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Is the U.S. Stock Market Sufficiently Efficient around Hurricanes?

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Abstract

This paper tests the U.S. stock market efficiency around all 18 hurricanes that have hit continental U.S. since 2000. Using an event-study methodology, the study analyzes the effect of those 18 hurricanes on a sample of 60 property-casualty insurance companies before and following the hurricanes' landfall. The study supports the semi-strong form market efficiency and concludes that market inefficiency only exists during the pre-landfall period. Moreover, a significant negative relationship is found between the wind speed and firms' risk exposure, which reiterates the market's ability to differentiate hurricanes by their damaging power and to discriminate P&C insurers by their existence of exposure.

1. Introduction

The test of market efficiency has aroused major attention in financial economics, not only because of the constantly changing nature of the stock market but also because of its real-world applications. The efficient-market hypothesis (EMH) asserts that one cannot consistently achieve returns in excess of average market returns, as any new public information has already been reflected in the price. In an inefficient stock market, however, investors can capitalize on the detected excess return by short-selling securities and make profit before the market corrects itself.

Studies of market efficient around hurricanes have gained more attention as natural disasters have taken place on a much more frequent and significant basis over the past 20 years. In 2012, super storm Sandy has caused an estimated total insured loss up to 20 billion[1] and is very likely to become the most expensive hurricane only second to Hurricane Katrina in 2005. The fact that hurricanes can cause tremendous devastation and yet they are considerably more predictable than other natural disasters such as earthquakes make them an interesting subject to examine.

Early research shows that the stock market reacts differently to Hurricane Hugo comparing to Hurricane Andrew (Lamb, 1998). The property and casualty industry is generally unaffected by Hugo whereas hurricane Andrew causes significant negative impact on insurers with exposure in Florida and Louisiana. In addition, Lamb (1995) concludes that for Hurricane Andrew, insurers with more exposure to the stricken area are more adversely affected by the hurricane.

[1]Holm, Erik, and Scism, Leslie. "Sandy's Insured-Loss Tab: Up to $20 Billion" The Wall Street Journal.

These specific examples raise the question of whether the discrimination happened only to those two specific hurricanes or if it is a more general phenomenon that can be applied to all hurricanes. Besides, since Hugo and Andrew took place in the 80s and 90s respectively, it is unclear whether similar market reaction would be observed in recent years' events.

This paper intends to contribute to the previous literature within the following two aspects. First, it would expand the scope of previous studies by increasing the average number of hurricanes from 2 to 18 and insurers interested from 37 (Lamb, 1995) to 60, respectively. In addition, it would advance the idea of incorporating storm characteristics from news reports (see Ewing et al., 2006) to include wind speed, a quantitative measure that records the development of the hurricane life cycle into the study.

This paper uses a standard event study methodology to analyze the impact of 18 hurricanes (see Table I) that have made landfall in the U.S since 2000 on the stock price of 60 publicly traded Property and Casualty insurance companies.

Table I: List of Hurricanes hit U.S. since 2000

No.	Hurricane	Date	Category	Landfall
1	Lili	2002/10/03	1	LA
2	Claudette	2003/07/15	1	TX
3	Isabel	2003/09/18	2	NC
4	Charley	2004/08/13	4	FL
5	Frances	2004/09/05	2	FL
6	Gaston	2004/08/29	1	SC
7	Ivan	2004/09/16	3	AL
8	Jeanne	2004/09/25	3	FL
9	Cindy	2005/07/05	1	LA
10	Dennis	2005/07/10	3	AL
11	Katrina	2005/08/29	3	LA
12	Rita	2005/09/23	3	TX

13	Wilma	2005/10/24	3	FL
14	Humberto	2007/09/13	1	TX
15	Dolly	2008/07/23	1	TX
16	Gustav	2008/09/01	2	LA
17	Ike	2008/09/13	2	LA
18	Irene	2011/08/27	1	NC

Source: National Hurricane Center Best Track Data HURDAT Atlantic Tracks File 1851-2011

This paper goes over previous empirical studies in Section 2. Section 3 discusses the Market Efficiency Hypothesis. Section 4 introduces the event study methodology and Section 5 discusses the data. Section 6 presents the results and Section 7 concludes.

2. Literature Review

Early research (Sprecher and Pertl, 1983) establishes a link between the occurrence of catastrophic events and change in firm's stock price. Schwert (1981) suggests that testing market efficiency with stock price data is more powerful than other measure in a sense that stock prices are more accurate as they take all relevant information into account as soon as they become available. Once the market receives relevant information, firm's stock prices will adjust rapidly to reflect the events' anticipated impact on the firm.

The literature on stock market efficiency in response to unanticipated hurricane occurrence is somewhat limited in quantity. There is, however, a large body of research on catastrophic losses resulting from such as earthquakes, airline crashes, and terrorist attacks.

Shelor et al. (1991) examine the valuation impact of the Loma Prieta earthquake and find significantly negative abnormal returns[2] (-1.65%) for real estate firms exposed to losses as

[2] Abnormal returns are calculated as the difference between actual and normal returns, where the actual returns are simply the security prices and the normal returns, or the theoretically appropriate required rate of return of

opposed to unexposed firms. The significantly negative abnormal return after the earthquake implies an inefficient market reaction as the actual return deviates from the expected return.

Shelor et al. (1992) extend the scope of his work by examining the market responses of the property and casualty insurers. He finds that, on the contrary, insurance companies' stock price move up by 1.66% after the earthquakes. The positive stock price movement suggests that investors' expectation of higher demand for insurance more than compensates the potential claim losses.

Extending the work of Shelor et al. (1991, 1992), Aiuppa et al. (1993) divide a sample of firms into those that do underwrite insurance premiums for earthquakes and those that do not. They find that earthquake insurers show significant positive stock price reactions, whereas, not surprisingly, non-earthquake insurers are generally not affected.

Within the literature that examines hurricanes alone, Lamb (1995) and Narayanan (1996) study the effects of Hurricane Andrew find a significant negative impact on the stock price of firms with direct exposure to the hurricane stricken states - Florida or Louisiana. The stock prices of other firms with no exposure in the two states are not significantly affected. In a later study, Lamb (1998) compares abnormal performance of property and casualty insurance companies' stock price around hurricane Hugo to hurricane Andrew and results show that Hurricane Hugo doesn't significantly impact the property and casualty industry (also see Gron, 1994; Cagle, 1996) whereas hurricane Andrew causes significant negative impact on insurers with exposure in Florida and Louisiana.

Cummins and Lewis (2003) examine the effects of hurricane Andrew and finds a strong

individual stocks, are estimated linearly from the market returns based on individual security's risk compared to the overall risk of the market (see CAPM). Please refer the section 4 for detailed calculation.

immediate but short-lived negative impact of insurer stock prices in response to catastrophic events by studying the effects of Hurricane Andrew. Ewing et al. (2006) incorporate storm characteristics[3] to study market responses to Hurricane Floyd and find an "overall but not constant negative" cumulative abnormal return around the life cycle of the hurricane. Blau et al. (2008) detect abnormal short selling activities of insurance securities around hurricanes Katrina and Rita. Hewitt (2012) expands the scope of previous analyses to study the market reaction of 12 hurricanes during hurricane season 2004 and 2005 and detects a window of inefficiency immediately after hurricane landfalls.

3. Theory

Studies on market efficiency are largely based on the efficient market hypothesis (EMH), which was developed by Prof. Eugene Fama[4] in the late 1960s. EMH asserts that in an active market composed of "rational and profit-maximizing investors", stocks always trade at their fair value to fully incorporate all available information. More precisely, the stock price determined by the "supply and demand" of the efficient market must equal the stock's intrinsic value. Therefore, it is impossible for investors to consistently earn abnormal returns through stock selection when the market is efficient, as stock prices will adjust rapidly to reflect the anticipated impact of an event on the firm's security once the market receives relevant information.

Later in 1967, Roberts[5] classified three forms of market efficiency – weak-form efficiency, semi-strong-form efficiency and strong-form efficiency for the first time. Weak form

[3] Ewing et al. (2006) uses information describing the development of the storm over time and space as storm characteristics
[4] Fama, Eugene F. 1965."The Behavior of Stock-Market Prices." *The Journal of Business*. 38(1): 34-105.
[5] Roberts, Harry V. 1967. "Statistical versus Clinical Prediction in the Stock Market." Unpublished manuscript.

efficiency asserts that security prices reflect all historical traded related information and repudiates technical analysis. Semi-strong form efficiency claims that security prices reflect all publicly available information and expectations about the future, and repudiates fundamental analysis. Strong form efficiency states that security prices reflect all information, including private or insider information. Therefore, even with the knowledge of material and non-public information, investors cannot consistently beat the market and make excess returns.

Prior empirical studies suggest that the semi-strong form is mostly supported while the strong form is generally not supported. Therefore, I will primarily test the validity of the semi-strong form market efficiency around hurricanes in this paper.

The impact of hurricanes on insurance firms' intrinsic value depends on the relative strength of two conflicting forces - downward pressure on firms' value is caused by a rapid depletion of surplus accounts due to the large reimbursements paid to policyholders (Sprecher and Pertl, 1983; Davidson, Chandy, and Cross, 1987); in contrast, upward pressure comes from an increase in both government required coverage and additional premium earnings (Shelor et al., 1992).

In practice, the negative effect usually operates in the short run whereas the positive effect takes a longer time to play a role. Therefore, it is reasonable to expect a decline in stock price right after the hit of the hurricanes but a positive return over a longer time horizon.

In an efficient market, abnormal returns are not achievable as soon as hurricanes make landfall because the information is rapidly reflected in security prices the moment the news is released. However, abnormal stock returns might exist before the landfall and their direction depends on the expectation of relative strength of the two opposing impacts attributable to the hurricanes. In contrast, when the stock market is not efficient, abnormal returns are achievable even after the hit of the hurricanes.

4. Event Study Methodology

In order to test the validity of the semi-strong form market efficiency, I utilized a standard event-study methodology (see Sprecher et al. 1983; Brown and Warner, 1984; Narayanan, 1996; Lamb, 1998) to analyze the stock prices' reaction to the occurrence of hurricanes.

An event study is an empirical method used to assess an event's impact on a firm's security, which is measured by abnormal returns attributable to the event. I follow the most literature in the field and use the Capital Asset Pricing Model to calculate the abnormal returns. More specifically, the abnormal returns are calculated by subtracting stocks' normal returns from their actual returns. The normal returns (theoretically appropriate required rate of returns) of each individual security are estimated based on the sensitivity of individual firm's performance to the overall market.

Assuming that the returns are multivariate normal and identically distributed, the expected return of a stock can be expressed through the market model as

$$r_{it} = \alpha_i + \beta_i\, r_{mt} + \varepsilon_{it},$$

$$\textit{With } E(\varepsilon_{it}) = 0,\ Var(\varepsilon_{it}) = \sigma_{\varepsilon i}^2 \textit{ and } Cov(r_{mt}, \varepsilon_{it}) = 0$$

where r_{it} is the dividend-adjusted return on property and casualty stock i (i = 1,2,…,N) on day t; r_{mt} is the respective market return on day t, α_i is the intercept with an expected value of zero, β_i is the OLS estimate of the slope coefficient of stock i, and ε_{it} is the residual of stock i on day t.

An estimation window of 300[6] day prior to the left side of the event window will be used to estimate the parameters α_i and β_i for my test. Figure 1 explains the timing sequence of the event study.

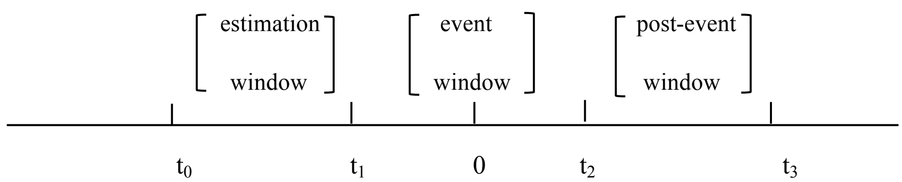

Figure 1: Time Line for an event study[7]

When a hurricane causes large insured losses, the impact on each security i will be reflected in the error term, ε_{it}. Therefore, the difference between the actual and normal return (i.e. the abnormal return) is calculated by examining the regression's residuals as

$$AR_{it} = \varepsilon_{it} = r_{it} - (\hat{\alpha}_i + \hat{\beta}_i\, r_{mt})$$

Then, in order to test if the U.S. stock market's response to different hurricanes and property and casualty insurers is constant, the abnormal returns are decomposed into wind speed, individual firm's risk exposure and their interaction term. The interaction term is included because intuitively the effect of risk exposure on abnormal returns depends on wind speed. Therefore, the guiding equation becomes:

$$AR_{ijt} = \alpha + \gamma_1\, Wind\ Speed_{jt} + \gamma_2\, Risk\ Exposure_{ij} + \gamma_3\, Wind\ Speed_{jt}\, Risk\ Exposure_{ij}$$

[6] 300 days are more than two times longer than the estimation window of 120 days suggested by MacKinlay, A Craig, 1997, "Event Studies in Economics and Finance", given a relatively large sample size (N=63)
[7] Adopted from MacKinlay, A Craig, 1997, "Event Studies in Economics and Finance". *Journal of Economic Literature.* 35 (1): 13.

where AR_{ijt} stands for the abnormal return for hurricane j and company i on day t and t is any number within the event window [t_1, t_2] where the effect of a hurricane on each individual stock is examined.

If the market is efficient in a semi-strong form, α, γ_1, γ_2 and γ_3 should be zero for an event window after hurricanes' landfall. At the same time, at least one of α, γ_1, γ_2 and γ_3 should be significantly different from zero for an event window before hurricanes' landfall. These two relationships match the Efficient Market Hypothesis that abnormal returns are observable before the hurricanes' landfall but they disappear after the hurricanes.

Therefore, the test hypotheses are rewritten as followings.

Null Hypothesis (H_0):

At least one of α, γ_1, γ_2 and $\gamma_3 \neq 0$ *for* $t_1 < 0$ & $\alpha = \gamma_1 = \gamma_2 = \gamma_3 = 0$ *for* $t_2 > 0$

Alternative Hypothesis (H_a):

$\alpha = \gamma_1 = \gamma_2 = \gamma_3 = 0$ *for* $t_1 < 0$ & *at least one of* $\alpha, \gamma_1, \gamma_2, \gamma_3 \neq 0$ *for* $t_2 > 0$

5. Summary Statistics

The sample set of firms in my study includes 60 out of 95 P&C carriers that are currently listed under the property and casualty industry on Yahoo!Finance and Google Finance. I eliminated 35 companies, including 9 reinsurance companies and 26 that do not have corresponding premium information, from my sample. A complete list of the 60 companies can be found in Appendix - Table 1.

Since the hurricanes are examined over a 11 year time period, the companies that are currently listed did not necessarily exist when some of the early hurricanes hit U.S. Therefore, I examine the 18 hurricanes separately, take out those companies that do not have enough observations for some specific hurricanes, and come to a final number of companies for each hurricane (Table II).

Table II: Number of Companies for each Hurricane

Hurricane	Date	# of firms	Hurricane	Date	# of firms
Lilli	10/03/2002	46	Dennis	07/10/2005	54
Claudette	07/15/2003	49	Katrina	08/29/2005	54
Isabel	09/18/2003	49	Rita	09/23/2005	54
Charley	08/13/2004	52	Wilma	10/24/2005	54
Frances	09/05/2004	52	Humberto	09/13/2007	58
Gaston	08/29/2004	52	Dolly	07/23/2008	59
Ivan	09/16/2004	52	Gustav	09/01/2008	59
Jeanne	09/25/2004	52	Ike	09/13/2008	59
Cindy	07/05/2005	54	Irene	08/27/2011	63

Source: NOAA's National Climatic Data Center HURDAT Atlantic Tracks File 1851-2011

The daily stock price (adjusted for dividend payments and capital actions) of the target firms r_{it} from January 3rd, 2000 to December 30th, 2011 are obtained from Yahoo!Finance[8]. There are 3,017 observations of daily stock price for each company and therefore a total of 181,020 observations for all 60 companies.

I use S&P 500 market index to calculate the market returns because the S&P 500 is the most widely used measure of overall stock market performance in the United States. A total number of 3,017 observations, r_{mt} are obtained from Yahoo! Finance.

[8] Yahoo!Finance. www. yahoofinanace.com (accessed Oct 23, 2012)

I use a 300-day period 10 days prior to day 0[9] (the day that the hurricane made landfall) to estimate the normal return within the event window. The 10-day break before the actual hurricanes make landfall in the U.S. is used to ensure that the estimation of normal returns is not contaminated by any anticipation of the imminent hurricane path and the subsequent level of destruction (Lamb, 1998). If the hurricane hit the U.S. on weekends or holidays, the first trading day after the landfall will become day 0 (Pertl et al., 1983). 7 out of 18 hurricanes in my sample (Gaston, Frances, Jeanne, Dennis, Gustav, Ike and Irene) made landfall on a non-trading day. In addition, for hurricanes that occurred consecutively (Alex, Charley, Gaston, Frances, Ivan and Jeanne in 2004, Cindy and Dennis, Katrina, Ophelia and Rita in 2005 and Dolly, Gustav and Ike in 2008), I use a 300-day estimation period 10 days prior to the first hurricane's event window to predict the normal return within the window as the stock prices were distorted after the hit of the preceding hurricane(s).

The abnormal returns are evaluated for two event windows, [-5, 0) and (0, +5] for each hurricane. The event windows of five workdays cover one week before and after hurricanes' landfall and are designed to test the market efficiency for the two time periods separately. The two event windows are designed based on the knowledge that the effect of large losses on the market price of the firm is short-lived (Sprecher et al. 1983) and also allow for information leakage and market anticipation of large losses caused by the imminent hurricanes. Different event windows[10] will be tested in the robustness test.

[9] In order to avoid hurricane seasons
[10] Event windows of [-10, 0) and (0, +10] are used for the robustness test

I obtain wind speed data from the National Hurricane Center[11]. It records the daily wind speed throughout the entire life cycle of the 18 hurricanes at 00 UTC, 06 UTC, 12 UTC and 18 UTC respectively. For simplicity, I use the wind speed at 00 UTC as the daily wind speed in this study. The wind speed is assumed to be 0 for days that are not affected by the hurricanes. There are 117 wind speed records for 3,017 workdays between January 3rd, 2000 and December 30th, 2011, with a mean speed of 60.5 km/h. The maximum wind speed of 150 km/h occurred on September 22th, 2005 during Hurricane Rita and the minimum wind speed of 10 km/h occurred during Hurricane Dennis. Appendix - Table 3 shows the average wind speed for the 18 hurricanes over a window period of [-5, +5], [-5, 0) and (0, +5] days.

I use insurers' direct premium written in the hurricane-stricken states as a proxy for their corresponding risk exposure. States are classified as affected when there are insured losses associated with the hurricane reported to the Insurance Services Office (ISO). I obtain the 18 hurricanes' estimated insured losses by state from the Property Claim Services (PCS). The stricken states for each of the 18 hurricanes are listed in Appendix – Table 2.

I obtain the state level premium data of the 60 insurance firms from Best's State/Line Reports - Property/Casualty - United States 2000 – 2011 (Lamb 1995, 1998). The average direct premium written in hurricane stricken states reaches 38,369,674 USD for the 60 firms from 2000 to 2011. While a few companies didn't have business in certain states, Allstate Insurance attained the highest direct premium written of 1,707,574,946 USD in Taxes in 2005.

Finally, the risk exposure of the 60 firms for the 18 hurricanes is measured by taking the weighted average of the direct premium written in all affected states, where the weights are

[11] "National Hurricane Center Best Track Data HURDAT Atlantic Tracks File 1851-2011" National Hurricane Center. http://www.nhc.noaa.gov/pastall.shtml#hurdat (accessed Oct. 23rd, 2012).

assigned proportionally based on the insured losses in each state. Appendix - Table 4 summarizes the risk exposure of each insurer from 2000 to 2011.

6. Analysis

6.1 Estimation Errors

The dataset includes both cross-sectional and time-series components. Therefore, all of the possible estimation issues - including multicollinearity, heteroskedasticity, serial correlation and nonstationarity - should be tested before finalizing model specification.

Recall from the Theory section, the semi-strong form market efficiency asserts that abnormal returns are not achievable as soon as hurricanes make landfall while they might exist before the landfall. Therefore, in order to most accurately assess the validity of the semi-strong form market efficiency, the abnormal returns are divided into two time periods – before and after hurricane landfalls and the estimation errors are also examined separately.

I first test for the multicollinearity on all explanatory variables – *Wind Speed*, *Risk Exposure* and their interaction term. Appendix - Table 5 shows their correlation coefficients for both before and after hurricane landfalls. Except for the interaction term, which is simply *Wind Speed * Risk Exposure*, the other two explanatory variables do not encounter the problem of multicollinearity. Since the interaction term is highly correlated with premium, it is eliminated from the main regression model[12].

[12] The main regression model is reduced to $AR_{ijt} = \alpha + \gamma_1\, Wind\ Speed_j + \gamma_2\, Risk\ Exposure_{ij}$, where AR_{ijt} stands for the abnormal return for hurricane *j* and company *i* on day t and t is any number within the event window $[t_1, t_2]$.

Next, I test the main regression model for heteroskedasticity. Since the stock returns are a pooled dataset of 60 individual firms over 18 discontinued time periods, the model' residuals are expected to be non-constant. I use a modified Wald statistics to test for group wise heteroskedasticity with the null hypothesis of homoskedasticity (STATA, 2000). Given a chi-squared p-value of 0.00 for both before and after landfall periods, I include the robust option that adjusts heteroskedasticity-corrected standard errors to remedy this problem.

Furthermore, I test for serial correlation using the Wooldridge Test, which assumes that there is no first order serial correlation. Given the chi-squared p-values of 0.3391 and 0.6897, no correction is needed since the test doesn't detect any first order serial correlation in both before and after landfall periods.

Lastly, I conduct the Fischer test to examine the nonstationarity of each explanatory variable. Non-stationary variables will cause potential spurious correlation and thus results in an overestimation of the R^2. Appendix - Table 6 lists the probability of each independent variable obtaining the chi-square value if the null hypothesis is true. Since one of the explanatory variables, *Risk Exposure* fails to reject the null hypothesis of stationary, I further the analysis and test the cointegration among model residuals. If the degrees of nonstationarity of the two explanatory variables were consistent (i.e. the residuals are stationary), the original model estimation would not cause biases to the results. Appendix - Table 7 displays the test result for the unit root of residuals. Since the residuals cointegrate, no remedy is required to fix the nonstationarity problem of the explanatory variables.

After correcting for the only estimation issue in the main regression model – heteroskedasticity, I conduct a Hausman test to select between fixed effect and random effects.

Given the p-values of 0.9676 and 0.9696 for before and after landfalls respectively, I am not able to reject the null hypothesis and conclude that the difference in coefficients is not systematic between random-effect and between-effect regressions. Thus, a random effects model yield consistent and accurate estimation.

6.2 Main Results

After correcting for the detected estimation errors, the main regression is reduced to

$$AR_{ijt} = \alpha + \gamma_1 \, Wind\ Speed_{jt} + \gamma_2 \, Risk\ Exposure_{ij},$$

where AR_{ijt} stands for the abnormal return for hurricane *j* and company *i* on day *t* and *t* is any number within the event window [-5, 0) and (0, +5] days where the effect of a hurricane on each individual stock is examined.

Recall from the *Theory* section that if the market is efficient in a semi-strong form, at least one of α, γ_1 and γ_2 should be statistically different from zero for the time period before hurricanes' hit and all of the coefficients should be zero after hurricanes' landfall. I expect a negative sign on *Wind Speed* because higher intensity is always associated with lower actual returns, which leads to lower abnormal returns. Similarly, I expect a negative sign on *Risk Exposure*. The more business an insurer writes in a hurricane stricken area, the greater the hurricane's impact on the firm's stock prices, which again, leads to lower abnormal returns.

The estimation results of two regression analyses – before and after hurricane landfalls are reported in Appendix - Table 8 and Appendix - Table 9, respectively. The statistically significant coefficients of *Wind Speed*, *Risk Exposure* and the constant in Table 8 indicate that the market is not efficient before hurricanes landfall. When *Wind Speed* increases by 1 km/h, the abnormal returns decrease by 0.00181%, holding *Risk Exposure* constant. Similarly, holding *Wind Speed* constant, one unit (i.e. one million USD) increase in *Risk Exposure* leads to a 0.000295% decrease in abnormal returns. In contrast, the statistically insignificant coefficients in Appendix - Table 9 suggest that the U.S stock market is efficient for the time period after hurricanes.

In summary, given the fact that the stock market is not efficient before hurricanes landfall but is proved to be efficient after landfalls, the semi-strong form market efficiency is supported.

6.3 Robustness

To further support the main regression results, three robustness checks are conducted and included in this section. First, I reduce the hurricane sample size to include only five of the most recent hurricanes in my new sample as people might argue that that conclusion is time sensitive and hurricanes specific. Testing with a different sample size over a more recent time frame can thus help evaluate the strength of the conclusion of semi-strong form market efficiency. The estimation results of the first robustness test are reported in Appendix - Table 10 and Appendix - Table 11. For the time period before hurricanes landfall, *Risk Exposure* loses its significance in explaining abnormal returns while *Wind Speed* and the constant remain significant. For the time period after hurricanes landfall, none of the coefficients are significant, which agrees with results of the main regression. Therefore, semi-strong form market efficiency is still supported with the sample of five most recent hurricanes.

I change the event window from ± 5 workdays to ± 10 workdays in the second robustness test as people might argue that the choice of event window is arbitrary and doesn't reflect the entire life cycle of a hurricane. An event window of ± 10 days measures exactly the market reaction exactly 2 weeks before and after the hurricane landfall. This event window covers the entire life cycle of all 18 hurricanes in the sample. Appendix - Table 12 and Appendix -Table 13 summarize the estimations from the new event window for both before and after hurricanes landfall. For the time period before hurricanes landfall, *Wind Speed* loses its significance while *Risk Exposure* and the constant remain significant. The loss of significance of *Winds Speed* is attributable to the inclusion of many more days with zero wind speed in this new event window. For the time period after hurricanes landfall, neither of the two explanatory variables and the constants is statistically significant. This result, again, supports the conclusion of semi-strong form market efficiency.

Lastly, I add an interaction term – *Day* **Wind Speed* to test the validity of semi-strong form market efficiency. The new variable *Day* is simply the number of days apart from hurricanes' landfall. This interaction term is included out of the consideration that the effect of wind speed on a firm's security varies by time. For example, the effect of a 60km/h wind speed on a firm's security 5 days before the hurricanes' landfall is theoretically smaller than the effect of the same wind intensity 1 day before the landfall. Appendix - Table 14 and Appendix -Table 15 summarize the estimations from the new regression for both before and after hurricanes landfall. For the time period before hurricanes landfall, only the constant term and *Wind Speed* is significant while the rest lose their significance. For the time period after hurricanes landfall, none of the explanatory variables, including the constant term is significant. This result, again, supports the conclusion of semi-strong form market efficiency.

7. Conclusion

This paper examines the U.S stock market efficiency around 18 hurricanes that have hit continental U.S. since 2000. A standard event study methodology is utilized to analyze the capital market responses to the hit of the hurricanes on the property and casualty insurance industry.

In order to most accurately assess the validity of the semi-strong form market efficiency, I divide the event window into two time periods – before and after hurricane landfalls. My findings are in line with previous literature (Lamb, 1995; Narayanan, 1996; Lamb 1998) that semi-strong form market efficiency is generally supported around hurricanes. The stock market reacts inefficiently before the hurricanes make landfall. I find a significant negative relationship between the wind speed and firms' risk exposure, which demonstrates the market's ability to differentiate hurricanes by their damaging power and to discriminate P&C insurers by their existence of exposure (Lamb, 1998). In contrast, the stock market responses efficiently after the hurricanes make landfall. All the coefficients lose their significance after the landfalls.

However, it is also important to note some of the limitations of the paper. First, even though the event windows that have been used in previous empirical research were adopted, there are still uncertainties about how long both effects will last, especially when take the information leakage into consideration. Questions like "What is an appropriate event window" and "How many days before a hurricane hit do people start to panic" are still up for debate.

Future research should focus on finding out the most ideal event window to assess the stock market's reaction and other potential independent variables that might explain the abnormal returns. As I mentioned earlier in the literature review section, the research on this topic is relatively new and limited; all of the existing empirical research has tested for no more than 12 hurricanes. Therefore, future studies are encouraged to examine even a larger sample of hurricanes and over a longer time period.

Appendix:

Table 1 - List of Property and Casualty Insurers

1. ACE Limited	31. Infinity Property and Casualty Corporation
2. Affirmative Insurance Holdings, Inc.	32. Kemper Corporation
3. Alleghany Corporation	33. Kingstone Companies, Inc.
4. Allied World Assurance Company Holdings, AG	34. Kingsway Financial Services Inc.
5. Alterra Capital Holdings Limited	35. Maiden Holdings, Ltd.
6. American International Group, Inc.	36. Markel Corporation
7. American National Insurance Company	37. Meadowbrook Insurance Group, Inc.
8. American Safety Insurance Holdings, Ltd.	38. Mercury General Corporation
9. AmTrust Financial Services, Inc.	39. Old Republic International Corporation
10. Arch Capital Group Ltd.	40. ProAssurance Corporation
11. Aspen Insurance Holdings Limited	41. RenaissanceRe Holdings Ltd.
12. AssuranceAmerica Corporation	42. RLI Corp.
13. AXIS Capital Holdings Limited	43. Safety Insurance Group, Inc.
14. Baldwin & Lyons, Inc.	44. Seabright Holdings Inc
15. Berkshire Hathaway Inc.	45 Selective Insurance Group, Inc.
16. Cincinnati Financial Corporation	46. State Auto Financial Corporation
17. CNA Financial Corporation	47. The Allstate Corporation
18. EMC Insurance Group Inc.	48. The Chubb Corporation
19. Endurance Specialty Holdings Ltd.	49. The Hanover Insurance Group, Inc.
20. Enstar Group Limited	50. The Hartford Financial Services Group, Inc.
21. Erie Indemnity Company	51. The National Security Group, Inc.
22. Everest Re Group, Ltd.	52. The Navigators Group, Inc.
23. Federated National Holding Company	53. The Progressive Corporation
24. First Acceptance Corporation	54. The Travelers Companies, Inc.
25. First American Financial Corporation	55. Tower Group, Inc.
26. Global Indemnity plc	56. United Fire Group, Inc.
27. Hallmark Financial Services, Inc.	57. Universal Insurance Holdings, Inc.
28. HCC Insurance Holdings, Inc.	58. W. R. Berkley Corporation
29. Homeowners Choice, Inc.	59. White Mountains Insurance Group, Ltd.
30. Horace Mann Educators Corporation	60. XL Group plc

Source 1: Yahoo!Finance Web. Oct 23rd, 2012. www.yahoofinance.com

Source 2: Google Finance Web. Oct 23rd, 2012. www.googlefinance.com

Table 2 - List of 18 Hurricanes Landfall State and Stricken State(s)

Hurricane	Landfall	Other Stricken State(s)
Lili	LA	MS
Claudette	TX	-
Isabel	NC	DE, ND, NJ, NY, PA, VA, WV
Charley	FL	NC, SC
Frances	FL	GA, NC, NY, SC
Gaston	SC	NC, VA
Ivan	AL	DE, FL, GA, LA, MD, MS, NC, NJ, NY, OH, PA, TN, VA, WV
Jeanne	FL	DE, GA, MD, NC, NJ, NY, PA, PR, SC, VA
Cindy	LA	AL, GA, MS
Dennis	AL	FL, GA, MS
Katrina	LA	AL, FL, GA, MS, TN
Rita	TX	AL, AR, FL, LA, MS, TN
Wilma	FL	-
Humberto	TX	-
Dolly	TX	NM
Gustav	LA	AL, AR, MS
Ike	LA	AR, IL, IN, KY, MO, OH, PA, TX
Irene	NC	CT, DC, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VA, VT

Source: Insurance Services Office (ISO)

Table 3: Summary Statistics - Average Wind Speed by Hurricanes
Window Period: [-5, +5] days

No.	Hurricane	Category	Obs	Mean	Std. Dev.	Min	Max
1	Lili	1	11	40.5	41.7	0	125
2	Claudette	1	11	35.0	24.1	0	60
3	Isabel	2	11	68.2	57.8	0	140
4	Charley	4	11	21.8	33.2	0	90
5	Frances	2	11	86.4	48.2	25	140
6	Gaston	1	11	66.5	47.8	0	120
7	Ivan	3	11	64.6	50.7	25	140
8	Jeanne	3	11	22.3	15.6	0	45
9	Cindy	1	11	16.4	20.0	0	65
10	Dennis	3	11	20.5	17.0	0	65
11	Katrina	3	11	33.2	43.3	0	140
12	Rita	3	11	44.6	54.8	0	150
13	Wilma	3	11	67.7	55.0	0	135
14	Humberto	1	11	7.3	17.5	0	55
15	Dolly	1	11	22.3	27.7	0	65
16	Gustav	2	11	48.6	29.4	15	115
17	Ike	2	11	42.7	43.8	0	115
18	Irene	1	11	44.6	39.1	0	95

Window Period: [-5, 0) days

No.	Hurricane	Category	Obs	Mean	Std. Dev.	Min	Max
1	Lili	1	5	56.0	24.9	30	90
2	Claudette	1	5	49.0	8.2	35	55
3	Isabel	2	5	119.0	18.5	95	140
4	Charley	4	5	30.0	30.2	0	65
5	Frances	2	5	112.0	7.6	105	120
6	Gaston	1	5	27.0	29.5	0	70
7	Ivan	3	5	90.0	59.9	25	140
8	Jeanne	3	5	30.0	5.0	25	35
9	Cindy	1	5	0.0	0.0	0	0
10	Dennis	3	5	28.0	23.6	0	65
11	Katrina	3	5	29.0	30.1	0	70
12	Rita	3	5	70.0	56.2	0	150
13	Wilma	3	5	96.0	49.7	30	135
14	Humberto	1	5	0.0	0.0	0	0
15	Dolly	1	5	18.0	24.7	0	45
16	Gustav	2	5	47.0	14.8	25	60
17	Ike	2	5	84.0	19.5	65	115
18	Irene	1	5	81.0	13.4	60	95

Window Period (0, +5] days

No.	Hurricane	Category	Obs	Mean	Std. Dev.	Min	Max
1	Lili	1	5	8	17.89	0	40
2	Claudette	1	5	16	23.02	0	50
3	Isabel	2	5	13	29.07	0	65
4	Charley	4	5	0	0.00	0	0
5	Frances	2	5	71	62.99	25	140
6	Gaston	1	5	98	35.81	35	120
7	Ivan	3	5	30	5.00	25	35
8	Jeanne	3	5	10	13.69	0	25
9	Cindy	1	5	30	19.69	20	65
10	Dennis	3	5	13	4.47	10	20
11	Katrina	3	5	16	23.02	0	50
12	Rita	3	5	4	8.94	0	20
13	Wilma	3	5	34	49.80	0	110
14	Humberto	1	5	5	11.18	0	25
15	Dolly	1	5	18	28.42	0	65
16	Gustav	2	5	48	43.67	15	115
17	Ike	2	5	0	0.00	0	0
18	Irene	1	5	8	17.89	0	40

Source: National Hurricane Center Best Track Data HURDAT Atlantic Tracks File 1851-2011

Table 4: Summary Statistics - Direct Premium Written by Company

company_id	Obs	Mean	Std. Dev.	Min	Max
1	198	99,480	59,372	23,381	204,587
2	55	12,433	20,652	0	53,295
3	198	48,143	41,733	0	148,869
4	44	2,426	706	1,257	3,045
5	187	2,561	4,724	0	15,660
6	198	273,482	191,255	0	573,718
7	198	26,173	17,365	0	69,201
8	198	530	476	46	1,500
9	44	8,814	6,647	2,319	16,888
10	198	24,210	20,462	2,119	71,052
11	110	4,900	6,806	0	20,137
12	198	767	1,784	0	7,458
13	110	34,360	28,731	7,613	96,905
14	198	430	610	0	1,876
15	198	240,261	142,042	14,313	431,824
16	198	23,935	20,888	75	58,861
17	198	133,041	70,748	6,627	238,617
18	198	5,860	3,960	330	12,794
19	165	2,722	3,351	0	8,322
20	198	185	761	0	3,316
21	198	33,288	58,608	0	184,730
22	198	974	1,515	0	5,296
23	198	0	0	0	0
24	198	2,806	4,320	0	17,417
25	11	1,102	0	1,102	1,102
26	110	4,852	5,897	0	15,792
27	198	4,900	10,605	0	31,110
28	198	11,661	14,739	29	47,427
29	11	0	0	0	0
30	198	16,981	7,590	784	29,901
31	165	12,583	14,613	0	40,756
32	198	34,460	59,721	0	181,492
33	198	235	970	0	4,224
34	187	14,054	18,504	58	50,309
35	11	1,786	0	1,786	1,786
36	198	32,820	20,101	806	70,772
37	198	4,282	7,618	23	24,173
38	198	30,165	28,825	0	86,059

Table 4 Cont.: Summary Statistics - Direct Premium Written by Company

company_id	Obs	Mean	Std. Dev.	Min	Max
39	198	11,834	15,645	279	51,322
40	198	51	119	0	451
41	198	2,602	3,715	0	15,058
42	198	10,630	8,463	552	30,420
43	165	653	2,451	0	9,797
44	11	0	0	0	0
45	198	6,405	12,186	0	48,190
46	198	15,614	11,953	318	46,285
47	198	812,912	482,578	40,984	1,614,784
48	198	146,702	93,165	12,063	286,308
49	198	26,963	15,733	0	60,998
50	198	173,674	115,569	8,689	356,856
51	198	2,311	2,767	0	9,089
52	198	4,231	3,448	17	10,682
53	198	294,031	175,960	15,446	531,869
54	198	357,127	210,026	26,889	735,658
55	55	17,844	30,816	81	78,830
56	198	14,539	12,390	0	33,070
57	44	555	972	0	2,218
58	198	21,515	21,238	638	67,459
59	198	22,896	12,571	3,295	46,629
60	198	34,475	22,115	2,190	86,202

Source: Best's State/Line Reports - Property/Casualty - United States 2000 – 2011

Table 5: Correlation Between Independent Variables

Before Landfall Period: Event Window [-5, 0)

	ab_ret	Wind Speed	Risk Exposure	Interact
ab_ret	1.0000			
Wind Speed	-0.0197	1.0000		
Risk Exposure	-0.0114	-0.0369	1.0000	
Interact	-0.0178	0.2233	0.7082	1.0000

After Landfall Period: Event Window (0, +5]

	ab_ret	Wind Speed	Risk Exposure	Interact
ab_ret	1.0000			
Wind Speed	0.0064	1.0000		
Risk Exposure	0.0075	-0.0694	1.0000	
Interact	-0.0162	0.2475	0.4515	1.0000

Table 6: Test for Nonstationarity: Using the Xtfisher
Before Landfall Period: Event Window [-5, 0)

Variables	Prob > chi2
Wind Speed	0.0000
Risk Exposure	1.0000

After Landfall Period: Event Window (0, +5]

Variables	Prob > chi2
Wind Speed	0.0000
Risk Exposure	1.0000

Table 7:Cointegration Test: Using the Xtfisher -
Before Landfall Period: Event Window [-5, 0)

Variables	Prob > chi2
Residuals	0.0000

After Landfall Period: Event Window (0, +5]

Variables	Prob > chi2
Residuals	0.0000

Table 8: Random Effects GLS Regression Results
Before Landfall Period: Event Window [-5, 0)

VARIABLES	ab_ret
Wind Speed	-0.00181**
	(0.000923)
Risk Exposure	-0.000295*
	(0.000152)
Constant	0.159***
	(0.0556)
Observations	4,494
Number of company_id	60

Notes(i): Estimations are evaluated over an event window of [-5,0)
Notes(ii):Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Random Effects GLS Regression Results
After Landfall Period: Event Window (0, +5]

VARIABLES	ab_ret
Wind Speed	0.000655
	(0.00134)
Risk Exposure	0.000163
	(0.000123)
Constant	0.0271
	(0.0503)
Observations	4,494
Number of company_id	60

Notes(i): Estimations are evaluated over an event window of (0, +5]
Notes(ii):Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Robustness1: Random Effects GLS Regression Results for 5 most Recent Hurricanes

Before Landfall Period: Event Window [-5,0)

VARIABLES	ab_ret
Wind Speed	-0.00865***
	(0.00248)
Risk Exposure	0.000318
	(0.000257)
Constant	0.488***
	(0.140)
Observations	1352
Number of company_id	60

Notes(i): Estimations are evaluated over an event window of [-5,0)
Notes(ii):Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Robustness1: Random Effects GLS Regression Results for 5 most Recent Hurricanes

After Landfall Period: Event Window (0, +5]

VARIABLES	ab_ret
Wind Speed	0.00368
	(0.00585)
Risk Exposure	-2.45e-05
	(0.000200)
Constant	0.199
	(0.146)
Observations	1352
Number of company_id	60

Notes(i): Estimations are evaluated over an event window of (0,+5]
Notes(ii):Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Robustness2: Random Effects GLS Regression Results - event window [-10,0) & (0, +10]

Before Landfall Period: Event Window [-10, 0)

VARIABLES	ab_ret
Wind Speed	-0.000336
	(0.000940)
Risk Exposure	0.000200*
	(0.000107)
Constant	0.459*
	(0.0265)
Observations	5590
Number of company_id	60

Notes(i): Estimations are evaluated over an event window of [-10,0)
Notes(ii):Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Robustness2: Random Effects GLS Regression Results - event window [-10,0) & (0, +10]

After Landfall Period: Event Window (0, +10]

VARIABLES	ab_ret
Wind Speed	-0.00255
	(0.00240)
Risk Exposure	6.94e-05
	(0.000101)
Constant	0.0284
	(0.0573)
Observations	5590
Number of company_id	60

Notes(i): Estimations are evaluated over an event window of (0, +10]
Notes(ii):Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Robustness3: Random Effects GLS Regression Results - event window [-5,0) & (0, +5]

Before Landfall Period: Event Window [-5, 0)

VARIABLES	ab_ret
Wind Speed	-0.0000461*
	(0.000028)
Risk Exposure	-6.64e-10
	(1.65e-09)
Day*Wind_Speed	-7.94e-06
	(0.0000103)
Constant	0.0025712***
	(0.0006532)
Observations	1352
Number of company_id	60

Notes(i): Estimations are evaluated over an event window of [-5,0)
Notes(ii):Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Robustness3: Random Effects GLS Regression Results - event window [-5,0) & (0, +5]

After Landfall Period: Event Window (0, +5]

VARIABLES	ab_ret
Wind Speed	-0.0000441
	(0.0000253)
Risk Exposure	2.23e-09
	(1.41e-09)
Day*Wind_Speed	-6.92e-07
	(0.0000295)
Constant	0.0000581
	(0.0008573)
Observations	1352
Number of company_id	60

Notes(i): Estimations are evaluated over an event window of (0, +5]
Notes(ii):Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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