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Hurricanes as News? A Comparison of the Impact of Hurricanes on Stock Returns of Energy Companies

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Hurricanes as News? A Comparison of the Impact of Hurricanes on Stock Returns of Energy Companies

Abstract

Recent hydro-meteorological disasters have sparked popular interest in climate change and on its role in driving these events. This paper focuses on the information provided by hurricanes in shaping public perceptions towards human-induced climate change. Because CO_2 emissions from combustion are a sizeable contributor to greenhouse gas concentrations, and their reduction is a key ingredient in any climate change mitigation strategy, we focus on the energy sector. We estimate the impact of hurricanes on the stock returns of the largest energy companies in the US. We consider the most notorious, damaging hurricanes over the last 25 years: Sandy (2012), Katrina (2005), Andrew (1992), and Hugo (1989). We categorize energy companies into five groups according to CO_2 intensity: coal, oil, natural gas, nuclear, and renewables. We find that the impacts of a given hurricane on the stock prices of energy companies differ by energy type. Compared to companies in the coal industry, companies in oil, natural gas and renewable energy industries all reveal significantly more positive cumulative average abnormal returns and the effect is the largest for renewables, followed by oil and natural gas. Similarly, the impacts of hurricanes on stock prices of energy companies differ by hurricane.

Key words: Climate Change; Energy Industry; Event Study; Hurricanes

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1. Introduction

The last twenty five years have seen an increase in the frequency and intensity of hydro-meteorological disasters globally (Figure 1, Figure 2). The same trend is found within the US. Figure 3 shows that meteorological followed by hydrological disasters are the most frequent disaster in the US in the last sixty years. In terms of specific types, two hydro-meteorological disasters, storms and floods, are the most recurrent. Regarding immediate monetary damages, among the four disaster groups, only damages caused by meteorological disasters have increased dramatically while those of the other groups have remained more stable since the 1950s (Table 1).

Although one reason behind this trend is an increase in exposure of people and property in floodplains, recent events (Hurricane Katrina, Hurricane Sandy, and Typhoon Haiyan) have sparked popular interest in climate change and on its role in driving extreme weather. This role has been extensively analyzed by the scientific community. For example, Mann and Emanuel (2006), Emanuel (2005), Emanuela (2011), and Kunkel, et al. (2013) argue that in the North Atlantic region, the decadal variations of the sea surface temperature itself, as well as the upward trend in the destructiveness of large storm systems, are driven mostly by anthropogenic changes in greenhouse gases and aerosols. Karim and Mimura (2008) show that in the Western Bangladesh, under a 2 ℃

sea surface temperature rise and a 0.3 m sea level rise, flood risk area from a storm surge would be 15.3% greater and depth of flooding would increase by as much as 22.7% within 20 km of the coastline. Further, based on a meta-analysis of projected future economic losses under a variety of climate change scenarios, Ranson, et al. (2014) find strong (but not conclusive) support that climate change will cause damages from tropical cyclones and wind storms to increase. Potential changes in damages are greatest in the North Atlantic basin, where the multi-model average predicts that a 2.5 ℃ increase in global surface air temperature would cause hurricane damages to increase by 63%.

Despite its potentially large impacts, the degree to which climate change is perceived as a risk by the wider public varies substantially and has been traditionally low in the United States (Leiserowitz, et al., 2014). Understanding what shapes the public perception of climate change, both of its extent and even of its existence, and explaining the variability of such beliefs has received considerable attention from a multitude of disciplines within the social sciences. Weber (2010) summarizes a consensus that acknowledges important roles of individual, social, and cultural forces, without denying the reality and power of external, physical and environmental forces. Our study investigates the role of one such external environmental factor: large, devastating hurricanes.

Climate change perceptions have traditionally been gathered using surveys such as the Gallup Poll Social Series survey. Our approach in this paper relies is radically different: we rely on stock market data for energy companies. This choice may seem strange, but we argue that it may provide useful information provided that stock markets reflect investors' preferences, expectations and beliefs and are efficient in incorporating new information. The focus on the energy sector is motivated by the fact that CO_2 emissions from combustion are a sizeable contributor to greenhouse gas concentrations, and their reduction is a key ingredient in any climate change mitigation strategy. At a micro level, previous studies have demonstrated that direct experience of local weather events is an important factor shaping climate change perceptions. For example, Spence, et al. (2011) show that those who report experience of flooding express more concern over climate change, see it as less uncertain, and feel more confident that their actions will have an effect on climate change. Importantly, these perceptual differences also translate into a greater willingness to save energy to mitigate climate change. If the same is true at the macro level we should expect stock markets, in particular those of energy companies, to react to events that change climate change perceptions.

Our paper focuses on the information provided by local weather events, hurricanes in the North Atlantic in particular, to the energy sector. Specifically, we conduct a series of event studies to measure the impact of hurricanes on the stock returns of the largest energy companies in the US. We categorize energy companies into five groups according to CO_2 intensity: coal, oil, natural gas, nuclear, and renewables. We consider the most notorious, damaging hurricanes affecting the US over the last 25 years: Sandy (2012), Katrina (2005), Andrew (1992), and Hugo (1989). We hypothesize that the impact of hurricanes on energy companies depends on their carbon intensity with a

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negative effect for coal and positive for nuclear and renewables, and that the impact has increased over time.

Earlier event studies on energy stock returns have estimated stock price reactions to nuclear accidents. Ferstl, et al. (2012) find significant negative abnormal returns for Japanese nuclear utilities as well as French and German nuclear utility and alternative energy stocks following Fukushima, while US stocks do not react significantly. Betzer, et al. (2013) find a wealth transfer from nuclear energy companies to renewable energy companies in Germany resulting from the shutdown of 7 German nuclear plants after the Fukushima disaster. Basse Mama and Bassen (2013) find positive and lingering effects of the Fukushima accident on the shares of alternative electric utilities while negative and long-lasting effects on Japanese utilities. Finally, Lopatta and Kaspereit (2014) and Kawashima and Takeda (2012) find that the share prices of firms who rely more on nuclear declined more after the Fukushima accident.

While abundant research has been done on nuclear accidents, this research does not tell us much about energy and climate change perceptions. Two previous studies study the effects of hurricanes on petroleum prices by affecting the refining industry concentrated in the Gulf of Mexico.[1] Given the importance of the energy sector in mitigating climate change, extreme events such as hurricanes, by shaping climate change perceptions, can have much broader, long lasting effects on the energy sector that go beyond those to the refining industry.

2. Methodology

We are interested in assessing the reaction of stock prices of energy companies following substantially damaging hurricanes. The market model developed by Fama, et al. (1969) is traditionally used in event studies. The validity of the significance tests of the estimated parameters in this model relies on the assumption of identically and independently distributed (i.i.d) market model residuals, however. In our case, since the hurricanes occur in the same time period for all firms and these firms are in the same industry, the i.i.d assumption on market model residuals is most likely violated. Therefore, as in Betzer, et al. (2013), Ferstl, et al. (2012), and Lopatta and Kaspereit (2014), we adopt the model first proposed by Izan (1978) and applied by Binder (1985) to address the contemporaneous correlation in market model residuals, and apply the seemingly unrelated regression (SUR) method by Zellner (1962) to conduct the estimation. Specifically, for each event (hurricane in our case) we estimate a series of systems of equations in which each equation has the following form:

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[1] Fink, J.D., K.E. Fink, and A. Russell. 2010. "When and how do tropical storms affect markets? The case of refined petroleum." *Energy Economics* 32:1283-1290. show that refined petroleum and crude oil prices appear to reflect storm effects at the 24-hour forecast horizon. They also find that category 4 hurricanes in coastal northwest Gulf of Mexico increase refined petroleum prices relative to crude oil by 13.5%. Fink, J., and K. Fink. 2014. "Do Seasonal Tropical Storm Forecasts Affect Crack Spread Prices?" *Journal of Futures Markets* 34:420-433. further find that seasonal forecasts of tropical storm activity in the Atlantic basin have a measurable effect on crack spread futures prices.

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$$R_{\mathrm{it}} = \alpha_{\mathrm{i}} + \beta_{\mathrm{i}} R_{\mathrm{mt}} + \sum_{\mathrm{k}=t_0-\mathrm{a}}^{\mathrm{k}=t_0+\mathrm{b}} \delta_{\mathrm{ik}} D_{\mathrm{kt}} + \varepsilon_{\mathrm{it}} \quad (1)$$

where R_{it} is the rate of return on the stock prices of firm *i* on day *t* and is calculated as $R_{it} = \frac{P_{i,t}}{P_{i,t-1}} - 1$, R_{mt} is the rate of return on the price index of a market portfolio of stocks on day *t* and is calculated as $R_{mt} = \frac{P_{m,t}}{P_{m,t-1}} - 1$, and ε_{it} is the error term with $E(\varepsilon_{it}) = 0$. D_{kt} are event window dummies which equal 1 if day *k* is in the event window and 0 otherwise. For each equation, there are a+b+1 dummy variables identifying the days in the event window.

Day t_0 ($t_0 = 0$) is the event day which is defined as the day when the first emergency was declared in the US. Day $t_0 - a$ is the day the hurricane formed, and it is hurricane specific. δ_{ik} is the abnormal return for firm *i* on day *k*, which is the prediction error in the traditional market model. It measures the impact of new information on the stock returns of company *i* on day *k*. Our sample includes *i*=1, 2, …, N companies (not necessarily the same for each event); *t*=1, 2, …, T where T equals the number of days in the estimation window plus the number of days in the event window. Section 3 discusses our choice of the companies and the estimation and event windows in detail.

From model (1), we obtain estimates of the daily abnormal returns for company *i* for each day *k* in the event window for each of our four hurricane events. For each hurricane, we have:

$$AR_{ik} = \delta_{ik} \,. \quad (2)$$

Based on AR_{ik}, we calculate the daily average abnormal returns (AAR) for each of the five energy categories for each event: coal, oil, gas, nuclear, and renewables. The grouped AARs are aggregations across firms and are calculated as:

$$AAR_{\mathrm{jk}} = \frac{1}{N_j} \sum_{\mathrm{i}=1}^{N_j} AR_{\mathrm{ik}} \quad (3)$$

where *j*=coal, oil, gas, nuclear, and renewables, and N_j is the number of companies in energy category *j*.

The cumulative average abnormal returns (CAAR) over an event window $[t_1, t_2]$ are given by:

$$CAAR_{\mathrm{j},t_1,t_2} = \sum_{\mathrm{k}=t_1}^{\mathrm{k}=t_2} AAR_{\mathrm{jk}} \quad (4)$$

The null hypotheses that the hurricanes did not have a significant impact on the daily stock returns of energy firms are

$$H_0\colon AAR_{\mathrm{jk}} = 0 \quad (5)$$

The significance of the daily average abnormal returns is assessed with a standard Wald statistic. To test the hypothesis of zero cumulative average abnormal returns, we calculate the *z*-score using the formula for the standard deviation of CAAR in Kawashima and Takeda (2012) and MacKinlay (1997):

$$\sigma(t_1, t_2) \approx \sqrt{(t_2 - t_1 + 1)\sigma_{AAR}^2} \quad (6)$$

where t_1, t_2 are days in the event window, and $t_1 \leq t_2$.

We also test the hypothesis that the impact of hurricanes on the stock returns of energy companies has increased over time, that is, it is larger for more recent hurricanes. We first stack the AARs and CAARs for each energy type and hurricane, and then

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regress the abnormal returns on energy type and hurricane while controlling the time difference between the trading days and the event day. The model is specified as:

$$\widehat{AAR}_{hjk} = \alpha_{hj} + \beta_1 D_{coal} + \beta_2 D_{oil} + \beta_3 D_{gas} + \beta_4 D_{nuclear} + \gamma_1 D_{Andrew} + \gamma_2 D_{Katrina} + \gamma_3 D_{Sandy} + \delta_{hj} k + \varepsilon_{hj} \quad (7)$$

$$\widehat{CAAR}_{hjk} = \alpha_{hj} + \beta_1 D_{coal} + \beta_2 D_{oil} + \beta_3 D_{gas} + \beta_4 D_{nuclear} + \gamma_1 D_{Andrew} + \gamma_2 D_{Katrina} + \gamma_3 D_{Sandy} + \delta_{hj} k + \varepsilon_{hj} \quad (8)$$

where *h* stands for hurricane (Hugo, Andrew, Katrina, Sandy), *j* stands for energy category (coal, oil, gas, nuclear, renewables), *k* stands for the difference of days between the trading day in the event window and the event day (-a, -a+1, -a+2, …, b as defined in model (1)). AAR_{hjk} and $CAAR_{hjk}$ are the daily average abnormal return and cumulative average abnormal return for hurricane *h*, energy category *j* and on day k respectively. D_{coal}=1 if AAR_{hjk} and $CAAR_{hjk}$ are aggregations across coal firms, and 0 otherwise. D_{oil}, D_{gas}, $D_{nuclear}$, and $D_{renewables}$ are defined similarly for oil, gas, nuclear and renewable energy firms, respectively. D_{Andrew}=1 if AAR_{hjk} and $CAAR_{hjk}$ are aggregations across firms in energy category *j* for hurricane Andrew, and 0 otherwise. $D_{Katrina}$ and D_{Sandy} are defined similarly. Model (7) and (8) use renewable energy and hurricane Hugo as reference group. We also report results using coal and Hurricane Sandy and Katrina as reference groups.

3. Data

3.1 Hurricanes, and Estimation and Event Windows

We examine the effects of four major hurricanes that hit the US between 1980 and 2010 (each of the hurricanes being the most costly in their decade) on the stock market returns of energy companies which are categorized into five groups according to their carbon intensity - coal, oil, natural gas, nuclear, and renewables. The occurrence dates and damage information are retrieved from National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center (NHC).

Typical lengths for the estimation period with daily data range from 100 to 300 days, while typical lengths for the event period range from 21 to 121 days (Peterson (1989). For our analysis, we define the day on which first emergency was declared in the US following the hurricanes as the event day. The Federal Emergency Management Agency (FEMA) records the dates of major disaster declarations and emergency declarations by disaster and state. The first emergency declaration dates are generally earlier than the first major disaster declaration dates. To avoid the problem of anticipation which is prevalent in event studies, we use the first emergency declaration dates as our day 0, but use the date in which the hurricane formed to create a pre-event window. For cases in which the event happened after the trading hours, the event day is the next trading day as for hurricane Sandy and Katrina. For hurricane Sandy, the emergency declaration was on a Sunday (10/28/2012) and the stock markets were closed on the following Monday and Tuesday, therefore, the event day is Wednesday (10/31/2012). For

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hurricane Katrina, the emergency declaration was on a Saturday (8/27/2005), so the next Monday (8/29/2005) is our event day.

The four hurricanes examined in this study all started as tropical storms in the Central or North Atlantic Ocean, and moved towards the mainland US several days later. The US declares emergency on the first day the hurricane landed on the US or one or two days later, so by using an event window that begins from the day the hurricanes started to form, we have a pre-event window and are able to avoid the anticipation problem. In summary, for each of our four events, the estimation window consists of the 250 trading days prior to the day the hurricane formed, corresponding to approximately one trading year. The event window spans from the day the hurricane formed till 30 days after day zero. Table 2 shows the hurricanes names, dates and damages.

3.2 Stock Price Data

Stock prices for US energy companies are collected from Datastream. We use the S&P 500 Index to represent the broad market index R_{mt} in equation (6). This index includes 500 large companies and captures approximately 80% of available market capitalization listed on the NYSE or NASDAQ.

In order to select the companies into one of the five energy types, we rely on widely used energy indices. For the coal industry, we use the Stowe Global Coal Index. To be included in the index, a company must generate at least 50% of its revenues from coal mining and coal related activities. We include all the 10 US companies listed in this index. In addition, we add 13 other companies into our sample. These 13 companies are listed as the major US coal producers in 2012 by Ventyx Velocity Suite and U.S. Department of Labor (2013), each produced more than 5 million short tons of coal in 2012, though their capacities are smaller than that of the companies in the Stowe Global Coal Index.

To choose oil and natural gas companies, we rely on NYSE Arca Indexes. The NYSE Arca Oil Index is used as reference for oil industry. The index is a price-weighted index of the leading companies involved in the exploration, production, and development of petroleum. The index has 20 constituents and we include the 12 companies domiciled in the US. The NYSE Arca Natural Gas Index is designed to measure the performance of highly capitalized companies in the natural gas industry involved primarily in natural gas exploration and production, and natural gas pipeline transportation and transmission. The index has 20 constituents, and we include all but the two Canadian companies.

To identify nuclear companies, we start with all the holding companies of the 100 nuclear power plants in the US from the Nuclear Energy Institute, which can also be retrieved from the Power Reactor Information System (PRIS) by the International Atomic Energy Agency (IAEA). We are left with 22 companies after excluding the institutes that are not publicly traded. From the 22 companies, only Exelon Corporation and Public Service Enterprise Group, Inc. have more than 50% of their electricity generated from nuclear. The other companies own nuclear power stations but have a lower percentage of nuclear shares in their electricity generation portfolio. Results should be interpreted keeping this in mind. Meanwhile, we check the components of the S&P Global Nuclear

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Energy Index to ensure we include all the most important companies. The S&P Global Nuclear Energy Index is comprised of the 24 largest publicly-traded companies in nuclear energy that meet investability requirements from both developed and emerging markets. Seven of the constituents in this index are from the US and are included in the 22 companies selected above, so we believe we include all of the major nuclear companies.

We use the constituents of the WilderHill Clean Energy Index (ECO) to identify companies operating in the "green economy." The WilderHill Clean Energy Index (ECO) has been widely used to measure the stock market performance of renewable energy companies (e.g. in Henriques and Sadorsky (2008), Kumar, et al. (2012), Managi and Okimoto (2013), and Sadorsky (2012). The index is comprised of publicly traded companies "whose businesses stand to substantially benefit from a societal transition toward the use of cleaner forms of energy" such as hydrogen fuel cells, wind, solar, wave, tidal, geothermal energy and biofuels (www.wilderhill.com). The index (as of the start of the 4th quarter of 2012) consisted of 51 stocks. We exclude 15 companies that are not domiciled in the US and three companies for which Datastream does not have data (Kaydon, Power-one and Zoltek). We include one additional company - Covanta Holding Corp, which is the largest energy-from-waste (EFW) company in the United States. Thus, we have 34 companies in our renewable category.

Table 3 shows the number of companies by energy type and hurricane. As it is evident from the table, the number of companies falls as we go back in time. This is because there were fewer companies in earlier times and even fewer that were publicly traded on stock markets. In the 1980s and 1990s, DataStream reports data of fewer traded companies than after the 2000s. For missing values, Brown and Warner (1985) dropped securities that have less than 30 daily returns in their entire 250 day estimation period or have missing return data in the last 20 days of the estimation period. Further, Ferstl, et al. (2012) excluded companies with more than 90 days of no trading in the estimation period or 5 days no trading in the event period. All of the stocks in our analysis have more than 30 days of return data if the data is available. Therefore, to guarantee enough observation in estimating model (1), we filter out companies using the method by Ferstl, et al. (2012). In total, we have 107 companies in the five energy groups for hurricane Sandy, 81 for Katrina, 54 for Andrew, and 48 for and Hugo (Table 3), and Table A.1. reports the specific companies included in each category for each hurricane.

4. Results

4.1. Hurricane Hugo

Table 4 shows the impact of Hurricane Hugo on the US stock markets by energy type. For each of the 5 groups of energy companies, Table 4 reports the average abnormal returns (AARs) and the cumulative average abnormal returns (CAARs) over the event window, while Figure 5.a. and 5.b. presents this information graphically. On the event day, there was no significant AAR for any type of energy companies, but for oil and gas companies, the AARs were significantly negative on the day after the event. And for oil companies, the average abnormal returns were even negatively significant on day -5 and -

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4. These results are not surprising given the concentration of oil refineries in the Gulf. However, overall except for nuclear, few AARs in Table 4 were statistically different from zero. As can be observed in Figure 5.a., abnormal returns oscillated around zero for all the energy groups. Nuclear industry's AARs exhibited the least volatility, while the AARs of renewable energy industry fluctuated the most.

Although the stock returns in the coal industry did not significantly respond to Hurricane Hugo on any day during the event window, the CAARs were significantly negative starting on day 7. Through the entire event window, CAARs are significant at the 1% level and amount to -2.97% by day 30. The oil and natural gas industries were the two industries most negatively affected, with CAAR of -7.41% and -4.55% by the end of the event window, respectively. The $CAAR_{-8,30}$ for nuclear companies is 2.89% and also statistically significant at a 1% level. Overall, the market reaction to Hurricane Hugo was positive for the renewable energy sector.

4.2. Hurricane Andrew

Table 5 and Figure 6.a. and 6.b. show the AAR and CAAR following Hurricane Andrew in 1992. Except a -0.62% average abnormal return for the nuclear industry, we do not observe significant abnormal returns on the event day for any other energy category, but there are more days with significant AARs overall. Different from Hurricane Hugo, the CAAR for the coal industry at the end of the event window were a significant 8.83% largely driven by positive AARs higher than 10% on days 24 and 29. For the nuclear industry, although AAR_{-3} is positive and significant, the larger and consistently negative AARs after the event led to a significant CAAR of -2.09% at the end of the event window for nuclear industry. Finally, companies in the renewable energy sector had a CAAR of -6.70% at the end of the event window.

Daily AARs were small and predominantly insignificant for oil industry over the whole event window, but accumulated into a significant -3.75% CAAR on day 30. The natural gas industry exhibited significant AARs through the event period and the AARs were less variable than for the coal industry (Figure 6.a.). However, except from day -1 to day 1, the CAARs were not statistically significant on any day for natural gas companies. The company stocks in the nuclear industry remained stable facing hurricane Andrew (Figure 6.a.), and ended the event period with a negative CAAR of 2.09%. On the other hand, the renewable stocks were fluctuating over the event period. Although the market reacted with a 3.28% increase on day -5 the CAARs at the end of the period were a significant -6.7%.

4.3. Hurricane Katrina

For Hurricane Katrina, there was no significant market reaction on the event day or before the event (Table 6, Figure 7.a., and 7.b.). This is consistent with the fact that many were caught off guard when Katrina strengthened from a tropical storm to a hurricane. Right after the event day, stock prices for the coal industry reacted positively which leads to significantly positive CAARs from day 2 to day 4. However, by the end of the event window the CAARs became a negative -3.54%. Oil and natural gas industries exhibited

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significantly positive CAARs starting 3 days after the event. The positive CAARs in the oil industry continued to grow until the peak on day 17, after which the CAARs declined to 4.13% by day 26 and not statistically significant from zero at the end. On the other hand, the CAARs of the natural gas industry by the end of the event period were large with a positive 7.42%. Nuclear and renewable energy companies, on average, experienced significant large increases in their stock prices that are offset by significantly negative daily AARs towards the end of the event window.

4.4. Hurricane Sandy

Table 7 and Figure 8.a. and 8.b. reports the daily ARRs and CAARs related to Hurricane Sandy for each of the five energy sectors. As Figure 8.a. shows, the daily AARs are highly fluctuating, though not as much as for hurricane Katrina. Though the CAARs in the coal industry were statistically significant on day 2 through day 5, they were predominantly negative and significant starting day 9, accumulating to -4.04% by the end of the event window. Similar to the coal sector, the CAARs in the natural gas and nuclear sectors, were significantly negative at the end of the event window (-5.32% and -6.30%, respectively). The significant positive AARs on day 17, 21 and 24 for the nuclear industry were not big enough to completely offset the previous negative AARs. On the other hand, oil and renewable energy sectors exhibited positive CAARs for most of the days in the event window period. Market responded, on average, with a 3.81% and 5.87% increase in stock returns of oil and renewable energy companies, respectively.

4.5. Comparison Across Events

The above results show that the impacts of hurricanes on stock market prices in the energy industry have not been homogenous. Figure 9.a. through Figure 9.e. display the cumulative average abnormal returns across the four hurricanes for each of the five energy types. Figure 9.a. shows that except for hurricane Andrew, the CAARs for companies in the coal industry were generally decreasing over the hurricane event period, and in the case of Sandy, the CAARs dropped by more than 5% at the worst. For the oil industry, the general trend is for the CAARs to increase over the hurricane period except during hurricane Hugo in 1989 (Figure 9.b.). Natural gas stocks experienced a period of increasing CAARs during hurricane periods (Andrew and Katrina) and then fell back to its original trend in 1989. For the CAARs of nuclear stocks, half of the time they were hovering over zero, while half of the other time they declined over the event window, and the decrease was larger in 2012 than in 1992. This may be due to people's increased awareness of nuclear energy after the Fukushima accident in 2011. Finally, for renewable energy companies, the CAARs were mostly increasing though it was significantly negative in the event of hurricane Andrew. Noticeably, the CAARs in the renewable sector declined sharply about a week later after the event day in the case of hurricane Sandy, and then increased continuously to more than 5% at the end of our event window (Figure 9.e.).

Given the above differences, the question begs whether the differences are statisticaly significant across energy types and over time, and whether recent hurricanes

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have a larger effect on the CAARs for the renewables sector. To answer this question, we investigate the determinants of abnormal returns by regressing the estimated AARs and CAARs on both energy sector dummy variables and hurricane dummy variables for the types of energy and hurricane, as well as controlling for the date when the abnormal returns are calculated. Table 8 reports the results.

4..6 Comparisons Over Time and Across Energy Sectors

Table 8 shows that the daily AARs are not statistically different for different types of energy defined according to carbon intensity, or for different hurricanes. However, in terms of the sign, compared with renewables, all the other four categories exhibit negative daily average abnormal returns, and compared with hurricane Katrina, the AARs are smaller for all the other three hurricanes.

On the other hand, CAARs exhibit significant differences for different types of energy and different hurricanes. Compared with stocks in the coal industry, companies in oil, natural gas and renewable energy industry all reveal significantly positive cumulative average abnormal returns and the effect is the largest for renewables, followed by oil and natural gas. When using renewable energy stocks as reference, we find significantly negative cumulative abnormal returns for all the other four energy types and the effects are bigger for nuclear and coal stocks than for natural gas and oil stocks.

Compared with hurricane Hugo (1989), all later hurricanes are associated with larger cumulative abnormal returns. The effect is only statistically significant for hurricanes Andrew and Katrina however. Hurricane Katrina leads to 4.76 % larger cumulative abnormal returns than Hugo. Additionally, we find that all other hurricanes resulted in smaller cumulative abnormal returns for all the energy companies than hurricane Katrina does, while the effects of Hugo and Sandy are similar.

5. Conclusions

This paper measures the impact of hurricanes on the stock returns of the largest energy companies in the US. We consider the most notorious, damaging hurricanes over the last 25 years: Hugo (1989), Andrew (1992), Katrina (2005), and Sandy (2012). We categorize energy companies into five groups according to CO_2 intensity: coal, oil, natural gas, nuclear, and renewables.

Cumulative average abnormal returns associated with hurricanes experienced very different paths for different types of energy stocks. In the coal industry, CAARs were mostly negative except for hurricane Andrew, and they have become more negative over time. This is consistent with a priori expectations. CAAR in the oil industry was largely negative for hurricane Hugo and Andrew, but that is not the case for hurricane Katrina and Sandy. This might be the result of people's preferenes shifting from coal to oil and we may find a negative cumulative abnormal return for oil stocks again in the future. Investors dumped natural gas stocks after hurricanes Hugo and Sandy, but not following hurricane Andrew and Katrina. Except for hurricane Katrina, the nuclear industry has seen negative cumulative abnormal returns following hurricanes. In the case of Sandy this may have been due to the recent Fukushima accident that reduced people's trust in

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nuclear companies especially in the wake of natural disasters. Finally, for renewable energy industry, the cumulative average abnormal returns (CAAR) usually increase right after the event day and then start decreasing in the mid-event window. However, in the case of hurricane Sandy, the CAARs for renewables increased again during the end of the event window and stayed as positive. This contributes to us believing that people have been more aware of pollution and begin to vote for clean energy recently.

We also compare the magnitudes of the abnormal returns among energy types and hurricanes. We find that the cumulative average abnormal returns are more negative for conventional and nuclear energy stocks compared with renewable energy stocks, and nuclear companies have a slightly smaller abnormal returns than those in the coal industry, while renewables oil and natural gas stocks more positive abnormal returns than coal stocks. In addition, our results show that recent hurricanes induced bigger cumulative abnormal returns than the oldest one (Hugo). This is particularly the case with Katrina, which also happens to be the most costly.

We end on a note of caution regarding the limitations of our analysis. First, we only include publicly traded large companies in the corresponding industry. This is the case for a number of nuclear companies or institutes, and generally for smaller companies. Smaller companies normally have less diversified sources of energy generation, and then are less resilient to strong disaster shocks and have bigger abnormal returns. Omitting smaller stocks will cause regression attenuation bias, ie. biasing of our abnormal returns towards zero. Second, we only consider how carbon intensity affects the abnormal returns. Further analysis will investigate the role of other factors such as size, book-to-market equity, and whether companies suffered direct hurricane damages.

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Tables

Table 1.
Total Damage by Disaster Group in the US, 1953-2013 (billion 2012 US $)

Disaster Group	Decade							
	1950	1960	1970	1980	1990	2000	2010	Total
Climatological	0.52	0.00	2.90	3.75	11.81	17.11	30.89	15.54
Geophysical	0.03	1.05	0.54	6.73	30.33	2.40	0.01	11.56
Hydrological	0.00	1.22	0.86	0.89	28.26	15.57	9.05	15.87
Meteorological	1.76	4.73	7.26	24.00	85.61	309.17	144.70	125.59
Total	1.51	3.84	5.11	17.63	63.66	173.92	101.21	85.43

Source: Calculated by Authors Based on EM-DAT

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Table 2.
Statistics of the Hurricanes and Estimation and Event Windows

Hurricane Name	Formed	Dissipated	Emergency Declaration	Estimation Period	Event Window	Damage in US ($2012 billion)
Hugo	9/9/1989	9/23/1989	9/22/1989	9/13/1988-9/8/1989	9/11/1989-11/03/1989	12.96
Andrew	8/14/1992	8/28/1992	8/24/1992	8/20/1991-8/13/1992	8/14/1992-10/06/1992	43.36
Katrina	8/23/2005	8/31/2005	8/27/2005	8/26/2004-8/22/2005	8/23/2005-10/11/2005	88.17
Sandy	10/22/2012	10/31/2012	10/28/2012	10/25/2011-10/19/2012	10/22/2012-12/13/2012	50

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Table 3.
Number of Companies by Energy Type and Hurricane

Hurricane	Year	Coal	Oil	Natural Gas	Nuclear	Renewables	Total
Hugo	1989	7	8	8	20	5	48
Andrew	1992	7	10	10	20	7	54
Katrina	2005	16	10	15	22	18	81
Sandy	2012	23	11	18	22	33	107

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Table 4.
Abnormal Returns Caused by Hurricane Hugo

	Coal			Oil				Natural Gas				Nuclear				Renewables			
date	AAR	CAAR		AAR		CAAR		AAR		CAAR		AAR		CAAR		AAR		CAAR	
-8	0.0080	0.0080		-0.0004		-0.0004		-0.0020		-0.0020		0.0005		0.0005		-0.0122		-0.0122	
-7	0.0056	0.0136		0.0099		0.0095		0.0023		0.0004		0.0021		0.0026		0.0005		-0.0117	
-6	-0.0031	0.0105		0.0005		0.0101		0.0054		0.0058		0.0010		0.0036		0.0003		-0.0114	
-5	0.0011	0.0116		-0.0183	***	-0.0082		-0.0063		-0.0005		0.0007		0.0043		-0.0038		-0.0152	
-4	-0.0029	0.0087		-0.0122	*	-0.0204	**	-0.0038		-0.0043		0.0004		0.0047		-0.0061		-0.0213	
-3	-0.0045	0.0042		-0.0004		-0.0208	**	-0.0069		-0.0112		-0.0012		0.0034		0.0161		-0.0053	
-2	-0.0092	-0.0050		0.0000		-0.0209	**	-0.0042		-0.0154	*	0.0012		0.0046		0.0044		-0.0009	
-1	-0.0020	-0.0070		0.0023		-0.0185	*	0.0027		-0.0127		0.0023		0.0069		-0.0121		-0.0130	
0	-0.0006	-0.0076		-0.0030		-0.0215	**	0.0008		-0.0119		0.0006		0.0075		-0.0125		-0.0256	
1	-0.0004	-0.0080		-0.0029		-0.0244	**	-0.0064		-0.0183	**	0.0003		0.0078		0.0100		-0.0155	
2	0.0009	-0.0071		-0.0094		-0.0339	***	-0.0022		-0.0205	**	0.0009		0.0087		-0.0005		-0.0160	
3	0.0031	-0.0040		-0.0038		-0.0376	***	0.0028		-0.0178	**	0.0024		0.0111	*	0.0076		-0.0084	
4	-0.0002	-0.0042		-0.0012		-0.0389	***	0.0020		-0.0157	*	-0.0049	*	0.0061		0.0133		0.0050	
5	-0.0057	-0.0099		-0.0072		-0.0461	***	-0.0075		-0.0232	**	-0.0021		0.0040		-0.0052		-0.0002	
6	-0.0029	-0.0128		0.0051		-0.0410	***	0.0045		-0.0187	**	0.0006		0.0047		-0.0037		-0.0039	
7	-0.0035	-0.0163	*	0.0010		-0.0400	***	-0.0061		-0.0248	***	-0.0016		0.0031		0.0120		0.0081	
8	0.0015	-0.0148	*	-0.0046		-0.0446	***	-0.0010		-0.0258	***	-0.0020		0.0011		-0.0190		-0.0109	
9	0.0006	-0.0142	*	0.0025		-0.0422	***	-0.0059		-0.0318	***	-0.0075	***	-0.0064		0.0081		-0.0027	
10	-0.0022	-0.0164	**	-0.0010		-0.0432	***	-0.0069		-0.0387	***	-0.0016		-0.0080		0.0011		-0.0016	
11	-0.0067	-0.0231	***	0.0079		-0.0353	***	0.0154	*	-0.0233	***	-0.0012		-0.0093		0.0041		0.0025	
12	0.0057	-0.0174	**	-0.0037		-0.0390	***	-0.0011		-0.0244	***	0.0021		-0.0072		0.0181		0.0206	
13	0.0011	-0.0163	*	0.0020		-0.0370	***	-0.0014		-0.0257	***	0.0007		-0.0065		-0.0033		0.0173	
14	0.0004	-0.0159	*	0.0075		-0.0296	***	0.0017		-0.0240	***	0.0030		-0.0035		0.0134		0.0307	*
15	0.0010	-0.0149	*	0.0017		-0.0279	***	0.0034		-0.0207	**	0.0022		-0.0014		0.0012		0.0320	*
16	-0.0033	-0.0182	**	-0.0235	***	-0.0514	***	-0.0157	*	-0.0363	***	0.0117	***	0.0104	*	0.0116		0.0435	**
17	-0.0208	-0.0390	***	0.0022		-0.0492	***	-0.0106		-0.0469	***	-0.0074	**	0.0030		-0.0414	***	0.0022	
18	0.0072	-0.0318	***	-0.0027		-0.0519	***	0.0013		-0.0456	***	0.0061	**	0.0091		0.0085		0.0106	
19	0.0082	-0.0236	***	-0.0043		-0.0562	***	0.0034		-0.0422	***	-0.0056	*	0.0035		0.0123		0.0230	
20	0.0068	-0.0168	**	0.0012		-0.0550	***	0.0064		-0.0358	***	-0.0033		0.0002		0.0035		0.0265	
21	0.0128	-0.0040		-0.0043		-0.0593	***	-0.0040		-0.0398	***	-0.0020		-0.0018		-0.0077		0.0188	
22	-0.0047	-0.0087		-0.0141	**	-0.0734	***	-0.0074		-0.0472	***	-0.0048	*	-0.0066		0.0109		0.0296	*
23	0.0003	-0.0085		-0.0034		-0.0767	***	-0.0125		-0.0597	***	-0.0013		-0.0079		-0.0250	**	0.0047	
24	-0.0027	-0.0111		0.0019		-0.0748	***	0.0136		-0.0461	***	0.0056	*	-0.0023		0.0146		0.0193	
25	-0.0056	-0.0167	**	-0.0016		-0.0764	***	0.0004		-0.0457	***	0.0055	*	0.0033		-0.0040		0.0153	

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26	0.0001	-0.0167	**	-0.0098		-0.0862	***	-0.0026	-0.0484	***	0.0031		0.0064		-0.0074	0.0079
27	-0.0098	-0.0265	***	0.0081		-0.0781	***	-0.0019	-0.0502	***	0.0064	**	0.0128	**	-0.0084	-0.0005
28	0.0026	-0.0239	***	0.0127	*	-0.0655	***	0.0088	-0.0414	***	0.0035		0.0162	***	-0.0005	-0.0010
29	-0.0002	-0.0240	***	-0.0053		-0.0708	***	-0.0006	-0.0421	***	0.0087	***	0.0249	***	0.0035	0.0025
30	-0.0057	-0.0297	***	-0.0034		-0.0741	***	-0.0034	-0.0455	***	0.0040		0.0289	***	0.0140	0.0165

*** p<0.01, ** p<0.05, * p<0.1

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Table 5.
Abnormal Returns Caused by Hurricane Andrew

	Coal				Oil				Natural Gas				Nuclear				Renewables		
date	AAR		CAAR		AAR		CAAR		AAR		CAAR		AAR		CAAR		AAR		CAAR
-6	-0.0030		-0.0030		-0.0056		-0.0056		-0.0150	**	-0.0150		-0.0033		-0.0033		-0.0077		-0.0077
-5	-0.0068		-0.0098		-0.0175	*	-0.0231	**	0.0122	*	-0.0028		-0.0014		-0.0047		0.0328	**	0.0251
-4	0.0006		-0.0092		-0.0024		-0.0255	**	-0.0170	***	-0.0198		0.0035		-0.0011		-0.0218		0.0033
-3	0.0482	**	0.0390		0.0022		-0.0233	**	0.0078		-0.0120		0.0060	*	0.0049		0.0164		0.0196
-2	-0.0380	*	0.0011		-0.0018		-0.0251	**	-0.0079		-0.0199		0.0006		0.0055		-0.0215		-0.0019
-1	-0.0033		-0.0022		-0.0036		-0.0288	***	-0.0175	***	-0.0374	*	0.0050		0.0105	**	0.0239		0.0220
0	-0.0037		-0.0059		0.0146		-0.0142		-0.0065		-0.0438	**	-0.0062	*	0.0043		-0.0142		0.0078
1	-0.0042		-0.0101		0.0010		-0.0132		0.0021		-0.0417	*	-0.0008		0.0036		-0.0023		0.0055
2	0.0006		-0.0095		-0.0024		-0.0156		0.0133	**	-0.0285		-0.0029		0.0006		-0.0112		-0.0057
3	-0.0074		-0.0169		0.0002		-0.0154		0.0096		-0.0189		0.0019		0.0025		0.0223		0.0166
4	-0.0474	**	-0.0643		0.0180	*	0.0026		0.0059		-0.0130		-0.0025		0.0000		0.0109		0.0276
5	0.0579	***	-0.0064		0.0083		0.0109		0.0159	**	0.0028		-0.0045		-0.0045		-0.0235		0.0041
6	0.0038		-0.0026		-0.0142		-0.0033		-0.0074		-0.0046		-0.0031		-0.0077		-0.0065		-0.0025
7	0.0078		0.0052		-0.0029		-0.0062		0.0268	***	0.0222		-0.0067	*	-0.0144	***	0.0049		0.0024
8	-0.0077		-0.0025		-0.0054		-0.0117		-0.0188	***	0.0035		-0.0029		-0.0172	***	0.0219		0.0243
9	-0.0083		-0.0108		0.0016		-0.0101		0.0102		0.0136		0.0035		-0.0138	***	0.0057		0.0300
10	-0.0015		-0.0123		0.0061		-0.0040		0.0097		0.0233		0.0009		-0.0129	***	-0.0031		0.0269
11	0.0011		-0.0112		0.0018		-0.0021		-0.0234	***	-0.0001		-0.0020		-0.0149	***	-0.0296	*	-0.0027
12	0.0398	*	0.0286		0.0023		0.0002		0.0224	***	0.0223		-0.0043		-0.0192	***	0.0086		0.0059
13	0.0006		0.0293		-0.0024		-0.0023		-0.0249	***	-0.0027		-0.0021		-0.0213	***	0.0205		0.0264
14	-0.0004		0.0289		-0.0100		-0.0123		-0.0034		-0.0061		-0.0081	**	-0.0294	***	-0.0039		0.0226
15	0.0005		0.0294		0.0044		-0.0079		-0.0142	**	-0.0203		-0.0017		-0.0311	***	0.0012		0.0238
16	-0.0055		0.0239		0.0049		-0.0030		0.0115	*	-0.0087		-0.0009		-0.0320	***	0.0108		0.0346
17	-0.0054		0.0185		0.0044		0.0014		0.0214	***	0.0126		-0.0028		-0.0348	***	-0.0213		0.0133
18	-0.0088		0.0097		-0.0006		0.0007		-0.0019		0.0108		0.0022		-0.0326	***	-0.0058		0.0075
19	0.0243		0.0340		0.0092		0.0100		-0.0048		0.0060		-0.0007		-0.0333	***	0.0112		0.0186
20	-0.0006		0.0334		-0.0023		0.0076		0.0231	***	0.0291		0.0024		-0.0309	***	-0.0202		-0.0015
21	-0.0048		0.0286		0.0020		0.0096		-0.0275	***	0.0016		-0.0006		-0.0316	***	0.0342	**	0.0327
22	-0.0634	***	-0.0348		0.0003		0.0099		0.0034		0.0050		0.0054		-0.0262	***	-0.0211		0.0116
23	0.0080		-0.0268		-0.0085		0.0014		0.0107	*	0.0157		0.0036		-0.0226	***	0.0116		0.0232
24	0.1071	***	0.0803		-0.0019		-0.0005		0.0117	*	0.0274		-0.0019		-0.0244	***	-0.0126		0.0105
25	0.0018		0.0821		-0.0030		-0.0035		-0.0011		0.0263		0.0054		-0.0190	***	-0.0123		-0.0017
26	0.0015		0.0836	*	-0.0074		-0.0109		-0.0215	***	0.0047		0.0033		-0.0157	***	-0.0303	**	-0.0320
27	-0.0786	***	0.0050		-0.0061		-0.0170	*	0.0273	***	0.0320		-0.0009		-0.0166	***	0.0218		-0.0102

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28	-0.0019	0.0031	-0.0071	-0.0241 **	-0.0203 ***	0.0117	-0.0007	-0.0173 ***	-0.0224	-0.0325
29	0.1063 ***	0.1094 **	-0.0130	-0.0370 ***	-0.0021	0.0095	-0.0009	-0.0182 ***	-0.0227	-0.0553 **
30	-0.0210	0.0883 *	-0.0005	-0.0375 ***	-0.0030	0.0066	-0.0027	-0.0209 ***	-0.0117	-0.0670 ***

*** p<0.01, ** p<0.05, * p<0.1

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Table 6.

Abnormal Returns Caused by Hurricane Katrina

	Coal				Oil				Natural Gas				Nuclear				Renewables			
date	AAR		CAAR		AAR		CAAR		AAR		CAAR		AAR		CAAR		AAR		CAAR	
-3	0.0116		0.0116		-0.0010		-0.0010		0.0053		0.0053		0.0075		0.0075		-0.0008		-0.0008	
-2	-0.0021		0.0095		0.0114		0.0103		0.0168		0.0221		0.0009		0.0084		0.0101		0.0093	
-1	0.0053		0.0148		-0.0053		0.0050		-0.0016		0.0205		0.0042		0.0125		-0.0083		0.0010	
0	-0.0068		0.0079		-0.0082		-0.0032		-0.0058		0.0147		0.0004		0.0129		-0.0018		-0.0008	
1	0.0016		0.0096		0.0055		0.0023		0.0001		0.0148		0.0003		0.0132		0.0045		0.0037	
2	0.0342	*	0.0438	**	0.0221	*	0.0243		0.0219	**	0.0367		0.0013		0.0145		0.0278	***	0.0315	**
3	0.0075		0.0513	***	0.0176		0.0419	*	0.0156		0.0523	**	0.0014		0.0159	*	0.0044		0.0359	**
4	-0.0114		0.0399	**	0.0283	**	0.0703	***	0.0162		0.0685	***	0.0103	*	0.0261	***	0.0025		0.0384	***
5	-0.0209		0.0190		-0.0147		0.0556	**	-0.0188	*	0.0497	**	0.0024		0.0285	***	0.0028		0.0412	***
6	-0.0174		0.0016		-0.0094		0.0461	*	-0.0034		0.0463	*	-0.0021		0.0264	***	-0.0022		0.0390	***
7	0.0039		0.0055		-0.0012		0.0450	*	-0.0019		0.0443	*	-0.0053		0.0211	**	0.0021		0.0410	***
8	-0.0244		-0.0189		0.0051		0.0500	**	0.0010		0.0454	*	-0.0036		0.0176	**	0.0123		0.0533	***
9	0.0053		-0.0136		0.0196		0.0697	***	0.0080		0.0534	**	0.0027		0.0203	**	-0.0032		0.0501	***
10	-0.0186		-0.0322	*	-0.0208	*	0.0489	**	-0.0076		0.0458	*	-0.0028		0.0175	**	0.0218	***	0.0719	***
11	0.0002		-0.0319	*	-0.0029		0.0460	*	0.0010		0.0467	*	-0.0006		0.0169	*	-0.0045		0.0674	***
12	-0.0007		-0.0326	*	0.0136		0.0595	**	0.0123		0.0590	**	0.0028		0.0197	**	-0.0072		0.0602	***
13	-0.0094		-0.0421	**	-0.0024		0.0571	**	0.0020		0.0610	**	0.0046		0.0243	***	-0.0155	**	0.0447	***
14	0.0164		-0.0257		-0.0034		0.0537	**	-0.0019		0.0591	**	-0.0002		0.0241	***	-0.0116		0.0331	**
15	0.0129		-0.0128		0.0287	**	0.0824	***	0.0382	***	0.0973	***	-0.0011		0.0229	***	0.0036		0.0367	**
16	-0.0069		-0.0197		-0.0044		0.0780	***	0.0033		0.1005	***	0.0017		0.0246	***	-0.0021		0.0346	**
17	0.0241		0.0044		0.0270	**	0.1050	***	0.0155		0.1160	***	-0.0100	*	0.0146		-0.0073		0.0273	*
18	-0.0118		-0.0074		-0.0128		0.0922	***	-0.0146		0.1014	***	-0.0106	**	0.0041		-0.0144	*	0.0129	
19	-0.0062		-0.0136		-0.0213	*	0.0709	***	-0.0167		0.0848	***	0.0036		0.0077		0.0087		0.0216	
20	0.0123		-0.0013		0.0172		0.0881	***	0.0188	*	0.1035	***	0.0041		0.0118		0.0056		0.0272	*
21	-0.0061		-0.0075		-0.0046		0.0835	***	0.0027		0.1062	***	0.0018		0.0135		0.0058		0.0331	**
22	-0.0009		-0.0084		0.0079		0.0913	***	0.0209	*	0.1271	***	0.0064		0.0199	**	-0.0086		0.0245	*
23	-0.0016		-0.0100		-0.0060		0.0853	***	0.0113		0.1383	***	0.0013		0.0212	**	-0.0048		0.0196	
24	-0.0119		-0.0219		-0.0180		0.0673	***	-0.0114		0.1269	***	-0.0041		0.0171	*	0.0072		0.0269	*
25	0.0115		-0.0104		0.0050		0.0722	***	0.0227	**	0.1497	***	0.0169	***	0.0340	***	0.0097		0.0366	**
26	-0.0039		-0.0143		-0.0309	**	0.0413	*	-0.0167		0.1330	***	-0.0036		0.0303	***	0.0032		0.0398	***
27	-0.0052		-0.0195		-0.0290	**	0.0123		-0.0365	***	0.0965	***	-0.0168	***	0.0135		-0.0214	***	0.0184	
28	-0.0253		-0.0448	**	-0.0275	**	-0.0152		-0.0413	***	0.0552	**	-0.0092	*	0.0044		-0.0159	**	0.0025	
29	0.0094		-0.0354	*	0.0174		0.0022		0.0190	*	0.0742	***	0.0044		0.0088		-0.0033		-0.0008	

*** p<0.01, ** p<0.05, * p<0.1

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Table 7.
Abnormal Returns Caused by Hurricane Sandy

	Coal				Oil				Natural Gas				Nuclear				Renewables			
date	AAR		CAAR		AAR		CAAR		AAR		CAAR		AAR		CAAR		AAR		CAAR	
-5	0.0252	*	0.0252	*	-0.0072		-0.0072		-0.0099		-0.0099		-0.0037		-0.0037		-0.0025		-0.0025	
-4	0.0042		0.0294		-0.0055		-0.0127	*	0.0044		-0.0056		-0.0038		-0.0075		0.0142		0.0118	
-3	-0.0081		0.0213		0.0040		-0.0087		-0.0127		-0.0182	**	-0.0046		-0.0122		0.0078		0.0196	
-2	-0.0012		0.0202		0.0106		0.0019		0.0070		-0.0113		0.0029		-0.0093		0.0086		0.0282	**
-1	0.0212		0.0414	**	0.0050		0.0069		0.0072		-0.0041		-0.0004		-0.0097		-0.0058		0.0224	*
0	-0.0131		0.0283		0.0026		0.0095		-0.0051		-0.0091		0.0067		-0.0030		0.0010		0.0234	*
1	0.0092		0.0375	**	-0.0106		-0.0011		-0.0078		-0.0169	*	-0.0129	***	-0.0160		-0.0002		0.0232	*
2	-0.0065		0.0310	*	0.0023		0.0012		-0.0061		-0.0230	***	-0.0055		-0.0214	**	-0.0135		0.0096	
3	0.0168		0.0478	**	0.0095		0.0108		-0.0013		-0.0244	***	-0.0169	***	-0.0383	***	0.0106		0.0203	
4	-0.0133		0.0344	*	0.0131	**	0.0239	***	0.0006		-0.0238	***	-0.0033		-0.0416	***	0.0119		0.0322	***
5	-0.0387	**	-0.0043		0.0044		0.0283	***	-0.0004		-0.0242	***	-0.0124	**	-0.0539	***	0.0077		0.0399	***
6	0.0017		-0.0026		0.0038		0.0321	***	0.0012		-0.0230	***	0.0034		-0.0506	***	0.0021		0.0420	***
7	-0.0211		-0.0237		-0.0034		0.0287	***	-0.0032		-0.0262	***	-0.0109	**	-0.0615	***	-0.0063		0.0356	***
8	-0.0180		-0.0417	**	0.0005		0.0291	***	-0.0018		-0.0279	***	-0.0106	**	-0.0721	***	-0.0137		0.0220	*
9	0.0019		-0.0398	**	-0.0003		0.0289	***	0.0081		-0.0198	**	0.0036		-0.0685	***	-0.0165		0.0055	
10	-0.0175		-0.0572	***	0.0080		0.0369	***	0.0048		-0.0151	*	-0.0022		-0.0707	***	-0.0020		0.0035	
11	0.0014		-0.0559	***	0.0074		0.0443	***	-0.0063		-0.0213	**	-0.0057		-0.0764	***	-0.0054		-0.0019	
12	-0.0017		-0.0576	***	-0.0046		0.0397	***	0.0033		-0.0180	**	0.0072		-0.0692	***	-0.0079		-0.0098	
13	0.0004		-0.0572	***	-0.0051		0.0346	***	-0.0027		-0.0207	**	-0.0103	**	-0.0795	***	-0.0056		-0.0153	
14	-0.0052		-0.0624	***	-0.0012		0.0335	***	-0.0002		-0.0209	**	-0.0034		-0.0829	***	0.0011		-0.0143	
15	0.0059		-0.0565	***	0.0046		0.0381	***	0.0044		-0.0165	*	-0.0040		-0.0869	***	0.0091		-0.0051	
16	-0.0057		-0.0622	***	-0.0011		0.0370	***	-0.0064		-0.0229	***	-0.0084	*	-0.0954	***	0.0017		-0.0034	
17	-0.0034		-0.0656	***	-0.0063		0.0307	***	-0.0095		-0.0324	***	0.0124	**	-0.0830	***	0.0076		0.0042	
18	0.0058		-0.0598	***	-0.0014		0.0293	***	0.0014		-0.0310	***	0.0055		-0.0776	***	0.0173	*	0.0215	*
19	0.0028		-0.0570	***	0.0001		0.0294	***	-0.0066		-0.0376	***	0.0019		-0.0757	***	0.0006		0.0221	*
20	0.0038		-0.0532	***	-0.0019		0.0275	***	-0.0074		-0.0450	***	0.0045		-0.0711	***	0.0081		0.0302	**
21	0.0061		-0.0471	**	-0.0025		0.0250	***	-0.0068		-0.0518	***	0.0086	*	-0.0625	***	0.0110		0.0412	***
22	-0.0086		-0.0556	***	0.0017		0.0267	***	0.0062		-0.0456	***	-0.0045		-0.0670	***	-0.0029		0.0383	***
23	-0.0047		-0.0603	***	-0.0026		0.0241	***	-0.0073		-0.0529	***	-0.0045		-0.0715	***	0.0030		0.0413	***
24	0.0146		-0.0457	**	0.0025		0.0266	***	0.0138		-0.0391	***	0.0130	***	-0.0585	***	-0.0066		0.0347	***
25	-0.0149		-0.0607	***	0.0033		0.0299	***	-0.0017		-0.0408	***	-0.0042		-0.0627	***	0.0033		0.0379	***
26	-0.0003		-0.0610	***	0.0068		0.0366	***	-0.0038		-0.0446	***	-0.0024		-0.0650	***	0.0015		0.0394	***
27	0.0206		-0.0404	**	0.0015		0.0381	***	-0.0086		-0.0532	***	0.0020		-0.0630	***	0.0192	*	0.0587	***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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Table 8. Abnormal Returns over Time and across Energy Sectors

Variables	Daily Average Abnormal Returns			Cumulative Average Abnormal Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Energy Type						
Coal		-0.000173	-0.000173		-0.0209***	-0.0209***
(yes/no)		(0.00156)	(0.00156)		(0.00361)	(0.00361)
Oil	-0.000382	-0.000555	-0.000555	0.00964***	-0.0113***	-0.0113***
(yes/no)	(0.00156)	(0.00156)	(0.00156)	(0.00361)	(0.00361)	(0.00361)
Natural Gas	-5.60e-06	-0.000179	-0.000179	0.00946***	-0.0115***	-0.0115***
(yes/no)	(0.00156)	(0.00156)	(0.00156)	(0.00361)	(0.00361)	(0.00361)
Nuclear	-0.000205	-0.000378	-0.000378	-0.00464	-0.0256***	-0.0256***
(yes/no)	(0.00156)	(0.00156)	(0.00156)	(0.00361)	(0.00361)	(0.00361)
Renewables	0.000173			0.0209***		
(yes/no)	(0.00156)			(0.00361)		
Hurricane						
Hugo			-0.000912			-0.0476***
(yes/no)			(0.00140)			(0.00323)
Andrew	0.000410	0.000410	-0.000502	0.0143***	0.0143***	-0.0333***
(yes/no)	(0.00135)	(0.00135)	(0.00141)	(0.00313)	(0.00313)	(0.00326)
Katrina	0.000912	0.000912		0.0476***	0.0476***	
(yes/no)	(0.00140)	(0.00140)		(0.00323)	(0.00323)	
Sandy	0.000206	0.000206	-0.000706	0.00248	0.00248	-0.0451***
(yes/no)	(0.00139)	(0.00139)	(0.00145)	(0.00322)	(0.00322)	(0.00336)
Days Difference	-4.16e-05	-4.16e-05	-4.16e-05	-0.000201*	-0.000201*	-0.000201*
	(4.76e-05)	(4.76e-05)	(4.76e-05)	(0.000110)	(0.000110)	(0.000110)
Constant	8.53e-06	0.000182	0.00109	-0.0197***	0.00127	0.0489***
	(0.00146)	(0.00146)	(0.00155)	(0.00338)	(0.00338)	(0.00359)
Observations	710	710	710	710	710	710
R-squared	0.002	0.002	0.002	0.316	0.316	0.316

Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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Figures

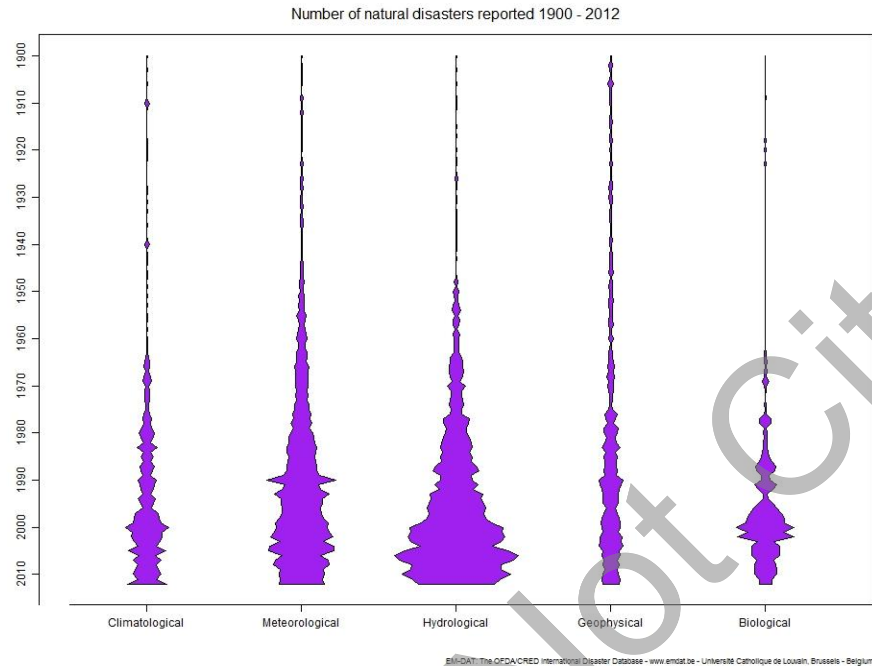

Figure 1. Number of Natural Disasters Reported 1900-2012

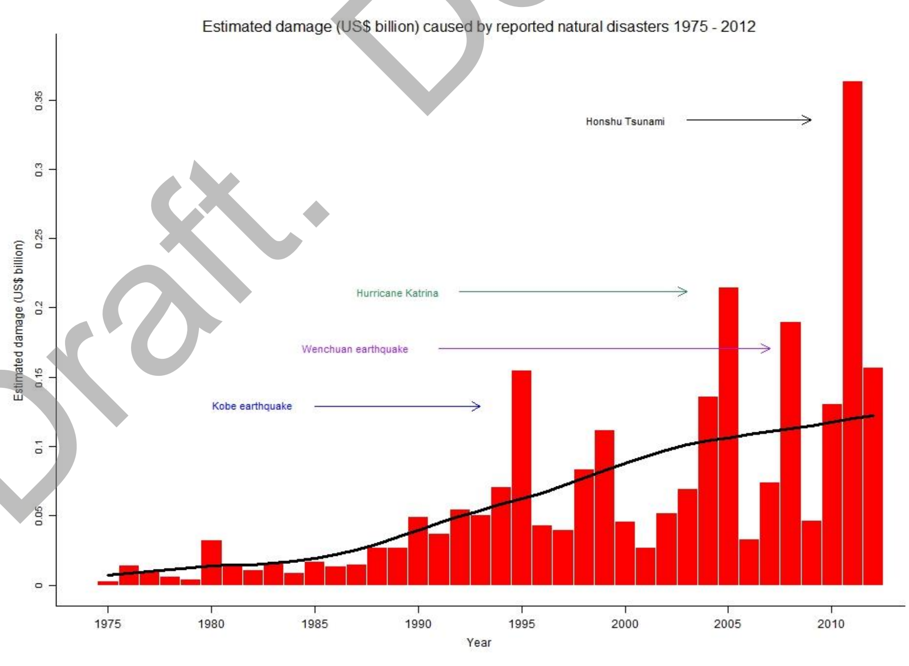

Figure 2. Estimated Damage Caused by Reported Natural Disasters 1975-2012

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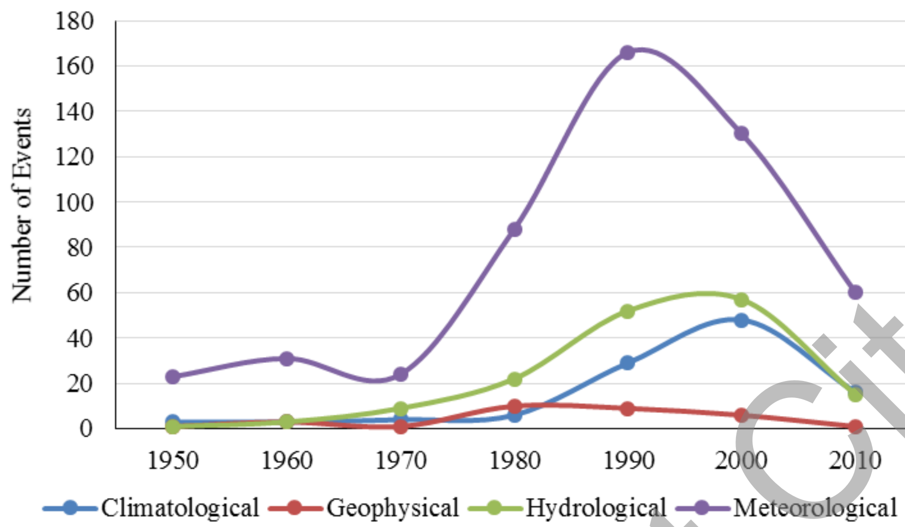

Figure 3. Frequency of Natural Disasters by Group in the US, 1953-2013
Source: Calculated by Authors Based on Data from EM-DAT

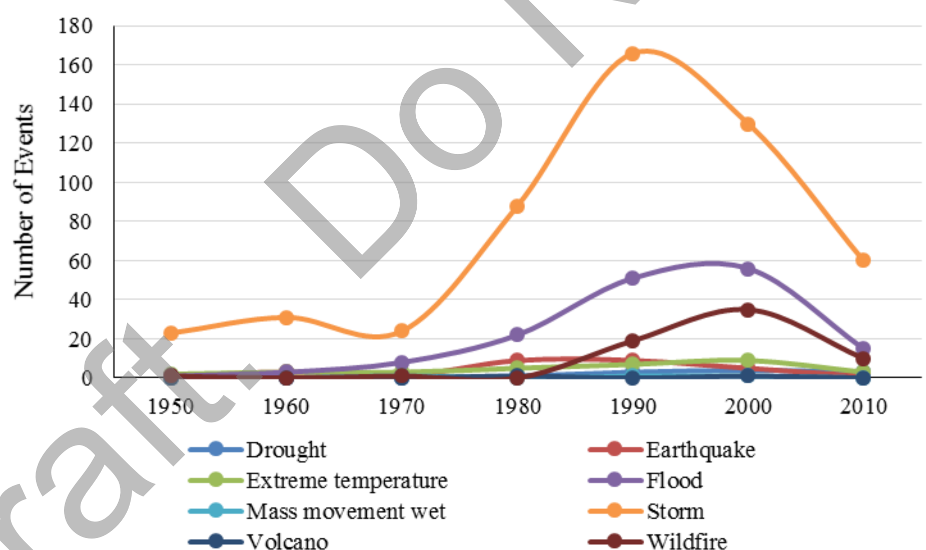

Figure 4. Frequency of Natural Disasters by Type in the US, 1953-2013
Source: Calculated by Authors Based on Data from EM-DAT

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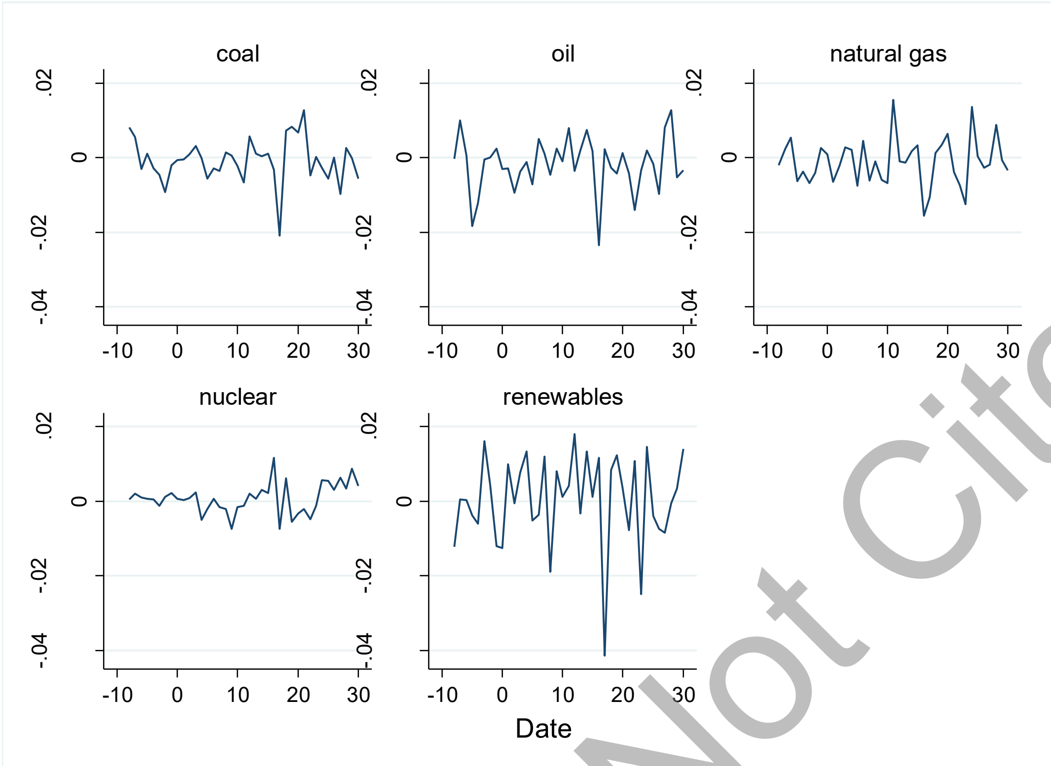

Figure 5.a. Average Abnormal Returns - Hurricane Hugo

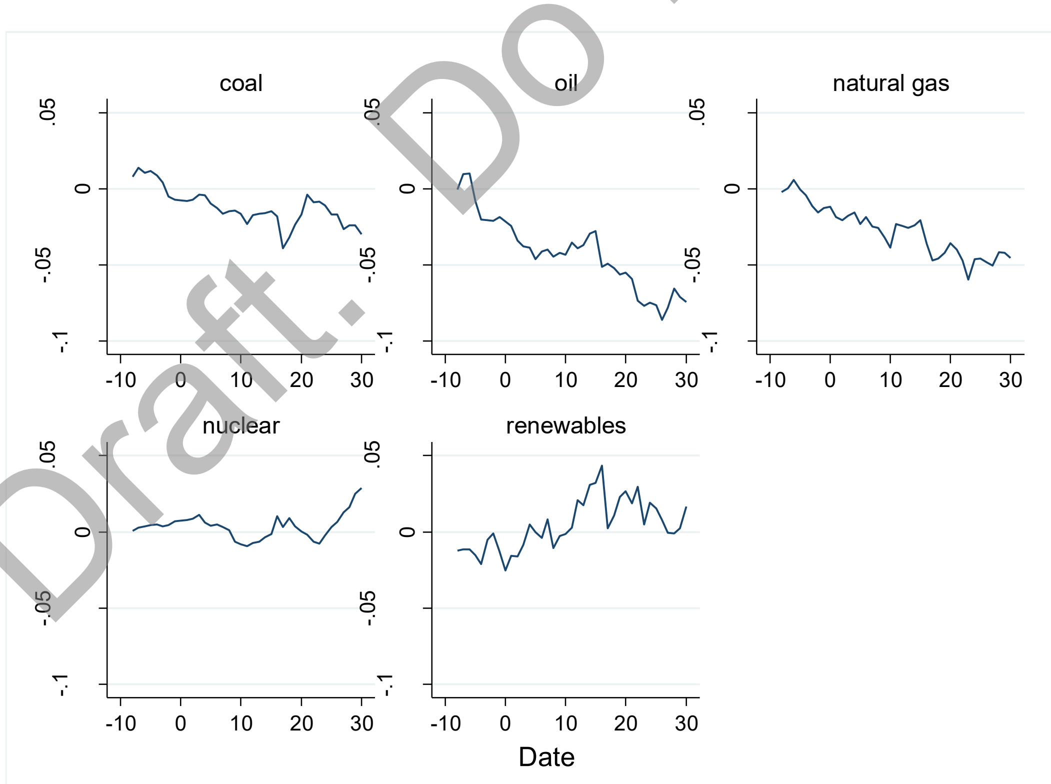

Figure 5.b. Cumulative Average Abnormal Returns - Hurricane Hugo

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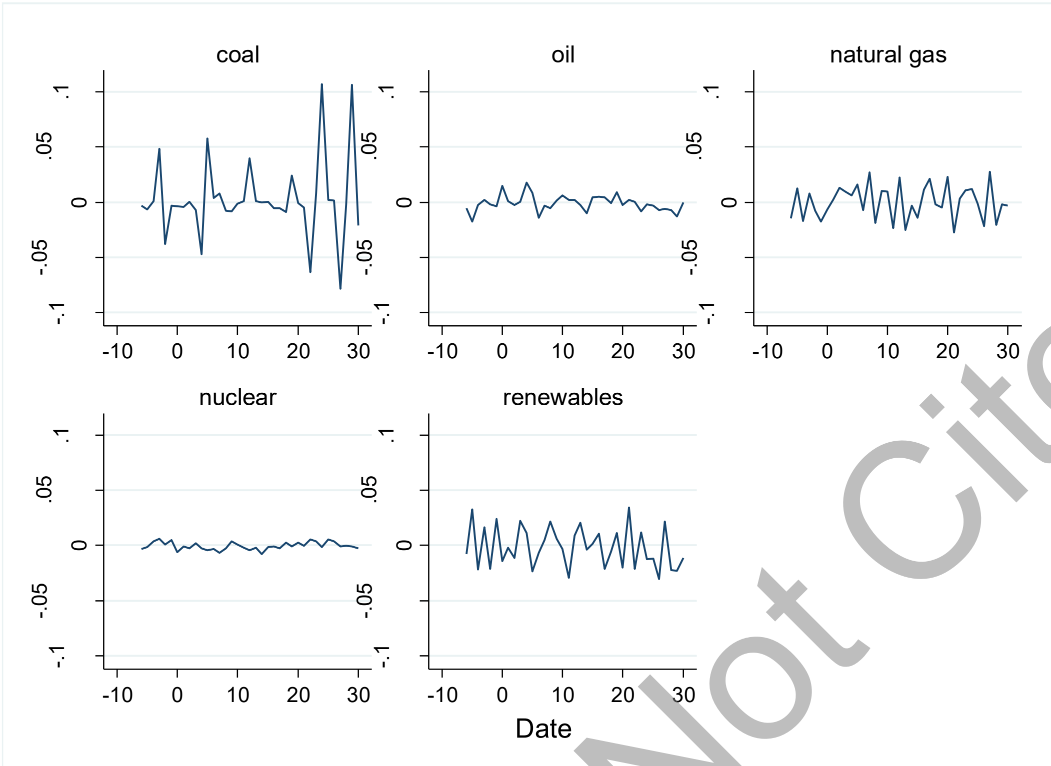

Figure 6.a. Average Abnormal Returns - Hurricane Andrew

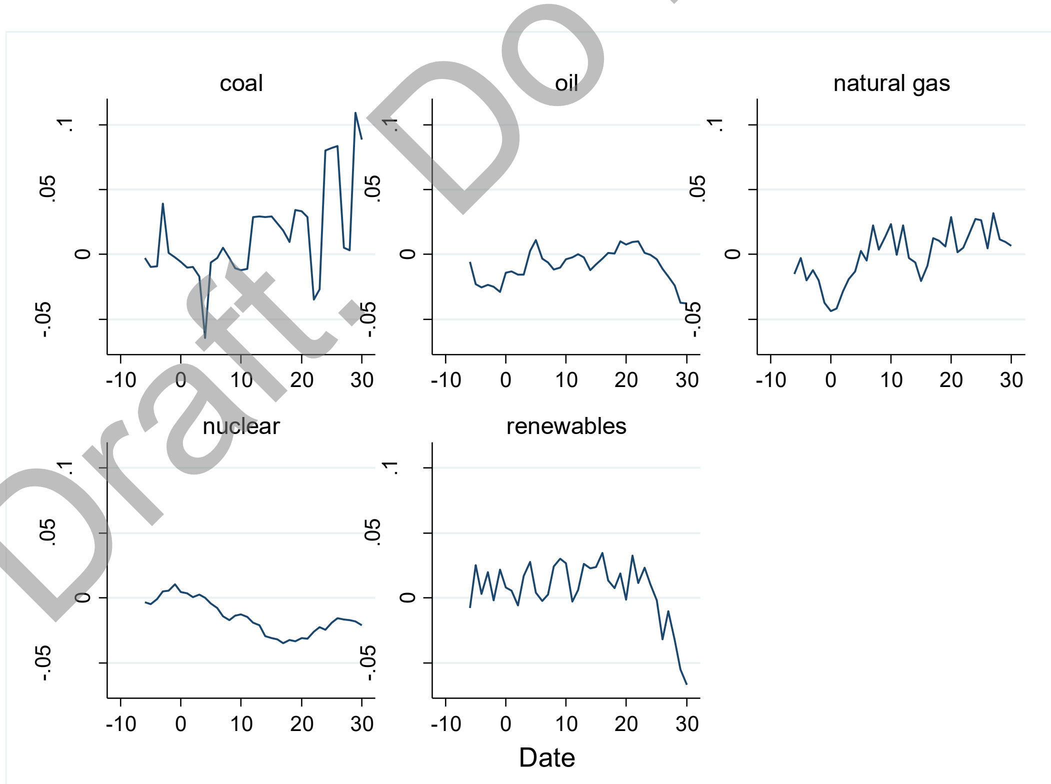

Figure 6.b. Cumulative Average Abnormal Returns - Hurricane Andrew

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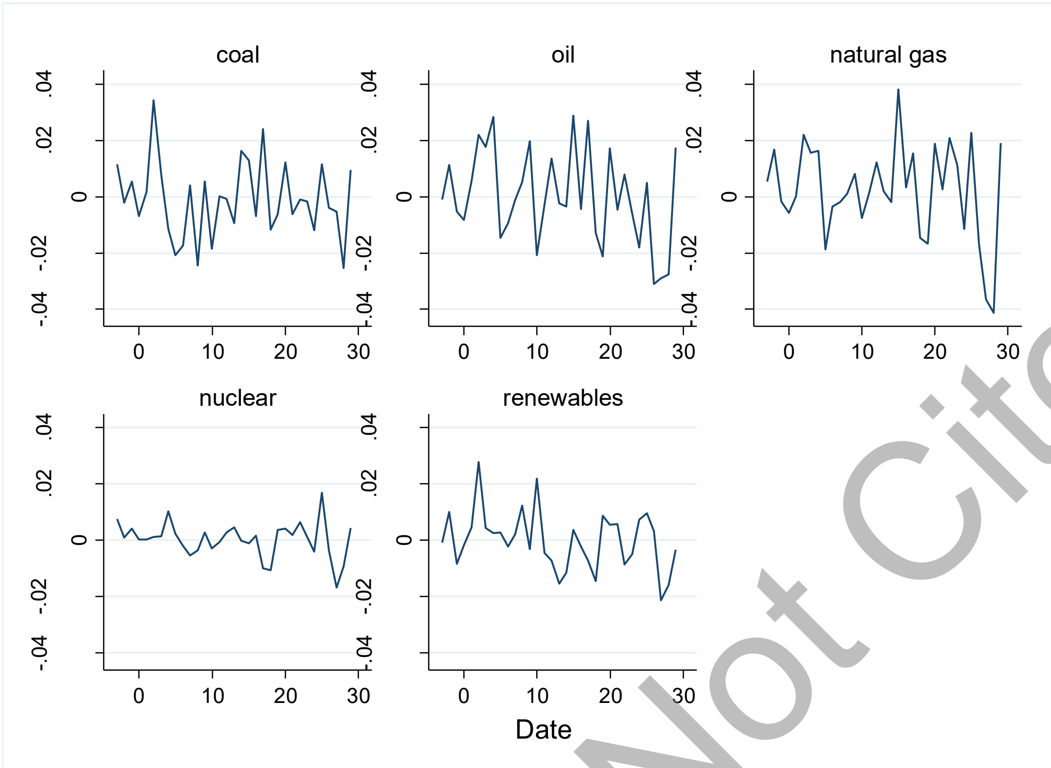

Figure 7.a. Average Abnormal Returns - Hurricane Katrina

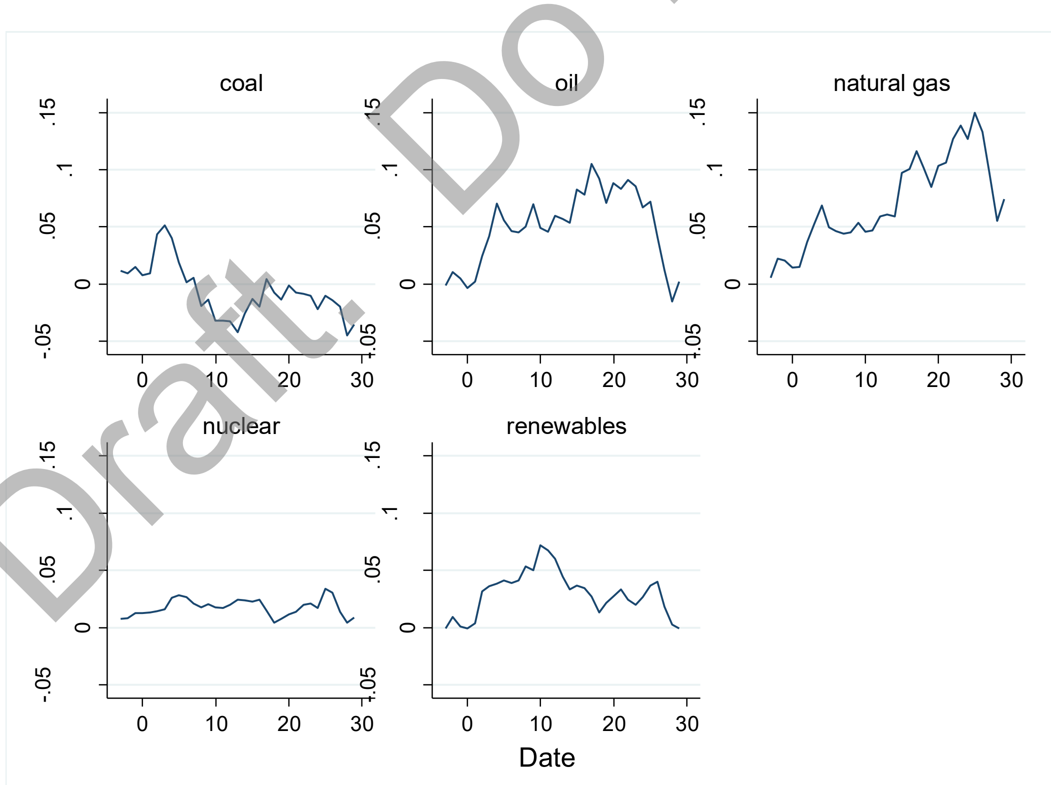

Figure 7.b. Cumulative Average Abnormal Returns - Hurricane Katrina

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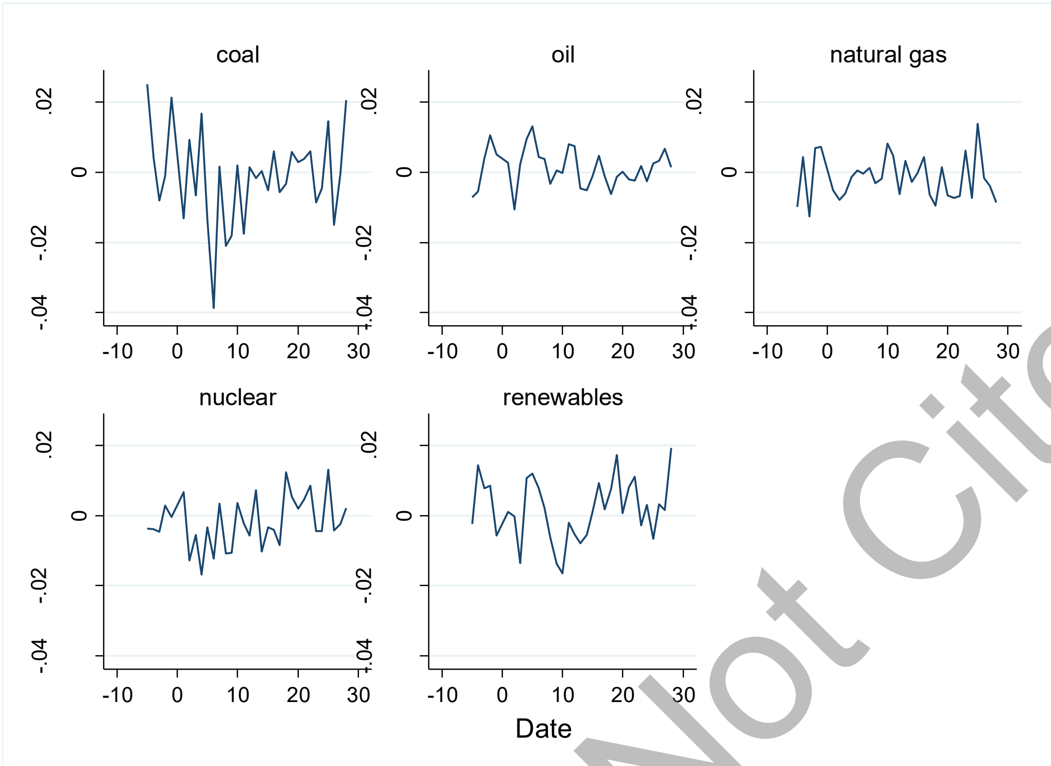

Figure 8.a. Average Abnormal Returns - Hurricane Sandy

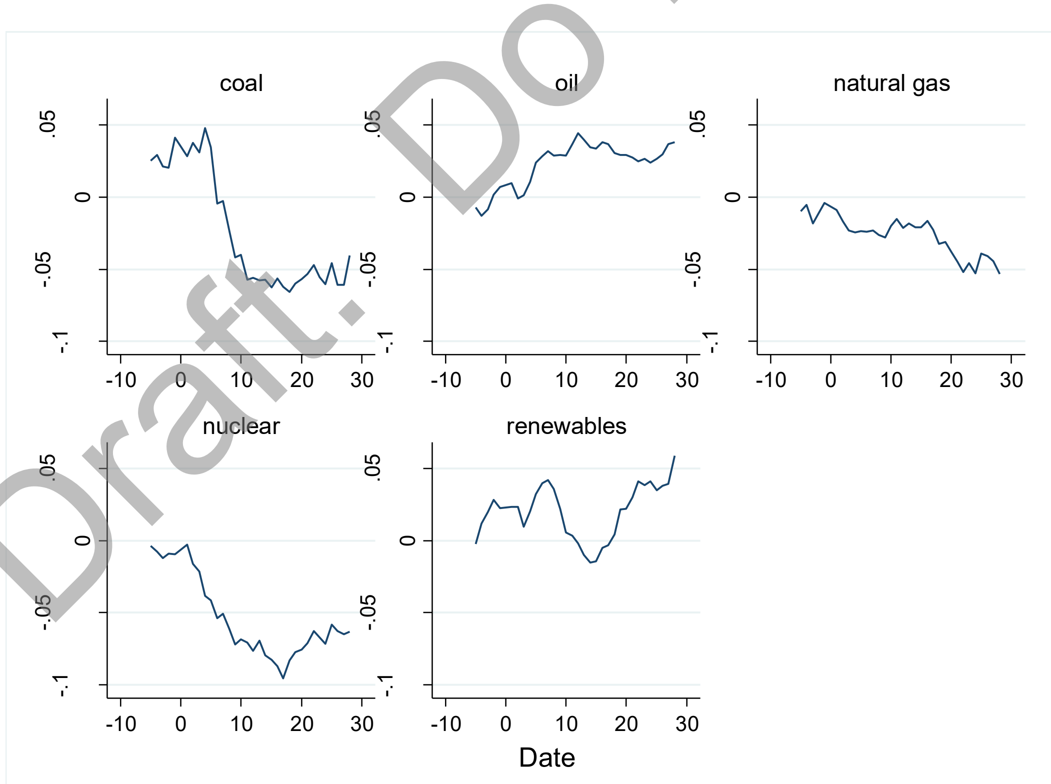

Figure 8.b. Cumulative Average Abnormal Returns - Hurricane Sandy

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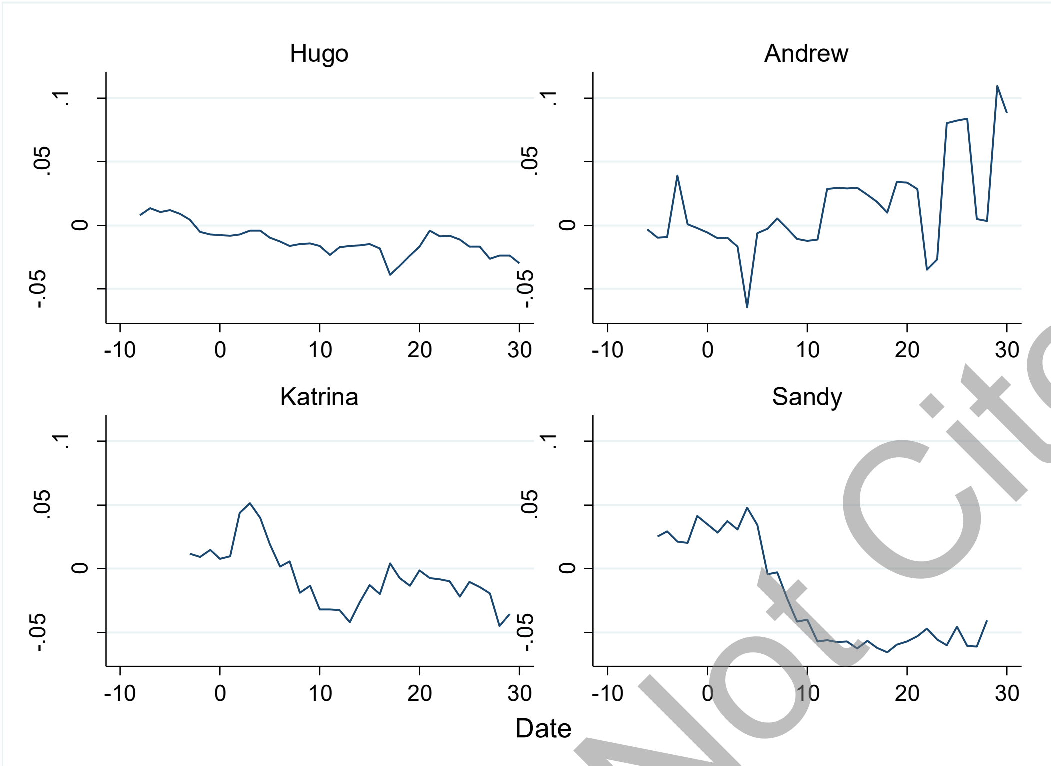

Figure 9.a. Cumulative Average Abnormal Returns - Coal

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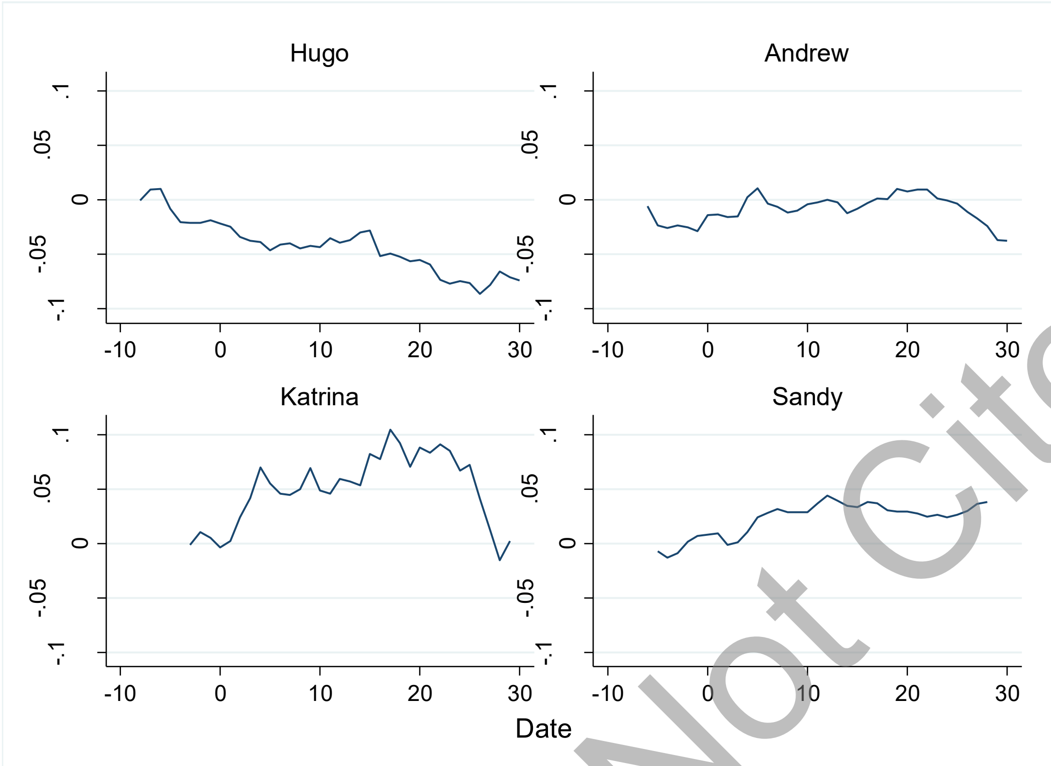

Figure 9.b. Cumulative Average Abnormal Returns - Oil

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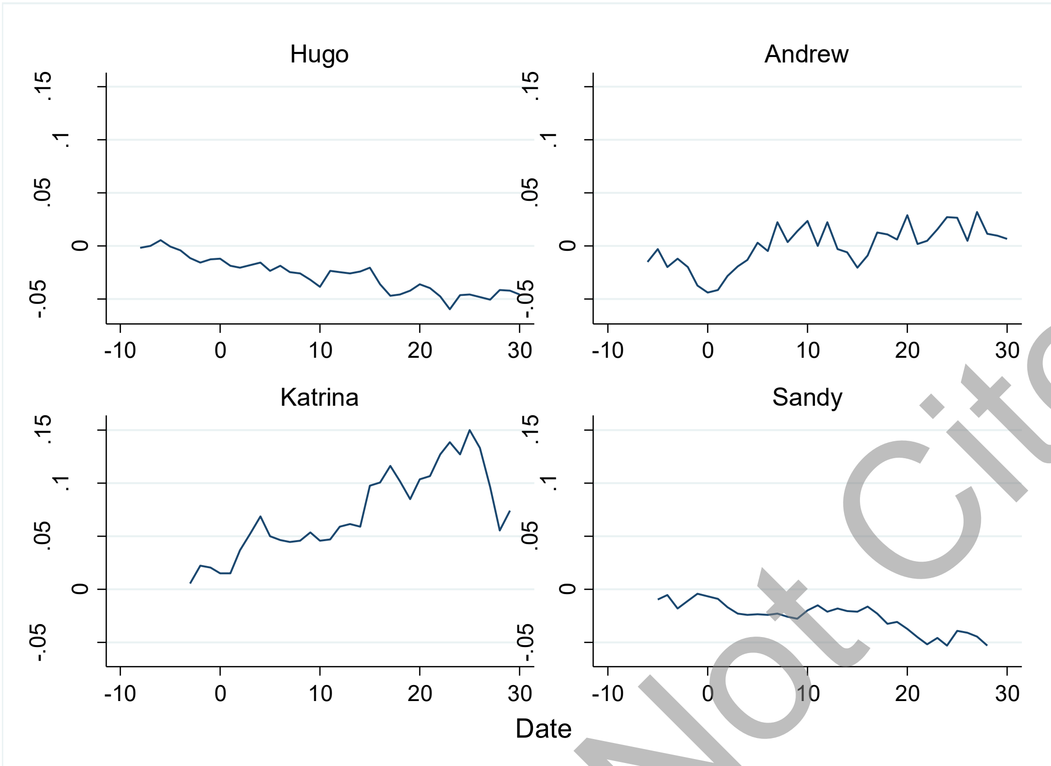

Figure 9.c. Cumulative Average Abnormal Returns – Natural Gas

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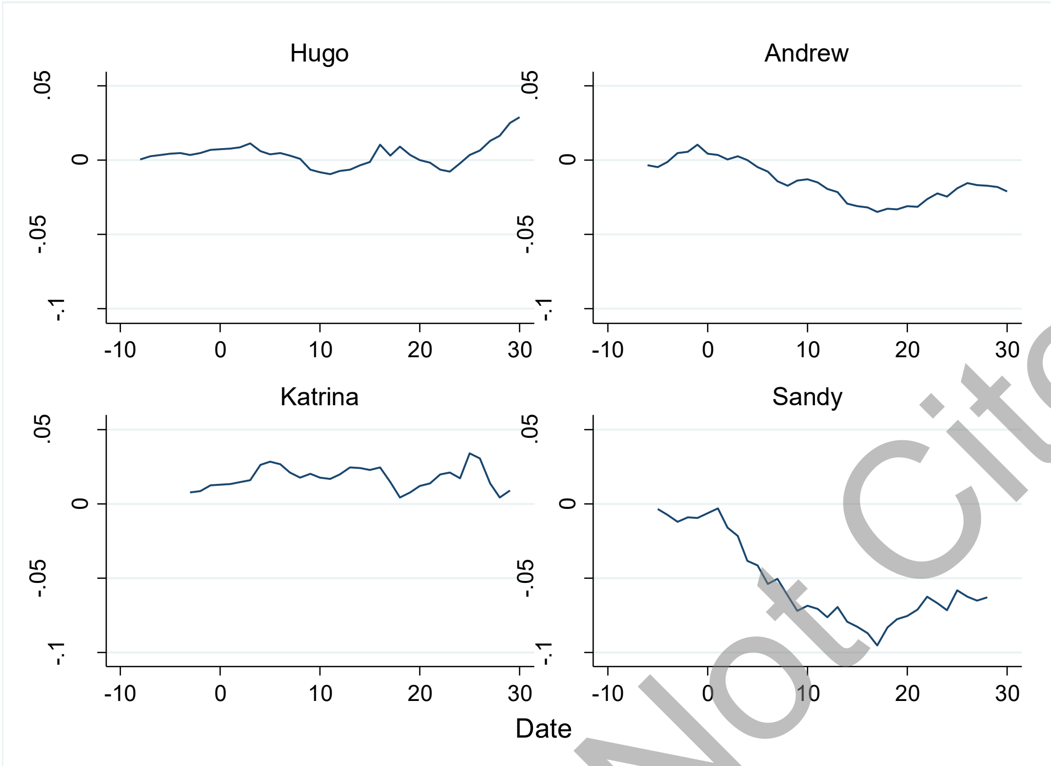

Figure 9.d. Cumulative Average Abnormal Returns - Nuclear

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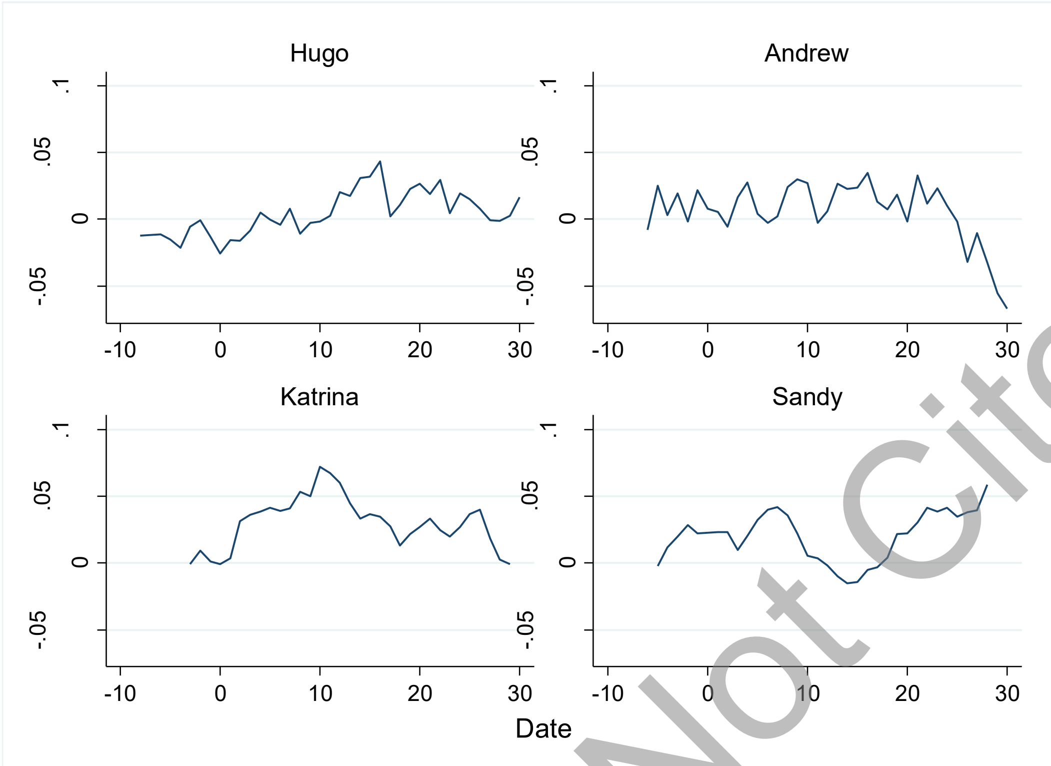

Figure 9.e. Cumulative Average Abnormal Returns - Renewables

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Appendix A

Table A.1.
Companies Included in Each Hurricane Event

Name	Ticker	Energy Type	Hugo	Andrew	Katrina	Sandy
Air Products & Chemicals	APD	Renewables	Yes	Yes	Yes	Yes
Ameresco	AMRC	Renewables				Yes
American Superconductor	AMSC	Renewables		Yes	Yes	Yes
Amyris	AMRS	Renewables				Yes
Calpine	CPN	Renewables				Yes
Cree	CREE	Renewables			Yes	Yes
Echelon Corporation	ELON	Renewables			Yes	Yes
EnerNoc	ENOC	Renewables				Yes
First Solar	FSLR	Renewables				Yes
Fuel Systems Solutions	FSYS	Renewables	Yes	Yes	Yes	Yes
FuelCell Energy	FCEL	Renewables			Yes	Yes
Gentherm	THRM	Renewables			Yes	Yes
Gevo	GEVO	Renewables				Yes
GT Advanced	GTAT	Renewables				Yes
Idacorp	IDA	Renewables	Yes	Yes	Yes	Yes
International Rectifier	IRF	Renewables	Yes	Yes	Yes	Yes
ITC Holdings	ITC	Renewables				Yes
Itron	ITRI	Renewables			Yes	Yes
Kior	KIOR	Renewables				Yes
Maxwell Technologies, Inc.	MXWL	Renewables	Yes	Yes	Yes	Yes
SUNEDISON	SUNE	Renewables			Yes	Yes
Molycorp	MCP	Renewables				Yes
OM Group	OMG	Renewables			Yes	Yes
Polypore Intl.	PPO	Renewables				Yes

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PowerSecure	POWR	Renewables			Yes	Yes
Quanta Services	PWR	Renewables			Yes	Yes
Rare Element Resources	REE	Renewables			Yes	Yes
Solazyme	SZYM	Renewables				Yes
STR Holdings	STRI	Renewables				Yes
SunPower	SPWR	Renewables				Yes
Tesla Motors	TSLA	Renewables				Yes
Universal Display	PANL/OLED	Renewables			Yes	Yes
Covanta Holding Corp	CVA	Renewables		Yes	Yes	Yes
Duke Energy Corp	DUK	Nuclear	Yes	Yes	Yes	Yes
Dominion Resources, Inc.	D	Nuclear	Yes	Yes	Yes	Yes
Pinnacle West Capital Corp.	PNW	Nuclear	Yes	Yes	Yes	Yes
FirstEnergy Corp.	FE	Nuclear	Yes	Yes	Yes	Yes
SCANA Corp.	SCG	Nuclear	Yes	Yes	Yes	Yes
DTE Energy Co.	DTE	Nuclear	Yes	Yes	Yes	Yes
PNM Resources, Inc.	PNM	Nuclear	Yes	Yes	Yes	Yes
Ameren Corp	AEE	Nuclear	Yes	Yes	Yes	Yes
Great Plains Energy, Inc.	GXP	Nuclear	Yes	Yes	Yes	Yes
PPL Corp.	PPL	Nuclear	Yes	Yes	Yes	Yes
Xcel Energy, Inc.	XEL	Nuclear	Yes	Yes	Yes	Yes
Westar Energy, Inc.	WR	Nuclear	Yes	Yes	Yes	Yes
American Electric Power Co. Inc	AEP	Nuclear	Yes	Yes	Yes	Yes
PG&E Corp.	PCG	Nuclear	Yes	Yes	Yes	Yes
Southern Co.	SO	Nuclear	Yes	Yes	Yes	Yes
NRG Energy, Inc.	NRG	Nuclear			Yes	Yes
Exelon Corp.	EXC	Nuclear	Yes	Yes	Yes	Yes
Public Service Enterprise Group, Inc	PEG	Nuclear	Yes	Yes	Yes	Yes
El Paso Electric Co.	EE	Nuclear			Yes	Yes

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Entergy Corp.	ETR	Nuclear	Yes	Yes	Yes	Yes
Edison International	EIX	Nuclear	Yes	Yes	Yes	Yes
NextEra Energy, Inc.	NEE	Nuclear	Yes	Yes	Yes	Yes
Apache Corporation	APA	Natural Gas	Yes	Yes	Yes	Yes
Chesapeake Energy	CHK	Natural Gas			Yes	Yes
Cabot Oil & Gas Corporation	COG	Natural Gas		Yes	Yes	Yes
Devon Energy Corporation	DVN	Natural Gas	Yes	Yes	Yes	Yes
EQT Corporation	EQT	Natural Gas	Yes	Yes	Yes	Yes
AGL Resources Inc.	GAS	Natural Gas	Yes	Yes	Yes	Yes
Kinder Morgan, Inc.	KMI	Natural Gas				Yes
National Fuel Gas Company	NFG	Natural Gas	Yes	Yes	Yes	Yes
Newfield Exploration Co.	NFX	Natural Gas			Yes	Yes
NiSource Inc.	NI	Natural Gas	Yes	Yes	Yes	Yes
Pioneer Natural Resources Co.	PXD	Natural Gas			Yes	Yes
QEP Resources, Inc.	QEP	Natural Gas				Yes
Range Resources Corporation	RRC	Natural Gas		Yes	Yes	Yes
Questar Corporation	STR	Natural Gas	Yes	Yes	Yes	Yes
Southwestern Energy Co.	SWN	Natural Gas	Yes	Yes	Yes	Yes
Ultra Petroleum Corp.	UPL	Natural Gas			Yes	Yes
Williams Companies	WMB	Natural Gas			Yes	Yes
WPX Energy, Inc.	WPX	Natural Gas				Yes
Anadarko Petroleum Corporation	APC	Oil	Yes	Yes	Yes	Yes
Chevron Corporation	CVX	Oil	Yes	Yes	Yes	Yes
ConocoPhillips	COP	Oil	Yes	Yes	Yes	Yes
EOG Resources, Inc.	EOG	Oil		Yes	Yes	Yes
Exxon Mobil Corporation	XOM	Oil	Yes	Yes	Yes	Yes
Hess Corporation	HES	Oil	Yes	Yes	Yes	Yes
Marathon Oil Corporation	MRO	Oil		Yes	Yes	Yes

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Marathon Petroleum Corporation	MPC	Oil				Yes
Noble Energy, Inc	NBL	Oil	Yes	Yes	Yes	Yes
Occidental Petroleum Corporation	OXY	Oil	Yes	Yes	Yes	Yes
Valero Energy Corporation	VLO	Oil	Yes	Yes	Yes	Yes
Joy Global Inc	JOY	Coal			Yes	Yes
Headwaters Inc	HW	Coal			Yes	Yes
Freightcar America	RAIL	Coal				Yes
CONSOL Energy Inc	CNX	Coal			Yes	Yes
Peabody Energy Corp	BTU	Coal			Yes	Yes
Cloud Peak Energy Inc	CLD	Coal				Yes
Westmoreland Coal Co	WLB	Coal	Yes	Yes	Yes	Yes
Alpha Natural Resources	ANR	Coal				Yes
Arch Coal	ACI	Coal	Yes	Yes	Yes	Yes
Walter Energy Inc	WLT	Coal			Yes	Yes
Alliance Holdings Gp Lp	AHGP	Coal				Yes
Alliance Resource Partners Lp	ARLP	Coal			Yes	Yes
Suncoke Energy Inc	SXC	Coal				Yes
Natural Resource Partners Lp	NRP	Coal			Yes	Yes
TECO Energy Inc	TE	Coal	Yes	Yes	Yes	Yes
Black Hills Corporation	BKH	Coal	Yes	Yes	Yes	Yes
James River Coal Co	JRCCQ	Coal			Yes	Yes
Allete Inc.	ALE	Coal	Yes	Yes	Yes	Yes
Oxford Resource Partners LP	OXF	Coal				Yes
Rhino Resource Partners LP	RNO	Coal				Yes
Hallador Energy Co	HNRG	Coal	Yes	Yes	Yes	Yes
America West Resources Inc	AWSR	Coal			Yes	Yes
NACCO Industries Inc	NC	Coal	Yes	Yes	Yes	Yes

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