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Examining Market Response Following Hurricane Landfall: Does the U.S. Stock Market React Efficiently to Hurricanes?

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Abstract: This paper examines market efficiency surrounding hurricanes in the immediate post-landfall period. Using hypotheses derived from distinctions between the efficient market hypothesis and the adaptive market hypothesis, it runs event studies on a sample of gulf-exposed property and casualty insurers for hurricanes that made landfall domestically in the 2004 and 2005 hurricane seasons. Testing these post-landfall inefficiency measurements shows that a statistically significant window of inefficiency exists immediately following hurricane landfall. This confirms the prediction of the adaptive market hypothesis, and as a result shows that hurricanes create opportunities for abnormal risk-adjusted returns in this market.

I. Introduction:

Exploiting periods of market inefficiency to generate abnormal risk-adjusted returns in equity markets is an ever-evolving pursuit of economic research. The results of such studies have real-world applications and profit potential, yet as quickly as inefficiencies are discovered they often disappear in similar fashion as investors exploit the inefficiency and it corrects itself. This fact serves as perpetual motivation to find new ways of thinking about market efficiency and its drivers, and as of late the scholarly community pondering this question has taken particular interest in market responses to crises, both man-made and natural.

The classic method of testing market efficiency is event study, which examines abnormal returns of specific equities around an event date and attempts to isolate whether or not markets anticipated the event's implications[1]. A limitation of this methodology as it applies to disasters is the necessary condition of knowing when the event will occur, a fact that makes attempts to run event study around most types of crises ineffective.

Coincidentally, hurricanes are predictable disasters. Modern technology is able to track progress towards land and storm severity very accurately, making these storms a good fit for event study analysis of market efficiency. Hurricanes, especially those in recent memory, are among the most devastating disasters of all

[1] I explain the event study methodology in-depth later.

time. The 2005 hurricane season[2] alone accounted for over $52 billion in insured losses in the United States. This figure is almost 93% of domestic insured losses for the entire year (Guidette, 2006). Taking advantage of this predictability, I run event study around hurricanes to determine whether the U.S. stock market reacts efficiently to hurricanes that make landfall domestically.

I now turn to the relevant literature surrounding hurricanes and market efficiency in an attempt to understand where the research currently stands. This research will serve as a stepping-stone for my study, providing a framework for its execution, bringing factors that need to be controlled to attention, and raising further questions to test.

The rest of the paper is organized as follows: I begin with a review of relevant literature and move from this to outline testable hypotheses in the theory section. I then, outline the event study methodology in detail, describe the data set I will be using, present my results, and make a few concluding remarks.

II. Previous Literature:

Literature on the topic of market efficiency surrounding hurricanes falls into two general categories: those that run event study around hurricanes themselves, and those that analyze the time-varying ways in which investors and markets adapt in their responses to these storms. Before discussing these studies, it is important to step back and review literature that examines the true economic impact of hurricanes.

[2] Which included hurricanes Katrina and Rita.

In the days, weeks, and even months following hurricanes, there is undeniable economic cost. Infrastructure damage alone disrupts the business process of affected areas, but these consequences phase out over time, and it is not out of the realm of possibility for an affected area to benefit economically from a hurricane long-term. Ewing and Kruse (2002) find that hurricane recovery in the high-risk area of Wilmington, North Carolina led to improvements in the economy of the area in the long run. Likewise, the unemployment rate in Corpus Christi, Texas improved due to the recovery activity of Hurricane Bert[3] (Ewing et al., 2005). This short- vs. long-term dichotomy in the economic impact of hurricanes makes any values of 'true economic cost' immediately suspect.

Lamb (1998) showed negative abnormal returns for property and casualty insurers in his event study around Hurricane Andrew[4]. These abnormal returns prove that the market responded *inefficiently* to Hurricane Andrew (Lamb, 1998). His event study differentiates between insurance firms with property and casualty exposure in the Gulf of Mexico region and those without exposure, and this differentiation allows him to discern that the market accurately differentiated these two types of firms. Firms with more exposure suffered greater abnormal losses in the post-hurricane period than their less-exposed competitors (Lamb, 1998).

Ewing, Hein, and Kruse (2006) take Lamb's work a step further and run their event study with a focus on the days leading up to Hurricane Floyd[5] instead of focusing solely on the abnormal returns post-landfall. The prices of property

[3] Landfall: August 1999.
[4] Landfall: August 1992.
[5] Landfall: September 1999.

and casualty insurers fell or rose abnormally based on the changing reports of projected landfall date, wind speed, and storm category (Ewing et al., 2006). These abnormal returns in the pre-hurricane period that did not exist in the post-hurricane period show an *efficient* response to Hurricane Floyd.

Recent research has taken the conclusions of these papers that markets respond efficiently to hurricanes in varying degrees and looked a step further: on the adaptations markets make in their responses to hurricanes. Blau, Ness, and Wade (2008) capitalize on the close proximity of the landfalls of two of the most notable hurricanes in the last decade, Katrina and Rita[6], and examine market anticipation and reaction to both. They show that abnormal short volume and price drop occurs in the exposed insurance firms three trading days after Katrina's landfall, while this same negative impact was priced into the market before Rita's landfall only 27 days later (Blau et al., 2008). The implication of this result is that stock market adapted and responded more efficiently pre-landfall to Hurricane Rita than it did to Hurricane Katrina[7].

The conclusion of the literature demonstrates an interesting point about markets, at least in the context of hurricane response efficiency. Within seasons investors learn from past inefficiency and modify their behavior to correct that inefficiency (Blau et al., 2008). The loose ends left by current research lead to a number of questions. I answer two such questions by testing hypotheses outlined in the following section. First, given the discrepancy between degrees of efficient

[6] Katrina Landfall: August 2005; Rita Landfall: September 2005.
[7] It should be noted that while my results echo the finding that the negative impact was priced into Hurricane Rita in the pre-landfall period, the abnormal price fluctuations that occur post-landfall tell a different story regarding the relative inefficiency generated by each storm. This is illustrated in Figures A.9 and A.11.

response to individual hurricanes in separate studies, does the market respond to hurricanes on an overall basis efficiently? When trying to design a trading strategy with abnormal risk-adjusted returns, if these returns can only be shown in hindsight on a hurricane-by-hurricane basis they are ineffective in the real world. If the market responds to hurricanes on an inefficient basis across all hurricanes, a similar trading strategy is profitable looking forward as well.

Second, is the observed variability seen in literature that examines pair of hurricane efficiency true across all hurricanes? Is this variability simply random, and market response to hurricanes on an overall basis is constant? Testing this hypothesis has implications as to how quickly the abnormal-risk adjusted returns that may exist disappear.

With a better understanding of current literature in mind, as well as a number of questions to consider, I now turn to theory to create testable hypotheses. These hypotheses will determine the data set that is necessary, as well as the formal empirical processes that are required to test them.

III. Theory

The efficient market hypothesis (EMH) is the underlying theory for any study testing market efficiency. It asserts that efficient markets are ones in which prices immediately reflect all available information and moves on to define the weak, semi-strong, and strong forms of market efficiency (Fama, 1970). Until recently, this theory on the behavior of capital markets has remained unquestioned. As of late, however, an alternative to the EMH, known as the adaptive market hypothesis (AMH) has taken hold. The AMH attempts to reconcile traditional finance theory with behavioral economics, describing a market that adapts and evolves rather than one that is static (Lo, 2004). Discrepancies between the EMH and AMH provide a theoretical base of testable hypotheses to explore.

Both the EMH and AMH state that current market prices reflect all fundamental information. The AMH incorporates a period of time during which market participants discern what information is fundamentally efficient and what information is inefficient noise. This period of inefficiency in the AMH is one of its key differences from the EMH: the prediction that abnormal risk-adjusted profit opportunities exist in financial markets (Lo, 2004). This distinction legitimizes my pursuit of inefficiency, especially in the immediate post-hurricane period when investors are most likely to be discerning the difference between fundamentally efficient information and inefficient noise:

Hypothesis 1:

The U.S. stock market responds to hurricanes efficiently[8].

An important note about this hypothesis: the definition of efficiency I use in this paper is as defined by the EMH. That is, I determine an efficient reaction as one in which no abnormal price fluctuations occur after the event date. If this

[8] Efficiency in this case as defined by the EMH.

hypothesis holds, the U.S. stock market behaves under the assumptions of the EMH in regards to hurricane response. If we are able to reject it and a period of inefficiency exists as defined by the AMH, these assumptions hold. In pursuing evidence of the brief inefficiency predicted by Lo's AMH, I tailor my event study to an untraditionally small window in the post-hurricane period, an assumption that is addressed when I walk through the event study methodology.

Moving forward, under the EMH investors react to all information as it becomes known as though in a vacuum. That is, investor reactions to similar information in previous periods have no impact on their reaction to information in the current period. In an EMH world, investors are static players who do not change their behavior across time periods. Under the AMH, however, investors change and adapt their behavior based on their motivation to exploit risk-adjusted profits left on the table by the potential inefficiencies of previous periods. Of course, the opposite may be the case and it may be investor frustration with the inability to generate abnormal risk-adjusted returns that leads them to adapt their efficient investment strategy, leading to inefficiency. Whatever the case may be, this distinction between the EMH and AMH provides another hypothesis to test:

Hypothesis 2:

The U.S. stock market's degree of efficiency in response to hurricanes is constant.

Once again, my ability to reject or accept this hypothesis points to whether the assumptions of the EMH or AMH hold truer in the case of variability of market response to hurricanes over time. If degree of efficiency is constant, investors exist in an EMH vacuum. If degree of efficiency is variable, AMH assumptions hold.

With a foundation for my question established in the literature and a pair of hypotheses to test derived from the EMH and AMH, I now outline the process of conducting an event study before moving on to describe my data set.

V. Event Study Methodology

As previously mentioned, event study is a process used in financial academia to assess the impact of an event on the value of a given company's stock. Within this basic use are a variety of applications, including the ability to estimate the cumulative abnormal returns due to an event (and the significance of this measurement), both for an individual company being tested but also across a sample of firms to give a measure of cumulative abnormal returns caused by the event itself on the firms. The basic process is as follows, and as each step is discussed I note the unique parameters I define to effectively test my hypotheses. I first need to estimate normal performance of each of my firms relative to the market. Once normal performance is derived I am able to calculate expected return and abnormal returns around an event. The summation of these abnormal returns gives me a cumulative measure of abnormal returns, which I test for significance both at the firm and sample level. If these cumulative abnormal returns are significant in the immediate post-hurricane period, market response to the hurricane was inefficient.

The purpose of the estimating normal performance is to derive how sensitive each of the firms in our data set is to performance of the greater market. This sensitivity is known as beta, and flows from the Capital Asset Pricing Model as Follows:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

In the above equation, $E(R_i)$ represents the expected return of firm i, which is the sum of the risk-free rate, R_f, and firm i's sensitivity to the market risk premium, with β_i representing this individual firm sensitivity and $(E(R_m) - R_f)$ representing the market risk premium. Stated another way, this sensitivity that beta measures is represented as:

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

Thus, beta is simply a measure of how sensitive the returns of each firm are to the returns of the market. Using data from the 2003 hurricane season[9], I calculate this sensitivity for each firm to market returns using a static estimation window, and this beta is used as a measure of normal performance relative to the market.

This static estimation window deviates from traditional event study. Typically, event studies use a lagged estimation window, such as the 10 trading days prior to the event window to estimate normal performance. Lagged estimation windows are problematic for this study, because often times in the two

[9] June 1st – November 30th

week window before hurricane landfall another storm is hitting the Gulf. A lagged estimation window that covers landfall of a previous hurricane will generate a significantly inaccurate beta, and the bias in this beta will impact the calculation of expected and abnormal returns. A static estimation window assures that my beta is free of bias, and if we assume that individual hurricanes themselves do not impact an individual firm's sensitivity to market returns (this is often a function intrinsic company properties, such as leverage and riskiness of capital structure) there is no need for a lagged estimation window anyway.

With a measure of beta for each of our firms, I am able to move on to calculating expected returns and abnormal returns in the event window. Once again, the proximity of hurricanes in these seasons prohibits an event window of traditional length, leading me to one that measures the cumulative abnormal returns from the date a hurricane makes landfall until the end of the 2nd trading day following. The reason for this small window traces back to the theory section of the paper and discussion of the short window of inefficiency the AMH incorporates allowing investors to sort fundamental from inefficient information in their investment decision. The only measure of cumulative abnormal return that is relevant to my hypotheses will occur shortly after event occurrence, and this window satisfies that requirement.

Calculating cumulative abnormal returns requires a calculation of abnormal returns for each day in the event window:

$$AR_{it} = R_{it} - \hat{\beta}_i R_{mt}$$

Abnormal return for firm *i* on day *t* is the return of that firm on day *t* removing the expected return for that day, measured by the beta for firm *i* from our estimation window multiplied by market return on day *t*.

Cumulative abnormal return is calculated from these daily abnormal returns, and is simply a summation of abnormal returns over the event window:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}$$

The results of the 192 event studies conducted across the 16 firms in the sample for all 12 hurricanes can be seen in appendix Tables A.1 to A.12. Diagrams of the cumulative abnormal return for each hurricane one week pre- and post-landfall can be seen in Figures A.1 to A.12. With a cumulative abnormal return measure for each of our firms for each hurricane, I estimate the cumulative abnormal return caused by each hurricane across firms by bootstrapping the estimation of this measure, a process that draws randomly from the 16 firms to provide a more accurate measure of standard error. While this process does not impact the coefficient estimates, the standard errors for each estimate converge with a large enough number of bootstrap repetitions, and the process allows a more accurate calculation of statistical significance.

With an understanding of the event study process and the data necessary to conduct one, I now describe the data set I use to test my hypotheses.

IV. Summary Statistics

Several considerations immediately limit the scope of the data set I am able to use. For one, market conditions since 2008 and the exposure of insurance firms to the financial crisis make the task of isolating abnormal returns to property and casualty insurers due to hurricanes in this time frame impossible. Additionally, the sparse numbers of hurricanes in many hurricane seasons (with none making landfall domestically in some seasons) makes measuring variability of response in-season impossible. With these factors in mind, and knowing activity in terms of storm frequency in the adjacent 2004 and 2005 hurricane seasons was significantly above average, these two hurricane seasons serve as the time window I use for analysis.

Determining how efficiently markets react to hurricanes requires an ability to measure the cumulative abnormal returns that occur after a given hurricane makes landfall. Historical closing price data for gulf-exposed property and casualty insurers as well as landfall date for all hurricanes over our sample period will combine in an event study to give us a measure of inefficiency to use in further regressions to test my hypotheses.

My data set consists of daily closing price from 2003 through 2005 for the 11 publicly traded property and casualty insurers used in Lamb's paper (1998) in addition to 5 industry competitors, as well as historical closing price of the S&P 500 over the same time horizon[10]. The firms are listed alphabetically in Table 1. Information on all hurricanes that made landfall in the 2004 and 2005 hurricane

[10] Historical closing price data comes from Yahoo Finance: http://www.finance.yahoo.com

seasons is listed in Table 2. With this data, I generate a daily return for each of our insurers over this three-year window, which I use to test for significant cumulative abnormal return over the period starting on landfall date and ending at the end of the second trading day following[11]. As previously stated, I use the 2003 hurricane season as my estimation window. The end result of this process is a measure of cumulative abnormal return generated by each hurricane across all insurers in the sample, a statistic I am able to test for significance using a bootstrapped standard error.

The measures produced from this methodology represent the cumulative abnormal return generated by each hurricane in the post-hurricane period. Keeping the true goal of the study in mind, however, necessitates altering this variable. The results of the event study will be a collection of positive and negative percentage estimates, and while the direction of these cumulative abnormal returns may be of interest to future studies, magnitude (not direction) of inefficiency is the true measure of efficiency, which is why I square the cumulative abnormal return estimates from my event study before testing their joint significance. Table 3 shows the characteristics of the cumulative abnormal return variable as well as its squared values, generated from the event study process.

The lack of discussion regarding independent variables is done purposefully. While one might ask how this study controls for, perhaps, macroeconomic conditions or company-specific structure without independent variables, the truth is that all of these factors are controlled for in the event study

[11] Landfall data comes from the National Oceanic and Atmospheric Association (NOAA)

process. Company specific factors (important because they likely influence the degree to which investors react inefficiently) are inherent in the event study process because of the estimation window. Normalizing returns to a broad index such as the S&P 500 controls for the macro environment. In essence, the study controls for more factors than I could list due to the incalculable number of variables that influence individual stock betas and the macro environment in which they trade.

VI. Empirical Results

A few preliminary observations that do not impact the hypothesis tests I conduct but will be expanded on in my concluding remarks are the notable overreaction in the positive direction following the landfall of Hurricane Rita[12] (Figure A.11) and the instance of only one true perfectly efficient reaction across all 192 event studies. For all practical purposes a number of firms reacted within a range that could be considered efficient to a number of hurricanes, and these results are not relevant to the central focus of the paper until the degree of efficiency of the individual companies in my sample are tested for significance jointly, yet I consider them worth noting nonetheless.

The results of my joint test across property and casualty insurers for the efficiency level of the market response to each hurricane can be seen in Table 4. The coefficient can be interpreted as the percentage change over landfall date and the two trading days following for each storm that is not accounted for by market

[12] Demonstrated by the significant positive overreaction in the post-hurricane period.

factors. While these percentages are small, the fact that the combined market capitalization of our sample of firms is approximately $300 billion makes even small percentages of abnormal returns economically significant.

In terms of statistical significance, 3 storms have large enough z-scores calculated using our bootstrapping method to reject that the true cumulative abnormal return caused by the storm is different from zero. The U.S. stock market reacted inefficiently in both a statistically significant way to Hurricanes Charley, Katrina, and Rita. As touched on before, the inefficient positive cumulative abnormal returns generated by Hurricane Rita in the post-hurricane period are an interesting point to note, yet as I am about to discuss, not relevant to the central focus of this study.

Negative cumulative abnormal returns in the post-hurricane period represent inefficient reactions, as the market underestimated the impact of the hurricane in the pre-hurricane period. Positive cumulative abnormal return estimates are also inefficient, as they represent overestimates of hurricane impact in the pre-hurricane period. While the drivers of these positive and negative abnormal reactions in the post-hurricane period may be of interest to future studies, they do not aid in testing either of the hypotheses of this study. This directional inefficiency is a topic I touch on in my concluding remarks. Ultimately, however, direction of inefficiency is irrelevant, magnitude is what matters, and for this reason when conducting estimates to test my hypotheses I square the cumulative abnormal return coefficients seen in Table 4 to generate a measure of overall inefficiency caused by each hurricane.

i. Hypothesis 1:

My first testable hypothesis is that markets react efficiently to hurricanes as defined by the efficient market hypothesis. As I discussed in my preliminary results, three hurricanes in my sample show statistically significant inefficient reactions but it remains to be seen whether the reactions of the market to the group of hurricanes as a whole are statistically inefficient. I test this hypothesis using a bootstrapped estimation of the true value and standard error of overall efficiency across hurricanes, a process that once again draws repetitively from the sample of cumulative abnormal returns for each hurricane to derive a bootstrapped standard error that strengthens my z-test of statistical significance. The result of this test can be seen in Table 5. I find that the U.S. stock market does not react efficiently to hurricanes on an overall basis.

The statistically significant estimation of my cross-hurricane efficiency coefficient allows me to reject the null hypothesis that the U.S. stock market reacts efficiently to hurricanes as defined by the EMH. This rejection demonstrates the existence of a brief post-hurricane period of inefficiency as predicted by the AMH, and I accept the alternate hypothesis that markets react inefficiently to hurricanes and the AMH assumptions hold when examining market behavior in response to hurricanes.

While the estimate in Table 5 shows a positive cumulative abnormal return, the interpretation is inherently different than the interpretation of the estimates in Table 4. In testing this efficiency hypothesis, direction of inefficiency was irrelevant and removed. Thus, our prediction in Table 5 does not imply that the market will react inefficiently in a positive direction in the post-hurricane period, as a similar result in Table 4 would imply. Rather, it estimates the magnitude the inefficiency regardless of direction.

This finding means abnormal risk-adjusted returns exist not only in response to individual hurricanes, but also hurricanes as a group[13]. This finding is important, as an investor with this knowledge does not need to know the characteristics of a hurricane or the macro environment that cause inefficiency in individual hurricanes to make profit, he or she only needs to execute their strategy over all hurricanes, as the overall market response to hurricanes is inefficient.

ii. Hypothesis 2:

My second testable hypothesis is that the market's degree of efficiency in response to hurricanes is constant. While rejecting my first null hypothesis led to the conclusion that the market responds inefficiently to hurricanes in my sample as a group and that the AMH assumptions govern market behavior in that respect, determining whether market efficiency is constant brings us a step closer to understanding the drivers of market efficiency surrounding hurricanes.

I regress my squared measure of cumulative abnormal return by both storm order and year of storm, simply trying to determine if:

$$CAR^2 = f(storm\ order)$$

[13] While this is true over our sample period, past performance does not indicate future results, and a similar trading strategy that may produce abnormal risk-adjusted returns in one period is not guaranteed to in another period.

Or if:

$$CAR^2 = f(year)$$

The results of my tests of this hypothesis are found in Table 6. Attempting to explain cumulative abnormal return by storm order within year and season as seen in regressions (i) and (ii) yields results that are not statistically significant enough to reject the null that the market's degree of efficiency in response to hurricanes is constant.

A limitation of this study that these results highlight is the extent to which the low number of observations limits not only the ability to make statistically significant claims but also its exposure to random variation when attempting to isolate drivers of variability in market efficiency. While these problems were not present in hypothesis 1 when looking at the hurricanes as a group, they make attempts to test the hurricanes against one another an ineffective endeavor. This fact, coupled with the low number of hurricanes that occur from year to year and even over spans of years, means it may be decades before there is enough storm data to accurately measure the constancy of market efficiency surrounding hurricanes. This thought will be expanded in the concluding remarks of the paper.

iv. Robustness

Another way of thinking about market efficiency and hurricanes is examining the reactions by company across hurricanes instead of estimating an inefficiency coefficient for each hurricane. While the inefficiency of the entire market response to hurricanes is the most valid way to explore my hypotheses, if companies themselves do not respond to hurricanes in a statistically significant manner over time the abnormal risk-adjusted returns from the inefficiency created by hurricanes cannot be realized by employing a trading strategy on a single company, an initial motivation of the paper. In addition, if companies themselves to not respond inefficiently over time it is likely that the inefficiency measured when I rejected the null hypothesis that the U.S. stock market reacts inefficiently to hurricanes was due to random chance in due to noise in the data showing statistical significance when observed by hurricane across companies.

Market response to hurricanes could be inefficient in a statistically significant way without company response across hurricanes over time being statistically significant. Consider the hypothetical case where the companies in my sample react to hurricanes randomly in terms of efficiency with a true mean inefficiency of 0. If enough companies react in the same direction in a random fashion to a particular hurricane, the event study methodology will detect statistically significant cumulative abnormal returns over the event window for that hurricane across companies. If these companies truly behave randomly, it is unlikely that these random efficiency measurements detected by the event study process will be strong enough in either direction to reject the null that any of my firms react efficiently to hurricanes on an individual basis. Admittedly, in a very improbable case both of these events could happen and statistical significance could possibly be detected by random chance when testing my results both vertically by hurricane and horizontally across hurricanes. Yet the improbability of this scenario lends robustness to my results in the case of detected statistical significance in both directions.

The results of this bootstrapped estimation of cumulative abnormal return for each company across hurricanes can be seen in Table 7. American Financial Group, Harleysville Group, Inc., and The Hanover Insurance Group, Inc. all show statistically significant inefficient reactions across hurricanes. When testing for joint significance across all companies, I again use a bootstrapped estimation of the squared term of each individual company's inefficiency measure. These results can be seen in Table 8, and I detect statistically significant inefficiency in my sample of companies across hurricanes. As previously stated, this finding adds robustness to my main results, and serves as validation that the inefficiency detected in my event studies exists.

The discrepancy between the estimated inefficiency when testing for joint significance using the method in my main results and the method outlined above highlights the random noise that exists in market data. This can be seen in the difference between estimates in Table 5 and Table 8. Without noise, the estimated inefficiency coefficient should be the same when looking jointly across companies or jointly across hurricanes, yet this is not the case. This small discrepancy, however, is not important to the pursuit of the paper, while the statistically significant coefficient of inefficiency that exists regardless of how it is tested is of great importance. If anything, the presence of no noise in the data would be more troubling to the study because of the realities of studying real-world market data and the noise that inevitably results.

An additional robustness consideration the study makes is the removal of Hurricane Rita from the sample and re-estimating the inefficiency coefficient across hurricanes. The inefficiency generated by Hurricane Rita is notably larger than that generated by other hurricanes, potentially large enough to generate statistical significance on its own as a part of the sample. The results of this rerun estimation can be seen in Table 9. The removal of Hurricane Rita does not impact the statistical significance of the inefficiency coefficient, lending further robustness to the main results of the paper.

Table 10 shows the results of cross-hurricane efficiency measurements using alternative post-landfall event windows. Each of these event studies uses the same methodology as previously outlined, and statistically significant inefficient reactions in 3 of these 4 windows show that the inefficiency detected in the window used for my main results is not a coincidence.

As a final robustness consideration, I test my first hypothesis without bootstrapping to examine whether or not the bootstrap methodology is creating false statistical significance. This result is seen in Table 11, and the statistically significant inefficient reaction shows that the bootstrap methodology does not impact my estimation. The coefficient estimates are the same in Table 5 and Table 11, as they should be because the bootstrap methodology only impacts the accuracy of the standard error measurement. Bootstrapping my main results is necessary because of the fact that estimates of individual hurricane efficiency are a product of my event study methodology (and therefore not exact). Table 11 shows that this bootstrapping process does not impact the statistical significance of these results. Table 12 shows my manual calculation of a 95% confidence interval, which I derive using my entire bootstrapped sample of estimates and dropping the highest and lowest 2.5%. This process further demonstrates the robustness of my statistical significance as zero is not within the interval.

VI. Discussion

With statistically significant inefficiency detected in price movements of my hurricane-exposed property and casualty insurers, I now discuss the real-world trading application of this information. As previously stated, new ways of thinking about market efficiency are motivated by opportunities that exist for risk-adjusted abnormal returns. With this in mind, I now explore trading strategies that generate abnormal risk-adjusted returns in the face of inefficient market response to hurricanes. A caveat of this discussion is the fact that my analysis of these strategies is only theoretical, no backtesting of their effectiveness has been done. A further consideration is that even in the presence of backtested success, past performance does not indicate future success.

i. Trading Strategies with Abnormal Risk-Adjusted Returns

A trading strategy based on the news of a pending hurricane, given the results of my event studies, will be successful in the immediate post-hurricane period if it is neutral and bullish on volatility. It is important to note that these characteristics describe the goals of options strategies, and simple buy/sell strategies on securities themselves are ineffective in this scenario.

I will cover options strategies briefly. An option is the right to buy or sell a security at a given price (strike price) within a specified time. The right to buy is known as a call option, and the right to sell is known as a put option. Both calls and puts can be bought and sold. Between these four options (buying calls, selling calls, buying puts, and selling puts), complicated strategies can be executed that limit risk and/or reward for the right to be successful in specific scenarios. The scenario we are targeting with our options play is a neutral move (profitable in either direction) with increased volatility in the future. Any such strategy will generate abnormal risk-adjusted returns in the post-hurricane period, due to the statistically significant inefficient market reaction to such events.

Four common options strategies fit this goal. They include the long straddle, long strangle, short condor, and short butterfly. While these strategies differ in subtle ways, the foundation of all of them is neutrally directed increase in volatility in the future. These strategies are engineered using a combination of buying and selling calls and puts at varying strike prices depending on where the underlying security currently trades. Each of these strategies is successful pending a large enough move in the share price of the underlying company in either direction.

VII. Conclusion

In this study, I examine market efficiency surrounding hurricanes. Inefficient market response to any event leads to windows in which abnormal risk-adjusted returns exist in equity markets. These abnormal risk-adjusted returns motivate the academic community to think of market efficiency in new ways. A recent development in the literature is study of the impact of natural disasters on market efficiency, as opposed to the more common focus on market efficiency during man-made crises such as financial collapses.

I conduct 192 event studies on 16 hurricane-exposed property and casualty insurers for all 12 hurricanes that made landfall in the United States during the 2004 and 2005 hurricane seasons. The results of all of these studies, as well as event window diagrams for each hurricane with bootstrap-estimated company results can be seen in Tables A.1 through A.12 and Figures A.1 through A.12. I use the results of these event studies to test 2 hypotheses derived from discrepancies between the Efficient Market Hypothesis (Fama, 1970) and the Adaptive Markets Hypothesis (Lo, 2004). The period of inefficiency post-event for investors to sort meaningful information from noise that Lo incorporates into his AMH forms the basis for the first hypothesis I test: that the U.S. stock market reacts to hurricanes efficiently as defined by the EMH, which does not allow for this period of inefficiency. Additionally, the static players in Fama's EMH do not change their behavior over time, while Lo's AMH investors are constantly changing their investment strategies. This distinction leads to my second testable hypothesis: that the degree to which the U.S. stock market efficiently responds to hurricanes is constant.

Using bootstrapped estimations of the coefficient of cumulative abnormal returns generated in the post-hurricane period, I generate a measure of inefficiency for each hurricane that incorporates the reactions of all companies in the event window. I test this statistic for significance using these bootstrapped standard errors, and these results can be seen in Table 4.

I explore my first hypothesis using these inefficiency measurements. To generate a measure of inefficiency that is neutral of positivity and negativity, I square each hurricane's inefficiency coefficient, and use another bootstrapped estimation across these all hurricanes to test whether or not they are jointly inefficient. The results of this process can be seen in Table 5, and I ultimately am able to conclude that hurricanes create statistically significant inefficiency in the U.S. stock market, and that Lo's AMH assumptions more accurately govern the behavior of players in this market than the assumptions of Fama's EMH, at least in terms of the existence of a post-landfall window inefficiency while investors sort fundamental information from inefficient noise.

I test my second hypothesis using the order of hurricane within season and the year in which the hurricane falls to attempt to isolate whether inefficiency is constant. As previously discussed, the low observation count negatively impacts this aspect of the study to detect statistical significance, and also leaves it subject to a plethora of random factors. Tests of the first hypothesis did not have this issue, as companies and hurricanes were tested jointly. Yet treating storms in an individual manner and attempting to discern between them makes tests with so few observations ineffective. It should also be noted that due to the relative scarcity of hurricane data because of the rarity of the storms, it might be some time before enough data exists to run a test of this type. I ultimately do not have enough evidence to reject the hypothesis that the U.S. stock market reacts to hurricanes at a constant degree of inefficiency.

For robustness, I first test inefficiency across hurricanes for each of the companies in my sample, and then estimate the overall inefficiency across companies using the same bootstrapped estimation method. Even when tested this way, companies responded to hurricanes in a jointly inefficient way, aiding in establishing that the results that rejected hypothesis 1 were not the result of random noise. Furthermore, I remove Hurricane Rita from my sample and once again find that hurricanes treated jointly react to hurricanes inefficiently.

True to the central motivation of the paper, I briefly note trading strategies that will generate abnormal risk-adjusted returns in the post-hurricane period according to the results of my study. While simple buy/sell strategies will not be effective, complicated options strategies that are direction neutral and bullish on future volatility will be profitable.

The existence of statistically significant inefficiency across hurricanes is an exciting conclusion of the paper, yet one question remains. What drives this inefficiency? According to the AMH, which I conclude governs market reaction across hurricanes in the immediate post-hurricane period, it is ultimately the players in a given market and their level of competition that determine their level of efficiency as a group (Lo, 2004). The validity of this thought remains to be seen in the context of market response to hurricanes. Any further findings in this regard only open the door to more opportunities for abnormal risk-adjusted returns, and as mentioned from the start, these profit opportunities serve as perpetual motivation to find pockets of inefficiency in markets wherever they exist, be it surrounding earnings announcement, mergers and acquisitions, or in the case of this study: hurricanes.

VIII. References

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IX. Tables and Figures

Table 1:

Property and Casualty Insurers

Company	Ticker
American Financial Group	AFG
American International Group, Inc.	AIG
Berkshire Hathaway, Inc.	BRK.A
Chubb Corporation	CB
Hanover Insurance Group, Inc.	THG
Harleysville Group, Inc.	HGIC
Markel Corporation	MKL
The Navigators Group, Inc.	NAVG
RLI Corporation	RLI
W.R. Berkley Corporation	WRB
Travelers Companies, Inc.	TRV
Cna Financial Corporation	CAN
Hartford Financial Services	HIG
State Auto Financial	STFC
Cincinnati Financial Corporation	CINF
Old Republic International Corporation	ORI

Table 2:

Hurricanes

Name	Landfall Date	Peak Category*	U.S. Landfall Category*
Alex	August 3, 2004	3	2
Charley	August 13, 2004	4	4
Gaston	August 29, 2004	1	1
Frances	September 5, 2004	4	2
Ivan	September 16, 2004	5	3
Jeanne	September 25, 2004	3	3
Cindy	July 5, 2005	1	1
Dennis	July 10, 2005	4	3
Katrina	August 29, 2005	5	3
Ophelia	September 14, 2005	1	1
Rita	September 23, 2005	5	3
Wilma	October 24, 2005	5	3

*As defined by the Saffir-Simpson Hurricane Wind Scale

Table 3:

Summary Statistics: Event Study Results by Hurricane

Variable	Obs.	Mean	Std. Dev.	Minimum	Maximum
Cumulative Abnormal Return	12	0.06	0.88	-1.03	2.08
CAR Squared	12	0.72	1.21	0.01	4.32

Table 4:

Bootstrapped* Estimations of Cumulative Abnormal Return Across All Companies by Hurricane

2004		2005	
Hurricane	CAR Estimate	Hurricane	CAR Estimate
Alex	-0.38%	Cindy	0.11%
	(0.52)		(0.28)
Charley	-0.55%	Dennis	-0.16%
	(0.23)**		(0.47)
Gaston	-0.44%	Katrina	-1.03%
	(0.43)		(0.52)**
Frances	0.63%	Ophelia	0.38%
	(0.44)		(0.32)
Ivan	-0.29%	Rita	2.08%
	(0.29)		(1.05)**
Jeanne	-0.77%	Wilma	1.15%
	(0.48)		(0.81)

*Standard errors bootstrapped using 1,000 repetitions
**Significant at the 5% level

Table 5:

Bootstrapped* Estimation of Market Reaction Efficiency to Hurricanes During the 2004 and 2005 Seasons

Estimate	Bootstrapped Standard Error	95% Confidence Interval
0.72%	0.35**	(0.06%,1.37%)

*Standard errors bootstrapped using 1,000 repetitions
**Significant at the 5% level

Table 6:

Bootstrapped Estimation of Change in Hurricane Efficiency

Variable	(i)	(ii)
Order	0.29	
	(0.19)	
Season		0.86
		(0.65)
R-Squared	0.18	0.14
Observations	12	12
Replications	1,000	1,000

Table 7:

Bootstrapped* Estimations of Cumulative Abnormal Return by Company Across Hurricanes

Company	CAR Estimate	Company	CAR Estimate
AFG	-0.77%	MKL	-0.21%
	(0.34)**		(0.34)
AIG	0.40%	NAVG	0.52%
	(0.29)		(1.66)
BRK.A	-0.23%	ORI	0.20%
	(0.36)		(0.19)
CB	0.41%	RLI	0.68%
	(0.57)		(0.35)
CINF	-0.18%	STFC	0.30%
	(0.26)		(0.50)
CNA	-0.55%	THG	-1.58%
	(0.53)		(0.51)**
HGIC	1.43%	TRV	0.10%
	(0.58)**		(0.78)
HIG	-0.30%	WRB	0.74%
	(0.51)		(0.93)

*Standard errors bootstrapped using 1,000 repetitions
**Significant at the 5% level

Table 8:

Bootstrapped* Estimation of Company-Specific Inefficiency Across Hurricanes During the 2004 and 2005 Seasons

Estimate	Bootstrapped Standard Error	95% Confidence Interval
0.46%	0.18**	(0.11%,0.81%)

*Standard errors bootstrapped using 1,000 repetitions
**Significant at the 5% level

Table 9:

Bootstrapped* Estimation of Market Reaction Efficiency to Hurricanes During the 2004 and 2005 Seasons Without Hurricane Rita

Estimate	Bootstrapped Standard Error	95% Confidence Interval
0.39%	0.13**	(0.14%,0.64%)

*Standard errors bootstrapped using 1,000 repetitions
**Significant at the 5% level

Table 10:

Bootstrapped Estimation of Market Reaction Efficiency to Hurricanes: Alternate Post-Landfall Windows

	(i)	(ii)	(iii)	(iv)
Estimate	1.04%	1.28%	0.58%	0.62%
	(0.35)**	(0.66)	(0.17)**	(0.18)**

*Window (i): four trading days including landfall, Window (ii): five trading days including landfall, Window (iii): three trading days starting day after landfall, Window (iv): four trading days starting day after landfall
**Significant at the 5% level

Table 11:

Non-Bootstrapped Estimation of Market Reaction Efficiency to Hurricanes During the 2004 and 2005 Seasons

Estimate	Standard Error	95% Confidence Interval
0.72%	0.34**	(0.01%,1.52%)

*Standard errors bootstrapped using 1,000 repetitions
**Significant at the 5% level

Table 12:

Manual Confidence Interval* of Bootstrapped Main Results
(0.36,1.65)

*95% Confidence Interval

X. Appendix

Table A.1:

Event Study Results* for Hurricane Alex

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	-0.07%	MKL	0.62%
AIG	1.04%	NAVG	-6.44%
BRK.A	-1.19%	ORI	-0.53%
CB	-1.36%	RLI	1.14%
CINF	1.73%	STFC	0.44%
CNA	-0.47%	THG	-1.63%
HGIC	2.52%	TRV	-3.05%
HIG	0.60%	WRB	0.59%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Table A.2:

Event Study Results* for Hurricane Charley

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	-1.54%	MKL	-0.97%
AIG	0.36%	NAVG	0.03%
BRK.A	0.82%	ORI	-0.11%
CB	-0.91%	RLI	-1.56%
CINF	-1.42%	STFC	-0.45%
CNA	-1.67%	THG	-0.96%
HGIC	-0.68%	TRV	1.66%
HIG	-1.60%	WRB	0.07%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Table A.3:

Event Study Results* for Hurricane Gaston

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	-3.25%	MKL	-0.06%
AIG	0.99%	NAVG	-3.08%
BRK.A	0.42%	ORI	-0.34%
CB	-0.36%	RLI	0.59%
CINF	0.14%	STFC	-0.91%
CNA	-4.64%	THG	0.15%
HGIC	1.85%	TRV	1.35%
HIG	0.11%	WRB	0.09%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Table A.4:

Event Study Results* for Hurricane Frances

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	0.61%	MKL	2.60%
AIG	1.34%	NAVG	-0.23%
BRK.A	0.32%	ORI	0.46%
CB	1.02%	RLI	0.99%
CINF	-0.23%	STFC	-1.00%
CNA	-1.89%	THG	-4.29%
HGIC	3.68%	TRV	-0.06%
HIG	2.19%	WRB	0.82%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Table A.5:

Event Study Results* for Hurricane Ivan

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	-0.61%	MKL	0.13%
AIG	0.03%	NAVG	-2.92%
BRK.A	-0.35%	ORI	0.63%
CB	0.60%	RLI	-0.27%
CINF	0.53%	STFC	-1.46%
CNA	-2.51%	THG	-0.52%
HGIC	-0.29%	TRV	1.21%
HIG	1.31%	WRB	-0.11%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Table A.6:

Event Study Results* for Hurricane Jeanne

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	-0.84%	MKL	0.39%
AIG	-1.31%	NAVG	-1.74%
BRK.A	-1.38%	ORI	0.94%
CB	-0.96%	RLI	0.73%
CINF	-0.11%	STFC	-0.98%
CNA	0.60%	THG	-0.66%
HGIC	3.78%	TRV	-4.86%
HIG	-3.27%	WRB	-2.70%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Table A.7:

Event Study Results* for Hurricane Cindy

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	-0.45%	MKL	-0.39%
AIG	0.99%	NAVG	0.23%
BRK.A	1.25%	ORI	-0.46%
CB	0.23%	RLI	1.31%
CINF	-0.51%	STFC	-2.19%
CNA	1.59%	THG	-0.94%
HGIC	-1.07%	TRV	1.90%
HIG	0.85%	WRB	-0.55%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Table A.8:

Event Study Results* for Hurricane Dennis

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	-1.81%	MKL	-2.81%
AIG	-0.02%	NAVG	1.46%
BRK.A	-1.48%	ORI	-0.33%
CB	-0.40%	RLI	2.64%
CINF	-1.39%	STFC	1.83%
CNA	-0.87%	THG	-1.19%
HGIC	4.42%	TRV	-0.35%
HIG	-2.00%	WRB	-0.33%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Table A.9:

Event Study Results* for Hurricane Katrina

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	-1.07%	MKL	-0.90%
AIG	-1.10%	NAVG	-0.63%
BRK.A	-0.70%	ORI	-0.26%
CB	-1.17%	RLI	0.57%
CINF	-1.20%	STFC	4.05%
CNA	-0.91%	THG	-4.67%
HGIC	2.06%	TRV	-4.97%
HIG	-3.66%	WRB	-2.02%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Table A.10:

Event Study Results* for Hurricane Ophelia

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	-0.15%	MKL	0.20%
AIG	0.06%	NAVG	-0.85%
BRK.A	-2.59%	ORI	1.43%
CB	1.82%	RLI	2.42%
CINF	-0.56%	STFC	0.59%
CNA	-0.50%	THG	-0.55%
HGIC	0.45%	TRV	1.68%
HIG	0.45%	WRB	2.23%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Table A.11:

Event Study Results* for Hurricane Rita

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	-1.61%	MKL	-0.42%
AIG	2.42%	NAVG**	17.50%
BRK.A	2.16%	ORI	1.11%
CB	0.39%	RLI	-1.46%
CINF	0.91%	STFC	1.84%
CNA	1.71%	THG	1.23%
HGIC	2.28%	TRV	4.51%
HIG	0.59%	WRB	0.11%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

**Final Katrina losses calculated at $1.17/share

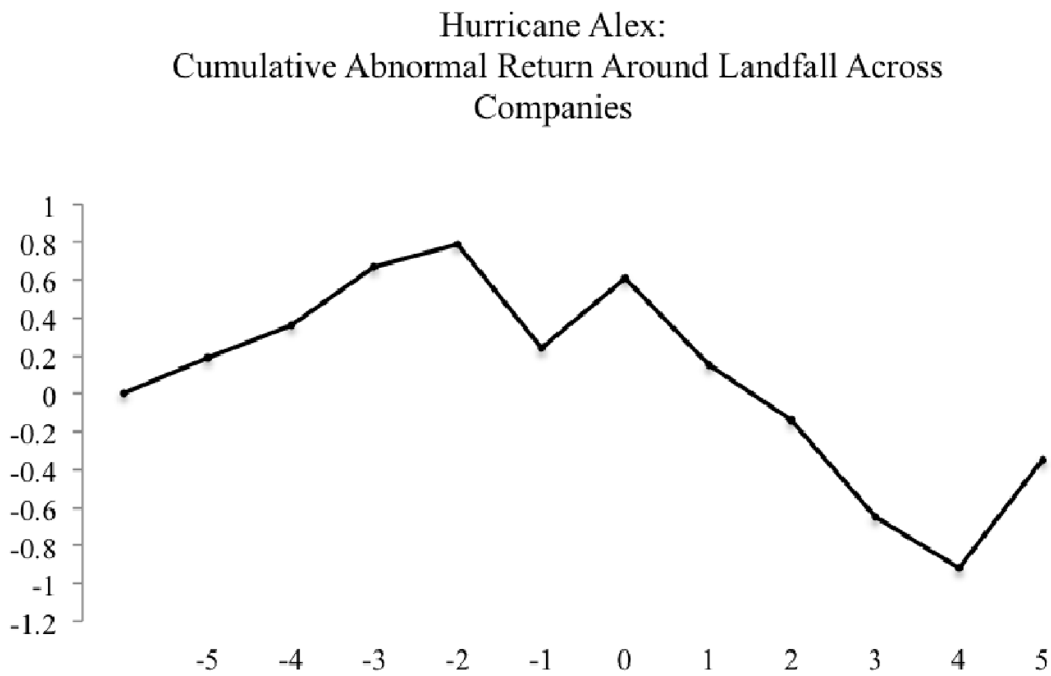
Table A.12:

Event Study Results* for Hurricane Wilma

Company	Cumulative Abnormal Return	Company	Cumulative Abnormal Return
AFG	1.52%	MKL	-0.91%
AIG	-0.03%	NAVG	2.89%
BRK.A	-0.07%	ORI	-0.17%
CB	6.08%	RLI	1.10%
CINF	0.00%	STFC	1.84%
CNA	-0.79%	THG	-4.88%
HGIC	-1.80%	TRV	2.14%
HIG	0.88%	WRB	10.67%

*Using 2003 hurricane season as estimation window (June 1st - November 30th) and an event window of landfall date + 2 trading days

Figure A.1:



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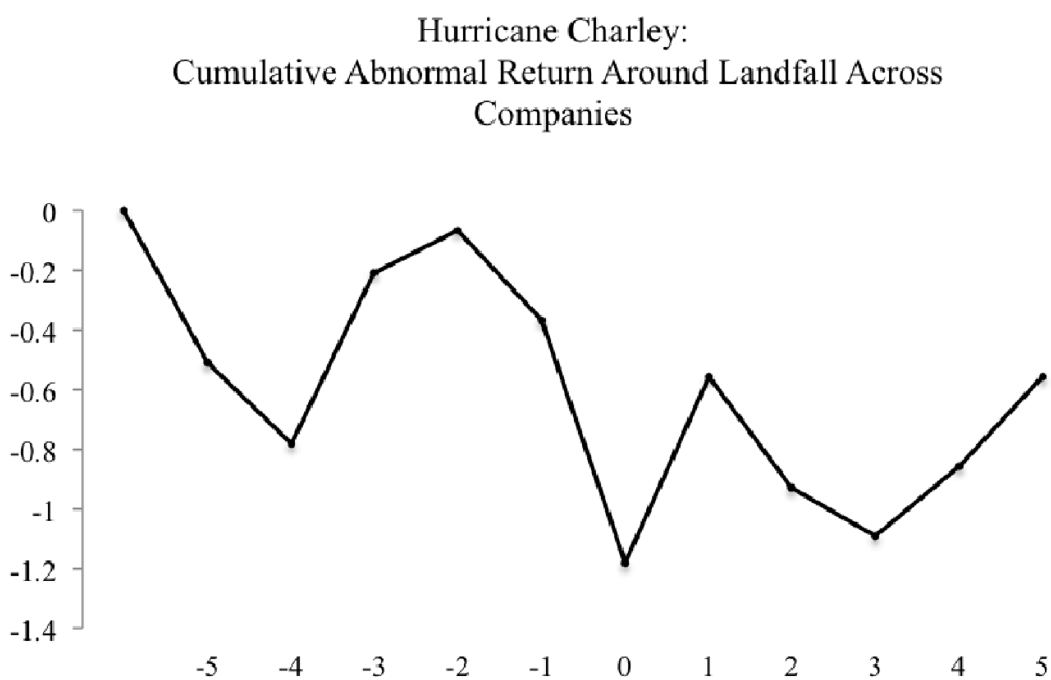

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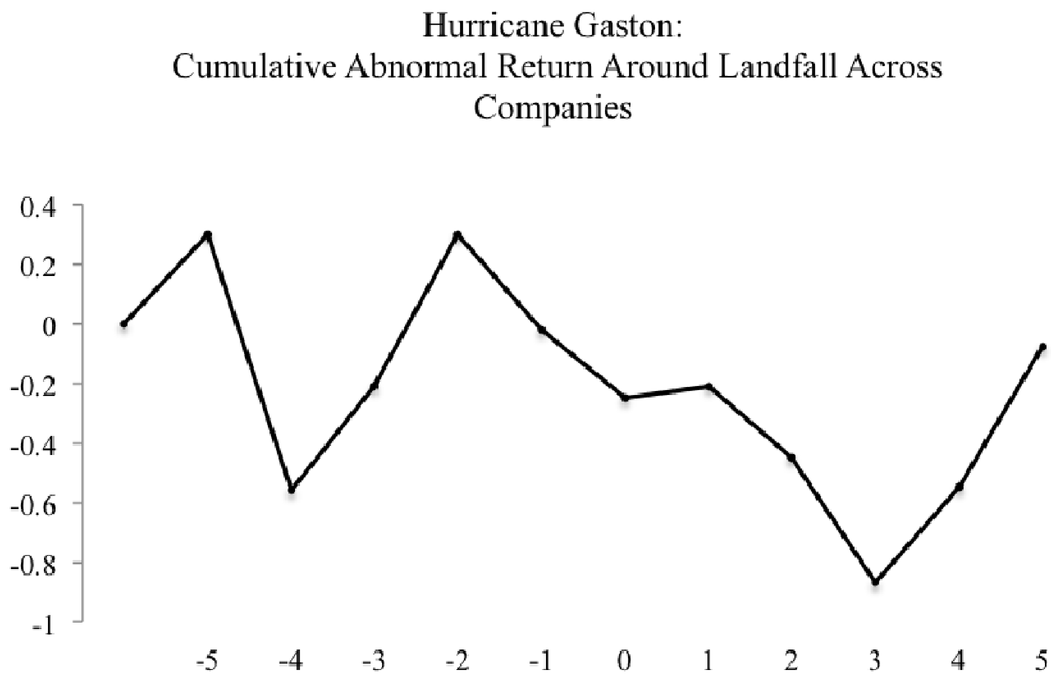

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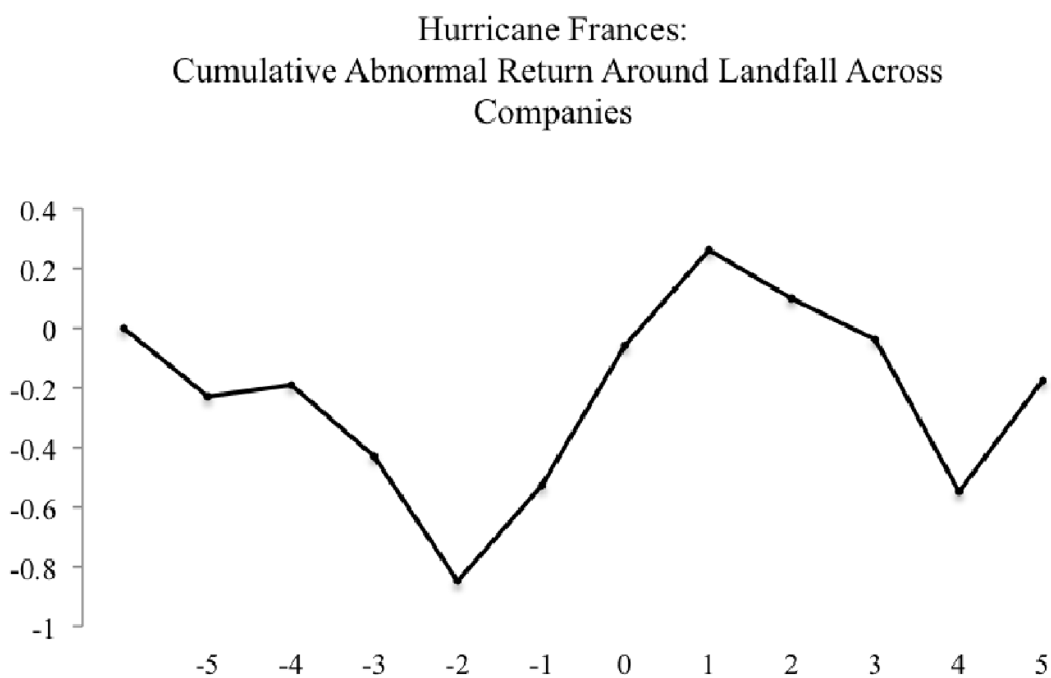

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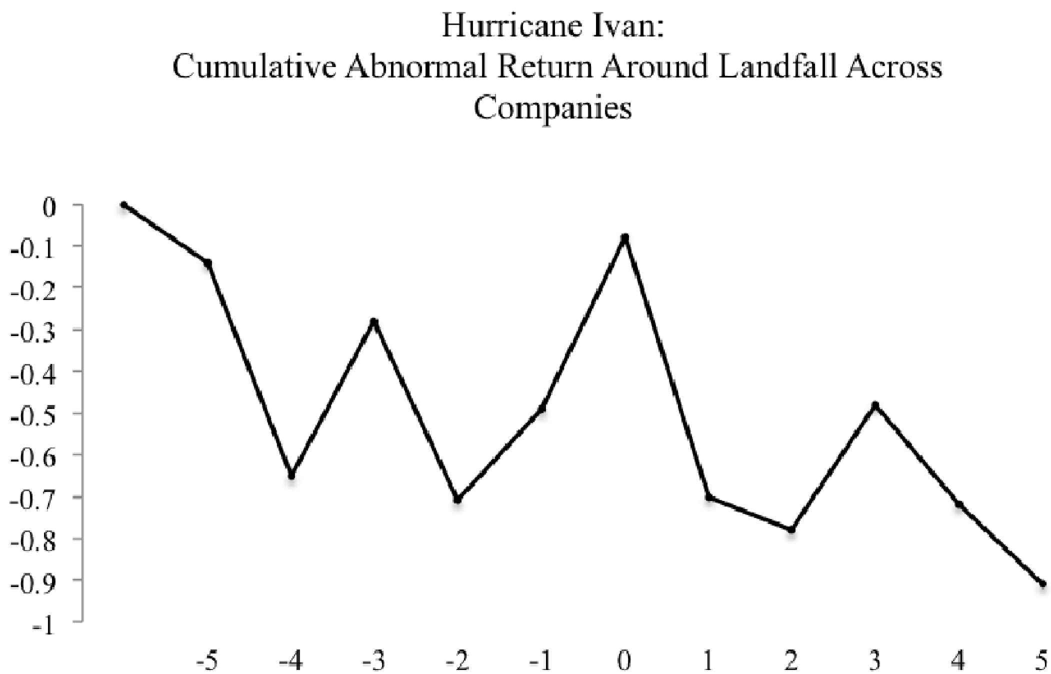

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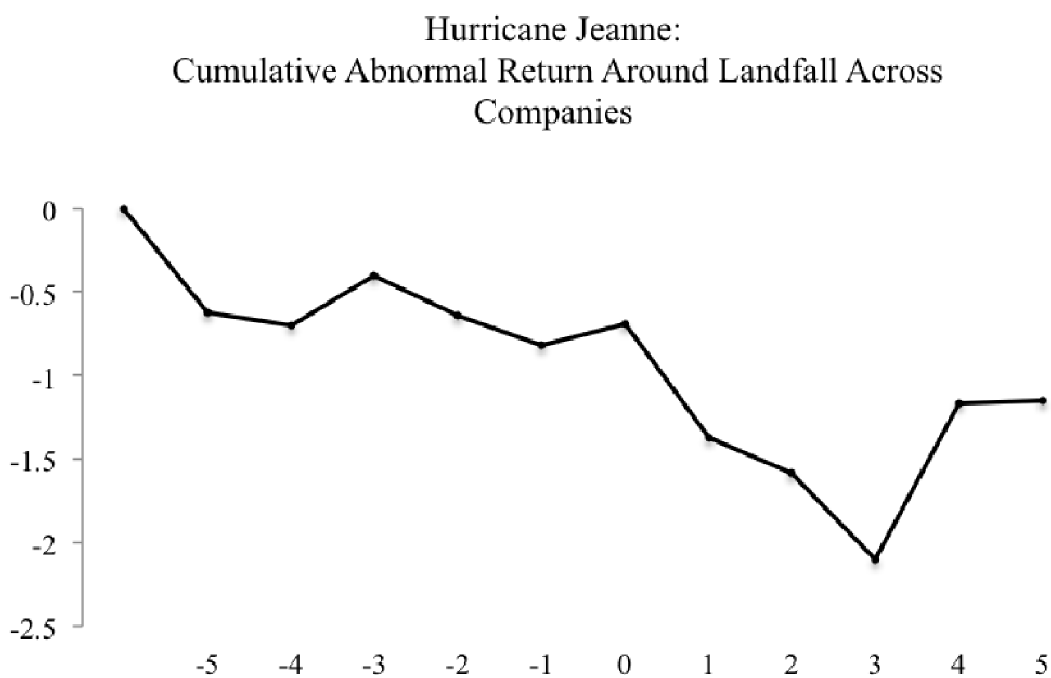

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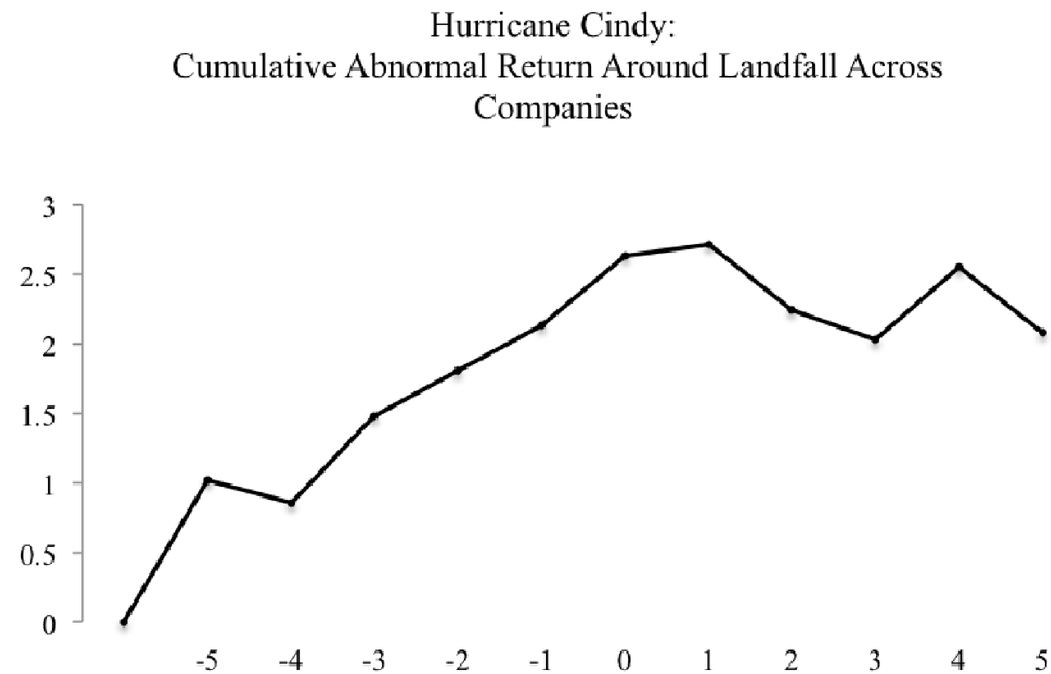

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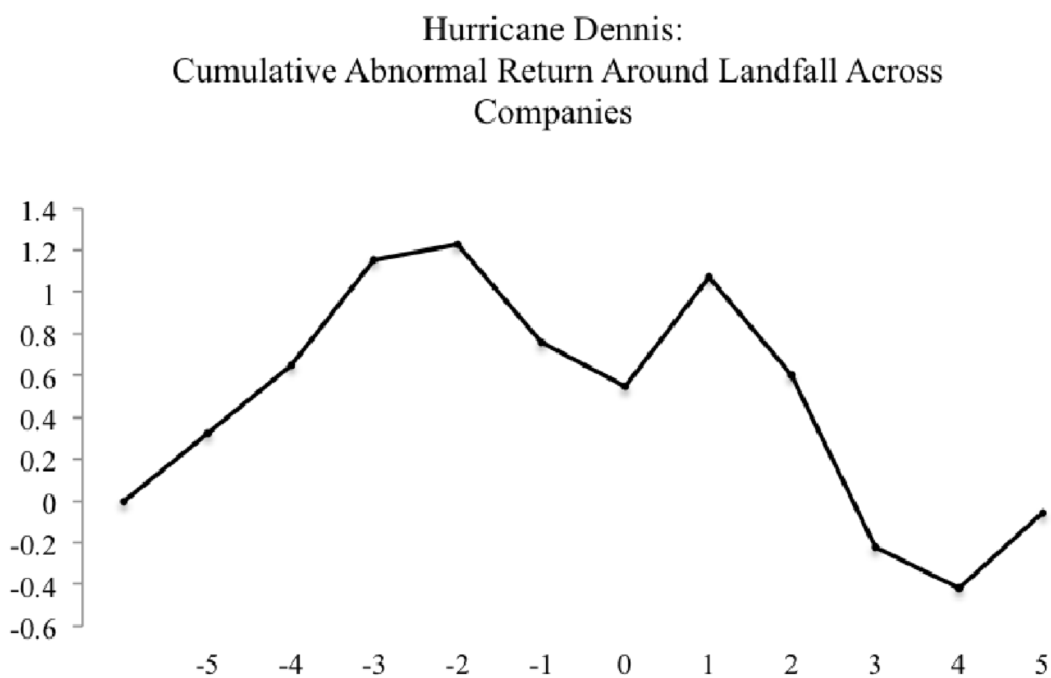

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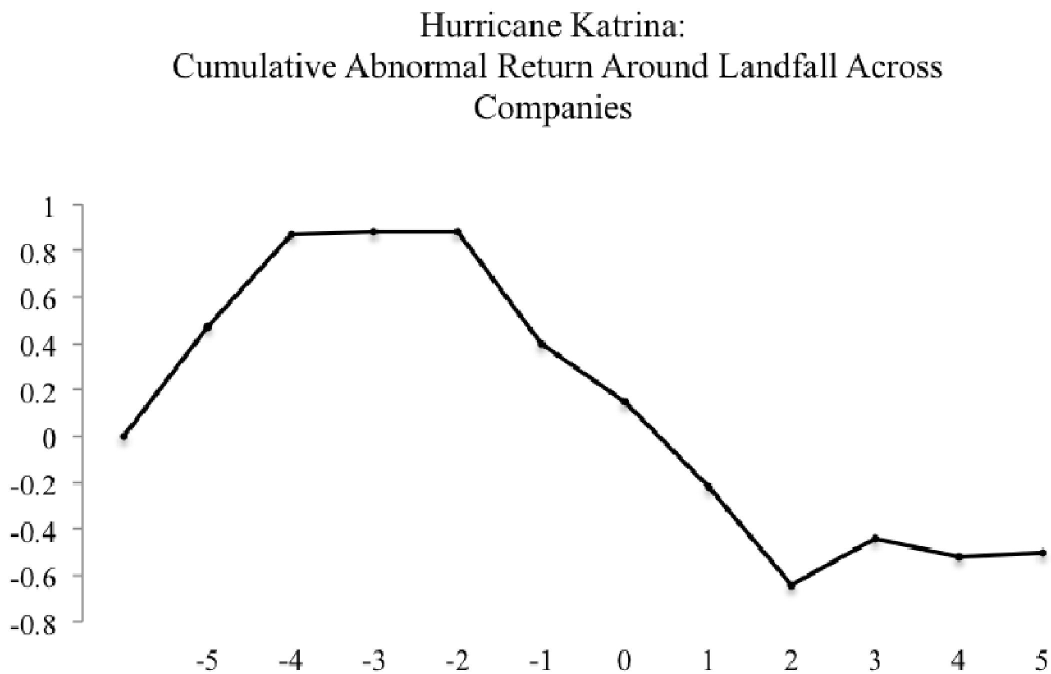

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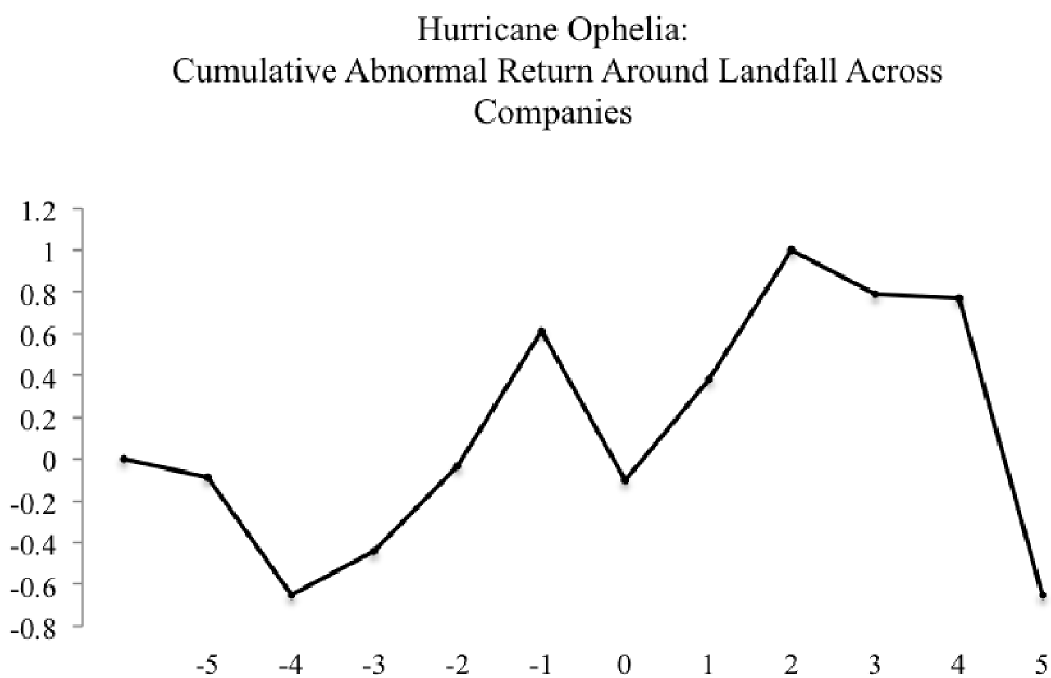

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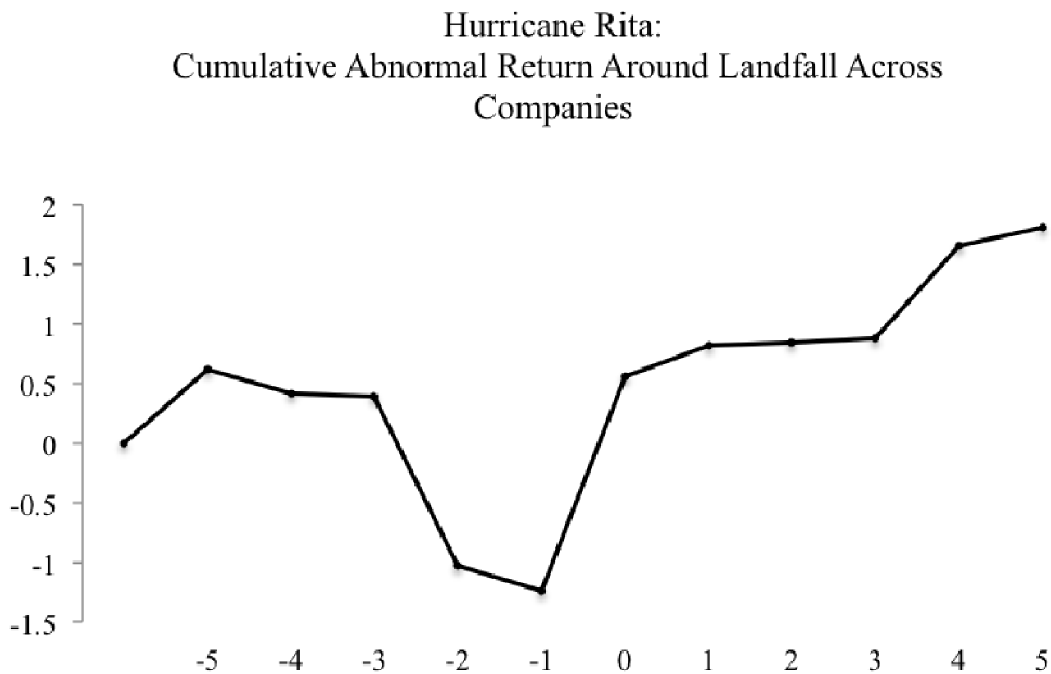

Figure A.12: