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Stormy Markets: The Effect of Hurricanes on Different Stock Sectors in the U.S.

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ABSTRACT

Keywords: Hurricanes, stock market, CARS

This study examines the financial impacts of five very impactful hurricanes in the US; Katrina, Ike, Sandy, Harvey, and Florence, on different stock market sectors by using cumulative abnormal returns (CARs) in t-tests and regression models. The findings show that the Consumer Goods sector is quite resilient as it shows positive significant coefficients in short-term and long-term windows. This could indicate increased demand in the population for essential goods in the days after the hurricane occurred. On the other hand, the Energy and Utilities sector show a very mixed response, with short-term positive impacts but also long-term negative impacts, likely due to prolonged disruptions and high costs for recovery. The Financials and Real Estate sector shows varied responses as well, which shows the sensitivity of this sector to hurricane-specific characteristics. Overall market reactions change from hurricane to hurricane. Recommendations for policymakers are to enhance the usage of insurance sectors by companies and this way promoting financial stability. Limitations of methods used are acknowledged, such as approximate normality and data compromises.

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CHAPTER 1 Introduction

Climate change puts various parts of the economy at risk, such as financial markets, businesses and communities. The rising temperatures that accompany this climate change, cause many destructive weather events, of which hurricanes are one of the most destructive forces. They can inflict serious financial losses, especially in vulnerable sectors, via impacting supply chains, infrastructure and economic consumption. In 2005, Hurricane Katrina brought 160 billion dollar worth of damage and severely impacted transportation, energy and insurance industries (Knabb, Rhome, & Brown, 2011). Hurricane Harvey in 2017 disrupted the economy and business in similar ways, by causing massive floods in Texas (Blake & Zelinsky, 2018). Climate change, causing the increase in the frequency and severity of these hurricanes, pose direct risks from property damage to supply chain disruptions and systematic risks such as changes in consumer behavior, economic innovations or policy changes. Some sectors such as agriculture, tourism and manufacturing seem to be among some of the most vulnerable for these risks. Agricultural business could experience crop destruction and the erosion of soil and manufacturing can face interruptions in supply chains. The infrastructure of energy generating facilities can suffer severe damage, leading to production costs. This way, hurricanes can lead to (temporarily) business closures, long term operational changes, and higher insurance or rebuilding costs. Hurricanes also bring destruction of buildings, which leads to significant declines in company valuation. All of these consequences are linked to long recovery periods, which can change the market dynamic by impacting stock prices and investor confidence. Understanding the relationship between climate events, hurricanes specifically, and their impact on capital markets is crucial for policymakers, business and investors so that they can decrease risk or even benefit from the opportunities. This research seeks to explain the ways via which these hurricanes impact different equity sectors. Along with that, it tries to find ways to build resilience, and come up with investment and risk management strategies, helping stakeholders deal with the challenges that hurricanes bring along.

There are several papers which help us understand the relationship between hurricanes and financial markets. For example, Feria-Domínguez et al. (2017) highlight the market reaction of Property and Casualty insurance companies after major hurricanes in the United States, which showed significant positive cumulative abnormal returns the days around the landfall. This stresses that investors expect high financial costs of rebuilding and compensation. Another research, done by Burke et al. (2015), gives us deeper insights into the overall economic impact of hurricanes and emphasizes the importance of resilience planning and adaptation strategies. Betzer, Doumet, and Rinne (2011) demonstrate that negative abnormal returns are experienced by energy producing companies when a hurricane strikes. This study emphasizes how quickly the market prices these operational disruptions into stocks. Further on, the research done by Ferderer and Bashir (2021) analyzes a broader set of economic impacts of hurricanes on different industries, after which they find significant sectoral volatility with negative returns in energy, utilities, and construction. They highlight the importance of effective disaster preparation and a quick response to such events. Lastly, MacKinlay (1997) provides an overview of the methodology of event studies, which is often conducted to assess the impact of hurricanes on stock markets by calculating abnormal returns. Such research is crucial in understanding how stock prices adjust to new hurricane-related information. Together, these studies show the significant financial consequences of hurricanes and why it is important for companies to account for climate risks in their financial decision-making.

Theoretical frameworks, like the market model and the Efficient Market Hypothesis (EMH) can help us understand the relationship between these hurricanes and financial markets. The market model is a statistical model used to estimate the normal returns of a stock based on the relationship between the stock's returns and the returns of a market index. EMH posits that financial markets incorporate all available, so including climate-related, information into instruments' prices. This suggest that abnormal returns after hurricane strikes are short-term and limited. Big price spikes in stocks after hurricanes might be due to the unexpected severity of the storms and the market not having priced this information in. Building on these theories and empirical research, I seek to analyze the effect of hurricanes on different equity industries by using a dataset of S&P500 stocks over multiple years, representing many different industries. This way, I aim to analyze the vulnerability of various sectors and their returns to hurricanes and where we can capitalize on opportunities. Therefore, the research question of this study is: How do hurricanes affect the performance of different equity sectors in financial markets?

Analyzing the impact of hurricanes on equity sectors, this paper uses data between 120 days before and 20 days after significant hurricane events. Five hurricanes will be studied: Katrina, Sandy, Harvey, Irma, and Florence, because of their similarity in severity, economic impact and data availability. I will apply event windows of -1 to +1 days in the short term, -5 to +5 days in the medium term, and -20 to +20 days in the long term. Normal, abnormal and cumulative abnormal returns will be computed using the market model. Industry-specific differences will be analyzed using industry dummy variables that capture the differential impact across sectors. The control variables taken into account are ROA, market capitalization, liquidity and a distance to landfall variable. Set values at the start of each window will be used for these control variables. In addition, t-tests will be conducted and regression analysis will be applied.

This paper will be informative on sectoral vulnerabilities and opportunities relevant to both investors and policymakers so that they can manage the financial impacts of hurricanes. The research also seeks to identify occasions where market inefficiencies or mispricing occur, presenting opportunities for arbitrage strategies. Such insights can encourage investors to capitalize on market anomalies and incorporate climate risk considerations effectively into their portfolios. The findings from this analysis can also inform policymakers and corporate decision-makers about handling the challenges posed by climate change in the global financial environment.

There are 3 main objectives of this research:

1. To quantify the abnormal returns and cumulative abnormal returns for each firm affected by the hurricanes.
2. To test whether these cumulative abnormal returns are significantly different from zero.
3. To analyse the sectoral differences in stock market responses to hurricanes.

The hypothesis is that hurricanes will have various effects on sectors within the equity markets, with certain sectors being more sensitive and others more resilient to extreme hurricanes. For example, the expectation is that energy and utilities sectors may experience greater negative returns after hurricanes due to distribution networks being disrupted, because they rely heavily on natural resources. Volatility might increase in these stock sectors. Sectors focused on renewable energy or climate event repair might see increased demand and therefore positive returns. I expect the analysis to show temporal effects of the hurricanes on the equity sector. This will be clarified by the differences in short-term versus long-term shocks that influence sectoral performance. When examining the direct market reactions compared to the long-term effects, I aim to provide insights into how resilient different sectors are to climate risks and how fast the market adapts. The research will also identify cases where market inefficiency or mispricing creates an opportunity for arbitrage strategies. These insights would stimulate investors to capitalize on market anomalies and take climate events into consideration when making portfolio decisions. Policymakers could also benefit in how to address the challenges of global financial markets under conditions of climate change.

My thesis is structured as follows; Chapter 2 will discuss the theoretical framework, which provides a review of the two main models I use in my research. In the third chapter, I will give a detailed description of the data sources, a justification for the selection of hurricanes and a brief description of each hurricane and methods used for the data preprocessing. In chapter 4 I outline the methodology used for testing my hypothesis. The fifth chapter then discusses the results which follow from the analysis, along with a discussion about limitations of the research. Finally, in the sixth chapter I draw conclusions from my results.

CHAPTER 2 Theoretical Framework

The theoretical framework of this research is based on financial theories which explain the relationship between risk factors and market returns. To analyze the impact of hurricanes on stock returns, an event-study approach is used in which I will be referring to two main economic theories: the Market Model and the Efficient Market Hypothesis (EMH). In this chapter, the details of the event study are first explained carefully, after which I will be discussing the two economic theories. In the last paragraph of this chapter, I will be linking the framework to previous studies, which have been discussed in the introduction of my research.

2.1 Event study framework

To assess the impact of the hurricanes on the stocks' returns, I will use multiple event windows and examine the short-, medium- and long-term impact of the storms. These time windows are critical for capturing the degrees of market reaction and adjustments to the hurricane events. The windows are built around the landfalls of each hurricane, as the landfall of each hurricane has a clear location and is comparable across events. The landfall of a hurricane is the point where the storm came to land.

- Short-term: [-1, +1] days
- Medium-term: [-5, +5] days
- Long-term: [-10, +10] days

The short term window spans from one day before to one day after the event. This window is crucial for capturing the direct reaction of the market to the hurricane. Often times, hurricanes cause immediate physical damage, which usually leads to rapid adjustments in stock prices as investors follow the news on the climate events. According to the Efficient Market hypothesis, prices should incorporate all available information on a stock quickly and directly. The immediate aftermath of a hurricane should therefore reflect most of the event's impact on the prices. Investors' sentiment, like panic selling or speculative buying, is also captured in this window, as it is often the consequence of these types of disasters.

Then, the medium-term windows offers a broader analysis of the hurricane's impact, as it will capture not only the immediate effects but also the effects of the adjustment period. Hurricanes usually have prolonged effects on the economy, caused by long damage assessment, recovery efforts and a continuous news flow. Five days before and after the event, will allow us to capture the extended effects. It will also show how the market slowly digests information over a longer period of time, any delayed reactions will be included. During this window, companies and regulators may also start to implement recovery measures to the damage.

Finally, the long term windows looks at the sustained impact of the hurricane event on stock returns, taking into account the 10 days before the landfall and the 10 days after the landfall. Hurricanes can have a lasting effect on infrastructure, supply chains and the overall operation of companies. Some policy and strategic adjustments, done by companies after the hurricane, will be captured with this window. Companies could announce these updates to their operations in the days following the first impact. Additionally, the stabilization of stock prices after the first shock and volatile movements can be observed, which will help us understand the overall impact once the direct panic has settled.

2.2 The Market Model

In an event study, "normal returns" are the expected returns of a stock if the hurricane had not occurred. The Market Model is a statistical model that gives an estimation of normal returns of a stock based on the relationship between the return of the stock in relation to the market index return. It assumes a linear relationship between stock return and market index return. The formula is as follows:

$$R(it) = \alpha i + \beta i \ * \ Rmt(t) + \epsilon it$$

Where:

- Rit is the return of stock i at time t.
- Rmt is the return of the market index at time t.
- αi and βi are the intercept and slope estimated using OLS regression based on returns from the estimation window (120 days before the event).

A window of 120 days is chosen for its ability to capture the typical movements and trends in a stock's price. This period is generally considered adequate for robust estimation of normal returns. According to Brown and Warner (1980), such a long estimation window will improve the reliability of the normal returns, reducing their variance. It also smooths out volatility and noise, therefore providing an accurate representation of the expected returns. In order to prevent influence of the hurricane's event on the normal returns, the estimation windows end 10 days before the landfall. This 10 day period is chosen to take into account the reacting of market participants to major events like hurricanes. Usually, in the week before the actual landfall, forecasts and warnings become more serious and concrete. The consequence could be abnormal trading activity in the days prior to the striking of the hurricane, as investors change their portfolios. According to MacKinlay (1997), it's also recommended to end the estimation window several days before the event window starts.

Then, the abnormal returns are calculated by subtracting the estimated normal returns from the actual returns during the event windows. Additionally, cumulative abnormal returns will be calculated and analyzed to understand the impact of hurricanes on stock returns.

2.3 Efficient Market Hypothesis (EMH)

The EMH suggests that financial markets are efficient when incorporating information, this would mean that asset prices reflect all available information at any given time. According to EMH, it is impossible to consistently get higher returns than the overall market via stock picking and timing, because stock prices should only react to new information.

There are three forms of EMH:

- Weak form: All past trading information is reflected in stock prices.
- Semi-strong form: All public information is reflected in stock prices.
- Strong form: All information, public and private, is reflected in stock prices.

For this research, EMH suggests that the stock market will incorporate the information about hurricanes quickly into the stock's prices, which would lead to a direct impact on the returns. The abnormal returns that are estimated in the event windows can be examined to determine whether the market instantly discounts information on hurricanes and adjusts the stock price accordingly. Price surges after a hurricane comes to land might be due to unexpected magnitudes of the hurricanes. This can be the reason why the information hasn't been priced in by the market.

2.4 Link to previous research

Multiple studies have used these frameworks to investigate the impact of natural disasters on equity markets. For example, Ferderer and Bashir (2021) used the Market Model for analysing vulnerabilities in different sectors to hurricanes, after which they found significant differences in stock market responses between sectors. Additionally, MacKinlay (1997) used the Market Model and EMH in his event study to show the financial market response to a different set of natural disasters.

My research also uses the market model to estimate normal returns, which are then compared to actual returns during hurricane events to derive the abnormal returns. This way, the EMH is tested by observing how fast and efficiently the stock prices take in the information surrounding the hurricane events.

CHAPTER 3 Data

This study will look into the effect of 5 major US hurricanes on the stocks of the S&P500. US hurricanes are more directly applicable to US-based companies and industries, which makes the research more relevant to investors and stakeholders within the US market. This way, I can minimize the influence of external factors related to events in other regions. However, we do have to keep in mind that companies differ in how much of their business is done in the US compared to in the rest of the world. Therefore, companies that earn a lot from outside US practices, might be affected less by the hurricanes. I will use daily data of five hurricanes that occurred within the United States. These will first be discussed in detail, after which I will present the variables used and it's sources.

3.1 The Hurricanes

1. Hurricane Katrina (29-08-2005):
A catastrophic hurricane which caused major floodings in New Orleans and massive damage across the Gulf Coast. Damages were over $125 billion. The effects in terms of energy production and distribution were big, infrastructures and communities were severely affected. The destruction of oil refineries and oil pipelines created fuel shortages and caused the prices of the essential commodity to soar. The same hurricane devastated many homes and local business ventures, which disrupted the local economy and left thousands of people homeless.

2. Hurricane Ike (13-09-2008):
Hurricane Ike is another one of the most devastating storms with big impacts in the Gulf Coast of the United States, particularly in the State of Texas. With losses estimated at $37.6 billion, many power outages, damage to infrastructure and disruption of various industries caused by Ike, are seen. Many sectors, from energy production to commercial fishing, were affected, and Texas' economy was hurt badly. Ike's destruction illustrated how durability in infrastructure and proper disaster preparation are necessary to combat impacts of future hurricanes.

3. Hurricane Sandy (29-10-2012):
Hurricane Sandy, also known as Superstorm Sandy, hit the eastern coastal areas of the United States with enormous devastation in New York and New Jersey states. Damaging more than $70 billion worth of property, Sandy caused huge power blackouts, lots of infrastructure damages in terms of transportation, and inflicted significant economic losses on businesses within the affected states. With the critical infrastructure affected, such as the subway systems and tunnels, the damage caused by the storm showed the vulnerability of urban areas. This again called for better preparedness and resilience to disasters.

4. Hurricane Harvey (25-08-2017):
Hurricane Harvey led to record-breaking rainfall and catastrophic flooding in Texas, especially in the Houston metropolitan. The storm's estimated cost is over $125 billion, which impacted many businesses and homes. The hurricane also caused heavy rains, which were a major problem in energy, manufacturing, and retail operations. The impacts of the hurricane were not only seen directly, but also long-term.

5. Hurricane Florence (14-09-2018):
Hurricane Florence hit North and South Carolina with rainfall and flooding. The storm caused estimated damages of $24 billion to houses and agricultural land, but also to businesses. The catastrophic floods resulted in economic disruptions, mainly in the agricultural sector where crop losses and livestock deaths were over hundreds of millions dollar.

3.1.1 Hurricane justification

These hurricanes were selected because they caused significant economic impacts, attracted a high level of media attention, and because there is a large amount of data available for each event. The variety of the geography they affect and the extent to which they impact a number of industries form a decent base for understanding the economic impact of hurricanes. Another important point that was considered, is the need for non-overlapping hurricane windows, as this would cause problems with the integrity of the normal returns and as it would be the reason for complicated analysis. Lastly, these hurricanes have similar numbers of economic damage, which makes them suitable for regression comparison. Katrina, Sandy and Harvey are among the most economically damaging hurricanes in the history of the United States. Ike and Florence costed slightly less, however still causing significant damage.

3.2 Data sources

Data for this research is primarily derived from the Compustat and CRSP databases via the WRDS platform. The dataset includes daily returns for the stocks of the S&P 500 index from 120 days before to 30 days after the five significant hurricanes. This way, I can make sure that there is enough data for the estimation of normal returns and for the time windows, of which the largest one is +10 days. The daily returns without dividends are fetched from the Crsp database and the market returns for the entire S&P500 index during the estimation windows are fetched from Compustat. I choose to exclude the dividends from the returns and incorporate only real prices, as the goal is to isolate the direct impact of hurricanes on stock price movements themselves.

Because the S&P500 constituents are occasionally updated, the historical constituents available closest to the start of each hurricane dataset (120 days before landfall) are chosen for the entire hurricane data. Choosing fixed constituents will allow for clear analysis and comparison between different time windows and normal returns. Additionally, given the relatively short event window and the fact that the S&P500 is usually rebalanced quarterly, the likelihood of significant changes in the composition of the index is relatively low.

ROA, market capitalization and liquidity are derived from the quarterly fundamentals section of the Compustat database. Geographic locations for the company's headquarters were found in the Compustat company section and the locations and data of each hurricane's landfall were derived from NOAA, which is the National Oceanic and Atmospheric Administration. The addresses of the companies' headquarters were then geocoded, after which the distances to the landfall were calculated. The fetching of the data and merging of the various datasets is done in a Python environment.

3.3 Trading days within event windows

As this study will use event windows for each hurricane t-test and regression, weekends and holidays have to be taken into account. For a few hurricanes, some windows contained less days than others, as the event windows were kept constant, but the days of the week during which the storms took place differed. This causes some event windows for particular hurricanes to have less trading days included, than others. This is not inherently a problem, as regressions will be conducted per hurricane. However, for one of the hurricanes, there is no return data during the short term event window. For this hurricane Sandy, the markets got shut down in anticipation of the huge storm to prevent extreme volatility and panic selling. This decision was made by the board of the NYSE and NASDAQ in consultation with government officials (FIA, 2013; SIFMA, 2019). For this reason, only medium term and long term analysis was conducted on hurricane Sandy.

3.4 Control variables for OLS-regression

To isolate the effect of hurricanes on stock returns, the following control variables are included in the OLS-regressions:

1. **Distance to landfall:** Captures the regional differences of the hurricane's landfall's impact
2. **Market Cap (Size):** Larger firms may have different reactions compared to smaller firms.
3. **Liquidity:** More liquid stocks might react more quickly to news events.
4. **ROA:** Measures the company's profitability relative to its total assets.
5. **Industry-**dummy: Tells us what industry the stock belongs to.

These variables are added to isolate the actual differences between the impacts on the various industry sectors, making sure that we are not observing the differences in market capitalization, liquidity or financial performance between the sectors of stocks in the S&P500. In the following paragraphs, I will explain the reasoning behind the different control variables.

3.4.1 Distance to landfall

This variable is included to capture the different impact of hurricanes on companies of which the headquarters are based nearby the hurricane's landfall compared to those which are located further away. The proximity of a company's operation to the landfall can significantly impact the extent of the damage. Companies that are located closer to where the hurricane hit, are likely to experience more severe disruptions than companies further away. The geographic coordinates of the hurricanes' landfall locations are sourced from the National Oceanic and Atmospheric Administration (NOAA) database. The headquarters' locations of the companies are obtained from Compustat. Every S&P500 company must be a US company, still a small number of global headquarters were not located in the United States. For these companies, the US based headquarter was chosen instead. With geocoding, the smallest distance between the landfall coordinates and the headquarters' coordinates is calculated.

3.4.2 Market capitalization

Market capitalization is the total value of a company's outstanding shares, and is a proxy for the size of a company. It is calculated by multiplying the common outstanding shares with the closing price of that day. Larger firms often have more resources and better access to capital markets, this could potentially influence their resilience to climate-events like hurricanes. On the other side, smaller firms might be more vulnerable to these events because of their limited resources. Using market capitalization as a control variable allows us to account for these size-related differences, so that we can make sure that the difference we see in abnormal returns between sectors is not caused by differences in average market cap per industry. We want to find the industry-internal differences of the impact of the hurricane, and some industries in the S&P500 might contain higher market capitalization companies than others. The market capitalization for each stock is set at the beginning of the estimation period, as market capitalization figures are not available daily.

3.4.3 Liquidity: average trading volume

The liquidity of each stock is measured with the average trading volume over the estimation period. The number of stocks traded for each company's trading days is added to the dataset and then divided by the total number of trading days in this period. This will smooth out any temporary fluctuations in the stock's volume, additionally any noise from the volatile volume spikes during the days surrounding the landfall will not be taken into account. This variable is meant to measure how easily a stock can be bought or sold in the market. Liquid stocks typically have bigger reactions to news events, including natural disasters. In order to make sure we actually observe the differences between the industry effects, it is important to make sure that some industries are not composed of much more liquid stocks.

3.4.4 ROA

ROA is a proxy for profitability and measures how efficiently a company is using its assets to make profits. It provides insight into the company's efficiency and financial health. It is used as a control variable in this regression, because companies with higher ROA may be better positioned to deal with and recover from the financial shocks that are caused by the hurricanes. When we control for ROA, we can isolate the internal differences between the effects of the hurricane on the different industries. Without including ROA, it’s possible that some sectors do financially better than others. ROA is calculated by dividing the net income by the total assets. Just like the approach for incorporating the variable market capitalization, the ROA for the event windows will be fetched at the start of each event window.

3.4.5 Industry dummies

Including industry-dummy variables is crucial for analyzing the various hurricane impact between the sectors within the S&P 500. Each industry has its own unique characteristics and vulnerabilities that can influence how stock prices react to climate events. Using industry-dummies in our research allows us to capture these internal differences. This aspect of the analysis ensures we can find the degree to which different industries in the S&P500 are exposed to varying degrees of risk from hurricanes. For example, industries such as energy and utilities may face direct damage and operational disruptions, this leads to significant impacts on stock returns. Conversely, industries that are less directly affected by hurricanes could show slower responses in their stock prices. For each industry named in the following section, the company will either have a 0 or a 1, 1 meaning it belongs to that specific industry and 0 meaning it doesn’t.

3.4.5.1 Industry classification

For clear analysis, we group the industries into broader categories using the SIC codes. The specific SIC codes tied to each group can be seen in appendix B.

The constructed groups are as follows:

1. Consumer Goods(Consumer Discretionary, Consumer Staples): SIC codes 2000-3999.
2. Energy and Utilities: SIC codes 4900-4999 and 4600-4699.
3. Technology and Communications (Information Technology, Communication Services): SIC codes 4800-4899, 7370-7379 and 7380-7399.
4. Financials and real estate: SIC codes 6000-6999.
5. Healthcare: SIC codes 8000-8099.
6. Industrials and Materials: SIC codes 1000-1999 and 4000-4999.
7. Other (no industry): 9997.

Real estate was grouped with financials, both of these sectors are influenced by financial regulations and interest rates. Additionally, real estate alone had too little companies in its category within the S&P500 constituents. Consumer discretionary and consumer staples are grouped together, both of these sectors are driven by consumer demand and spending. By grouping them together, I can get a good understanding of the impact of hurricanes on consumer behavior. Energy and utilities are both strongly influenced by infrastructure and energy prices and share similar economic risks, grouping them together also makes sense. Further on, technology and communications are in the same category, because they are both driven by technological advancements and communication services. Communication services being down because of hurricane strikes could influence these sectors together. Healthcare is unique in the focus it has on medical aid and as hurricanes often end in deaths and injured, the choice was made to group this sector alone. Lastly, industrials and materials are grouped together. These industries both involve manufacturing, construction and raw materials, which are all influenced by the supply and prices of commodities. This supply could be heavily affected by the effects of the storms.

Grouping similar characteristics together can improve the reliability and robustness of the regression, so that not too many dummy variables have to be included with too little companies in each category. Simplifying the industry categories this way also makes the analysis more manageable, while reducing complexity.

3.5 Cleaning of the data

During the data fetching process, I encountered some missing values for a number of variables. For the control variables ROA and Market Capitalization, no values were missing as the closest available figures to the start of the estimation window were chosen and these types of figures are usually released quarterly. I allowed the values to be outdated for a maximum of 6 months. Further on, for the daily trading volume during the estimation period and the SIC codes that were used to form the industry dummies, no values were missing either. For the calculation of the last control variable in the dataset, distance to landfall, multiple values were used; the location of each of the company's headquarters and the coordinates of the hurricanes' landfalls. The coordinates of the landfalls were well documented on NOAA, however with the locations of the company's headquarters there were some problems. First of all, there was no valid database of historical headquarters locations available. This problem will be discussed in the limitations section of this research. Additionally, even though all companies in the S&P500 are US-based, a handful of global headquarters were located outside of the US. To combat this problem, the US-based headquarters for these companies were fetched manually.

For the dividend excluding returns, some values were missing. Some of these missing values were due to national holidays, as these are often not trading days. These rows were excluded from the dataset. The remaining missing returns for each hurricane amounted to about 0.5% of the data. For example, for

Hurricane Katrina, this was 290 out of 52.191. This number of 52.191 consists of approximately 500 stocks times roughly 105 trading days that were fetched. This results in a percentage of 0.56% of missing values from the data for this hurricane. The missing data for the rest of the hurricanes can be found in appendix A.

3.5.1 Imputation of returns

The missing values for each hurricane were filled in using multiple imputation methods, as removing the rows would cause the calculation of the estimation periods to be inefficient. Multiple imputation methods create multiple complete datasets by imputing missing values for several times. Each imputed value is drawn from a plausible distribution created by the iterative imputer from the ‘fancy impute library’ in python, which primarily uses Bayesian regression techniques. The event windows did not contain any missing values, and no imputation methods were needed or conducted on these rows, as it would cause the regression to become invalid.

CHAPTER 4 Method

In the following chapter, I will go through the specific methodologies utilized to get the results for this study. This includes: calculating normal returns, the calculation of abnormal returns and the CARs, conducting the t-tests, and finally: performing the OLS-regressions and checking it's assumptions.

4.1 Normal Returns

The market model will be used to estimate the normal returns by regressing a stock's returns on the returns of a market index, using data from the estimation window of 120 days before the event until 10 days before the landfall. From this market model, each company's individual parameters will be estimated. The predicted returns for each day within the event windows will be calculated, based on these parameters and the market return of those particular days.

As stocks do not trade over the weekend, only the returns of the trading days (Monday until Friday, with the exception of holidays) are used in the calculations of normal and abnormal returns.

Estimating the coefficients α_i and β_i for each company, with the following formula**:**

$R(it) = \alpha i + \beta i \times Rmt + \epsilon it$

Where:

- R(it) is the return of stock i at time t during the estimation window.
- Rmt is the return of the market index at time t.
- αi and βi are the intercept and slope estimated using OLS regression based on returns from the estimation window.

The normal returns are then calculated with these set parameters for each company and the market return of the days within the event windows. The same formula is used for these predicted returns calculations:

$E(R)(it) = \alpha i + \beta i \ * \ Rmt$. Where E(R) stands for the expected returns, the rest of the variables remain the same.

4.1.1 Abnormal returns and CARS

When the normal returns are calculated, the next step is to determine the abnormal returns. They represent the deviation of actual returns from the normal returns which are expected. The deviations capture the impact of the hurricanes on the affected company returns. The abnormal returns are calculated as follows:

$AR(it) = R(it) - E(R)it$

Where:

- AR(it) is the abnormal return of company i at time t.
- R(it) is the actual return of stock i on day t.
- E(R)it represents the normal return of stock i on day t.

After calculating the abnormal returns of each trading day within the event windows, the cumulative abnormal returns are calculated by adding each window's days' abnormal returns. The CARS are beneficial, because they capture the total impact over the event window, while the AR just captures each day's effect. This cumulative AR value will also smooth out daily volatility spikes and offer a clear picture of the overall impact of the hurricane on a short, medium and long term window.

For each window per hurricane, this is calculated as follows:

$CAR(i) = \sum AR(it)$

Where:

- CAR(i) is the cumulative abnormal return over the time window for company i.
- AR(it) is the abnormal return of each day in the event window.

4.2 T-tests

To test whether the cumulative abnormal returns for each event window and hurricane are significantly different from zero, a t-test is performed. In total, this amounts to 14 tests; for each of the 5 hurricanes and each of the 3 event windows, with the exception of the short event window for hurricane Sandy. For this storm, the markets got shut down the day of the landfall and the day after the hurricane. For Sandy, only medium and long term event windows are used. Tests and regressions for each hurricane are conducted separately instead of all 5 together, because of heterogeneity concerns. Each hurricane will likely have a different severity of economic impact and different interaction effects between the control variables and the hurricane-specific characteristics. Combining the hurricanes into one regression would lead to misleading conclusions.

The following hypothesis will be tested:

- H0: $CAR = 0$
- Ha: $CAR \neq 0$

The formula for this test-statistic is as follows:

$$T = \frac{\overline{CAR}}{\frac{s_{car}}{\sqrt{N}}}$$

Where:

- T is the t-test result.
- $\overline{CAR}$ is the sample mean of the Cumulative Abnormal Returns (CARs).
- s_{car} is the sample standard deviation of the CARs.
- N is the sample size.

The p-value is then calculated for each test and compared to a significance level of 0.05.

4.3 OLS-regression

After conducting the t-tests, a regression model is run for each time window and each hurricane to measure the impact of different industries on the size of the CARS. Industry dummies are used to compare the effects of the hurricane between various sectors. 14 regressions are performed in total.

The regression model is specified as:

$$\begin{aligned} CAR(i) = \alpha i \, + \, \beta 1 \times \, Market\ cap \, + \, \beta 2 \, \times Liquidity \, + \, \beta 3 \, \times \, ROA \, + \, \beta 4 \, \times \, ESG - rating \\ + \, \beta 5 \, \times \, Distance\ to\ landfall \, + \, \beta 6 \times Tech\ and\ Communications \\ + \, \beta 7 \times Financials\ and\ Real\ Estate \, + \, \beta 8 \times Consumer\ Goods \\ + \, \beta 9 \times Energy\ and\ Utilities \, + \, \beta 10 \times Healthcare \\ + \, \beta 11 \times Industrials\ and\ Materials \, + \, \epsilon it \end{aligned}$$

Where:

- CAR(it) is the cumulative return of company i.
- αi is the intercept.
- ϵit is the error-term.

To be able to run the OLS-regression, the model has to fulfill some assumptions. Some of these assumptions can be tested, as others cannot. Testing for autocorrelation will be excluded, as all CARs are from individual different companies, so the different CARs don't contain a time-series component relative to each other. The tested assumptions include:

1. Linearity: The relationship between the dependent variable and each independent variable is linear.

2. Homoscedasticity: The variance of the error terms is constant across all levels of the independent variables.
3. Normality of residuals: The residuals of the regression model are normally distributed.
4. No perfect multicollinearity: The independent variables are not perfectly linearly related to each other.
5. Zero mean of residuals: The mean of the residuals of the model has to be zero.

4.3.1 Linearity

To test this assumption, scatter plots of the residuals versus the fitted values are made. The scatter plots will be analysed for obvious patterns or deviating curves. Additionally, Q-Q plots are generated to assess whether the residuals follow an approximate normal distribution. Deviations from a straight line in the Q-Q plot can point to non-linear relationships in the model.

4.3.2 Heteroskedasticity

To deal with potential heteroskedasticity of the standard errors, scatterplots of the fitted values are plotted and a Breusch-Pagan test is performed. This test is used to detect heteroscedasticity in regression analysis. Heteroscedasticity occurs when the variance of the residuals is inconstant across the observations, which might lead to invalid inference in the regression. The following hypothesis are tested:

- H_0 : Variance of error term is constant.
- H_a : Variance of error term is not constant.

With the test statistic as follows:

$$LM = \mathrm{n} \times R^2$$

Where:

- LM is the Breusch-pagan test result.
- n is the number of observations
- R^2 is the coefficient of determination from the auxiliary regression

For the regressions with a p-value lower than 0.05 for the Breusch-Pagan test, robust standard errors are applied.

4.3.3 Normality of residuals

To test this assumption, Q-Q plots of the residuals are created and analysed. These plots compare the quantiles of the residuals with those of a normal distribution. If the residuals are normally distributed, the points will fall approximately along a 45-degree line.

4.3.4 Multicollinearity

Before running the regression, multicollinearity between the control variables will have to be ruled out, as multicollinearity can inflate standard errors and make the estimation of the individual coefficients difficult. A correlation matrix is constructed and the Variance Inflation Factor (VIF) is used to detect multicollinearity.

4.3.5 Zero mean of residuals

To test the last assumption in our list, the mean of the residuals is calculated. A mean close to zero shows that this assumption is fulfilled. Large deviations from zero could indicate violations of the OLS model.

CHAPTER 5 Results & Discussion

In this chapter, I will present the results of my study. This starts with the summary statistics of the CARs, after which I will be moving on to the t-tests, the testing of the OLS-assumptions, the actual regressions themselves and finally, the discussion of the results and limitations of the research.

5.1 Summary statistics CARS

Hurricane	Window	Count	Mean	Std	Min	25%	50%	75%	Max
Katrina	CAR short-term	497.000	-0.002	0.016	-0.085	-0.011	-0.002	0.006	0.077
Katrina	CAR medium-term	497.000	-0.002	0.043	-0.344	-0.021	-0.002	0.017	0.205
Katrina	CAR long-term	497.000	-0.005	0.054	-0.399	-0.029	-0.005	0.023	0.224
Ike	CAR short term	499.000	0.001	0.030	-0.311	-0.010	0.001	0.013	0.109
Ike	CAR medium-term	499.000	-0.005	0.175	-2.139	-0.046	-0.000	0.053	0.438
Ike	CAR long-term	499.000	0.003	0.162	-1.939	-0.063	-0.006	0.058	0.725
Sandy	CAR medium-term	498.000	0.004	0.051	-0.359	-0.016	0.004	0.029	0.255
Sandy	CAR long-term	498.000	0.015	0.069	-0.285	-0.023	0.009	0.057	0.267
Harvey	CAR short-term	505.000	0.004	0.018	-0.116	-0.003	0.003	0.010	0.209
Harvey	CAR medium-term	505.000	0.001	0.033	-0.161	-0.014	-0.000	0.015	0.184
Harvey	CAR long-term	505.000	0.003	0.045	-0.202	-0.017	0.005	0.025	0.192
Florence	CAR short-term	505.000	0.001	0.018	-0.133	-0.008	0.001	0.011	0.054
Florence	CAR medium-term	505.000	0.004	0.038	-0.138	-0.022	0.001	0.026	0.148
Florence	CAR long-term	505.000	0.003	0.050	-0.124	-0.033	0.000	0.038	0.179

Table 1:Summary statistics for the Cumulative abnormal returns. Every hurricane and event window combination is placed within the rows, for which the count, mean, standard deviation, the minimum and maximum values and quintiles are reported.

These statistics give an overview of the CARS for the five hurricanes over various event windows. The table gives us an understanding of the distribution of the CARS across the different hurricanes. For example, for the short term for hurricane Katrina, the mean CAR is -0.002, so -0.2% that day. The minimum value is -0.085, and the maximum value is 0.077. When CARS are multiplied by 100, the returns can be observed in percentages.

5.2 T-tests

Hurricane	Window	T-statistic	P-Value
Katrina	CAR short-term	-3.208	0.001
Katrina	CAR medium-term	-1.075	0.283
Katrina	CAR long-term	-2.009	0.045
Ike	CAR short term	0.965	0.335
Ike	CAR medium-term	-0.619	0.536
Ike	CAR long-term	0.448	0.654
Sandy	CAR medium-term	1.691	0.091
Sandy	CAR long-term	4.974	0.000
Harvey	CAR short-term	4.412	0.000
Harvey	CAR medium-term	0.554	0.580
Harvey	CAR long-term	1.470	0.142
Florence	CAR short-term	0.849	0.396
Florence	CAR medium-term	2.296	0.022
Florence	CAR long-term	1.468	0.143

Table 2: T-test results. The table provides the t-test results for the CARs for different hurricanes and event windows. It reports the t-value and p-value after testing whether the CARs are significantly different from zero.

The t-test results in Table 2 show the statistical significance of the cumulative abnormal returns. We test here whether the CARs are significantly different from zero, which would suggest impact of hurricanes on stock returns.

For Hurricane Katrina, the short-term window has a p-value of 0.001, showing that the CARs are significantly negative. In the medium-term window, the p-value is 0.283, this tells us that the CARS are not significantly different from zero. The initial negative impact observed in the short-term window, disappears over the medium term. In the long-term window, the p-value is 0.045, indicating significantly negative CARs again, which implies a long term effect of the hurricanes on the stocks. For Hurricane Ike, the short-term window has a p-value of 0.335, indicating that the CARs are not significantly different from zero. In the medium-term window, the p-value is 0.536, and in the long-term 0.654, these both show no significant impact on stock returns. Further on, for hurricane Sandy, the medium-term window shows a p-value of 0.091, not being significant at the 5% level, but being close to significance indicates potential medium term impact. In the long-term window, the p-value is 0.000, which clearly shows positive CARs and therefore a positive impact on stock returns over the long term. Then for hurricane Harvey, the short term window has a p-value of 0.000, suggesting significant CARs. In the medium-term window, the p-value is 0.580 and in the long term 0.142, both showing no significant impact on the returns. Lastly, for hurricane Florence, the p-value for the short term is 0.396, meaning CARs are not significantly different from zero. The medium term p-value is 0.022, showing significance on this time window. Finally, the long term p-value is 0.143, with no significant long-term impacts on the stock returns.

5.3 Testing of the OLS-assumptions

In the next section, I focus on testing the OLS regression assumptions which I discussed in the methodology section. The key assumptions tested are linearity, homoscedasticity, normality of residuals, perfect multicollinearity and zero mean of residuals.

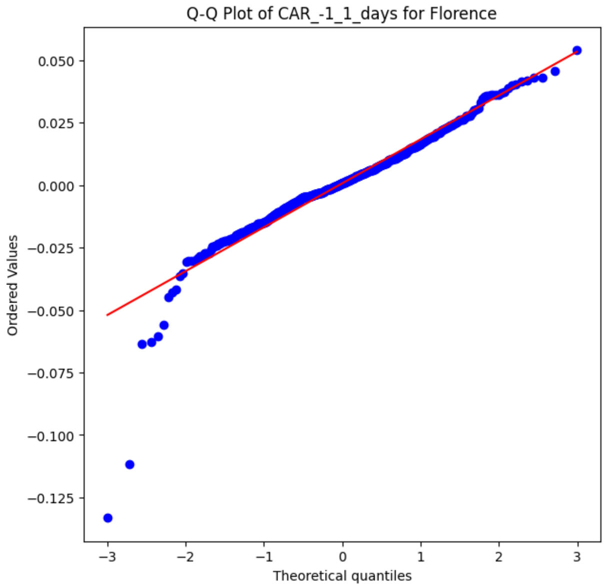

Figure 1: Q-Q Plot of CAR for the short event window, for Florence. This Q-Q plot is used to determine whether or not the cumulative abnormal returns are normal for Florence over the short term event window. The plot compares the quantiles of the CAR data to the quantiles of a standard normal distribution, which is the red line.

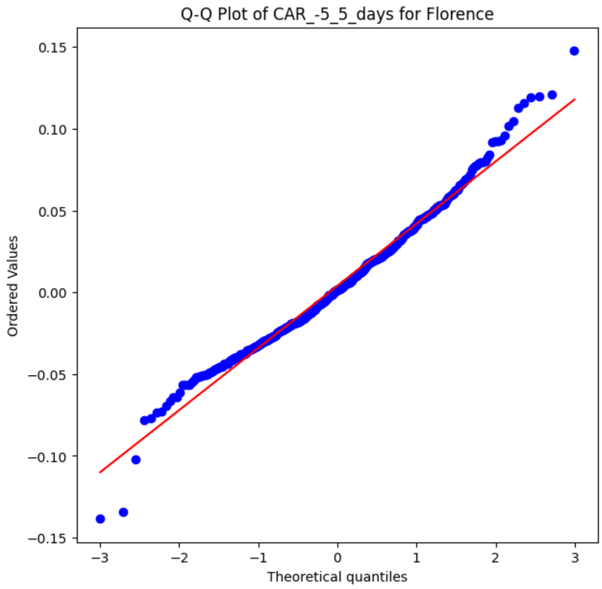

Figure 2: Q-Q Plot of CAR for medium event window, for Florence. This Q-Q plot is used to determine whether or not the cumulative abnormal returns are normal for Florence over the medium term event window. The plot compares the quantiles of the CAR data to the quantiles of a standard normal distribution, which is the red line.

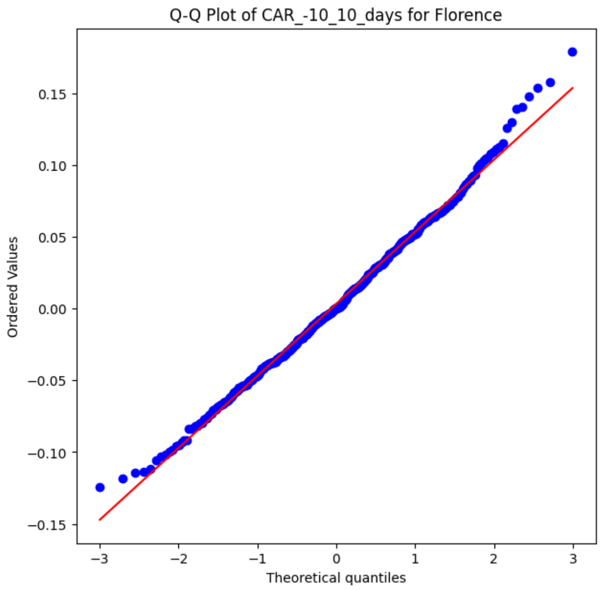

Figure 3: Q-Q Plot of CAR for long event window, for Florence. This Q-Q plot is used to determine whether or not the cumulative abnormal returns are normal for Florence over the long term event window. The plot compares the quantiles of the CAR data to the quantiles of a standard normal distribution, which is the red line.

These plots compare the quantiles of the residuals from the regression models to the quantiles of a standard normal distribution, presented on the 45 degree line. The Q-Q plots for Hurricane Florence for each event window were chosen to be shown here because they represent the other plots for the rest of the hurricanes well. Each hurricane shows progression in their Q-Q plots, as we move up to a higher event window, the residual points become more closely aligned to the 45 degree line. The deviations show that the residuals in the short-term window exhibit more skewness and kurtosis, which reveal there is no exact, but rather approximate, normality. The Q-Q plots for the other hurricanes, which are available in appendix C, show similar or more extreme patterns. Generally, the closer alignment of points along the 45-degree line in the long-term windows means better fulfilment of the normality assumption. The deviations observed in the short-term and medium-term windows suggest results should be interpreted with caution.

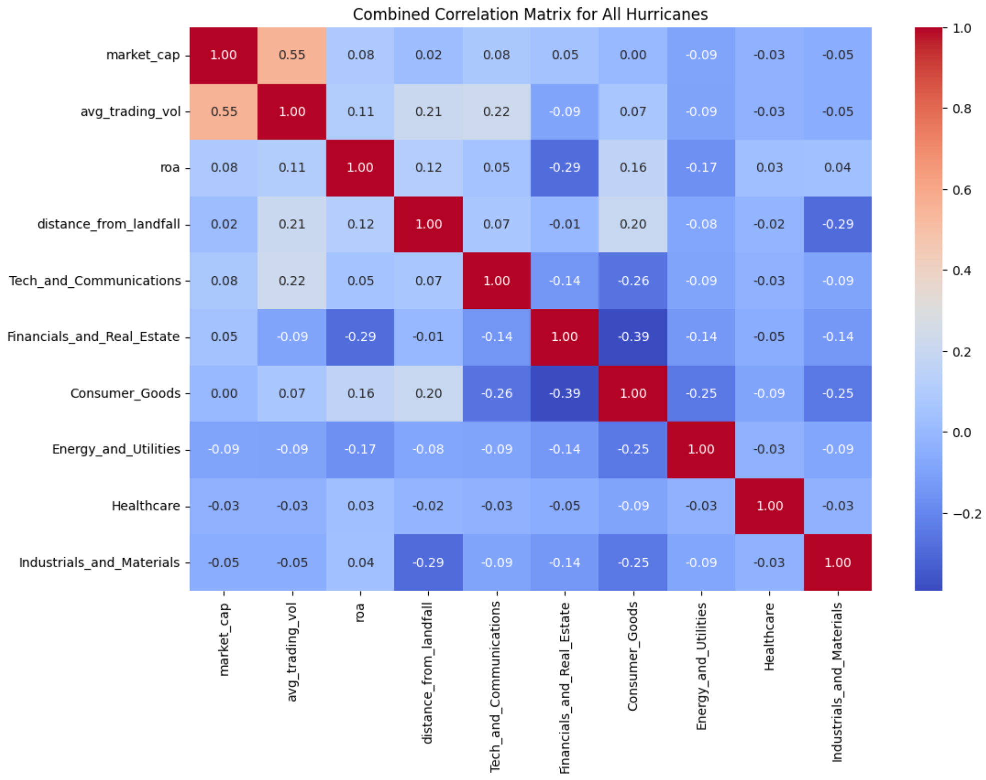

Figure 4: Combined Correlation Matrix for all hurricanes. This figure shows the correlation coefficients between various independent variables. This matrix helps with identifying (perfect)multicollinearity.

The control variables remain consistent for all hurricanes and there are no bigger differences than 0.01 within the correlations, so I chose to combine the correlation matrix for all events. This simplifies the analysis of multicollinearity. None of the correlations are above the 0.7 threshold, which is often cited as problematic for multicollinearity (Gujarati, 2003). The correlation between Market Capitalization and Average Trading Volume is the highest out of all correlations, but is well below the critical level. This suggests that multicollinearity is not an issue in this study.

	Katrina	**Ike**	**Sandy**	**Harvey**	**Florence**
Market capitalization	1.838	1.920	1.999	2.093	2.083
Average trading volume	1.970	2.037	2.171	2.263	2.247
ROA	1.806	2.253	2.394	2.522	2.465
Distance from landfall	4.344	4.859	4.726	4.773	4.787
Tech and communications	1.423	1.364	1.373	1.442	1.430
Financials and real estate	1.619	1.711	1.551	1.609	1.631
Consumer Goods	2.724	2.725	2.646	2.576	2.604
Energy and Utilities	1.164	1.194	1.185	1.219	1.228
Healthcare	1.033	1.028	1.032	1.043	1.045
Industrials and Materials	1.113	1.122	1.120	1.136	1.141

Table 3: VIF values for each hurricane. It reports the values for each independent variable across different hurricanes. These values are used to determine whether there are multicollinearity problems.

The VIF values for each hurricane's regression models are also below the accepted threshold of 10 for VIFs (Kutner et al., 2004). These two tests make sure that the standard errors of the estimated coefficients are not inflated due to multicollinearity.

Hurricane	**Window**	**Test Statistic**	**P-value**
Katrina	CAR short-term	28.612	0.001
Katrina	CAR medium-term	30.691	0.001
Katrina	CAR long-term	23.716	0.008
Ike	CAR short term	24.728	0.006
Ike	CAR medium-term	21.370	0.019
Ike	CAR long-term	12.738	0.239
Sandy	CAR medium-term	19.370	0.036
Sandy	CAR long-term	29.073	0.001
Harvey	CAR short-term	16.550	0.085
Harvey	CAR medium-term	30.579	0.001
Harvey	CAR long-term	35.917	0.000
Florence	CAR short-term	6.992	0.726
Florence	CAR medium-term	14.265	0.161
Florence	CAR long-term	23.013	0.011

Table 4: Breusch-Pagan test results. The table represents the test-statistics for each hurricane and event window combination. Test-statistics and p-value are reported to determine heteroscedasticity in the model. A p-value of less than 0.05 shows that there is heteroscedasticity and that robust standard errors are necessary.

The Breusch-Pagan test results show varying levels of heteroskedasticity per hurricane and event window. Notably, there is a pattern where residuals spread out more with more outliers as the event window shortens. This implies that heteroskedasticity increases with shorter event windows. This can also be seen in the scatterplots in appendix D. The presence of heteroskedasticity in the models means that the variance of the residuals is not constant. This violates one of the assumptions of the OLS regression, which assumes homoscedasticity. Robust standard errors are used to adjust for heteroskedasticity in the hurricane and event windows combinations which require these robust standard errors according to the Breusch-Pagan test. This makes sure that the estimated coefficients are reliable. The hurricanes which do not need robust standard errors are: Ike long-term, Harvey short-term, Florence both short- and medium-term.

Hurricane	Window	Mean Error
Katrina	CAR short-term	4.733e-18
Katrina	CAR medium-term	2.982e-17
Katrina	CAR long-term	-2.234e-19
Ike	CAR short term	1.322e-16
Ike	CAR medium-term	7.564e-17
Ike	CAR long-term	1.221e-16
Sandy	CAR medium-term	-1.134e-17
Sandy	CAR long-term	7.401e-17
Harvey	CAR short-term	2.922e-17
Harvey	CAR medium-term	1.412e-17
Harvey	CAR long-term	1.047e-17
Florence	CAR short-term	4.710e-18
Florence	CAR medium-term	1.062e-16
Florence	CAR long-term	1.651e-16

Table 5: Mean errors for the regression models for each window and hurricane combination.

Table 5 presents the mean errors for the regression models for each window and hurricane combination. The values reported are extremely close to zero, so it is quite likely that these regression models satisfy the condition of zero mean of residuals.

5.4 The regressions

Variable (Katrina)	Long Coefficient	Short Coefficient	Medium Coefficient	Long P-value	Short P-value	Medium P-value
Average trading volume	0.000	0.000	-0.000	0.643	0.059	0.695
Constant	-0.034	-0.014	-0.029	0.000	0.000	0.000
Consumer goods	0.020	0.010	0.021	0.010	0.000	0.001
Distance from landfall	0.000	-0.000	0.000	0.560	0.496	0.717
Energy and utilities	0.055	0.015	0.044	0.000	0.000	0.000
Financials and real estate	0.014	0.008	0.016	0.086	0.002	0.014
Healthcare	0.015	0.015	0.012	0.408	0.000	0.287
Industrials and materials	0.039	0.016	0.033	0.000	0.000	0.001
Market capitalization	0.000	0.000	0.000	0.435	0.457	0.515
ROA	0.238	0.145	0.392	0.246	0.009	0.038
Tech and communications	0.020	0.008	0.017	0.041	0.005	0.012

Table 6: Regression results Katrina. This table displays the summed up regression results for Katrina for each of the event windows. The columns represent the coefficients and p-values for short, medium, and long windows. Each row corresponds to a different independent variable.

In the regression results for Hurricane Katrina, multiple coefficients are significant. For the short-term window**,** the constant term is significantly negative at -0.014, which indicates a decline in stock returns immediately after the hurricane. The Consumer Goods sector shows a positive significant coefficient of 0.010, suggesting a 1% increase in abnormal returns if the stock belongs to this industry, all other variables kept constant. The Energy and Utilities sector also has a significant positive coefficient of 0.015, which suggest a 1.5% increase in returns if the stock belongs to this sector compared to when it does not, if all other variables are kept constant. Financials and Real Estate and Healthcare sectors show significant positive impacts with coefficients of 0.008 and 0.015, respectively. The Industrials and Materials sector has a positive significant coefficient of 0.016. Additionally, the control variable ROA is significant with a coefficient of 0.145.

In the medium-term window, the constant term remains significantly negative at -0.029. The Consumer Goods sector shows a significant positive coefficient of 0.021, suggesting a 2.1% increase in cumulative abnormal returns if the stock belongs to this sector compared to when it does not, all other variables kept constant. The Energy and Utilities sector has a positive coefficient of 0.044 and Industrials and Materials of 0.033. ROA is still significant with a coefficient of 0.392, indicating higher abnormal returns for more profitable companies.

Finally, for the long-term window, the Consumer Goods sector maintains a significant positive coefficient of 0.020 and the Energy and Utilities sector shows the highest impact with a coefficient of 0.05. Industrials and Materials also have a significant positive coefficient of 0.039. The Tech and Communications sector now also shows significant positive returns with a coefficient of 0.020. ROA becomes insignificant.

Variable (Ike)	Long Coefficient	Short Coefficient	Medium Coefficient	Long P-value	Short P-value	Medium P-value
Average trading volume	-0.000	0.001	-0.000	0.397	0.006	0.700
Constant	-0.002	-0.004	0.008	0.941	0.284	0.647
Consumer goods	0.000	0.019	-0.005	0.993	0.000	0.619
Distance from landfall	-0.000	-0.000	-0.000	0.228	0.000	0.491
Energy and utilities	-0.033	0.025	-0.036	0.372	0.000	0.234
Financials and real estate	0.112	0.008	-0.017	0.000	0.237	0.694
Healthcare	0.015	0.020	0.011	0.854	0.086	0.600
Industrials and materials	0.027	0.032	-0.001	0.459	0.000	0.946
Market capitalization	0.000	-0.000	-0.000	0.458	0.048	0.317
ROA	0.423	0.057	0.766	0.423	0.481	0.042
Tech and communications	-0.011	0.015	-0.012	0.749	0.000	0.454

Table 7: Regression results Ike. This table displays the summed up regression results for Ike for each of the event windows. The columns represent the coefficients and p-values for short, medium, and long windows. Each row corresponds to a different independent variable.

In the regression results for Hurricane Ike, several coefficients across different event windows are significant. For the short-term window, the Consumer Goods sector shows a positive significant coefficient of 0.019, suggesting a 1.9% increase in abnormal returns immediately following the hurricane if the stock belongs to this sector compared to when it does not, when all other variables are kept constant. The Energy and Utilities sector also has a significant positive coefficient of 0.02. Additionally, the Industrials and Materials sector displays a significant positive coefficient of 0.032. For this hurricane, the Average Trading Volume becomes significant as well at 0.001.

Then for the medium-term window, the significant coefficient is found for ROA with a coefficient of 0.766. Lastly, in the long-term window, the Financials and Real Estate sector stands out again with a significant positive coefficient of 0.112. This suggests that the financial sector experiences a significant boost in the aftermath of Hurricane Ike.

Variable (Sandy)	Long Coefficient	Medium Coefficient	Long P-value	Medium P-value
Average trading volume	0.000	0.000	0.066	0.801
Constant	0.006	0.003	0.699	0.752
Consumer goods	0.021	0.006	0.057	0.384
Distance from landfall	0.000	0.000	0.637	0.446
Energy and utilities	-0.044	-0.013	0.001	0.201
Financials and real estate	-0.002	-0.001	0.882	0.949
Healthcare	0.035	0.017	0.487	0.409
Industrials and materials	-0.014	-0.021	0.371	0.033
Market capitalization	-0.000	-0.000	0.002	0.349
ROA	0.082	0.006	0.767	0.970
Tech and communications	0.014	-0.001	0.404	0.927

Table 8: Regression results Sandy. This table displays the summed up regression results for Sandy for each of the event windows. The columns represent the coefficients and p-values for medium- and long-term windows. Each row corresponds to a different independent variable.

In the regression results for Hurricane Sandy, multiple coefficients are significant. As there is no short-term window, we start with the medium-term window. The Industrials and Materials sector shows a significant negative coefficient of -0.021, suggesting a 2.1% decrease in cumulative abnormal returns if the stock belongs to this sector compared to when it does not, keeping all other variables constant. For the long-term window, the Energy and Utilities sector shows a significant negative coefficient of -0.044. This indicates that the Energy and Utilities sector experiences a serious negative impact because of Sandy. Additionally, the constant term in the long-term window is significantly positive at 0.018, meaning a general increase in stock returns independent from the sectors.

Variable (Harvey)	Long Coefficient	Short Coefficient	Medium Coefficient	Long P-value	Short P-value	Medium P-value
Average trading volume	0.000	0.000	0.000	0.130	0.322	0.236
Constant	0.016	0.006	0.008	0.133	0.022	0.335
Consumer goods	-0.008	-0.003	-0.003	0.350	0.233	0.621
Distance from landfall	0.000	-0.000	0.000	0.317	0.876	0.991
Energy and utilities	-0.012	-0.004	-0.005	0.146	0.181	0.468
Financials and real estate	-0.043	-0.003	-0.023	0.000	0.254	0.000
Healthcare	-0.011	-0.011	-0.012	0.453	0.153	0.450
Industrials and materials	0.012	0.001	0.010	0.264	0.717	0.261
Market capitalization	-0.000	-0.000	-0.000	0.073	0.281	0.136
ROA	-0.541	-0.059	-0.193	0.149	0.274	0.477
Tech and communications	-0.012	-0.000	0.005	0.244	0.888	0.502

Table 9: Regression results Harvey. This table displays the summed up regression results for Harvey for each of the event windows. The columns represent the coefficients and p-values for short, medium, and long windows. Each row corresponds to a different independent variable.

Numerous coefficients are significant in the Harvey results. For the short-term window, the constant term is significantly positive at 0.006, indicating that stock returns generally increased immediately following the hurricane. The Financials and Real Estate sector shows a significant negative coefficient of -0.043 in the long-term. This shows a negative impact on the Financials and Real Estate sector over the long term.

Additionally, the Energy and Utilities sector in the short-term window shows a significant positive coefficient of 0.015. This indicates that this sector benefits from the immediate effects of the hurricane.

Variable (Florence)	Long Coefficient	Short Coefficient	Medium Coefficient	Long P-value	Short P-value	Medium P-value
Average trading volume	-0.000	0.000	-0.000	0.775	0.505	0.691
Constant	0.003	-0.009	-0.008	0.815	0.027	0.302
Consumer goods	0.026	0.014	0.022	0.013	0.000	0.000
Distance from landfall	-0.000	0.000	0.000	0.206	0.223	0.973
Energy and utilities	-0.024	0.005	-0.015	0.036	0.329	0.093
Financials and real estate	0.016	0.011	0.012	0.172	0.006	0.094
Healthcare	0.008	0.007	0.013	0.737	0.543	0.509
Industrials and materials	0.039	0.011	0.048	0.006	0.030	0.000
Market capitalization	0.000	-0.000	0.000	0.524	0.445	0.217
ROA	-0.224	-0.130	-0.251	0.247	0.099	0.077
Tech and communications	0.022	0.008	0.010	0.107	0.097	0.252

Table 10: Regression results Florence. This table displays the summed up regression results for Florence for each of the event windows. The columns represent the coefficients and p-values for short, medium, and long windows. Each row corresponds to a different independent variable.

For the short-term Florence regression, the Consumer Goods sector shows a significant positive coefficient of 0.014. This indicates a 1.4% increase in cumulative abnormal returns, when the stock belongs to this sector compared to when it does not, all other variables remaining constant. The constant term in the short-term window is also significantly negative at -0.009. In the medium-term window, the Consumer Goods sector continues to show a significant positive coefficient of 0.013. This suggests remaining positive performance for the Consumer Goods sector following the hurricane. Lastly, for the long term window, the Energy and Utilities sector has a significant negative coefficient of -0.024. This indicates a significant negative impact on the Energy and Utilities sector over the long term due to Hurricane Florence. Additionally, the Consumer Goods sector continues to have a significant positive coefficient of 0.015, demonstrating the robustness of this industry.

5.5 Discussion

The research question phrased in the beginning of this research, was: ‘How do hurricanes affect the performance of different equity sectors in financial markets?’. The following paragraphs will continue to answer this question and address the learnings of this research.

The regression analyses of the five hurricanes, which are Katrina, Ike, Sandy, Harvey, and Florence, have both similarities and differences. Within each hurricane, specific sectors show significant abnormal returns. The Consumer Goods sector shows positive significant coefficients consistently, which could be due to increased consumer demand, which can increase after a hurricane hits. A potential reason for this could be because of the need for essential goods during the recovery period.

The Energy and Utilities sector also shows significant coefficients for many hurricanes, for some positive and for others negative. For example, Hurricane Katrina and Hurricane Florence show significant positive impacts on the short-term window, potentially because of high demand for energy and utilities services during the recovery period in the aftermath of the hurricane. On the contrary, Hurricane Sandy and Hurricane Florence show significant negative impacts in the long term, this could be due to these storms causing great damage in certain Energy and Utilities company's facilities. The impact of hurricanes differs significantly across short, medium, and long-term windows. Short-term impacts are often significant and bigger than other event windows, showing direct reactions from market participants as it often includes panic selling or speculative buying. Long-term impacts might capture the sector's recovery period well, with some sectors showing significant negative impacts over these longer periods. Looking at these returns, it seems really important to consider the different timeframes when analysing the cumulative abnormal returns. Another conclusion which can be drawn from this analysis, is that hurricanes all seem to have their own unique effects and that no hurricane really is comparable. The Financials and Real Estate sector experiences significant positive impacts in Ike's long-term window, but significant negative impacts in Harvey's long-term window. Different hurricanes seem to have varying sensitivities to certain sectors, this could be influenced by the severity of the hurricane, the location of the landfall and overall market conditions during the time of the hurricane.

The constants confirm that overall market impact varies per hurricane. Katrina shows a consistently negative constant term for each window, meaning a general market decline, likely due to the severity and the tremendous damage this hurricane did. In contrast, Harvey shows a significant positive constant term in the short term, perhaps driven by recovery opportunities spotted by investors. Additionally, the degree of heteroskedasticity and outliers increases with shorter windows, meaning complexity and variability of impacts grow as the windows become smaller. This increasing heteroskedasticity with shorter windows might require more robust modelling approaches to capture these dynamics accurately than current approaches. Lastly, the overall fit of the model should be discussed by examining the R-squared. As there are 14 regressions, I have placed the 14 model fit results in Appendix E. Higher R-squared values suggest a better fit of the model to the observed data, which can be an indication that the control variables effectively capture the variability in the CARs caused by the hurricanes. These values seem to be higher for the short-term window, but overall relatively low. Even though this is typical in financial event studies, it does suggest that the fit of the model could be improved. This could be done via adding or changing the existing set of control variables. Especially market capitalization, liquidity and the distance variable do not seem to be significant, so these would have to be examined in future research.

The hypothesis discussed in the introduction of this research stated that hurricanes would have varying effects on different equity sectors, with some sectors being more sensitive than others. I also mentioned that I expected the returns of Energy and Utilities to be significantly negative and that I expected temporal effects of hurricanes. I do not reject my hypothesis as I have found similar results.

5.5.1 Limitations

This paper has several limitations that must be discussed. First of all, my study uses a fixed set of S&P 500 constituents, based on the closest period where the constituents were available to the start of each estimation window (before, not after). This fixed sample approach may misrepresent the event's impact, especially if large firms with significant weight in the index enter or exit during the event window. This could skew the results. Further on, the study relied on the current headquarters' locations for distance calculations, because historical data was not available. Some companies might have relocated, even though a quick analysis showed that many of them stayed the same. However, this does affect the distance variable and its significance in the regressions, and can potentially explain why it also turned out to be insignificant in the actual regressions. Then to discuss the assumptions, the assumption of approximate normality of returns is another limitation. Both the t-test and the OLS regression rely on the normality assumption. Approximate normality was used to avoid the complexity of transformations or other complex tests, however it is a clear limitation. Lastly, I decided to exclude ESG ratings in this analysis, but they were considered. Time constraints and data availability prevented ESG from being a control variable. Incorporating them, or some other environmental policy variable, into research could still provide better insights. Companies with higher ESG ratings might be able to adjust better after climate events due to their management of environmental and social risks.

My results align with previous research in multiple ways. Ferina-Dominguez et al. (2017) identified significant positive cumulative abnormal returns for property and casualty insurance companies at the days surrounding the landfall, which also suggests that expectations of high financial rebuilding costs are high in the market. Burke et al. (2015) emphasized the overall impact of hurricanes on financial markets and found significant results which led to the belief that resilience planning is important. This is consistent with the findings in my study on sectors like Consumer Goods and Energy and Utilities. My study also found similar results to the research of Betzer et all. (2011), who found negative abnormal returns for energy-producing companies, similar to this study’s long term negative Energy and Utilities impact.

5.5.1.1 Research suggestions

For this research, an index analysis was used. Conducting portfolio analysis, creating portfolios for each sector, could provide more detailed findings, as it could isolate sector-specific effects well. Additionally, future research should explore a bigger range of event windows and estimation periods to assess the robustness of the findings and get even better insights into the short-, medium- and long-term effects of hurricanes. More advanced methods to ensure normality can also be explored. When it comes to control variables, ESG would be a good addition to the model.

CHAPTER 6 Conclusion

My study analyses the financial impacts of five major hurricanes; Katrina, Ike, Sandy, Harvey, and Florence, on different stock market sectors by using t-tests and regression methods on cumulative abnormal returns. The primary purpose of the research is to analyse the impact of major hurricanes on the performance of different equity sectors within the U.S. financial markets. If we can understand how various sectors respond to these type of climate-changing events, we can better prepare and mitigate the financial risks associated with these hurricanes, as climate change becomes one of our society's greater problems with time. To achieve this goal, the study uses an event study methodology to analyse the financial impact of the chosen hurricanes on stock market sectors. The analysis involved the collection of data of the historical S&P500 stocks during the time of the hurricanes, after which event windows were constructed, in the short-, medium- and long-term. Cumulative abnormal returns were then calculated for each stock in the dataset and statistical analysis was conducted with t-tests and regressions.

The results from this method show large resilience within the Consumer Goods sector with positive coefficients in the short and long run, for all hurricanes. This resilience could be due to increased demand for essential goods after the hurricane hit, meaning that investors could capitalize on this fact by holding Consumer Goods stocks, especially essential goods, during these events. On the other hand, the Energy and Utilities sector shows mixed responses. These were positive in the short term as reflected by Katrina and Florence, suggesting immediate emergency need and re-construction. However, Sandy and Florence showed high recovery costs and disrupted services with their long-term negative effects. Additionally, the sector Financials and Real Estate showed multiple responses, indicating it's sensitivity to specific hurricane characteristics. Insurance companies might have high costs after hurricane events and unpredictable events like hurricanes itself might bring investment risks and uncertainty to the finance sector, which could explain the negative effects. These were demonstrated by hurricane Harvey's results. Explanations for the positive impact can include investment opportunities from reconstruction and innovation, which can be seen in the results for hurricane Ike.

Impact of hurricanes on financial markets can vary greatly depending on the timeframe that we look at. We often see direct market reactions when looking at the short-term effects, this could be a drop in stock prices due to the sudden shock. When we look at medium and long-term impacts, the results are more complex. Prolonged recovery and economic disruptions are observed and highlight the necessity to consider multiple timeframes when analysing such events. When we look at the overall market reactions, we see different outcomes. Hurricane Katrina generally led to a market decline, shown in the negative constants for the regressions. However, Hurricane Harvey showed positive short-term market reactions, which could be due to investor optimism, as investors might have predicted worse outcomes for this hurricane. This could generally be a big reason for why markets react positively to hurricanes, expected outcomes of the hurricane as spread via broadcasting and social platforms might turn out to be not so significant. Recovery efforts might also be a reason for stocks' prices to increase after a hurricane. The t-tests for abnormal returns back up these findings and therefore confirm the general market response to hurricanes.

Understanding these impacts of hurricanes on returns can help investors make informed decisions and policymakers develop strategies to enhance market resilience and support recovery efforts. The findings highlight the importance of considering event-specific characteristics and sectoral dynamics in risk management and investment strategies. Even though my research is really insightful, it also has some limitations, including the reliance on current headquarters for distance calculations, and the assumption of approximate normality of returns. Future research should therefore explore alternative windows, portfolio analyses, the inclusion of ESG ratings and the changing of the existing set of control variables for a better model fit and a more comprehensive understanding.

Finally, I would like to do some recommendations for policymakers and investors. This includes that policymakers should prioritize the boosting of infrastructure in vulnerable sectors, such as Energy and Utilities. This could help to mitigate the long-term negative impact of hurricanes. Further on, promoting robust insurance methods could be really beneficial for industries that are hit hard by these events and could help stabilize them. Understanding how hurricanes impact returns can make sure investors make better-informed decisions for their portfolios and could help them develop strategies to enhance market resilience. The findings of this study highlight the importance of considering specific characteristics of each climate event and the benefits of adjusting investment strategies according to different sectors.

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APPENDIX A Missing values return

Hurricane	Missing values	Percentage
Katrina	290	0.556
Ike	402	0.775
Sandy	619	1.195
Harvey	238	0.453
Florence	277	0.527

Table 11: Missing values of the return without dividend. For each of the 5 hurricanes, the percentages are given in %.

APPENDIX B Detailed SIC to industry mapping

1. Consumer Goods (Consumer Discretionary, Consumer Staples):

- Food and Kindred Products: 2000-2099
- Tobacco Products: 2100-2199
- Textile Mill Products: 2200-2299
- Apparel and Other Finished Products: 2300-2399
- Lumber and Wood Products: 2400-2499
- Furniture and Fixtures: 2500-2599
- Paper and Allied Products: 2600-2699
- Printing and Publishing: 2700-2799
- Chemicals and Allied Products: 2800-2899
- Petroleum Refining and Related Industries: 2900-2999
- Rubber and Miscellaneous Plastics Products: 3000-3099
- Leather and Leather Products: 3100-3199
- Stone, Clay, Glass, and Concrete Products: 3200-3299
- Primary Metal Industries: 3300-3399
- Fabricated Metal Products: 3400-3499
- Industrial and Commercial Machinery and Computer Equipment: 3500-3599
- Electronic and Other Electrical Equipment: 3600-3699
- Transportation Equipment: 3700-3799
- Instruments and Related Products: 3800-3899
- Miscellaneous Manufacturing Industries: 3900-3999

2. Energy and Utilities:

- Electric, Gas, and Sanitary Services: 4900-4999
- Pipelines, Except Natural Gas: 4600-4699

3. Technology and Communications (Information Technology, Communication Services):

- Communications: 4800-4899
- Business Services (including Information Technology): 7370-7379
- Miscellaneous Business Services: 7380-7399

4. Financials and Real Estate:

- Depository Institutions: 6000-6099
- Non-depository Credit Institutions: 6100-6199

- Security and Commodity Brokers: 6200-6299
- Insurance Carriers: 6300-6399
- Real Estate: 6500-6599

5. Healthcare:

- Health Services: 8000-8099

6. Industrials and Materials:

- Metal Mining: 1000-1099
- Coal Mining: 1200-1299
- Oil and Gas Extraction: 1300-1399
- Mining and Quarrying of Nonmetallic Minerals: 1400-1499
- Building Construction: 1500-1599
- Heavy Construction: 1600-1699
- Construction Special Trade Contractors: 1700-1799
- Manufacturing (Miscellaneous): 4000-4099
- Railroad Transportation: 4000-4099
- Local and Suburban Transit: 4100-4199
- Motor Freight Transportation and Warehousing: 4200-4299
- United States Postal Service: 4300-4399
- Water Transportation: 4400-4499
- Transportation by Air: 4500-4599
- Pipelines, Except Natural Gas: 4600-4699
- Transportation Services: 4700-4799

7. Other (no industry):

- Miscellaneous Industry: 9997

APPENDIX C Q-Q plots remaining hurricanes

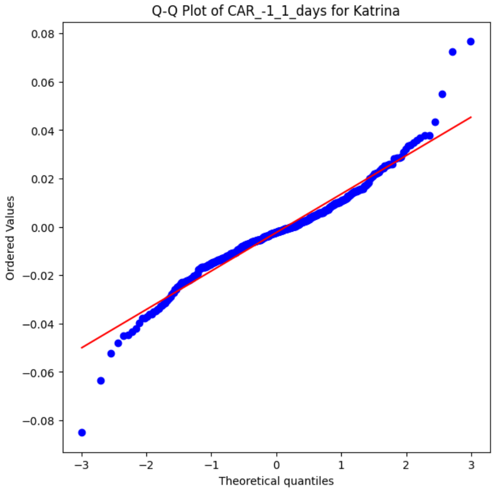

Figure 5: Q-Q plot Katrina short term.

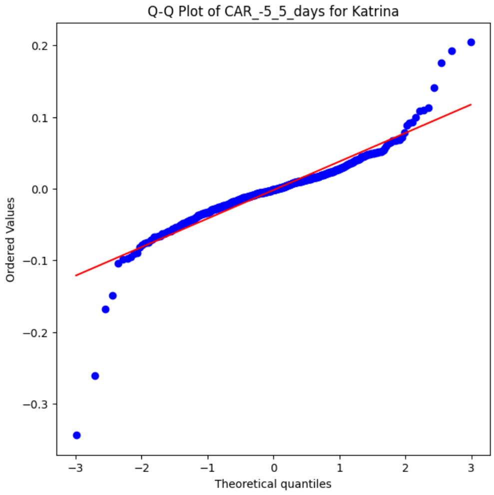

Figure 6: Q-Q plot Katrina medium term.

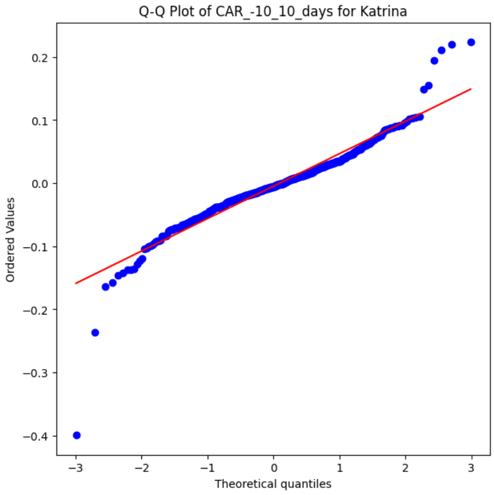

Figure 7: Q-Q plot Katrina long term.

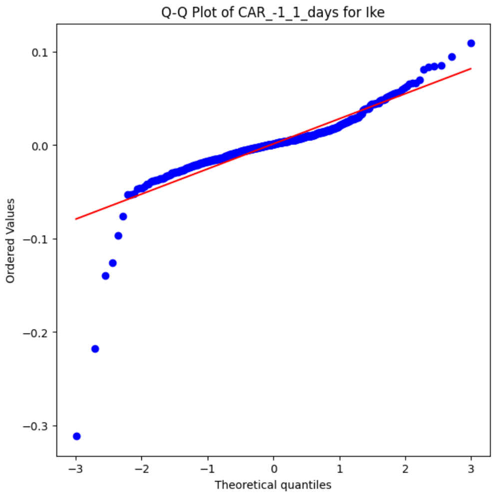

Figure 8: Q-Q plot Ike short term.

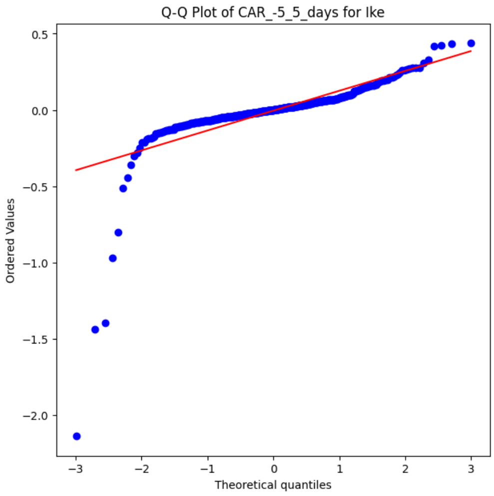

Figure 9: Q-Q plot Ike medium term.

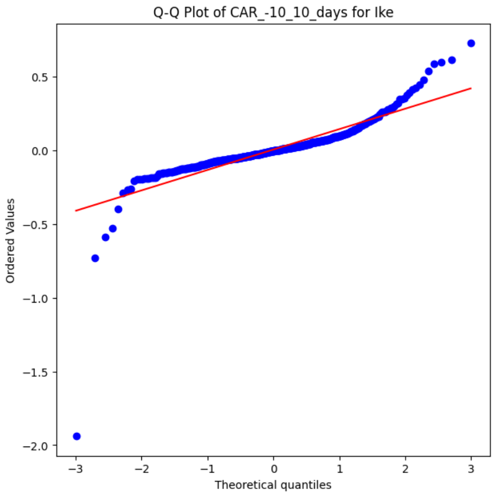

Figure 10: Q-Q plot Ike long term.

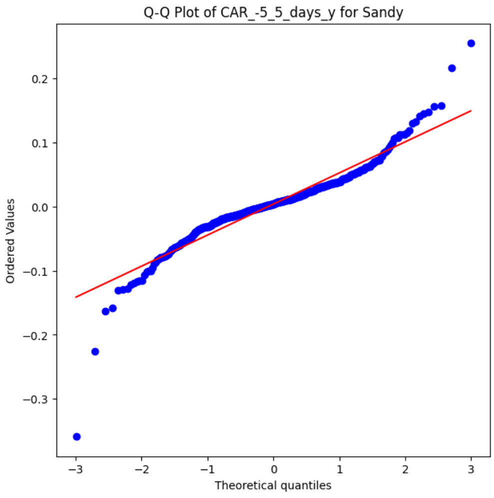

Figure 11: Q-Q plot Sandy medium term.

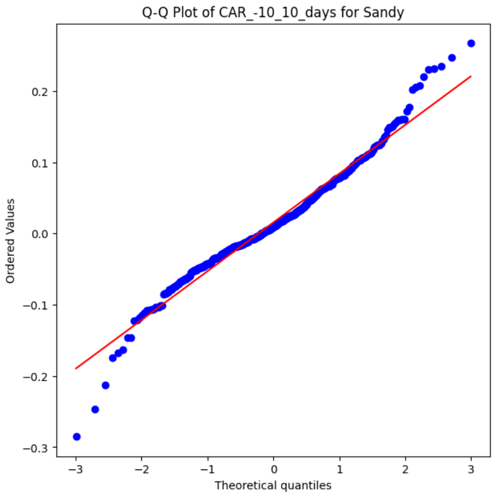

Figure 12: Q-Q plot Sandy long term.

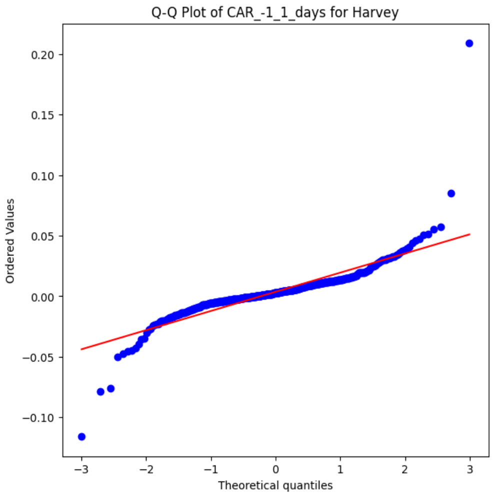

Figure 13: Q-Q plot Harvey short term.

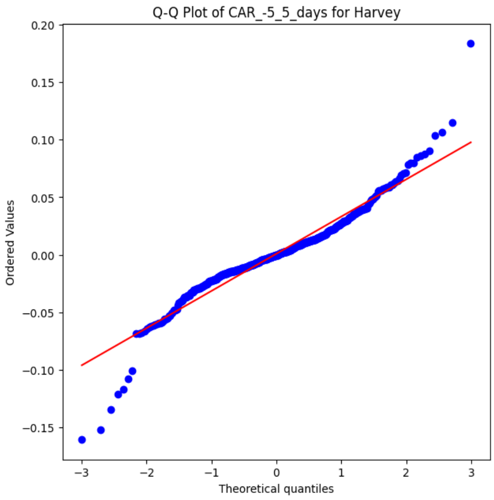

Figure 14: Q-Q plot Harvey medium term.

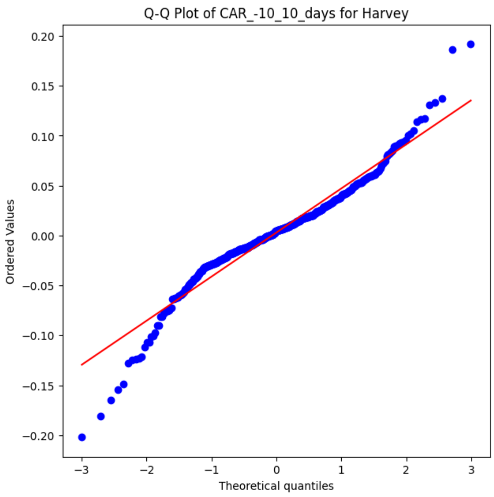

Figure 15: Q-Q plot Harvey long term.

APPENDIX D Residuals error terms

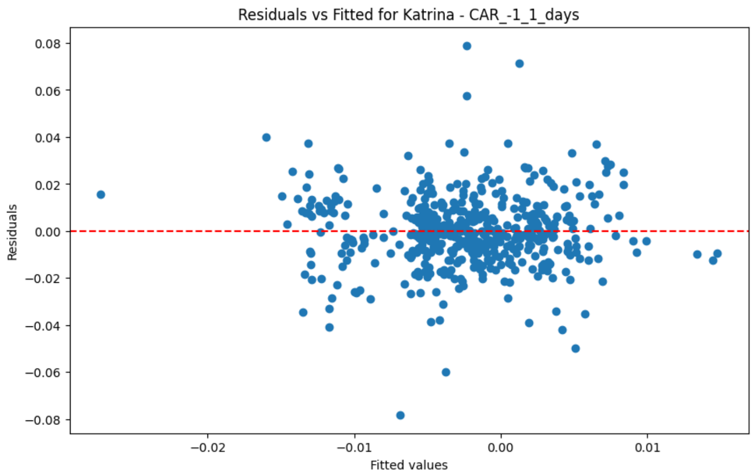

Figure 16: Scatterplot residuals error terms Katrina short term.

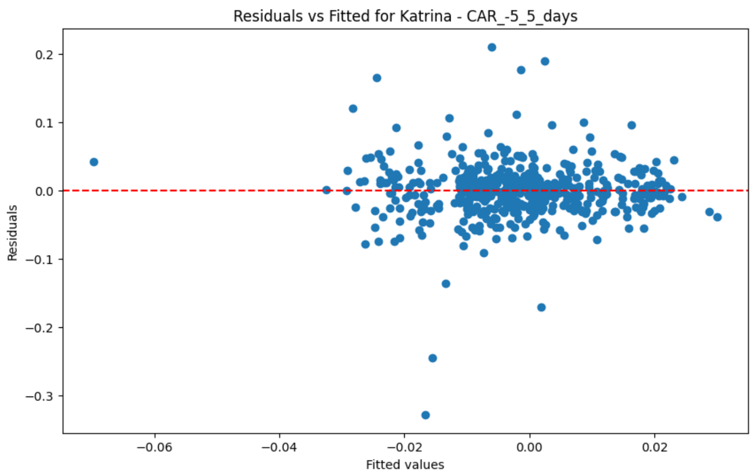

Figure 17: Scatterplot residuals error terms Katrina medium term.

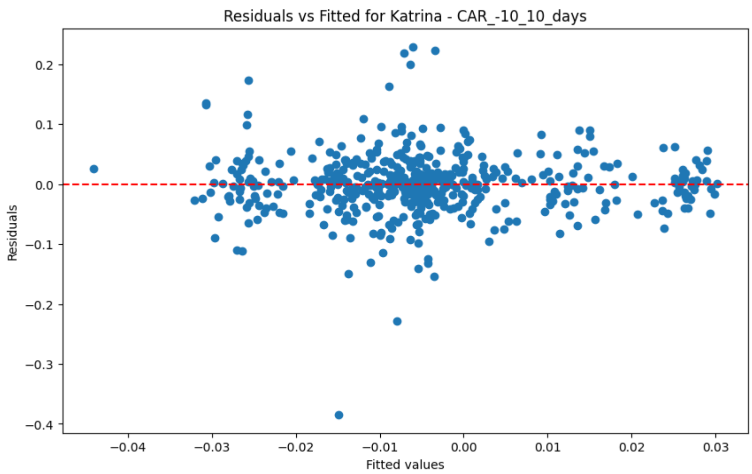

Figure 18: Scatterplot residuals error terms Katrina long term.

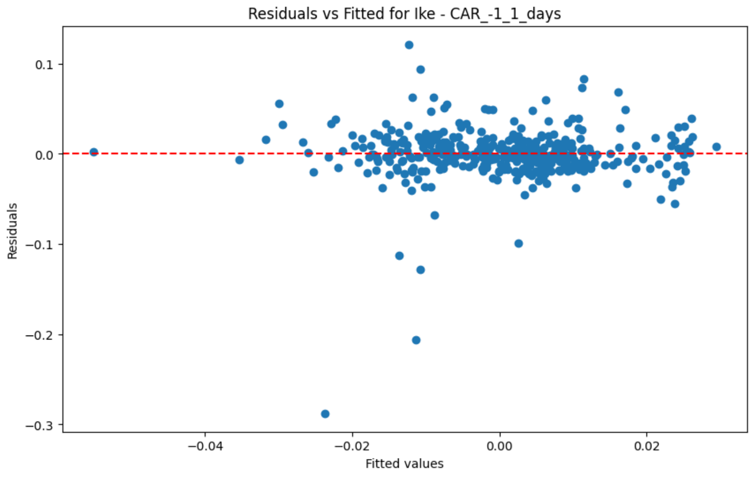

Figure 19: Scatterplot residuals error terms Ike short term.

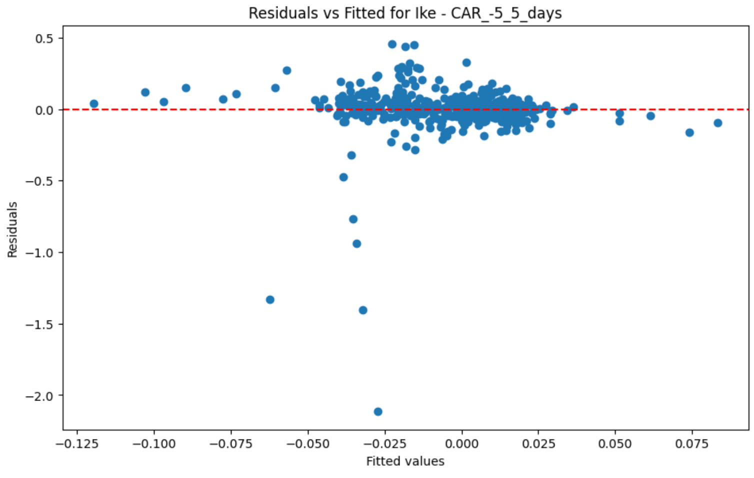

Figure 20: Scatterplot residuals error terms Ike medium term.

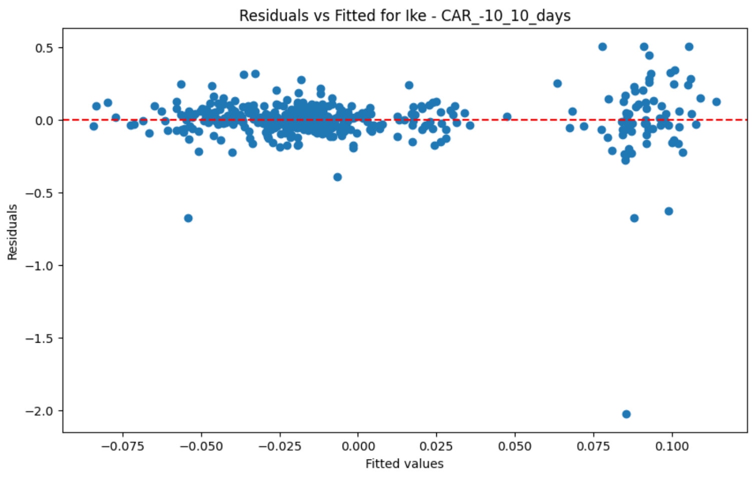

Figure 21: Scatterplot residuals error terms Ike long term.

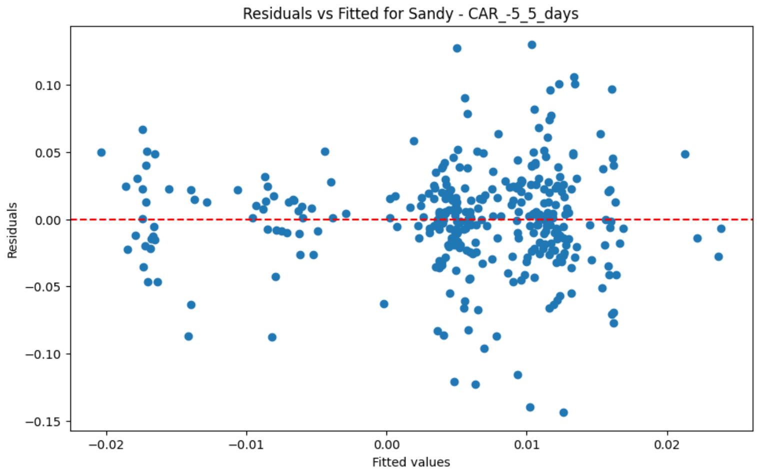

Figure 22: Scatterplot residuals error terms Sandy medium term

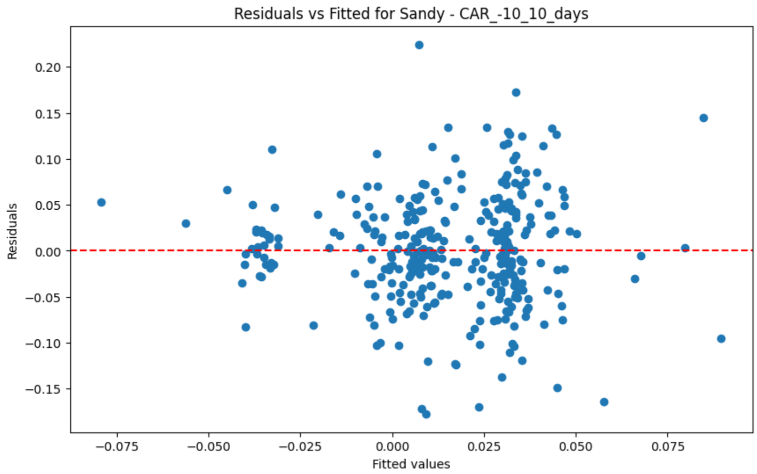

Figure 23: Scatterplot residuals error terms Sandy long term.

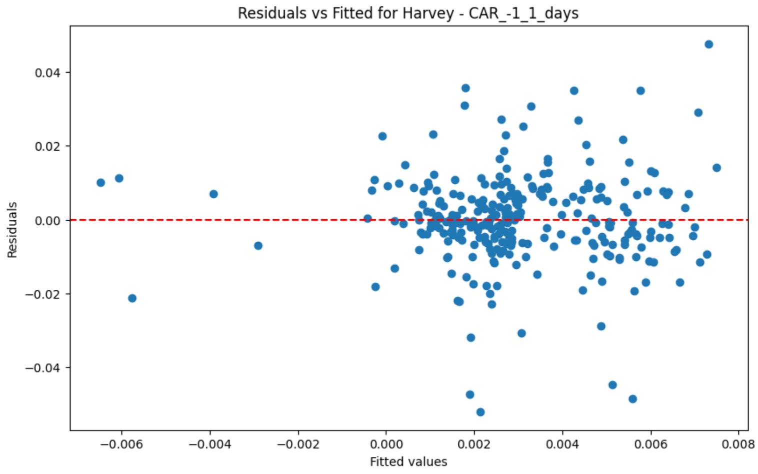

Figure 24: Scatterplot residuals error terms Harvey short term.

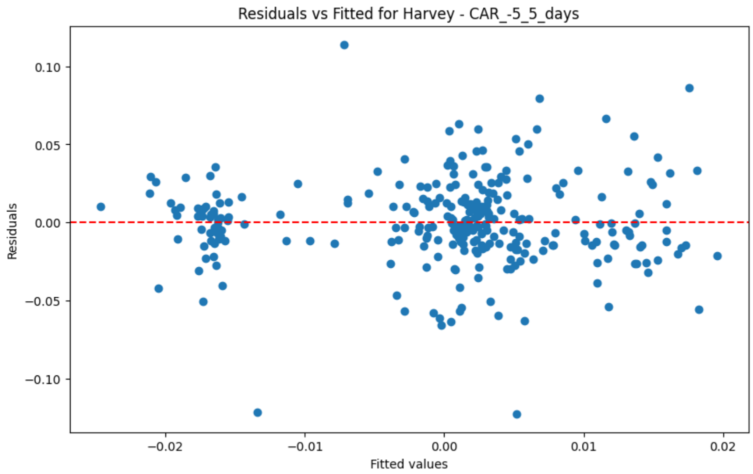

Figure 25: Scatterplot residuals error terms Harvey medium term.

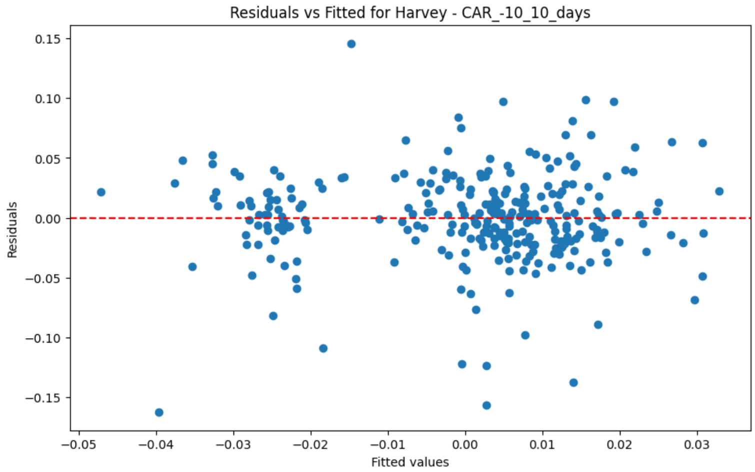

Figure 25: Scatterplot residuals error terms Harvey long term.

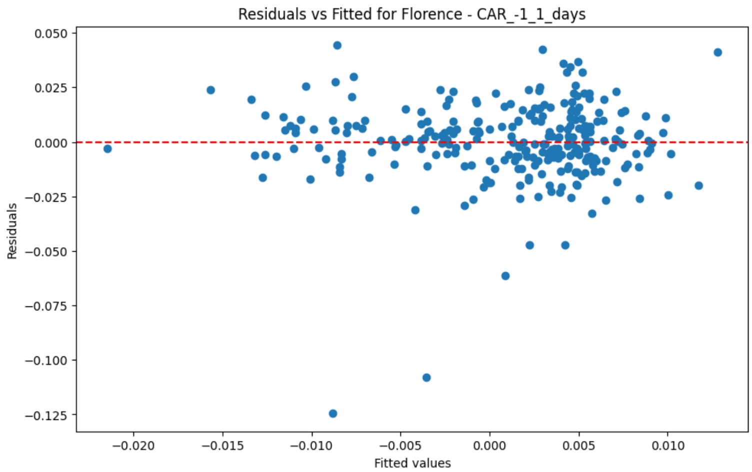

Figure 26: Scatterplot residuals error terms Florence short term.

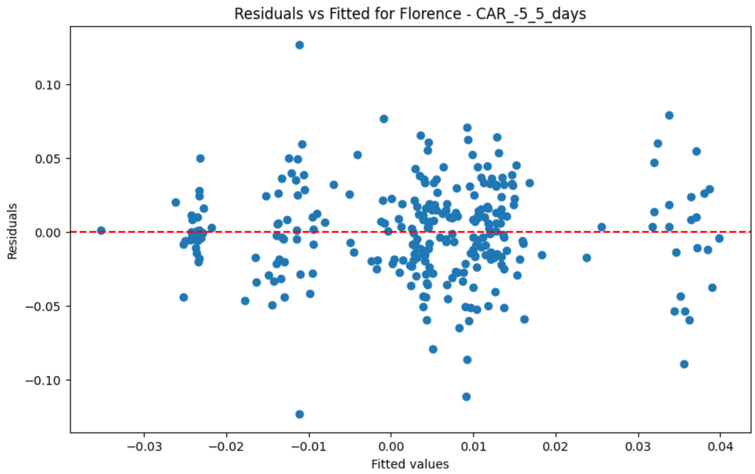

Figure 27: Scatterplot residuals error terms Florence medium term.

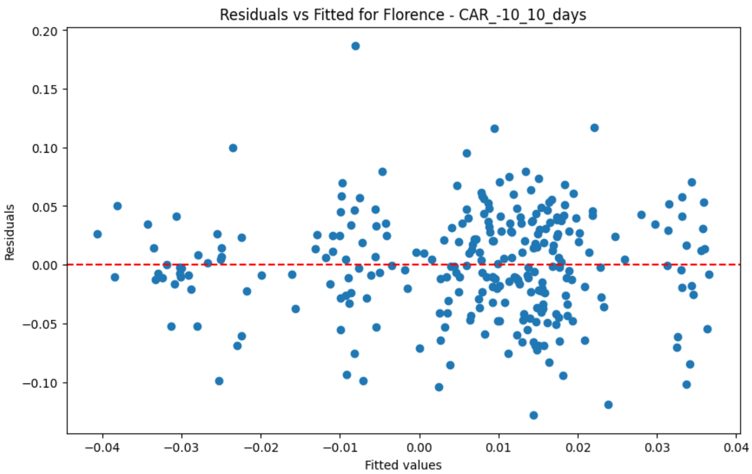

Figure 28: Scatterplot residuals error terms Florence long term.

APPENDIX E Regression statistics

Katrina	Adjusted R Square	Multiple R	Observations	R Square	Standard Error
Window					
CAR short-term	0.087	0.324	497.000	0.105	0.007
CAR medium-term	0.065	0.289	497.000	0.084	0.022
CAR long-term	0.048	0.259	497.000	0.067	0.025

Table 12: Katrina regression statistics.

Ike	Adjusted R Square	Multiple R	Observations	R Square	Standard Error
Window					
CAR short-term	0.123	0.380	411.000	0.145	0.011
CAR medium-term	-0.010	0.121	411.000	0.015	0.048
CAR long-term	0.058	0.285	411.000	0.081	0.073

Table 13: Ike regression statistics.

Sandy	Adjusted R Square	Multiple R	Observations	R Square	Standard Error
Window					
CAR medium-term	0.020	0.223	333.000	0.050	0.020
CAR long-term	0.116	0.378	333.000	0.143	0.037

Table 14: Sandy regression statistics.

Harvey	Adjusted R Square	Multiple R	Observations	R Square	Standard Error
Window					
CAR short-term	-0.008	0.167	285.000	0.028	0.007
CAR medium-term	0.079	0.334	285.000	0.112	0.030
CAR long-term	0.121	0.389	285.000	0.152	0.041

Table 15: Harvey regression statistics.

Florence	Adjusted R Square	Multiple R	Observations	R Square	Standard Error
Window					
CAR short-term	0.059	0.305	274.000	0.093	0.011
CAR medium-term	0.152	0.428	274.000	0.183	0.019
CAR long-term	0.094	0.357	274.000	0.128	0.026

Table 16: Florence regression statistics.