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ANALYSIS OF RESILIENCE IN US STOCK MARKETS DURING NATURAL DISASTERS

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SCHOOL OF INDUSTRIAL AND SYSTEMS ENGINEERING

BY

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To my family, who has always encouraged me to pursue my dreams.

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Abstract

Different studies relating to resilience have been performed on stock markets for disasters around the world. Researchers have tried to figure out if stock markets were resilient or not during a particular disaster.

In this piece of work we have compared stock markets during different major disasters in the history of United States. We have created different metrics such as vulnerability, recoverability and reactivity to base performance of stock markets during times of various disasters.

The data that has been used was obtained in the form of daily closing prices of Property and Casualty Sector and Overall Sector New York Stock Exchange prices. We compute the daily volatility of each stock and then calculate the overall weighted volatility of the sector using market capitalization of each company operating in the sector. A time series is generated using the difference between the overall market volatility and sector volatility. Breakout Detection is used to find out points of breakout. We have utilized these breakout points to calculate key metrics of resilience. Disasters are ranked according to the stock market performance and an overall resilience ranking is established.

We were able to find that all the disasters included in the study had an impact but stock markets demonstrated different level of resiliency. Relative resiliency for these disasters was calculated. Another interesting

finding was obtained by using path mapping of the hurricanes studied. Although we were able to get an idea about the relationship between locations of hurricane entry, further studies with more number of disasters need to be performed before we reach conclusive results.

Chapter 1

Introduction

1.1 Purpose of the Study

All thanks to technology, stock markets have become sensitive to external factors like never before. Information and event news is available readily to both the buyer and the seller. Trading stocks can be done from the comfort of one's home. This technology shift has made the stockholder more aware and a quick responder to the events affecting the stock market.

Researchers in past have done studies relating to the impact of various natural disasters on the returns in the stock markets. To the best of our knowledge no one has compared stock market resiliency during different natural disasters till now. Questions like, how long did it take for the market to return to normalcy after an event? How long did the market stay vulnerable? Are the effects of disasters on stocks volatility reversible?, etc. still need to be answered. Wouldn't it be great if we could compare the resiliency of a stock market during different disasters using parameters like vulnerability, recoverability, reactivity, etc.?When we talk about the insurance sector specifically, numerous studies have been done around the world analyzing effect of returns due to disasters. There are varied opinions in terms of how the natural disasters affect these returns. Some studies say the insurance sector sees better returns after an event while others have concluded that it is the other way around [1].

Resiliency of market to a disruption at a given time can be gauged by change in its liquidity [2], and as per many market microstructure theories, there exists an inverse relationship between volatility and liquidity [3] [4]. Therefore, change in volatility can be linked to the measure of resilience, or in other words it can be used to determine the period of instability in the market. As there are different sectors in the stock market and their volatility depends on the investor sentiment as well as overall perception of that sector, it won't be possible to accurately measure the effect of an event on the stock market as a whole. Rather we will have to study each sector in their individuality.

1.2 Natural Disasters & Insurance Sector

According to National Weather Service III United States has lost $501.1 Billion and 22,240 people lost their lives in top 10 natural disasters during 1980-2010[5]. During natural disasters primary losses occur in properties like houses, cars, businesses and legal liabilities. As the property insurance covers these losses, companies operating in the sector are bound to experience financial losses in terms of claims and payouts after an event. There can be a similar balancing affect with cash inflows due to new ‘panic' subscriptions. In fact, some analysts have found companies gaining in terms of stock returns after the disasters because of this effect [6]. As discussed above, numerous studies in the past have shown that whether it is positive or negative disasters do affect the insurance sector stocks. Hence, the Property &Casualty Insurance (P&C) sector was an interesting choice for our analysis.

1.3 Problem Definition

Previous works by researchers have focused on calculating the nature of returns after a natural disaster in particular economies. Our focus will be to find out the period of instability in the market due to natural disasters. Another interesting observation will be the stock market’s ‘reaction time’ or reactivity to the event. We are also interested in measuring the change in volatility during events. In this piece of work we would like to study property insurance stock sector during major natural disasters in the history of United States.

1.4 Structure of Thesis

Chapter 2 encompasses a literature review of resilience and a background on how stock market resilience has been studied in the past. In Chapter 3 we have discussed the methodology used in our analysis. Chapter 4 presents the results of analysis on case studies that we have considered for our thesis. Finally, Chapter 5 is the concluding chapter of this piece of work.

Chapter 2

Literature Review

2.1 Previous Studies

Several studies have analyzed the impact of a disaster on stock markets in terms of returns. But quantitative study on characteristics like vulnerability, recoverability and reactivity haven't been done to the best of our knowledge.

A lot of study has been done in the field of stock market returns during different calamities. Researchers in [7] used GARCH model to analyze stock market behavior during and after earthquakes. They found the stock markets to be resilient to these disasters. Auto Regressive Moving Average Model (ARMA) was used to examine the impact of natural disasters in Australian stocks [8]. It was found that the disasters have an impact on the stock market which can be both positive and negative depending on the situation.

2.2 Resilience

The term resilience is so broad that it has been used in relation to humans, infrastructure, networks, systems, etc. It can broadly be defined as the ability of an individual or a system to bounce back from an unfavorable disruptive state. Moreover, resilience can even be found in world's economic machinery. A study published in 1972 called as "The limits of Growth" tried to compute the effects of depletion of resources [9]. Figure 2.1 shown below illustrates various quantified parameters and their nature of resiliency plotted alongside decline in resources.

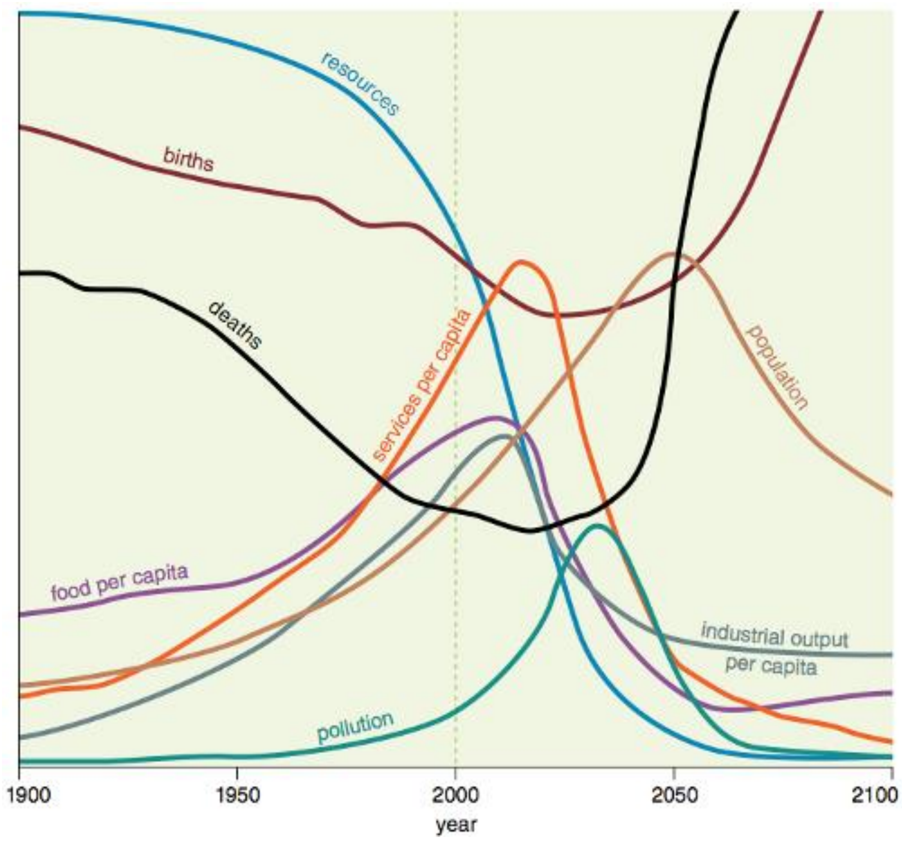


Figure 2.1 : Global economic parameters exhibiting resilience

The transition functions can be for cases with increasing system function such as deaths and births in this illustration or with decreasing system function such as food, services, population, pollution and industrial output.

2.3 Resilience and Stock Markets

Resilience in stock markets can be defined as the ability to “withstand shocks or financial crises” [10].In Figure 2.2 [7], the authors have used the concept of resilience to illustrate the transition of a system that experiences a disruptive event. The figure below describes S_0 as the Original State; S_d as the disruptive state and S_f as the recovered final stage. For an event performance in these stages is the measure of reliability, vulnerability and recoverability as shown in Figure 2.2.

Reliability:

In time series, reliability can be measured by the time t_0 to the time when a disruptive event occurs. A more resilient system will have high reliability.

Vulnerability:

Vulnerability can be measured by the loss in performance level of the system after a disaster strikes and till it reaches a stable disrupted state. More resilient systems are less vulnerable.

Recoverability:

We can measure recoverability by the time when a disrupted stable state is reached to the time system recovery is completed and another post disaster stable state is achieved.

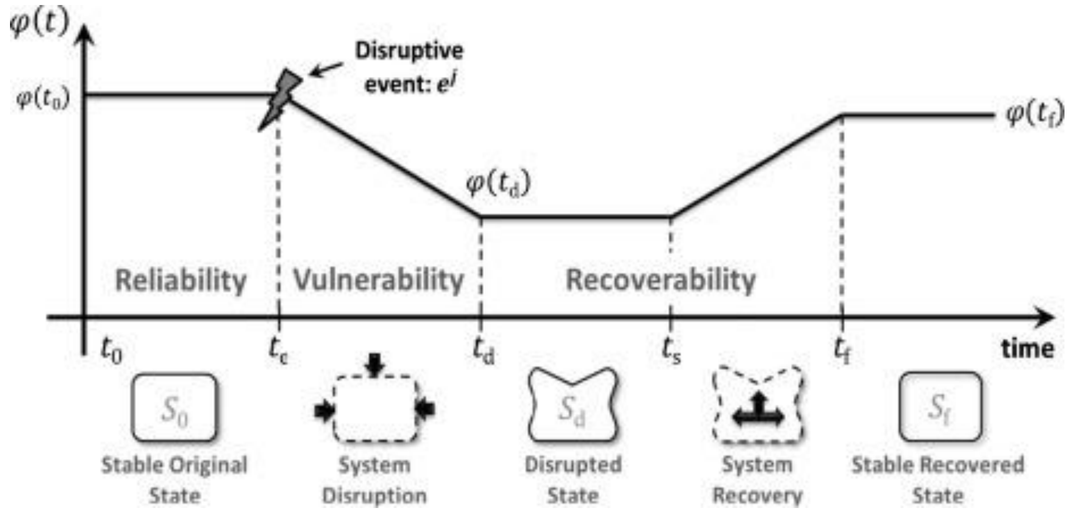


Figure 2.2 : State transitions during a disruptive event

When under pressure due to external factors and events, stock markets tend to exhibit state transitions similar to the ones observed in Figure 2.2.In further chapters we have based our research on the idea of resilience while considering transition in state of the stock market volatility. We have discussed Vulnerability, Recoverability and new parameter 'Reliability' with respect to transitions in state of stock market volatility during a disruptive event.

Chapter 3

Methodology

3.1 Data Extraction and Selection

Data for property and casualty insurance companies listed on the NYSE was collected from 'Yahoo Finance' [11]. Aggregate data for NYSE was also gathered for the same time period. The time period selected for the data is 50 days before and after the median of the dates of the occurrence of event on the US soil.

The selection of events is done based on the damage incurred by them in United States. The top five largest disasters according to their damage in dollars are selected. The other interesting thing that is common between these disasters is that all of them are famous hurricanes.

3.2 Annualization/ Black and Scholes Model

Black and Scholes Model [12] assumes that with time stock pricing follows a Brownian Motion or a Wiener process. While considering a long period of time expected returns in stock prices can be assumed to be lognormal in nature, following

$$dS_t = \mu S_t \, dt + \sigma S_t \, dW_t$$

where W_t is used to generate the random variable. The result being that while annualizing the return the volatility increases by square root of the number of time periods in a year. The variance is also changed by the multiple of number of time periods.

3.3 Return & Volatility

Market return for a particular stock for a particular day *(i)* can be calculated by using the *ith* adjusted closing price and *(i-1)th* adjusted closing price as follows,

$$R_i = \ln \frac{\left(c_{adj}\right)_i}{\left(c_{adj}\right)_{i-1}}$$

where R_i is the market return for *ith* day, $\left(c_{adj}\right)_i$ is the adjusted closing price for the same and $\left(c_{adj}\right)_{i-1}$ is the adjusted closing price for the *i-1th* day. Adjusted closing price is different from the closing price in terms that it has been adjusted for the splits and dividends that might have occurred in the course of time and is therefore preferred over closing price while calculating returns.

We calculated statistical volatility over a period of *N* trading days by using the equation

$$V_j = \sqrt{\frac{1}{N}\sum_{i=j-N+1}^{j}(R_i - \mu)^2}$$

where V_j is the statistical volatility of a particular stock on *jth* day and R_i is the market return for *ith* day. The measure μ is defined as the average market return for *N* days and is computed by

$$\mu = \frac{1}{N}\sum_{i=j-N+1}^{j} R_i$$

For our study we considered *N*=10 days, which is one of the commonly used interval in stock market analysis [13]. Now as it is assumed that volatility models in stock markets undergo Brownian motion [12], we had to annualize the volatility in order to obtain better results. For this we multiply volatility by the square root of 252, i.e. average number of trading days during a year.

3.4 Property and Casualty Insurance Sector Volatility

As we are interested in the volatility of overall sector rather than one single stock we compute the volatility of P&C sector using weights. A particular stock is assigned weight according to its average market cap for that particular year versus the average total market cap of the sector. Sector volatility is computed by adding all the individual weighted volatilities.

Average yearly market caps data for different companies were obtained from a computational knowledge engine [14].

$$V_s = \frac{V_1 \cdot C_1 + V_2 \cdot C_2 + \cdots + V_n \cdot C_n}{C_1 + C_2 + \cdots + C_n}$$

For a particular day, V_s is the sector volatility, V_1 is the statistical volatility of Stock 1, V_2 is the statistical volatility of Stock 2 and so on. C_1 is the average market capital for Stock 1 for that particular year, C_2 is the average market capital for Stock 2 for that particular year and so on.

3.5 Sector Volatility vs Market Volatility

Different sectors tend to react differently with regard to an event [15]. The overall market volatility is always changing because of a mix of reasons. Generally, some sectors tend to be more volatile than the others. We want to try to isolate the effect of disaster on a particular sector, in this case-P&C. To accurately gauge the changes in volatility in a certain sector over a period of time we need to be able to compare it to the overall trend in the market. The change in difference between overall market volatility and sector volatility over a period of time can be a good indicator of abnormal fluctuations in a particular sector. It is given by

$$\Delta V = V_s - V$$

where, ΔV is the difference between sector volatility and overall market volatility, V_s is the sector volatility and V is the overall market volatility on a particular day. Generally the P&C sector is perceived to be more volatile and hence we decide to subtract overall volatility from sector volatility. This ΔV is used as a time series in analyzing the 'breakouts' using EDM breakout detection.

3.6 Breakout Detection- EDM

To detect the breakouts in ΔV we used a novel technique called E-Divisive with Medians (EDM) [16]. This method has previously been used in detecting twitter breakouts [16]. The EDM method involves detecting divergence in the mean by using E-statistics [17]. Unlike other methods of breakout detection EDM is robust to anomaly. We used multiple point detection in time series data for our particular case.

Breakout Detection Function in R:

breakout (Z, min.size, method, beta, degree, plot)

Arguments:

Z: Time series with 'timestamp' and 'count'.

min.size: number of observations between breakouts.

method: type of detections, one or multiple.

beta*: a real number constant used to control the amount of penalization.

degree*: degree of penalization polynomial.

*both the penalization arguments are used to maximize the divergence between two adjacent breakouts while fighting against oversegmentation/overfitting.

For this analysis we used:

min.size: 10, as it was the number of observations for calculating the ‘standard deviation of returns’ or volatility.

method: multi, as we were looking for multiple breakouts in our time series.

beta: 0.02

degree: 3

3.7 Path Mapping

Since all the disasters included in the study turn out to be hurricanes we used path mapping to see if the “direction of attack” or area of entry had any correlation with our analysis. We utilized Tableau software and geo data available on National Hurricane Center website [18] to plot geo diagrams of the paths for these disasters.

3.8 Reactivity as a Parameter of Resilience

During our analysis we observed that there was a period of lag between the time of disruptive event and spike in volatility. We have term this phenomenon as 'Reactivity'. Reactivity is a usually not observed in other systems and might be a feature unique to stock market and similar financial systems. For a stock market a larger lag denotes more confidence in the market. Reactivity can be utilized to gauge market sentiment. If there is a large lag in between the disaster and the spike it means that the investors were optimistic about the market for a longer period of time. Similarly, a small lag will show that there was less confidence, more panic and hence an instantaneous spike in volatility.

Chapter 4

Analysis & Results

4.1 Case Studies

- Hurricane Ivan: Hurricane Ivan hit the US coasts on September 16th 2004 and had severe damage in states of Texas and Florida. With damaging winds as strong as 165mph it reached category 5 strength during its course.
- Hurricane Katrina: Katrina was the biggest hurricane in terms of damage that the United States has seen till date. It hit the US coasts on Aug 29th 2005 and damaged property and destroyed lives across numerous southern states including Louisiana, Mississippi, Florida, etc. The velocity of strongest winds reached 175 mph. It was labeled as a category 5 tropical cyclone.
- Hurricane Wilma: Hurricane Wilma was the most intense hurricane ever recorded in the Atlantic Ocean. It hit the coasts of Florida on October 24th 2005 and had gusty winds of up to 183 mph. It was also a category 5 tropical cyclone.
- Hurricane Ike: Ike was a category 4 tropical cyclone which hit the US coasts in the states of Texas and Louisiana. The fastest winds were about 145 mph. The other interesting part about this tropical

cyclone is that it hit the US Coasts on September 13th 2008, just a few days before one the biggest stock market crash of the decade.

- Hurricane Sandy: Although Sandy was a category 3 tropical cyclone with winds up to 115 mph, it causes huge property loss due to the fact of its widespread reach. The affected areas included states ranging from Florida all the way to New York and New Jersey. It is the second costliest natural disaster in the US history after Katrina.

Table 4.1: Natural disasters used in the case study

Year	Name	Damage (Billions)	Area(s) Affected	Hit US Coasts	End Date
2004	Ivan	$18.80	TX, FL	Sep-16	Sep-24
2005	Katrina	$108	FL, LA, MS, AL, GA, KY, OH	Aug-29	Sep-01
2005	Wilma	$21	FL	Oct-24	Oct-25
2008	Ike	$29.50	TX, LA	Sep-13	Sep-15
2012	Sandy	$71.40	East Coast	Oct-26	Oct-28

4.2 Results

To analyze the results we computed various metrics for each disaster. Vulnerability can be calculated by the difference between average volatility before the disaster and average volatility after the stock market reaches a stable state. Recoverability is computed by finding the difference between first and second breakout date.Reactivity can be gauged by the time disaster strikes to the time the volatility reaches a stable state. Since we considered data from 50 days before and after for all the disasters, reliability could not be measured.

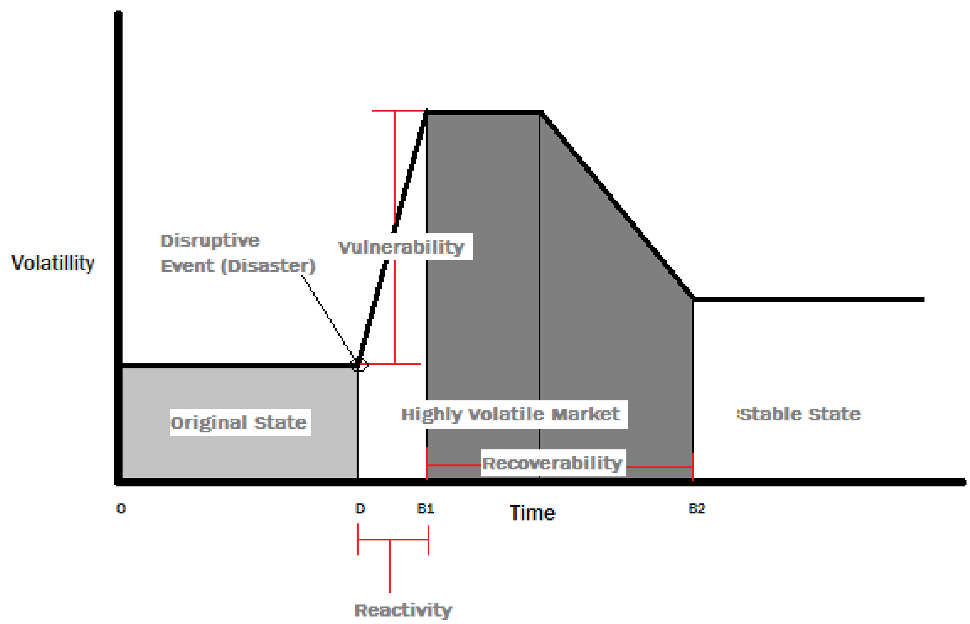


Figure 4.1 : Stock market state transitions over time

Volatility (*ΔV)* transitions overtime for a disruptive event/disaster is illustrated in Figure 4.1.

O-D is the number of days between the start date and disaster. *B1-B2* is the number of days between first and second breakout. *AvgΔV[O-D]*, *AvgΔV[B1-B2]* and *Avg ΔV[B2-End]* are the average volatilities for the respective durations.

Table 4.2: Different parameters for various disasters

Disaster	D-B1	B1-B2	Avg ΔV [O-D]	Avg ΔV [B1-B2]	Avg ΔV [B2-End]	Avg ΔV [O-D]- Avg ΔV [B1-B2]
Ivan	19	15	6.95%	24.58%	8.76%	17.63%
Katrina	18	14	5.81%	10.64%	1.46%	4.83%
Wilma	7	15	5.90%	7.42%	5.66%	1.52%
Ike	3	10	18.89%	84.59%	34.60%	65.70%
Sandy	26	10	3.15%	9.00%	5.25%	5.85%

A generalized schematic below in Figure 4.2 shows a comparison of Average *ΔV*during, before and after the event.

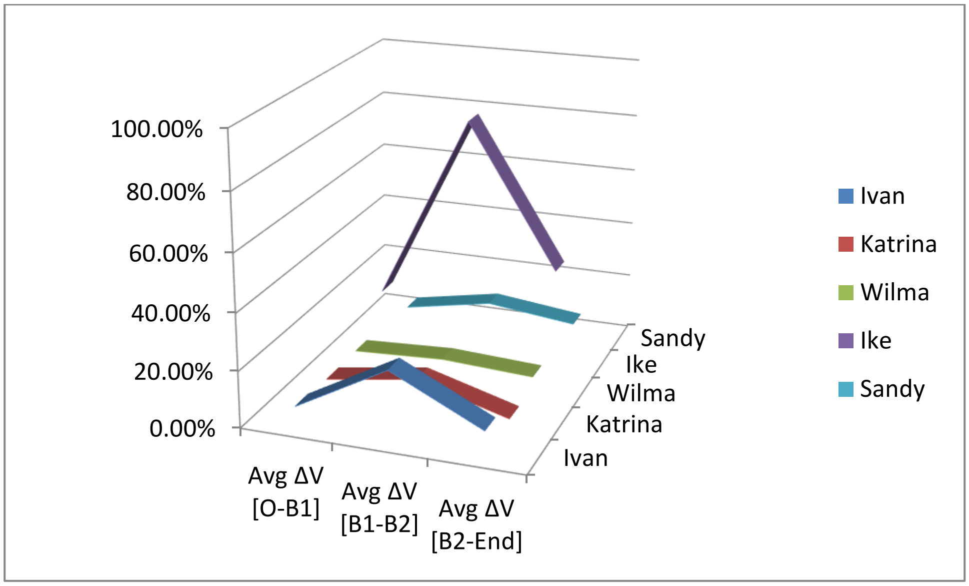


Figure 4.2 : Comparison of change in volatilities during disasters

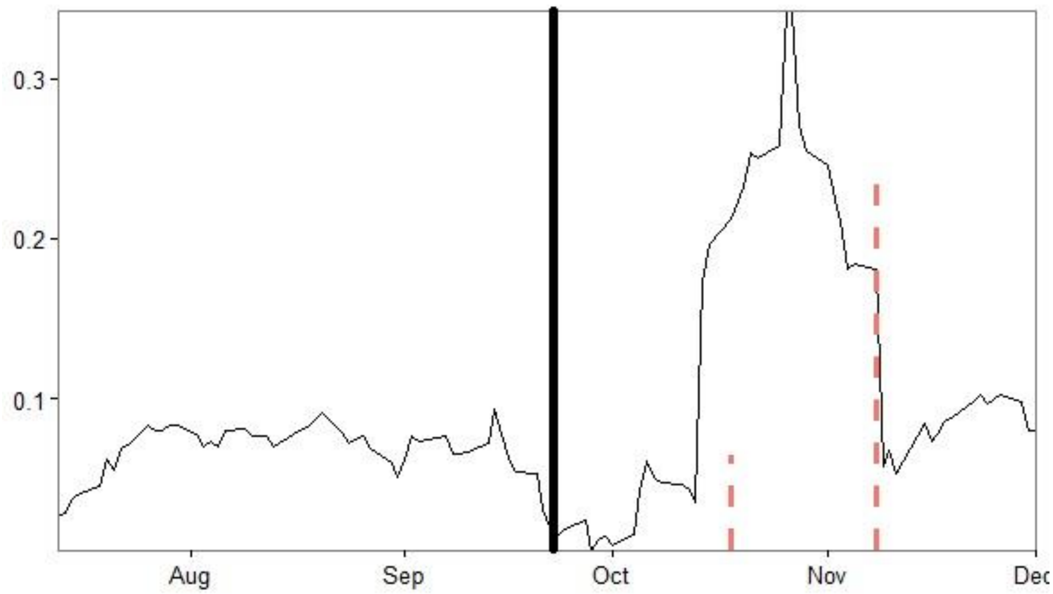


Figure 4.3 : Breakouts and Path Mapping for Ivan

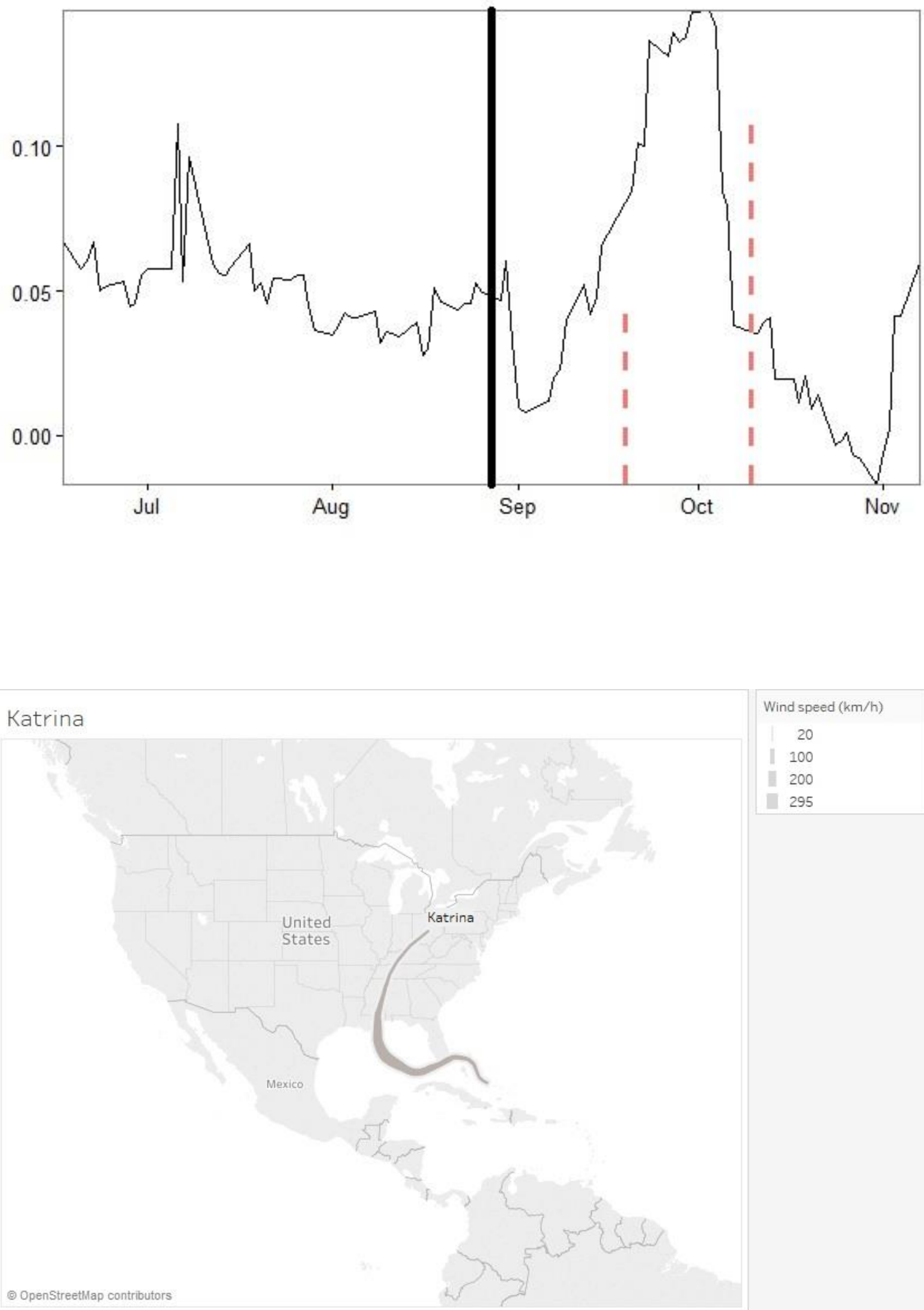
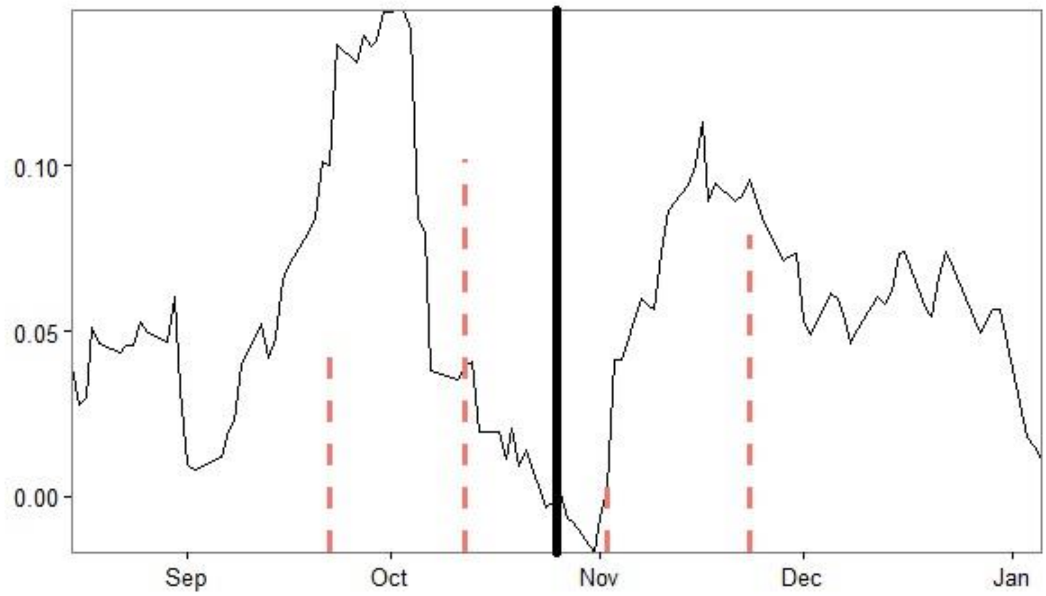


Figure 4.4 : Breakouts and Path Mapping for Katrina



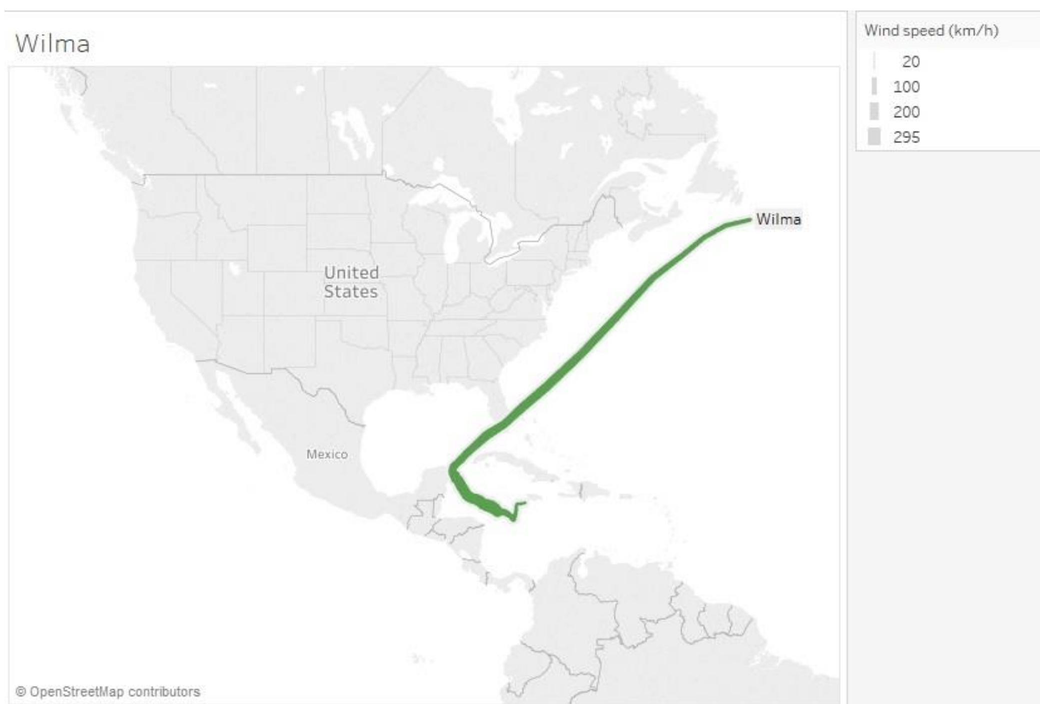


Figure 4.5 : Breakouts and Path Mapping for Wilma

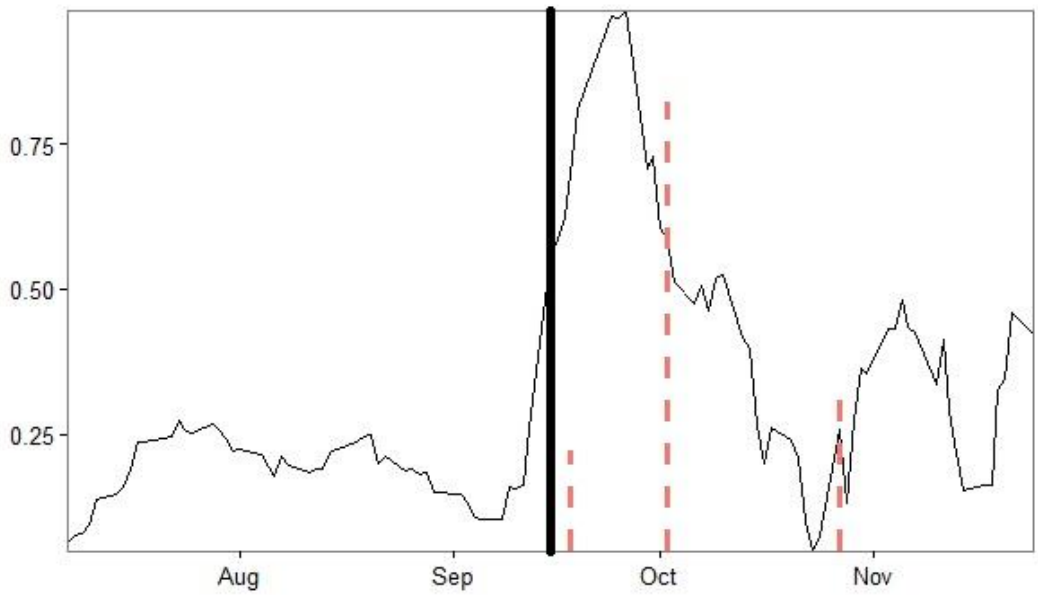


Figure 4.6 : Breakouts and Path Mapping for Ike

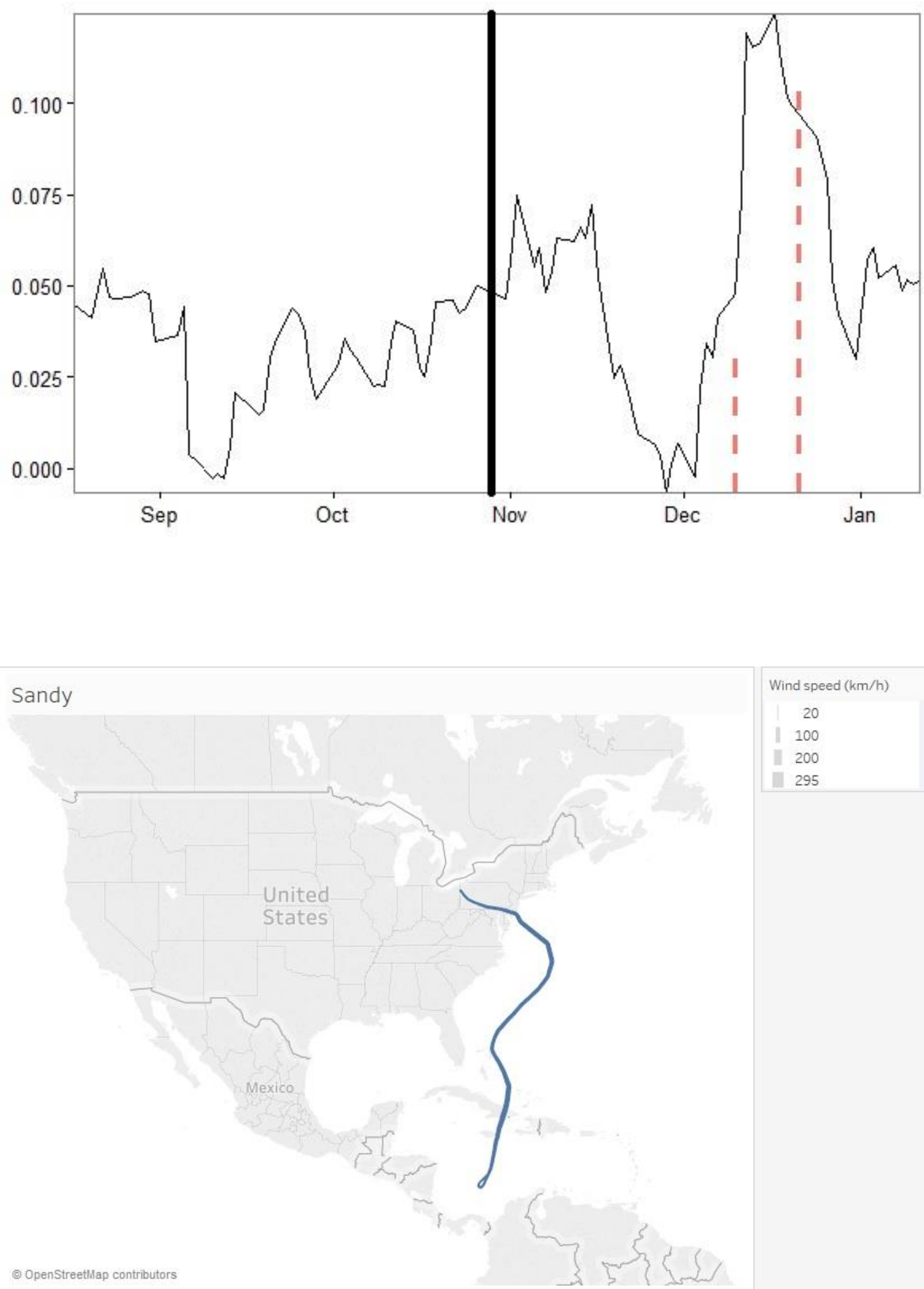


Figure 4.7 : Breakouts and Path Mapping for Sandy

4.3 Discussion

The results obtained above paint a clear picture in terms of resiliency of natural disasters. Analysis of the five biggest natural disasters in US history shows that they did affect the P&C sector. The study shows that stock market was most vulnerable to Hurricane Ike. This incredibly high vulnerability can be attributed a combined result of the disaster and already present uncertainty in market prevailing due to one of the biggest market crash in the US history. Stock market during Hurricane Ivan came in second in terms of vulnerability followed by stock market during Sandy, Katrina and Wilma. In terms of recoverability, disasters occurring after 2005 happen to have a greater recoverability than the ones before that which can also be attributed to availability of more information and data. Duration of recovery for these disasters came down from approximately 3 trading weeks to 2 trading weeks. In terms of reactivity, the market during Ike was most reactive. Stock market in times of Wilma ranked came in second. Wilma hit approximately 20 days after Katrina and existing insecurity in the market after Katrina could have led to the quick reaction to the event. Markets during other hurricanes in the list were less reactive to the impact. In terms of reactivity, Sandy outperformed all, this can be credited to the fact that it was the latest of all the disasters. Advancement in technology, availability of more data, more and more ongoing research in the field has diminished the panic in stock markets prevalent during a disaster.

While analyzing the path and “direction of attack” we observed that insurance stocks tend to be more volatile and less resilient during hurricanes that enter the United States from Gulf of Mexico. Even though there weretwo big hurricanes entering from the Atlantic Ocean insurance stocks were less volatile and more resilient during that period of time. The exception to the above observation was hurricane Katrina which was the biggest natural disaster in US history. It entered the country from Gulf of Mexico, regardless the stock markets were more resilient. The reason behind this anomaly can be attributed to the cashflow in forms of large number of new subscriptions and hedge funds getting involved in reinsurance after 2004 [19] taking away the liability of the insurance companies operating at that time. Although the analysis of relationship between path and resilience was interesting it won’t be fair to conclude anything from data used from five disasters only. More study needs to be performed in this area before reaching any definitive result.

Relative Resiliency Ranking

Although the parameters are significant and complete in themselves we have also tried to come up with an overall resiliency ranking in order to be able to compare the market resilience during a disaster as a whole.

Assuming all the three parameters to have equal weights, weranked the disasters and calculated the overall resilience of stock market during a disaster. The lower the rank more resilient the stock market in comparison to others. Relative resilience was found by arranging the disaster with the lowest combined rank as most resilient and so on.

Table 4.3: Results- Relative Resiliency Ranking

Disaster	*Ranking*			Overall Resiliency
	Vulnerability	Recoverability	Reactivity	
Ivan	4	5	2	4
Katrina	2	3	3	2
Wilma	1	5	4	3
Ike	5	1	5	4
Sandy	3	1	1	1

Vulnerability:

Vulnerability was highest during Ike followed by Ivan, Sandy and Katrina. Market during Wilma was least vulnerable.

Recoverability:

When talking in terms of recoverability insurance sector during Sandy and Ike recovered quickly followed by Katrina. Stocks during Wilma and Ivan took the longest to recover.

Reactivity:

In our analysis we found out that insurance sector during hurricane Sandy was least reactive followed by Ivan, Katrina and Wilma. Stock market during Ike had the highest reactivity.

Overall Resiliency:

According to our analysis out of the above disasters insurance sector in stock market was most resilient during the period of hurricane Sandy followed by hurricane Katrina. Wilma followed next, stock markets were least resilient during Ivan and Ike.

Chapter 5

Conclusion

The real motivation behind this research was unavailability of research material on quantifying the metrics related to resilience in stock markets. To the best of our knowledge nobody has performed study in this field-being able to compare various stock market situations during disasters.

In our study we find that however much we try to isolate the sector volatility caused by the disaster there will always be presence of some effect of the overall market sentiment (as in case of 2008 Market Crash/ Hurricane Ike) on the sector. We have tried to minimize this effect by utilizing relative volatility instead of volatility.

One of the biggest hurdles in data intensive studies is being able to gather clean and accurate data. A large portion of our time was invested in trying to find financial data and making it useable for our study.

During the study it was found out that stock markets exhibit a time lag while reacting to a disruptive event before showing change in performance levels. We termed this phenomenon as ‘reactivity’. In our study reactivity has been used as a resilience parameter. Reactivity can be used while analyzing resilience in other systems which showcase similar behavior when reacting to a disruptive event.

In this work, we used Breakout detection tool developed by Twitter to find out breakout points in time series. The breakout detection EDM technique is robust and quick. For our study we used multiple breakout analysis which can be made enhanced and with more options similar to the case of single breakout analysis. Breakout detection uses penalization arguments (beta, degree) to strike a balance between too much segmentization and too less breakouts. We had to come up with multiple simulations before achieving ~ 2 breakouts for every time series. A tool that takes number of breakouts as an input parameter and is robust can be very useful for studies similar to ours.

Our hypothesis that advancement in technology affects resiliency in stock markets in a positive way was proved by the case of Sandy which although was the second biggest disaster in terms of damage but was less vulnerable, quickest to recover and was least reactive .

While calculating volatility we annualized it using the cue from Black and Scholes Model that stock markets follow a Brownian Motion. Also the N for calculating the volatility was considered 10 (2 trading weeks). It can be increased or decreased to observe changes in volatility. Also, while we used statistical volatility for our study, some researchers might be interested in considering High Low Range Volatility for their analysis.

Another portion of the study that we were interested in was geographical path mapping of the disaster using Tableau. We plotted geo points of the data retrieved from hurricane servers into continuous lines. It was concluded that location of entry point of a hurricane also affects the resiliency of the stock market. More hurricanes can be analyzed in future to further strengthen our findings.

Future studies can include analysis of different types of natural disasters all around the globe. An approach to include reliability as a key metric can be determined. More robust tools for determining significant shifts and a better capability at understanding, analyzing and quantifying market sentiment are needed.

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