SCHOOL OF ECONOMICS AND MANAGEMENT

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Exploring the impact of natural disasters on the return volatility of the stock market and insurance industry in the US

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Abstract

This study utilizes data from 2000 to 2024 together with an EGARCH approach to model the volatility of two indices, the S&P 500 and the S&P 500 Property and Casualty Insurance Sub Industry Index. Which in this paper acts as proxies for the stock market and the property and casualty insurance industry in the US respectively. Data from The Emergency Events Database is used to incorporate disaster events as dummy variables into the conditional variance equation of the EGARCH model, to determine what kind of impact natural disasters have on the volatility. The main results from the study indicate that natural disasters have no significant impact whatsoever on the volatility of the two indices. With no notable differences being observed regardless of whether the disasters are treated as one group, separated into different subtypes or grouped based on the length of the event.

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1. Introduction

The area of interest in this paper is going to be related to how natural disasters impact the volatility of the S&P 500 and the S&P 500 Property and Casualty Insurance Sub Industry Index. Natural disasters are by themselves very unpredictable and they can cause a massive amount of loss both in terms of humanitarian costs and financial costs, this disaster risk is also not spread out evenly around the globe causing some countries to be more at risk compared to others. However, we have seen the humanitarian costs fall with Formetta and Feyen (2019) providing evidence of a decrease in the mortality rates over time, while data seems to indicate that the average annual number of events is increasing at the same time (EM-DAT, 2024). While some of this is driven by the increased reporting and coverage of disaster events, Banholzer, et al. (2014) discuss how climate change could also be a key factor for the increased frequency of climate related disasters.

The US is one of the most frequently affected countries when it comes to natural disasters. Between 2000-2024 there were 596 reported natural disasters in The Emergency Events Database (EM-DAT, 2024), an average of almost 25 incidents per year. The most common disaster type in the US is *Meteorological*, covering disaster types such as extreme temperatures, storms and tropical cyclones. This is followed by *Hydrological* which covers different types of floods. The third type is *Climatological* which encompasses droughts and wildfires. The final type and the most uncommon one is *Geophysical* which covers earthquakes and volcanic activity. The inherent nature of these events is not something that we can change and just stop from happening, and as such it is something that humanity will have to deal with as time goes on. Climate change, as noted previously is also one factor that has led to an increase in the frequency of natural disasters globally, and it is also quite probable that the frequency will continue to increase if climate change ramps up even further and becomes an even bigger issue. It seems like we are not only forced to continue having to deal with these events in the future but also the potential continued increased frequency of the events. Since it is very unlikely that the underlying factors causing the events will change in the near future the focus for individuals at risk should instead be shifted to preparedness and mitigation so that they can be resilient against these disaster events, in other words insurance that covers the impact of natural disasters.

Due to this, one of the main industries that will bear a lot of the risk associated with the financial costs is the insurance industry and more specifically the property and casualty (P&C) insurance sector. US based P&C insurance firms account for 40% of the total written premiums in the top fifty firms in the whole industry globally. With both the top ranked firm and nineteen other firms being based in the US (S&P Global, 2023). The financial services sector that the insurance industry resides in, is also the second largest sector in the US stock market just behind information technology (S&P Global, 2024), with P&C insurance being the biggest sector within the insurance industry (Insurance Information Institute, 2022).

This shows that the P&C insurance industry in the US is not only just a big part of the whole industry globally but also that it is very intertwined with the financial market in the US. This is one of the big motivations as to why the understanding of this topic should be an important issue. Disaster events will continue to happen, individuals will continue to be affected and the P&C insurance industry will continue to be exposed to these disaster risks as people try to remain resilient and mitigate the effects through insurance. Results from the study by Hagendorff, et al. (2014) indicates that US insurance firms are able to withstand the effects associated with large disaster events and because of this the P&C insurance industry will continue to grow and remain as one of the largest and most important sector of the financial market. It should become important for policymakers, insurance firms and investors alike to understand how these disaster events can impact the volatility, so that adequate risk management measures can be done for resilience to prevail in an industry acting as a financial backbone for a majority of people in disaster risk zones. However, just like how the severity and frequency of disaster events is different around the globe, previous research on the topic also seems to differ. This paper will hopefully add some additional insights into what kind of impact natural disasters have on the volatility, with the use of the S&P 500 and the S&P 500 P&C Insurance Industry Index as proxies for the stock market and the P&C insurance industry in the US.

1.1 Purpose of the study

The main purpose of this paper is to understand how the volatility of the stock market and the P&C insurance industry in the US reacts to natural disasters. This will be done by first determining what kind of impact natural disasters as a single group have on the volatility of the previously mentioned indices. After this effect has been established, natural disasters will be split up into four distinct separate groups based on subtypes to determine whether the impact on volatility differs between the different types of natural disasters. Finally, natural disasters will be split up into two different groups based on the length of the event window to see if the impact on volatility is different based on how long the disaster event lasts.

The main research questions that the paper tries to answer can be concretized as:

I. What kind of impact does a natural disaster event have on the volatility of the stock market and the P&C insurance industry in the US?
II. Do different subtypes of natural disasters have different impact on the volatility?
III. Does the length of the natural disaster event change the impact on the volatility?

1.2 Disposition

The disposition of the paper after the introduction will be as follows, a general overview of the impact and consequences of natural disasters will be presented in the first part of chapter two to provide the relevant background foundation. The second part of this chapter will provide a short summary of the usage of insurance, property and casualty insurance and volatility in the stock market. Then in chapter three the paper continues with a review of previous research regarding natural disasters and how they impact returns and volatilities of both the broad stock market and the insurance industry. Chapter four will then follow with a discussion and presentation of the data, method and models that will be used in the paper. The fifth chapter will provide a presentation of the major results from the study and a discussion of the results. The paper will then end with a summary and a conclusion in chapter six.

2. Background and Theory

2.1 Natural disasters

Natural disasters are unpredictable and recurring extreme events which are caused by the environmental factors of earth itself, and some times a singular event can lead to multiple follow up events such as earthquakes leading to tsunamis. These events can lead to massive humanitarian costs in the form of loss of life or by having a negative impact on the quality of life of the people that are affected. A different type of cost that is also associated with these type of events is the financial cost of asset losses such as housing, factories and equipment and then the cost of rebuilding the infrastructure or replacing the loss of assets. The damages caused by these events are not negligible either, data from the Emergency Events Database indicate that natural disasters has led to an estimated total amount of cost of more than 3.4 trillion US dollars around the world since the year 2000 (EM-DAT, 2024). However not every single type of natural disaster will have the same impact around the world, it can vary both in the intensity of the actual natural disaster but also in the response and recovery efforts in the aftermath of an event, with the development level of the country playing a big role in how severe the impact can be. It is also possible to observe quite a big difference in both the disaster types and amount of disasters around the world with some continents and countries having a very high natural disaster risk while others are at no risk at all (EM-DAT, 2024).

When it comes to the US there are four major groups of natural disasters that affect the country, the first group is meteorological which covers extreme temperature events and storms such as tornados and tropical cyclones, this is also the most common type of natural disaster and the most costly one in the US. The second group is hydrological which includes flooding events and mass movements caused by the rain and the flooding such as landslides and rockfall. The third group is climatological which encompasses droughts and wildfires. The final major group of natural disasters that affect the country is geophysical, which is related to disaster types such as earthquakes and volcanic activity (EM-DAT, 2024). Figure 1 shows the distribution of these different natural disaster and is presented on the next page.

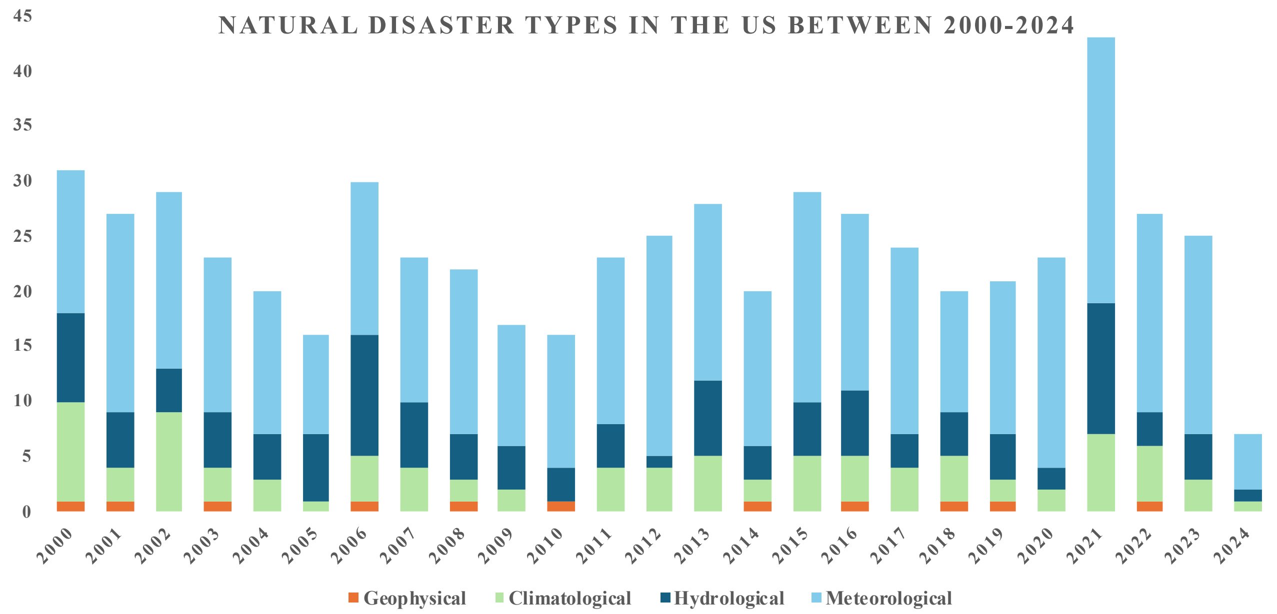

Figure 1. *Stacked bar chart showing the total number of natural disasters that occurred each year in the US with different colors representing different disaster types. Data source: EM-DAT (2024).*

While some efforts and investments can be made into early warning systems that are able to detect when and where disaster events will occur, these are not completely perfect, and only works for types that can be a little predictable such as knowing where a cyclone or tsunami will make landfall based on forecasts. This will obviously not work for every single different type of disaster and while an early warning system works well to mitigate the humanitarian costs of the event due to being able to evacuate early, the financial costs still have to be accounted for as well. Houses, factories, infrastructure and heavy equipment are not as easy to just move out of a danger zone with the help of an early warning system as with humans. One could of course argue that we shouldn't build in areas that are highly susceptible to disaster events but we have to keep in mind both how unpredictable the events are and the circumstances of the people. Not every one will have the resources to just relocate to a better place and especially not if there is a substantial loss of assets causing financial distress after a disaster event.

With this in mind together with the understanding that the underlying factors causing the events will not change in the immediate future, it becomes easy to understand the importance of dealing with the events *after* they have already occurred instead, through prevention and the mitigation of the impact these events can have on society. Which will lead us to the usage of insurance and one of the biggest financial sectors in the world, the insurance industry.

2.2 Usage of insurance

The concept of insurance, a way to eliminate or shift some of the risk away from oneself is not something new. Masci (2011) provides a summary of the history of insurance, showing that people were well aware of the concept of risk and tried to come up with creative solutions to handle it throughout history. Both from the point of view of a financial perspective with merchants splitting their cargo into smaller shipments on different boats to mitigate the risk of losing everything, but also by hunting food with a group of people instead of only relying on one single person. The main idea of risk and its potential consequences has always been present and has affected civilizations. The need and demand to be able to effectively shift the financial risk or spread it to a larger set of people gave rise to an opportunity in the market, this opportunity is what led insurance to evolve and materialize as its own separate product (Swiss Re, 2013a).

The fundamental idea behind how insurance works is quite simple and has been largely unchanged compared to how early variants of insurance worked during the early time periods as presented in the review by Masci (2011). An insurance premium is paid to another individual or firm that then becomes the insurer. The insurer will then pool all of the insurance premiums from different clients together as a fund and in the event that an insurance claim gets triggered, compensation will be paid out from this fund. This is obviously also dependent on the specific insurance contract but the overall general idea is the same. This basically leads to the shifting of the risk towards the insurer instead and the people paying the insurance premium can be content with financial protection of the items that are insured. The way that the insurers could generate profits through this would be done together with statistics to determine the likelihood of events and setting the insurance premium to a level close to or above the expected loss for individual items, hoping that the event which could trigger the insurance claim would in fact not happen.

While the usage and development of insurance was spreading quite rapidly in countries located in Europe, it took a bit longer for insurance to become a common thing in the US (Swiss Re, 2013b). But even though there were some hiccups along the way which led to early insurance firms in the US to not be so successful, and the fact that the insurance industry in the US is quite young relative to the other large economies it still expanded rapidly and is today the largest market for insurance in the world. Both in terms of the demand side with the biggest total amount of insurance premiums being paid but also on the supply side with the majority of the largest insurance firms around the world being based in the US (S&P Global, 2023).

2.3 Property and casualty insurance

While there are a few different insurance sectors within the industry there is one that is of special interest and will be the central theme regarding insurance in this paper, and that is property and casualty (P&C) insurance. One of the main reasons for this is because this type of insurance usually covers damages done to structures such as homes and other buildings but also assets and items on the property, which should lead to a high exposure towards the impact of natural disasters. In his paper, Lamb (1995) found that P&C insurance firms with direct exposure towards Hurricane Andrew, through written premiums had a significant negative effect on their stock price while no significant effect was seen in the P&C firms without direct exposure. Similar results were found in the multi event study by Schuh and Jaeckle (2023) where they also found that hurricane events led to a significant negative abnormal return for P&C firms. Showing that there is a link between natural disasters and P&C insurance stock performance, as long as the firm provide services in the natural disaster areas. One could of course also argue that health and life insurance should have a high exposure to natural disasters as well but it is much easier to evacuate people and animals compared to buildings and homes if a disaster event is expected to occur. As such, taking a look at P&C insurance specifically should lead to the highest possibility of finding any potential effects of natural disasters on the volatility.

Moving on to statistics, data shows that the homeownership rate in the US is estimated to be around 65%, meaning that majority of the people in the US are owners of their own house as opposed to just renting (US Census Bureau, 2024). One can also find that almost every single homeowner in the US has purchased property insurance with the number being almost 90% (Insurance Information Institute, 2023), a very high number. It is quite easy to understand why such a vast majority of people buy insurance in the first place, since for this same majority of people it is also highly probable that the house itself will become their most highly valued asset and as such it is something that they would want to protect against potential damages. This is also the second major reason as to why the property and casualty insurance sector is chosen to be studied in the paper, almost every single homeowner will be exposed to this type of insurance.

2.4 Volatility in the stock market

Variance is a measure of the dispersion of data - how spread out the data is around the mean, taking the square root of this leads us to volatility. In the context of financial markets and in this paper the volatility is related to how the returns of different indices deviate around a mean level. With this in mind it is easy to also relate volatility to risk and uncertainty, a higher volatility indicates that the price of an asset has a large spread in the distribution of potential prices which means that the returns can swing around more wildly and cause very large sudden positive or negative changes in the value, as explained by Ruppert and Matteson (2015) or any other book in finance. This leads to uncertainty about the value of the asset since the movement can be quite erratic and extreme compared to a low volatility asset where the price is more stable and does not swing around as much. A rational risk averse investor presented with two investment alternatives, both of them having the same expected return but one of them having a lower volatility compared to the other would always choose the low volatility alternative due to the fact that it is associated with a lower level of risk while at the same time providing the same expected return.

However, the volatility of an asset is often not constant in time, with a quick glance at any time series of an asset you can usually observe some periods that are very volatile while others are calm. Changes in overall stock market volatility is usually caused by financial crises or by country level macro factors as found in the papers by Wang and Moore (2009), Beltratti and Morana (2006) such as changes in the exchange rate regime or monetary policy. These factors impact investor sentiment and can cause uncertainty in the value of an asset due to the fact that people are just unsure about what will happen next. Benali and Feki (2017) show that the occurrence of disaster events increase the loss ratio of insurance firms, disrupting their cost-to-income structure and causing profitability to be negatively affected. Major losses for these type of insurance firms will occur when a large disaster event happens, many insurance claims have to be paid out simultaneously and the collected premiums can't cover the costs. Relating this back to investor sentiment and uncertainty, a specific natural disaster type triggering an increase in volatility would show that people are unsure and uncertain about the P&C insurance industry and their ability to withstand the financial aftermath of claims needing to be paid out due to the disaster. This could help insurance firms and policymakers understand which type of natural disasters cause the most uncertainty in the market and which areas to focus on for investments and funding to be able to handle and mitigate the impact of these disaster types better in the future.

3. Previous Research

3.1 The general stock market

While there is quite extensive research on how natural disasters impact the overall stock market this research is mainly focused on returns and the gaining from loss theory, which states that investors might move funds into certain industries that will see an increase in demand due to rebuilding and recovery in the aftermath of a disaster event, causing a significant positive effect on the returns. However, research about the impact on the insurance industry specifically is a bit scarce. The results are also not conclusive and seems to be different depending on which country the events occur in. Wang and Kutan (2013) explore the impact of natural disasters on the stock market and insurance industry using a GARCH model approach in both the US and Japan and their study finds that natural disasters do not have any statistically significant effect on the returns of the composite indices in both countries, a result that was also found previously in Australia by Worthington (2008) which is also a much smaller stock market relative to the previous ones. A potential explanation for this is also given in the paper by Wang and Kutan (2013) namely that the broad stock markets can just diversify away the impact of a localized natural disaster and as such there should be no significant effect on the returns.

However, these results do not seem to hold everywhere. Nguyen and Chaiechi (2021) use a similar GARCH approach to determine the effects in the general Hong Kong stock market and find that there is a short but significant negative impact on the returns. Which could indicate that the Hong Kong stock market might not be able to diversify away the impacts of natural disasters as efficiently as in the US, Japan and Australia. Previous research regarding the impact on volatility is also a bit split with research showing different directions of the potential effect. The paper by Wang and Kutan (2013) shows that while the US stock market sees an increase in volatility one day after a tropical cyclone the Japanese stock market shows no impact on volatility at all after any type of natural disaster. Similar results to the US stock market is also found in Hong Kong by Nguyen and Chaiechi (2021) with an increase in the volatility of the market after a disaster event.

Other scholars also provide insightful results by approaching the topic from a different point of view. Bourdeau-Brien and Kryzanowski (2017) take a look at the impact on volatility on a firm level in the US rather than the overall market and find that the volatility becomes twice as high for firms in the affected region during meteorological disaster events. Ruiz and Barrero (2014) find both statistically significant positive and negative returns for different sectors of the stock market in Chile, they also find that the volatility of the overall stock market in Chile more than doubles during the first week of the disaster event. While there seems to be a bit of a difference in the results between some countries, the overall takeaway for the US specifically is that some disaster events can lead to a significant increase in the volatility of the stock market, especially those firms that are located in the region affected by the disaster event.

3.2 The insurance industry

The results for the insurance industry is a bit more interesting but also almost always limited to only returns, the paper by Wang and Kutan (2013) indicate that the only type of natural disaster that has a significant impact on the returns of the insurance industry in the US is volcanic activity (geophysical) with a negative effect three days after the event occurred. In the paper they argue that the explanation for this is that it takes some time for insurance claims to be made and paid out, and the true extent of damages might not be visible until days after the event. When it comes to the Japanese insurance industry it is instead every single type other than volcanic activity that is causing a statistically significant effect. Earthquakes and tsunamis have a bit of a delay in the effect similar to the US market while tropical cyclones are significant already at the same day as the event. All three of these disaster types produce a significant positive effect on the return which the authors argue might indicate some evidence for the hypothesis of gaining from loss, Yamori and Kobayashi (2002) however finds evidence of the opposite while determining the impact of the Harshen-Awaji earthquake in 1995. Their findings indicate that the disaster event had a significant negative effect on the returns for P&C insurance firms in Japan.

The paper by Wang and Kutan (2013) also shows that the US insurance industry sees an increase in volatility three days after a volcanic activity event that is of larger magnitude compared to the effect on the general stock market. And while there was no effect on the volatility of the stock market in Japan the paper shows that there is a significant effect in the insurance industry with an increase in volatility four to five days after an earthquake or tsunami event. The same argument that was brought up previously can also be used here, the actual financial damages done by an event will take some time to estimate and due to this there will also be a bit of a lag in the insurance claims being paid out. The increase in volatility due to a specific disaster type might be a possible indication that market participants do not believe the insurance industry in the US is adequately prepared to handle volcanic activity events. While in Japan it seems like it is earthquakes and tsunamis that are causing the most amount of uncertainty in the insurance industry.

A very comprehensive study on the topic was done by Montero, et al. (2024). This paper investigates how natural disasters impact the volatility of the whole property and liability insurance industry in the US in the immediate one and three month period after an event, using both an index and individual insurance firms. The modeling of volatility is done by first testing different specifications of GARCH models on the various different firms and indices then comparing each model performance against each other to find the optimal one, the results of which will be very helpful to this paper and will be brought up again in a later chapter. The other main finding in the paper is that there is a significant decrease in the volatility for 68% of the individual insurance firms in the one month post disaster period while there is no significant effect on the Dow Jones Property and Casualty Insurance Index that is used as a measure for the whole property and liability insurance industry in the paper. Majority of the firms that are producing a significant result in the three month post disaster period is still also showing a decrease in the volatility, but while the total number of firms with significant effects decreased, the overall magnitude of the effects for the remaining firms are larger compared to the one month post disaster period. The effect on volatility for the insurance industry index remains insignificant in this longer post disaster period as well. The result they observe for the insurance industry as a whole is different compared to what Wang and Kutan (2013) observed, once again reiterating the fact that research in the area is not fully certain and that there is a bit of a conflict in the results. One explanation that is given by Montero, et al. (2024) For the significant decrease in volatility in the one month post event period is reinsurance. Which is basically a way for individual insurance firm to spread their risk by getting insurance from another firm, so any potential big losses would be neutralized or made smaller by the reinsurance.

4. Data and Methodology

4.1 Data

The dataset on natural disaster events will be acquired through The Emergency Events Database (EM-DAT) provided by the Centre for Research on the Epidemiology of Disasters (CRED) UCLouvain in Brussels. The database provides comprehensive information about the impact of natural disasters around the world at a country level by tracking things such as the type of disaster, humanitarian impact (total affected, injured, deaths), economic costs and the insured damage (adjusted for inflation) which shows the costs that the insurance companies cover. This database is chosen as a source because it is the most widely used database for academic research regarding natural disasters and it provides all the information that is needed to be able to answer the research questions in the paper. The time period that is chosen to be used in the analysis is between 2000-2024, the reason for this is because of issues with time biases due to less reporting and coverage of disaster events before the year 2000. However not every single natural disaster event will be recorded in the database, only events which are considered as having a ”substantial impact”. For a disaster event to be included it has to fulfill at least one of the requirements of: the death of at least ten people, hundred people affected or a declaration of a national emergency. This should not lead to any issues in the analysis since it can easily be argued that a small and less impactful event that only affect a very small number of individuals would probably not cause any noticeable or significant effect on the indices that are being used as proxies for a country wide market. The initial sample contains 596 disaster events but after cleaning the data and removing events that did not cause any financial damage the final size of the sample decreases to 460 events.

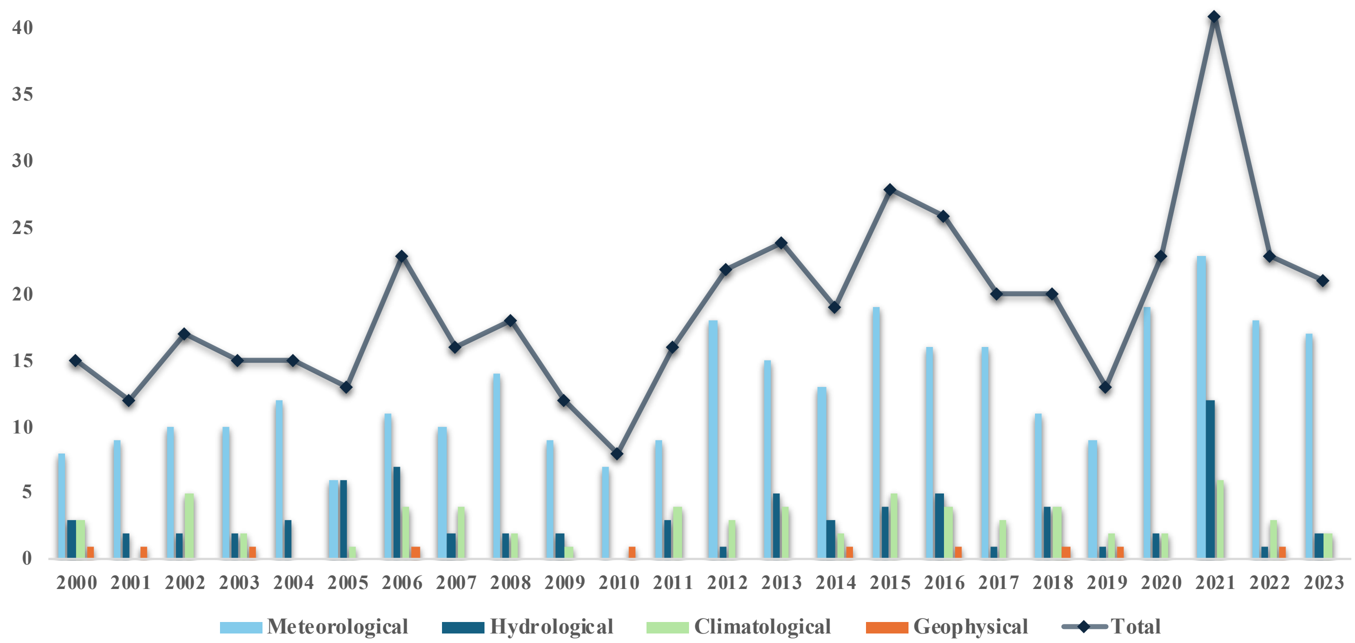

Figure 2. *The bars in the graph represent the number of events that occurred each year in the US for the four different disaster types while the line shows the total sum of disaster events each year. Data source: EM-DAT (2024).*

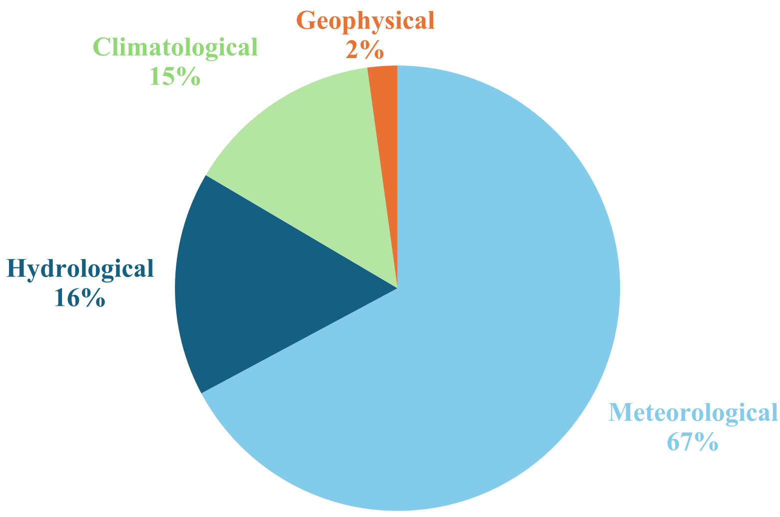

Figure 3. *Pie chart showing the percentage of total events that is attributed to each disaster type in the US during the whole time period that is being studied in the paper. Data source: EM-DAT (2024).*

From Figure 3 it is possible to see that even after making the sample size smaller it is still the meteorological type that dominates with geophysical at the bottom. There is however a much smaller gap between the amount of hydrological and climatological events compared to the initial dataset. One can also observe from Figure 2 that the worst year in terms of total amount of natural disasters was 2021 while 2010 was the most calm year in the time period between 2000-2023. Meteorological disaster events are continuously reoccurring with multiple events every single year closely followed by hydrological disaster events that happen every year except for 2010. The most rare disaster type is still geophysical with only ten total number of events in the whole time period, the most recent one occurring in 2022.

	Meteorological	**Hydrological**	**Climatological**	**Geophysical**
Total events	309	75	66	10
Median	11.5	2	3	0
Annual max	23	12	6	1
Annual min	6	0	0	0
Annual frequency	12.88	3.13	2.75	0.42

Table 1. *Descriptive statistics of the natural disaster dataset that will be used*

The annual maximum for the first three disaster types in Table 1 all occurred during 2021, which unsurprisingly is also the worst year in the dataset. Every disaster type also had an annual minimum of zero except for meteorological which had its lowest amount of events of six in 2005. The annual frequency (mean) is higher than the median for meteorological and hydrological events while it is lower than the median for climatological. This indicates that there are a couple of bad years with a large number of events that are making the distribution skewed with a longer tail to the right which pushes the annual frequency upwards for the two first disaster types. The opposite is true for the climatological type, here we instead have a few relatively calm years with a low number of events that make the tail longer on the left side pushing the annual frequency down.

Let us now move to the other type of data that will be used. To investigate the impact of disaster events on the volatility of both the US stock market and the P&C insurance industry, financial time series of both the relevant indices will be needed. The first one is the S&P 500 and it will be used as the main index for the US stock market since it is widely regarded as the best, including 80% of the whole US stock market capitalization which would give a very good representation of the US financial market as a whole. The second index that will be used is the S&P 500 Property & Casualty Insurance (Sub Ind) which is an index only covering property and casualty insurance firms which we know since earlier is the type of firms that should be affected the most by natural disaster events. The data on the different financial time series of the stock indices will be accessed through S&P Capital IQ. The time series data is composed of daily (trading day) index values for the time period between 2000/01/03 - 2024/01/03 leading to 6041 observations for the two indices that will be used.

Before being able to use the natural disaster data together with the time series data some data preprocessing and data cleaning had to be done first. A new data frame was constructed using the dates in the time series data as the active trading days. The four first columns in the data frame contains index values and log returns. The remaining columns are all dummy variables associated with a specific disaster type or event length using the event start date and event end date in the disaster data as the event window. The first problem that arises is when the start date or end date is on a non trading day, a date that is not included in the time series. The solution to this was to compare all disaster event dates against the active trading days in the time series data and if there was no match the event date would be shifted forwards to the closest trading day, the same thing was then also done with the end date of the event. For example, if a disaster event started on a Saturday and had an end date on Sunday then the whole disaster date event period would be shifted forwards to Monday since that would be the closest trading day forward in time. So even though the whole event takes place during two non trading days, the market cannot react to the event until trading opens and in the example that would be on Monday.

After this shift in the event dates was done for the problematic events in the whole dataset, it was possible to construct the dummy variables. Three different groups of dummies were constructed based on the research questions. The method of how the dummies are coded into 1/0 are the same for all of the dummies, the only thing that separates them are of course the specification of the dummy. Using the first dummy as an example, the specification of this one is a natural disaster. This dummy is coded as 1 for the start and end date of the event together with all the active trading days between the two. Due to the shifting of event dates prior, every single start and end date will be on a trading day, if the disaster event initially started on a trading day and ended on a non trading day the end date of the event would have been shifted forward to the closest trading day leading to no breaks in the dummies due to non trading. The other dummies follow the same technique but are specified differently. The second group of dummies are used as an indicator for the type of disaster, Meteorological, Hydrological, Climatological and Geophysical. The final set of dummies are related to the length of the disaster, with ”One Day Event” indicating events that start and end on the same day while ”Multi Day Event” indicates events where the start and end dates differ. An example from the data frame for the dummy variables will be provided on the next page to finish up this part of the paper.

Date	Disaster	Meteorological	Hydrological	Climatological	Geophysical	One day event	Multi day event
03/01/00	1	1	0	0	0	0	1
04/01/00	1	1	0	0	0	0	1
05/01/00	0	0	0	0	0	0	0

Table 2. *Three first rows in the dummy variable data frame, with each row representing a trading day and each column representing a specific dummy variable. A (1) indicates the presence of that specific dummy variable on that day while a (0) indicates the opposite, dummies within the same color group are mutually exclusive. Example from table: A disaster event started on the third of January 2000 and ended the next day, the disaster subtype was Meteorological and a Multi day event because it did not start and end on the same date, a (1) gets placed under the corresponding columns for each row in the event period.*

4.2 Method

Now that the data preprocessing has been done the next step to successfully answer the research questions is to actually model the volatility of the indices. An EGARCH(1,1), Exponential Generalized Autoregressive Conditional Heteroskedasticity model as proposed by Nelson (1991) is chosen because of its great properties of being able to model both the time varying and asymmetric properties of volatility, but also due to the great performance in modeling the volatility of the relevant indices in both the paper by Wang and Kutan (2013) , and also in the paper by Montero, et al. (2024) The general formula for the conditional variance in the EGARCH(1,1) model is:

$$ln(\sigma_t^2) = \omega + \alpha \left[\frac{|x_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \beta ln(\sigma_{t-1}^2) + \gamma \frac{x_{t-1}}{\sqrt{\sigma_{t-1}^2}} \tag{1}$$

Where the sigma (σ^2) is the conditional variance that we are trying to model, also note that the variance is logged on the left hand side of the equation meaning there does not need to be any restrictions on the signs of the parameters on the right hand side. The omega (ω) can be seen as the constant variance in the model, it captures any long term trend in the variance and is the baseline level which the variance should hover around. The alpha (α) coefficient is related the absolute value of the shock in the previous period, capturing how the size and magnitude of the previous shock impacts the volatility today, a significant positive value means that a big shock in volatility yesterday leads to an increase in volatility today and as such the model can capture volatility clustering. The beta (β) coefficient captures the persistence of the volatility from the previous period, meaning that the volatility today is also dependent on the level of volatility from the previous day with a significant value closer to one indicating a stronger relationship between consequent periods. Gamma (γ) indicates any presence of asymmetrical effects, a significant negative value of the parameter means that negative shocks in the previous time period will cause the volatility to increase more today compared to a positive shock of the same magnitude, for a significant positive value of the parameter the opposite is true. The x_t term incorporates the times series of returns from the market index and the property and casualty insurance index, these returns are modeled by a simple conditional mean equation of the form: $x_t = \sigma_t z_t \ with \ z_t \sim N(0,1)$ (2)

The first thing that needs to be done to make use of the model is to convert the index values in the time series of the different indices into log returns to induce stationarity in the time series, the stationarity test results are located in Table A1 in the appendix. Next, the different dummy variables are placed into three separate groups to test the different research questions. The first group only includes one dummy variable and that is the ”Disaster” variable, indicating an 1 if any type of natural disaster occurred on the date otherwise always being 0. The second group includes four dummy variables for the four different types of disasters that is studied in the paper, ”Meteorological”, ”Hydrological”, ”Climatological” and ”Geophysical”. These dummy variables are similar to the first group but now instead split up into four types to indicate the specific disaster type. The final group of dummy variables are ”One_day_event” and ”Multi_day_event”, and as their name suggests these dummy variables indicate whether a disaster event started and ended on the same date or if the event lasted for multiple days.

The dummy variables will be added to the conditional variance equation in the EGARCH model, extending the equation. Each dummy group will be used in their own separate EGARCH specification meaning that there will be three different conditional variance equations for each of the indices and a total of three different structures for the EGARCH models. These models will be named model one, two and three. The full specification of each model with the addition of the dummy variables that are added to the previous generic conditional variance equation is presented below.

Model 1:

$$ln(\sigma_t^2) = \omega + \alpha \left[\frac{|x_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \beta ln(\sigma_{t-1}^2) + \gamma \frac{x_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \delta_D D_t \qquad (3)$$

Model 2:

$$ln(\sigma_t^2) = \omega + \alpha \left[\frac{|x_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \beta ln(\sigma_{t-1}^2) + \gamma \frac{x_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \delta_M M_t + \delta_H H_t + \delta_C C_t + \delta_G G_t \qquad (4)$$

Model 3:

$$ln(\sigma_t^2) = \omega + \alpha \left[\frac{|x_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \beta ln(\sigma_{t-1}^2) + \gamma \frac{x_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \delta_{One} One_t + \delta_{Multi} Multi_t \qquad (5)$$

All parameters will be estimated with maximum likelihood estimation (MLE) in Gretl for each of the separate models and indices. The estimated delta (δ) coefficients in each of the equations above will show us how the volatility is affected in the presence of the specific dummy variable, and the significance of these coefficients is what will lead us to the answers for the research questions in the paper.

5. Results and Discussion

Figure 4 and 5 shows the estimated conditional volatility from equation (3) during the entire time period that is studied. It is possible to observe systematic increases and decreases in volatility that has a close relationship the time series of residuals, indicating that the model performed well in capturing the dynamics of the volatility for both return series. Also note that the constant in the conditional mean equation is equal to zero for all models so the times series of residuals will essentially just be equal to the original time series of returns, and while it seems like there are two different lines in the figures for the estimated conditional volatility, they are both the exact same line and the line below zero is just a flipped sign mirrored version of the original positive conditional volatility line.

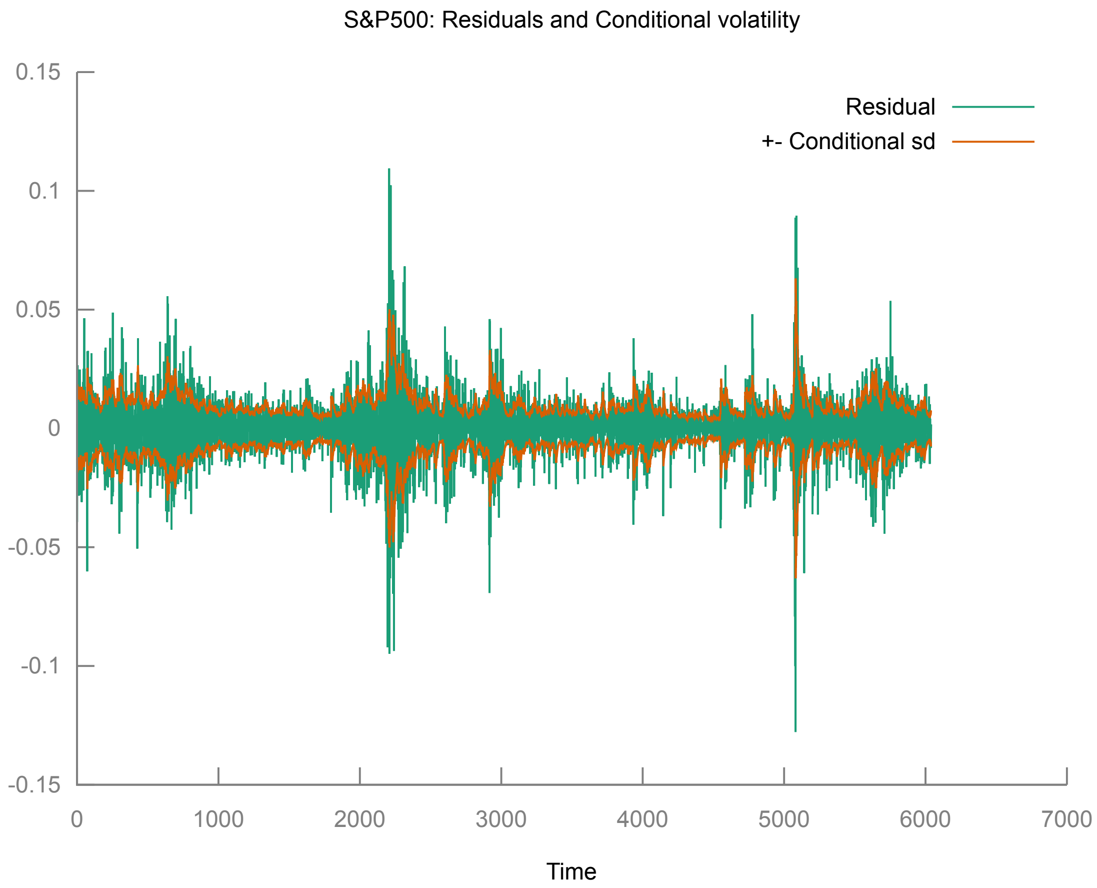

Figure 4. *Graph showing the estimated conditional standard deviation from model 1 for the S&P 500 plotted against the residuals of the time series of returns. The time series of residuals closely matches the original times series of returns since the constant term in the conditional mean equation in the model is equal to zero. Also note that the two orange lines for the conditional volatility is the exact same line but with mirrored (flipped signs).*

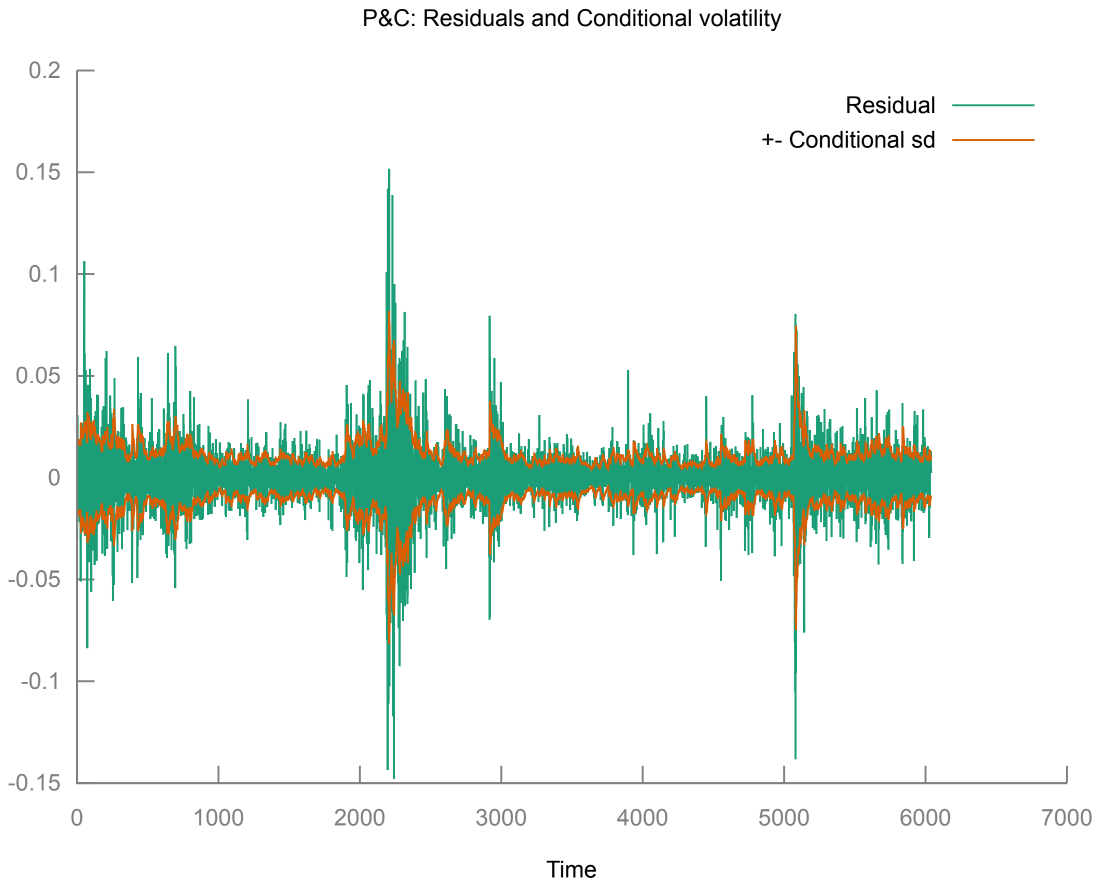

Figure 5. G*raph showing the estimated conditional standard deviation from model 1 for the P&C insurance index plotted against the residuals of the time series of returns. The time series of residuals closely matches the original times series of returns since the constant term in the conditional mean equation in the model is equal to zero. Also note that the two orange lines for the conditional volatility is the exact same line but with mirrored (flipped signs).*

Table 3 is presented on the next page which will highlight the results from the maximum likelihood estimation of the parameter coefficients for the different EGARCH specifications. Specific model results for each index will be located in the appendix in Table A2-A7. From Table 3 it is possible to see that the four parameter coefficients (ω, α, β, γ) that are estimated in all models are statistically significant at the 1% level, showing once again that the EGARCH model performed well in capturing the volatility dynamics of both the indices.

	S&P 500	P&C Insurance
Model 1		
ω	-0.3777 ***	-0.2973 ***
α	0.1546 ***	0.1906 ***
β	0.9720 ***	0.9827 ***
γ	-0.1393 ***	-0.0981 ***
δ_D	-0.0058 (0.4332)	-0.0057 (0.3676)
Model 2		
ω	-0.3758 ***	-0.2995 ***
α	0.1518 ***	0.1909 ***
β	0.9719 ***	0.9824 ***
γ	-0.1397 ***	-0.0977 ***
δ_M	-0.0058 (0.5930)	-0.0153 (0.1081)
δ_H	-0.0037 (0.7720)	-0.0039 (0.7399)
δ_C	-0.0061 (0.4864)	-0.0010 (0.8783)
δ_G	-0.0724 * (0.0747)	-0.0312 (0.5585)
Model 3		
ω	-0.3778 ***	-0.2950 ***
α	0.1539 ***	0.1854 ***
β	0.9720 ***	0.9829 ***
γ	-0.1397 ***	-0.0999 ***
δ_{One}	0.0397 (0.7125)	0.1395 * (0.0757)
δ_{Multi}	-0.0051 (0.5036)	-0.0034 (0.5874)

Table 3. *The table presents the main results for the estimated parameter coefficients in each of the models for both indices. The p-value is presented in parenthesis below the estimated coefficients in the cases where the p-value is larger than zero. The stars represent different levels of significance with, *** = 1%, ** = 5% and * = 10%.*

For the S&P 500 the range for omega lies between (-0.3778, -0.3758) while it is between (-0.2995, -0.2950) for the P&C Insurance, indicating that the baseline level of volatility is lower for the S&P 500 index. The alpha parameter lies between (0.1518, 0.1546) for S&P 500 while it lies between (0.1854, 0.1909) for the P&C Insurance, indicating that there is a significant positive relationship between the size of the shock in the previous period and the volatility in this period for both indices, with the relationship being stronger for the insurance index. The beta parameter is very similar for the two indices, estimated to be around 0.972 for the S&P 500 index while it is estimated to be around 0.983 for the P&C Insurance index. This means that both the indices have a very high persistence in their volatility. The gamma parameter is significant and negative for both of the indices but the magnitude differs between the two with it being estimated to lie between (-0.1397, 0.1393) for the S&P 500 and between (-0.0999, -0.0977) for the P&C Insurance. Both indices show significant asymmetrical effects, with the estimated coefficients indicating that negative shocks increase volatility more in the P&C Insurance index compared to the S&P 500.

The results from the EGARCH models are also consistent with what one could surmise from a visual inspection of the time series of returns presented in Figure A1in the appendix. It is quite clear that the overall baseline level of volatility during the whole time period is higher for the P&C Insurance index, with the magnitude of the spike in returns going in both directions being higher for this index. Volatility clustering can also be observed in both indices with some periods having clusters of very high fluctuations in the returns while other periods are very calm with low fluctuations. Both of the time series also show high persistence in the volatility with the range of returns going in both directions still remaining within similar levels throughout the whole time period even though there are some big spikes.

When it comes to the estimated delta coefficients for the different dummy variables in each model it is possible to see that every single one of them are insignificant. With only a potential very weak argument to be made at the 10% significance level for geophysical events (-0.0724) in the S&P 500 and for one day events (0.1395) in the P&C

Insurance index. Since the level of significance that is used in the paper is at 1%, both of them are seen as insignificant. And the overall results indicate that natural disasters do not seem to have any significant effect on the volatility of the indices, the results are in accordance with Montero, et al. (2024) but in contrast to the papers by Nguyen and Chaiechi (2021) and Ruiz and Barrero (2014). One explanation for this would be that the US stock market is the largest one in the world and is very developed compared to the stock markets in the smaller countries that are used in the other papers. These results are also not that surprising since the S&P 500 covers roughly 80% of the total US stock market and as such is exposed to multiple different sectors and industries in the economy, some of which will have no exposure risk at all towards disaster events. So unless a majority of the firms in the whole stock market is affected, no impact on the volatility of the index will be noticed.

A similar argument can be made for the P&C insurance industry index, even though it only covers one specific sector it is still composed of a multitude of individual insurance firms. While Montero, et al. (2024) and Bourdeau-Brien and Kryzanowski (2017) find that disaster events have a significant impact on the volatility of some insurance firms, this is mainly the firms that are highly exposed and located in the area of the event. It is highly unlikely that every single firm in the index is exposed to every single disaster event. The magnitude of any significant losses or impact on volatility for firms that are heavily exposed to a disaster could just be so small that it would be offset and washed away by other firms in the index which are not as heavily exposed or exposed at all. This could be an explanation as to why the total effect of natural disasters on the volatility of the P&C insurance index and indirectly the P&C insurance industry as a whole is insignificant.

As noted previously, the results for the indices are consistent with the results found in the paper by Montero, et al. (2024) but they differs from the results found by Wang and Kutan (2013). A potential explanation for this is due to the differences in how the natural disaster variables were specified. In the paper by Wang and Kutan (2013) they look at very specific disaster types such as tropical cyclones and earthquakes rather than a whole subtype, and the way their dummies are set up is not to cover the whole period between start and end dates but rather, just on the day the event started and then 1-5 lagged dummies of the same disaster type to capture any effect in the days after an event occurred. Using such short event windows for the dummy variables can cause issues with inference as shown in the paper by Lu and Chen (2011). In my study I instead specify the dummy variables to cover the whole event period from the day the event starts up until the end date for every single disaster and as such get more comprehensive and realistic dummy variables for the days the disaster event actually took place, a longer event window on average as shown by Lu and Chen (2011) should also lead to less issues with inference in my model. I also use more general subtypes for the natural disaster groups, tropical cyclones are included in the ”Meteorological” group and earthquakes are included in the ”Geophysical” group, both of these subtypes also cover many other different types as well which might not have the same impact as the other in the group even though they are related. The usage of general groups instead of specific disaster types will cause the dummy variables for the subtypes in my study to become a bit more diluted and as such it becomes much more difficult and complex to find and separate any potential effects.

Any further research should use the more comprehensive dummy variable specification of the event dates to get the correct event period with start-end date and longer event windows minimizing inference issues. This should be combined with the more specific disaster type approach for the dummies as well instead of subtypes that cover many related but different types so that any potential effect doesn’t get diluted by the others in the group. Firm specific data on P&C insurance firms and regular firms that are exposed to natural disaster events should also be considered instead of broad market indices. To see if there is any potential impact on volatility for individual firms while they are outside of the dampening effect of diversification that was observed when looking at the S&P 500 and P&C insurance industry indices.

6. Conclusion

This paper made use of an EGARCH model based on the framework by Nelson (1991) together with natural disasters as dummy variables in the conditional variance equation, to determine the impact natural disasters have on the volatility of the general stock market and P&C insurance industry in the US using data from 2000 to 2024. With the S&P 500 and S&P 500 (P&C) Insurance Industry Index acting as proxies for the general stock market and the P&C insurance industry in the US. The study first found that generic natural disaster events did not have any significant effect on the volatility of either index. Secondly the study did also not find any significant effect on the volatility of any of the indices when the disasters were divided into their own separate groups based on the disaster subtypes of ”Meteorological”, ”Hydrological”, ”Climatological” and ”Geophysical”. Finally, the disasters were divided into different groups based on length to see if the length of the event mattered but this did also not lead to any significant effect on the volatility of the two indices.

While these results were consistent with the study by Montero, et al. (2024) the results did differ a bit compared to Wang and Kutan (2013), one explanation for the difference in results could be due to the specification of the dummy variables, discussed more in depth in the results section. The paper also very briefly touches upon further research within the same topic, with the the main discussions being in regards to the specification of the dummy variables and the type of data that could be used. To conclude, while natural disasters can impact investor sentiment and can cause uncertainty and impact volatility for some insurance firms and regular firms in the US, as shown by Bourdeau-Brien and Kryzanowski (2017) and Montero, et al. (2024). They do not seem to have any effect on the volatility of the S&P 500 or the S&P 500 (P&C) Insurance Industry Index. Indicating that as a whole, both the general stock market and the P&C insurance industry in the US can effectively diversify away any impact natural disasters have on the volatility.

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Appendix

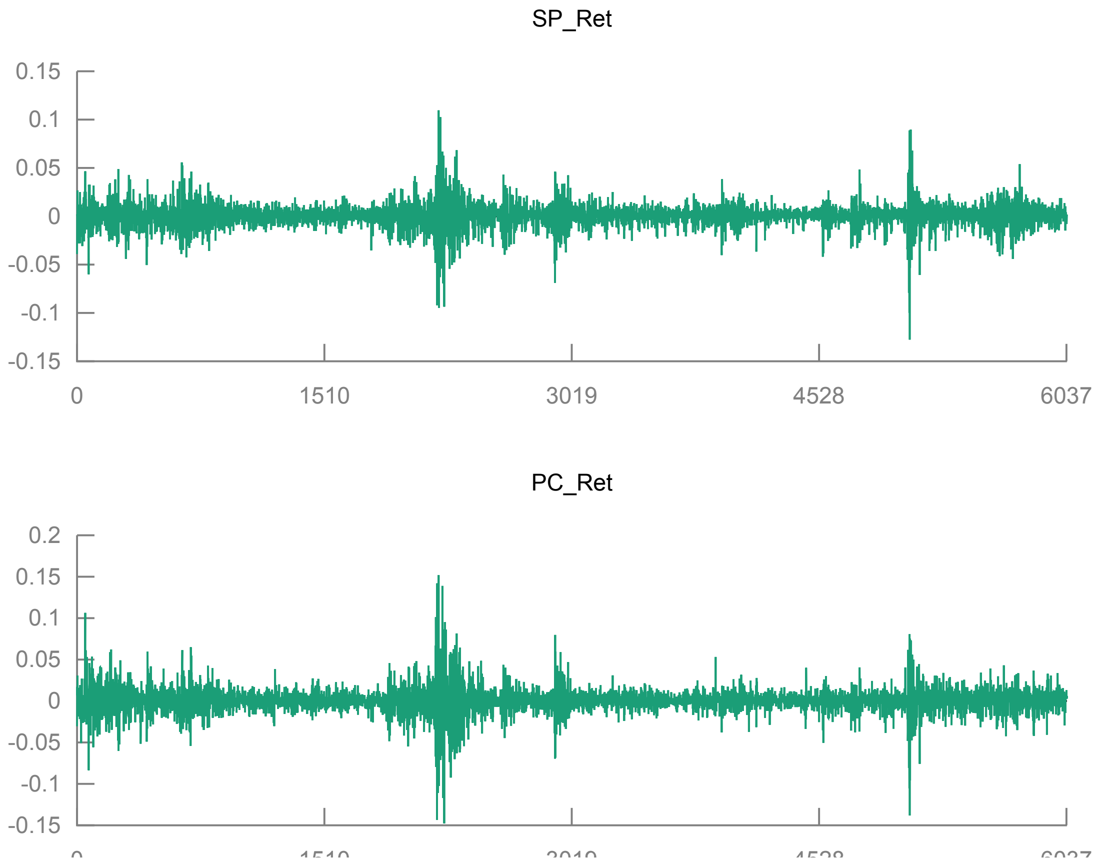

Figure A1. *Time series plot of the two indices with the y-axis representing log returns and x-axis representing the time period, values closer to 0 indicates further back in time (2000) while the larger values towards 6037 indicate more recent times (2024).*

Max lags = 15	S&P 500	P&C Insurance
ADF with constant	4.228e-46	1.082e-49
ADF with constant + trend	3.912e-66	3.352e-77
KPSS	>0.1	>0.1

Table A1. *p-value results from ADF and KPSS tests on the time series of logged returns. ADF null hypothesis = time series has a unit root - non stationary. KPSS null hypothesis = series has no unit root - series is trend stationary. Both tests indicate that the time series are stationary.*

S&P 500	Coefficient	Std. error	p-value
c	0	0	0
omega	-0.377705	0.0515623	2.38e-13
Disaster	-0.00578252	0.00737852	0.4332
alpha	0.154647	0.0197709	5.20e-15
gamma	-0.139338	0.0164995	3.04e-17
beta	0.971977	0.00470236	0.0000
	Log likelihood	**AIC**	**BIC**
	19574	−39136	−39096

Table A2. *The estimated parameter coefficients using model 1 for S&P 500, (c) is the constant term in the conditional mean equation and is equal to zero for all models and indices. Dummy variables are colored green. Log likelihood, AIC and BIC is mainly used as a comparison tool between models.*

S&P 500	Coefficient	Std. error	p-value
omega	-0.375801	0.0536756	2.54e-12
Meteorological	0.151851	0.0108611	0.5930
Hydrological	0.971889	0.0128432	0.7720
Climatological	-0.139658	0.00882476	0.4864
Geophysical	-0.00580464	0.0405989	0.0747
alpha	-0.00372085	0.0199536	2.74e-14
gamma	-0.00614289	0.0168506	1.15e-16
beta	-0.0723672	0.00488143	0.0000
	Log likelihood	**AIC**	**BIC**
	19576	−39135	−39075

Table A3. *The estimated parameter coefficients using model 2 for S&P 500, dummy variables colored green.*

S&P 500	Coefficient	Std. error	p-value
omega	-0.377819	0.0508986	1.15e-13
One day event	0.0397159	0.107771	0.7125
Multi day event	-0.00506960	0.00757972	0.5036
alpha	0.153923	0.0196016	4.08e-15
gamma	-0.139705	0.0163375	1.22e-17
beta	0.972001	0.00467288	0.0000
	Log likelihood	**AIC**	**BIC**
	19574	−39135	−39088

Table A4. *The estimated parameter coefficients using model 3 for S&P 500, dummy variables colored green.*

P&C Insurance index	Coefficient	Std. error	p-value
omega	-0.297299	0.0425477	2.80e-12
Disaster	-0.00565946	0.00628090	0.3676
alpha	0.190628	0.0209462	8.96e-20
gamma	-0.0980893	0.0105230	1.15e-20
beta	0.982745	0.00357579	0.0000
	Log likelihood	**AIC**	**BIC**
	18406	−36800	−36759

Table A5. *The estimated parameter coefficients using model 1 for P&C Insurance, dummy variables colored green*

P&C Insurance index	Coefficient	Std. error	p-value
omega	-0.299471	0.0435921	6.43e-12
Meteorological	-0.0150323	0.00935447	0.1081
Hydrological	-0.00393692	0.0118604	0.7399
Climatological	-0.00102307	0.00667928	0.8783
Geophysical	-0.0312035	0.0533390	0.5585
alpha	0.190867	0.0214880	6.54e-19
gamma	-0.0976938	0.0105848	2.72e-20
beta	0.982370	0.00366512	0.0000
	Log likelihood	**AIC**	**BIC**
	18408	−36798	−36738

Table A6. *The estimated parameter coefficients using model 2 for P&C Insurance, dummy variables colored green*

P&C Insurance Index	Coefficient	Std. error	p-value
omega	-0.294961	0.0417413	1.59e-12
One day event	0.139508	0.0785498	0.0757
Multi day event	-0.00341800	0.00629834	0.5873
alpha	0.185390	0.0209815	9.93e-19
gamma	-0.0999131	0.0104854	1.59e-21
beta	0.982876	0.00351119	0.0000
	Log likelihood	**AIC**	**BIC**
	18408	−36803	−36756

Table A7. *The estimated parameter coefficients using model 3 for P&C Insurance, dummy variables colored green*