IMPACT OF NATURAL DISASTERS ON U.S PROPERTY LIABILITY INSURERS' AND INDICES' STOCK PRICE VOLATILITY

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by

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ABSTRACT

Purpose – The purpose of this thesis is to assess if natural disasters impact the volatility of 19 property-liability insurers in the United States of America (USA) and 3 stock indices over a 10-year period using GARCH (1,1), IGARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1). Additionally, we implement the Value at Risk (VaR) and Extreme Value Theory (EVT) method to generate the worst loss over a target horizon that will not be exceeded with a given level of confidence. In this regard, this thesis will be a pioneer in examining the performance of capital markets in a context of unusually high uncertainty and build upon existing mixed-viewed literature with regards to capital market behavior in such conditions.

Design/methodology/approach – The daily closing prices for each property-liability insurer and stock index are collected over a sample period from January 1st 2010 till December 31st 2020. The sampled period is segregated into two sub-sample periods: the in-sample period extending from January 1st 2010 till December 31st 2017, and the out-of-sample period extending from January 1st 2018 till December 31st 2020. Accordingly, in-sample returns are then calculated from daily closing prices and utilized to estimate the parameters of the selected volatility models, based on the constraints and assumptions of each model. Subsequently, the calculated in-sample parameters are implemented to forecast the volatilities for both periods (in-sample and out-of-sample). Next, the three chosen error metrics RMSE, MAE and MAPE are used to identify the optimal model for each stock during both the in-sample and out-of-sample periods. Next, a dummy variable

was employed to measure the impact of natural disasters on the chosen stocks and indices. Afterwards, through the use of the Volatility Update Historical Simulation method, future return scenarios are generated for the Dow Jones U.S Property and Casualty Insurance Index (DJUSIP) on daily basis over the period December 6th 2018 till December 31st 2020. The Value at Risk (VaR) is then calculated for 250 days at four confidence levels (90%, 95%, 97.5% and 99% confidence levels). Eventually, in order to determine the accuracy of the underlying VaR model the Kupeic test is performed. Lastly, we incorporate Extreme Value Theory (EVT) into our calculations as it assumes a separate distribution for extreme losses in order to estimate the probability of extreme values.

Findings – Results showed that the IGARCH (1,1) has proven to be the optimal model for the majority of the chosen insurance companies during the in-sample period. On the other hand, the EGARCH (1,1) model performed best for a substantial number of insurance companies, particularly, AFG, UFCS.O, GBLI.O, HALL.O and the chosen stock indices (SPX, IXIC and DJI). As for the remaining stocks, PGR, MSADY.PK, CINF.OQ, WRB, WTM, HMN and HCI the GARCH (1,1) and GJR-GARCH (1,1) proved to outperform other models. The same calculations applied for the in-sample period are applied to the out-sample period. The results reflect homogeneity among the indices, SPX, IXIC, DJI and two insurance companies, AFG and UFCS.O. In addition, the EGARCH model was also the most accurate model for RLI, SIGI.O, ARGO.K, UVE, DGICA.O and FNHC.O but only for the out-of-sample period. Among all of the chosen stocks, IGARCH out-performed other models for SAFT.O for both in-sample and out-sample periods. Alternatively, IGARCH performed best for the out-sample period of HMN and GBLI.O whereby. With regards to the remaining stocks, the GARCH (1,1) model proved to be the best performing model for both in-sample and out-sample period for PGR, WRB, WTM and HCI. Specifically, for the out-sample period, the GARCH model out-performed other models for CB, MSADY.PK and CINF.OQ while the IGARCH (1,1) and GJR-GARCH were chosen for the in-sample period, respectively. Lastly, the GJR-GARCH is the optimal model for HALL.O for the out-sample period. After determining the optimal model for the in-sample and out-sample periods, we set the pre-disaster period to 0 and to 1 for both the- one month and three-month post disaster periods. The outcome highlighted that that during the in-sample period, volatility is more likely to be negatively impacted by natural disasters and during the out-sample period, the majority of stocks' volatility are positively impacted by natural disasters. Furthermore, using the Rolling Window procedure and by incorporating the optimal model into the Volatility-Weighted Historical Simulation method, the Value at Risk (VaR) was estimated for 250 days between 06/06/2018 till 03/06/2019 at 90%, 95%, 97.5% and 99% confidence levels for Dow Jones Property & Casualty Insurance Index (DJUSIP:DJI). The computed VaR results were then compared to actual returns in order to determine the number of days/exceptions in which actual returns exceeded VaR estimates across the 250 days period. Lastly, the Kupiec Test was performed and the outcome reflected that VaR provides a very accurate measure in determining the level of downside risk at all confidence intervals. Lastly, we incorporate Extreme Value Theory (EVT) into our calculations at 95% and 99% confidence interval, the VaR was estimated

to be 2.33% and 7.79%. Based on the VaR, the Expected Shortfall (ES) was estimated to be 6.79% and 7.80%, respectively at 95% and 99% confidence level. When comparing the VaR obtained through EVT and the volatility adjusted model, we note that the volatility adjusted model yielded a higher VaR thus, we can conclude that the model is overestimating the loss.

Research limitations/implications – This thesis has potential limitations. A particular limitation is that with the majority of research in this area the analysis on the impact of natural disasters has been made in segregation from other effects, such as macroeconomic, political and calendar announcements. While this simplifies research, it is tricky as natural disasters may be vulnerable to contamination caused by macroeconomic announcements independent of the disaster or catastrophe itself. For example, Shelor et al. (1992) analysis of the 1989 Loma Prieta earthquake compromised the outcome of the research as it failed to take into consideration the lowering of official US interest rates two days later. Moreover, multiple property-liability insurance companies were excluded from the dataset as there was no sufficient data for the chosen timeframe (01/01/2010 till 31/12/2020) andthere are many property-liability insurance companies that are private and thus, these could not be included. Therefore, the dataset used could have been wider and more inclusive.

Originality/value – The findings of this thesis investigated the behavior of the 19 U.S insurance stocks, 3 U.S indices, a property-liability composite index for Value at Risk (VaR) and Extreme Value Theory (EVT) and 252 natural disasters, over the period

extending from 01/01/2010 till 31/12/2020, which makes its dataset comprehensive, exhaustive and novel to those of preceding research;

Keywords – GARCH(1,1), IGARCH(1,1), EGARCH(1,1), GJR-GARCH(1,1), property-liability insurers, insurance, natural disasters, natural catastrophes, hurricanes, typhoons, flooding, earthquake volatility, GARCH models, in sample, out of sample, VaR, EVT, Value at Risk, Extreme Value Theory, realized volatility, Kupiec test, Chubb Limited, CB, Progressive Corp, PGR, MS&AD Insurance Group Holdings, MSADY.PK, Cincinnati Financial Corporation, CINF.OQ, W. R. Berkley Corp, WRB, American Financial Group, Inc., AFG, RLI Corp, RLI Selective Insurance Group Inc, SIGI.O, White Mountains Insurance Group Ltd, WTM, Horace Mann Educators Corporation, HMN, Argo Group International Holdings Ltd., ARGO.K, Safety Insurance Group, Inc., SAFT.O, United Fire Group, Inc., UFCS.O, Universal Insurance Holdings, Inc., UVE, HCI Group Inc, HCI, Donegal Group Inc., DGICA.O, Global Indemnity Group LLC, GBLI.O, FedNat Holding Company, FNHC.O, Hallmark Financial Services, Inc., HALL.O, S&P 500, SPX, Nasdaq Composite, IXIC, Dow Jones Industrial Average, DJI, dummy variable.

Chapter 1: Introduction

1.1 General Background

Historically, man-made risks such as Wall Street Crash and the subprime financial crisis posed the greatest threats to market continuity. However, natural disasters (for example storms, floods, hurricanes, fires, cyclones, earthquakes and tsunamis) continue to cause severe and increasing damage to global economies (Ritchi & Roser, 2019). Such financial losses from natural disasters are of grave concern to insurance companies and the industry as a whole as they customarily provide financial cover for the losses incurred from and are often responsible for providing financial coverage for damages incurred due to the above-mentioned natural disasters.

As a starting point, it is important to reflect and examine definitions pertaining to natural disasters and catastrophes frequently used in contemporary works. Natural disasters are geophysical events (i.e., natural hazards) categorized by substantial variation from climatic trends. Such hazards may follow geographic/seasonal patterns and are considered predictable, i.e. typhoons and hurricanes, or they might follow an extremely irregular pattern in terms of reoccurrence, i.e. droughts and floods. Hence, natural disasters are described as rapid, instantaneous or profound impact of the natural environment upon the socio-economic system (Alexander, 2017). The property insurance industry has coined the term "catastrophe" to denote a man-made or natural disaster that is remarkably severe. An event is classified as a catastrophe by the insurance industry when claims are forecasted to reach a certain dollar threshold, currently set at USD 25 million, and more than a specific number of insurance companies and policyholders are impacted (Spotlight on: Catastrophes - insurance issues).

When it became obvious back in the 70s that exposure to insured losses from natural disasters was on an upward trend, insurers were swift to identify that greater knowledge and expertise were required in this area. Since then, seasoned insurance specialists and experienced scientists have been assessing and analyzing the entire spectrum of natural hazards through models based on geographical, seismographical and meteorological information to estimate the probabilities of catastrophes and the losses resulting therefrom (Hull, 2018). While this provides a basis for setting premiums, it does not alter the “all-or-nothing” nature of these risks for insurance companies (Hull, Risk Management and Financial Institutions, 2012). In traditional insurance markets, such as automotive insurance, the insurer faces a substantial number of independent risks that tend to follow a relatively predictable pattern through time. Thus, by charging a premium that is used by the insurance company to invest and earn a return prior to paying off the losses (claims) incurred, the company will be able to run a profitable business. However, from an insurer’s standpoint, catastrophic losses due to natural disasters are much more challenging. Instead of a large number of risks that are on the vicinity of a relatively predictable year-to-year pattern, catastrophic losses tend to be irregular. Therefore, natural disasters pose a wide spectrum of problems for insurers.

To begin with, because catastrophic events are categorized as low frequency high severity events, the insurer may suffer losses in excess of the premiums charged for coverage, thus, the firm may not have sufficient resources to compensate for the losses. Hence, the firm may have to exit states whereby there is a substantial exposure to catastrophic risks or to go bankrupt (Viscusi & Born, 2006). Secondly, the distribution of losses due to catastrophes may change over time for a variety of reasons. The hurricane season between 1971-1994 averaged 8.5 storms per year, however, in the subsequent decade, 1995-2005, the average increased to 15 storms per year. To the extent that insurers are rational Bayesian [1]decision makers, one would expect them to update their risk beliefs over time when writing insurance coverage (Viscusi & Born, 2006). Lastly, catastrophic losses affect the rate structure even for firms that remain functional in the presence of natural disasters (Born & Viscusi, 2006). Suppose an insurer is writing policies in a high-risk state that is known to be prone to major disasters at least once every ten years. In the year that the disaster occurs, the company will suffer losses that exceed the premiums charged. Thus, for the company to realize a profit, the insurer will have to charge more for insurance in the upcoming years whereby there are no catastrophes in order to compensate for the loss.

Based on the above, in recent years, economic forces have begun to accelerate convergence between financial markets and property-liability insurance. A vital driver of convergence is the increase in property values in geographical zones susceptible to catastrophic risk. Trillions of dollars in property exposure exist in disaster prone areas in the U.S.A, Asia and Europe resulting in significant increases in insured losses from

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[1] Statistical methods based on Bayes' theorem which describes the probability of an event, based on prior knowledge of conditions that might be related to the event

property catastrophes (Cummins & Weiss, 2009). Hurricane Andrew (1992) resulted in extraordinary losses amounting to $24 billion. This event was dwarfed by the losses incurred in 2005, when Hurricanes Katrina, Rita, and Wilma (KRW) and other events pooled to cause insured losses of USD 114 billion (At USD 144 billion, global insured losses from disaster events in 2017 were the highest ever, sigma study says, 2018). While these losses are enormous relative to the total equity capital of global reinsurers (Capital Markets: The Reinsurance Evolution Continues, 2014), they represent less than 1% of the value of U.S. stock and bond markets. The increased efficiency realized by financing this type of risk in securities market has led to the development of innovative financial instruments such as catastrophic risk (Cat) bonds and options to off-set the losses (Cummins & Weiss, 2009).

It is now clear that natural disasters have established the potential to adversely affect financial activity. The above concerns have given rise to developing literature, which seeks to examine the impact of natural events on capital markets. Somewhat surprisingly, there is no recent analysis whatsoever that addresses aspects of how catastrophic risks affect insurance markets and capital markets. There have, of course, been extensive discussions of a conceptual nature as well as analyses of the potential role of reinsurance, but there has been no empirical examination of how catastrophic risks affect stock price volatility in capital markets.

1.2 Importance of the Study

This thesis serves as a guide to examine and study catastrophic risks and their impact on insurer's and overall capital market stock prices and volatility. Currently, the literature around the relationship between catastrophic risks and stock price volatility in capital markets is scarce and mixed. Despite the availability of literature on the impact of natural disasters on insurer's stock price volatility, the most recent research was conducted in 2017 whereby Michael Bourdeau-Briena and Lawrence Kryzanowskib examined the effect on volatility focusing on the stocks of local U.S firms. Yet, no research has been conducted recently following the surge in natural disasters due to climate change and increase in population in catastrophe prone areas. Taking into consideration the propensity of inclination for natural disasters to be addressed through capital markets and the importance to address the research gaps, an accurate forecast based on recent data of the impact of natural disasters on capital market volatility is essential. Accordingly, mixed literature and mounting importance of studying future risks in order to provide insurance against catastrophic loss at a reasonable price allows insurance companies to hedge against catastrophic risks and manage the impacts of projected climate change on future catastrophic risk in the United States.

1.3 Purpose of the Study

The purpose of this thesis is to assess if natural disasters positively or negatively impact the volatility of capital markets in the United States of America (USA) over a 10-year period using some of the most popular forecasting models in estimating volatility.

The selected models are the GARCH (1,1), IGARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1). Moreover, we will apply a dummy variable in order to check if natural disasters impact volatility. Lastly, we will implement the Value at Risk (VaR) and Extreme Value Theory (EVT) method to generate the worst loss over a target horizon that will not be exceeded with a given level of confidence. Daily stock prices of 19 property insurance companies will be used over a 10-year period from 2010 to 2020. In addition, the daily prices of 3 U.S stock indices, namely, S&P 500, Dow Jones Industrial Average and Nasdaq Composite will be used for the same period. Each of the stock indices used are comprised of the biggest companies within the U.S. economy and cover various sectors. In this regard, this thesis will be a pioneer in examining the performance of capital markets in a context of unusually high uncertainty and build upon existing mixed-viewed literature with regards to capital market behavior in such conditions.

To address the research gaps highlighted previously, the general research question can be expressed as follows:

i. *Do catastrophic losses arising from natural disasters impact the stock price volatility of U.S.A property-liability insurance companies and indices?*

The paper is organized as follows. Chapter 2 examines and discusses the available literature with regards to empirical evidence about the impact of natural disasters on insurer's stock prices and empirical evidence about the impact of natural disasters on volatility. Chapter 3 proceeds by describing the GARCH-type models that will be used to model volatility. Then, estimation of value at risk (VaR) using the volatility updated historical simulation method and subsequent back-testing methodology are highlighted. Lastly, an in-depth description and analysis of the data is presented. Chapter 4 highlights the findings of the research whereby we estimate the parameters of the chosen volatility models and forecast the volatility for each stock and index for the in-sample period and out of sample period. In addition, Value at Risk (VaR) is calculated and the model's accuracy is subsequently assessed and the Extreme Value Theory (EVT) is presented and estimated. Accordingly, the empirical results are then presented and evaluated. Chapter 5 concludes the thesis, presents the limitations, and provides future recommendations.

Chapter 2: Literature Review

Volatility in capital markets has been a constant and continuous concern for both academics and policymakers. In an era whereby natural disasters continuously cause severe damage to a disruption to financial activity, global economies and international trade, insurance companies have become acutely sensitive to volatility and downside risks. This aversion has only intensified following the gut-wrenching market swings and regulatory changes of recent years (Hargis & Marx, 2015). Thus, natural disasters have clearly established the potential to adversely affect financial activity. The above concerns have given rise to developing literature, which seeks to examine the impact of natural events on capital markets. However, until date, empirical evidence on the effect of natural disasters on insurer stock prices and volatility has been mixed. This chapter shall examine and segregate available literature into two subsections (1) Empirical evidence about the impact of Natural Disasters on insurer's stock prices (2) Empirical evidence about the impact of Natural Disasters on volatility.

2.1. Empirical evidence about the impact of Natural Disasters on insurer's stock prices

Although a multitude of studies examine the impact of natural disasters from an economic perspective, only a handful have examined the financial aspect (Panwar & Sen, 2018). Contrary to the economic analysis of natural disasters, financial analysis is exclusively concerned with the financial impact on entities directly impacted, whereby market prices are utilized to collectively value all costs and benefits. Thus, it is within this confined context that most of the existing financial research related to natural disasters is placed and has solely focused on the property-liability insurance industry. Nevertheless, there is still no consistent conclusion on whether or not the stock prices of insurance companies drop or rise after severe natural disasters.

To begin with, due to the claim payments made to policyholders for damages, insurers incur large losses. While some of these losses are offset by reinsurance, usually, it is expected that these losses cause stock prices to decline amid the disaster. Lamb (1995) conducted an exposure-based analysis of property-liability insurer stock values around the time of Hurricane Andrew. The study classified property-liability insurers with regards to their loss exposure. Accordingly, the outcome indicated that insurers with policies written in the affected areas witnessed a negative stock price reaction and unexposed firms sustained no price response. Thus, the study proves that the market predicted information efficiently and discriminated amongst insurers based on their level of exposure (magnitude and existence). A year later, Angbazo & Narayanan (1996) conducted a similar study using the daily returns of 48 companies while utilizing two methodologies: generalized least squares and modified event study methodology. Accordingly, their study yielded abnormally significant negative returns on day 0 (day Hurricane Andrew occurred), a greater negative return on day +1 as investors began to assess the damage and lastly negative return on day -3 (days prior to occurrence date) which may be due, according to the authors, to the fact that the market anticipated the hurricane. In summary the authors found that natural disasters negatively influence insurance stocks and the effect is only slightly offset by the consequent premium increases. Similarly, Cagle (1996) re-examined the impact of natural disasters on insurers' stock prices: the case of Hurricane Hugo. The author hypothesized that following a natural disaster, there may be demand or supply changes that increase premiums. The net effect of the premium increase and damage claims could be examined through insurers' stock price performance following a natural disaster. Regardless of which effect dominates, the stock prices of insurers exposed to damage claims from the natural disaster should be adversely affected relative to unexposed insurers. Accordingly, to quantify this, stock price reactions to Hurricane Hugo are projected through market model prediction errors for equally weighted portfolios of property- liability and multi-line insurers. The portfolio was constructed of high and low exposure insurers; high exposure insurers had direct premium written of at least USD 100,000 or greater. High exposure portfolio included 16 insurers. Whereas, low exposure insurers had direct premium written less than USD 100,000. Low exposure portfolio included 15 insurers. Moreover, regression analysis was utilized to highlight the connection between insurers' exposure to claims and stock price reaction to the hurricane. A major concern that is highlighted in this study is the cross-sectional dependence. This is essential as the event affects various insurers within the same line of business and at the same time. Having said the above, empirical results for Hurricane Hugo indicated that insurers with high exposure to claims witnessed a substantial negative stock price reaction, while the stock prices of those with low exposure were unaffected. The researcher concluded that following South Carolina's Hurricane Hugo [insured loss USD4.2 billion], insurers with high exposure witness substantial negative price however, insurers with low exposure remained unaffected.

While the above literature argued the negative impact of natural disasters on insurer stock prices, it is stated that insurers will benefit from catastrophic events, as there will be an increase in required coverage and subsequently additional premium earnings. A research conducted by Slania (2018) highlighted that, immediately after a natural disaster, property and casualty insurers' stock prices take a hit. Accordingly, as investors assess damages within the first two to four weeks, stock prices lag and Earnings per Share (EPS) go on a downward trend. However, the expectation of premium increase tends to drive stock prices back up. Thus, within a few months following the natural disaster, stock prices reach levels high than they were prior to the natural disaster. Shelor et al. (1992) studied the impact of the 1989 Loma Prieta (California) earthquake on property-liability insurer stock values. The researchers focused on two samples: i) forty-seven property-liability insurance companies and ii) thirty-two multiline (life, health, property, liability...) insurance companies. Accordingly, the daily return data was used to establish the financial impact of the earthquake of the firms' value. Moving a step further, the authors also examined the connection between stock price reaction and California and total earthquake net premium written using a multiple regression cross sectional analysis. Lastly, the authors concluded that the Loma Prieta earthquake in California caused a significant positive stock value response for both multi-line and property-liability insurers. Noting that investors' expectations of increased demand for coverage had offset the losses caused by the earthquake. Likewise, Aiuppa et al. (1993) established that, following Loma Prieta earthquake in California [insured loss USD 2.5 billion] insurer's stock values increased. The methodology used by the authors was based on cumulative abnormal returns (CARs) examined under a two-index model. To determine whether the earthquake had a positive/negative impact on insurance companies with/without earthquake coverage, the sample of insurance companies was divided into two groups (based on the availability of earthquake coverage or lack thereof). The results revealed that while none of the cumulative abnormal returns for non-earthquake insurers is significant, cumulative abnormal returns for earthquake insurers are positive and significant.

It is now clear that within the property insurance industry, two opposing views exist. With the essentially narrow focus of financial analysis into natural disasters and numerous limitations faced by existing research, Worthington & Valaddakani (2004) examined the impact of natural disasters on the Australian equity market. The data set used was comprised of the daily price and returns over the period extending from the 31st of December 1982 to the 1st of January 2002 for the All-Ordinaries Index (AOI), an index of shares in Australia made up of 500 of the largest companies listed on the Australian Securities Exchange, and a record of forty-two severe floods, storms, earthquakes, wildfires and cyclones during this period with an insured exceeding AUD 5 mil. and/or total loss exceeding AUD100 mil. Given that the time series data on price and returns are available in consistently spaced intervals and the fact that the timings of the natural disasters is known with certainty, intervention analysis was applied to measure both the duration and impact of natural disasters on the Australian capital market. Intervention analysis is based on the Box-Jenkins methodology whereby an autoregressive moving average (ARMA) model is supplemented by dummy variables to evaluate the impact of abnormal events. Since first proposed by Box & Tiao (1975), this technique has been employed in a variety of financial contexts. To further emphasize the importance, Ho & Wan (2002) utilized intervention analysis to examine structural breaks after the 1997 Asian financial crisis and St. Pierre (1998) and Bhar (2001) used intervention analysis to test the volatility impacts of introducing option contracts and the volatility and return dynamics of the Australian spot and futures markets respectively. Likewise, intervention analysis has also been utilized in research related to natural disasters with Fox (1995, 1996) examination of the impact of Hurricane Hugo on business environments. Consequently, Worthington &Valaddakani (2004) conclude that cyclones, bushfires and earthquakes have a significant impact on market returns, unlike severe floods and storms. The net effects can be positive and/or negative with most effects being felt on the day of the event and with some adjustment in the days that follow. The obvious argument is that the information represented by these events and disasters is relatively incomplete at the time of the event and, depending on the type of natural disaster, may take some days before a fuller information set is obtained.

Lastly, contrary to what has been stated previously, multiple studies conclude that major natural catastrophes have had minimal/insignificant impact on the markets. The costliest natural catastrophe recorded to date is the 2005 landfall of Hurricane Katrina in Louisiana, with an estimated destructive cost of around USD 150 billion, of which $62 billion was covered by the insurance industry; this was less than a single percentage point of movement on the New York Stock Exchange. The markets were generally unmoved by the Hurricane Katrina loss; the S&P500 index saw an eight-day 3% rally in the days following the hurricane. The second most expensive natural catastrophe in history, at around USD 122 billion reconstruction cost, was the 2011 Tohoku earthquake, tsunami, and subsequent nuclear power plant meltdown in Japan. The events caused initial market turbulence; the Tokyo Nikkei index declined 1.7% on the same day though it rallied later on. While international markets across the world dipped slightly with European stocks down 1%, US markets trended upwards and continued doing so after the earthquake. Other major natural catastrophes have tended to have similarly minimal impacts on the markets (Mahalingam, et al., 2018). Major natural disasters have had similarly minimal impacts on capital markets. The most destructive tsunami historically that occurred in 2004 around the Indian Ocean had no clear impact on stock markets; 20 days later, the S&P decreased by 3.8%.

2.2. Empirical evidence about the impact of Natural Disaster on Volatility

Volatility is undeniably an important and fundamental concept in the field of finance. The availability of extensive studies and research indicate the significance of measuring volatility in multiple fields, such as risk management and finance among others. An incorrect estimation of future volatility may cause substantial impact on financial decisions. An overstated volatility may cause a loss of opportunity, whereas, an underestimated volatility may lead to greater risk exposure (Naimy & Hayek, 2018). For the past decade, forecast of volatility has been the subject of a wide scope of studies, many of which aim to evaluate the ability between different forecasting models and assess their predictive abilities across different financial assets however, studies assessing the impact of natural disasters on stock price volatility remains limited.

Worthington (2008) was among the pioneers to utilize ARCH modelling to study the impact of natural disasters; the study modeled financial market effects of all recent historical record of natural disasters in Australia. The author employed two data sets in his analysis; the first set is the daily closing price for the Australian Stock Exchange All Ordinaries index over a 23-year period ranging from 01/01/1980 till 30/06/2003. The second data set was sourced from Emergency Management Australia, a database containing records of Australian natural disasters compiled using estimates from published disaster articles and reports and insurance industry bodies. Given that the emphasis in this study is focused solely on the market effects irrespective of magnitude, the data used to categorize each natural disaster is limited to its duration, timing and broad geographic location. In order to evaluate the volatility, numerous GARCH-M (p,q) models were initially fitted to the data and compared based on the Schwarz Criterion Akaike and Information Criteria whereby a GARCH(1,1) model was considered the most appropriate for modelling the market returns. Methodology incorporating GARCH(p,q) can quantify both short and long-term memory in returns and permits all lags to exert an impact thus constituting a longer-term memory model. This is an essential characteristic of asset returns where there is a tendency for volatility clustering is observed. An implication caused by volatility clustering is that volatility shocks today will influence the expectation of future volatility and GARCH(p,q) quantifies this degree of persistence/continuity in volatility. Nevertheless, this particular specification has largely shown to be a parsimonious representation of conditional variance that adequately fits most financial time series. The author concludes that intraday return volatility in the Australian market is most appropriately described by a GARCH-M (1,1) model and that the inclusion of natural disasters in the mean equation does not account for any of the variation observed in daily market returns. Hence, natural disasters have no significant impact on returns.

Five years later, Thomann (2013) investigated the impact of natural disasters and 9/11 attacks on the volatility of insurance stocks and the correlation of insurance stocks with the market. The study was constructed based on two hypothesis; *volatility hypothesis* whereby new information pertaining to the occurrence of a natural disaster causes a surge in insurers' stock price volatility and that subsequently leads to significant volatility peaks and *correlation hypothesis* whereby news about the occurrence of a catastrophe increases the volatility of insurance stocks. We expect these catastrophe related share price changes, which should not affect the overall stock market. The dataset used included the daily return data of property-casualty insurance companies from 01/1988 till 12/2006 along with the data for the ten largest insured natural disasters within the same timeframe. The author fit two multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models, a Conditional Correlation (CC) GARCH model and a Dynamic Conditional Correlation (DCC) GARCH model, to the data. The research is supplemented by calculating the effect of natural disasters on the Value at Risk (VaR) of a portfolio consisting of insurance stocks. The outcome obtained supports the author's hypotheses. Natural disasters resulted in increases in insurer stock volatility. Moreover, it may take up to a few days following the natural disaster for the catastrophe-induced volatility peak is reached. It was also concluded that hurricane season led to a decrease in the correlation between insurer stocks and the overall stock market.

With increasing damages to two of the world's largest economies, U.S.A and Japan, due to natural disasters, Wang and Kutan (2013) examined the impact of natural disasters on U.S and Japan stock market volatility. The authors' data included the daily prices of Nikkei 225 Stock Average, S&P 500 Composite Price Index, 10-year U.S bond yield, 10-year Japan bond yield and US Dollar-Japanese Yen exchange rate over a 22-year period. Since it is likely that natural disasters may happen on holidays /weekends, during which stock markets are closed, disasters were accorded with the most recent trading day after the disaster. Accordingly, four individual natural disaster dummy variables were employed to represent each event separately in estimations based on the date of occurrence. The authors concluded that the conditional volatility of returns of U.S and Japanese insurance sector are affected by natural disasters whereas, only the Japanese composite market is insusceptible to natural disasters. Wang and Kutan (2013)'s paper is one of the few studies to address whether or not natural disasters increase the volatility of stock returns. Employing GARCH dummy variable methodology, they provide evidence that disasters increase volatility on the U.S. market but have no impact on the Japanese market. However, they offer no explanation for the opposing conclusions.

Most recently, Michael Bourdeau-Briena and Lawrence Kryzanowskib (2017) re-examined the effect on volatility by once again focusing on the stocks of local firms instead of the whole market. While Wang and Kutan (2013) did find evidence consistent with an increase of conditional volatility in the first few days following a natural disaster in the U.S, they notice no such increase in Japan, but the authors provide no explanation for the conflicting results. Accordingly, the authors revisit the issue of disaster-induced volatility but employ a different methodology. Previous research examining the GARCH dummy variable model through Monte Carlo simulation validated that the distribution properties of the maximum likelihood estimator for the variance dummy variable coefficient in GARCH models may create misrepresentative inferences in event studies with short-event timeframes. In this regard, Lu and Chen (2011) recommended including a minimum of 100 observations in the event timeframe when using the GARCH dummy variable methodology to ensure reliable statistical inference. Given that the scope of the study was over a short period of time, the authors opted for the alternative approach suggested by Bialkowski et al. (2008) who fundamentally compare the conditional volatility estimated using a GARCH model to the variation in the residuals observed during the event period. Their test statistic represents the multiplicative effect of an event on volatility. Finally, the authors set aside the ARMA structure for the conditional mean equation and opted for a parsimonious GARCH(1,1) model with normally distributed standardized residuals for the conditional variance equation in order to reduce the number of parameters to estimate and obtain more accurate cumulative abnormal volatility (CAV) forecasts. In conclusion, Michael Bourdeau-Briena and Lawrence Kryzanowskib establish that following floods, hurricanes and extreme weather conditions, conditional volatility increases. Yet, no change in volatility is detected for other major storm-like events. It is still unclear why some firms experience negative consequences from natural events while others face positive impact.

In light of the foregoing and with the ever-growing impact of natural disasters and their impact on capital markets, there is a crucial need to study the impact of natural disasters on property-liability insurer stock price volatility. However, despite growing importance and interest, the most relevant study was conducted decades ago, most recent literature focus on various types of catastrophes such as terrorism and artificial disasters and lastly, there is no consolidated view as to the impact of natural disasters on volatility. Therefore, it is now apparent that a study analyzing the impact of natural disasters on property-liability insurer stock price volatility is inevitable with questions being raised concerning the strength of these opposing views. Chapter 3 continues by first presenting and defining the basic structure and assumptions of each volatility model. It then unravels the implemented procedures and methodology and subsequently analyzes the employed data while underlining the required specificities to model the impact on capital markets.

Chapter 3: Methodology and Procedure

3.1 Introduction

The literature review in the aforementioned section reveals a lack of consolidated view and current literature studying the impact of natural disasters on property-liability insurer stock price volatility and overall market volatility. In this chapter, first, we include a general description and justification of the GARCH-type models that will be used to model volatility of property-liability insurers and overall U.S market stock prices following natural disasters. Next, the method for parameter estimation is identified. Third, in order to evaluate the forecasting ability of the models, the estimated volatility should be compared to the realized volatility. Subsequently, the selection criteria that will be utilized to identify the most appropriate model is described. Once the ideal GARCH-type model is selected, it is used to forecast the one-day ahead conditional variance for all stocks chosen. Accordingly, after determining the optimal model and in order to capture whether natural disasters have changed the volatility structure of the selected data series, a dummy variable will be added to the selected GARCH-type model. Then, estimation of value at risk (VaR) using the volatility updated historical simulation method and subsequent back-testing methodology are highlighted. Lastly, an in-depth description and analysis of the data is presented in order to identify whether or not the examined models can be applied.

3.2. Daily Returns

The notion S*t* denotes the daily stock price observations of the respective insurance company and U.S indices data series at time *t* whereby *t = 1,2,…,n*. Hull (2012) defined volatility as "the standard deviation of the proportional change in the variable during a day" (Hull, Risk Management and Financial Institutions, 2012). Hence, we converted daily observations extracted into daily returns using the below formula:

$$u_t = \frac{S_t - S_{t-1}}{S_{t-1}} \tag{1}$$

Whereby u_t is the return at day *t*, $S_t - S_{t-1}$ are respectively the stock prices at the end of day *t* and at the end of the previous day *t* – 1. Thus, the GARCH models can be specified as:

$$X_t = u_t + \sigma Z_t \tag{2}$$

Where, μt and σt denote the conditional mean and volatility process, respectively.

Fundamentally, we utilize GARCH (1,1), IGARCH(1,1), EGARCH and GJR-GARCH(1,1) to model the impact of natural disasters on volatility. The following section will provide a description of the applied models.

3.3 Models

3.3.1 Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

Robert F. Engle (1982) introduced the “Autoregressive Conditional Heteroskedasticity (ARCH)” model. The model was a pioneer in modeling conditional heteroskedasticity in volatility through allowing the conditional variance to vary over time as a function of historical errors leaving the unconditional variance unchanged by allocating equal weights to the squared residuals solely and overlooking past variances. The model was modest and instinctive however, it had limitations and usually required multiple parameters to adequately capture its volatility process. Bollerslev (1986) built upon the ARCH process by addressing the weaknesses identified in Engle’s model, and proposed a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework allowing a more adaptable lag structure and longer memory (Naimy, Haddad, Fernández-Avilés, & El Khoury, 2021). Given that GARCH incorporates an extra parameter, which is the long term mean variance, it permits tracking the persistence of the variance around the mean. Hence, the conditional variance pertaining to the standard GARCH (1, 1) process, introduced by Bollerslev, is represented as:

$$\sigma_t{}^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad \textbf{(3)}$$

$$\omega = \gamma V_L \qquad \textbf{(4)}$$

Based on the above, σ_t^2represents the variance estimate at day t, α and β represent the weights given to the associated return (u_{t-1}^2) and variance on the previous day (σ_{t-1}^2), respectively. V_L, the long run variance and γ is the weight assigned to V_L. When applying equation (4) above, the parameters ω, α and β can be projected using the Maximum Likelihood Method (MLE) whereby γ will be calculated using:

$$\gamma = 1 - \alpha - \beta \qquad \textbf{(5)}$$

Accordingly, V_L will be set as:

$$V_L = \frac{\omega}{\gamma} \qquad \textbf{(6)}$$

In order to guarantee a stable GARCH process and uphold a positive weight allocated to V_L, it is essential that $\alpha + \beta < 1$. It is worth mentioning that GARCH models integrate the volatility clustering phenomenon which is a distinguishing feature of market behavior.

3.3.2 Integrated Generalized Autoregressive Conditional Heteroskedasticity (IGARCH)

Engle and Bollerslev (1986) subsequently revealed a specific class of GARCH models termed Integrated GARCH (IGARCH) whereby unconditional variance is non-existent. This happens when the weights α and β sum up to 1. Given that β is now defined as 1- α with restrictions $\omega \geq 0$, $\alpha \geq 0$, 1 - $\alpha \geq 0$ accordingly, IGARCH (1, 1) is represented as:

$$\sigma_t{}^2 = \omega + \alpha u_{t-1}^2 + (1 - \alpha)\sigma_{t-1}^2 \qquad \textbf{(7)}$$

A fundamental aspect of the IGARCH model is that the model indicates infinite persistence of the conditional variance to a shock in squared returns. Consequently, in the majority of empirical studies, the volatility process is found to be mean reverting. Hence, the IGARCH model seems to be too restrictive as it implies infinite persistence of a volatility shock (Tayefi & Ramanathan, 2016).

3.3.3 Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH)

Nelson (1991) presented the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model which is an extended version of GARCH that incorporates the asymmetric effect on volatility caused by positive and negative news. Moreover, the author elaborated that negative shocks can have a greater impact on volatility than positive shocks with the same magnitude. Accordingly, EGARCH (1,1) can be defined as per the below:

$$\ln({\sigma_t}^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad \textbf{(8)}$$

Whereby ω is the long-term average value, β signifies the persistence parameter, α represents the size effect and lastly, γ captures the sign (leverage) effect. An asymmetric effect is demonstrated when $\gamma \neq 0$. To better demonstrate this, when γ negative, positive news will impact volatility less than negative news. Additionally, the above equation presumes that errors are normally distributed with a mean equivalent to $\sqrt{\frac{2}{\pi}}$.

3.3.4 Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH)

Glosten et al. (1993) introduced GJR-GARCH which models negative and positive shocks on the conditional variance asymmetrically through the usage of an indicator function, *I*. The model is akin to the previously discussed EGARCH (1,1) as both models incorporate the asymmetric effect of negative and positive shocks. Nonetheless, GJR-GARCH is expressed as:

$$\sigma_t{}^2 = \omega + (\alpha + \gamma I_{t-1})u_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad \textbf{(9)}$$

Whereby, if $u_{t-1} < 0$ then $I_{t-1} = 1$ and 0 otherwise. It is worth mentioning that negative shocks impact volatility by $\alpha_t + \gamma_t$ while positive shocks impact volatility by a_t. Contrary to EGARCH, the leverage effect is present whenever $\gamma > 0$ thus, bad news have a more prevalent effect on volatility than good news and vice versa. Parameter restrictions are reminiscent of GARCH such that ω, α and $\beta \geq 0$ and the persistence in this model relies on α, β and $\gamma_k$with k reflecting the average value of standardized errors.

3.4. Parameter Estimation using Maximum Likelihood Methodology

The maximum likelihood estimation (MLE) is a technique used to estimate the parameters of a statistical model by means of fitting the model to the observed data. Generally speaking, the likelihood of observed data is the probability of obtaining that specific set of data given the chosen probability model. The MLE approach will be applied in this thesis to estimate the parameters of the GARCH (1,1), IGARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1) models used in this thesis.

The likelihood function is expressed as per the below:

$$L^* = \prod_{t-1}^{T} f(y_{t-1}, y_{t-2}, \ldots, y_1, \theta_1, \theta_2, \ldots, \theta_k) \quad \textbf{(10)}$$

However, in finance the likelihood function is frequently substituted with the log likelihood function (LLF) which is the preferred method as it is efficient, reliable and consistent. LLF equation expressed below:

$$\ln L^* = \prod_{t-1}^{T} \ln f(y_{t-1}, y_{t-2}, \ldots, y_1, \theta_1, \theta_2, \ldots, \theta_k) \quad \textbf{(11)}$$

Whereby f is the conditional probability density function, y_t and θ_t are the value of the time series and model parameters, respectively.

3.5. Realized Volatility

To begin with, it is important to compare the estimated volatility to the realized volatility in order to evaluate the accuracy of the model used. Accordingly, Merton (1980) recommended a model to compute the realized volatility based on the asset's returns. The model was simple and proposed that when the sampled variable contained several observations, the sum squared returns is a precise estimation of volatility (Naimy, Haddad, Fernández-Avilés, & El Khoury, 2021). Hence, the equation that will be implemented to obtain the annual realized volatility "σ_t" is defined as follows:

$$\sigma_t = \sqrt{\frac{252}{22} \sum_{t-22}^{t-1} u_i^2} \quad \textbf{(12)}$$

Based on the above, t embodies the day of observation and u_i is the return on day i whereby $t-22 < i < t-1$. Consequently, this specifies that the monthly realized volatility "σ_t" is obtained as per the most recent 22 daily returns and in order to annualize the outcome, monthly results are multiplied by 252/22.

3.6. Distribution and Model Selection

Selecting the most appropriate model to describe the observed data is a crucial part of research and thus, various statistical approaches have been recommended for dealing with this issue. Accordingly, for the purpose of this thesis the goodness of fit test will be based on two of the most widely used model selection criteria: Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

The Akaike Information, Akaike (1974) is expressed as:

$$AIC = -2\ln(\hat{L}) + 2k \quad \textbf{(13)}$$

The Bayesian Information Criterion, Schwarz (1978), is expressed as:

$$BIC = -2\ln(\hat{L}) + kln(n) \quad \textbf{(14)}$$

Whereby $\hat{L}$ denotes the likelihood of the model given the data, k is the number of unknown parameters and n is the number of observations. Additionally, the forecasting ability of models is assessed using three test statistics; the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE). To begin with, the Mean Absolute Error (MAE) calculates the average scale of errors in a set of data without taking into consideration the direction. MAE is simply the average of the absolute difference between predicted data and actual observation whereby all differences have equal weights.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \tag{15}$$

Whereby, e_t is expressed as:

$$e_t = \hat{y}_t - y_t \tag{16}$$

With $\hat{y}_t$ representing the predicted value and y_t the actual observation.
Moving one step forward, the Root Mean Square Error (RMSE) is the squared root of average squared errors, expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2} \tag{17}$$

Given that the errors are squared before they ae averaged, the model allocates comparatively high weights to large errors. Thus, the RMSE is more useful when data contains large errors which are detrimental.

Lastly, the Mean Absolute Percentage Error (MAPE), expressed below, scales residuals against actual values:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{|y_t|} \quad \textbf{(18)}$$

The lower the measure of these test statistics, the better the performance. A lower measure indicates a better performance. Accordingly, ranks obtained through the various evaluation methods will be presented. Thus, the optimal GARCH model will be employed to formulate VaR projections.

3.7 Employing Dummy Variables to the Optimal Model

After determining the optimal model, we move to answer whether natural disasters impact the volatility structure of the selected insurance companies and indices. The idea is to add a dummy variable (D) to the chosen GARCH-type model for the next trading date after the occurrence of the disaster. The dummy is equal to 0 for the pre-disaster period and 1 for post-disaster period. Subsequently, we estimate the GARCH-type model while adding the dummy variable to the variance equation as ϕD_t. A positive sign of ϕ parameter implies that the volatility has increased post-disaster period, whereas a negative sign of ϕ sign suggests that the volatility has decreased post-disaster period. It is important to check whether the ϕ parameter is statistically significant, otherwise the dummy variable is incapable of delivering robust results.

Considering the importance of market risk, and in order to complement the above-mentioned methodology and present well-rounded risk estimations, we will proceed with calculating the Value at Risk (VaR).

3.8. Value at Risk (VaR)

The term 'risk management' has exploded in popularity with millennials. Out of all the methods that fall under the risk management umbrella, Value at Risk (VaR) may be regarded as one of the key measures established to quantify financial market risk. In this regard, Jorion (2001) defined the term as "the worst expected loss over a given horizon under normal market conditions at a given level of confidence. For instance, a bank might say that the daily VaR of its trading portfolio is $1 million at the 99 percent confidence level. In other words, under normal market conditions, only one percent of the time, the daily loss will exceed $1 million[2]." (p.22) Accordingly, VaR is a standard risk measure that is regularly used in risk management to measure and quantify the level of downside risk as a sole value.

The VaR estimate for GARCH-type models depends on the one-day-ahead forecast conditional variance σ_{t+1}^2 and mean μ_{t+1} of the volatility model given the information available at time *t*. Accordingly, the one-day-ahead VaR forecast is calculated as:

$$VaR_{t+1}(a) = \mu_{t+1} + F^{-1}(a)\sigma_{t+1} \qquad \textbf{(19)}$$

Where $F^{-1}(a)$ is the corresponding a^{th}- quantile (1% or 5%) of the distribution. Consequently, once the optimal volatility model has been calculated for the dataset, their corresponding VaR will be forecasted.

2 Jorion, P. (2001) Value at Risk: The New Benchmark for Managing Financial Risk. 2nd Edition, McGraw-Hill, United States of America

3.8.1 Historical Simulation Methodology

Over the last decade, various approaches have been suggested to model VaR. The simplest and most straightforward model is the basic historical simulation. The model involves using “n” day-to-day variations in stock prices observed in the past as a roadmap to estimate the probability distribution of the change in the value of these assets between today and tomorrow thereby providing “n-1” alternate scenarios of what could be the resulting value of those assets on the succeeding day using the following expression:

$$Value\ under\ ith\ scenario = v_n \frac{v_i}{v_{i-1}} \qquad \textbf{(20)}$$

Whereby v_n is the fixed value reflecting the asset’s price on the most recent trading day of the selected time series, v_i reflects stock values of day i, and v_{i-1} represents the stock value n day i-1 and. While the above historical simulation methodology is simple to implement, it has its limitations. The main limitation is the assumption that the market returns are independent, identically-distributed (IID) something which is often far from reality. In reality, market returns often exhibit autocorrelation whereby the market return of today is partially dependent on yesterday’s return (Ding, Granger, & Engle, 1993).

To limit the impact of autocorrelation, Hull and White (1998) proposed a modification to the above-mentioned model to capture market returns, which reflect volatility changes during the period the data covers. Furthermore, the authors suggested an additional adjustment by integrating “volatility updating” to the original methodology.

Accordingly, when this approach is implemented, the equation for the value of each stock under the i^{th} scenario becomes:

$$Value\ under\ ith\ scenario = v_n \frac{v_{i-1} + (v_i - v_{i-1})\sigma_{n+1}/\sigma_i}{v_{i-1}} \quad \textbf{(21)}$$

As reflected above, the chief modification to the basing model is identified through the volatility parameters "σ_{n+1}" and "σ_i" signifying the most recent volatility estimate and volatility estimated at day i. Accordingly, the proposed modification by Hull and White (1998) captures volatility changes in a spontaneous technique thereby producing VaR estimations that incorporate new information.

Based on the above, we will compute the VaR for the index Dow Jones U.S Property and Casualty Insurance Index (DJUSIP) for the period spanning from January 1st 2018 till December 31st 2020 at the 1%, 5% and 10% levels of significance. DJUSIP was chosen as it includes a wide spectrum of property-casualty insurance companies in one index, thus encompassing the majority of the data.

3.9 Back-Testing Value at Risk (VaR)

Value at Risk (VaR) models are considered valuable if their ability to predict future risks is accurate. Therefore, VaR models should always be back-tested through proper methodology to ensure that the obtained VaR outcomes are reliable and consistent. Back-testing involves comparing projected VaR projections to actual profits/losses. Jorion (2001) denotes tests as 'reality checks'. Hence, if a VaR estimate is accurate when it precisely conveys the level of coverage in line with its confidence level, then for the $(1\text{-}x)^{th}$ percentile VaR, the failure rate across the whole sample will be equivalent to *x*.

In order to assess the accuracy of the estimated VaR in projecting returns, the actual realized returns should be compared to the out-of-sample VaR forecasts for the same timeframe whereby this is quantified as a violation ratio (Naimy & Bou Zeidan, 2019) . For instance, if violations occur on *x* % of the days, we can thereby presume that the methodology used to calculate VaR is sensible. Conversely, if the actual losses exceed the VaR estimation, across the same timeframe, then the VaR limit is believed to have been violated whereby an exception is recorded. Moreover, if the number of exceptions recorded are less than expectations, thereby this indicates an excessively conservative VaR estimate. Alternatively, if the number of exceptions recorded exceed expectations, thereby the estimated VaR thoroughly understates the asset's real level of risk (Naimy, Haddad, Fernández-Avilés, & El Khoury, 2021).

Having said the above, we should examine if the observed number of exceptions is sensible compared to the estimated forecasts in order to evaluate the accuracy of the model. Hence, a range of different testing methodologies have been recommended for back-testing, however, for the purpose of this thesis, we will perform Kupiec's Unconditional Coverage Test suggested by Kupiec (1995) to conclude whether or not the VaR model used should be accepted.

3.9.1 Unconditional Coverage Test

Kupiec's test, also referred to as the proportion of failures (POF) test, is the most commonly acknowledged test based of failure rates proposed by Kupiec (1995). Kupiec's test measures if the number of exceptions is consistent with the confidence level (Iorgulescu, 2012). Alternatively, Kupiec's test will reject the VaR estimate if it understates/overstates the actual VaR. The null hypothesis for the POF-test is expressed as:

$$H_0 : p = \hat{p} = \frac{x}{T} \qquad \textbf{(22)}$$

Whereby:

p - The failure rate suggested by the confidence level.

$\hat{p}$ - The observed failure rate.

x - Number of exceptions/violations.

T- Number of trials.

In line with Kupiec (1995), the likelihood-ratio (LR) takes the form of:

$$LR_{POF} = -2\ln\frac{\left[(1-p)^{T-x}p^{x}\right]}{\left[1-\left(\frac{x}{T}\right)\right]^{T-x}\left(\frac{x}{T}\right)^{x}} \sim X^2 \qquad \textbf{(23)}$$

Based on the above, if the value of LR_{POF} surpasses the critical value of the χ^2 distribution, the model will be deemed inaccurate and thus, the null hypothesis will be rejected. As previously highlighted, the number of violations, expressed as *"x"*, is computed by recording the number of times the actual/real loss surpasses estimated VaR, alternatively, this the number of exceptions recorded once all days are accounted for. The following subsection shall present and analyze the data pertaining to stock prices of the insurance companies and indices chosen.

3.10 Data and Descriptive Statistics

3.10.1. Data on natural disasters

The data pertaining to natural disasters was obtained from Centre for Research on the Epidemiology of Disasters (CRED)'s EM-DAT, the international disaster database. CRED is a World Health Organization Collaborating Centre and the database includes all declared disasters. The database highlights the beginning and end date of each natural disaster, disaster group, disaster subgroup, disaster type and subtype. Moreover, the disaster damages and insured damages are identified. The full sample ranging from 01/01/2010 till 31/12/2020 contains 251 events. The disaster types identified include: Drought, Earthquake, Extreme Temperature, Flood, Landslide, Storm, Volcanic Activity and Wildfires. However, there are 21 disasters with no financial information regarding the total damages therefore, these disasters shall be excluded from our dataset. After implementing the above criterion, 230 events remain. Moreover, a lot of these disasters might not be severe enough to impact the stock market. Therefore, we shall consider a disaster as "major" when damage exceeds USD 25 million, as identified by the insurance industry as the threshold whereby an event is classified as a catastrophe (Spotlight on: Catastrophes - insurance issues). After implementing this benchmark, 216 events meet our major disaster threshold. Lastly, event papers that study the short-term effects of natural disasters experience implementation challenges as natural disasters are heterogeneous events with inconstant event durations and inexact start dates. Thus, in order to alleviate the impact of such limitation we use the "Incident Start Date" as extracted from EM-DAT as the event date. When the date falls on a market holiday or weekend, we use the next trading day as the event date.

It is worth mentioning that damages caused by storms (tornado, winter storm, blizzard, lightning, thunderstorms) amount to 78% of the overall damage caused by natural disasters. Additionally, storms have the highest frequency of occurrence, with 151 storms witnessed across the chosen timeframe. Thus, we can deduce that storms are high frequency and high severity natural disasters. The second largest share is damage caused by floods, comprising 7.86%. Fundamentally, the remaining disaster types make up merely a combined share of 14%. Accordingly, a summary of the data by damage caused ('000, USD) is reflected in the below table and illustrated graphically in Figure 1:

Disaster Type	**Sum of Total Damages ('000 US$)**	**Percentage (%) of Total Damages**	**Frequency Disasters**
Volcanic activity	500,000.00	0.067%	1
Earthquake	900,000.00	0.120%	2
Landslide	900,000.00	0.120%	1
Extreme temperature	4,100,000.00	0.546%	3
Drought	42,200,000.00	5.616%	7

Wildfire	56,933,000.00	7.577%	23
Flood	59,114,000.00	7.867%	28
Storm	586,754,300.00	78.088%	151
Total	**751,401,300.00**	**100%**	**216**

Table 1: The relative USD ('000), % and disaster frequency distribution of damages caused by natural disasters between 2010 and 2020. Data gathered using Centre for Research on the Epidemiology of Disasters (CRED)'s EM-DAT, the international disaster database

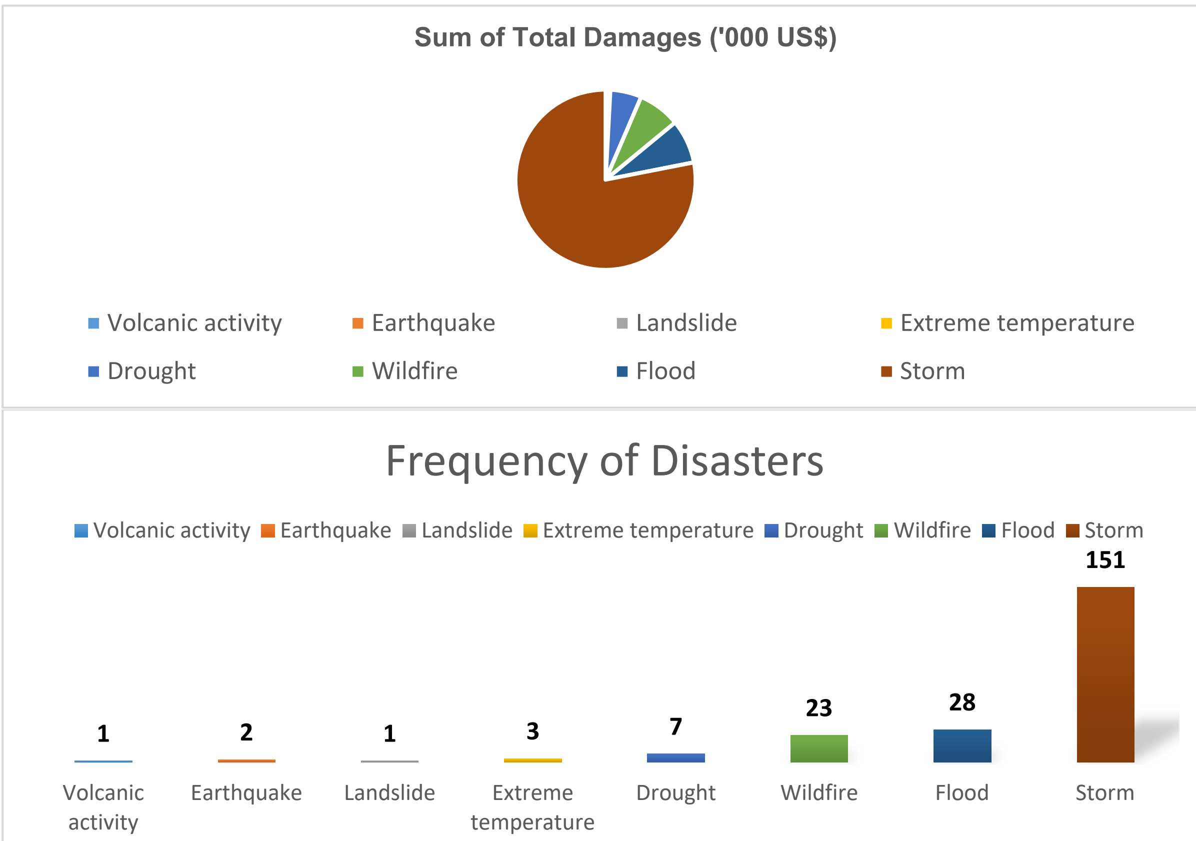


Figure 1: The relative USD ('000), % and disaster frequency distribution of damages caused by natural disasters between 2010 and 2020.

3.10.2. Data on stock prices

In order to answer the research questions, two data sets related to stock prices are identified: U.S Property-Liability Insurers and major U.S Stock Indices. To begin with, using an equity stock screener, we curated a list of 62 small-to-mega cap property-liability insurance companies in the U.S. Secondly, we collect daily historical stock price data for the above-mentioned insurance companies from 01/01/2010 till 31/12/2020 using the Reuters platform. Accordingly, we only consider stocks with continuous 10-year data between January 2010 and December 2020, thus reducing the dataset to 19 insurance companies yielding a total of 2,769 daily observations per company (see table 2 for list of stocks included in data).

Insurance Company	**Ticker**
Chubb Limited	CB
Progressive Corp	PGR
MS&AD Insurance Group Holdings	MSADY.PK
Cincinnati Financial Corporation	CINF.OQ
W. R. Berkley Corp	WRB
American Financial Group, Inc.	AFG
RLI Corp	RLI
Selective Insurance Group Inc	SIGI.O
White Mountains Insurance Group Ltd	WTM
Horace Mann Educators Corporation	HMN
Argo Group International Holdings Ltd.	ARGO.K
Safety Insurance Group, Inc.	SAFT.O
United Fire Group, Inc.	UFCS.O
Universal Insurance Holdings, Inc.	UVE
HCI Group Inc	HCI
Donegal Group Inc.	DGICA.O
Global Indemnity Group LLC	GBLI.O

FedNat Holding Company	FNHC.O
Hallmark Financial Services, Inc.	HALL.O

Table 2: The chosen list of insurance companies included in our dataset.

Our second dataset includes the daily stock prices of 3 U.S stock indices, *S&P 500, Dow Jones Industrial Average and Nasdaq Composite* for the same time range. The S&P 500, one of the most commonly followed equity indices, is a stock-market index that measures the stock price performance of 500 large companies listed on U.S. stock exchanges. The Dow Jones Industrial Average is a stock market index that captures the stock performance of 30 large cap companies listed on U.S stock exchanges. While it is a commonly trailed stock index, it is not considered an adequate representation of the overall market as it only contains 30 companies and does not use weighted arithmetic mean. Lastly, the Nasdaq Composite is a stock market index that includes nearly all stocks listed on the NASDAQ stock market and its composition is significantly weighted to companies in the information technology (IT) sector. Accordingly, the three chosen stock indices are considered to be the 3 most followed stock market indices in the U.S. We collect daily historical stock price data for the above-mentioned stock indices from 01/01/2010 till 31/12/2020 using Reuters platform yielding a total of 2,769 daily observations per index.

The descriptive statistics of the daily stock returns for both insurance companies and indices are reflected in Table 3 and 4 below. All statistics were performed using the E-Views tool. Due to space consideration, the outcome is reflected on the next page. When going over the outcome obtained, we note that the average return is approximately

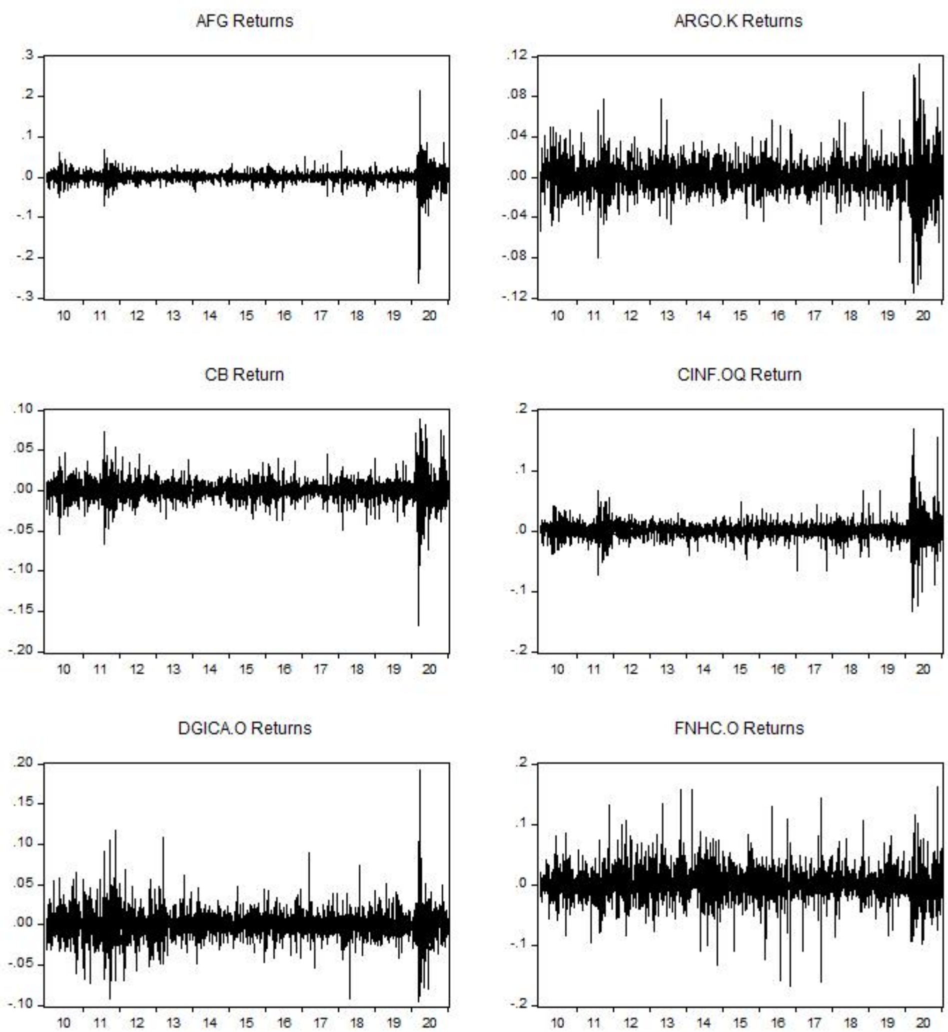
0%. Additionally, insurance stocks reflect a higher standard deviation than the chosen stock indices due to their lower volatility nature. Moreover, the high kurtosis observed for all of the chosen data suggests that the series follows a heavy-tailed leptokurtic distribution paired with significantly high probability of outlier values and a peak larger than that of a normal distribution. Lastly, in order to validate the outcome, the Jarque-Bera test, based on Jarque & Bera (1987), rejects the null hypothesis of a normal distribution for all series given that the calculated test statistics are higher than the critical values.

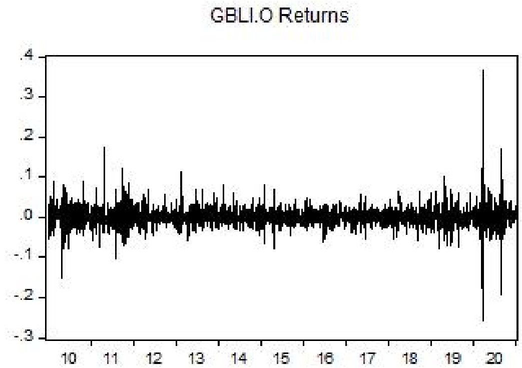
	Observations	Mean	Median	Max.	Min.	Std. Dev.	Variance	Std. Error	Skewness	Kurtosis	Jarque-Bera	Probability	Sum	Sum Sq. Dev.
CB	2,768	0.0007	0.0012	0.2129	-0.2629	0.0170	0.0003	0.0003	-1.0960	55.8817	323080.4000	0.000	1.8223	0.7983
PGR	2,768	0.0004	0.0003	0.1123	-0.1155	0.0172	0.0003	0.0003	-0.1225	10.0710	5773.5180	0.000	1.2186	0.8199
MSADY.PK	2,768	0.0005	0.0005	0.0887	-0.1677	0.0141	0.0002	0.0003	-0.5369	17.3115	23755.3600	0.000	1.4167	0.5511
CINF.OQ	2,768	0.0006	0.0008	0.1683	-0.1331	0.0159	0.0003	0.0003	0.1444	20.6538	35953.9100	0.000	1.5585	0.7016
WRB	2,768	0.0001	0.0000	0.1927	-0.0954	0.0180	0.0003	0.0003	0.6715	12.6192	10879.6800	0.000	0.3362	0.8961
AFG	2,768	0.0005	0.0000	0.1617	-0.1689	0.0267	0.0007	0.0005	0.1326	8.7532	3825.5940	0.000	1.3517	1.9768
RLI	2,768	0.0005	0.0000	0.3661	-0.2559	0.0239	0.0006	0.0005	0.8897	33.4009	106957.9000	0.000	1.3571	1.5827
SIGI.O	2,768	0.0002	0.0000	0.4704	-0.5665	0.0319	0.0010	0.0006	-0.2927	71.5391	541829.8000	0.000	0.6782	2.8100
WTM	2,768	0.0010	0.0008	0.2739	-0.2001	0.0251	0.0006	0.0005	0.7000	17.5442	24622.7700	0.000	2.7168	1.7364
HMN	2,768	0.0006	0.0007	0.1361	-0.1443	0.0181	0.0003	0.0003	0.1972	10.5920	6665.6140	0.000	1.6358	0.9048
ARGO.K	2,768	0.0002	0.0000	0.1322	-0.0936	0.0181	0.0003	0.0003	0.0119	6.0608	1080.5580	0.000	0.6187	0.9083
SAFT.O	2,768	0.0007	0.0008	0.1214	-0.0948	0.0138	0.0002	0.0003	0.0841	10.0944	5808.0630	0.000	2.0071	0.5273
UFCS.O	2,768	0.0007	0.0007	0.1573	-0.1367	0.0159	0.0003	0.0003	0.0904	18.2614	26866.0300	0.000	1.9177	0.6967
UVE	2,768	0.0004	0.0005	0.1195	-0.0954	0.0145	0.0002	0.0003	0.1109	9.7171	5209.4390	0.000	1.0327	0.5780
HCI	2,768	0.0006	0.0006	0.1448	-0.1971	0.0168	0.0003	0.0003	-0.2552	15.6687	18540.4800	0.000	1.7733	0.7763
DGICA.O	2,768	0.0004	0.0002	0.2019	-0.1858	0.0232	0.0005	0.0004	0.3140	14.4520	15171.3600	0.000	1.0985	1.4861
GBLI.O	2,768	0.0007	0.0000	0.1674	-0.3073	0.0266	0.0007	0.0005	-0.7621	16.3205	20732.3400	0.000	1.9462	1.9541
FNHC.O	2,768	0.0006	0.0008	0.1196	-0.1543	0.0136	0.0002	0.0003	-0.1390	20.8563	36782.7900	0.000	1.7503	0.5145
HALL.O	2,768	0.0005	0.0003	0.1667	-0.1156	0.0131	0.0002	0.0002	1.3324	28.2825	74540.4200	0.000	1.3295	0.4777
SPX	2,768	0.0005	0.0007	0.0938	-0.1198	0.0110	0.0001	0.0002	-0.5781	18.1640	26674.5900	0.000	1.3676	0.3361

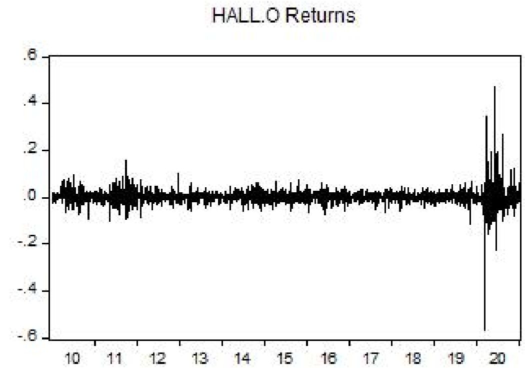
IXIC	2,768	0.0007	0.0011	0.0935	-0.1232	0.0123	0.0002	0.0002	-0.5655	12.8986	11448.2400	0.000	1.9294	0.4162
DJI	2,768	0.0004	0.0007	0.1137	-0.1293	0.0110	0.0001	0.0002	-0.5828	23.4238	48265.8400	0.000	1.2301	0.3323

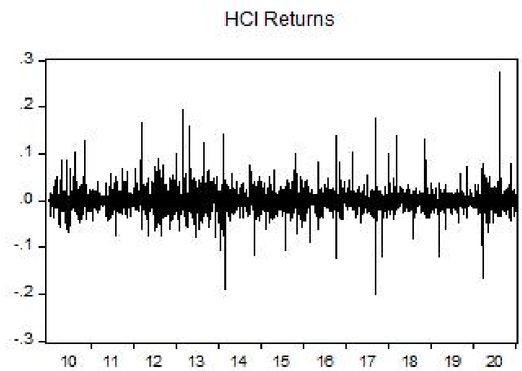
Table 3: Summary Statistics of the daily returns of the chosen insurance companies' and stock indices over the sample period Jan 4th 2010– December 31st 2020.

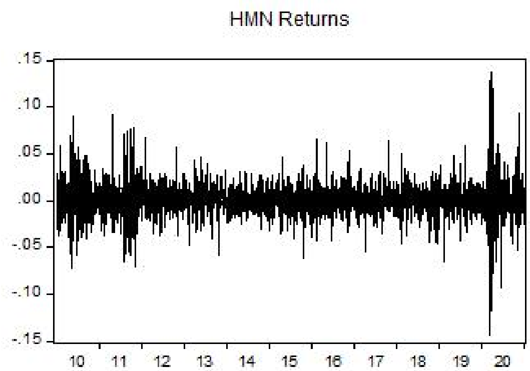
Going a step further analyzing historical returns, Figure 2 below confirms a distinctive feature of leptokurtosis that emerges due to patterns of volatility clustering (changes in volatility over time) in the market whereby there are periods of high (low) volatility followed by periods of high (low) volatility. Consequently, based on the plot of returns below, persistence and volatility clustering are visible, which implies that volatility can be forecasted.

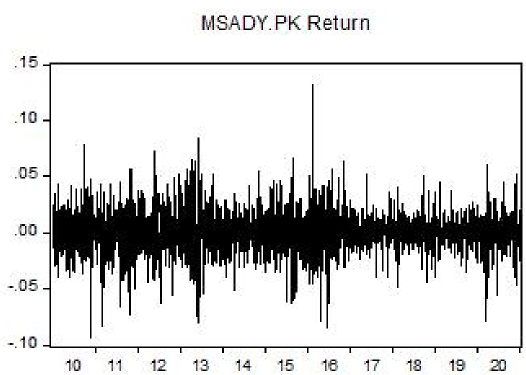


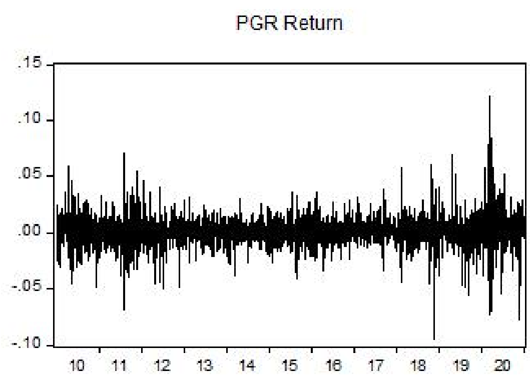

GBLI.O Returns
.4
.3
.2
.1
.0
-.1
-.2
-.3
10 11 12 13 14 15 16 17 18 19 20

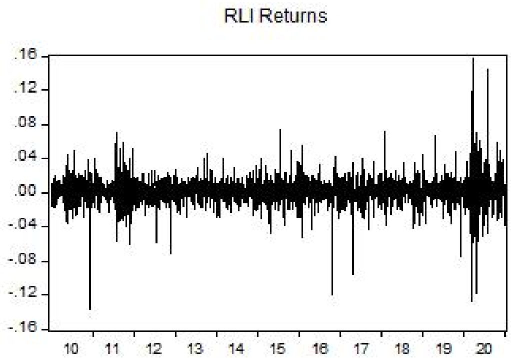

HALL.O Returns
.6
.4
.2
.0
-.2
-.4
-.6
10 11 12 13 14 15 16 17 18 19 20

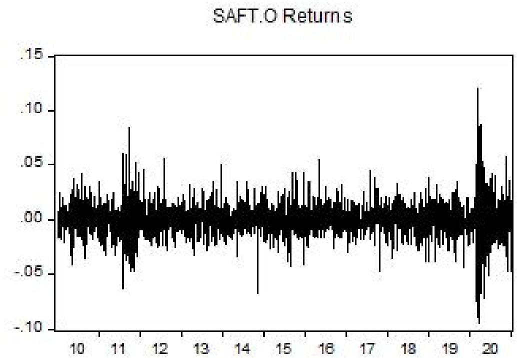

HCI Returns
.3
.2
.1
.0
-.1
-.2
-.3
10 11 12 13 14 15 16 17 18 19 20

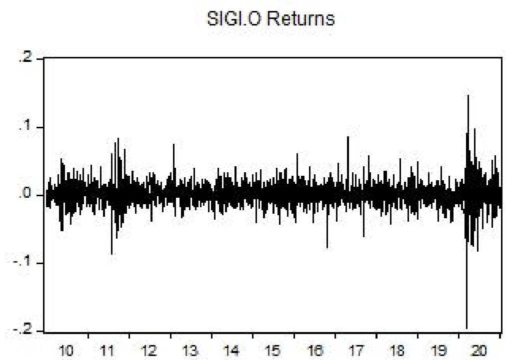

HMN Returns
.15
.10
.05
.00
-.05
-.10
-.15
10 11 12 13 14 15 16 17 18 19 20

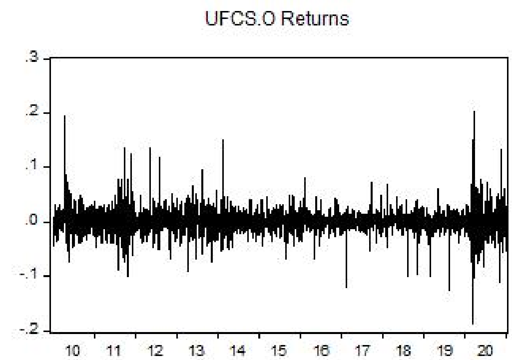

MSADY.PK Return
.15
.10
.05
.00
-.05
-.10
10 11 12 13 14 15 16 17 18 19 20

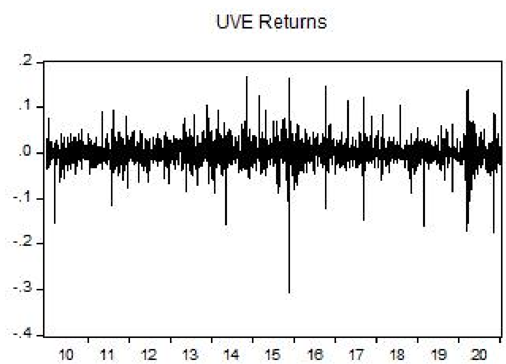

PGR Return
.15
.10
.05
.00
-.05
-.10
10 11 12 13 14 15 16 17 18 19 20

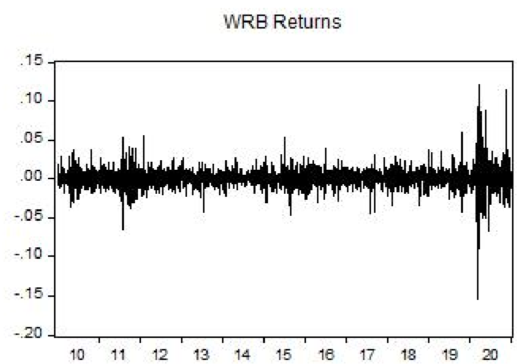

RLI Returns
.16
.12
.08
.04
.00
-.04
-.08
-.12
-.16
10 11 12 13 14 15 16 17 18 19 20

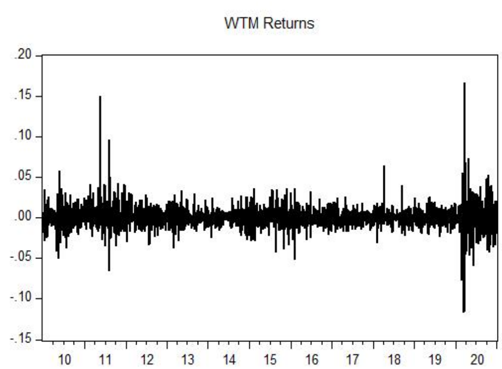

SAFT.O Returns
.15
.10
.05
.00
-.05
-.10
10 11 12 13 14 15 16 17 18 19 20


SIGI.O Returns
.2
.1
.0
-.1
-.2
10 11 12 13 14 15 16 17 18 19 20


UFCS.O Returns
.3
.2
.1
.0
-.1
-.2
10 11 12 13 14 15 16 17 18 19 20


UVE Returns
.2
.1
.0
-.1
-.2
-.3
-.4
10 11 12 13 14 15 16 17 18 19 20


WRB Returns
.15
.10
.05
.00
-.05
-.10
-.15
-.20
10 11 12 13 14 15 16 17 18 19 20


WTM Returns
.20
.15
.10
.05
.00
-.05
-.10
-.15
10 11 12 13 14 15 16 17 18 19 20

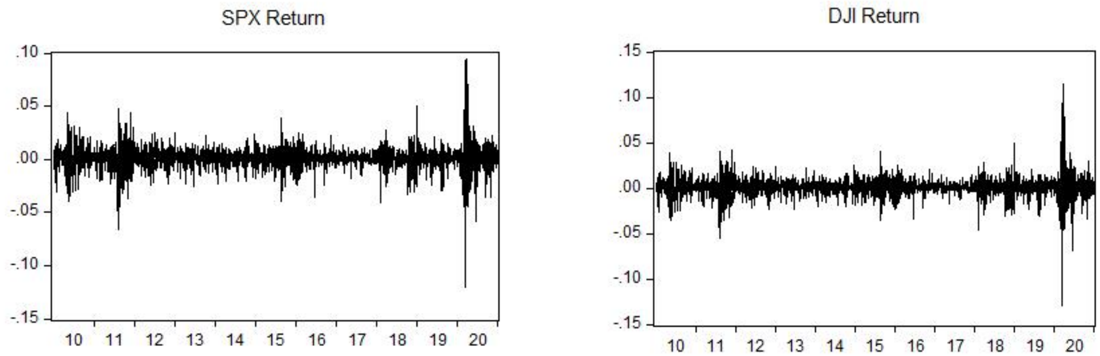


Figure 2: Time series plot of the daily simple returns of the chosen stocks and indices over the sample period Jan 4th, 2010– December 31st 2020.

Successively, the Durbin-Watson statistics test, Durbin-Watson (1950, 1951), a test statistic utilized to identify the presence of autocorrelation in the residuals of a regression, confirmed that there is no serial correlation in the residuals of all series. Given that no autocorrelation is identified, no corrective measures are required. Thus, our series does not exhibit an AR, MA or ARMA process; our data series is more likely to show an ARCH effect. The outcome of the Durbin-Watson test are reflected in the below Table 4.

Durbin-Watson Test Statistics	
Ticker	**Statistics**
CB	2.25
PGR	2.254
MSADY.PK	2.134
CINF.OQ	2.265
WRB	2.263
AFG	2.208
RLI	2.289
SIGI.O	2.304
WTM	2.226
HMN	2.335
ARGO.K	2.051
SAFT.O	2.325
UFCS.O	2.38
UVE	2.184
HCI	2.168
DGICA.O	2.37

GBLI.O	2.382
FNHC.O	2.117
HALL.O	2.084
SPX	2.305
IXIC	2.255
DJI	2.201

Table 4:Durbin-Watson Test Statistics confirming no serial correlation in the residuals of all series over the sample period Jan 4th 2010– December 31st 2020

Lastly, the Augmented Dickey-Fuller (ADF) test statistic, suggested by Dickey & Fuller (1979), was computed. Table 5 reflects the results and corresponding P-Values for both data series. Based on the below outcome, we reject the null hypothesis of non-stationarity and affirm that returns are stationary, signifying that no remediation in the return series is required.

Augmented Dickey-Fuller Test Statistics		
Ticker	**Statistics**	**P-Value**
CB	-19.77411	0
PGR	-29.01706	0
MSADY.PK	-56.26255	0.0001
CINF.OQ	-16.18459	0
WRB	-19.47089	0
AFG	-26.55926	0
RLI	-20.01478	0
SIGI.O	-61.25953	0.0001
WTM	-36.73296	0
HMN	-62.34835	0
ARGO.K	-54.03127	0.0001
SAFT.O	-62.04331	0.0001
UFCS.O	-32.25076	0
UVE	-36.66628	0
HCI	-57.09415	0.0001

DGICA.O	-63.33413	0.0001
GBLI.O	-31.16197	0
FNHC.O	-55.75972	0.0001
HALL.O	-20.91346	0

Augmented Dickey-Fuller Test Statistics		
Ticker	**Statistics**	**P-Value**
SPX	-20.11686	0
IXIC	-20.49317	0
DJI	-17.52443	0

Table 5: Augmented Dickey-Fuller Test Statistics confirming the stationarity of the chosen data series over the sample period Jan 4th 2010– December 31st 2020

Lastly, prior to estimating volatility, using E-Views, we conducted the heteroskadicity test for ARCH effect of the squared residuals. Accordingly, the outcome yielded a Chi-Square less than 5% therefore, the null hypothesis is rejected certifying that there is an ARCH effect. We now have the complete validation to proceed with applying GARCH-type models.

To conclude, Chapter 3 has meticulously and systematically described the models employed. Additionally, for Value at Risk (VaR), evaluation techniques were also described. Lastly, the chapter highlighted a thorough description and statistical analysis of the chosen data and ensured that the full justification to apply GARCH volatility models was covered. Chapter 4 continues by presenting the findings under each of the volatility models.

Chapter 4: Findings

Following the theoretical description of the adopted methods introduced in the previous chapter, Chapter 4 reports and presents the study's detailed findings under each of the chosen volatility models, GARCH (1,1), IGARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1) for the in-sample period. After calculating the volatilities of all the stocks and indices within the in-sample data using the chosen models, we proceed to compute the realized volatility. Subsequently, the same calculations applied for the in-sample period are applied to the out-sample period, however, the in-sample parameters obtained are used to forecast the conditional volatilities for the out-sample period. Subsequently, the optimal model is chosen based on the outcome of three error metrics selected for both the in-sample and out-sample periods. Next, after determining the optimal model and in order to capture whether natural disasters have changed the volatility structure of the selected data series, a dummy variable will be added to the selected GARCH-type model. Moving a step further, Value at Risk (VaR) is calculated and the model's accuracy is assessed using Kupiec Test. Lastly, in order to provide well-rounded risk measures, we incorporate Extreme Value Theory (EVT) into our calculations as it assumes a separate distribution for extreme losses in order to estimate the probability of extreme values.

4.1. In-Sample Modeling

Upon extracting the historical daily stock prices for each of the three chosen indices and nineteen insurance companies for the chosen dataset and subsequently computing the respective daily returns, the daily conditional variance for each historical observation is calculated for each of the GARCH (1,1), IGARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1) models using equations (3), (7), (8) and (9), respectively. Successively, results are annualized supposing 250 trading days/year and thus, by taking the square root of the annualized variance, the annualized volatility is obtained.

4.1.1 In-Sample Parameters' Estimation

First, each volatility model parameter estimation is undertaken for the in-sample dataset period extending from 01/01/2010 till 29/12/2017. In order to select the most appropriate model to describe the observed data, it is important to begin with fitting the GARCH model's distribution of the error term. Accordingly, assuming three error distributions (Normal Distribution, Student's T Distribution and Generalized Error Distribution), we applied the GARCH (1,1) model for the entire sampled period ranging from 01/01/2010 till 31/12/2020. Based on the outcome highlighted in Table 6, the use of heavy-tailed/ highly skewed tails is warranted as they provide better results when applying goodness of fit measures. The Generalized Error Distribution (GED) exhibits preeminence as it has the lowest AIC and BIC along with the highest log-likelihood value. Accordingly, GED is selected for all stocks within the sample except for RLI whereby it is demonstrated that Student's T distribution is the best-selected model. Accordingly, the sum of the log likelihood estimates is maximized using the "Solver" function on excel conditional on the constraints and conditions defined previously in section 3.3. Once the likelihood function is maximized, the resulting parameters attained are the ones used to estimate the conditional volatilities for the chosen period.

	Normal Distribution			Student's T Distribution			Generalized Error Distribution (GED)		
Ticker	AIC	BIC	LLF	AIC	BIC	LLF	AIC	BIC	LLF
CB	-6.097553	-6.088992	8446.062	-6.09651	-6.085809	8445.618	-6.426566	-6.415865	8902.581
PGR	-5.573898	-5.565337	7721.061	-5.667655	-5.656954	7851.869	-5.80197	-5.791269	8037.827
MSADY.PK	-4.831363	-4.822802	6693.022	-4.833928	-4.823227	6697.574	-4.91366	-4.902959	6807.962
CINF.OQ	-6.089007	-6.080446	8434.23	-6.088103	-6.077402	8433.978	-6.280912	-6.270211	8700.922
WRB	-6.762176	-6.753615	9366.233	-6.761381	-6.75068	9366.132	-7.023618	-7.012917	9729.199
AFG	-6.193219	-6.184658	8578.511	-6.1933	-6.182599	8579.624	-6.489046	-6.478345	8989.084
RLI	-6.031599	-6.023039	8354.749	-6.074792	-6.064091	8415.55	-6.060739	-6.050038	8396.093
SIGI.O	-6.15418	-6.14562	8524.463	-6.192192	-6.181491	8578.091	-6.366592	-6.355891	8819.547
WTM	-6.296368	-6.287807	8721.322	-6.304883	-6.294182	8734.111	-6.358921	-6.34822	8808.926
HMN	-5.599451	-5.59089	7756.44	-5.598534	-5.587833	7756.17	-5.800822	-5.790121	8036.239
ARGO.K	-5.883461	-5.8749	8149.652	-5.930778	-5.920077	8216.162	-6.172204	-6.161503	8550.417
SAFT.O	-6.565313	-6.556753	9093.676	-6.564528	-6.553826	9093.588	-6.754815	-6.744114	9357.041
UFCS.O	-4.354506	-4.345945	6032.814	-4.353728	-4.343027	6032.736	-4.719226	-4.708525	6538.768
UVE	-3.972487	-3.963926	5503.908	-3.972015	-3.961314	5504.255	-4.160339	-4.149638	5764.99
HCI	-4.073476	-4.064915	5643.727	-4.098062	-4.087361	5678.767	-4.152397	-4.141696	5753.994
DGICA.O	-5.08982	-5.081259	7050.855	-5.074624	-5.063923	7030.817	-5.217793	-5.207092	7229.034
GBLI.O	-4.419118	-4.410557	6122.268	-4.417771	-4.40707	6121.404	-4.706926	-4.696225	6521.739
FNHC.O	-4.695499	-4.686939	6504.919	-4.694768	-4.684067	6504.906	-4.823956	-4.813255	6683.768
HALL.O	-4.193702	-4.185141	5810.18	-4.19686	-4.186159	5815.553	-4.496316	-4.485615	6230.149

	Normal Distribution			Student's T Distribution			Generalized Error Distribution (GED)		
Ticker	AIC	BIC	LLF	AIC	BIC	LLF	AIC	BIC	LLF
SPX	-6.50075	-6.492187	9001.038	-6.500003	-6.489299	9001.005	-6.890773	-6.880069	9541.831
IXIC	-6.160378	-6.151815	8529.964	-6.159376	-6.148671	8529.576	-6.581988	-6.571284	9114.472
DJI	-6.635023	-6.62646	9186.872	-6.634276	-6.623572	9186.838	-6.938314	-6.92761	9607.627

Table 6: Goodness-of-Fit of the GARCH (1,1) Model assuming three innovation term distributions and covering the overall sampled period for each of the chosen stocks.

4.1.2. Model Selection – In-Sample Period

The below subsections specify the model parameters estimated when using the maximum likelihood function across the in-sample period for each of the chosen stocks and indices.

4.1.2.1 GARCH (1,1)

GARCH (1,1)							
	ω	α	β	α + β	Υ	VL	LLF
Chubb Limited (CB)	0.0000041 5	0.1100350 4	0.8613483 9	0.9713834 3	-	19.05%	8197.9334
Progressive Corp (PGR)	0.0000027 3	0.0573293 6	0.9240806 5	0.9814100 2	-	19.156%	8041.16487
MS&AD Insurance Group Holdings (MSADY.PK)	0.0000076 5	0.0666955 3	0.9157058 6	0.9824013 9	-	32.975%	7022.50309
Cincinnati Financial Corporation (CINF.OQ)	0.0000065 1	0.0988628 7	0.8618143 3	0.9606772 0	-	20.35%	8067.28270

W. R. Berkley Corp (WRB)	0.00000312	0.16267576	0.83732424	0.99999999	-	20.345%	8293.7912
American Financial Group, Inc. (AFG)	0.00000094	0.00602482	0.98663984	0.99266466	-	17.864%	8159.772
RLI Corp (RLI)	0.00000140	0.00601648	0.98671941	0.99273589	-	21.96%	7641.26934
Selective Insurance Group Inc (SIGI.O)	0.00000142	0.00611756	0.98671382	0.99283138	-	22.23%	7540.87645
White Mountains Insurance Group Ltd (WTM)	0.00000114	0.05343179	0.93880913	0.99224091	-	19.13%	8164.698964
Horace Mann Educators Corporation (HMN)	0.00000140	0.00632536	0.98670146	0.99302682	-	22.39%	7361.57776
Argo Group International Holdings Ltd. (ARGO.K)	0.00000117	0.00623249	0.98672750	0.99295999	-	20.42%	7663.23149
Safety Insurance Group, Inc. (SAFT.O)	0.00000106	0.00602550	0.98672918	0.99275468	-	19.16%	7826.370417
United Fire Group, Inc. (UFCS.O)	0.00000153	0.00942797	0.98650604	0.99593401	-	30.65%	6836.13058911
Universal Insurance Holdings, Inc. (UVE)	0.00000472	0.00607359	0.98671594	0.99278953	-	40.45%	6314.19377212
HCI Group Inc (HCI)	0.00000454	0.00601520	0.98671971	0.99273491	-	39.53%	6389.87542894
Donegal Group Inc. (DGICA.O)	0.00000138	0.00635067	0.98669954	0.99305021	-	22.27%	7282.72297238
Global Indemnity Group LLC (GBLI.O)	0.00000128	0.00932118	0.98657048	0.99589167	-	27.94%	6894.08755067
FedNat Holding Company (FNHC.O)	0.00000517	0.00603528	0.98671854	0.99275382	-	42.22%	6282.35053962
Hallmark Financial Services, Inc. (HALL.O)	0.00000125	0.01008303	0.98637519	0.99645822	-	29.74%	6895.50441704
S&P 500 (SPX)	0.00000065	0.00600000	0.98672000	0.99272000	0.0073	14.979%	8537.03
Nasdaq Composite (IXIC)	0.00000075	0.00600000	0.98672000	0.99272000	0.0073	16.084%	8261.50
Dow Jones Industrial Average (DJI)	0.00000055	0.00600000	0.98672000	0.99272000	0.0073	13.785%	8669.19

Table 7: GARCH (1,1) Model parameters estimation when maximum likelihood function is maximized across the in-sample period for each of the chosen stocks and indices.

To begin with, we can observe that the ARCH term, "α", which represents how volatility responds to new information, ranges between 0.6% and 16% with WRB having an "α" of 16%. The comparatively high disturbance observed for WRB, as compared to the rest of the dataset, is mainly due to the catastrophic loss left by Hurricane Sandy whereby WRB suffered a significant number of losses. Conversely, "α" pertaining to AFG, RLI, SIGI.O, HMN, ARGO.K, SAFT.O, UVE, HCI, DGICA.O, FNHC.O and the chosen indices is approximately 0.6% suggesting new information has a relatively low effect on their volatilities.

Next, a relatively high "β" is observed for all stocks and indices. A relatively high "β" suggests that the returns of the chosen stocks and indices are justifiable and have high importance in influencing future variance.

Lastly, the "ω" term for all stocks and indices is minor and close to zero. The sum of α and β measures the persistence of shocks to conditional variance, meaning that the effect of a volatility shock vanishes over time at an exponential rate. It is worth mentioning that none of the stock's summation of α + β is equal to 1, thereby demonstrating that the conditional variance is not strictly stationary. Moving a step further, the long-term volatilities of all stocks and indices range between 13% and 42%.

4.1.2.2 IGARCH (1,1)

IGARCH (1,1)							
	ω	α	β	α + β	Y	VL	LLF
Chubb Limited (CB)	0.00000094	0.07287735	0.92712265	1.00000000	-	-	8190.3413
Progressive Corp (PGR)	0.00000000	0.01859002	0.98140998	1.00000000	-	-	8028.08800
MS&AD Insurance Group Holdings (MSADY.PK)	0.00000000	0.01859418	0.98140582	1.00000000	-	-	7009.67847
Cincinnati Financial Corporation (CINF.OQ)	0.00000000	0.01859052	0.98140948	1.00000000	-	-	8033.16432
W. R. Berkley Corp (WRB)	0.00000331	0.16778927	0.83221073	1.00000000	-	-	8293.8085
American Financial Group, Inc. (AFG)	0.00000094	0.01859000	0.98141000	1.00000000	-	-	8132.13560
RLI Corp (RLI)	0.00000461	0.08731585	0.91268415	1.00000000	-	-	7635.20822
Selective Insurance Group Inc (SIGI.O)	0.00000152	0.04986005	0.95013995	1.00000000	-	-	7551.51118
White Mountains Insurance Group Ltd (WTM)	0.00000149	0.09855264	0.90144736	1.00000000	-	-	8169.172580
Horace Mann Educators Corporation (HMN)	0.00000713	0.14215333	0.85784667	1.00000000	-	-	7390.21313
Argo Group International Holdings Ltd. (ARGO.K)	0.00000135	0.05361587	0.94638413	1.00000000	-	-	7669.40699
Safety Insurance Group, Inc. (SAFT.O)	0.00000076	0.03962754	0.96037246	1.00000000	-	-	7840.987614

United Fire Group, Inc. (UFCS.O)	0.00002574	0.20883166	0.79116834	1.00000000	-	-	6836.47023860
Universal Insurance Holdings, Inc. (UVE)	0.00001754	0.09761230	0.90238770	1.00000000	-	-	6362.37187756
HCI Group Inc (HCI)	0.00025237	0.74658341	0.25341659	1.00000000	-	-	6400.50034463
Donegal Group Inc. (DGICA.O)	0.00000102	0.04104358	0.95895642	1.00000000	-	-	7316.87599486
Global Indemnity Group LLC (GBLI.O)	0.00003448	0.32825833	0.67174167	1.00000000	-	-	6955.62557445
FedNat Holding Company (FNHC.O)	0.00000294	0.02752675	0.97247325	1.00000000	-	-	6261.64415536
Hallmark Financial Services, Inc. (HALL.O)	0.00001798	0.18576645	0.81423355	1.00000000	-	-	6933.59162928
S&P 500 (SPX)	0.00000238	0.18664435	0.81335565	1.00000000	-	-	8715.27
Nasdaq Composite (IXIC)	0.00000251	0.14258623	0.85741377	1.00000000	-	-	8369.42
Dow Jones Industrial Average (DJI)	0.00000232	0.19827885	0.80172115	1.00000000	-	-	8837.65

Table 8: IGARCH (1,1) Model parameters estimation when maximum likelihood function is maximized across the in-sample period for each of the chosen stocks and indices.

As previously highlighted, the IGARCH model validates the presumptions drawn from the GARCH model and provides further clarification with regards to persistence in variance as new information remains crucial for future forecasts across all horizons. Noticeably, "β", the GARCH component, the estimate for all stocks and indices are approximately cognate in both models (GARCH and IGARCH). Given that the unconditional variance in the IGARCH model is not finite and no mean reversion is exhibited, "ω", the omega term, is now a constant. Nonetheless, it is important to note that the "ω" term for PGR, MSADY.PK and CINF.OQ has a value of 0 whereas it is close to 0 for others. While this verifies that the IGARCH model provides a good fit for these stocks, this also draws attention towards advanced GARCH models as they may provide better explanation to volatility. Additionally, it is worth mentioning that as "ω" becomes zero, the IGARCH model becomes similar to the Exponentially Weighted Moving Average (EWMA) Model.

4.1.2.3 EGARCH (1,1)

EGARCH (1,1)							
	ω	**α**	**β**	**α + β**	**ϒ**	**VL**	**LLF**
Chubb Limited (CB)	-0.22952444	0.14675884	0.97432098	1.1211	-0.06394079	18.116%	8201.599

Progressive Corp (PGR)	-0.17959649	0.09777924	0.97952804	1.0773	-0.04782667	19.678%	8052.13998
MS&AD Insurance Group Holdings (MSADY.PK)	-0.11145518	0.09846148	0.98556088	1.0840	-0.0335	33.328%	7031.04006
Cincinnati Financial Corporation (CINF.OQ)	-0.31698366	0.10062129	0.96448942	1.0651	-0.08777148	18.223%	8090.23062
W. R. Berkley Corp (WRB)	-0.57871201	0.24913625	0.93651139	1.1856	-0.03679596	16.58%	8312.8875
American Financial Group, Inc. (AFG)	-0.42456077	0.16280629	0.95347862	1.1163	-0.11868827	16.49%	8272.34329
RLI Corp (RLI)	-0.44888155	0.11536512	0.94660551	1.0620	-0.01802175	23.63%	7682.50522
Selective Insurance Group Inc (SIGI.O)	-0.35394750	0.09938312	0.95807403	1.0575	-0.08115148	23.22%	7595.35010
White Mountains Insurance Group Ltd (WTM)	-0.21172542	0.18369905	0.97575573	1.1595	-0.09407606	20.07%	8195.578942
Horace Mann Educators Corporation (HMN)	-0.48122143	0.20928531	0.94128124	1.1506	-0.04508170	26.26%	7409.19267
Argo Group International Holdings Ltd. (ARGO.K)	-1.00208949	0.20364651	0.88321138	1.0869	-0.08125953	21.67%	7701.15092
Safety Insurance Group, Inc. (SAFT.O)	-0.43681513	0.13586301	0.94962343	1.0855	-0.02279925	20.71%	7856.021706
United Fire Group, Inc. (UFCS.O)	-0.22949323	0.12698050	0.96921754	1.0962	0.01553349	38.02%	6864.98239844
Universal Insurance Holdings, Inc. (UVE)	-0.70935017	0.18759860	0.90103432	1.0886	-0.06722407	43.91%	6392.19281286
HCI Group Inc (HCI)	-2.70267743	0.39769761	0.62913962	1.0268	-0.05404685	41.35%	6448.95544168
Donegal Group Inc. (DGICA.O)	-0.08001172	0.10324398	0.98959698	1.0928	-0.03175773	33.79%	7325.20596115
Global Indemnity Group LLC (GBLI.O)	-0.59116205	0.29249351	0.92337381	1.2159	-0.07394043	33.40%	6974.49358518
FedNat Holding Company (FNHC.O)	-3.04306242	0.25439745	0.57911208	0.8335	-0.13032500	42.56%	6330.81939551
Hallmark Financial Services, Inc. (HALL.O)	-0.80347055	0.29820616	0.89535843	1.1936	-0.00871666	34.01%	6950.75171607
S&P 500 (SPX)	-0.44678933	0.14870663	0.9537	1.1024	-0.2053	12.645%	8787.88
Nasdaq Composite (IXIC)	-0.53401515	0.11053770	0.9429	1.0534	-0.1972	14.726%	8442.64
Dow Jones Industrial Average (DJI)	-0.51415643	0.15074629	0.9473	1.0981	-0.1938	12.003%	8905.69

Table 9: EGARCH (1,1) Model parameters estimation when maximum likelihood function is maximized across the in-sample period for each of the chosen stocks and indices.

EGARCH model is defined in terms of log of the conditional variance, which implies that σ_t^2 maintains positivity and, thus, there are no restrictions on the sign of the model parameters. Hence, the leverage effect is exponential, rather than quadratic. The ARCH term "α" signifies the size (magnitude) of shocks to variance effects in future volatility in the returns. Whereas the GARCH term, "β", represents the persistence of past volatility and how it assists in predicting future volatility. However, the key parameter to observe is the leverage effect term "γ" as it describes how the sign of the shock affects the future volatility of returns.

The leverage coefficient "γ" ranges between -0.08% and 1%, whereby the parameter reflects a negative value for all stocks except UFCS.O. For negative leverage coefficient, this implies that negative shocks have a greater impact on volatility as opposed to positive shocks of the same magnitude. Hence, this indicates that the volatility spillover mechanism is asymmetric

Secondly, the ARCH term "α" is positive for all insurance company stocks and indices whereby the highest values are displayed by HCI (39%) and HALL.O (29%). Accordingly, this indicates that the chosen stocks and indices commonly exhibit a positive relationship between their current variances and past variances, in absolute value, indicating that the greater the magnitude of shocks to their variance, the higher their volatility is.

Thirdly, the GARCH term "β" is relatively significant for all stocks and indices, except FNHC and HCI, revealing the persistence of past volatility whereby past volatility explains current volatility.

Lastly, the long-term volatility "VL" of the chosen stocks and indices ranges between 12% and 43.9%. Given that long-term volatility is an average level towards which variances revert to this further highlights the increased volatility.

4.1.2.4 GJR-GARCH (1,1)

GJR-GARCH (1,1)							
	ω	α	β	α + β	Y	VL	LLF
Chubb Limited (CB)	0.00000352	0.04682154	0.88048742	0.92730897	0.09455420	18.61%	8208.12097222
Progressive Corp (PGR)	0.00000306	0.02681327	0.92441767	0.95123095	0.0551	18.989%	8049.38485
MS&AD Insurance Group Holdings (MSADY.PK)	0.00000598	0.05255365	0.92803894	0.98059260	0.0107	32.632%	7024.28879
Cincinnati Financial Corporation (CINF.OQ)	0.00000619	0.09067186	0.86779667	0.95846853	0.00655772	20.114%	8069.06767
W. R. Berkley Corp (WRB)	0.00000094	0.00000000	0.98895000	0.98895001	0.00650000	17.362%	8200.5533
American Financial Group, Inc. (AFG)	0.00000089	0.00000000	0.98915940	0.98915940	0.00650001	17.119%	8145.629828
RLI Corp (RLI)	0.00000144	0.00000000	0.98895000	0.98895000	0.00650000	21.51%	7631.57610
Selective Insurance Group Inc (SIGI.O)	0.00000151	0.00000000	0.98899970	0.98899970	0.00650000	22.08%	7543.27043

White Mountains Insurance Group Ltd (WTM)	0.00000098	0.00000000	0.98895000	0.98895001	0.00650000	17.69%	8053.473913
Horace Mann Educators Corporation (HMN)	0.00000151	0.00000000	0.98945204	0.98945204	0.00650002	22.73%	7340.79618
Argo Group International Holdings Ltd. (ARGO.K)	0.00000128	0.00000000	0.98920390	0.98920390	0.00650001	20.61%	7658.18093
Safety Insurance Group, Inc. (SAFT.O)	0.00000112	0.00000001	0.98917369	0.98917370	0.00650001	19.25%	7820.973999
United Fire Group, Inc. (UFCS.O)	0.00000174	0.00000000	0.99173902	0.99173903	0.00650018	29.48%	6811.39861444
Universal Insurance Holdings, Inc. (UVE)	0.00006423	0.05140699	0.80775599	0.85916298	0.11856918	44.37%	6397.82606624
HCI Group Inc (HCI)	0.00000482	0.00000000	0.98895000	0.98895001	0.00650000	39.30%	6382.70777664
Donegal Group Inc. (DGICA.O)	0.00000180	0.00000000	0.98932983	0.98932984	0.00650002	24.63%	7245.51084448
Global Indemnity Group LLC (GBLI.O)	0.00000096	0.00000000	0.99355129	0.99355129	0.00650037	27.39%	6878.80951373
FedNat Holding Company (FNHC.O)	0.00000560	0.00000000	0.98895000	0.98895001	0.00650000	42.38%	6278.66608784
Hallmark Financial Services, Inc. (HALL.O)	0.00000183	0.00000000	0.99155663	0.99155663	0.00650045	29.68%	6856.28561272
S&P 500 (SPX)	0.00000083	0.00000000	0.9890	0.9890	0.0065	16.283%	8481.86
Nasdaq Composite (IXIC)	0.00000053	0.00000000	0.9890	0.9890	0.0065	12.999%	8255.48
Dow Jones Industrial Average (DJI)	0.00000073	0.00000000	0.9890	0.9890	0.0065	15.267%	8614.66

Table 10: IGARCH (1,1) Model parameters estimation when maximum likelihood function is maximized across the in-sample period for each of the chosen stocks and indices.

Despite the fact that the GJR-GARCH model is much like the EGARCH model is that it reflects the asymmetry effects on volatility, the former integrates the non-negativity constraint on three parameters: ω, α, and β, thus, only the leverage term can be negative. Additionally, the GJR-GARCH model is different from the standard GARCH model as it introduces a dummy variable “I_{t-1}” paving the way for the conditional variance to increase in response to bad shocks more than good shocks.

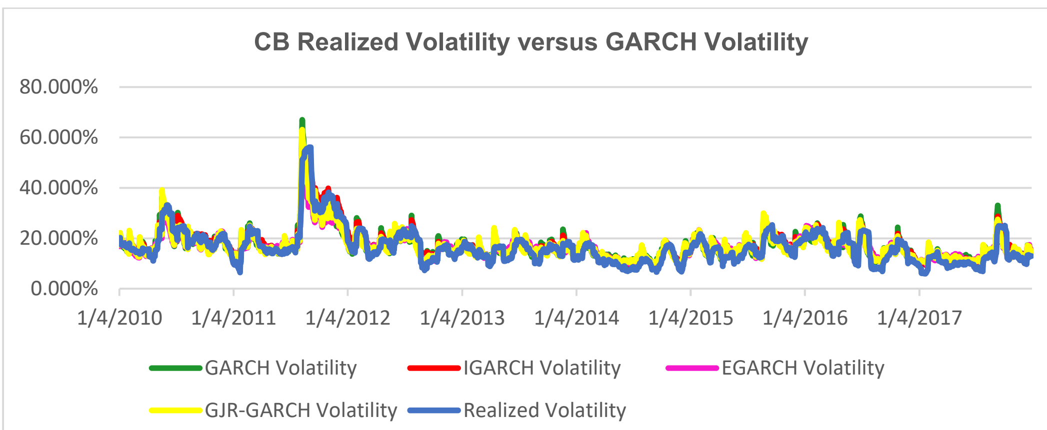
To begin with, the lower beta of insurance company stocks evidences that stock price movements are relatively less explicable and are subject to more ‘spikes’. Whereas, the higher beta of observed in the stock indices evidences that stock price movements are relatively more explicable and are subject to less ‘spikes’.

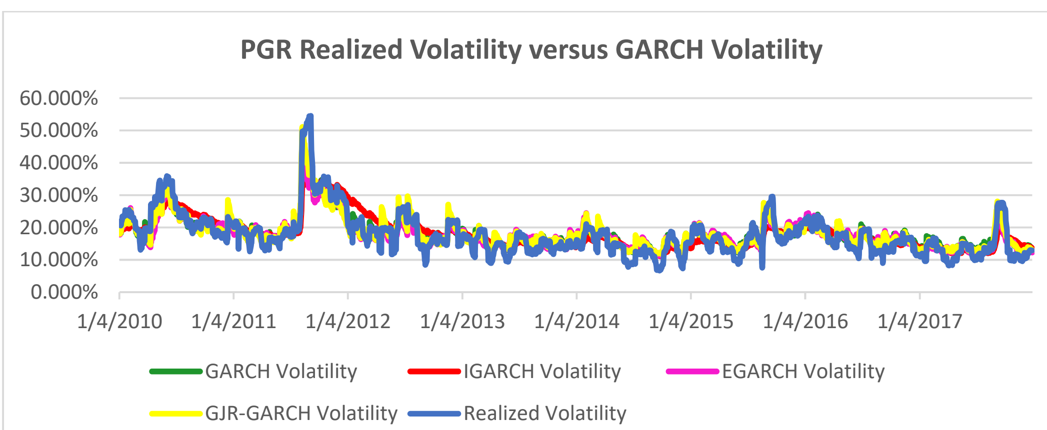
The leverage coefficient “γ” ranges between 0.65% and 11%. In this case, results are not consistent with what was obtained with the EGARCH model whereby negative leverage coefficients imply the absence of leverage effect. The outcome obtained through the GJR-GARCH model claims that positive news have a higher impact on volatility than negative news.

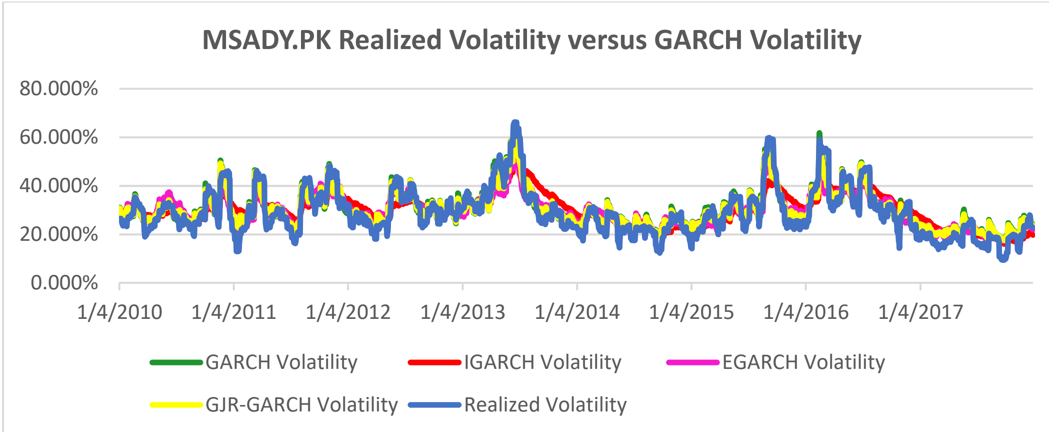
Lastly, the long-term volatility "VL" of the chosen stocks and indices ranges between 13% and 44%, similar to what was obtained through the standard GARCH model and EGARCH model.

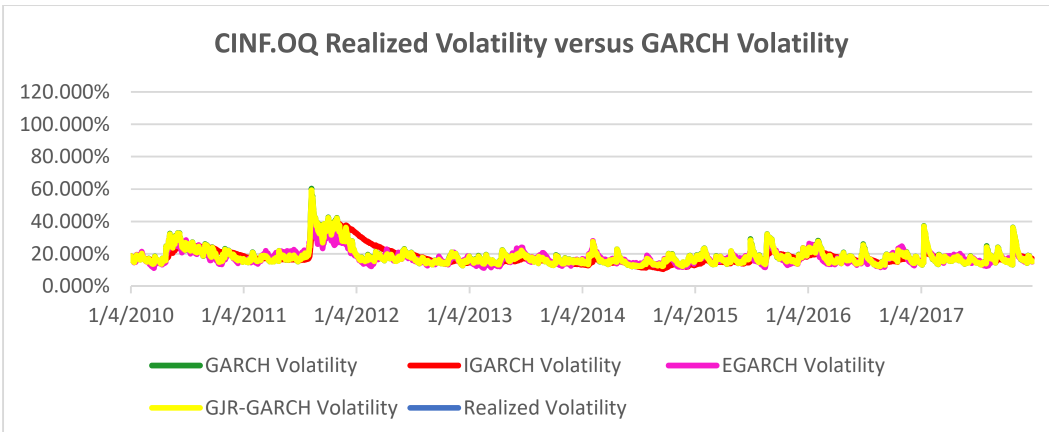
4.1.3 Realized Volatility

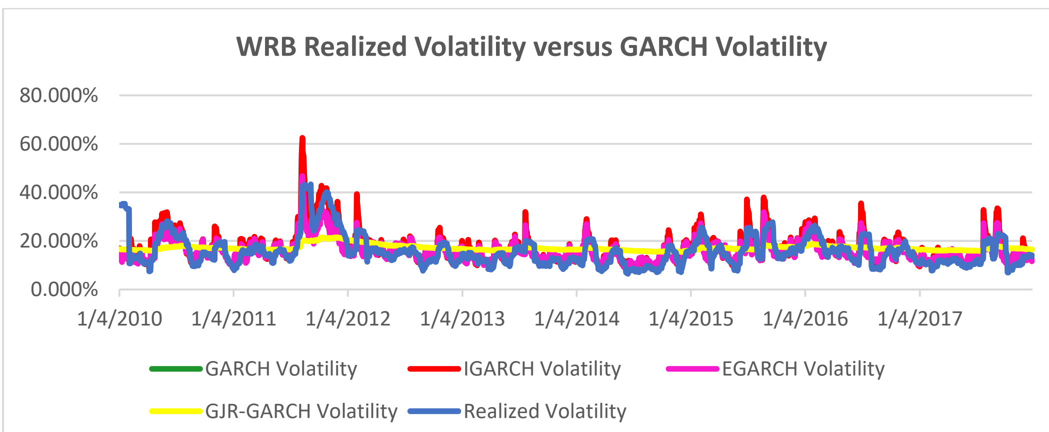
After calculating the volatilities of all the stocks and indices within the in-sample data using the chosen models, we proceed to compute the realized volatility using equation (12) listed under section 3.5. As highlighted previously, the annualized volatilities are calculated using the monthly volatilities multiplied by "trading months per trading year'' or 252/22. Accordingly, the below plots demonstrate the realized volatility against the estimated GARCH volatilities for each of the chosen stock in the dataset during the in-sample period:

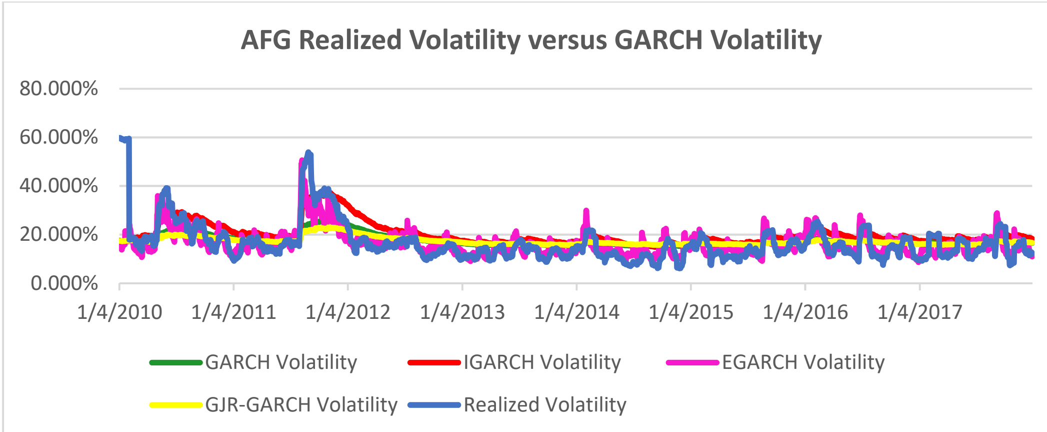


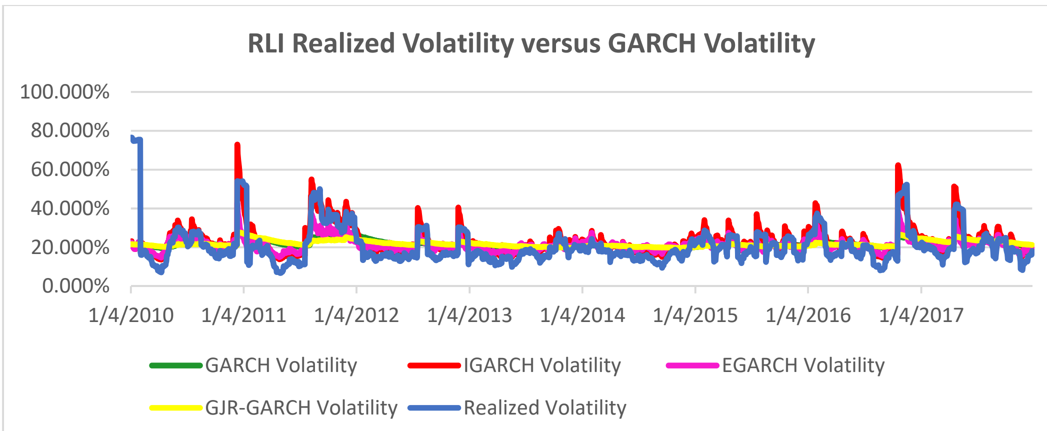


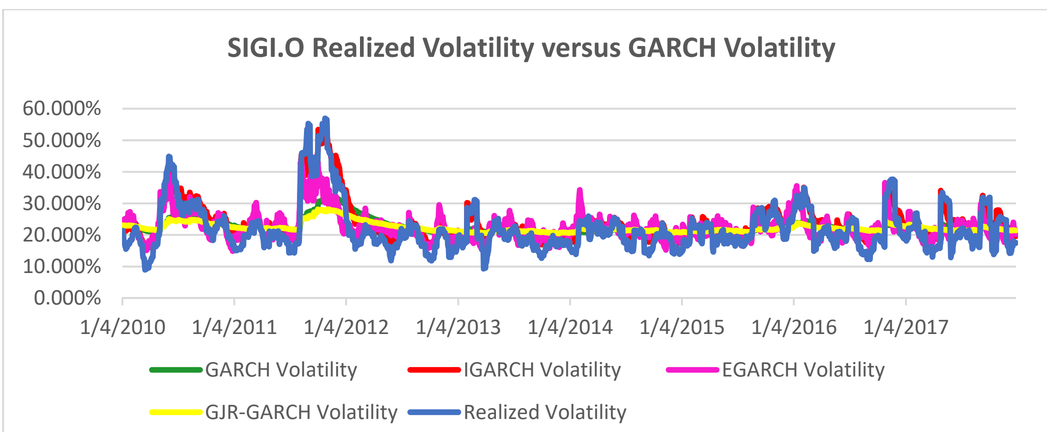

MSADY.PK Realized Volatility versus GARCH Volatility
80.000%
60.000%
40.000%
20.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

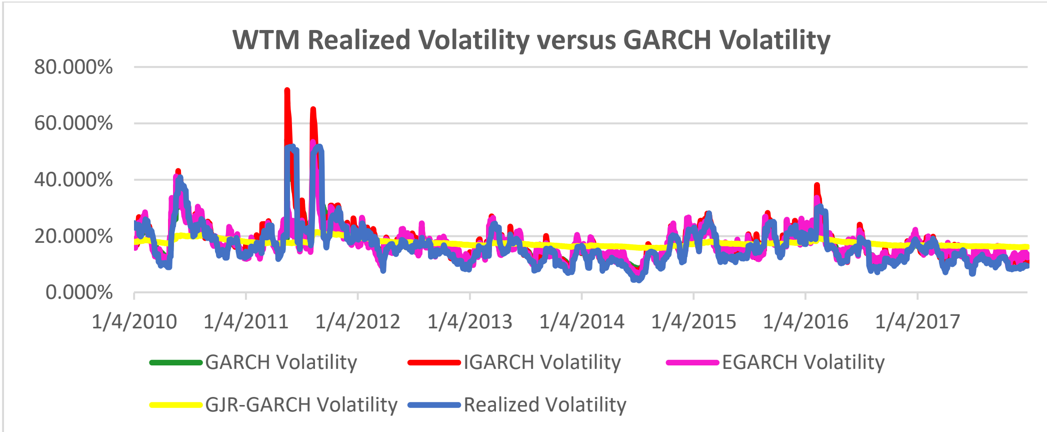

CINF.OQ Realized Volatility versus GARCH Volatility
120.000%
100.000%
80.000%
60.000%
40.000%
20.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

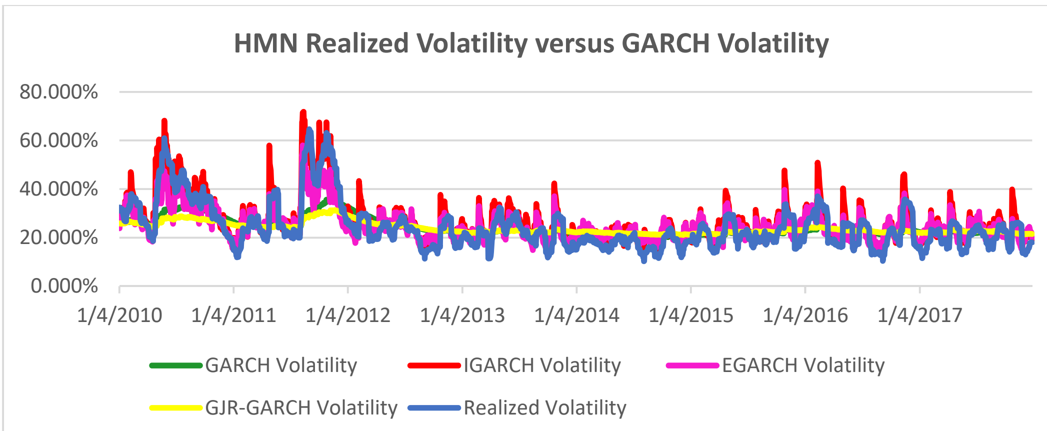

WRB Realized Volatility versus GARCH Volatility
80.000%
60.000%
40.000%
20.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

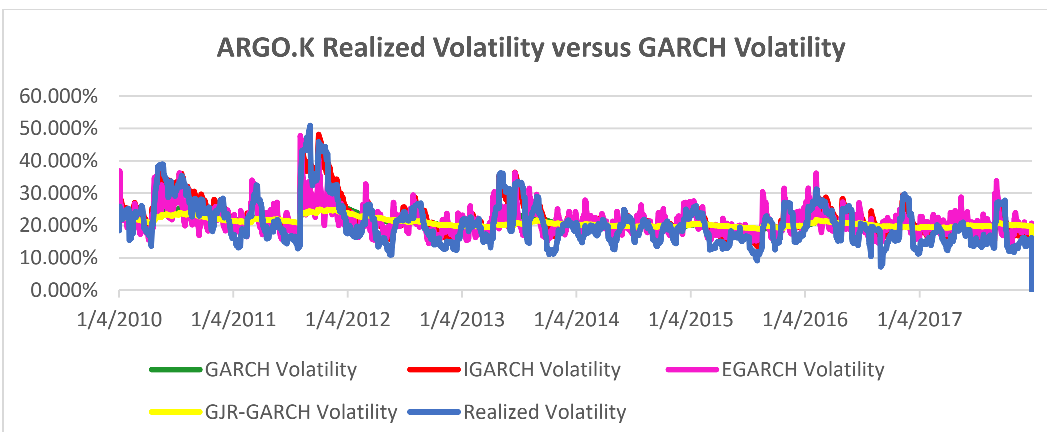

AFG Realized Volatility versus GARCH Volatility
80.000%
60.000%
40.000%
20.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

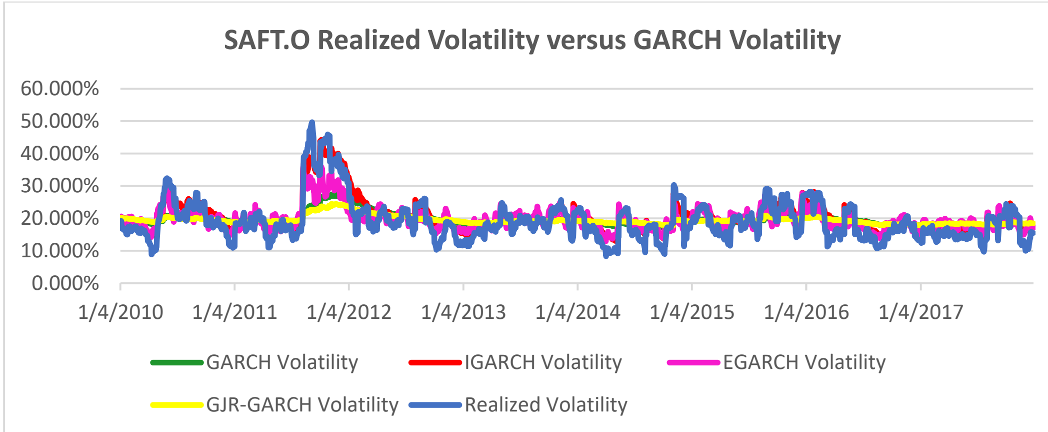

RLI Realized Volatility versus GARCH Volatility
100.000%
80.000%
60.000%
40.000%
20.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

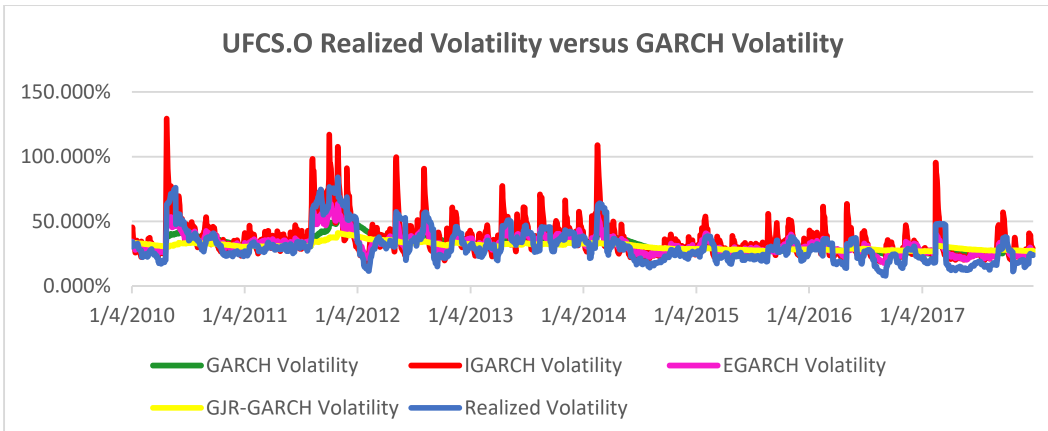

SIGI.O Realized Volatility versus GARCH Volatility
60.000%
50.000%
40.000%
30.000%
20.000%
10.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

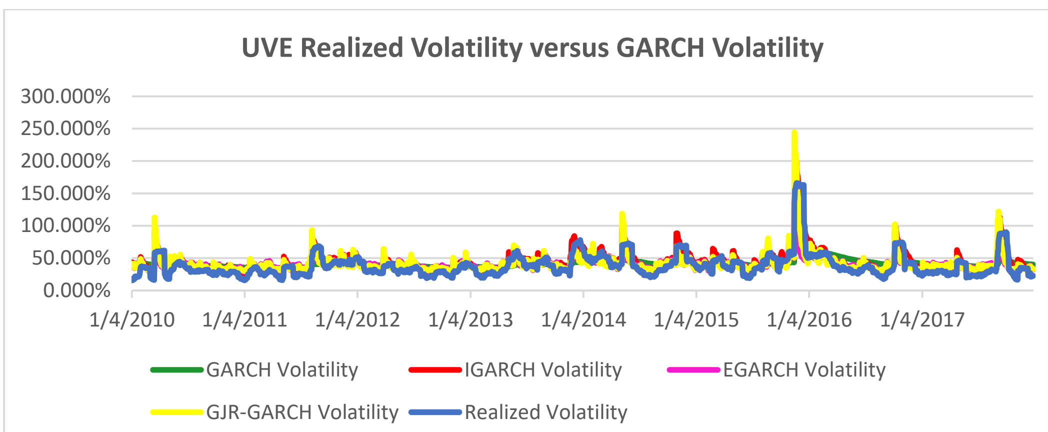

WTM Realized Volatility versus GARCH Volatility
80.000%
60.000%
40.000%
20.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

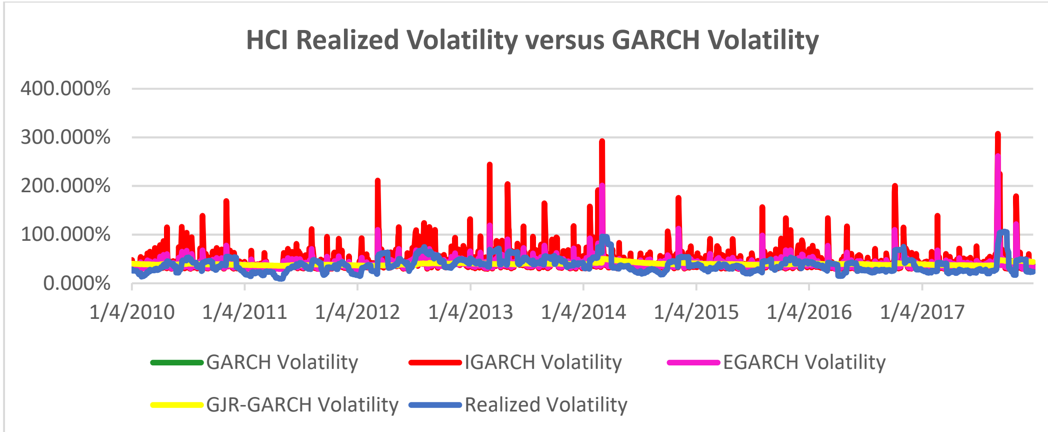

HMN Realized Volatility versus GARCH Volatility
80.000%
60.000%
40.000%
20.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

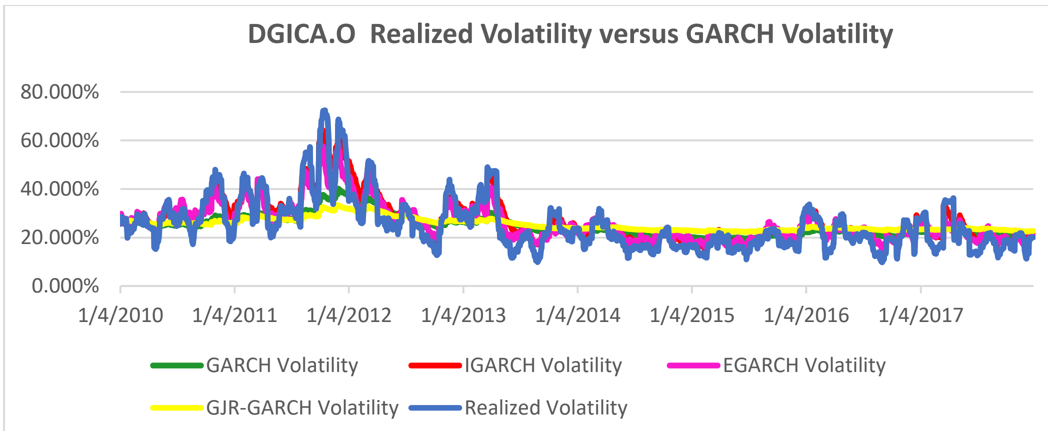

ARGO.K Realized Volatility versus GARCH Volatility
60.000%
50.000%
40.000%
30.000%
20.000%
10.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

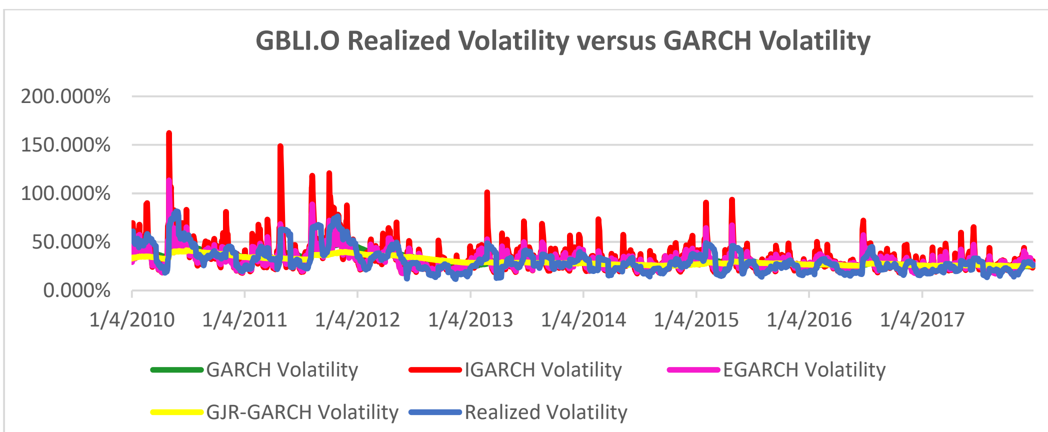

SAFT.O Realized Volatility versus GARCH Volatility
60.000%
50.000%
40.000%
30.000%
20.000%
10.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

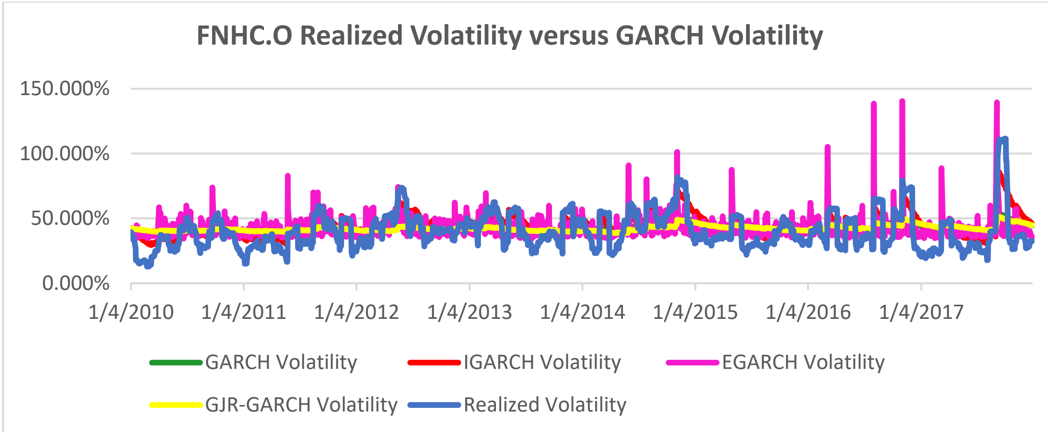

UFCS.O Realized Volatility versus GARCH Volatility
150.000%
100.000%
50.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

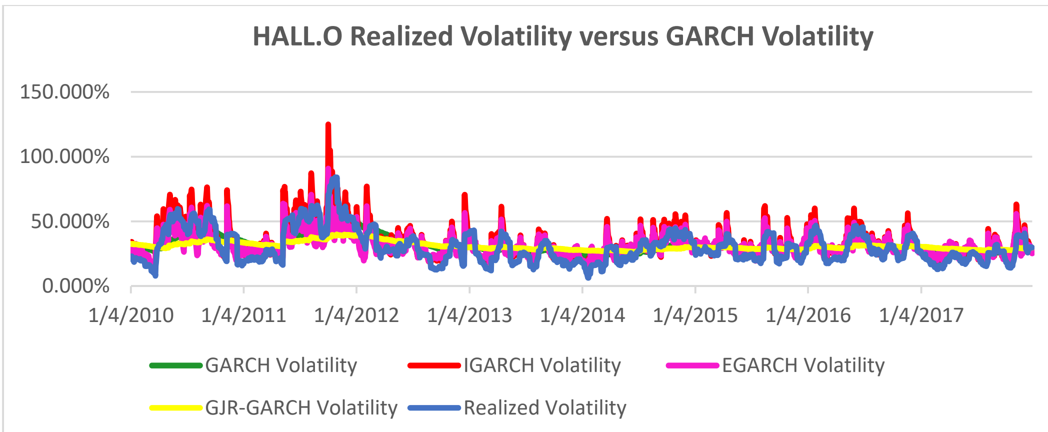

UVE Realized Volatility versus GARCH Volatility
300.000%
250.000%
200.000%
150.000%
100.000%
50.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

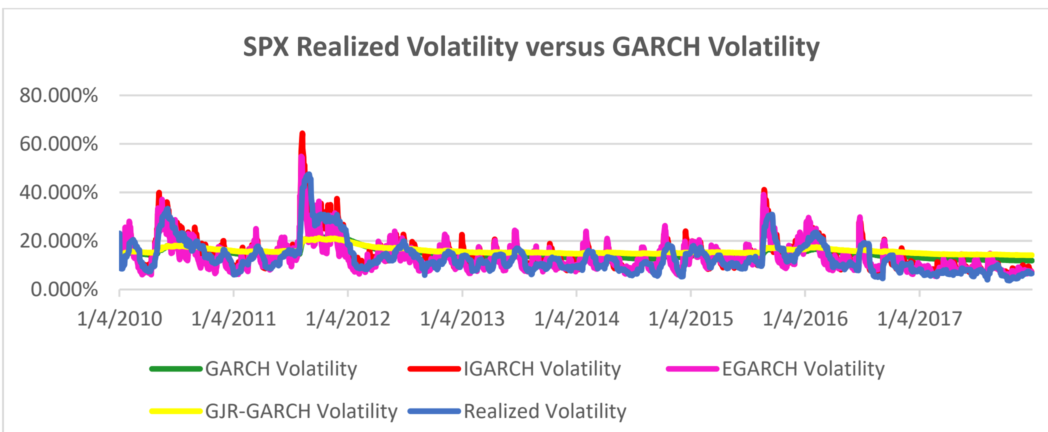

HCI Realized Volatility versus GARCH Volatility
400.000%
300.000%
200.000%
100.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

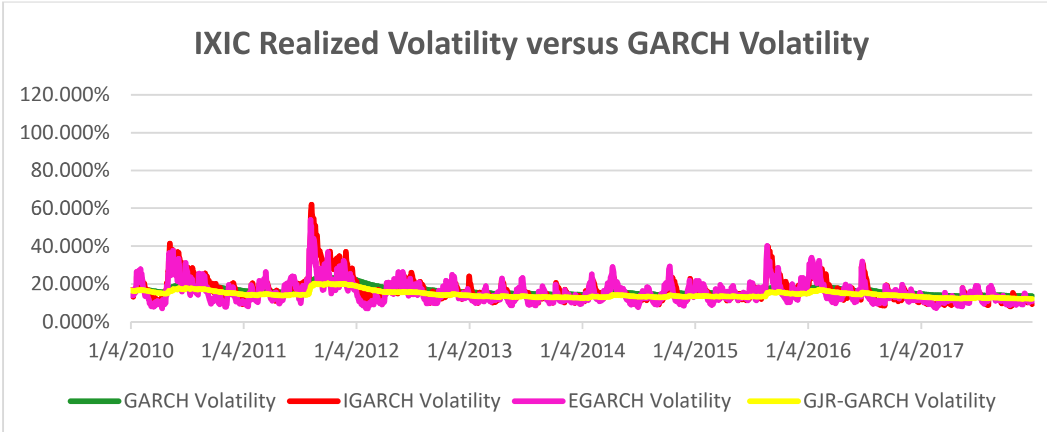

DGICA.O Realized Volatility versus GARCH Volatility
80.000%
60.000%
40.000%
20.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility


GBLI.O Realized Volatility versus GARCH Volatility
200.000%
150.000%
100.000%
50.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility


FNHC.O Realized Volatility versus GARCH Volatility
150.000%
100.000%
50.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility


HALL.O Realized Volatility versus GARCH Volatility
150.000%
100.000%
50.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility


SPX Realized Volatility versus GARCH Volatility
80.000%
60.000%
40.000%
20.000%
0.000%
1/4/2010
1/4/2011
1/4/2012
1/4/2013
1/4/2014
1/4/2015
1/4/2016
1/4/2017
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility



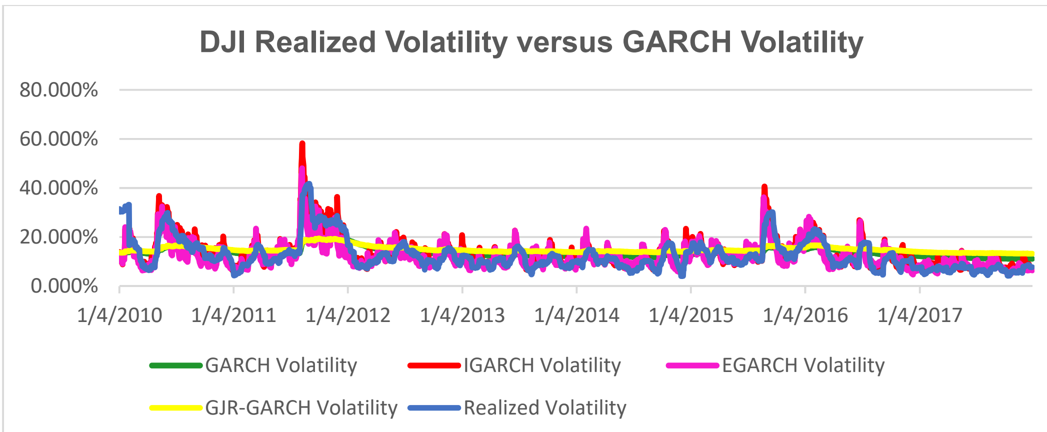


Figure 3:Realized Volatility plotted versus GARCH Models' Volatilities for each stock and index across the chosen in-sample period.

4.1.3.1 Optimal Model

Next, the calculated realized volatilities are compared to the calculated in-sample volatilities using each of the chosen GARCH models in order to identify the most accurate model for predicting the volatilities. The comparison is performed using the three chosen test statistics (discussed in section 3.6): the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE). These test statistics identify the optimal in-sample volatility model by deducting the calculated volatility from the realized volatility for each of the chosen volatility models. Accordingly, the volatility model with the lowest error difference is regarded as the most accurate. The below table highlights the error statistics with the respective ranking for the chosen in-sample dataset under each of the selected models:

		GARCH	IGARCH	EGARCH	GJR-GARCH
CB	**MAE**	0.02292	0.01737	0.02380	0.02423
	Ranking	2	1	3	4
	RMSE	0.03048	0.02198	0.03234	0.03201
	Ranking	2	1	4	3
	MAPE	0.15683	0.12687	0.16004	0.16434
	Ranking	2	1	3	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
CINF.OQ	**MAE**	0.02817	0.03087	0.03368	0.02774
	Ranking	2	3	4	1
	RMSE	0.03797	0.04200	0.04581	0.03740
	Ranking	2	3	4	1
	MAPE	0.18521	0.19433	0.20804	0.18247
	Ranking	2	3	4	1

		GARCH	IGARCH	EGARCH	GJR-GARCH
PGR	**MAE**	0.01903	0.02626	0.02343	0.02151
	Ranking	1	4	3	2
	RMSE	0.02489	0.03658	0.03188	0.02811
	Ranking	1	4	3	2
	MAPE	0.12584	0.16046	0.14648	0.13893
	Ranking	1	4	3	2

		GARCH	IGARCH	EGARCH	GJR-GARCH
MSADY.PK	**MAE**	0.03077	0.04778	0.03655	0.02994
	Ranking	2	4	3	1
	RMSE	0.03867	0.05893	0.04610	0.03773
	Ranking	2	4	3	1
	MAPE	0.12378	0.17752	0.13911	0.12075
	Ranking	2	4	3	1

		GARCH	IGARCH	EGARCH	GJR-GARCH
WRB	**MAE**	0.02874	0.02936	0.02963	0.04662
	Ranking	1	2	3	4
	RMSE	0.04081	0.04155	0.04252	0.05903
	Ranking	1	2	3	4
	MAPE	0.18699	0.19106	0.19066	0.34015
	Ranking	1	2	3	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
AF	**MAE**	0.04618	0.05302	0.03567	0.04828

	Ranking	2	4	1	3
	RMSE	0.07075	0.07204	0.06056	0.07406
	Ranking	2	3	1	4
	MAPE	0.30271	0.38210	0.20820	0.31169
	Ranking	2	4	1	3

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
RLI	**MAE**	0.06291	0.04584	0.05045	0.06648
	Ranking	3	1	2	4
	RMSE	0.09244	0.07348	0.08178	0.09525
	Ranking	3	1	2	4
	MAPE	0.3349	0.24557	0.25538	0.35621
	Ranking	3	1	2	4

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
SIGI.O	**MAE**	0.04576	0.02650	0.03868	0.04784
	Ranking	3	1	2	4
	RMSE	0.06179	0.03252	0.05153	0.06551
	Ranking	3	1	2	4
	MAPE	0.21818	0.14116	0.18059	0.22481
	Ranking	3	1	2	4

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
WTM	**MAE**	0.01946	0.02158	0.02898	0.04840
	Ranking	1	2	3	4
	RMSE	0.02817	0.03054	0.04516	0.06911
	Ranking	1	2	3	4
	MAPE	0.13850	0.14497	0.18512	0.35032
	Ranking	1	2	3	4

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
HMN	**MAE**	0.05170	0.03807	0.04107	0.05664
	Ranking	1	4	3	2
	RMSE	0.07123	0.04794	0.05293	0.07953
	Ranking	1	4	3	2
	MAPE	0.22027	0.17258	0.17891	0.23820
	Ranking	1	4	3	2

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
ARGO.K	**MAE**	0.04241	0.02456	0.03929	0.04584
	Ranking	3	1	2	4
	RMSE	0.05479	0.02983	0.05058	0.05933
	Ranking	3	1	2	4
	MAPE	0.22028	0.14054	0.20133	0.23556
	Ranking	3	1	2	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
SAFT.O	**MAE**	0.03833	0.02398	0.02999	0.04092
	Ranking	3	1	2	4
	RMSE	0.05122	0.03036	0.03926	0.05543
	Ranking	3	1	2	4
	MAPE	0.21495	0.14763	0.16704	0.22772
	Ranking	3	1	2	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
UFCS.O	**MAE**	0.07233	0.07366	0.05579	0.08342
	Ranking	2	3	1	4
	RMSE	0.09613	0.09678	0.07045	0.11427
	Ranking	2	3	1	4
	MAPE	0.28055	0.26618	0.21204	0.30925
	Ranking	3	2	1	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
UVE	**MAE**	0.11309	0.07866	0.09332	0.08964
	Ranking	4	1	3	2
	RMSE	0.16017	0.09637	0.139914	0.13168
	Ranking	4	1	3	2
	MAPE	0.33118	0.23904	0.26739	0.25542
	Ranking	4	1	3	2

		GARCH	IGARCH	EGARCH	GJR-GARCH
HCI	**MAE**	0.10245	0.14983	0.11014	0.11090
	Ranking	1	4	2	3
	RMSE	0.13365	0.22876	0.15200	0.14383
	Ranking	1	4	3	2
	MAPE	0.33953	0.43561	0.33891	0.36408
	Ranking	2	4	1	3

		GARCH	IGARCH	EGARCH	GJR-GARCH
DGICA.O	**MAE**	0.05747	0.03364	0.03759	0.06764
	Ranking	3	1	2	4
	RMSE	0.07865	0.04374	0.04903	0.09078
	Ranking	3	1	2	4
	MAPE	0.23829	0.15750	0.16488	0.29127
	Ranking	3	1	2	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
GBLI.O	**MAE**	0.06915	0.08260	0.06591	0.07726
	Ranking	2	4	1	3
	RMSE	0.09036	0.11579	0.08718	0.10407
	Ranking	2	4	1	3
	MAPE	0.24932	0.27924	0.22606	0.26995

	Ranking	2	4	1	3

		GARCH	IGARCH	EGARCH	GJR-GARCH
FNHC.O	MAE	0.10255	0.08032	0.10756	0.10997
	Ranking	2	1	3	4
	RMSE	0.12937	0.10219	0.14163	0.13810
	Ranking	2	1	4	3
	MAPE	0.30050	0.25219	0.30048	0.32378
	Ranking	3	1	2	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
HALL.O	MAE	0.07518	0.06383	0.06539	0.09083
	Ranking	3	1	2	4
	RMSE	0.09039	0.08216	0.08250	0.11024
	Ranking	3	1	2	4
	MAPE	0.30046	0.23747	0.24297	0.35725
	Ranking	3	1	2	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
SPX	MAE	0.04279	0.04058	0.02176	0.04935
	Ranking	3	2	1	4
	RMSE	0.05455	0.05584	0.03151	0.05871
	Ranking	2	3	1	4
	MAPE	0.41661	0.26848	0.14452	0.46789
	Ranking	3	2	1	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
IXIC	MAE	0.04084	0.03727	0.02664	0.03559
	Ranking	4	3	1	2
	RMSE	0.05399	0.05431	0.03828	0.04911
	Ranking	3	4	1	2
	MAPE	0.30720	0.22025	0.14906	0.23295
	Ranking	4	2	1	3

		GARCH	IGARCH	EGARCH	GJR-GARCH
DJI	MAE	0.04028	0.03742	0.02069	0.04391
	Ranking	3	2	1	4
	RMSE	0.05250	0.05150	0.03033	0.05206
	Ranking	4	2	1	3
	MAPE	0.39491	0.26682	0.14656	0.44368
	Ranking	3	2	1	4

Table 11: Error Statistics under each Volatility Model for each stock and index across the in-sample period.

4.1.4.2 Optimal Model Results

Ticker	Optimal Model
CB	IGARCH (1,1)
PGR	GARCH (1,1)
MSADY.PK	GJR- GARCH (1,1)
CINF.OQ	GJR- GARCH (1,1)
WRB	GARCH (1,1)
AFG	EGARCH (1,1)
RLI	IGARCH (1,1)
SIGI.O	IGARCH (1,1)
WTM	GARCH (1,1)
HMN	GARCH (1,1)
ARGO.K	IGARCH (1,1)
SAFT.O	IGARCH (1,1)
UFCS.O	EGARCH (1,1)
UVE	IGARCH (1,1)
HCI	GARCH (1,1)
DGICA.O	IGARCH (1,1)
GBLI.O	EGARCH (1,1)
FNHC.O	IGARCH (1,1)
HALL.O	EGARCH (1,1)

Ticker	Optimal Model
SPX	EGARCH (1,1)
IXIC	EGARCH (1,1)
DJI	EGARCH (1,1)

Table 12: Summary of the optimal volatility model for each stock and index across the chosen in-sample period.

As reflected in the table above, the Integrated-GARCH (1,1) has proven to be the optimal model for the majority of the chosen insurance companies. It is worth noting that although shocks to the volatility series are inclined to have long memories and, consequently, tend to influence future volatilities for a long horizon, Engle and Bollerslev (1986) proposed the IGARCH model to capture this schematic fact along with making conditional volatility infinite and shocks permanent. Therefore, the prevalence of IGARCH may be due to the persistent variance whereby recent information remains significant when predicting volatility.

Secondly, the EGARCH (1,1) model performed best for a substantial number of insurance companies, particularly, AFG, UFCS.O, GBLI.O, HALL.O, and for the three indices, SPX, IXIC and DJI. As obtained previously, the generalized error distribution (GED) is the prominent distribution for the chosen stocks. Following the same line of thought, Nelson (1991) suggested the use of EGARCH model with GED based on the fact that the GED accommodates more fat-tails than normal error distribution. Additionally, EGARCH permits the inclusion of asymmetry in the reaction of the conditional variance to the innovation term reliant on the magnitude of the shock and the positive/negative sign. As for the remaining stocks, PGR, WRB, WTM, HMN, HCI, MSADY.PK and CINF.OQ the GARCH (1,1) and GJR-GARCH (1,1) proved to outperform other models.

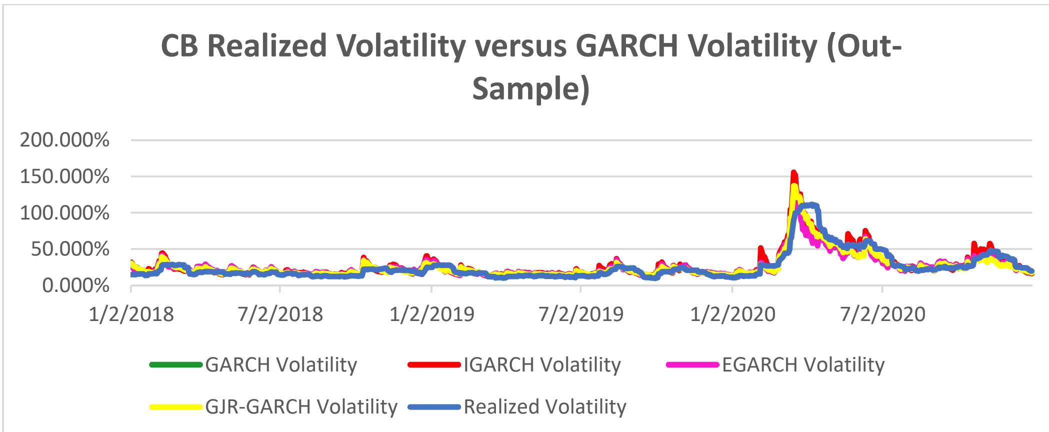
Having said the above, the IGARCH has proven to be the prevalent model when modeling insurance company stocks. The rankings obtained (Table 12) are consistent with what can be visually witnessed in the plotted volatilities (Figures 3) whereby the majority of the volatilities estimated with IGARCH (1,1) appear to be, graphically, the best fit with regards realized volatilities.

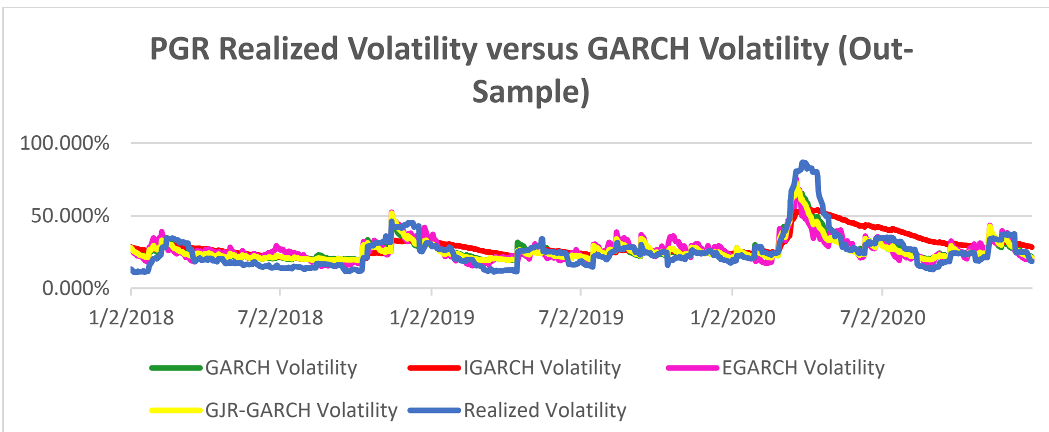
4.2 Out-Sample Modeling

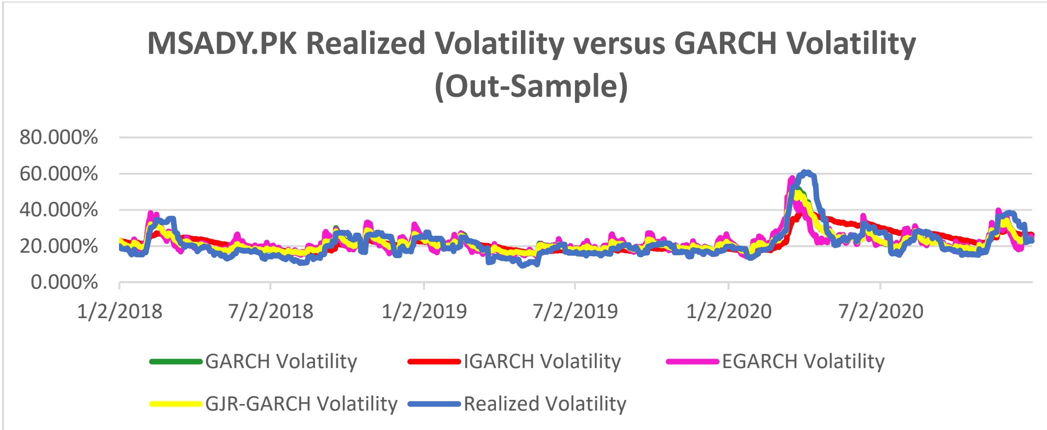
The same calculations applied for the in-sample period were applied to the out-sample period extending from 01/01/2018 till 31/12/2020. Accordingly, the sole change that is applied is that the in-sample parameters obtained in the previous section are utilized to forecast the conditional volatilities for the out-sample period. Thus, the parameters are plugged into formulas rather than being re-estimated.

4.2.1. Out-Sample Parameters' Estimation

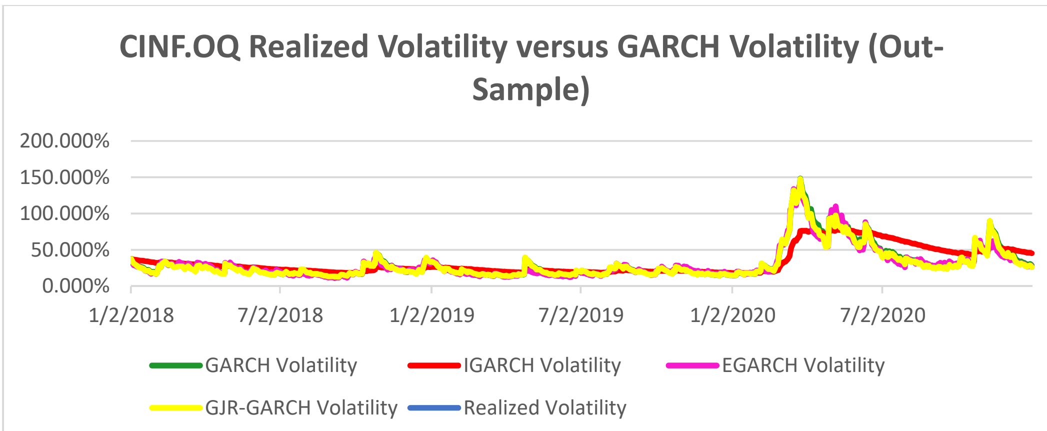
Realized volatilities are calculated similar to section 4.1.3 and are subsequently compared to the calculated out-sample volatilities. The below figures plot the realized volatility in contrast to the calculated GARCH volatilities for each stock and index across the out-sample period.



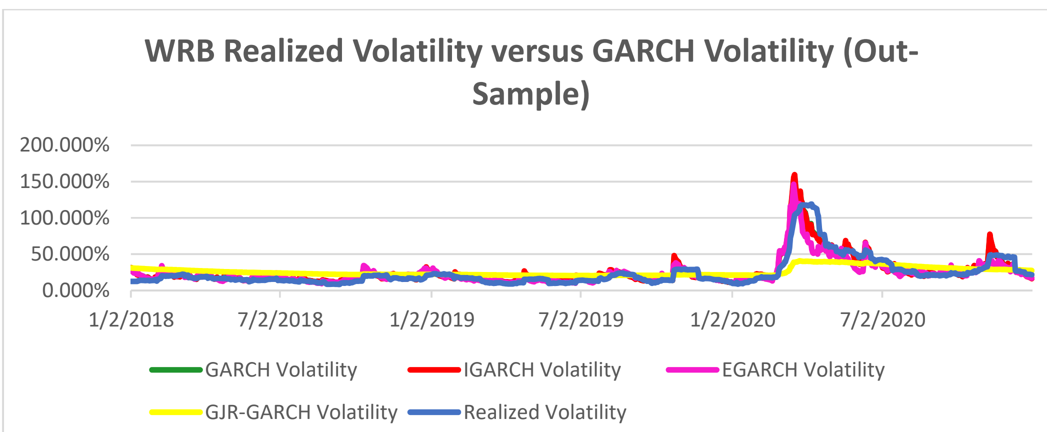




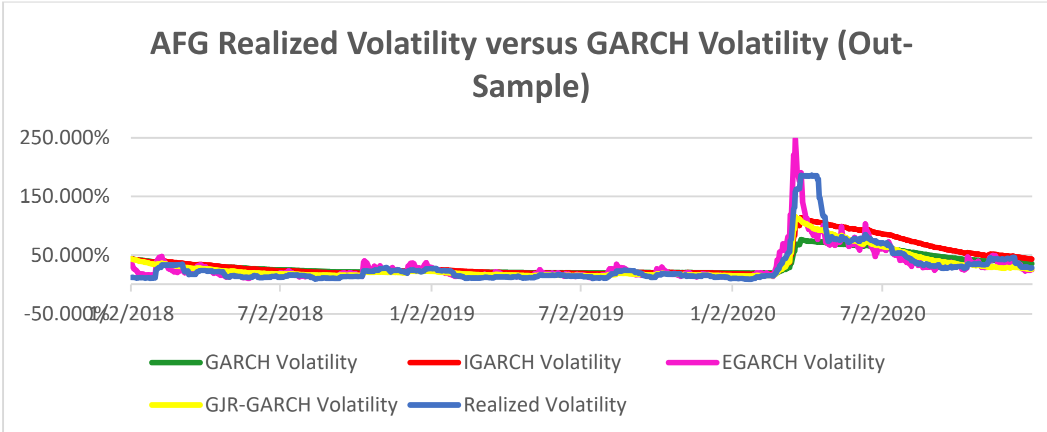
MSADY.PK Realized Volatility versus GARCH Volatility (Out-Sample)
80.000%
60.000%
40.000%
20.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

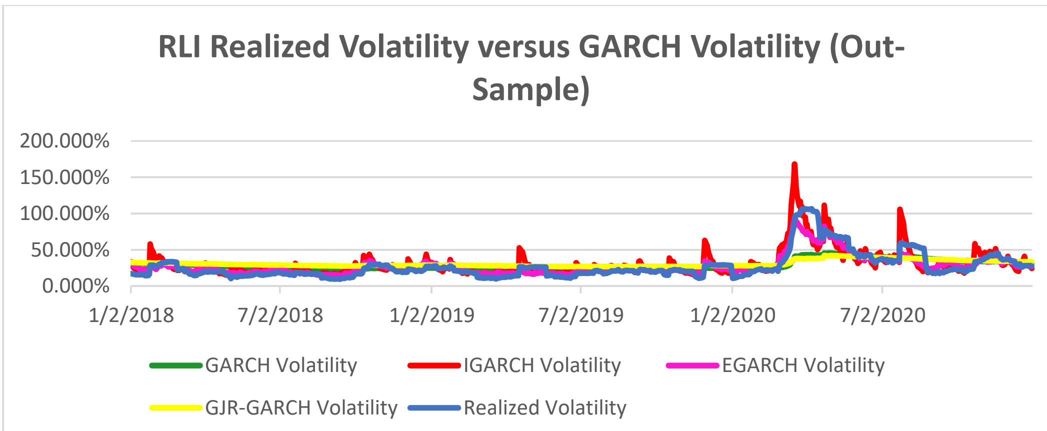


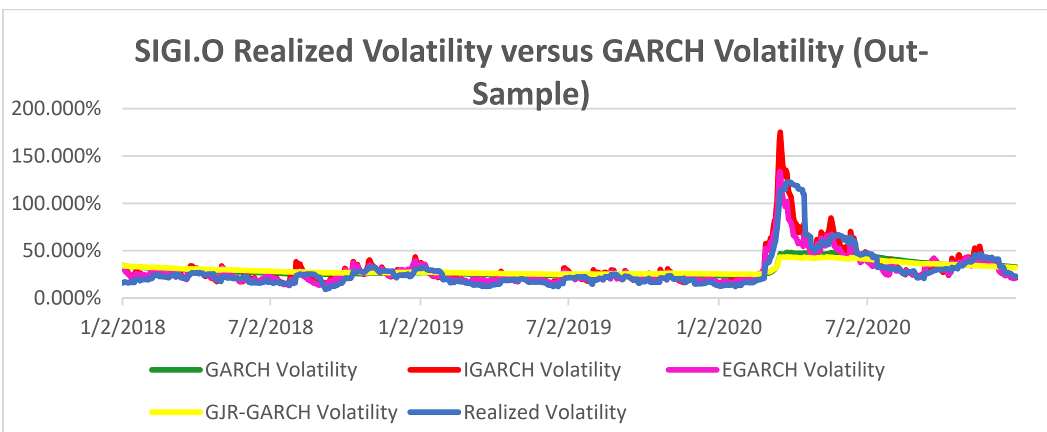
CINF.OQ Realized Volatility versus GARCH Volatility (Out-Sample)
200.000%
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

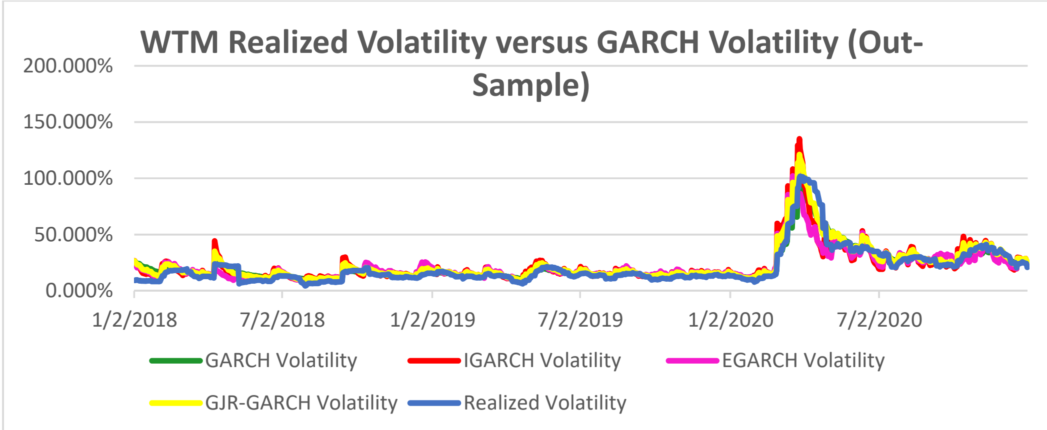


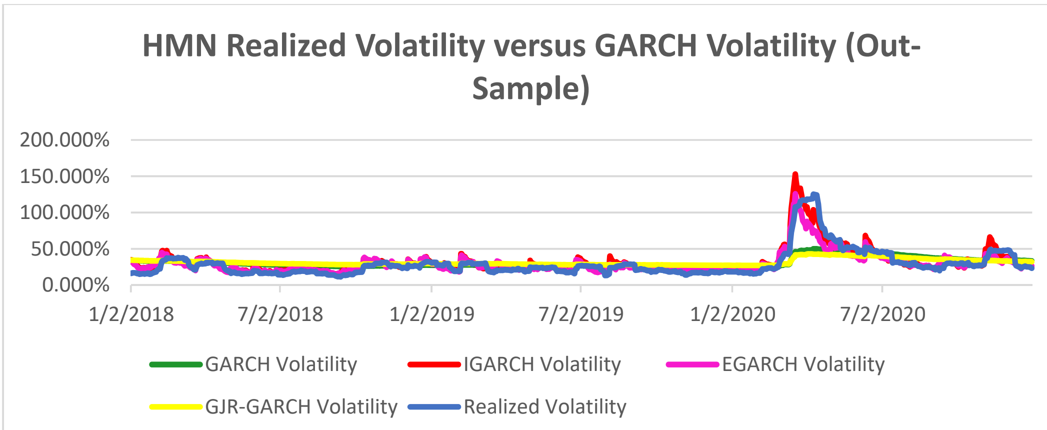
WRB Realized Volatility versus GARCH Volatility (Out-Sample)
200.000%
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

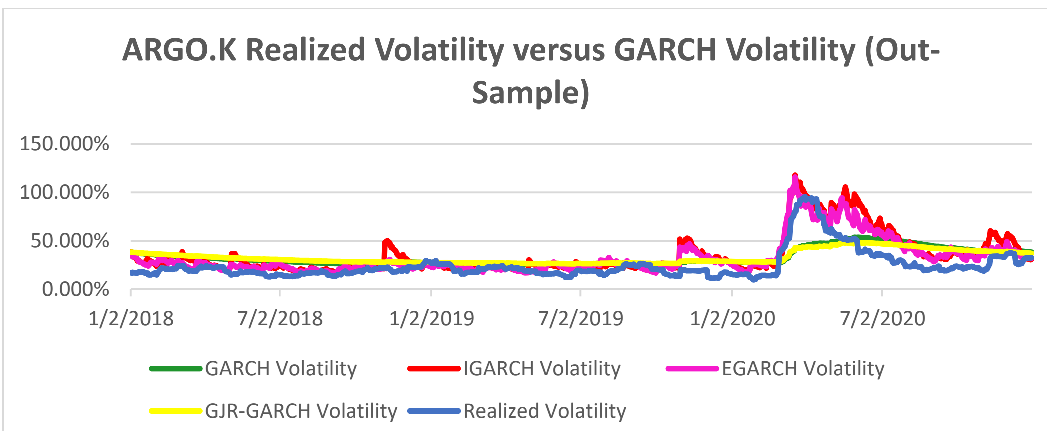

AFG Realized Volatility versus GARCH Volatility (Out-Sample)
250.000%
150.000%
50.000%
-50.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

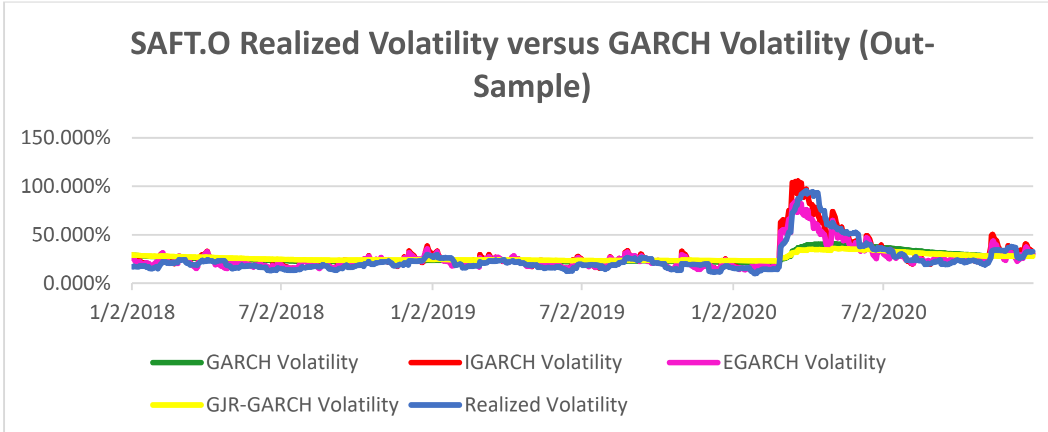

RLI Realized Volatility versus GARCH Volatility (Out-Sample)
200.000%
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

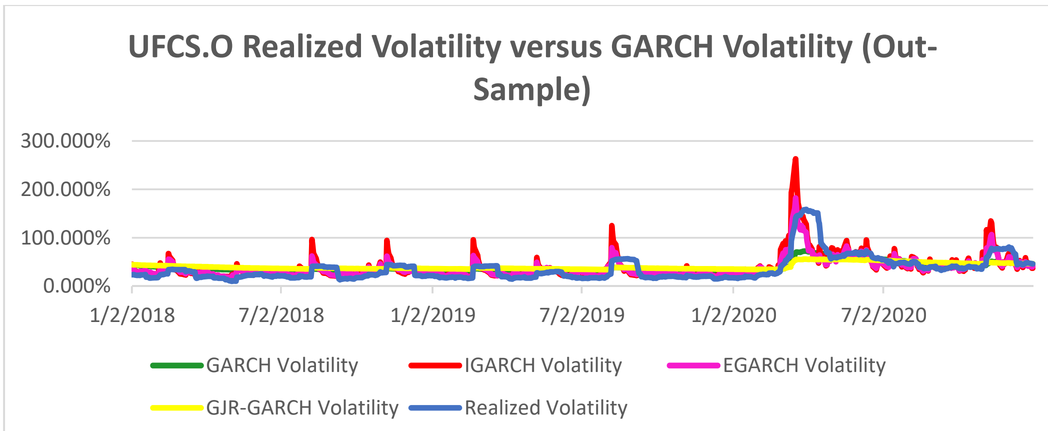

SIGI.O Realized Volatility versus GARCH Volatility (Out-Sample)
200.000%
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

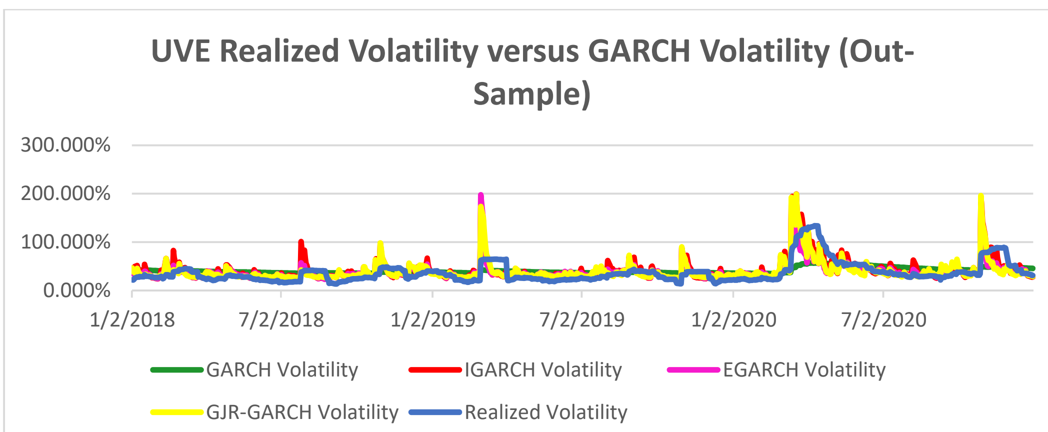

WTM Realized Volatility versus GARCH Volatility (Out-Sample)
200.000%
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

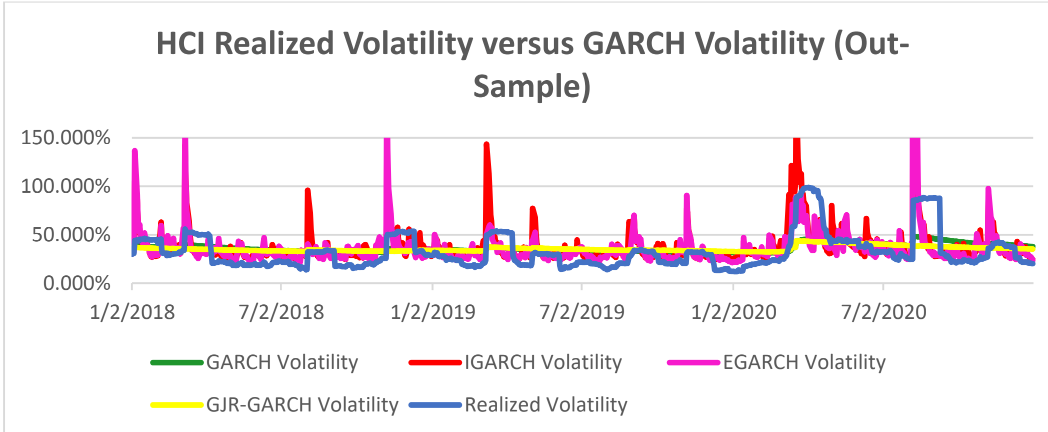

HMN Realized Volatility versus GARCH Volatility (Out-Sample)
200.000%
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

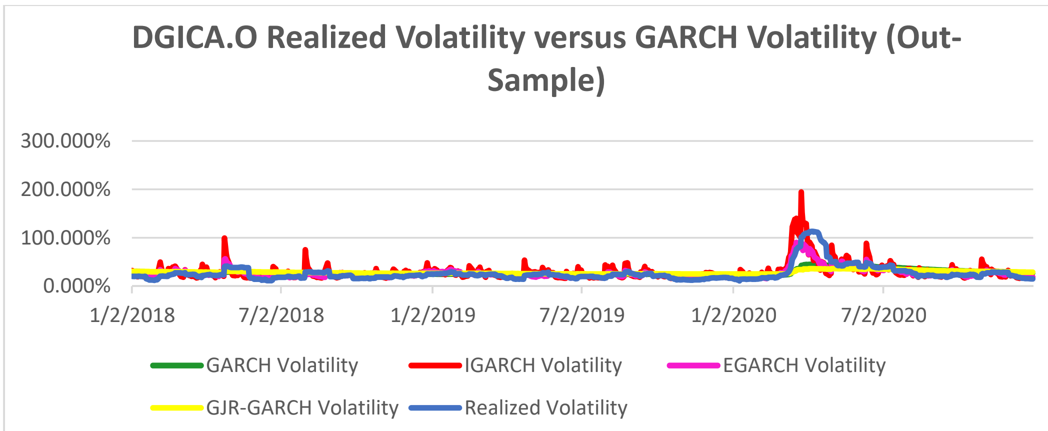

ARGO.K Realized Volatility versus GARCH Volatility (Out-Sample)
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

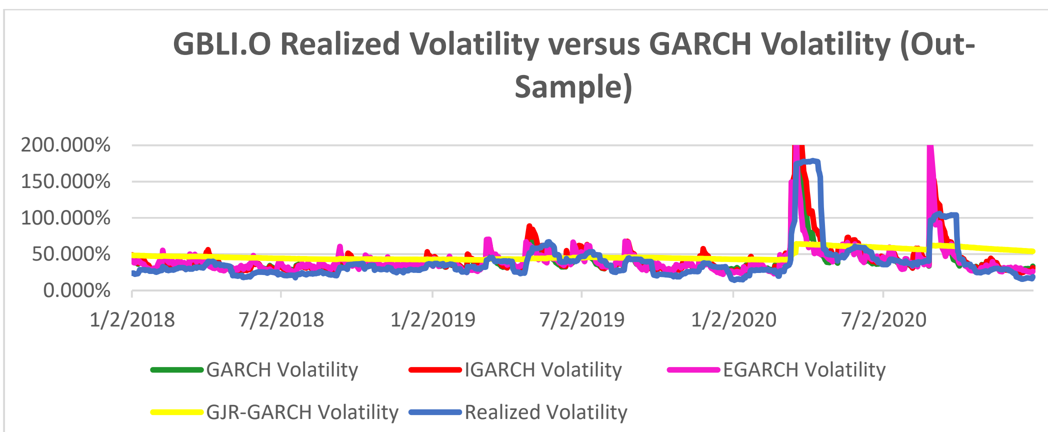

SAFT.O Realized Volatility versus GARCH Volatility (Out-Sample)
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

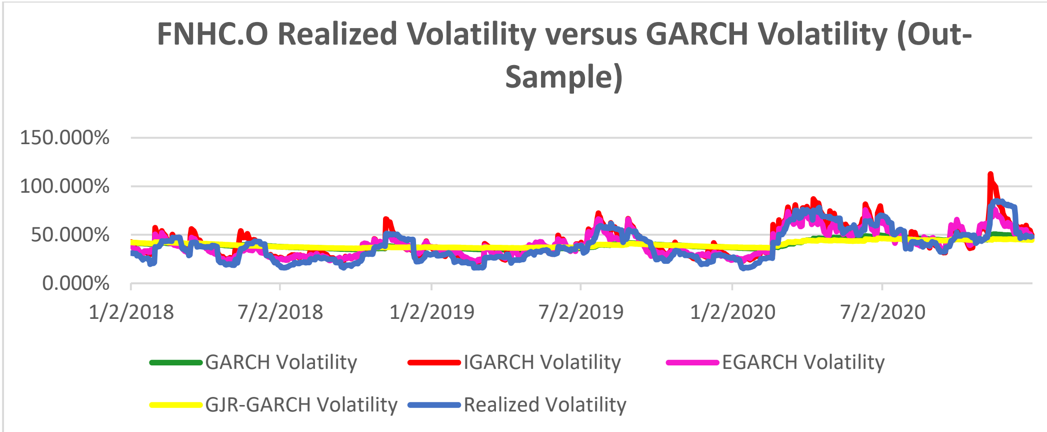

UFCS.O Realized Volatility versus GARCH Volatility (Out-Sample)
300.000%
200.000%
100.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

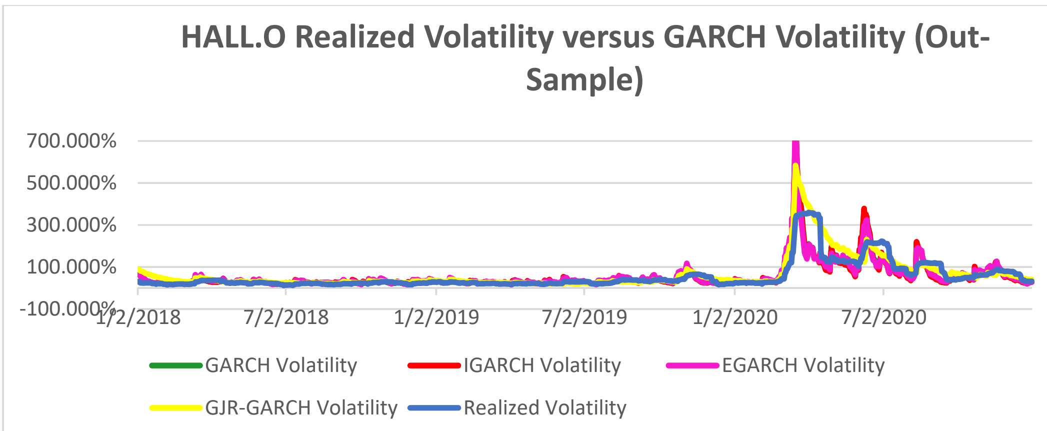

UVE Realized Volatility versus GARCH Volatility (Out-Sample)
300.000%
200.000%
100.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

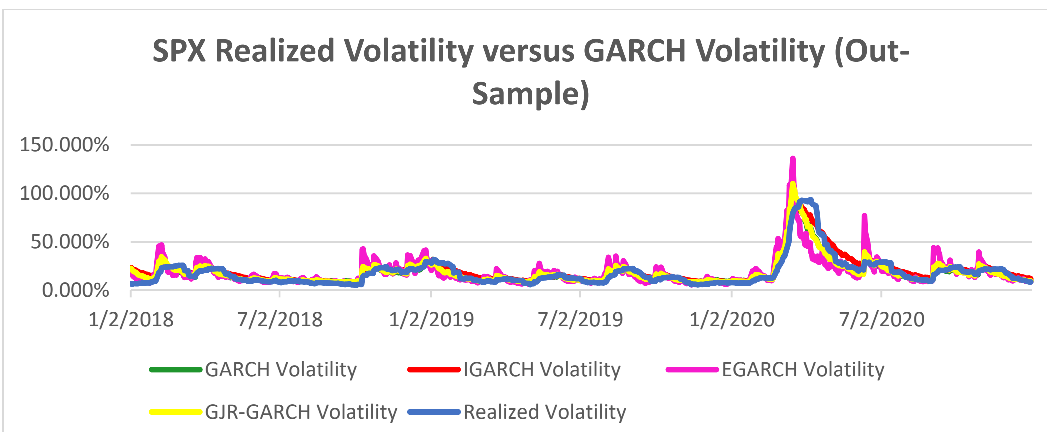

HCI Realized Volatility versus GARCH Volatility (Out-Sample)
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility

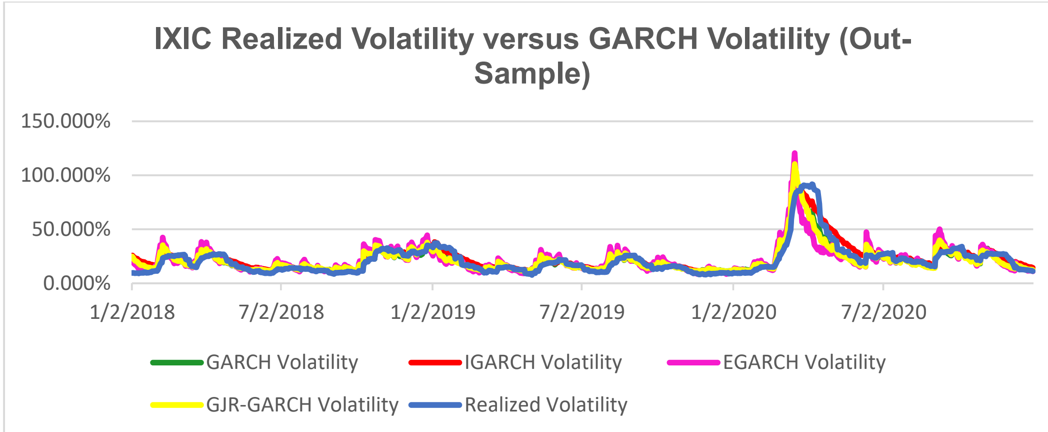

DGICA.O Realized Volatility versus GARCH Volatility (Out-Sample)
300.000%
200.000%
100.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility


GBLI.O Realized Volatility versus GARCH Volatility (Out-Sample)
200.000%
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility


FNHC.O Realized Volatility versus GARCH Volatility (Out-Sample)
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility


HALL.O Realized Volatility versus GARCH Volatility (Out-Sample)
700.000%
500.000%
300.000%
100.000%
-100.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility


SPX Realized Volatility versus GARCH Volatility (Out-Sample)
150.000%
100.000%
50.000%
0.000%
1/2/2018
7/2/2018
1/2/2019
7/2/2019
1/2/2020
7/2/2020
GARCH Volatility
IGARCH Volatility
EGARCH Volatility
GJR-GARCH Volatility
Realized Volatility



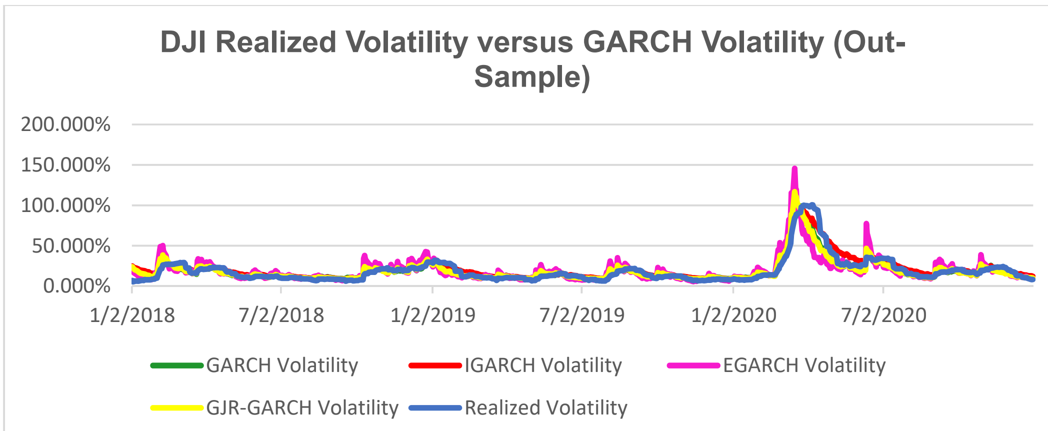


Figure 4: Realized Volatility plotted versus GARCH Models' Volatilities for each stock and index across the chosen out-sample period.

Afterwards, the realized volatilities are compared to the calculated out-sample volatilities in order to identify the optimal model for forecasting each stock's volatility for the out-sample period. The comparison is conducted using the three chosen error statistics: RMSE, MAPE and MAE. The below table highlights the out-sample error statistics values in addition to their ranking under each of the selected models.

		GARCH	IGARCH	EGARCH	GJR-GARCH
CB	**MAE**	0.042337704	0.053304851	0.052325237	0.044443193
	Ranking	1	4	3	2
	RMSE	0.064008476	0.082311954	0.083940081	0.068888824
	Ranking	1	3	4	2
	MAPE	0.181211842	0.222065863	0.207223354	0.181442783
	Ranking	1	3	4	2

		GARCH	IGARCH	EGARCH	GJR-GARCH
PGR	MAE	0.044581	0.070839	0.059265	0.048615
	Ranking	1	4	3	2
	RMSE	0.062415	0.091323	0.083841	0.067923
	Ranking	1	4	3	2
	MAPE	0.21033	0.329904	0.259663	0.220792
	Ranking	1	4	3	2

		GARCH	IGARCH	EGARCH	GJR-GARCH
MSADY.PK	MAE	0.03054	0.042574	0.042032	0.030953896
	Ranking	1	4	3	2
	RMSE	0.040557	0.057027	0.058155	0.041484472
	Ranking	1	3	4	2
	MAPE	0.154151	0.207584	0.198219	0.155720995
	Ranking	1	4	3	2

		GARCH	IGARCH	EGARCH	GJR-GARCH
CINF.OQ	MAE	0.049497	0.093186	0.060783	0.053324625
	Ranking	1	4	3	2
	RMSE	0.070658	0.12817	0.090604	0.079413049
	Ranking	1	4	3	2
	MAPE	0.198316	0.394367	0.219359	0.203162891
	Ranking	1	4	3	2

		GARCH	IGARCH	EGARCH	GJR-GARCH
WRB	MAE	0.0450865	0.0476182	0.0532576	0.1064408
	Ranking	1	2	3	4
	RMSE	0.0758494	0.0802967	0.097157	0.1612267
	Ranking	1	2	3	4
	MAPE	0.19527	0.2045155	0.2076484	0.5150622
	Ranking	1	2	3	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
AFG	MAE	0.117914	0.124682	0.066521	0.073660953
	Ranking	3	4	1	2
	RMSE	0.212217	0.182411	0.148547	0.15010228
	Ranking	4	3	1	2
	MAPE	0.515114	0.528543	0.219968	0.291412536
	Ranking	3	4	1	2

		GARCH	IGARCH	EGARCH	GJR-GARCH
RLI	MAE	0.0927241	0.0723766	0.0545452	0.114833373
	Ranking	3	2	1	4
	RMSE	0.1395603	0.1095485	0.0782464	0.159986873
	Ranking	3	2	1	4
	MAPE	0.4040147	0.2872637	0.2292512	0.533159003
	Ranking	3	2	1	4

GARCH	IGARCH	EGARCH	GJR-GARCH

SIGI.O	**MAE**	0.0925	0.050922	0.049876	0.103363372
	Ranking	3	2	1	4
	RMSE	0.147407	0.083093	0.087632	0.159222992
	Ranking	3	1	2	4
	MAPE	0.359485	0.186815	0.174366	0.406050351
	Ranking	3	2	1	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
WTM	**MAE**	0.0302632	0.0476983	0.046738	0.037328678
	Ranking	1	4	3	2
	RMSE	0.0476187	0.0768974	0.077266	0.052776994
	Ranking	1	3	4	2
	MAPE	0.1979952	0.2625155	0.2454946	0.229679221
	Ranking	1	4	3	2

		GARCH	IGARCH	EGARCH	GJR-GARCH
HMN	**MAE**	0.090024	0.049784	0.055351	0.104024705
	Ranking	3	1	2	4
	RMSE	0.145043	0.071052	0.083372	0.160707462
	Ranking	3	1	2	4
	MAPE	0.341499	0.184763	0.195941	0.398318657
	Ranking	3	1	2	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
ARGO.K	**MAE**	0.122497	0.109984	0.089775	0.125274868
	Ranking	3	2	1	4
	RMSE	0.148379	0.14771	0.117893	0.149601771
	Ranking	3	2	1	4
	MAPE	0.580351	0.491046	0.415537	0.601710977
	Ranking	3	2	1	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
SAFT.O	**MAE**	0.075641	0.0389	0.040903	0.084123172
	Ranking	3	1	2	4
	RMSE	0.117232	0.055791	0.0619	0.128430289
	Ranking	3	1	2	4
	MAPE	0.317767	0.166801	0.165778	0.355097737
	Ranking	3	2	1	4

		GARCH	IGARCH	EGARCH	GJR-GARCH
UFCS.O	**MAE**	0.13652	0.118662	0.09911	0.16364887
	Ranking	3	2	1	4
	RMSE	0.188071	0.188295	0.148704	0.223568082
	Ranking	2	3	1	4
	MAPE	0.510878	0.354176	0.315314	0.617555201
	Ranking	3	2	1	4

		GARCH	IGARCH	EGARCH	GJR-GARCH

UVE	**MAE**	0.135462	0.12614	0.119444	0.122904004
	Ranking	4	3	1	2
	RMSE	0.182562	0.185783	0.17596	0.187340627
	Ranking	2	3	1	4
	MAPE	0.42907	0.359883	0.337411	0.341616863
	Ranking	4	3	1	2

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
HCI	**MAE**	0.127498818	0.135363785	0.141084004	0.131465214
	Ranking	1	3	4	2
	RMSE	0.161468466	0.200629528	0.485614207	0.169809279
	Ranking	1	3	4	2
	MAPE	0.480770848	0.44958771	0.428594009	0.485788589
	Ranking	3	2	1	4

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
DGICA.O	**MAE**	0.077868	0.079978	0.049501	0.092205749
	Ranking	2	3	1	4
	RMSE	0.129974	0.134984	0.088273	0.148168776
	Ranking	2	3	1	4
	MAPE	0.32092	0.293032	0.184676	0.382050153
	Ranking	3	2	1	4

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
GBLI.O	**MAE**	0.107486524	0.101710832	0.112992252	0.191846438
	Ranking	2	1	3	4
	RMSE	0.189154776	0.173905381	0.216413657	0.264881905
	Ranking	2	1	3	4
	MAPE	0.270618135	0.255817575	0.275457931	0.577711452
	Ranking	2	1	3	4

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
FNHC.O	**MAE**	0.109624334	0.059692317	0.060627812	0.116639685
	Ranking	3	1	2	4
	RMSE	0.133690333	0.073356521	0.073031673	0.142287637
	Ranking	3	2	1	4
	MAPE	0.344738075	0.18277033	0.181312295	0.363700508
	Ranking	3	2	1	4

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
HALL.O	**MAE**	0.197050368	0.20310072	0.197644128	0.154132907
	Ranking	2	4	3	1
	RMSE	0.419824642	0.433868125	0.427086684	0.295891554
	Ranking	2	4	3	1
	MAPE	0.310467276	0.318197245	0.321965249	0.315145272
	Ranking	1	3	4	2

GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**

SPX	**MAE**	0.073455	0.075334	0.034065	0.076240603
	Ranking	2	3	1	4
	RMSE	0.118549	0.126816	0.068407	0.100370298
	Ranking	3	4	1	2
	MAPE	0.521077	0.377235	0.14851	0.595531932
	Ranking	3	2	1	4

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
IXIC	**MAE**	0.072738	0.071704	0.047585	0.061204127
	Ranking	4	3	1	2
	RMSE	0.115343	0.119736	0.085979	0.085173483
	Ranking	3	4	1	2
	MAPE	0.383379	0.32682	0.17627	0.354720378
	Ranking	4	2	1	3

		GARCH	**IGARCH**	**EGARCH**	**GJR-GARCH**
DJI	**MAE**	0.074539	0.076217	0.041317	0.073728504
	Ranking	3	4	1	2
	RMSE	0.12527	0.135916	0.083744	0.09823227
	Ranking	3	4	1	2
	MAPE	0.468724	0.37333	0.167112	0.569940677
	Ranking	3	2	1	4

Table 13: Summary of the optimal volatility model for each stock and index across the chosen out-sample period

4.3 Optimal Model Results

Ticker	**In-Sample**	**Out-Sample**
CB	IGARCH (1,1)	GARCH (1,1)
PGR	GARCH (1,1)	GARCH (1,1)
MSADY.PK	GJR- GARCH (1,1)	GARCH (1,1)
CINF.OQ	GJR- GARCH (1,1)	GARCH (1,1)
WRB	GARCH (1,1)	GARCH (1,1)
AFG	EGARCH (1,1)	EGARCH (1,1)
RLI	IGARCH (1,1)	EGARCH (1,1)
SIGI.O	IGARCH (1,1)	EGARCH (1,1)
WTM	GARCH (1,1)	GARCH (1,1)
HMN	GARCH (1,1)	IGARCH (1,1)
ARGO.K	IGARCH (1,1)	EGARCH (1,1)
SAFT.O	IGARCH (1,1)	IGARCH (1,1)
UFCS.O	EGARCH (1,1)	EGARCH (1,1)
UVE	IGARCH (1,1)	EGARCH (1,1)
HCI	GARCH (1,1)	GARCH (1,1)
DGICA.O	IGARCH (1,1)	EGARCH (1,1)
GBLI.O	EGARCH (1,1)	IGARCH (1,1)

FNHC.O	IGARCH (1,1)	EGARCH (1,1)
HALL.O	EGARCH (1,1)	GJR-GARCH (1,1)
SPX	EGARCH (1,1)	EGARCH (1,1)
IXIC	EGARCH (1,1)	EGARCH (1,1)
DJI	EGARCH (1,1)	EGARCH (1,1)

Table 14: Optimal Models for each stock and index under the In-Sample & Out-Sample Periods

As highlighted in the table above, the results reflect homogeneity among the indices, S&P 500 (SPX), Nasdaq Composite (IXIC), Dow Jones Industrial Average (DJI), and two insurance companies, American Financial Group, Inc. (AFG) and United Fire Group, Inc. (UFCS.O) whereby the Exponential-GARCH (EGARCH) model has proven to perform best for both the in-sample and out-sample period. In addition, the EGARCH model was also the most accurate model for RLI Corp (RLI), Selective Insurance Group Inc (SIGI.O), Argo Group International Holdings Ltd. (ARGO.K), Universal Insurance Holdings, Inc. (UVE), Donegal Group Inc. (DGICA.O) and FedNat Holding Company (FNHC.O) but only for the out-of-sample period given that the Integrated-GARCH (IGARCH) performed better during the in-sample period.

Remarkably among all of the chosen stocks, IGARCH out-performed other models for Safety Insurance Group, Inc. (SAFT.O) for both in-sample and out-sample periods. This may be caused by the lack of a long-run average variance in the IGARCH model highlighting that any disturbance in the market causes an everlasting change in SAFT.O's volatility structure. Alternatively, IGARCH performed best for the out-sample period of Horace Mann Educators Corporation (HMN) and Global Indemnity Group LLC (GBLI.O) whereby, GARCH and EGARCH performed better during the in-sample period, respectively.

With regards to the remaining stocks, the GARCH model proved to be the best performing model for both in-sample and out-sample period for Progressive Corp (PGR), W. R. Berkley Corp (WRB), White Mountains Insurance Group Ltd (WTM), and HCI Group Inc (HCI). Specifically, for the out-sample period, the GARCH model out-performed other models for Chubb Limited (CB), MS&AD Insurance Group Holdings (MSADY.PK) and Cincinnati Financial Corporation (CINF.OQ) while the IGARCH (1,1), GJR- GARCH (1,1) and GJR-GARCH (1,1) were chosen for the in-sample period, respectively. Lastly, the GJR- GARCH is the optimal model for Hallmark Financial Services, Inc. (HALL.O) for the out-sample period.

4.4 Employing Dummy Variables to the Optimal Model

After determining the optimal model for the in-sample and out-sample periods, we set the pre-disaster period to 0 and to 1 for both the- one month and three-month post disaster periods. The one-month and three-month periods were chosen as usually the effects of a natural disaster are not immediately felt due to loss adjusters collecting data, forms filled, insurance companies valuating the claims and payment. Thus, the chosen period is crucial as it may take up to a few months following the natural disaster for the catastrophe-induced volatility peak is reached. Subsequently, using the software E-Views, we estimate the GARCH-type model while adding the dummy variable to the variance equation as ϕD_t. As previously highlighted, we are using daily observations, hence, we inputted 1 to daily observations one day after the disaster until 1 month, and 0 otherwise following each and every event. A positive sign of ϕ parameter implies that the volatility has increased post-disaster period, whereas a negative sign of ϕ sign suggests that the volatility has decreased post-disaster period. Additionally, we check the p-value to identify whether the ϕ parameter is statistically significant, otherwise the dummy variable is incapable of delivering robust results. It is worth mentioning that we used the optimal GARCH model for each of the chosen stock and indices in the in-sample and out-sample period, even though the out-sample models are based on estimates. The below tables highlight the outcome of the impact of dummy variable on insurance companies and indices for in-sample and out-sample period:

Dummy Variable - 1 Month Period Post Disaster						
Ticker	**Coefficient Value (In-Sample)**	**P-Value (In-Sample)**	**Statistically Significant (Y/N) (In-Sample)**	**Coefficient Value (Out-Sample)**	**P-Value (Out-Sample)**	**Statistically Significant (Y/N) (Out-Sample)**
AFG	0.002782	0.0002	Y	-0.012356	0.0000	Y
ARGO.K	-0.010157	0.0000	Y	-0.016397	0.0000	Y
CB	0.001098	0.0000	Y	0.000852	0.0002	Y
CINF.OQ	0.003707	0.0000	Y	0.21695	0.0000	Y
DGICA.O	0.002209	0.0000	Y	0.028127	0.0000	Y
FNHC.O	0.00211	0.0000	Y	0.011883	0.0000	Y
GBLI.O	-0.013535	0.0000	Y	0.007214	0.0466	Y
HALL.O	-0.023165	0.0000	Y	0.016304	0.0000	Y
HCI	-0.003863	0.0000	Y	-0.007361	0.0000	Y
HMN	-0.001421	0.0000	Y	0.014493	0.0000	Y
MSADY.PK	0.004422	0.0000	Y	0.00996	0.0000	Y
PGR	-0.02227	0.0000	Y	0.010534	0.0000	Y
RLI	-0.000996	0.0483	Y	0.006267	0.0005	Y
SAFT.O	-0.010124	0.0000	Y	0.026974	0.0000	Y
SIGI.O	-0.003131	0.0000	Y	0.016049	0.0000	Y
UFCS.O	-0.011187	0.0000	Y	0.01724	0.0000	Y
UVE	-0.002312	0.0001	Y	0.017596	0.0000	Y
WTM	-0.011489	0.0000	Y	-0.009343	0.0000	Y
WRB	-0.005378	0.0000	Y	0.002763	0.2356	N
IXIC	0.010099	0.0000	Y	-0.017020	0.0000	Y
DJI	-0.0081040	0.0001	Y	-0.0058690	0.0210	Y
SPX	0.005122	0.0000	Y	-0.017456	0.0000	Y

Table 15: Outcome of implementing one-month post disaster dummy variable into the volatility equation along with the P-Value for both in-sample and out-sample periods.

Dummy Variable - 3 Month Period Post Disaster						
Ticker	**Coefficient Value (In-Sample)**	**P-Value (In-Sample)**	**Statistically Significant (Y/N) (In-Sample)**	**Coefficient Value (Out-Sample)**	**P-Value (Out-Sample)**	**Statistically Significant (Y/N) (Out-Sample)**
AFG	0.006564	0.0192	Y	0.041913	0.0992	N
ARGO.K	-0.042967	0.0000	Y	0.0102	0.7592	N
CB	-0.010679	0.0000	Y	0.041301	0.0000	Y
CINF.OQ	-0.002526	0.1193	N	0.092518	0.2116	N
DGICA.O	-0.018072	0.0000	Y	0.025601	0.9291	N
FNHC.O	0.090005	0.0000	Y	-0.061851	0.9762	N
GBLI.O	0.009075	0.4105	N	-0.228573	0.8770	N
HALL.O	0.033114	0.0000	Y	0.068799	0.3734	N
HCI	0.008815	0.0000	Y	0.019844	0.0000	Y
HMN	-0.00791	0.0000	Y	-0.016638	0.0000	Y
MSADY.PK	-0.025048	0.0000	Y	0.014811	0.0000	Y
PGR	-0.025225	0.0000	Y	0.049551	0.0426	Y
RLI	-0.002015	0.2162	N	0.037256	0.8055	N
SAFT.O	-0.000527	0.3162	N	0.016847	0.0000	Y
SIGI.O	-0.005845	0.0000	Y	0.009847	0.9741	N
UFCS.O	0.001617	0.5447	N	0.015236	0.8801	N
UVE	0.057387	0.0000	Y	0.028094	0.0000	Y
WTM	-0.011661	0.0000	Y	-0.007942	0.0000	Y
WRB	0.009236	0.0166	Y	0.083442	0.0461	Y
IXIC	0.007792	0.1774	N	0.036177	0.7093	N
DJI	-0.0037810	0.0000	Y	0.0247010	0.9033	N
SPX	-0.001374	0.7233	N	0.025828	0.6280	N

Table 16: Outcome of implementing three-month post disaster dummy variable into the volatility equation along with the P-Value for both in-sample and out-sample periods.

Based on the above results, we observe that approximately 64% of the stocks witnessed a decrease in volatility when applying one-month post-disaster dummy variable for the in-sample period. When investigating the changes, we note that this phenomenon is due to multiple scenarios. To begin with, reinsurance coverage offsets losses incurred by insurance companies. For example, in 2011 ARGO.K started to market its first catastrophe bond, allowing the company to cover itself against losses due to natural disasters specifically, event losses from hurricanes and earthquakes in the United States. Hence, the company became well positioned to provide coverage following natural disasters without witnessing adverse changes in market prices following disasters. Similarly, HCI, announced a comprehensive reinsurance program that provides cover against hurricanes and other catastrophic losses up to USD 968 million with coverage increasing up to USD 1.93 billion in 2020. In summary, as long as catastrophic losses remain within the insurance company's reinsurance plan, they don't impact the company financially. Secondly, several of the chosen insurance companies did not have insured losses where catastrophes hit. For example, WTM, had no coverage in the area where Tropical Storm Lee hit. Likewise, SAFT.O provides coverage in a limited number of U.S states namely, Massachusetts, Maine, and New Hampshire whereby only 18 natural disasters out of the chosen 164 affected these states during the chosen timeframe.

Conversely, 64% of the stocks witnessed positive change in volatility when applying one-month post-disaster dummy variable for the out-sample period. The increase in volatility observed is in line with the studies conducted by Thomann (2013), Wang and Kutan (2013) and Bourdeau-Briena and Kryzanowskib (2017) and this can be explained through a multitude of factors. First and foremost, claims incurred due to natural disasters influence insurers' financial liabilities hence, impacting the insurer's solvency. To illustrate, as a result of the concentration of natural disasters in the Midwest area during Q1 2020, both the net income and property-casualty underwriting income of CINF.OQ, in addition, their stock prices decreased by approximately 25%. Similarly, due to consecutive storms in April 2020 and while SIGI.O observed high net premium written, these earnings were offset by higher catastrophe losses. Thus, the insurer observed a 65% decrease in their bottom line. Specifically with regards to floods, due the high number of floods, WRB had to pay significant claims due to "business interruption" insurance as it is difficult to get a flooded plant, factory or business operational. Secondly, following a natural disaster, we might witness supply/demand shifts related to increase in premiums. Thus, the net effect of the claims incurred and increase in premium might be studied through the resulting insurer stock price performance after a natural disaster. Irrespective which effect dominates, the stock prices related to exposed insurers are more likely to be adversely impacted relative to unexposed insurers. To exemplify, in 2020 with the increase in wildfires, hurricanes and tornadoes, CB, FNHC.O and CINF.OQ have all had premium increases and cutting coverage on less profitable policies in order to sustain their stock price performance.

Lastly, when applying a 3-month post-disaster dummy variable, 41% of stocks witnessed a decrease in volatility during the in-sample period whereas 27% observed a positive change in volatility. As for the out-sample period, 9% of stocks witnessed a decrease in volatility during the out-sample period as opposed to 36% witnessing a positive change in volatility. Thus, in summary the results when applying the 3-month dummy variable are coherent with the one-month dummy variable whereby during the in-sample period, volatility is more likely to be negatively impacted by natural disasters and during the out-sample period, the majority of stocks' volatility are positively impacted by natural disasters.

4.5. Value at Risk (VaR) and Back Testing

The following section highlights the estimation of the value at risk (VaR) for Dow Jones U.S Property and Casualty Insurance Index (DJUSIP) at various confidence levels (90%, 95%, 97.5% and 99% CLs) and in subsequently applying the related Kupiec Likelihood Ratio Test, which is used to check the model's efficiency by back testing the estimated VaR results.

4.5.1. Estimating the Variance Using Rolling Window

The number of simulated VaR chosen is 250 days however since the rolling window procedure is performed for each and ever time interval of 400 days, we are required to obtain an additional 400 days of incremental data of the index's daily price. Thus, the the rolling window chosen extends from 06/06/2018 till 03/06/2019 leading to 650 daily prices ranging from 06/06/2018 till 31/12/2020. The rolling window was chosen based on the out-sample period, 01/01/2018 to 31/12/2020, whereby we chose the most recent 650 trading days in the out-sample. Subsequently, the 'rolling returns' for the chosen index are calculated based on the previously obtained 'rolling prices' leading to a total of 399 returns. Consequently, the daily variances are estimated 399 times using the 'rolled returns' and the selected parameters.

Similar to the calculation applied within sections 4.1 and 4.2 in order to identify the optimal model, the same steps were followed for DJUSIP. The outcome yielded IGARCH (1,1) as the optimal model. Therefore, the optimal volatility model for the index is integrated into the rolling window procedure to compute the variance 99,750 times (399 x 250). Particularly, the parameters from the IGARCH (1,1) model are used to compute the variances. It is worth mentioning that we re-estimated the parameters to perform the calculations within this section. The resulting volatilities are obtained by taking the square root of the variance.

4.5.2. Adjusting the Value of DJUSIP

As proposed by Hull and White (1998), the "rolled" values obtained in the preceding subsection are updated using equation (20) from section 3.8.1 in order to adjust for volatility variations witnessed in the market. Accordingly, we generate 399 scenarios for the dates between 06/06/2018 till 03/06/2019. Based on that, return scenarios are generated from the values computed. To illustrate, the return scenarios for the date 12/06/2018 is calculated as per equation (21):

Return on 12/06/2018 under ith scenario = $\frac{(V_{Ai}-V_{12.06.2018})}{V_{12.06.2018}}$

Whereby “V_{Ai} ” constitutes 1 of the 399 adjusted values noting that the scenario number “i” corresponds to 1 < i < 399. In order to obtain the percentage change in price, or the return in other words, the actual value of the DJUSIP on 12/06/2018 is represented by “$V_{12.06.2018}$”, is subtracted from each of the obtained 399 adjusted values and thus the results are divided by “$V_{12.06.2018}$”.

4.5.3. VaR Calculation and Comparison with Actual Returns

Once all return scenarios are generated for the period extending from 06/06/2018 until 03/06/2019, the 90th, 95th, 97.5th and 99th percentiles of the loss distribution are calculated leading to 250 VaR estimates at each confidence level. Table 17 below presents the daily actual returns, the VaR estimates and number of exceptions at each confidence level.

DJUSIP									
Day	**1**	**2**	**3**	**4**	**5 → 246**	**247**	**248**	**249**	**250**
Date	**06/06/2018**	**07/06/2018**	**08/06/2018**	**09/06/2018**	**10/06/2018 → 28/05/2019**	**29/05/2019**	**30/05/2019**	**31/05/2019**	**03/06/2019**
VaR at 90% CL	-0.902%	-0.854%	-0.934%	-0.936%	…	-1.29%	-1.22%	-1.19%	-1.22%
Exceptions	1	1	1	1	27	1	1	1	1
VaR at 95% CL	-1.21%	-1.18%	-1.27%	-1.27%	…	-1.73%	-1.68%	-1.64%	-1.67%
Exceptions	1	1	1	1	12	1	1	1	1
VaR at 97.5% CL	-1.49%	-1.36%	-1.56%	-1.46%	…	-2.15%	-2.11%	-2.06%	-2.10%
Exceptions	1	1	1	1	10	1	1	1	1
VaR at 99% CL	-1.77%	-1.72%	-1.82%	-1.85%	…	-2.57%	-2.43%	-2.38%	-2.42%
Exceptions	1	1	1	1	5	1	1	1	1
Actual Returns	0.01%	1.11%	-0.89%	0.49%	…	-0.56%	0.51%	1.24%	0.00%

Table 17: Illustration of the Actual Returns, Value at Risk, and Number of Exceptions Estimates for DJUSIP at the Different Levels of Significance between 06/06/2018 until 03/06/2019.

The VaR results reflected in the table above, whereby “α” is 10%, 5%, 2.5% and 1%, related to the 90^{th}, 95^{th}, 97.5^{th} and 99th percentile, respectively. The function used is calculated 250 times at each confidence level in order to determine the VaR at each of the 250 days included in the dataset. As illustrated in the table, it is evident that the VaR increases with each increase in the related confidence level. Subsequently, the actual return is then compared to each VaR estimated under each of the chosen confidence levels. On dates whereby the actual return exceeded the VaR, we recorded an exception. Figure 4 illustrates the outcome graphically comparing the actual returns with the VaR estimates across the entire 250-day sample period.

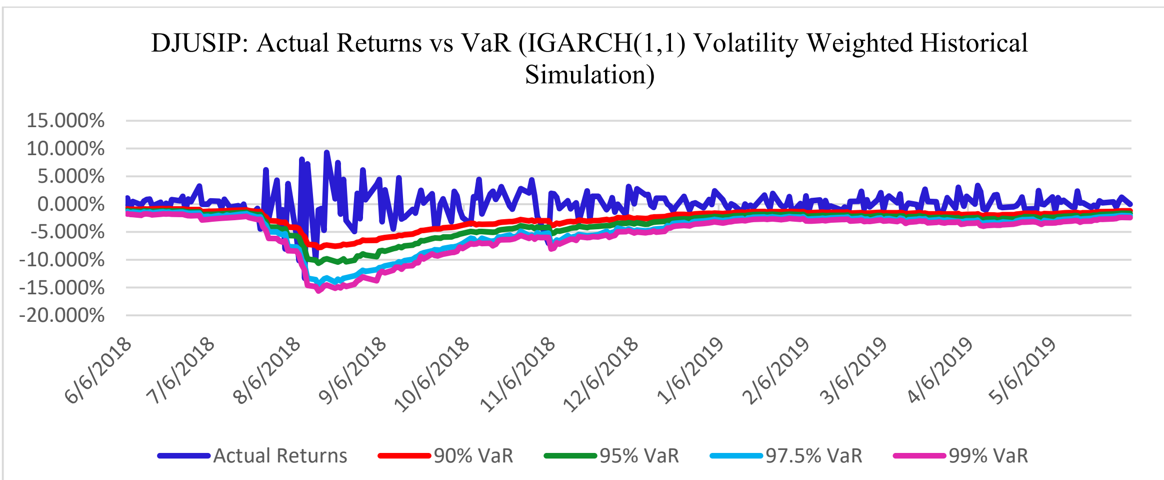


Figure 5: DJUSIP Value at Risk vs Actual Returns for over the entire 250 days sampled

4.5.4. Kupiec Test Results

Complementary to what was defined in section 3.9.1, in order to evaluate the accuracy of the applied VaR model in estimating returns, we implement back-testing procedures, in this case the Kupiec Test. Accordingly, the level of accuracy is encapsulated in a single number known as the Likelihood Ratio (LRK) (refer to equation 23). The parameters required to estimate the LRK can be summed up as follows: the number of exceptions, probability of failure and number of VaR trials.

The total number of exceptions, otherwise known as "X", is calculated four times, once at each confidence level. Whereas, the failure rate "p" refers to 10%, 5%, 2.5% and 1% for a 90%, 95%, 97.5% and 99% VaR respectively. Lastly, the total number of trials "T", is 250.

Seeing as the cumulative number of exceptions for the index at the 90% VaR confidence level is 27, thus, the respective LR_K can be calculated as:

DJUSIP LR_K at 90% CL = $-2\ln\left[(1-0.1)^{(250-27)} x\ 0.1^{27}\right] + 2\ln\left[1-\left(\frac{27}{250}\right)^{250-27}\right] x\ (\frac{27}{250})^{27} =$ 40.88243

Similar calculations are performed at each confidence level following the computation of the number of exceptions. The Kupiec Test results are illustrated in Table 18.

Index	Model Integrated into the Volatility Weighted Historical Simulation Method	VaR Confidence Level	Number of Exceptions	Non-Rejection Interval	LRK	Critical Value	Outcome
DJUSIP	IGARCH(1,1)	90%	27	[17 , 35]	0.173727	3.84	Accept
		95%	12	[7 , 20]	0.021324	3.84	Accept
		97.50%	10	[2 , 11]	1.958063	3.84	Accept
		99%	5	[0 , 5]	1.95681	3.84	Accept

Table 18: The Kupiec Test Results of DJUSIP.

The Kupiec Test outcome shows that the VaR provides a very accurate measure for the level of downside risk at all the confidence intervals, 90%, 95%, 97.5% and 99% whereby the number of exceptions was within expectations. In order to further accurately quantify risk, the following subsection will apply further elaborated tools such as the Extreme Value Theory (EVT). EVT was first used in the 1920s and it provides better-fit distributions to fit extreme events. As opposed to VaR methodologies, no assumptions are made about the identity of the distribution of observations. Given that EVT aims to rectify downfalls faced by applying VaR, it can be very useful for predicting extreme-loss situations and crashes.

4.6. Extreme Value Theory (EVT)

Our aim is to illustrate the tail distribution estimation of DJUSIP's daily returns for the period 01/01/2018 till 31/12/2020 and use the results to quantify market risk. The application has been executed using Stata. We will implement the peak-over-threshold methodology which involves following these steps: select the threshold u, fit the Generalized Pareto Distribution (GPD) function to the exceedances over u, compute interval estimates and lastly perform diagnostic checks.

4.6.1. Selecting the threshold μ

In order to begin applying the EVT estimation procedure, the first step is selecting the appropriate threshold u as it implies a proper balance between bias and variance. To illustrate, a value for u that is too small will lead to bias as the asymptotic assumption behind the estimation might not be satisfied. Similarly, too high u will bring about a model categorized by large variance given that only few observations will be used to fit it. Having said that, to support the choice of u, we employ the mean excess plot, a graphical tool used in the selection of a threshold and we perform statistical analysis of the data in order to choose a u close to the 95th percentile of the empirical distribution. From a closer inspection of the figure 6 and the statistical data obtained we select a value of u= 0.0216354

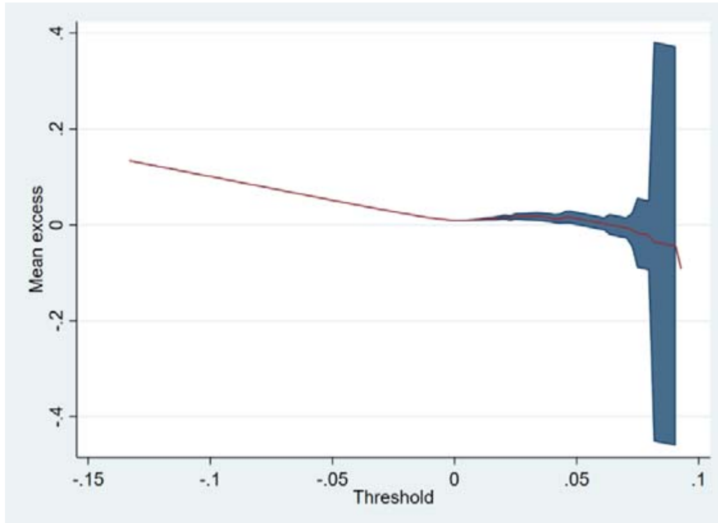


Figure 6: DJUSIP mean excess plot to select the appropriate threshold.

4.6.2. Model Fitting

After selecting the appropriate threshold, it is now possible to fit the Generalized Pareto Distribution (GPD). There are numerous methods for estimating the scale parameter ($\hat{\sigma}$), and shape parameter ($\hat{\xi}$) such as, Moment method, Probability Weighted Moments method, Pickands estimator and Maximum Likelihood method. However, the only method that extends directly to models incorporating non-stationarity and combines theoretical efficiency is the maximum likelihood method (ML). Accordingly, the ML estimates for the scale parameter ($\hat{\sigma}$), shape parameter ($\hat{\xi}$) and the 95% confidence intervals are revealed in table 19 below:

Parameter	95% Lower Confidence Interval	Estimate	95% Upper Confidence Interval
$\hat{\xi}$	-5.003474	-4.408875	-3.814276
$\hat{\sigma}$	-0.2601662	0.2484567	0.7570796

Table 19: Maximum Likelihood estimates for fitting the Generalized Pareto Distribution (GPD) along with the 95% confidence intervals.

The scale parameter ($\hat{\sigma}$) should always satisfy the condition $\hat{\sigma}$>0, thus based on the above, $\hat{\sigma}$ = 0.2484567. Additionally, the shape parameter ξ is associated with the behavior of the tail of the distribution and is associated with the rate of decay of the tail of the distribution. Having said that, the GPD comprises three known distribution types, depending on the value of parameter $\hat{\xi}$. Based on the results obtained, when $\hat{\xi}$< 0, the function is equivalent to a short-tailed Pareto distribution whereby the tail of the distribution is heavier than the normal distribution.

4.6.3. Diagnostic Plots

We then proceed to perform diagnostic checks on the accuracy of the fitted GPD at the selected threshold. Figure 7 presents the probability–probability (PP), quantile–quantile (QQ) plot, density plot and return plot. The PP plot exhibits a generally linear trend. Moreover, the QQ plot shows that the points of the exceedances do not diverge significantly from the linear trend except after the selected threshold. Additionally, a convex-shaped QQ plot (i.e starting bottom left and curving round to the right) indicates a thinner tail with $\hat{\xi}$ < 0, coherent with the outcome achieved. With regards to the density plot, it is consistent to the fitted histogram particularly at the extreme tail. The return level plot reflects a graph of the empirical estimates of the return level function plotted against the estimated return levels from the fitted model. Accordingly, it can be observed there are no significant departures from the curve and the majority of the points lie approximately on the line. In general, we can conclude that the diagnostic plots show satisfactory support for the fitted GP distributions.

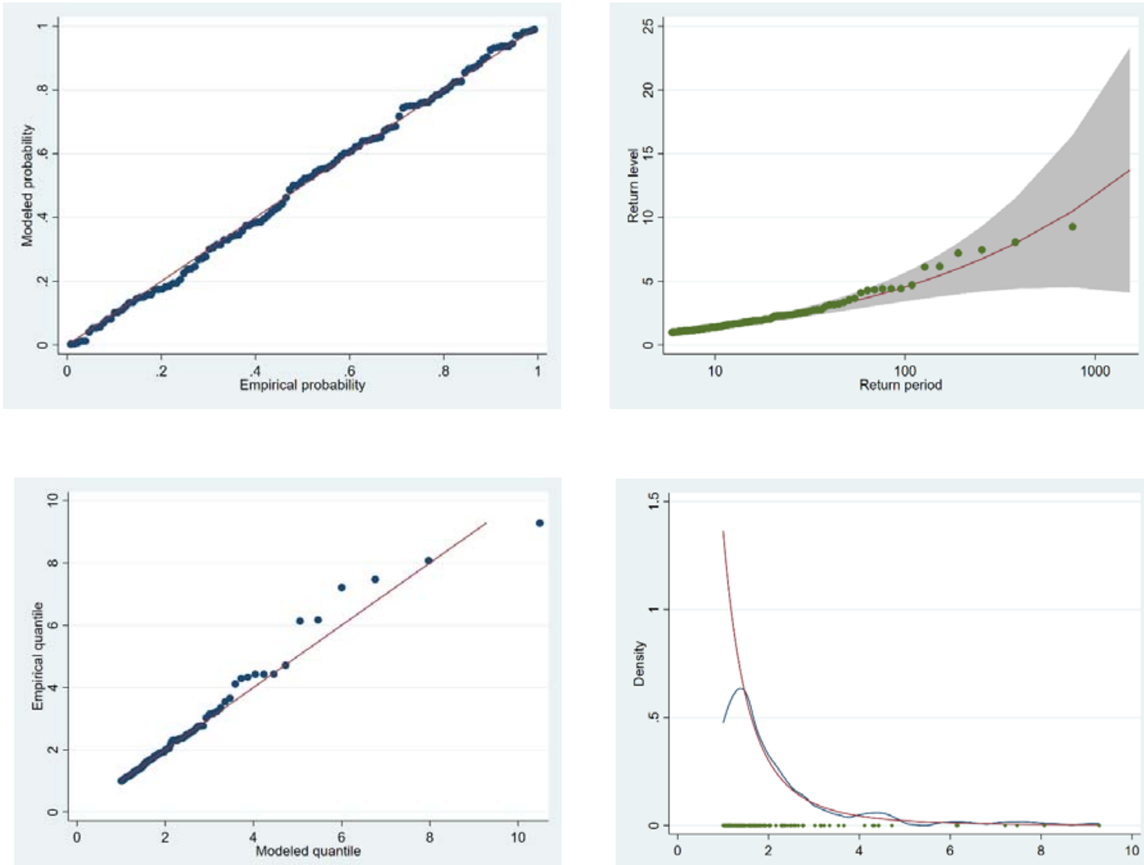


Figure 7: Diagnostic check using probability–probability (PP), quantile–quantile (QQ) plot, density plot and return plot.

4.6.4. Estimating Value at Risk (VaR) and Expected Shortfall (ES)

EVT is integrated into our thesis in order to remedy deficiencies observed in VaR, as it estimates the likelihood of extreme values by assuming a separate distribution for extreme losses. In addition, we incorporated expected shortfall (ES) as it is the expectation of loss that is beyond the VaR level. To calculate VaR using EVT we use the below equation:

$$VaR = \mu + \frac{\hat{\sigma}}{\hat{\xi}}\left\{\left[\frac{n}{n_u}(1-q)\right]^{-\hat{\xi}} - 1\right\} \qquad (24)$$

Whereby, μ is the threshold selected, $\hat{\sigma}$ is the scale parameter, $\hat{\xi}$ is the shape parameter, n is the sample size, n_u is the number of observations above the threshold and q is the chosen confidence interval. Accordingly, at 95% and 99% confidence interval, the VaR was estimated to be 2.33% and 7.79%, respectively. Thus, we are 95% (99%) confident that our loss will not exceed 2.33% (7.79%) within the given time horizon.

According to Hull (2012), ES estimates "if things do get bad, how much can the company expect to lose?". Hence, in order to calculate the ES, equation (25) is applied:

$$ES = \frac{[VaR + \hat{\sigma} - (\hat{\xi} * \mu)]}{(1 - \hat{\xi})} \quad (25)$$

Based on the VaR, the ES was estimated to be 6.79% and 7.80%, respectively at 95% and 99% confidence level. Table 20 below summarizes all parameters used to calculate the VaR and ES at both interval levels:

Parameter	**Scenario 1 (95% Confidence Level)**	**Scenario 2 (99% Confidence Level)**
μ	0.0216	0.0216
$\hat{\sigma}$	0.248457	0.248457
$\hat{\xi}$	-4.408875	-4.408875
n	755	755
n_u	38	38
q	95%	99%
VaR	**2.33%**	**7.79%**
ES	**6.79%**	**7.80%**

Table 20: Value at Risk (VaR) and Expected Shortfall (ES) parameters used at 95% and 99% confident level, respectively.

Having said the above, when comparing the VaR estimated using EVT, we note that the values are lower. As estimated in the previously, VaR is 9.833% and 15.29% at 95% and 99% confidence interval, respectively. Given that the volatility adjusted VaR is higher, we can conclude that the model is overestimating the loss.

To conclude, Chapter 4 had systematically presented the study's detailed findings under each of the chosen volatility models, for the chosen periods. Next, a dummy variable was employed to measure the impact of natural disasters on the chosen stocks and indices. Furthermore, VaR was calculated, and the model's accuracy was assessed using Kupiec Test. Lastly, in order to provide well-rounded risk measures, we incorporated Extreme Value Theory (EVT) into our calculations as it assumes a separate distribution for extreme losses in order to estimate the probability of extreme values and estimate VaR and ES. Chapter 5 concludes and provides the related recommendations.

Chapter 5: Conclusion and Recommendations

5.1 Summary and Review of Results

Given the highly destructive, costly and impactful nature of natural disasters, coupled with their growing importance in capital markets, the need to forecast their impact on volatility has become increasingly imperative. Thus, the significance of a wide study encompassing the behavior of capital markets with respect to natural disasters has become climacteric as it unveils unknown characteristics and improves existing findings. Hence, this thesis contributes to existing literature by bringing up to date the current research around modeling the impact of natural disasters on U.S Insurance Companies and Indices stock price volatility through a spectrum of GARCH-type volatility models. It also aims to calculate the maximum loss at various confidence intervals using Value at Risk and Extreme Value Theory using up to date data for both stock prices and natural disasters.

To begin with, this thesis assessed and presented the detailed findings under each of the chosen volatility models, GARCH (1,1), IGARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1) for the in-sample period ranging between 01/01/2010 till 31/12/2017. After calculating the volatilities of nineteen U.S insurance stocks (Chubb Limited, Progressive Corp, MS&AD Insurance Group Holdings, Cincinnati Financial Corporation, W. R. Berkley Corp, American Financial Group, Inc., RLI Corp, Selective Insurance Group Inc, White Mountains Insurance Group Ltd, Horace Mann Educators Corporation, Argo Group International Holdings Ltd., Safety Insurance Group, Inc., United Fire Group, Inc., Universal Insurance Holdings, Inc., HCI Group Inc., Donegal Group Inc., Global Indemnity Group LLC, FedNat Holding Company and Hallmark Financial Services, Inc.) and three U.S stock indices (S&P 500, Dow

Jones Industrial Average and Nasdaq Composite) within the in-sample period using the volatility models, we proceed to compute the realized volatility. Subsequently, the forecasted volatilities under each of the chosen volatility models were compared to the realized volatilities using three error metrics MAE, RMSE and MAPE in order to determine the optimal model for each insurance company and index.

Results showed that the Integrated-GARCH (1,1) has proven to be the optimal model for the majority of the chosen insurance companies, CB, RLI, SIGI.O, ARGO.K, SAFT.O, UVE, DGICA.O and FNHC.O. On the other hand, the Exponential-GARCH (1,1) model performed best for a substantial number of insurance companies, particularly, AFG, UFCS.O, GBLI.O, HALL.O and the chosen stock indices (SPX, IXIC and DJI). As for the remaining stocks, PGR, MSADY.PK, CINF.OQ, WRB, WTM, HMN and HCI, the GARCH (1,1) and GJR-GARCH (1,1) proved to outperform other models.

Moving forward, the same calculations applied for the in-sample period were applied to the out-sample period which ranges between 01/01/2018 till 31/12/2020. The sole change that was applied is that the in-sample parameters obtained were used to forecast the conditional volatilities for the out-sample period. Subsequently, the optimal model was chosen based on the outcome of error metrics selected for both the in-sample and out-sample periods. The results reflected homogeneity among the indices, SPX, IXIC, DJI and two insurance companies, AFG and UFCS.O whereby the EGARCH model was proven to perform best for both the in-sample and out-sample period. In addition, the EGARCH model was also the most accurate model for RLI, SIGI.O, ARGO.K, UVE, DGICA.O and FNHC.O but only for the out-of-sample period given that the IGARCH performed better during the in-sample period. Among all of the chosen stocks, IGARCH out-performed other models for SAFT.O for both in-sample and out-sample periods. Alternatively, IGARCH performed best for the out-sample period of HMN and GBLI.O whereby GARCH and EGARCH performed better during the in-sample period, respectively. With regards to the remaining stocks, the GARCH (1,1) model proved to be the best performing model for both in-sample and out-sample period for PGR, WRB, WTM and HCI. Specifically, for the out-sample period, the GARCH model out-performed other models for CB, MSADY.PK and CINF.OQ while the IGARCH (1,1) and GJR-GARCH were chosen for the in-sample period, respectively. Lastly, the GJR-GARCH is the optimal model for HALL.O for the out-sample period.

Next, after determining the optimal model for the in-sample and out-sample periods, we set the pre-disaster period to 0 and to 1 for both the- one month and three-month post disaster periods. The chosen period is crucial as it may take up to a few months following the natural disaster for the catastrophe-induced volatility peak is reached. It is worth mentioning that we used the optimal GARCH model for each of the chosen stock and indices in the in-sample and out-sample period. The outcome obtained highlighted the fact that during the in-sample period, volatility was more likely to be negatively impacted by natural disasters and during the out-sample period, the majority of stocks' volatility were positively impacted by natural disasters. When investigating the changes, we note that the negative impact on volatility is due to the fact that reinsurance coverage offsets losses incurred by insurance companies and the fact that several of the chosen insurance companies did not have insured losses where catastrophes hit. On the other hand, positive impacts on volatility are mainly because claims incurred due to natural disasters influence insurers' financial liabilities hence, impacting the insurer's solvency. Moreover, following a natural disaster, we might witness supply/demand shifts related to increase in premiums. Thus, the net effect of the claims incurred and increase in premium might be studied through the resulting insurer stock price performance after a natural disaster. Irrespective which effect dominates, the stock prices related to exposed insurers were more likely to be adversely impacted relative to unexposed insurers.

Furthermore, using the Rolling Window procedure and by incorporating the optimal model into the Volatility-Weighted Historical Simulation method, the Value at Risk (VaR) was estimated for 250 days between 06/06/2018 till 03/06/2019 at four confidence levels (90%, 95%, 97.5% and 99% confidence levels) for Dow Jones Property & Casualty Insurance Index (DJUSIP:DJI). The computed VaR results were then compared to actual returns in order to determine the number of days/exceptions in which actual returns exceeded VaR estimates across the 250 days period. Lastly, the Kupiec Test was performed using the number of exceptions produced to assess the accuracy of the VaR model in estimating the returns of the chosen index at each confidence level. The outcome of The Kupiec Test reflected that VaR provides a very accurate measure in determining the level of downside risk at all confidence intervals 90, 95% 97.5% and 99% whereby the LRK values were below the critical value of "3.84". Lastly, in order to provide well-rounded risk measures, we incorporated Extreme Value Theory (EVT) into our calculations as it assumes a separate distribution for extreme losses in order to estimate the probability of extreme values. Accordingly, at 95% and 99% confidence interval, the VaR was estimated to be 2.33% and 7.79%. Based on the VaR, the Expected Shortfall (ES) was estimated to be 6.79% and 7.80%, respectively at 95% and 99% confidence level. When comparing the VaR obtained through EVT and the volatility adjusted model, we note that the volatility adjusted model yielded a higher VaR thus, we can conclude that the model is overestimating the loss.

5.2. Outcome of the Research

Recent literature examines the short-term impacts of natural disasters on capital markets and reaches opposing conclusions. While some studies maintain that returns are not affected by these events (e.g., Worthington, 2008; Wang & Kutan, 2013), others conclude that natural disasters remarkably affect stock returns (e.g., Worthington & Valadkhani, 2004). Thus, the findings of this thesis are unconventional to those of previous research, as this thesis is the first and most recent to examine the volatility of nineteen U.S insurance companies and three U.S stock indices along with the Value at Risk for the Dow Jones Property & Casualty Insurance Index all together, specifically with the application of multiple GARCH Models and the Volatility Updating Historical Simulation Method for VaR in addition to incorporating EVT into our calculations.

Most recently, Michael Bourdeau-Briena and Lawrence Kryzanowskib (2017) concluded that conditional volatility increases following floods, hurricanes, severe winter weather and episodes of extreme temperature and opted for a parsimonious GARCH(1,1) model. In addition, Wang and Kutan (2013) employed GARCH dummy variable methodology, and provided evidence that disasters increase volatility on the U.S. market but have no impact on the Japanese market and chose EGARCH as the optimal model for their dataset, based on the highest log-likelihood value. However, as per the outcome of this thesis, after employing the dummy variable one-month and three-month after the date of occurrence of the disaster, it was observed that volatility is more likely to be negatively impacted by natural disasters during the in-sample period, while the majority of stocks' volatility are positively impacted by natural disasters during the out-sample period. Additionally, the best performing model for this thesis was the IGARCH during the in-sample and out-sample periods. Subsequently, the EGARCH model performed best for a number of insurance companies, particularly, AFG, UFCS.O, GBLI.O, HALL.O and the chosen stock indices (SPX, IXIC and DJI) during the in-sample period and the results reflected homogeneity among the indices (SPX, IXIC, DJI) and two insurance companies (AFG and UFCS.O) whereby the EGARCH model was proven to perform best for both the in-sample and out-sample period. In addition, the EGARCH model was also the most accurate model for RLI, SIGI.O, ARGO.K, UVE, DGICA.O and FNHC.O during the out-sample period.

Based on the above, it is remarkable to note that till date, no study has investigated the impact of natural disasters on the behavior of U.S insurance companies and indices stock volatility along with their Value at Risk. Therefore, this thesis complemented previous research and built upon them by adding the Value at Risk model to calculate the worst possible loss at various confidence intervals. Based on the results obtained, it is evident that the VaR increases with each increase in the related confidence level.

It is expected to observe certain discrepancies in outcomes given the unexpected nature of natural disasters. The outcome is also affected by the number of stocks considered and models employed in the research. As evidenced from the available review of literature, minimal to no effort has been devoted for the U.S property liability insurance industry as most of the previous research focused solely on the market as a whole or companies outside the insurance industry, whereby the majority of the papers integrated no more than two volatility models. A different justification may be linked to the time frame employed, as most of the previous research were conducted no less than 4 years ago and from which various periods were chosen. Worthington (2008) examined the behavior of Australian Stock Exchange All Ordinaries index over a 23-year period ranging from 01/01/1980 till 30/06/2003. Wang and Kutan (2013) considered the period from 11/09/1989 till 08/04/2011. Lastly, Bourdeau-Briena and Lawrence Kryzanowskib (2017) used the data for the period extending from 01/01/1990 till 30/06/2015. Therefore, this thesis has investigated the behavior of the 19 U.S insurance stocks, 3 U.S indices, a property-liability composite index for VaR and EVT and 252 natural disasters, over the period extending from 01/01/2010 till 31/12/2020, which makes its dataset comprehensive, exhaustive and novel.

Based on previous research, it remains vague why certain firms experience a positive impact from natural disasters while others experience negative consequences. However, when we employed the dummy variable and investigated the reasons, we note that the decrease in volatility following a natural disaster is due to the fact that reinsurance coverage offsets losses incurred by insurance companies. Hence, the company becomes well positioned to provide coverage following natural disasters without witnessing adverse changes in market prices following disasters. Moreover, several of the chosen insurance companies did not have insured losses where catastrophes hit. On the other hand, volatility increases following natural disasters due to multiple reasons. First and foremost, claims incurred due to natural disasters influence insurers' financial liabilities hence, impacting the insurer's solvency. Additionally, following a natural disaster, we might witness supply/demand shifts related to increase in premiums. Thus, the net effect of the claims incurred and increase in premium might be studied through the resulting insurer stock price performance after a natural disaster. Irrespective which effect dominates, the stock prices related to exposed insurers are more likely to be adversely impacted relative to unexposed insurers.

5.3 Limitations

This thesis has potential limitations. A particular limitation is that with the majority of research in this area, the analysis on the impact of natural disasters has been made in segregation from other effects, such as macroeconomic, political and calendar announcements. While this simplifies research, it is tricky as natural disasters may be vulnerable to contamination caused by macroeconomic announcements independent of the disaster or catastrophe itself. For example, Shelor et al. (1992) analysis of the 1989 Loma Prieta earthquake compromised the outcome of the research as it failed to take into consideration the lowering of official US interest rates two days later.

Moreover, multiple property-liability insurance companies were excluded from the dataset as there was no sufficient data for the chosen timeframe (01/01/2010 till 31/12/2020) and there are many property-liability insurance companies that are private and thus, these could not be included. Therefore, the dataset used could have been wider and more inclusive.

5.4 Future Recommendations

In an era whereby natural disasters continuously cause severe damage to disruption to financial activity, global economies and international trade, insurance companies have become acutely sensitive to volatility and downside risks. Throughout the various sections of this thesis, several questions can be raised that could be of interest for future research with regards to the impact of natural disasters on capital markets.

The first involves the comparison of the impact of natural disasters across international markets. A considerable amount of literature already exists for U.S markets however, a comparison between national and international markets, such as Australia, EU countries, United Kingdom and Japan, would stipulate whether or not natural disaster effects are confined to national markets or have the ability to impact global economies.

Another captivating area for future research would be to use the outcome of this thesis to pave the way for better hedging techniques. The increasing demand for borrowing to cope with the increasing cost of losses due to natural disasters paired with stagnant budgets create a liquidity squeeze for all the institutions involved once a natural disaster hits. Accordingly, the possible use of catastrophe hedges, such as catastrophe bonds, can provide post-disaster reconstruction financing.

A concluding recommendation for potential areas of study in this field would include a comprehensive analysis of the catastrophe modelling tools utilized by insurers and reinsurers. While currently, there are no standardized risk modelling techniques, it would be intriguing to examine the tools being used to pinpoint impending risks and how the risk assumptions within these models are updated based on climate change threats. It is now as crucial as ever to create better meteorological forecasting tools along with emergency management plans in order to mitigate the adverse effects of natural disasters that are significantly increasing in frequency and severity. Thus, it is important for financial policymakers and regulators, to unite, communicate and generate disaster recovery plans that can be implemented to provide quick, flexible and effective contingency plans/responses to these events.

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