2019

Relationship Between Financial Markets and Natural Disasters in the US

Esteban Giraldo
egiraldo1108@gmail.com

Relationship Between Financial Markets and Natural Disasters in the US

By

Esteban Giraldo

An Honors Project Submitted in Partial Fulfillment

of the Requirements for Honors in the

Department of Economics and Finance

Rhode Island College

2019

TABLE OF CONTENTS

ACKNOWLEDGEMENTS

First, I would like to express my most sincere gratitude to Dr. Kemal Saatcioglu, for his extensive efforts in helping me complete this project. Similarly, I would like to give a special thanks to Dr. Sanae Tashiro, who got me started in the process for this project. I would also like to extend a thank you to the members of the Economics and Finance Departmental Honors Committee, including: Dr. Kazemi, Dr. Aydogdu, Dr. Blais, and Dr. Basu, for their time and input during the presentations, as well as the notes I received to improve this paper. Also, I would like to thank the Economics and Finance Department Chair, Dr. Karim. Everyone's involvement is highly appreciated, and this paper reflects the contributions from those mentioned.

ABSTRACT

The objective of this study is to find out how different sectors of the market, as defined by the Bloomberg Industry Classification Standard (BICS), react before and after different natural disasters, such as hurricanes, earthquakes and tornados. Public cross sectional and time series data from NOAA, Unisys Weather, and the USGS were collected, in order to build a data set that could be used for this study. OLS regressions, as well as fixed effects regressions were used to achieve the results. Among the major findings is a highly significant upward reaction in the returns of the energy sector when property damage from a tornado occurs.

INTRODUCTION

Do stock prices get affected by natural disasters? This is a question that has recently started to be studied more in academic literature, but one that still needs further exploration since it could have important trading implications as natural disasters –hurricanes, tornados, and earthquakes– are natural phenomena that occur on a repeated basis. Does the overall financial market proxied by S&P 500 or the Dow Jones Industrial Average get affected uniformly or do different sectors within the financial markets such as financials, materials, utilities, technology, health care, energy, consumer staples, and consumer discretionary show different reactions to such events? While several studies to date have looked at the overall financial market reaction to disasters, this study, to our knowledge, is the first to conduct a systematic analysis of the reaction of all available individual sectors to natural disasters and attempts to find whether a long, short, or a combination strategy generates positive returns.

The goal of this study is to come up with a model, or at the very least some rules to use in case of natural disasters, to mitigate financial losses for individuals. The study uses historical sector price data of the week an event occurs to assess the price reaction to the event. It further uses historical sector price data over a longer term to see what type of price trends occur after the natural disaster. If there are observable price trends for the overall market or for some sectors within the market, perhaps they can be turned into trading strategies that will yield positive returns. These strategies could then be used by individuals that live in natural disaster-prone areas and thus are susceptible to losses in the case of natural disasters as well as companies such as insurers, that would be adversely affected by natural disasters as financial tools that would help them hedge their exposure to natural disasters.

Major objectives of this project were to come up with a working model using a dataset that includes weekly returns by sector, compared to different natural disasters occurring per week and hopefully coming up with the effect of said natural disasters on returns. This paper collects twenty-eight years of weekly returns in the different sectors of the market, as well as data of twenty-eight years of hurricanes per week, and earthquakes per week. Along with tornados per week, the damage attributed to each tornado is also collected. All the data is for disasters that happened on the continental United States. Recently researchers have started paying attention to this topic especially since the occurrence of natural disasters has increased as climate change takes effect on our world. For example, Koerniadi, et. al. (2012) find evidence suggesting earthquakes, hurricanes and tornados could negatively affect market returns several weeks after the events, while other disasters such as flood, tsunami and volcanic eruption may have limited impact on market returns.

The major contribution of this paper to the existing literature is a detailed look at twenty-eight years of weekly disaster data and its effect on stock markets not only in the aggregate but also on a sector basis. This paper's major findings include a confirmation of a negative effect on the cumulative stock market, when a catastrophe has occurred with high statistical significance. Furthermore, it confirms that returns for the market as whole go down when Property Damage from a tornado occurs. But when broken down by sector, this same Property Damage has a positive effect on the returns of the energy sector, and it is highly statistically significant. Other significant findings when broken down by sector are, that the returns of the DOW Jones Industrial Average and the Industrial sector are both affected negatively when a catastrophe transpires.

LITERATURE REVIEW

Several studies show there is a correlation between asset prices and natural disasters. [Barro (2009), Koerniadi, et. al. (2012), Nakamura (2013), Seetharam (2017)] They investigate the extent of the decline before and immediately after a disaster, and the length of time a recovery takes to develop. This paper builds on their work in setting the parameters for the dataset and their analysis.

Barro (2009), Koerniadi, et. al. (2012), and Nakamura (2013) focus on large scale disasters such as World Wars and Pandemics. They attempt to come up with a risk premium in order to make up for the potential loss during these great disasters. Nakamura (2013) finds a rather large value for their risk premium and reports: *"Our model generates a sizable equity premium from* *disaster risk, but one that is substantially smaller than in simpler models. It implies that a large value of the intertemporal elasticity of substitution is necessary to explain stock-market crashes at the onset of disasters."* [Nakamura (2013)]. The data for this study comes from an annual consumption dataset created by Barro and Ursua (2008) which includes 100 years of data from 24 different countries. Nakamura (2013) uses the Markov-Chain Monte-Carlo (MCMC) methods to conduct the empirical analysis. The goal of the study was to judge the size of the shocks during a disaster period, as well as the extent of recovery after disasters. Although this study focuses on disasters that from peak to trough last about 6 years; it also tests if a disaster started and ended immediately. The findings are that equities fare extremely poorly relative to bonds at times of a disaster, and this behavior generates a large equity premium in normal times. [Nakamura (2013)]. This disaster effect coincides with the hypothesis of this paper that natural disasters will have a negative effect on stock returns. In comparison to these long-term disasters, however, weather catastrophes occur and end pretty much as soon as they begin.

In his "Rare Disasters, Asset Prices, and Welfare Costs" article published in the American Economic Review, Barro (2009) builds on his previous work with a data set that considers 60 events for 35 countries over 100 years. It adds more parameters to account for asset pricing in different economies. This study also focuses on large economic disasters; but Barro notes: *"In contrast, the probability parameter p and size parameter b refer to major economic disasters,* *such as those that occurred in many countries during World Wars I and II and the Great Depression. ... To go further, decreases in p or b constitute reductions in the probability or size of disasters not yet seen or, at least, not seen in the 20th century. Included here would be nuclear conflicts, large scale natural disasters (tsunamis, hurricanes, earthquakes, asteroid collisions), and epidemics of disease (Black Death, avian flu)."* [Barro (2009)]. When we apply these results to weather related disasters, we can conclude that the welfare costs of disaster risk will lower GDP, therefore the perception of a disaster can create the fear that the stock market will drop because of the forward-looking decline in aggregate consumption, making the analysis in this paper relevant.

In "Natural disasters – Blessings in disguise?" Koerniadi, et. al. (2012) examine the impact of natural disasters on market returns and on several industries. The authors indicate the reason for their study as the prediction by Oxford University researchers that natural disasters will increase in the coming decade due to global warming. The study includes earthquakes, hurricanes, tornados, floods, tsunamis, and volcanic eruptions, that occurred in numerous countries with developed stock markets. They study how these events affect market returns and the returns of several industries, expected to be most affected in a negative or positive manner. They find that natural disasters do in fact have a negative effect on certain sectors and industries. The setup of Koerniadi, et. al. (2012) is the most similar to this research paper. Where they differ is that the focus of this study is only on US based catastrophes and markets, and Koerniadi, et. al. (2012) does not include macroeconomic control variables, such as CPI or GDP. They do find that market returns react negatively to earthquakes, hurricanes and tornados which is in line with the questions and expectations of this paper.

Seetharam (2017) describes the impact of 122 major catastrophic events, on publicly listed companies that were geographically affected by these events. The study compares the returns of exposed companies to non-exposed companies, using a standard cross-sectional event study methodology. Another question Seetharam (2017) attempts to answer is whether the impact to exposed companies is worse on multi-plant firms vs. single-plant firms. The findings include: *"The estimates suggest a sizable decline in the value of exposed firms relative to nonexposed firms. The immediate effect … is small and only significant at the 10% level, but the effect in longer horizons are all larger and significant at the 1% level."* The study estimates the fall in market valuation to be 0.3 and 0.7 percentage points in the 15-day horizon and the 45-day horizon, respectively. The adverse impact is found to be mainly centered on single-plant standalone firms and multi-plant firms seem to retain their adaptive capacity to counter the adverse costs of extreme weather. The results of this study are very relevant to this study because it has similar findings of negative effects from catastrophes on market returns or company valuations while using a cross-sectional event study methodology as opposed to the fixed effects OLS method used here.

THEORY AND TESTABLE HYPOTHESIS

The theory in this paper is that when natural disasters occur, there will be a measurable negative effect on weekly returns in most sectors and market indices. The findings here are similar to those in Koerniadi, et. al. (2012): *"We find that different natural disasters have different impacts on the returns of the market and on those of industries. Our evidence suggests that while earthquake, hurricane and tornado could negatively affect market returns several weeks after the events, other disasters such as flood, tsunami and volcanic eruption may have limited impact on market returns".* Furthermore, these disasters could potentially have a positive effect on other sectors.

Unlike Koerniadi, et. al. (2012) the data for this study is controlled for inflation, unemployment, GDP, the purchasing managers index, and mortgage applications, to help show the isolated effects on returns caused by catastrophes and property damage. This paper hypothesizes that, if a natural disaster occurs, there will be a quantifiable effect on weekly returns.

Hypothesis	**Independent Variable**	***β***	**Expected Sign**	**Theory/Existing Findings**
H1	Returns	$\beta 1$	$\beta 1 < 0$	Natural disasters will have a negative effect on weekly financial market returns (Y).

DATA

This paper uses financial and economic data obtained from the Bloomberg terminals in the Rhode Island College Finance Lab. It contains twenty-eight years of weekly price data starting in January 1990 and going through April 2018, for the overall market indices Dow Jones Industrial Average (DJIA), Standard & Poor's 500 (S&P 500), Nasdaq Composite, and Russell 2000, as well as the following nine sectors: Materials, Industrials, Technology, Health Care, Consumer Staples, Consumer Discretionary, Energy, Financials, Utilities. Once this data was collected the price information was used to calculate the returns per week for the 28 years of data which left 1,456 observations for each sector and market index, or 18,928 total return observations.

Hurricane data was taken from the Unisys Weather website[1]. The data was broken down by week and category for each hurricane that occurred in the past twenty-eight years were provided. The earthquake data was found on the United States Geological Survey (USGS) website[2] where it was listed by date. The tornado information along with the property damage data contained in this paper was acquired from the National Oceanic and Atmospheric Administration (NOAA) website[3]. Dummy variables were used to designate if there was an event that week (1) or not (0).

---

1 https://www.unisys.com/industries/government/unisys-federal/unisys-weather

2 https://pubs.usgs.gov/gip/earthq4/severitygip.html

3 https://www.nssl.noaa.gov/education/svrwx101/tornadoes/

The data for natural disasters was collected starting with tornados greater than EF-3 on the Enhanced Fujita Scale[4], which includes tornados with wind speeds of 136 mph or higher. EF-3 damage is considered severe, and roofs, heavy cars, trees and structures with weak foundations will be blown away some distance with the damage increasing with each category up to EF-5 where winds exceed 200 mph. The property damage in millions of dollars accredited to each tornado was also recorded when this value was higher than $2.5 million. Moving onto hurricanes, data for those greater than category 3 were collected. These hurricanes have wind speeds higher than 111 mph. According to the Saffir-Simpson Hurricane Wind Scale which is used by NOAA, *"hurricanes reaching category 3 or higher are considered major hurricanes because of their potential for significant loss of life and damage.[5]"* Finally, earthquakes greater than 4 on the Richter scale were added to the data set. According to the USGS, earthquakes of magnitude 4 and higher are felt by people and some damage can occur.

The economic data collected from the Bloomberg terminal were the top-rated market indicators by analysts in Bloomberg, which were mortgage applications and the Purchasing Managers Index. Also, the Federal Reserve Economic Data (FRED) website[6] was used to collect twenty-eight years of monthly data for CPI, real GDP, and the Unemployment Rate. These

---

4 https://weather.com/storms/tornado/news/enhanced-fujita-scale-20130206

5 https://www.nhc.noaa.gov/aboutsshws.php

6 https://fred.stlouisfed.org

macroeconomic indicators were selected due to the extensive research that shows these fundamental variables to have power in predicting stock returns. Chen, Roll and Ross (1986) find that changes in aggregate production, inflation, and the short-term interest rates are among the macroeconomic factors that have some power to predict stock returns and they conclude that expected returns are a function of business conditions. The unemployment rate, also followed closely by the federal reserve, was selected as a barometer of economic activity proxying for the health of the current economy.

In total the dataset contains 29,120 different datapoints which are observations of the same entities per week, year over year, for twenty-eight years. This makes it a cross-sectional panel-data, so regression methods were adjusted as such. The dependent variables used in the empirical model are the returns of the indexes and the sectors used (Y). After some data analysis, the individual dummy variables of Hurricanes, Tornados and Earthquakes were found not to be statistically significant on their own. Subsequently, they were combined to create a consolidated variable called Catastrophe which did show statistical significance when it came to predicting market returns. The independent variables used in the study include this new Catastrophe dummy variable ranging from 0 to 3 (X_1), Consumer Price Index or CPI (X_2), Unemployment Rate (X_3), Gross Domestic Product or GDP (X_4), Purchasing Managers Index or PMI (X_5), Mortgage

Applications (X_6), and Property Damage (X_7). CPI, Unemployment Rate, GDP, PMI, and Mortgage Applications are used as control variables.

DESCRIPTIVE STATISTICS

Table 1 shows all the variables in this study listed with their Mean, Standard Deviation, Minimum, Maximum, Standard Error, and Variance. The relevant variables are the independent variables: catastrophes and the property damage. The dependent variables are the sector and market index returns. This is because the project is about the effect of the catastrophes on returns as time goes by. CPI, Unemployment Rate, GDP, PMI, and Mortgage Applications are in the model as control variables because it is obvious that returns do not solely depend on catastrophes. In order to have the model explain more of the change in returns, the control variables were added.

Table 2, Panels A through M present the correlation matrices for the variables for each index or sector. The sector with the highest weekly return for the last twenty-eight years was the Technology sector with a 0.25% weekly return, with the second highest return being the NASDAQ at 0.23%. This makes sense considering the NASDAQ index is heavily weighted in the Technology sector. The sector with lowest weekly return for the last twenty-eight years was the Utilities sector with 0.09% weekly return. Another interesting finding is that the mean for Property Damage caused by a tornado is $22.69 million.

Additionally, in the various panels of Table 2 it was found that the control variables were not correlated with each other, so they could be used in the model. The sector with the highest correlation to catastrophe was Industrials, and the index with the highest correlation to catastrophe was the Dow Jones. The Dow Jones and the Industrials sector have a positive correlation of 0.914. The sector with the highest correlation to property damage was energy at 0.034, which is unexpected because this implies that when a tornado causes property damage, the energy sector returns go up.

EMPIRICAL METHODS

This paper uses empirical analysis with the standard linear regression model using Ordinary Least Squares (OLS).

$$Y_i = \alpha + X_{1i}\beta_1 + X_{2i}\beta_2 + X_{3i}\beta_3 + X_{4i}\beta_4 + X_{5i}\beta_5 + X_{6i}\beta_6 + X_{7i}\beta_7 + \varepsilon_i$$

where Y_i denotes the dependent variable implying weekly Returns, $\boldsymbol{X_i}$ is a 7x1 vector of weekly explanatory variables, $\boldsymbol{\beta}$ is 7x1 vector of unknown parameters, and ε_i is an error term. Explanatory variables (X_i) include: (1) Catastrophe; (2) CPI; (3) Unemployment Rate, (4) GDP, (5) PMI, (6) Mortgage Applications, and (7) Property Damage.

To control for potential heteroskedasticity in the dataset, OLS with white heteroskedasticity-consistent standard error was ran on the dataset.

The last model used was the Entity Fixed Effects Regression Model. This is because the data contains omitted variables that change from sector to sector which could affect Returns in a quantifiable way.

$$Y_i = \alpha + X_{1i}\beta_1 + X_{2i}\beta_2 + X_{3i}\beta_3 + X_{4i}\beta_4 + X_{5i}\beta_5 + X_{6i}\beta_6 + X_{7i}\beta_7 + D_{1i} + \ldots + D_{12i} + \varepsilon_i$$

where Y_i denotes the dependent variable implying weekly Returns, $\boldsymbol{X_i}$ is a 7x1 vector of explanatory variables, $\boldsymbol{\beta}$ is a 7x1 vector of unknown parameters, and ε_i is an error term. Explanatory variables (X_i) include: (1) Catastrophe; (2) CPI; (3) Unemployment Rate, (4) GDP, (5) PMI, (6) Mortgage Applications, and (7) Property Damage. Dummy variables D_1 through D_{12} are the entities or sectors used to control for unobservable variables (or characteristics) that vary from one entity to another but do not change over time.

EMPIRICAL RESULTS

We first examine the relationship of the weekly returns of market indices and S&P 500 sectors, to weather catastrophes through a fixed effects regression. The estimated model, presented in Table 3, is:

$$Y_i = -0.148 - 0.067x_1 - .063x_2 + .019x_3 + 0.019x_4 + 0.007x_5 - 0.008x_6 + 0.0001x_7$$

where Y_i is the weekly S&P500 index returns, and x_1 through x_7 are the explanatory variables of catastrophe, consumer price index, unemployment rate, gross domestic product, purchasing managers index, mortgage applications, and property damage, respectively.

Using the data with particular attention to how catastrophes affect returns, an empirical analysis is performed and this model is created. The results outlined in Table 3 show that there is in fact heteroskedasticity in the dataset, because when the OLS was run with the white heteroskedasticity-consistent standard errors, the standard errors in the regressions went down significantly. The next finding from Table 3 is that Catastrophes do have an effect on Returns. According to the coefficient of Catastrophe, for every unit catastrophe increases, weekly returns decrease by 6.7%, with a statistical significance level of 5%. This confirms this paper's hypothesis of catastrophes having a negative effect on returns. On Table 3 Property Damage also has a negative effect on returns: when property damage goes up by 1 unit ($1 million), weekly returns go down by 0.02%, at the 1% significance level. Most of the control variables also influence returns as expected and CPI, GDP and Mortgage Applications are found to be statistically significant at least at the 10% level. The entity fixed effects model was confirmed to be useful in this case because R^2 increased from .033 to .036 when the entity fixed effect was included.

Table 4 contains the regressions ran for each index or sector returns while controlling for heteroskedasticity. In order to narrow down which sector had the lowest p-value, the models were run by sector because there was a highly significant coefficient for catastrophe. The Industrials sector (Table 4 – Panel L) had the second lowest p-value and according to column 4 the returns go down by 1.4% every time catastrophe increases by 1 unit, at a statistical significance level of 15%. Industrials also had the highest negative correlation with catastrophe out of all the other sectors. The p-value for the Dow Jones (Table 4 – Panel A) was even lower just above the 10% level of significance at 0.105.

One more interesting discovery is that the variable Property Damage has highly significant results for the energy sector on Table 4 – Panel G. For every unit that Property Damage goes up, energy sector returns go up by .01%, at the 5% level of significance. These findings are very exciting because they offer a clue on which way to continue this research. Diaz de Gracia (2016) investigate the impact of oil prices on stock returns from January 1974 to December 2015 and find that in the short run a significant positive impact to oil prices is beneficial to energy stock prices. They also find that this relationship becomes statistically significant after 1986. [Liu, et. al. (2017)]. This could explain why the Energy sector returns increase when there is property damage from a tornado, because when infrastructure and pipelines are damaged this can cause a contraction in the oil supply which in the short term leads to an increase in the price of oil and therefore, leading to an increase in Energy sector prices. We leave investigating the long-term effects of this on Energy sector prices to a future study.

CONCLUSIONS AND DISCUSSION

When large scale external shocks occur, stock markets are expected to be affected in different ways depending on the index or industry. The worse the disaster (and the more unexpected it is) the higher the stock market reaction is expected to be. This study finds that there is in fact a negative relationship between catastrophes and returns, with high statistical significance which is consistent with the literature that has been compiled by academia. According to the findings, when a catastrophe happens, returns go down but historically not by much. This can be attributed to the sheer size of the financial markets, especially in the US where NYSE alone trades at a daily volume of $169 billion. *"The costliest natural catastrophe recorded to date is the 2005 landfall of Hurricane Katrina in Louisiana, with an estimated destructive cost of around $150 billion, of which $62 billion was covered by the insurance industry. This is less than a single percentage point of movement on the New York Stock Exchange."* [Mahalingam, et. al. (2018)]. As the global economy becomes more intertwined, and weather disasters become more destructive, we would expect the costs to keep increasing making the negative effects greater on financial markets as time goes on.

Market indices and Industries were also tested against catastrophes, and the Dow Jones and Industrials sector had the highest statistical significance in this test at 15% and 10.5%, respectively. One explanation for this is that when catastrophes ensue, the destruction of property take its toll on these industries, such as Airlines, Air freight, Road and Rail, and Transportation Infrastructure. The price of oil can be pushed up when a catastrophe transpires, which directly hurts the industries just mentioned because it makes their cost to operate more expensive. This cost increase compiled with the capital investment necessary to fix whatever broke after a catastrophe, can drive investors to sell off the Industrials as soon as bad weather hits. Since the Dow Jones is heavily weighted with Industrials, and since it has a very high correlation with it, these effects show up in both asset classes.

The highest statistical significance of the explanatory variables to any sector is the positive relationship between the Property Damage variable to the energy sector. *"The oil and gas industry has been favoured by investors in recent years due to the increasing oil prices during the period between 2008 and 2014. The number of mutual funds and exchange traded funds that invest in oil and gas industry companies also increased during this period."* [Ramos and Veiga (2011)]. This positive relationship between oil prices and asset prices explains the positive coefficient generated for property damage. A more counterintuitive argument is that due to the destruction of property, capital investments will follow, some paid for by insurances. This would lead to upgraded infrastructure at a lower cost than if they paid for it without the insurance payout.

FUTURE RESEARCH

Future research should include more controlled variables, and new variables like P/E ratios, Return on Equity, Risk free rate, 10-year T-bill rate, WTI Oil price and the Price to dividend ratio. This would be important in order to continue to increase the R-squared for this model. Expanding this research can lead to a pathway for investing during different types of events that are unexpected and affect returns.

The next step to further this research would be to perform an event study as in Ruiz, et. al. (2014). *"These studies are useful because the event's effect is immediately reflected in stock prices (Fama, et al., 1969). Therefore, a measure of the economic impact of the event can be easily developed using the observed prices of securities over a short period of time."* [Ruiz, et. al. (2014)]. There could be several event studies performed, one using the returns of when the largest Property Damages recorded happen. Another study that can be done is to come up with a predictions for the timing of catastrophes (for example using time series analysis or even artificial intelligence or neural networks) and then investigate in the event study the months when catastrophes are abnormally high or low compared to the predictions, to see if the contemporaneous or subsequent returns are also abnormally high or low.

TABLES

TABLE 1
Descriptive Statistics

All Samples n=1,456						
Variables	Mean	Std. Dev.	Min	Max	Std. Err.	Variance
Dow Jones	0.174	2.189	-18.151	11.291	0.057	4.792
S&P 500	0.164	2.235	-18.196	12.025	0.058	4.997
Nasdaq	0.232	3.014	-25.304	18.978	0.078	9.089
Russell	0.189	2.764	-16.400	16.382	0.072	7.641
Materials	0.149	2.925	-15.329	15.159	0.076	8.557
Industrials	0.179	2.599	-17.413	12.422	0.068	6.753
Technology	0.252	3.440	-21.490	15.700	0.090	11.843
Healthcare	0.206	2.409	-18.425	9.583	0.063	5.806
Cons Stap	0.174	1.972	-15.940	10.979	0.052	3.890
Cons Disc	0.200	2.682	-18.283	17.064	0.070	7.192
Energy	0.167	2.942	-25.034	13.011	0.077	8.660
Financials	0.186	3.537	-23.702	33.851	0.092	12.517
Utilities	0.093	2.257	-20.236	8.315	0.059	5.094
Catastrophe	0.555	0.671	0.000	3.000	0.017	0.450
CPI	2.474	1.303	-2.100	6.300	0.034	1.699
Unem. R	5.989	1.553	3.800	10.000	0.041	2.403
GDP	2.435	2.423	-8.200	7.800	0.063	5.857
PMI	52.092	4.757	34.500	61.400	0.124	22.630
Mortgage Apps	0.666	11.235	-40.500	112.100	0.294	126.217
Property Damage	22.694	176.414	0.000	4987.000	4.623	501.483

TABLE 2
Variable Correlation Matrices by Index or Sector

Table 2 – Panel A: Correlation Matrix for S&P500

All Samples n=1,456

Variables	**S&P 500**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
S&P 500	1							
Catastrophe	0.009	1						
CPI	-0.059	0.138	1					
Unemployment	0.022	-0.021	-0.199	1				
GDP	0.018	0.020	0.080	-0.729	1			
PMI	0.037	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.019	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	0.011	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel B: Correlation Matrix for Dow Jones Industrial Average

All Samples n=1,456

Variables	**DOW**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
DOW	1							
Catastrophe	-0.043	1						
CPI	-0.039	0.138	1					
Unemployment	0.008	-0.021	-0.199	1				
GDP	0.025	0.020	0.080	-0.729	1			
PMI	0.034	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.068	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	0.011	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel C: Correlation Matrix for Nasdaq

All Samples n=1,456

Variables	**Nasdaq**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Nasdaq	1							
Catastrophe	-0.017	1						
CPI	-0.051	0.138	1					
Unemployment	0.026	-0.021	-0.199	1				
GDP	0.007	0.020	0.080	-0.729	1			
PMI	0.025	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.036	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	0.007	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel D: Correlation Matrix for Russell 2000

All Samples n=1,456

Variables	**Russell 2000**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Russell 2000	1							
Catastrophe	-0.041	1						
CPI	-0.041	0.138	1					
Unemployment	0.032	-0.021	-0.199	1				
GDP	0.003	0.020	0.080	-0.729	1			
PMI	0.028	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.025	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage		0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel E: Correlation Matrix for Consumer Discretionary Sector

All Samples n=1,456

Variables	**Consumer Disc.**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Consumer Disc.	1							
Catastrophe	-0.015	1						
CPI	-0.059	0.138	1					
Unemployment	0.041	-0.021	-0.199	1				
GDP	0.001	0.020	0.080	-0.729	1			
PMI	0.006	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.025	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	0.012	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel F: Correlation Matrix for Consumer Staples Sector

All Samples n=1,456

Variables	**Consumer Staples.**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Consumer Stap.	1							
Catastrophe	-0.039	1						
CPI	-0.0008	0.138	1					
Unemployment	0.015	-0.021	-0.199	1				
GDP	-0.0008	0.020	0.080	-0.729	1			
PMI	0.008	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.039	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	0.012	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel G: Correlation Matrix for Energy Sector

All Samples n=1,456

Variables	**Energy**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Energy	1							
Catastrophe	-0.007	1						
CPI	-0.012	0.138	1					
Unemployment	-0.002	-0.021	-0.199	1				
GDP	0.017	0.020	0.080	-0.729	1			
PMI	0.051	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.072	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	0.034	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel H: Correlation Matrix for Technology Sector

All Samples n=1,456

Variables	**Tech**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Technology	1							
Catastrophe	-0.015	1						
CPI	-0.049	0.138	1					
Unemployment	0.008	-0.021	-0.199	1				
GDP	0.012	0.020	0.080	-0.729	1			
PMI	0.031	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.031	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	0.011	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel I: Correlation Matrix for Financials Sector

All Samples n=1,456

Variables	**Financials**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Financials	1							
Catastrophe	-0.019	1						
CPI	-0.041	0.138	1					
Unemployment	0.013	-0.021	-0.199	1				
GDP	0.041	0.020	0.080	-0.729	1			
PMI	0.019	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	0.003	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	-0.002	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel J: Correlation Matrix for Utilities Sector

All Samples n=1,456

Variables	**Utilities**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Utilities	1							
Catastrophe	-0.004	1						
CPI	-0.003	0.138	1					
Unemployment	-0.002	-0.021	-0.199	1				
GDP	0.035	0.020	0.080	-0.729	1			
PMI	0.048	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.041	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	0.023	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel K: Correlation Matrix for Healthcare Sector

All Samples n=1,456

Variables	**Healthcare**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Healthcare	1							
Catastrophe	0.009	1						
CPI	-0.012	0.138	1					
Unemployment	-0.005	-0.021	-0.199	1				
GDP	0.003	0.020	0.080	-0.729	1			
PMI	0.009	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.044	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	-0.003	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel L: Correlation Matrix for Industrials Sector

All Samples n=1,456

Variables	**Industrials**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Industrials	1							
Catastrophe	-0.041	1						
CPI	-0.039	0.138	1					
Unemployment	0.016	-0.021	-0.199	1				
GDP	0.027	0.020	0.080	-0.729	1			
PMI	0.041	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	-0.054	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	0.005	0.114	0.032	0.081	-0.064	0.031	-0.018	1

Table 2 – Panel M: Correlation Matrix for Materials Sector

All Samples n=1,456

Variables	**Materials**	Catastrophe	CPI	Unem. R	GDP	PMI	Mort. Apps	Prop. Damage
Materials	1							
Catastrophe	-0.031	1						
CPI	-0.035	0.138	1					
Unemployment	0.013	-0.021	-0.199	1				
GDP	0.033	0.020	0.080	-0.729	1			
PMI	0.031	-0.023	-0.011	-0.280	0.538	1		
Mortgage Apps	0.006	-0.014	0.012	0.035	-0.002	-0.056	1	
Property damage	-0.003	0.114	0.032	0.081	-0.064	0.031	-0.018	1

TABLE 3
Empirical Results: Fixed Effects Empirical Method

Dependent Variable: S&P500 Index returns				
n=18,928	Regular (robust)		Fixed Effects (robust)	
Independent Variables	(1)		(2)	
Intercept	-0.158	**	-0.148	
	(0.336)		(0.027)	
Catastrophe	-0.066	**	-0.067	**
	(0.028)		(0.003)	
CPI	-0.063	***	-0.063	***
	(0.018)		(0.002)	
Unemployment Rate	0.019		0.019	
	(0.013)		(0.001)	
GDP	0.019	*	0.019	*
	(0.011)		(0.001)	
PMI	0.007		0.007	
	(0.006)		(0.001)	
Mortgage Applications	-0.007	**	-0.008	***
	(0.003)		(0.002)	
Property Damage	0.000	***	0.000	*
	(0.000)		(0.000)	
Other Control Variables	NO		NO	
Entity Dummy Variables	NO		YES	
R-Square	0.033		0.036	
F(7, 18928)	7.6	F(19,18928)	3.6	

Notes: Standard errors are shown in parentheses.
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

TABLE 4
Empirical Results: OLS by Sector

Table 4 – Panel A: Dependent Variable: Dow Jones Industrial Average

n=1,456

Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.253	0.384	0.357	0.234	-0.165	-0.041	0.025
	0.074	0.127	0.278	0.303	0.763	0.962	0.960
Catastrophe	-0.1422*	-0.127	-0.127	-0.128	-0.127	-0.131	-0.135
	0.085	0.086	0.086	0.086	0.086	0.084	0.084
CPI		-0.056	-0.055	-0.056	-.0526	-.052	-.054
		0.044	0.045	0.045	0.046	0.051	0.052
Unemployment Rate			0.004	0.015	0.010	0.012	0.008
			0.038	0.039	0.040	0.038	0.038
GDP				0.025	0.015	0.018	0.023
				0.025	0.030	0.032	0.031
PMI					0.008	0.006	0.005
					0.018	0.017	0.018
Mortgage Applications						-0.013	-0.013
						0.009	0.008
Property Damage							0.000
							0.001
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.000	0.002	0.005	0.006	0.006	0.007	0.009

Notes: Standard errors are shown under respective variable.
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel B: Dependent Variable: S&P 500

n=1,456

Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.148	0.389	0.296	0.158	-0.329	-0.295	-0.280
	0.076	0.130	0.284	0.310	0.779	1.048	1.050
Catastrophe	0.030	0.058	0.058	0.057	0.058	0.057	0.051
	0.087	0.088	0.088	0.088	0.088	0.087	0.088
CPI		-0.103**	-0.100*	-0.102**	-.097**	-.097*	-0.098*
		0.453	0.046	0.046	0.047	0.055	0.055
Unemployment Rate			0.014	0.026	0.021	0.021	0.020
			0.039	0.040	0.041	0.042	0.041
GDP				0.028	0.016	0.017	0.015
				0.025	0.031	0.034	0.034
PMI					0.010	0.010	0.010
					0.015	0.019	0.019
Mortgage Applications						-0.004	-0.034
						0.008	0.008
Property Damage							0.000
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.002	0.002	0.003	0.016	0.005	0.005	0.005

Notes: Standard errors are shown under respective variable.
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel C: Dependent Variable: Nasdaq							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.272	0.532	0.328	0.218	-0.233	-0.141	-0.101
	0.102	0.175	0.384	0.418	1.050	1.315	1.321
Catastrophe	-0.071	-0.041	-0.041	-0.042	-0.041	-0.044	-0.051
	0.118	0.119	0.119	0.119	0.118	0.116	0.116
CPI		-0.112*	-0.104*	-0.105*	-0.101	-0.101	-0.104
		0.061	0.062	0.062	0.063	0.061	0.062
Unemployment Rate			0.031	0.041	0.036	0.036	0.035
			0.052	0.054	0.055	0.058	0.058
GDP				0.022	0.011	0.013	0.013
				0.034	0.042	0.046	0.046
PMI					0.010	0.008	0.007
					0.020	0.024	0.024
Mortgage Applications						-0.009	-0.009
						0.010	0.010
Property Damage							0.000
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.000	0.002	0.005	0.005	0.005	0.005	0.005

Notes: Standard errors are shown under respective variable
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel D: Dependent Variable: Russell 2000							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.284	0.457	0.156	0.106	-0.638	-0.580	0.533
	0.094	0.161	0.352	0.383	0.963	1.248	1.250
Catastrophe	-0.169	-0.149	-0.149	-0.150	-0.148	-0.149	-0.155
	0.108	0.109	0.109	0.108	0.109	0.099	0.100
CPI		-0.074	-0.064	-0.064	-0.057	-.056	-.0606
		0.056	0.057	0.057	0.058	0.065	0.065
Unemployment Rate			0.046	0.050	0.042	0.042	0.040
			0.048	0.049	0.051	0.055	0.056
GDP				0.010	-0.008	-0.007	-0.007
				0.031	0.038	0.042	0.042
PMI					0.015	0.015	0.014
					0.019	0.023	0.023
Mortgage Applications						-0.006	-0.006
						0.012	0.123
Property Damage							0.000
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.000	0.002	0.003	0.004	0.004	0.005	0.005

Notes: Standard errors are shown under respective variable
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel E: Dependent Variable: Consumer Discretionary Sector							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.234	0.513	0.164	0.091	0.459	0.517	0.579
	0.091	0.155	0.341	0.372	0.018	1.235	1.241
Catastrophe	-0.062	-0.030	-0.031	-0.031	-0.032	-0.034	-0.039
	0.105	0.105	0.106	0.106	0.105	0.101	0.102
CPI		-0.120**	-0.107*	-0.108*	-0.111**	-0.111*	-0.114*
		0.054	0.055	0.055	0.056	0.064	0.065
Unemployment Rate			0.053	0.060	0.064	0.065	0.062
			0.046	0.047	0.049	0.048	0.048
GDP				0.015	0.024	0.025	0.026
				0.030	0.037	0.040	0.040
PMI					-0.008	-0.009	-0.010
					0.018	0.023	0.023
Mortgage Applications						-0.006	-0.006
						0.013	0.013
Property Damage							0.000
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.003	0.003	0.005	0.005	0.005	0.005	0.006

Notes: Standard errors are shown under respective variable
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel F: Dependent Variable: Consumer Staples Sector							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.238	0.217	0.078	0.074	-0.117	-0.048	0.014
	0.067	0.114	0.251	0.274	0.688	0.796	0.800
Catastrophe	-0.115	-0.117	-0.118	-0.118	-0.117	-0.120	-0.125
	0.077	0.077	0.078	0.078	0.078	0.076	0.077
CPI		0.009	0.014	0.01398	.01576	.0159	.0125
		0.040	0.041	0.041	0.041	0.045	0.045
Unemployment Rate			0.021	0.022	0.019	0.020	0.019
			0.034	0.035	0.036	0.031	0.031
GDP				0.001	-0.004	-0.002	0.002
				0.022	0.027	0.028	0.028
PMI					0.004	0.003	0.002
					0.013	0.015	0.015
Mortgage Applications						-0.007	-0.007
						0.006	0.006
Property Damage							0.000
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.002	0.002	0.002	0.002	0.002	0.003	0.004

Notes: Standard errors are shown under respective variable
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel G: Dependent Variable: Energy Sector							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.185	0.246	0.296	0.201	-1.533	-1.358	-0.122
	0.100	0.171	0.375	0.409	1.020	1.342	1.349
Catastrophe	-0.033	-0.026	-0.026	-0.027	-0.023	-0.029	-0.043
	0.115	0.116	0.116	0.116	0.116	0.109	0.109
CPI		-0.026	-0.028	-0.029	-0.013	-.0121	-.0156
		0.059	0.061	0.061	0.062	0.070	0.070
Unemployment Rate			-0.008	0.001	-0.019	-0.017	-0.021
			0.051	0.053	0.054	0.055	0.056
GDP				0.020	-0.024	-0.020	-0.012
				0.033	0.041	0.039	0.039
PMI					0.037*	0.033	0.031
					0.020	0.025	0.025
Mortgage Applications						-0.018*	-0.018*
						0.011	0.011
Property Damage							0.001**
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.004	0.005	0.005	0.005	0.005	0.007	0.009

Notes: Standard errors are shown under respective variable
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel H: Dependent Variable: Technology Sector							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.293	0.577	0.594	0.480	-0.339	-0.248	-0.173
	0.117	0.199	0.438	0.477	1.199	1.474	1.480
Catastrophe	-0.074	-0.040	-0.041	-0.042	-0.040	-0.043	-0.051
	0.134	0.135	0.136	0.136	0.136	0.137	0.138
CPI		-0.122*	-0.122*	-0.124*	-.1162	-.115*	-0.121
		0.069	0.071	0.071	0.072	0.068	0.068
Unemployment Rate			-0.002	0.008	-0.002	-0.001	-0.003
			0.059	0.062	0.063	0.061	0.061
GDP				0.023	0.003	0.005	0.008
				0.039	0.048	0.049	0.050
PMI					0.017	0.016	0.014
					0.023	0.027	0.027
Mortgage Applications						-0.009	-0.009
						0.010	0.009
Property Damage							0.000
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.002	0.002	0.004	0.004	0.004	0.004	0.004

Notes: Standard errors are shown under respective variable
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel I: Dependent Variable: Financials Sector							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.245	0.495	0.393	0.049	0.715	0.704	0.746
	0.120	0.206	0.450	0.490	1.232	1.714	1.719
Catastrophe	-0.106	-0.076	-0.077	-0.079	-0.081	-0.080	-0.078
	0.138	0.139	0.139	0.139	0.139	0.130	0.130
CPI		-0.108	-0.104	-0.107	-0.113	-0.113	-0.116
		0.072	0.073	0.073	0.074	0.099	0.100
Unemployment Rate			0.016	0.046	0.054	0.053	0.048
			0.070	0.063	0.065	0.059	0.059
GDP				0.070*	0.087*	0.087	0.089
				0.040	0.045	0.064	0.064
PMI					-0.014	-0.013	-0.014
					0.024	0.030	0.030
Mortgage Applications						0.001	0.006
						0.021	0.021
Property Damage							0.000
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.000	0.000	0.001	0.004	0.004	0.004	0.005

Notes: Standard errors are shown under respective variable
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel J: Dependent Variable: Utilities Sector							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.099	0.105	0.136	-0.029	-0.961	-0.883	-0.801
	0.077	0.131	0.288	0.313	0.787	1.001	1.005
Catastrophe	-0.012	-0.011	-0.011	-0.012	-0.010	-0.013	-0.023
	0.088	0.089	0.089	0.089	0.089	0.087	0.087
CPI		-0.003	-0.004	-0.005	0.003	.0036	-.0007
		0.045	0.047	0.047	0.047	0.050	0.050
Unemployment Rate			-0.005	0.010	-0.001	0.001	-0.017
			0.039	0.040	0.041	0.037	0.036
GDP				0.034	0.011	0.013	0.016
				0.025	0.031	0.032	0.032
PMI					0.020	0.018	0.017
					0.015	0.019	0.019
Mortgage Applications						-0.008	-0.007
						0.007	0.007
Property Damage							0.003
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.000	0.002	0.002	0.002	0.002	0.003	0.003

Notes: Standard errors are shown under respective variable
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel K: Dependent Variable: Healthcare Sector							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.191	0.250	0.307	0.312	0.077	0.164	0.174
	0.082	0.140	0.307	0.335	0.841	0.986	0.992
Catastrophe	0.028	0.035	0.035	0.035	0.036	0.033	0.038
	0.094	0.095	0.095	0.062	0.095	0.093	0.094
CPI		-0.025	-0.027	-0.027	-0.025	-.0248	-.025
		0.049	0.050	0.050	0.050	0.052	0.052
Unemployment Rate			-0.009	-0.009	-0.012	-0.011	-0.013
			0.042	0.043	0.044	0.039	0.040
GDP				-0.001	-0.007	-0.005	-0.002
				0.027	0.033	0.034	0.034
PMI					0.005	0.003	0.003
					0.016	0.018	0.019
Mortgage Applications						-0.009	-0.009
						0.008	0.008
Property Damage							-0.001
							0.002
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.001	0.002	0.002	0.002	0.002	0.002	0.002
Notes: Standard errors are shown under respective variable							
***, **, * indicate significant at the 1%, 5% and 10% level, respectively.							

Table 4 – Panel L: Dependent Variable: Industrials Sector							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.269	0.428	0.295	0.124	-0.505	-0.390	-0.330
	0.088	0.151	0.331	0.360	0.905	1.170	1.179
Catastrophe	-0.162	-0.144	-0.144	-0.145	-0.143	-0.148	-0.147
	0.101	0.102	0.102	0.102	0.102	0.096	0.097
CPI		-0.068	-0.063	-0.065	-.0588	-.058	-0.062
		0.052	0.054	0.054	0.054	0.064	0.064
Unemployment Rate			0.020	0.035	0.028	0.029	0.024
			0.045	0.046	0.047	0.050	0.050
GDP				0.035	0.019	0.022	0.026
				0.029	0.036	0.041	0.042
PMI					0.013	0.011	0.010
					0.018	0.021	0.021
Mortgage Applications						-0.012	-0.012
						0.011	0.011
Property Damage							0.000
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.022	0.024	0.024	0.003	0.004	0.004	0.005

Notes: Standard errors are shown under respective variable

***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

Table 4 – Panel M: Dependent Variable: Materials Sector							
n=1,456							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.142	0.285	0.203	-0.020	-0.154	-0.169	-0.146
	0.091	0.156	0.341	0.371	0.934	1.103	1.109
Catastrophe	-0.123	-0.106	-0.106	-0.107	-0.108	-0.107	-0.108
	0.105	0.106	0.106	0.105	0.106	0.103	0.103
CPI		-0.061	-0.058	-0.060	-.0590	-.059	-.0618
		0.054	0.055	0.055	0.056	0.056	0.057
Unemployment Rate			0.012	0.032	0.031	0.030	0.029
			0.046	0.048	0.049	0.042	0.043
GDP				0.046	0.042	0.042	0.043
				0.030	0.037	0.039	0.040
PMI					0.003	0.003	0.003
					0.018	0.021	0.021
Mortgage Applications						0.001	0.002
						0.012	0.012
Property Damage							0.000
							0.000
Other Control Variables	NO	NO	NO	NO	NO	NO	NO
Dummy Variables	YES	YES	YES	YES	YES	YES	YES
R-Square	0.002	0.002	0.003	0.003	0.003	0.004	0.004

Notes: Standard errors are shown under respective variable

***, **, * indicate significant at the 1%, 5% and 10% level, respectively.

REFERENCES

Barro, R. (2009) “Rare Disasters, Asset Prices, and Welfare Costs,” *The American Economic Review,* 99(1), pp. 243-264.

Barro, R. and J.F. Ursua. (2008) “Macroeconomic Crises since 1870,” *NBER Working Paper No. 13940.*

Chen, N., R. Roll, and S. Ross. (1986) “Economic forces and the stock market,” *Journal of Business*, 59, pp. 383–403.

Diaz, E.M. and F.P. de Gracia. (2016) “Oil price shocks and stock returns of oil and gas corporations,” *Finance Research Letters*.

Fama, E. F., L. Fisher, M.C. Jensen, and R. Roll. (1969) “The adjustment of stock prices to new information,” *International Economic Review*, 10(1), pp. 1-21.

Koerniadi, H, C. Krishnamurti, and A. Tourani-Rad. (2011) “Natural Disasters - Blessings in Disguise?” *24th Australasian Finance and Banking Conference*. Available at SSRN: https://ssrn.com/abstract=1913664 or http://dx.doi.org/10.2139/ssrn.1913664

Liu, J. and A. Kemp. (2017). “Forecasting the sign of U.S. oil and gas industry stock index excess returns employing macroeconomic variables.” Available at SSRN: https://ssrn.com/abstract=2990880 or http://dx.doi.org/10.2139/ssrn.2990880

Mahalingam, A., A. Coburn, C.J. Jung, J.Z. Yeo, G. Cooper, and T. Evan. (2018). "Impacts of Severe Natural Catastrophes on Financial Markets", *Cambridge Centre for Risk Studies.*

Nakamura, E. (2013). "Crises and Recoveries in an Empirical Model of Consumption Disasters," *American Economic Journal: Macroeconomics,* 5(3), pp. 35-74.

Ruiz, J. and M. Barrero. (2014). "The Effects of the 2010 Chilean Natural Disasters on the Stock Market," *Estudios de Administracion*, 21(1), pp.31-48.

Seetharam, I. (2017). "Environmental Disasters and Stock Market Performance," *Stanford University Working Paper*.

Appendix A: Websites where Data was Collected.

https://earthquake.usgs.gov/earthquakes/map

www.finance.yahoo.com

https://www.nhc.noaa.gov/aboutsshws.php

https://pubs.usgs.gov/gip/earthq4/severitygip.html

http://www.spc.noaa.gov/climo/torn/STAMTS14.txt

http://weather.unisys.com/hurricane/index.php

https://weather.com/storms/tornado/news/enhanced-fujita-scale-20130206