20.44%	1
Munich Re	MUV2.DE	15.22%	1
Hannover Re	HNR1.DE	32.32%	1

Note: This table shows the list of selected companies. Exposure describes how much of their claim payments are related to natural disaster protection. RI is an indicator for reinsurance (=1) or primary insurance (=0)
Source: Own Table. Data: see extension 1 to bibliography

4.2.2 Section 2: Natural Disasters

Severity in the case of this paper is measured in economic damage (US$), which is depicted as "Cost". "Insured loss" gives the amount that has been paid by insurance companies in direct relation to said event. The focus lies on the top twelve natural disasters by economic damage, which (1) are related to climate indicators that are driven by climate change, (2) caused the damage in a short period ($<$20 days) and (3) are unaffected by any exogenous noise. (1) is needed to have a scientific basis for forecasting. (2) is needed to successfully quantify the investors' behavior with a certain degree of confidence. The insured damage does not matter in this paper as the only effect analyzed is the direct behavior of the stock price after a disaster occurred. This direct effect is likely to be caused by the immediate expectations of investors about the occurred disasters' impact and not the true value. (3) is necessary to attribute the price effects to the natural disaster with some degree of confidence. Table 2 provides an overview of the selected disasters. The "Crisis" variable is a dummy indicating whether the event happened during an active recession period. "Interest rate change" is an indicator of central bank activity. As the stock market in general but also insurers and reinsurers are highly dependent on interest rate decisions this is also likely to have a high influence on stock prices. The "duration" parameter is calculated as the difference between the "date start" and "date end" variables, which are two indicators for when the event has started and ended. The duration needs to be $<$20 days as stated above. A shorter period would cause issues as some events, especially tropical cyclones, are logged based on their first observation and not their date of landfall which is typically the date they cause the most damage. A longer duration would also bias the analysis as the related stock price effect would dilute. A list of the top events ($>$10 bln. US$ damage) can be found in the Appendix (Appendix D).

Table 2: List of selected disasters

	Cost	Insured loss	Fatalities	Event	Type	Year	Name	Date	Days
1	167.40	85.00	1540.00	Hurricane Katrina	Tropical cyclone	2005	United States	2005-08-23	9
2	133.20	31.00	107.00	Hurricane Harvey	Tropical cyclone	2017	United States	2017-08-17	18
3	95.50	31.00	3059.00	Hurricane Maria	Tropical cyclone	2017	Puerto Rico	2017-09-16	15
4	71.40	33.00	233.00	Hurricane Sandy	Tropical cyclone	2012	United States	2012-10-22	8
5	48.20	33.00	134.00	Hurricane Irma	Tropical cyclone	2017	United States	2017-08-30	16
6	33.00	8.20	184.00	German flooding	Flood	2021	Germany	2021-07-12	8
7	26.10	7.40	74.00	Hurricane Michael	Tropical cyclone	2018	United States	2018-10-07	10
8	26.00	12.00	87.00	Hurricane Wilma	Tropical cyclone	2005	United States	2005-10-15	13
9	23.00	15.00	237.00	Winter storm	Winter storm	2021	North America	2021-02-13	5
10	19.30	9.00	77.00	Hurricane Laura	Tropical cyclone	2020	United States	2020-08-20	10
11	16.00	4.30	58.00	Hurricane Irene	Tropical cyclone	2011	United States	2011-08-20	9
12	15.00			Typhoon Hagibis	Tropical cyclone	2019	Japan	2019-10-04	19

Note: This table shows the summary of the selected natural disasters which are the basis of our analysis. The list is sorted in descending order based on the "Cost" column. Cost is the total direct economic damage caused by the stated natural disaster. This excludes any damage that is caused as consequence of the damages caused by natural disasters such as diseases, loss of life or loss of economic activity. Insured losses are measured as the total claims paid by primary insurers and reinsurance companies with regards to this particular event. A full list of the exclusion criteria can be found in Appendix D.
Source: Own Graphic. Data: See Appendix D.

4.2.3 Section 3: Climate indicators and tropical cyclones

Three major climate indicators were used to model the relationship between economic damage and natural disasters in the context of climate change. (1) Ocean heat content, measured in Zettajoules (10^{21} Joules) and updated monthly. The ocean heat content provided by NASA/NOAA is an index capturing the total thermal energy stored in the top oceanic layer to a depth of 2000m. (2) Land surface temperature anomaly and (3) sea surface temperature anomaly. (2) and (3) measure the annual positive or negative distance to a reference value. Data for (2) is taken from the GHCNm dataset, which provides monthly updates of the temperature anomaly via NOAA. Data for (3) is taken from ICOADS via NOAA, which produces the monthly ERSST dataset for long-term analysis. (3) is used as a control variable for the SST as deviations should be following a similar pattern.

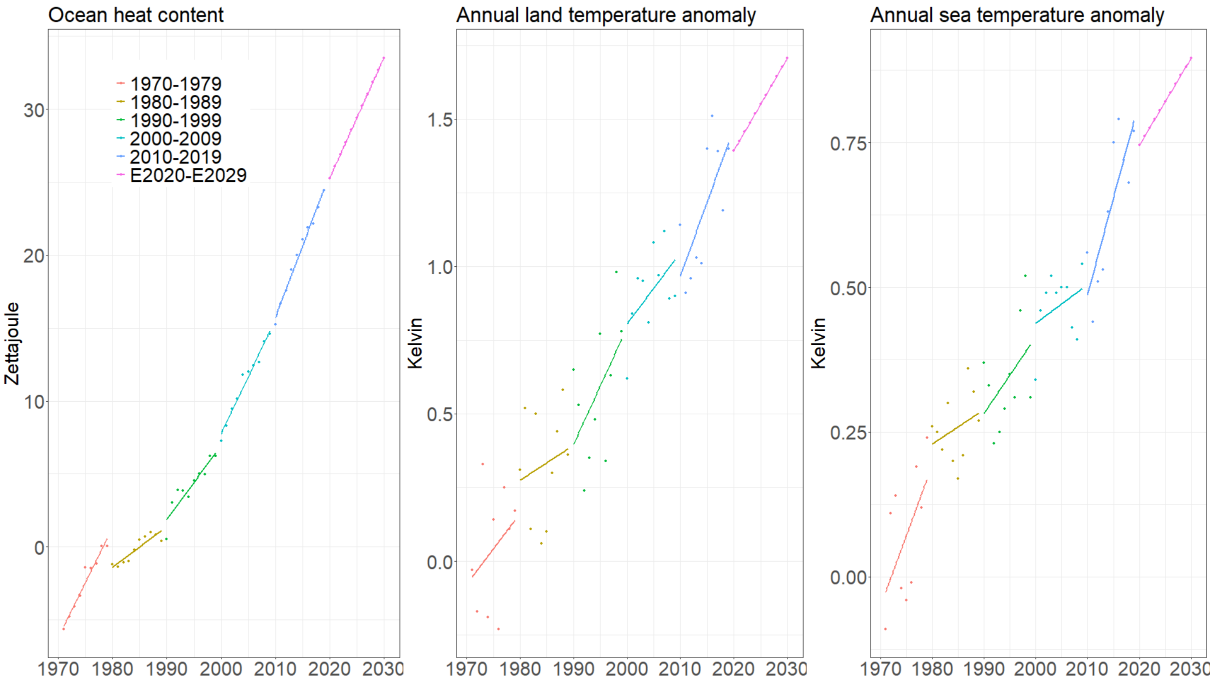
In 1987, Kerry Emanuel has shown that these three indicators, primarily the SST, have a direct impact on the global climate as well as being heavily influenced by global warming (Emanuel, 1987). Emanuel also found that there is a non-linear relationship between the SST and maximum hurricane intensity (Emanuel, 1987). In later studies by DeMaria and Kaplan (1994), Emanuel's results were proven using a longer sample period (31 years)(Demaria & Kaplan, 1994). DeMaria and Kaplan additionally found that there are other variables influencing the maximum storm intensity besides SST – though SST being a solid indicator for tropical cyclone activity. Recent research supports these findings and intensifies the initially discovered linkages (Lin et al., 2013; Trenberth et al., 2018; "World ocean heat content and thermosteric sea level change (0-2000m), 1955-2010", 2012). To encompass unobserved deviations by omitted variables such as the vertical wind shear (Demaria & Kaplan, 1994), the model in this paper follows a linear trend pattern to define the lower bound (Setup 1) and a growth-factor trend for the upper bound forecasts (Setup 2). Furthermore, since the majority of catastrophe damage comes from weather-related events such as hurricanes or precipitation-driven floods (Figure 4), other climate indicators become rather irrelevant for this model. Figure 5 shows the historical development per decade of the three variables for the period from 1970 to 2029. To forecast these variables, the relationship between GHG emissions and the Earth Energy Imbalance (EEI) is used. As GHG emissions increase, a positive radiative imbalance is caused at the top of the atmosphere. This drives global warming through an accumulation of heat energy in the earth's system which is absorbed by the ocean for up to 90%. As a direct consequence, the ocean heats up accordingly (Aaboe et al., 2022). Under the assumption that GHG emissions continue to increase in the next decade (Marchal et al., 2011), the three climate indicators used in this paper will behave similarly (Langsdorf et al., 2022; Masson-Delmotte et al., 2021). Having established this relationship, Holt's linear trend method (Gardner, 1985) is applied in setup 1 to capture the linear trend development and forecast the period of 2020-2029. With special regards to tropical cyclones in the north Atlantic region, the power dissipation index (PDI) implies a similar trend. The PDI measures the activity of cyclones by accounting for their strength, duration and frequency (Division, 2014)(Appendix E). We have learned that tropical cyclones account for the majority of destruction and are by far the most prominent threats. To better establish the linkage between climatic indicators and tropical cyclones, here is a short introduction to tropical cyclones from the AOML (C. Landsea, 2000). For tropical cyclone development, there are necessary but not sufficient conditions as variations in other environmental conditions have a considerable impact. The necessary conditions are:

1. Ocean water temperature of 26.5°C throughout a sufficient depth and warm SST.
2. Fast-cooling atmosphere potentially unstable to moist convection.
3. Relatively moist layers near the mid-troposphere.
4. 500km distance to the equator for cyclogenesis to occur.
5. Pre-existing near-surface disturbance with sufficient velocity and convergence.
6. Low vertical wind shear between the 850 and 200mb levels.

Under the variations in other environmental conditions category falls the El Niño-Southern Oscillation (ENSO). ENSO is primarily affected by SST anomalies. Positive anomalies, or warmings, are called El Niño events and describe large-scale, multi-year fluctuations in the ocean-atmospheric system (Dettinger et al., 2000; C. Landsea, 2000; Patricola et al., 2014).

To provide a simplified summary; OHC and SST cause differences in temperature and oceanic as well as atmospheric pressure. These differences cause cyclogenesis. Cyclogenesis, which describes cyclonic circulation, can further develop into any sort of cyclone (macroscale, synoptic scale, mesoscale or microscale) (Zehr et al., 1992).

Figure 5: Climatic indicators



Note: These three figures show the decadal development of the climatic indicators used in this thesis.
Sources: NASA, OHC retrieved at: https://climate.nasa.gov/vital-signs/ocean-heat/, NCEI by NOAA, Temperature anomalies retrieved at: https://www.ncei.noaa.gov/cag/global/time-series/globe/land/12/12/1970- 2020. Verified: WMO State of the Global Climate 2021.

4.2.4 Section 4: Model

Forecasting was done for each company with altering specifications. There are two different setups (Setup 1 & 2) that are distinguished based on the amplification and probability of a shock. On an individual basis, the return input for the shock variable is based on five different periods, namely 14, 7, 6, 5 and 3 days. In total, this leads to ten runs for each company.

The model is developed to employ shocks based on a simple combination of historical data and forecasted data to explore the effect of global warming on insurance stock returns through the impact of selected natural disasters. The algorithm starts with the simple development of the stock price. Equation 1 describes the standard historical stock price development on the return (r_{t-1}) and stock price (S_{t-1}).

$$S_t = S_{t-1}(1 + r_{t-1}) \tag{1}$$

As part of the forecast, the R-library "pdqr" was used (Chasnovski, 2021). The pdqr package creates custom distributions based on input data which can then be transformed. Since all returns of the selected companies are heavily leptokurtic with normally low variance, we can account for this by using a custom distribution function. Either by tail manipulation of a Pearson type-1 (generalized beta) distribution or by using the mentioned R-package. The manual modification would allow us to vary the tails, but we used the R-package based on the argumentation that stock prices tend to perform similarly as they did in the past if there is no unexpected shock (Jegadeesh & Titman, 1993, 2002) and denote this function as $sample\_dist\_stock(sds(1))$. We do not employ randomness as in the long run (10 years), asset prices themselves do not follow stochastic processes. $sds(1)$ draws a random number from this distribution each time called. This approach was also used to easily capture the positive drift of the stock price and incorporate other relevant price information. If no shock is applied, the stock price will follow its regular path. The $event(e)$ function will be described in the following paragraphs. The shock indicator will later be added based on probabilities. Equation (2) defines the general return without probabilities. Note that the "1" in brackets denotes that for each observation this function is called individually.

$$r_{t-1}(e_t(1), sds(1)) := \begin{cases} e_t(1), & shock = 1 \\ sds(1), & shock = 0 \end{cases} \tag{2}$$

The event function is built as follows (3),

$$e_t := r_{t,s} + \mu_{r,s} a_s, \quad s = 1 \tag{3}$$

where $r_{t,s}$ describes the returns randomly drawn from a distribution function based on historical adverse returns in an $x - day$ period after a disaster event happened with $x \in \{14, 7, 6, 5, 3\}$ days. $\mu_{r,s}$ is the mean return of the subset of adverse returns for the $x - day$ period. a_s is the amplification of these returns based on the forecast methodology described in section 3. For the $x - day$ returns, a subset of data was created from the twelve natural disasters shown in section 2. $s = 1$ indicates that this function is only run in the case of an employed shock, which can also be seen in equation (2). $\mathbb{H}$ is the notation for Holt's SES forecasting method (Gardner, 1985). The subscript yc (yearclass) deones the decade in which the event happened, that is $yc \in \{1, ..., 6\}$ for the periods indicated in section 3. T is the notation for the analyed period of the data subsets for $T \in \{14, 7, 6, 5, 3\}$ days. N is the number of observations in a dataset.

Setup 1

The mentioned parameters are defined as follows.

$$\mu_{r,s=1} := \frac{1}{TN} \sum_{n=1}^{N} \sum_{t=1}^{T} r_{n,t,s=1} \tag{4}$$

$$a_{s=1} := \frac{\mathbb{H}_{yc=6}[d]}{\sum_{n=1}^{N} d_{yc=5}}, \; d = damage \; (US\$ \; Billion) \tag{5}$$

For each observation, the algorithm draws a random number z from a discrete uniform distribution with $z \in \mathcal{U}\{1, a_{s=1}\}$. The amplification parameter calculated in (5.1) is thus the upper bound or best-case scenario. The same principle is applied to equation (4) in the algorithm. For each observation, a random number x is drawn from a discrete uniform distribution with $z \in \mathcal{U}\{\mu_{r,s=1}, 0\}$ if $\mu_{r,s=1}$ is negative or vice versa if positive.

Plugging (4) and (5.1) into equation (3) yields equaton (6) for the standard event function.

$$e_t = r_{t,s=1} + \frac{1}{TN} \sum_{n=1}^{N} \sum_{t=1}^{T} (r_{n,t,s=1}) \frac{\mathbb{H}_{yc=6}[d]}{\sum_{n=1}^{N} d_{yc=5}} \tag{6}$$

Combining and rewriting equation (2) and (6) yields the following algorithm for forecasting the stock returns without probabilities (7).

$$r_{t+1} = \mathbb{1}_{s=1}\left(r_t + \frac{1}{NT}\sum_{n=1}^{N}\sum_{t=1}^{7}(r_{n,t})\frac{\mathbb{H}_{yc+1}[d]}{\sum_{n=1}^{N} d_{yc=5}}\right) + \mathbb{1}_{s=0}(sds(1)) \tag{7}$$

In a final step, probabilities are added for the indicators. The probability of whether a shock is employed or not is defined in equations (9) and (10).

$$p(s) = \mathbb{H}_{yc+1}[p(e_h|d > c)], \begin{cases} c = 1 \ Billion \ US\$ \\ e_h = historical \ event \end{cases} \tag{8}$$

In the algorithm, for each forecasted observation it is determined whether this observation is a shock (disaster) or not based on the probability function described in (8.1) or (8.2). This triggers the indicator function to be either 1 or 0 and thus the event function $e_t(1)$ or the $sds(1)$ function.

$$\mathbb{1}_{s=x} := \begin{cases} x = 1, \ if \ p(s) = 1 \\ x = 0, \ if \ p(s) = 0 \end{cases} \tag{9}$$

Rewritten in simple terms the algorithm can be concluded as follows in equation (10).

$$r_{t+1} = \mathbb{1}_{s=1}(r_t + \mu_t a_t) + \mathbb{1}_{s=0} sds(1) \tag{10}$$

To finally calculate the stock price for each point in time, the equation introduced in (1) is used.

Setup 2

In setup 2, equations (5) and (8) change. Instead of using Holt's SES method, a simple average growth-rate approach was used. The equations look as follows.

$$g_{yc=6} = \frac{1}{5}\sum_{yc=1}^{5}\left(\frac{\sum_{n=1}^{N} d_{yc}}{\sum_{n=1}^{N} d_{yc-1}}\right) \tag{11}$$

The probability is calculated similarly to (5.2) and (5.3), with one additional step.

$$p(s) = g_{p(e_h|d>k)} p(e_h|d > k)_{yc=5} \tag{12}$$

The parameters for the first setup that are not company-dependent look as follows.

- $p(s) \approx \ 3.37\%$
- $a_{s=1} \approx \ 37.78\%$

- $J = 250$, number of forecasted paths
- $K = 500$, number of observations per path
- $L = 100$, mumber of iterations for J and K (12.5Mio. Observatons per Stock)

The parameters for the second setup that are not company-dependent look as follows.

- $p(s) \approx$ 7.40%
- $a_{s=1} \approx$ 180.94%
- $J = 250$, number of forecasted paths
- $K = 500$, number of observations per path
- $L = 100$, mumber of iterations for J and K (12.5Mio. Observatons per Stock)

4.2.5 Section 5: Output

Notes and basis of interpretation

The output is a trend indicator and not a target price due to the model setup and its assumptions.

Note that we worked with the average returns and not annualized returns. The average returns are naturally much smaller but are unable to predict an accurate target price, especially over the long forecasting period.

Given our initial assumptions on the model, the reflected price development during the forecasting period is likely to be driven by natural disasters but do not allow for an accurate forecast as these kinds of disasters are extremely hard to predict. There is an inherent tradeoff between accuracy and meaningfulness of interpretation.

Statements about confidence are based on qualitative argumentation and do not represent any statistical measures, except stated otherwise.

The structure of the algorithm allows the important assumption that, by forecasting the regular returns based on the return distribution of the past 20 years, all relevant information that could severely affect the stock price is already priced in – markets are efficient up to today. This means the effect calculated based on the forecasts is at least partially driven by the employed shocks which are natural disasters. Since these disasters are carefully selected as described in section 2, with medium to high confidence the effect is driven by the employed disasters.

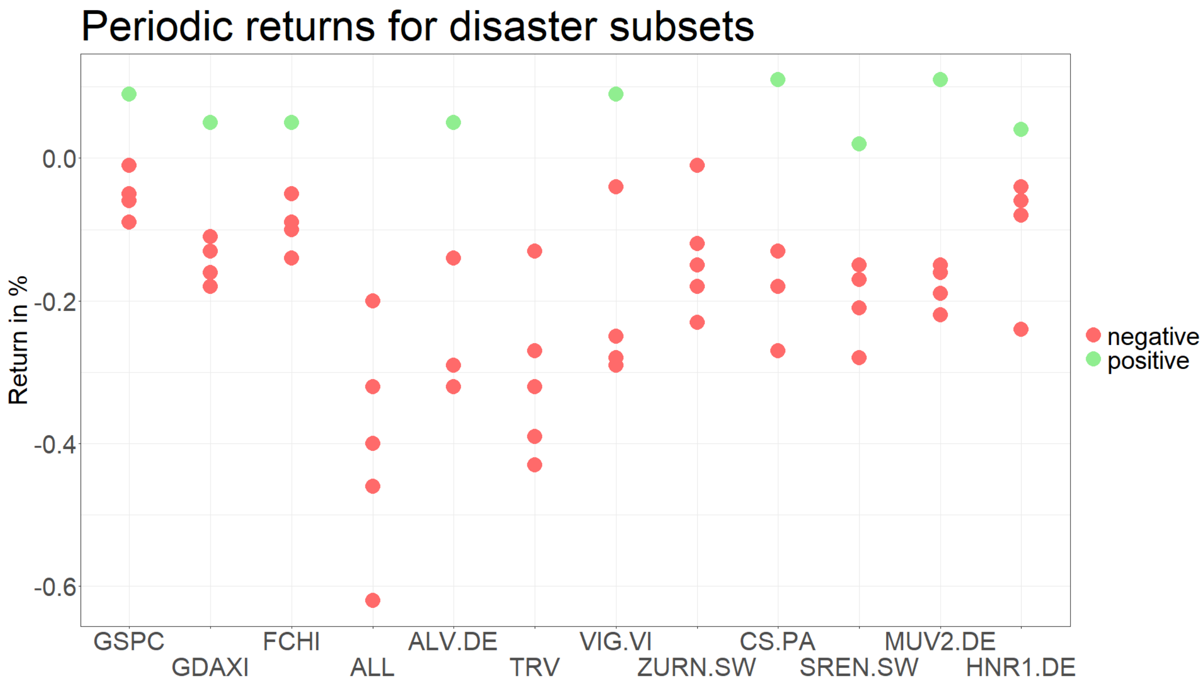
Additionally, the individual behavior of the companies is assumed to remain unchanged, which implies that the companies do not change their core operations and related activities over time. This has multiple implications - first, since insurers and especially reinsurers pursue a lot of hedging and other mitigation efforts, the negative forecasted effect already captures the historic efforts. This implies that, if these companies do not pursue additional activities, we can interpret the effect with higher confidence. On the other hand, additional efforts above what has been captured from the past is not reflected in this forecast. Depending on the volume, it might be possible to severely reduce the estimated effects. Second, the business model may shift. If the estimated outcome represents the true effect, with high confidence we can assume that companies 23 would reduce the exposure to geographical regions in which the combined ratio constantly exceeds 100, which has already happened in the past (Born & Viscusi, 2006). Alternatively, they increase the insurance premia for high-risk areas to compensate for the additional risk, which is common practice and partially defined under the so-called "insurance cycle" (Doherty & Garven, 1995).

4.3 Discussion and interpretation

Two observations are of primary relevance. (1) There is a measurable difference in adverse returns in the aftermath of natural disasters compared to the market and the individual average return. (2) The effect, given the period, is not strong enough to be irreversible. Table 3 provides a summary of the adverse returns identified in a given period for each stock. We identify that there are adverse returns in the short-term aftermath of a natural disaster. This effect is strongest for the 7-day period and is approximately stable over the shorter periods. This implies the existence of a possible relationship between natural disasters and negative asset price reactions. On an individual basis, the effect is by far the strongest for US stocks, ALL (Allstate) and TRV (Travelers), with an average effect of -0.4% and -0.308%, respectively. Interestingly, these are the stocks that are ranked first and third in terms of exposure as well as being heavily exposed to tropical cyclone activity in the USA. Compared to the control panel, each stock shows a positive drift for the long run whilst having negative returns for the subset periods, except SREN.SW (Swiss Re). Swiss Re is the only company that has a general negative return trend and thus shows the smallest difference to the control out of all re-/insurers. The adverse effect can thus be partially attributed for all companies to the existence of natural disasters, except for Swiss Re. In comparison to the peer group consisting of the three indices, we identify that

the adverse effect is stronger on average for the underwriters than for the indices, further strengthening the implication that the effect is attributable to an exogenous shock. In Figure 6 we can further observe that the average returns for the indices are much more clustered than for individual stocks. No matter the period, the indices are less volatile and do not react as strongly. Building on the fact that we excluded variables that heavily influence the market in general and the fact that the returns of the random control group are different, verifies our initial expected relationship.
A full list of the outputs can be found in Appendix F.

Figure 6: Adverse returns graphic summary



Note: This figure plots the period returns for each disaster subset. That is, each point describes the average return for the 14-, 7-, 6 -,5- and 3-day subsets for each individual stock/ index. Green dots indicate positive average returns. Red dots indicate negative average returns. Source: Own analysis.

Table 3: Adverse returns table summary

	14d	7d	6d	5d	3d	MeanIS	Control	Diff
ZURN.SW	-0.01	-0.18	-0.15	-0.12	-0.23	-0.138	0.027	-0.165
ALV.DE	0.05	-0.32	-0.29	-0.32	-0.14	-0.204	0.022	-0.226
CS.PA	0.11	-0.27	-0.18	-0.18	-0.13	-0.13	0.061	-0.191
SREN.SW	0.02	-0.21	-0.17	-0.15	-0.28	-0.158	-0.075	-0.083
ALL	-0.20	-0.62	-0.46	-0.4	-0.32	-0.400	0.070	-0.470
TRV	-0.13	-0.43	-0.32	-0.27	-0.39	-0.308	0.023	-0.331
MUV2.DE	0.11	-0.22	-0.16	-0.19	-0.15	-0.122	0.003	-0.125
HNR1.DE	0.04	-0.24	-0.08	-0.06	-0.04	-0.076	0.065	-0.141
VIG.VI	0.09	-0.28	-0.29	-0.25	-0.04	-0.154	0.030	-0.184
GSPC	0.09	-0.01	-0.05	-0.06	-0.09	-0.024	0.017	-0.041
FCHI	0.05	-0.09	-0.10	-0.14	-0.05	-0.066	0.010	-0.076
GDAXI	0.05	-0.11	-0.13	-0.18	-0.16	-0.106	0.110	-0.216
MeanAS	0.009	-0.308	-0.233	-0.216	-0.191			

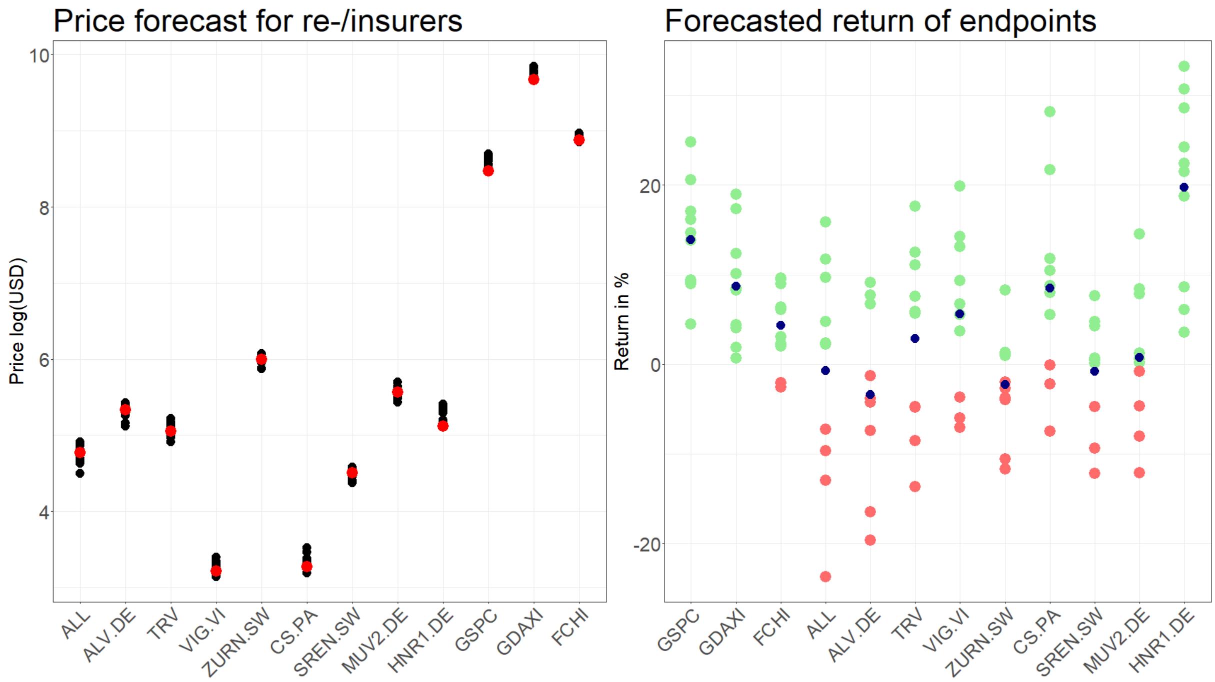
Note: All values are in % terms. This table shows the output of the adverse returns for each stock (rows) and each subset period (column). The column "MeanIS" is the average over all subsets for each individual stock. The row "MeanAS" is the average over the subset time period and all stocks. The "Control" column shows the average returns for the random sampling control groups. The control mean is a measure to verify that in normal times, the average stock return for the given subset period is different than what is measured for the disaster subsets. The control algorithm randomly samples subsets of periods for the implied 14-,7-,6-,5- and 3-day periods over the 20-year return period and calculates the mean. We run 500 random samples in total. The "Diff" column is the difference between the MeanIS and Control.
Source: Own analysis.

Recalling the forecasting algorithm as $S_{t+1} = S_t(1 + r_t)$, $r_t = \mathbb{1}_{s=1}(r_{t-1} + \mu_t a_t) + \mathbb{1}_{s=0} sds(1)$, the endpoints are a combination of the event returns and historical returns. Intuitively, companies with a higher historical return are likely to have higher returns in the future within our model. This partially manages to offset the negative effect of natural disasters. This is why, in the case of TRV (Travelers) and ALL (Allstate), the trend is not as bad as initially expected based on the measured adverse returns of the disaster subsets. This can be seen in Figure 7 (Left), which shows the forecasted prices for the selected companies and the peer group. For the peer group consisting of three major indices, the expected target prices generally lie above the initial price. Although we have identified adverse returns, these are too small to have a negative effect in the long run. This result is in line with results found by Ben Ammar et al. On the other hand, the majority of insurers and reinsurers tend to be at risk, except for Hannover Re (HNR1.DE) which is mostly due to the enormous historic capital gains. This trend is supported by the idea of fear-induced behavior.

Figure 7 (Right) shows the main results of the forecasted returns. While the majority is expected to perform well, some companies show strong negative development. Allstate and Allianz are the most extreme with possible returns approaching -25% and -20%, respectively. ALV.DE is particularly interesting in comparison to TRV. Given the adverse returns of TRV (-0.308%) and ALV.DE (-0.204%), we would expect TRV to perform worse than ALV.DE. This is not the case, as shown in Figure 7. The positive drift of TRV is big enough to offset a majority of the impact caused by natural disasters. This can also be seen by checking the average forecasted return, denoted by the dark blue dot. A third possible combination is that the company is not severely affected by natural disasters and has a strong positive drift, which is the case for Hannover Re. With only small adverse returns and strong historic returns, the stock is very likely to be an outperformer in the future. For the peer group, we have a clear indication that these are not affected by natural disasters. In any case, and in the majority of cases for FCHI, the indices will continue to perform well.

On average, insurers and reinsurers are likely to continue to underperform, partially explained by climate change. But there seems to be no significant deviation from the regular return pattern.

Figure 7: Forecasted price trend



Note: The left figure shows the forecasted endpoints as the asset price in log(USD). The log scale was used because values are so different that there would be no visible difference in lower priced stocks. The red dots indicate the initial price at S=0 (begin of forecasting period). The black dots indicate the endpoints at S=500. The right figure shows the return over the forecast period for each stock and index. The return is calculated using standard return metrics for the period of S=0 and S=500. The light green dots indicate positive forecasted returns. The red dots indicate negative forecasted returns. The blue dots indicate the average forecasted return.
Source: Own analysis.

4.4 Drawbacks

One major drawback of the model is the fact that there is no exact relationship between climatological data and disaster intensity or severity. The global climate is too complex for an exact assessment. Although there are indicators, which we have used in this forecast, there might be a bias in the outcome. To tackle this effect, a lower and upper-bound scenario was developed rather than an explicit forecast.

A second drawback is the assumption regarding efficient markets. We base part of our interpretation on the fact that historic returns consider all variables influencing asset prices and use this fact to broadly explain efforts to mitigate disaster impacts in our forecast. It does provide a plausible basis for interpretation but it is very unlikely that the companies do not adapt their business to new challenges, which is why this is a major drawback and needs further research and modification of the model.

Third, the model only focuses on a very specific segment of natural disasters. The model needs enhancement in the types of disasters that are yet unknown to maybe also be impacted by climate change and cause economic damage.

Last, the model amplifies positive returns similarly to negative returns. This is more of a technical flaw that does not really have an impact on the outcome as we only focus on the adverse returns. There is some explanatory power in the outcome if returns are positive but much less than if negative. In a next step, this could be a starting point to improve the model and explain recovery periods for insurance and reinsurance stocks after shocks. This could be particularly interesting for developing trading strategies related to the insurance sector.

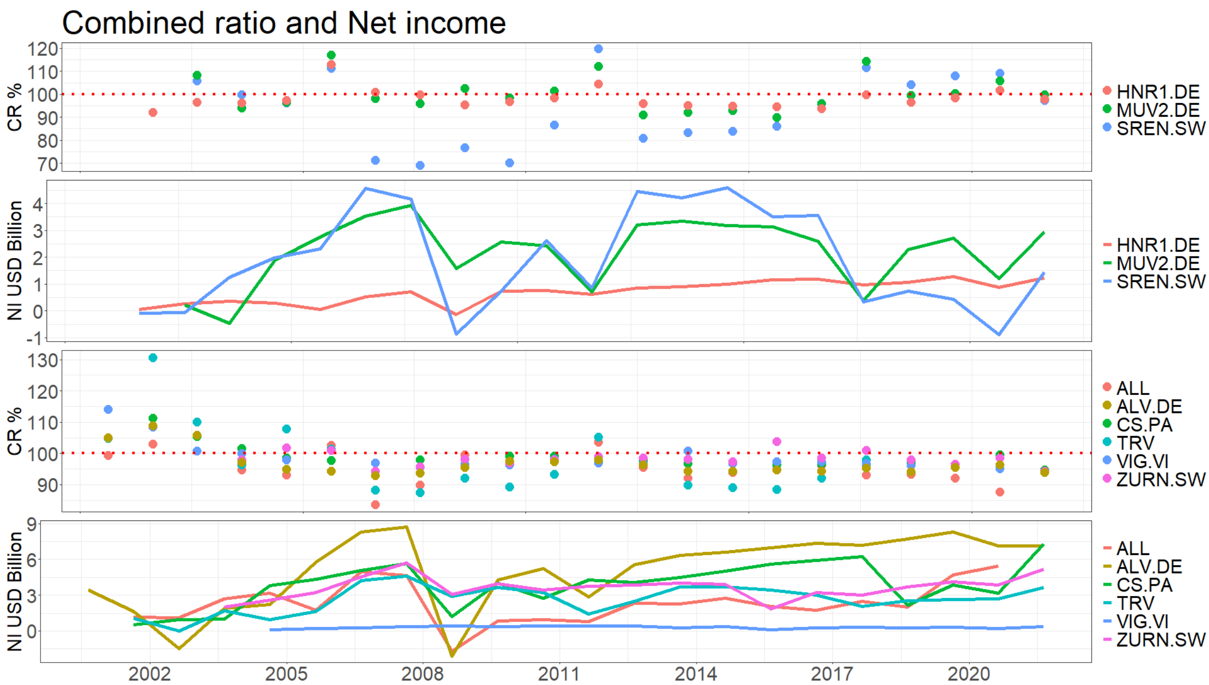
5 Real Effects

5.1 The relationship between combined ratio and net income

To analyze the real effects of natural catastrophes on underwriters, we take a look at the relationship between the combined ratio and the net income. The combined ratio is a key performance indicator in the PCI segment to measure the total expenses of the core operations (Hayes, 2020). Naturally, a higher combined ratio implies a lower net income for the particular segment. Figure 8 plots the combined ratio and the net income for the period from 2001 to 2021. The combined ratio is calculated as the sum of the expense ratio and the loss ratio which represents the combination of underwriting expenses and claim payments (Hayes, 2020). A combined ratio above 100 indicates that the company has incurred a loss for the PCI segment. While most primary insurers' combined ratio is rather stable, reinsurers tend to be affected much stronger by shocks, especially in 2005, 2011 and 2017-2020. These dates coincide with some of the most severe natural disasters; 2005 with hurricanes Katrina and Wilma, 2011 hurricane Irene and for the last period we had tropical cyclones Harvey, Maria, Irma, Laura and Hagibis. The net income behaves accordingly. In years with severe shocks, the net income decreases as a direct effect, although the effect is not as severe for the net income of the total business as for the PCI segment. Nevertheless, there is a direct relationship that poses a threat to the net income. Using simple linear regression, we estimate this effect for each company and find that in any case there is a negative, mostly significant relationship which is strongest for Axa (-0.776**(1%)), Allianz(-0.445**(1%)) and weakest for Vienna (-0.007), Hannover Re (-0.033). Interestingly, the effect estimated is strongest for primary insurers and weakest for reinsurers, although in Figure 8 we identify a different pattern. This can be explained by reinsurance and is an indicator for a well-functioning risk-sharing system.

As retained earnings decrease, dividend payments could be at stake in the future. By taking a closer look at the annual reports of the primary insurers we identified that the abnormal swings in net income mostly stem from other sources than natural disasters (extension 1). For example, Travelers in 2002-2003 had a very high combined ratio due to the terrorist attack on September 11th and prior year asbestos reserve development (extension 1.4.2). Axa reports that the high combined ratio is explained by a combination of commercial risk claims and natural disasters in 2000 – none thereafter (extension 1.8.1, 2000-2001). Allianz similarly states that the combined ratio is driven by a combination of unexpected flooding damages and asbestos as well as the September 11th terrorist attack under business interruption insurance – none thereafter (extension 1.6.1, 2000-2002). Interestingly, the net income shows a different pattern, especially in 2008 and 2018. This is explained by the nature of the business model. Generally, the underwriting business only generates enough profit to keep the business running but does not generate excessive returns, which is why investing is a major component. In times of distress, when asset prices deteriorate, net income falls due to less revenue from investment activities but the combined ratio remains stable.

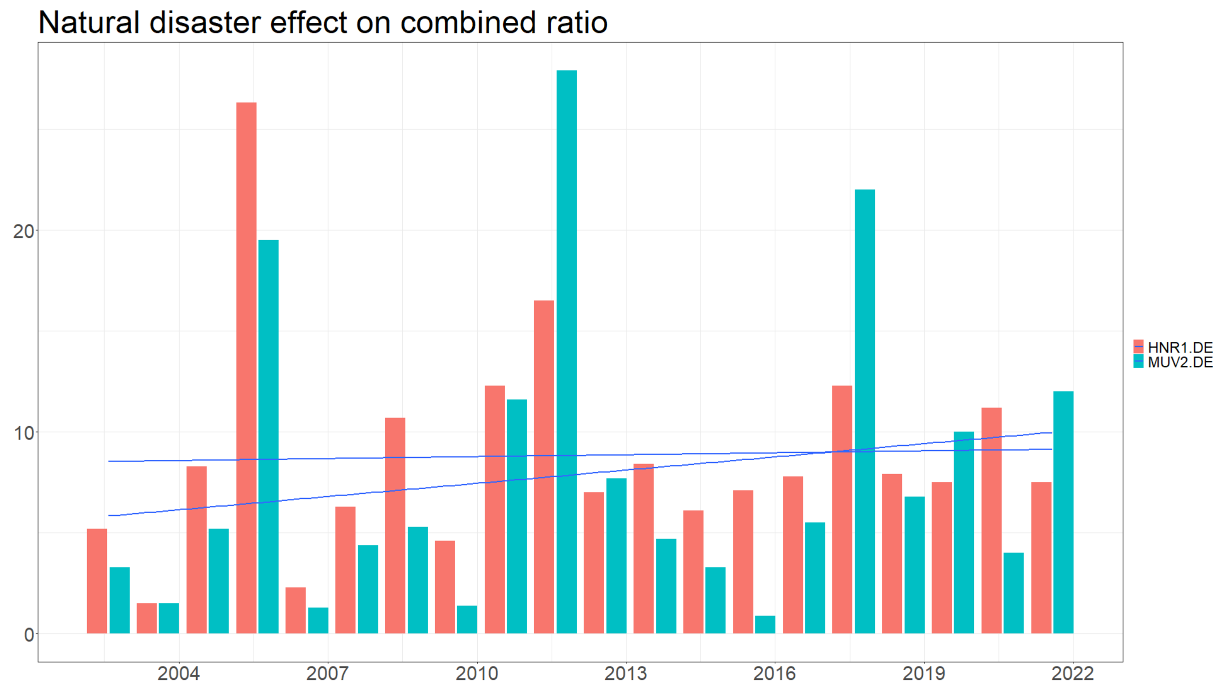
Figure 8: Combined ratio and net income



Note: This figure shows the combined ratio and net income for each individual company. The red line indicates the break-even point for re-/insurers. A combined ratio above indicates a loss for the PCI segment and a profit for below. The net income is the company's net income, often also referred to as comprehensive income under IFRS.
Source: See extension 1 to bibliography.

Taking a closer look at the annual report of Munich Re and Hannover Re, they provide detailed information on the determination of the combined ratio regarding natural disasters. On average, expenditures on natural disasters account for 5%-7% of the combined ratio. In extreme cases, the effect can increase to 25%, which can be seen in Figure 9. Particularly in the years mentioned above, we can identify a direct impact of natural disasters on the companies' expenses – which is intuitive. The blue line indicates the trend over the past two decades. For both underwriters, the slope is positive which indicates that in the future more losses will be attributed to natural disasters.

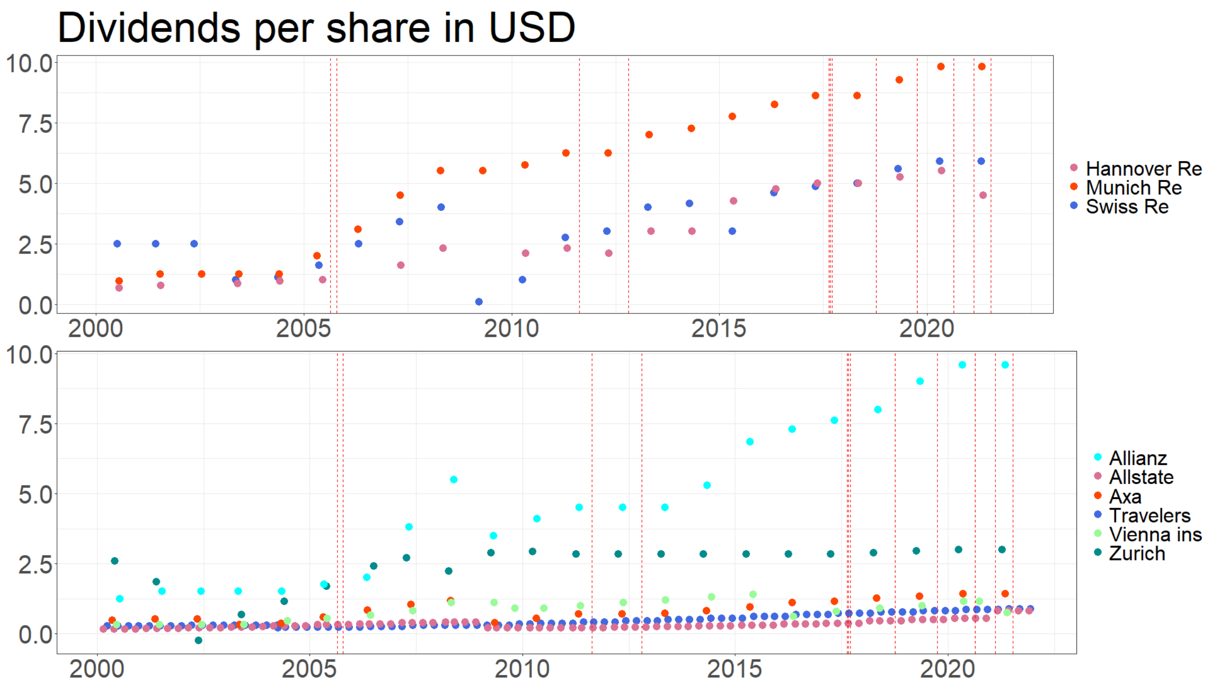
Figure 9: Natural disaster effect on combined ratio



Note: This figure plots the share of natural disaster expenses in the combined ratio over time for the two reinsurance stocks Hannover Re (HNR1.de: red) and Munich Re (MUV2.DE: blue). The blue lines indicate the trend in development.
Source: See extension 1 to bibliography.

As an investor owning insurance stocks, optimizing risk and total return is key. The negative effect on asset prices estimated in this model is different than the real impact. Given the ownership structure of most insurance firms, the traded volume and turnover is lower than in other sectors, which coincides with dividends being the dominant return driver (Damodaran, 2021)(Appendix H). This adds to the fact that asset prices do not react as extremely as intuitively expected to information entering the market regarding exogenous shocks. In the long run though, the real effects could cause much more damage to investors' returns than the forecasted negative effect on stock returns. By incurring consecutive losses, capital reserves threaten to run low which could lead to regulatory issues as well as crumbling dividend payments. Historically though, natural disasters have not had a negative impact on dividend payments, which can be seen in Figure 10. The companies themselves also do not specifically state any threat to dividend policies or capital requirement issues in the context of natural disasters. Though, there are different events that have major impacts on the cash positions and the ability to pay dividends. But these are more related to other kinds of crises such as the financial crisis in 2008 or the Covid-19 pandemic.

Figure 10: Dividends matched to natural disasters



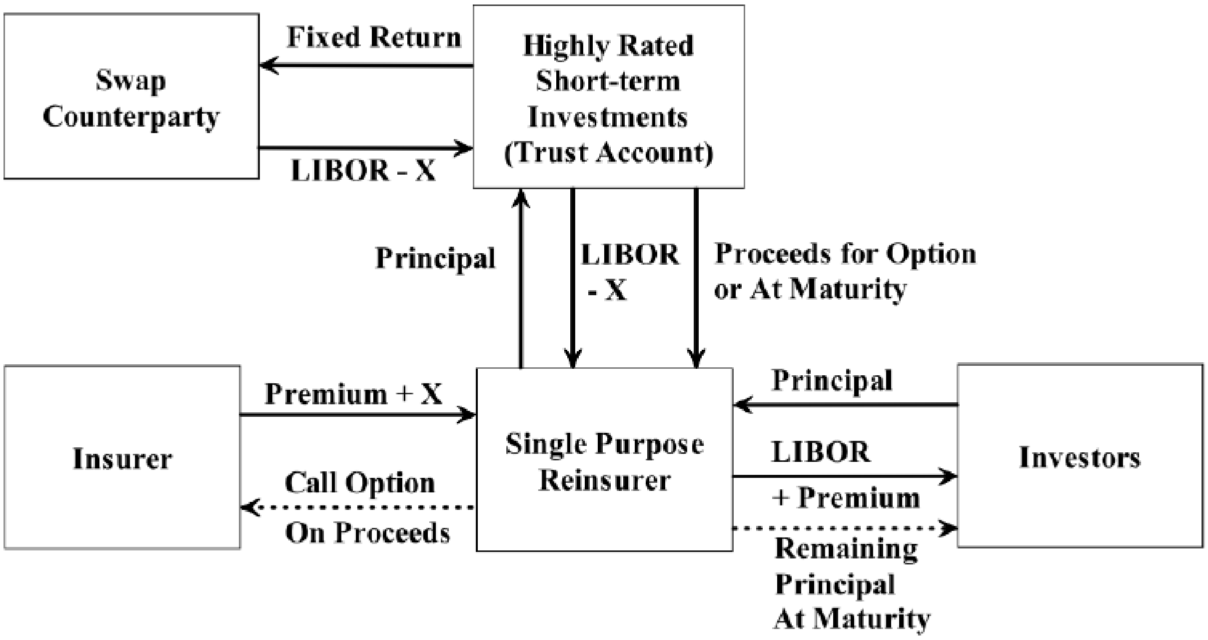
Note: This figure plots the dividend payments in USD for all relevant companies. The vertical red lines indicate the twelve selected natural disasters. The dividend for Zurich is expressed in log(USD) terms for better comparison, which explains the negative dividend in the year 2003.
Source: primary: https://finance.yahoo.com/, verified using Bloomberg & individual company reports (see extension 1 to bibliography).

5.2 Alternative risk transfer

Alternative risk transfer defines the usage of non-insurance or reinsurance-linked risk transfer via financial instruments (Evans, 2022). The biggest asset class in the insurance industry are Insurance-linked securities (ILS).

ILS were introduced in 1990 due to primary and reinsurers facing massive one-time losses due to natural disasters (Evans, 2022). "ILS encompasses the ILS asset class, which consists of catastrophe bonds (cat-bonds), collateralized reinsurance instruments and other forms of risk-linked securities such as warranties" (Evans, 2022). Though, the vast majority of ILS assets are cat bonds. Cat bonds are risk transfer instruments from insurers or reinsurers to investors. Cat bonds normally pay a fixed coupon until a disaster occurs which triggers a full or partial loss of principal (Braun et al., 2019). Normally, the maturity is 3-5 years which corresponds with the covered period. The typical structure of a cat bond agreement is shown in Figure 11.

Figure 11: Structure of a CAT bond



Note: This figure shows the underlying principle of catastrophe bonds.
Source: https://www.researchgate.net/figure/Typical-structure-of-a-CAT-bond_fig1_260519688.

The Cat Bond Investors, risk takers in this case, earn a combined return of premiums and return on collateral, which explains the excess returns in comparison with alternative assets (Braun, 2016). Simultaneously, the investor takes on the risk in case of an event. That is, depending on the contract specifications, an event such as a tropical cyclone meeting certain triggering criteria (often indemnity). In that case, all or part of the principal amount is lost (Evans, 2022).

Cat bonds are sought-after instruments due to two reasons. First, cat bond defaults are uncorrelated with defaults of most other securities (Braun, 2016; Commission, 2013). Second, over the past two centuries, cat bonds have managed to outperform equities, corporate bonds and hedge funds (Braun et al., 2019). But even those assets show signs of weakness. In 2019, Morana and Sbrana have found that, since the inception of cat bonds, their risk-return profile has steadily worsened. Investors earn continuously less return per unit of risk with each coming year (Morana & Sbrana, 2019). Focusing on the link between cat bond prices and natural disaster events, they find that there is no significant relationship. Most of the fall in multiples is explained by monetary policy and portfolio shift effects (Morana & Sbrana, 2019). But there seems to be a significant undervaluation of global warming risk (Morana & Sbrana, 2019). While there is no direct negative effect for investors associated with climate change, Lee and Yu suggest that the issuance of cat bonds increases the value of a reinsurance contract which benefits the underwriter (Lee & Yu, 2007). Given our trend of natural disasters, it is likely that cat bond market activity will continue to increase by large sums, especially given the fact that about 50% of outstanding risk capital is exposed to Atlantic hurricanes (Evans, 2022; Morana & Sbrana, 2019) and 50% of total cat bonds are emitted by reinsurance companies (Lee & Yu, 2007). In addition to this effect, O'Connell and Froot find that after large-scale events, reinsurance prices generally exceed "fair" values (Froot & O'Connell, 2008). This leads to the conclusion that the estimated effect in this paper, at least for reinsurance companies, may be fully compensated and thus not affect the investors' total return in any way.

5.3 Opportunities and global initiatives

Climate change and its identified implications for the insurance sector seem to be primarily and intuitively in a negative relationship. But there is huge untouched potential for underwriters. Holzheu and Turner estimate an insurance protection gap of 81 billion USD for the three major economies USA, China and Japan which is likely to be caused by natural disasters (Holzheu & Turner, 2018). Even though the gap has been widening historically and continues to do so, closing this gap yields huge potential profits and is economically beneficial for insurance takers, even if only closing the underinsurance gap (Holzheu et al., 2015).

Besides political and individual efforts to close this gap, there could be a natural, human-induced factor helping insurance companies boost their income. From 1989 to 1994, numerous economists analyzed the impact of earthquakes on insurance companies. They found that for these isolated catastrophic events, firm value has increased due to investors' expectations about additional cash inflow from new customers seeking earthquake protection (Aiuppa et al., 1993; Shelor et al., 1992). In the 2006 GFSR report a similar case is mentioned concerning tropical cyclones and reinsurers due to rising prices (Häusler et al., 2006). Although our analysis has not found such a relationship with regards to climate-related natural disasters, it is possible that, with time and continued economic growth, people will be willing to pay more for insurance. There is, however, an important difference between earthquakes and climate-induced events. The return period is much smaller for an exceptional tropical cyclone than for an earthquake.

Economic growth, especially in emerging markets, yields additional profit growth for the PCI sector. Swiss Re estimates that by 2040, total sector premiums will more than double from 1.8 trillion to 4.3 trillion USD, led by property insurance with an annual growth of 5.3% (Holzheu et al., 2021). There are also newer types of insurance arising. One that is becoming increasingly more popular but has been around for quite a while is "parametric insurance". Due to its simplicity, re/insurers could reduce their expense ratio and simultaneously attract more customers as the affordability increases (Commission, 2013). It also allows for better modeling, since the claim payments are defined beforehand (Re, 2018). This type of contract is well suited for poorer regions and provides opportunities beyond developed countries (Re, 2018).

Over the past two decades, several global initiatives have been launched to mobilize capital toward a green economy (Bacani et al., 2015). This includes shifts in capital allocation as well as governmental support in case of natural disasters. One of the most renowned is the Sendai Framework for Disaster Risk Reduction 2015-2030, a global agreement endorsed by the UN General Assembly which focuses on disaster risk reduction and state intervention ((UNGA), 2015). With global actions focusing precisely on disaster risk reduction and transfer, this may diversify the risk taken by underwriters and lessen the exposure.

6 Concluding remarks

Given our results, we conclude with high confidence that there will be no negative effect for investors with regards to capital gains and dividends. We base our conclusion on the following arguments. (1) Although we have identified adverse returns in short periods directly after natural disasters, historically, these tend to revert to mean return patterns. (2) The forecasted increase in frequency and severity is generally not enough pressure to force asset price crashes to an irreversible extent. Only an exclusively upper-bound scenario would likely be able to do so. (3) There are no negative real effects for investors collecting dividends. The dividend policy is unaffected by natural disaster impacts due to well capitalized firms and strong regulations. (4) Global and individual efforts are made to reduce natural disaster risks and impacts. Underwriters themselves have proven to be innovative when it comes to transferring risks. Which was the case with the introduction of catastrophe bonds in the 1990s and other ILS later on. The push for global cooperation is further strengthened as disasters not only cause direct economic damage but also have indirect macroeconomic and social costs. Be this the loss of life, loss of development or loss of opportunity, all are of primary relevance and strong action drivers. (5) Climate change may seem to have only negative aspects to it, but from an investor's and underwriters' perspective, there is huge untapped potential if acting right – whilst even helping global ecosystems to stabilize.

7 Further Research

A lot of topics mentioned are of interest for future research. Among the most interesting ones, one could analyze the impact of net income decreases on the company's equity position to identify possible emerging difficulties regarding capital requirements and dividend policy. With a majority of perils being of secondary type, this relationship could outweigh the relationship established in this model – which looks at primary perils. From thereon, put the natural disasters in a bigger context and add other kinds of disasters. With the global situation destabilizing and biological types of threats becoming more possible, insurers will face new, big challenges (AXA, 2020; McLennan et al., 2021).

Also, there needs to be more research done on the stabilizing impact of cat bonds on re-/insurance asset prices. Especially in the interesting context that cat bond multiples continue to worsen and might not outperform alternative investments anymore. With widening spreads and consequentially higher prices (Braun, 2016), investors may turn away from catastrophe bonds.

A third interesting topic considers the model developed in this paper. Especially with regards to mitigation efforts pursued by underwriters, one could modify the algorithm to include dynamic parameters that describe company-dependent behavior. Going further, differentiating between unexpected and expected damage could be insightful as well as analyzing the recovery periods after different kinds of natural disasters.

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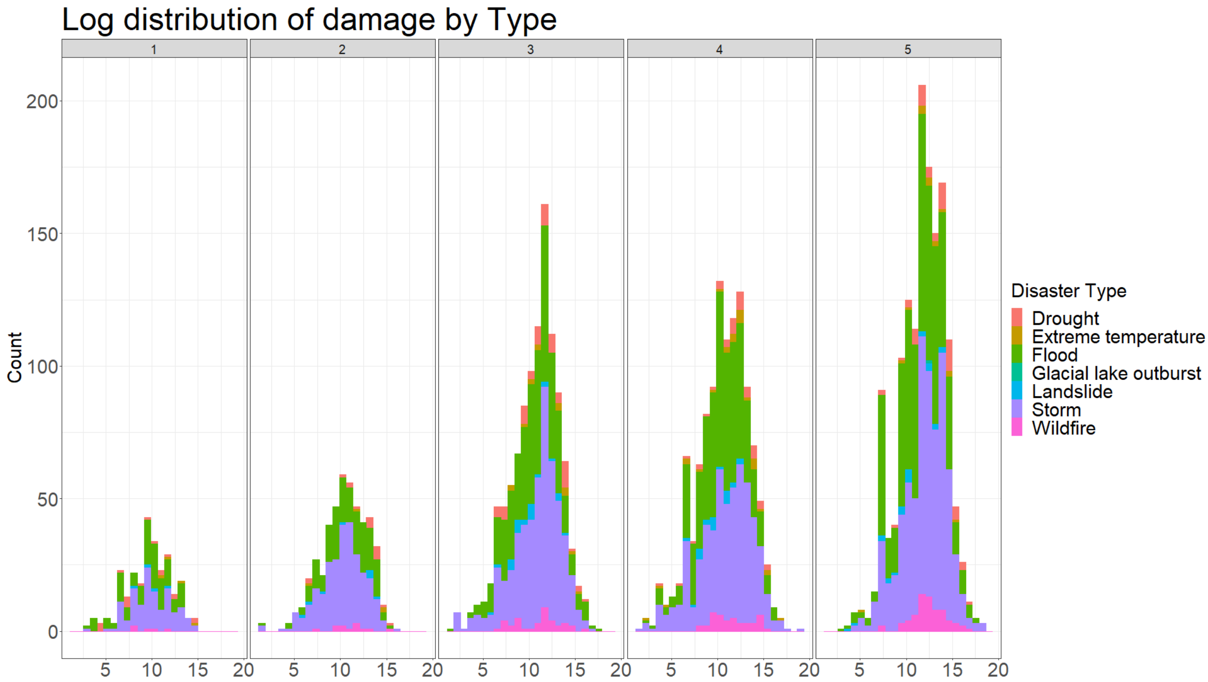
9 Appendix

Appendix A1

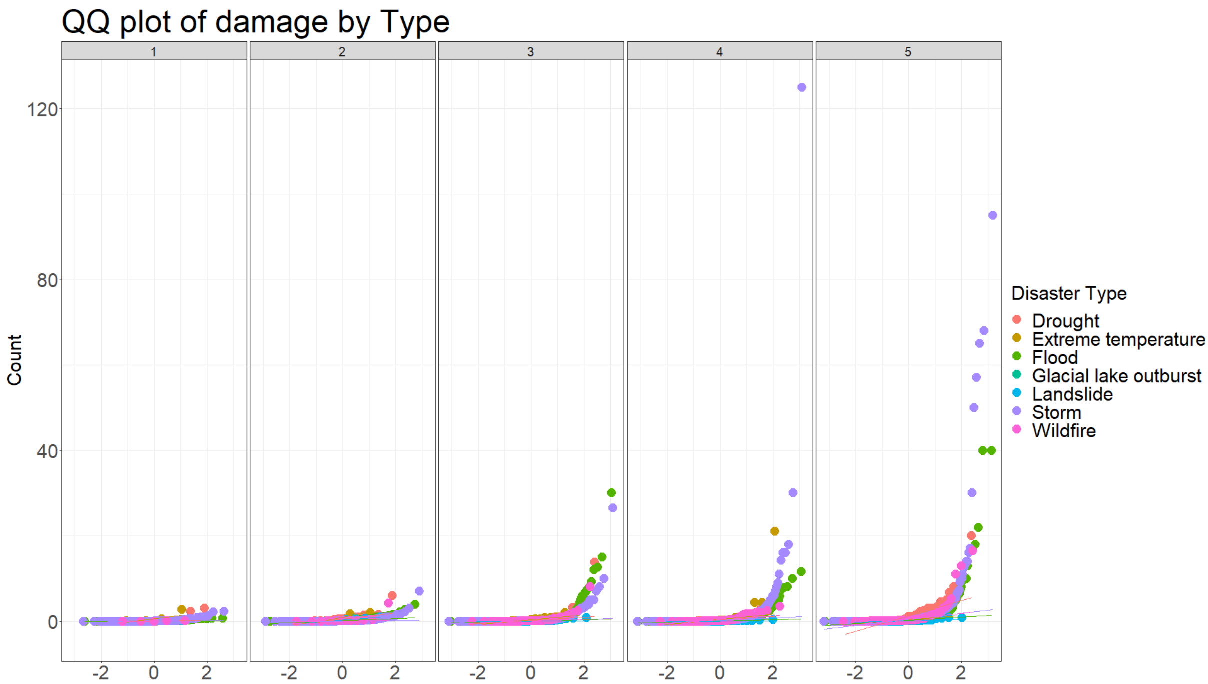
Figure 12: Distribution of damage by disaster type



Note: This plot shows the distribution of natural disasters by type. On the x-axis we have the damage in log(billions USD). The y-axis shows the number of events per damage. 1 bar equals 25 bins. The numbers indicate the yearclass (decade).
Source: Own graphic. Data: EM-DAT by CRED. Retrieved at: https://www.emdat.be/

Appendix A2

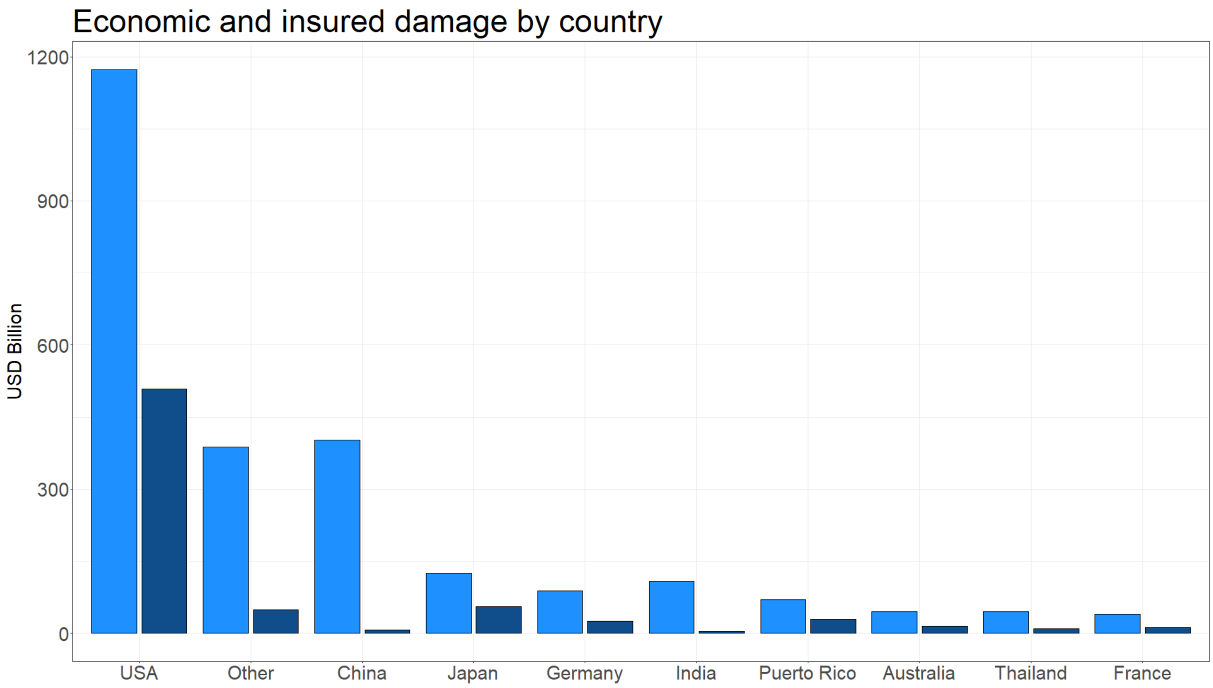
Figure 13: QQ-Plot of damage by disaster type



Note: We use the QQ-Plot to show the development of the extreme events. The distribution shows heavy right-sided tails which are mostly caused by storms (Tropical cylones). The numbers indicate the yearclass (decade).
Source: Own graphic. Data: EM-DAT by CRED. Retrieved at: https://www.emdat.be/

Appendix B1

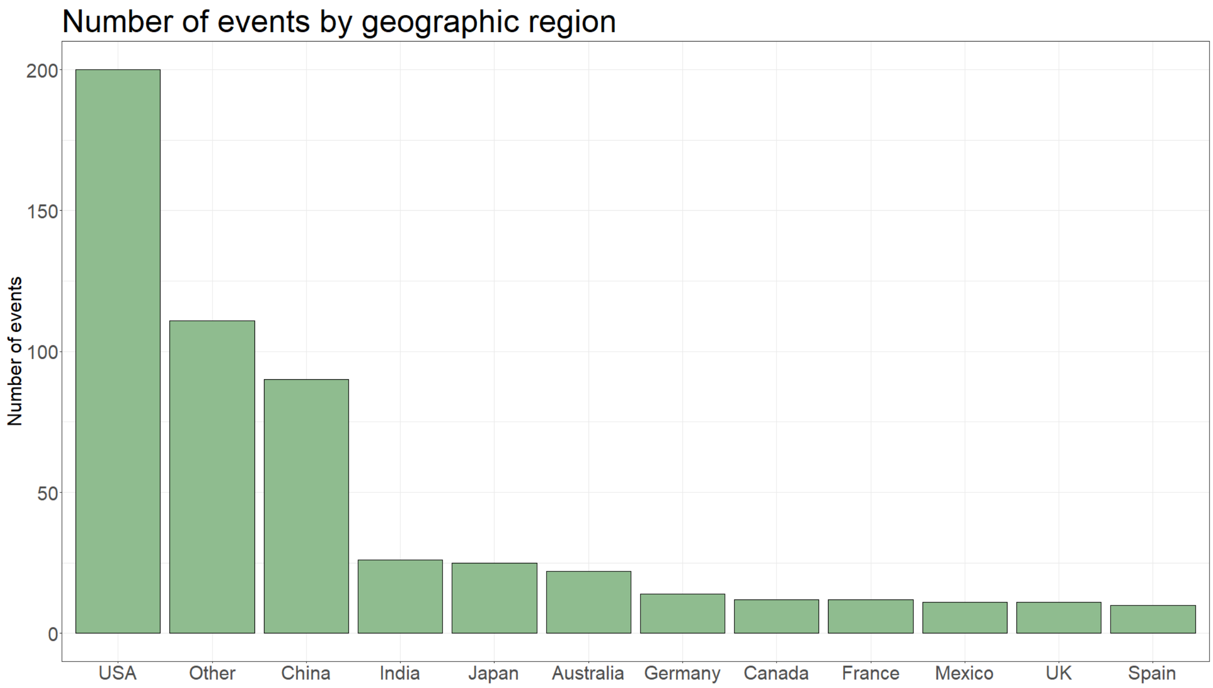
Figure 14: Ecnonomic and insured damage by country



Note: The light blue bars indicate the total economic damage in USD billion. The dark blue bars indicate the insured loss, measured in actual claim payments. "Other" is the sum of damage over all non-listed countries.
Source: Own graphic. Data: EM-DAT by CRED. Retrieved at: https://www.emdat.be/

Appendix B2

Figure 15: Number of natural disasters by geographic region



Note: This figure shows the number of natural disasters per geographic region. "Other" is the sum of occurrences over all non-listed countries. Source: Own graphic. Data: EM-DAT by CRED. Retrieved at: https://www.emdat.be/

Appendix C1

Table 4: List of all PCI companies screened

Ticker	Data	GWP	PC	Dis_PC	PC%Rev
ALV.de	1997	12228	11685	3401	27.81%
CS.PA	1990	96723	48729	28628	29.60%
G.MI	1986	69785	21525		0.00%
2601.HK	2010	54733	22778	2996	5.47%
2318.HK	2004	197191	42657	10841	5.50%
ZURN.SW	1998	63134	35518	12786.48	20.25%
MFC	1999	6536	107	107	1.64%
VIG.VI	2000	11002	4939.898	3487.634	31.70%
8630.T	2010	22945	20785	8952.0995	39.02%
8725.T	2008	22012	22012	6659.037	30.25%
		11389	*11389*	*3564.757*	
		9395	*9395*	*2480.28*	
		1228	*1228*	*614*	
8766.T	2005		30687	6073	19.79%
ALL	1993	88942	82716	26986	30.34%
TRV	1984	29700		10956	36.89%
HIG	1996	20523		1743	8.49%
TLX.DE	2012	41105	27179		0.00%
TLX.DE	2012	738	738	362	49.05%
NN.AS	2014	13800			
AIG	1985	25092	12808	4803	19.14%

Note: This table provides an overview of all insurance companies that were selected for screening. (1) ¿20% share of GWP is disaster related revenue. (2) Stock is listed and has sufficient data available. (3) Stock has exposure to disaster affected regions. GWP (million USD) is the Gross Written Premium. PC (million USD) is the GWP related to Property and Casualty. Dis_PC (million USD) is the GWP amount specifically related to natural disasters. PC%Rev (exposure criteria) is the share of Dis_PC to total GWP.
Source: Own table. Data: see extension 1 to bibliography.

Appendix C2

Table 5: List of Reinsurance companies screened

Ticker	Data	GWP	PC	Dis_PC	PC%Rev
SREN.SW	1995	40770	20832	8334.32	20.44%
MUV2.DE	1998	54890	28542.8	8355.29	15.22%
HNR1.DE	2000	24765	16744	8003.632	32.32%

Note: This table provides an overview of all reinsurance companies that were selected
Source: Own table. Data: see extension 1 to bibliography.

Appendix D

Table 6: List of top 52 natural disasters part 1

Cost	IL	Fat	Type	Year	Country	Start	End	Dur	Crisis	Policy	Attr	Include
423.7	41.0	19747	T	2011	JP	2011-03-11	2011-03-11	1	0	0	0	0
179.7	1.0	87587	EQ	2008	CHN	2008-05-12	2008-05-12	1	1	0	0	0
167.4	85.0	1540	TC	2005	US	2005-08-23	2005-08-31	9	0	0	1	1
133.2	31.0	107	TC	2017	US	2017-08-17	2017-09-03	18	0	0	1	1
95.5	31.0	3059	TC	2017	PR	2017-09-16	2017-09-30	15	0	0	1	1
71.8	1.8	451	WF	2019	AUS	2019-06-01	2020-03-01	275	0	1	1	0
71.4	33.0	233	TC	2012	US	2012-10-22	2012-10-29	8	0	0	1	1
65.2	31.0	115	TC	2021	US	2021-08-26	2021-10-04	40	0	0	1	0
60.65	17.0	104	D	2012	US	2012-01-01	2013-12-31	731	0	1	1	0
53.3	18.0	815	FL	2011	THL	2011-07-25	2012-01-16	176	0	1	1	0
48.2	33.0	134	TC	2017	US	2017-08-30	2017-09-14	16	0	0	1	1
47.5	19.3	185	EQ	2011	NZ	2011-02-22	2011-02-22	1	0	0	0	0
38.6	3.7	68	EQ	2004	JP	2004-10-23	2004-10-23	1	0	0	0	0
36.7	9.8	195	TC	2008	US	2008-09-01	2008-09-15	15	1	0	1	0
33	8.2	184	FL	2021	GER	2021-07-12	2021-07-19	8	0	0	1	1
32.3	20.6	278	FL	2020	CHN	2020-05-01	2020-09-01	124	0	0	1	0
27	8.0	525	EQ	2010	CHL	2010-02-27	2010-02-27	1	0	0	0	0
26.1	7.4	74	TC	2018	US	2018-10-07	2018-10-16	10	0	0	1	1
26	12.0	87	TC	2005	US	2005-10-15	2005-10-27	13	0	0	1	1
25	12.0	103	WF	2018	US	2018-01-01	2018-12-31	365	0	1	1	0
24.5		110	TC	2005	US	2005-09-18	2005-09-26	9	0	1	1	0
23		237	WS	2021	US,CA	2021-02-13	2021-02-17	5	0	0	1	1
22.92			FL	2016	CHN	2016-06-01	2016-09-01	93	0	0	1	0
21.1			FL	2010	CHN	2010-05-10	2010-09-01	115	0	0	1	0
20			TC	2004	US	2004-08-09	2004-08-15	7	0	1	1	0

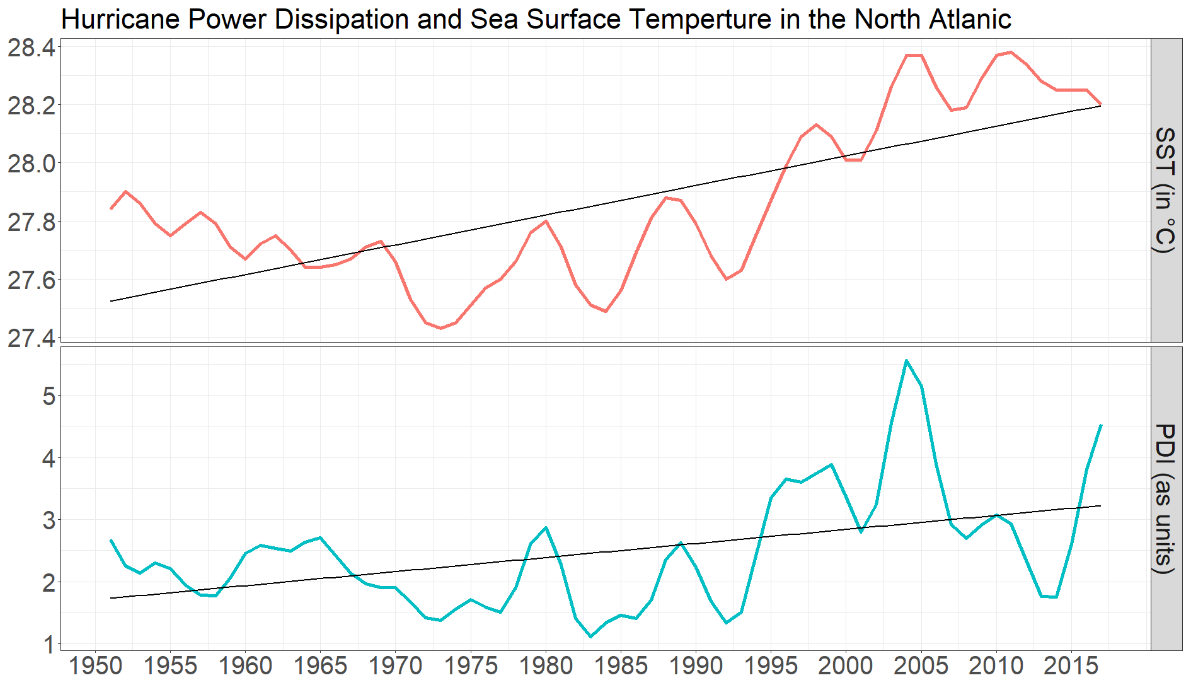
Table 7: List of top 52 natural disasters part 2

Cost	IL	Fat	Type	Year	Country	Start	End	Dur	Crisis	Policy	Attr	Include
19.3		77	TC	2020	US	2020-08-20	2020-08-29	10	0	0	1	1
19		308	EQ	2009	IT	2009-04-06	2009-04-06	1	1	0	0	0
18.1		27	EQ	2012	IT	2012-05-20	2012-05-20	1	1	0	0	0
16.9			FL	2014	IND	2014-09-02	2014-09-26	25	0	1	1	0
16		58	TC	2011	US	2011-08-20	2011-08-28	9	0	0	1	1
16		44	WF	2017	US	2017-10-08	2017-10-31	24	0	0	1	0
15.7		138366	TC	2008	MYM	2008-04-27	2008-05-03	7	1	1	1	0
15			FL	2002	GER	2002-08-12	2002-08-31	20	0	0	1	0
15			TC	2019	JP	2019-10-04	2019-10-22	19	0	0	1	1
13.86			FL	2013	GER	2013-05-01	2013-06-01	32	0	1	1	0
13.65		13	FL	2016	US	2016-08-12	2016-08-22	11	0	0	1	1
13.4		160000	EQ	2010	HT	2010-01-12	2010-01-12	1	0	0	0	0
12.7		134	TC	2017	CU	2017-08-30	2017-09-14	16	0	0	1	1
12.6		55	TC	2001	US	2001-06-04	2001-06-18	15	1	0	1	0
12.5		28	TC	2004	JP	2004-08-26	2004-09-13	19	0	0	1	1
12		16	FL	2008	US	2008-06-07	2008-07-01	25	1	0	1	0
12		4	SS	2020	US	2020-08-10	2020-08-11	2	0	0	1	1
11.9		348	T	2011	US	2011-04-25	2011-04-28	4	0	0	1	1
11.85		128	TC	2020	IND	2020-05-16	2020-05-21	6	0	0	1	1
11.7		12	TC	2013	CHN	2013-09-29	2013-10-07	9	0	0	1	1
11		8694	EQ	2015	NP	2015-04-25	2015-04-25	1	0	0	0	0
11			TC	2016	US	2016-09-28	2016-10-10	13	0	0	1	1
10.4		2	WF	2016	CA	2016-05-01	2017-08-02	459	0	1	1	0
10.1		3035	TC	2004	US	2004-09-13	2004-09-29	17	0	1	1	0
10		44	SS	2007	GER	2007-01-15	2007-01-22	8	0	0	1	1
10		153	TC	2008	US	2008-08-25	2008-09-07	14	1	0	1	0

Note: This table shows the summary of the selected natural disasters which are the basis of our analysis. Cost is the total direct economic damage in billion USD. Cost excludes any damage that is caused as consequence of the damages such as diseases, loss of life or loss of economic activity. Insured losses (IL), in billion USD, are measured as the total claims paid by primary insurers and reinsurance companies with regards to this particular event. Duration (Dur) indicates the period the event happened in and is measured in days. The crisis dummy indicates whether the event has happened during a period of recession (=1). The interest rate change dummy (Policy) indicates whether any important monetary policy changes have happened during this period (=1). The attributable (Attr) dummy indicates whether the disaster event can be attributed to a climatic indicator (=1). The include dummy indicates whether this event is included for the analysis or not.
Source: Own table. Data: EM-DAT by CRED retrieved at: https://www.emdat.be/. Swiss Re Sigma Series retrieved at: https://www.swissre.com/institute/research/sigma-research/World-insurance-series.html. Bank for International Settlements: https://www.bis.org/statistics/cbpol.htm.

Appendix E

Figure 16: Sea Surface Temperature and Hurricane Power Dissipation



Note: This figure plots the hurricane power dissipation index (PDI) for north Atlantic hurricanes in comparison to the average SST. The PDI is a measure for cyclone strength, duration and frequency.
Source: Own graphic. Data: retrieved at: https://www.epa.gov/climate-indicators/climate-change-indicators-tropical-cyclone-activity.

Appendix F

To be added later

Appendix G

Table 8: CRED Classification part 1

Disaster Group	**Disaster Subgroup**
Natural	Geophysical Meteorological Hydrological Climatological Biological Extraterrestrial
Technological	Industrial Transport Miscellaneous

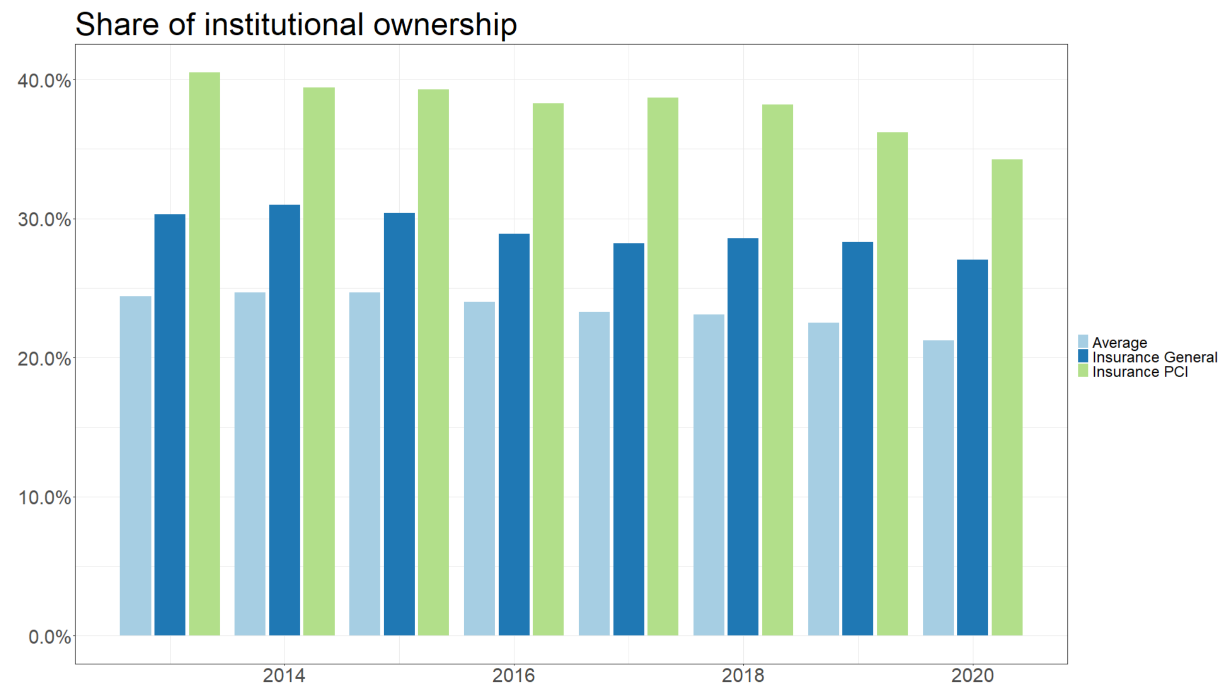
Table 9: CRED Classification part 2

Disaster Subgroup	Disaster Main Type	Disaster Subtype	Disaster Sub-Subtype
Meteorological	Storm	Extra-tropical Storm	
		Tropical Storm	
		Convective Storm	Derecho
			Hail
			Thunderstorm
			Rain
			Tornado
			Dust storm
			Blizzard
			Wind
			Severe Storm
	Extreme Temperature	Coldwave	
		Heatwave	
		Severe winter conditions	Snow/ice
			Frost/freeze
	Fog		
Hydrological	Flood	Coastal flood	
		Riverine flood	
		Flash flood	
		Ice jam flood	
	Landslide	Avalanche	
	Wave action	Rogue wave	
		Seiche	
Climatological	Drought		
	Glacial lake outburst		
	Wildfire	Forest fire	
		Land fire	

Note: The two tables above show the exact classification of natural disasters based on the CRED.
Source: Own table. Data: retrieved at https://emdat.be/explanatory-notes & https://www.emdat.be/classification

Appendix H

Figure 17: Share of institutional ownership



Note: Figure 17 shows the share of institutional ownership in global scale. The average (light blue) is the average over all industries. Insurance general (dark blue) represents primarily homeowners and car insurance. Insurance PCI (green) represents companies who have specialized in property and casualty insurance. Both have been included due to relevance.
Source: Own graphic. Data: retrieved at https://pages.stern.nyu.edu/ãdamodar/New_Home_Page/dataarchived.html