The Impact of Natural Catastrophes on Property/Liability Insurers: A Geographical Proximity Analysis

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ABSTRACT

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We investigate the impact of hurricanes, as an anticipated natural disaster, on the premium incomes and stock prices of property and casualty insurers in the United States. Our sample consists of forty-seven publicly traded insurance firms in the U.S. and the three most serious hurricanes during the period from 2006 to 2014. The three hurricanes are broken down into 150 state-level hazards, including twenty-seven states that were directly affected by the disasters, twenty-seven states that were close-by, and ninety-six states that were unaffected. Our results show that insurers in all areas have a significant premium increase after hurricanes. Premium changes are significantly different between any two types of areas in an event year. In addition, we observe that the expected benefits from potential premium increases after a catastrophe appear to dominate the costs insurance companies incur as a result of policyholders' reimbursement claims. However, while there are no obvious distinguishing results among areas, there is some discrimination. These results vary based on a state's geographical proximity to a disaster. Insurers in close-by states enjoy some advantages from hurricanes. In contrast, insurers in affected states suffer negative consequences. Finally, we observe that the severity of hurricanes causes significant differences in abnormal performance. Big companies suffer negative impacts due to hurricanes. Higher returns on assets are associated with higher abnormal returns.

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TABLE OF CONTENTS

1. Introduction 1

2. Literature Review 3

3. Hypothesis Development 10

4. Data and Methodology 13

5. Empirical Results 20

5.1 Univariate Analysis 20

5.1.1 Effect of hurricanes on premium income 20

5.1.2 Effect of hurricanes on shareholder wealth 22

5.2 Multivariate Analysis 24

5.2.1 Basic regression results 24

5.2.2 Additional analysis 26

6. Robustness Tests 28

7. Conclusions and Discussion 29

References 32

Appendices 36

Figure 1 Effect of Hurricanes on Premium Changes 36

Figure 2 Cumulative Abnormal Returns of Insurers 36

Table 1 The Top 3 Hurricanes between 2006 and 2014 37

Table 2 Sample Firms 38

Table 3 Variable Definition 39

Table 4 T-tests to examine whether premium changes are different from zero 40

Table 5 Difference Tests of Premium Changes by Region 41

Table 6 Abnormal Stock Price Performance 42

Table 7 Pearson Correlation Coefficients 43

Table 8 Basic Regressions of Insurers' Cumulative Abnormal Returns 44

Table 9 Regressions of Insurers' Cumulative Abnormal Returns with Year and Insurer Fixed Effects 47

Table 10 Regressions of Insurers' Cumulative Abnormal Returns Clustered by Year and Firm 54

Table 11 Robust Regressions of Insurers' Cumulative Abnormal Returns 55

Table 12 Regressions of Insurers' Cumulative Abnormal Returns with Interaction Terms 58

1. Introduction

There has been a significant rise in the frequency and severity of natural disasters. According to summary statistics provided by the National Oceanic and Atmospheric Administration (NOAA), tropical cyclones accounted for the majority of losses among billion-dollar disaster events between 1980 and 2014. Compared to other types of natural disasters, land falling tropical cyclones caused the most damage and had the highest average event cost. It is worth noting that during this period, sixty-five severe storms occurred, which represent the highest number of natural disasters that affected the U.S. During the same time period, tropical cyclones were the second most frequent type of disaster. Most recently, in 2014, there were eight weather and climate-related disaster events across the United States with losses exceeding $1 billion each.

Facing such losses from natural catastrophes, insurance can protect citizens and governments via its risk sharing mechanism, especially when considering the increase in the frequency and intensity of natural catastrophes over recent years. As Kunreuther (1996) has advocated, insurance could be a potentially valuable tool to encourage loss reduction against natural disasters and to supply recovery funds to disaster victims.

In addition to private insurance, governments should act as an insurance provider, especially if a given event is severe. Recent empirical work has stressed the need for government-assisted insurance to supplement private insurance arrangements (see Kunreuther, 1996; Litan, 2006; Botzen and Van Den Bergh, 2008; Michel-Kerjan, Lemoyne de Forges, and Kunreuther, 2012). For example, Greenberg, Lahr, and Mantell (2007) suggest a collaborative strategic planning analysis for federal and state governments.

Thus, it is necessary to ensure the ability of private insurance to deal with increasing losses from catastrophes. Our study adds to the extant literature that investigates how insurers can manage the risks and costs associated with catastrophic losses.

Managing risk is important for many parties: for citizens and enterprises that experience natural disasters; for private insurers who insure them; and for public policy makers who devise appropriate policies. Properly understanding catastrophic risks will help individuals and companies better protect their homes and businesses. In addition, a good understanding of natural disaster risks is useful for insurance firms that manage the risk. Furthermore, it is helpful for governments that complete the risk-control system as a whole. For instance, governments might choose to reimburse citizens, in part, for catastrophic losses when citizens are insufficiently insured. On the other hand, catastrophe insurance provided by the private sector can form a meaningful part of broader national strategies that deal with the increasing threats and costs of catastrophes (see Hagendorff, Hagendorff, and Keasey, 2015).

Our study aims to investigate the impact of hurricanes, as an anticipated natural disaster, on the premium incomes and stock prices of property and casualty insurers in the U.S. Our analyses address several research questions: Do hurricanes positively or negatively influence future premium income? How do the stock prices of property and casualty insurers react to catastrophic events? How do hurricanes affect insurance companies, based on their direct and indirect exposure to the event? How long do the effects last? Is there an industry-wide contagion effect because of catastrophic events?

Our sample consists of forty-seven publicly traded insurance firms in the U.S. and the three most serious hurricanes during the period from 2006 to 2014. The three hurricanes are broken down into 150 state-level hazards, including twenty-seven states that were directly affected by the disasters, twenty-seven states that were close-by, and ninety-six states that were unaffected. For each firm, we match the premium written in a given state with our classification of hurricane areas. We use direct premiums written to measure whether insurers have property and casualty insurance business in a given state. Then, we calculate the insurer's proportional exposure to a given hurricane. Loss figures for each hurricane are from the National Center for Environmental

Information of the National Oceanic and Atmospheric Administration. Premiums written and losses incurred in the homeowner line of business are from Bloomberg. All accounting data are from Compustat.

We investigate whether hurricanes positively or negatively influence insurers. In addition, we examine whether the insurers' premium income and/or stock price returns are affected by the existence of exposure and the degree of exposure to a given disaster. In other words, we test whether direct vs. indirect exposure to a disaster affects the stock performance among insurers differently. Lastly, we examine the relationship between a series of insurer/hurricane characteristics and insurers' cumulative abnormal returns.

Our study addresses a gap in the literature: there is no paper as detailed as ours that investigates insurance companies' exposure to hurricanes and how it affects their premium income and stock price returns. Natural disasters have been examined before. However, most prior studies focus on insurers' stock prices, not their premium changes. In addition, most prior studies do not consider the characteristics of insurers and hurricanes, and their conclusions are not consistent. Our paper meaningfully contributes to the current literature on this topic.

The remainder of this paper is organized as follows. The next section reviews the literature on the effects of catastrophes on insurance companies and other related industries. The third section presents the data and variables and discusses the methodology. The fourth section provides the results of our univariate and multivariate analyses. The fifth section tests the robustness of our results. The last section presents our conclusions.

2. Literature Review

Shelor, Anderson, and Cross (1992) were the first to examine two opposing hypotheses regarding the effects of natural hazards on insurance firm value. They argue that "rapid depletion of surplus accounts following a catastrophe may cause investors to discount property-liability insurer stock values" and that "insurers benefit from an isolated catastrophic event because of subsequent increased consumer or institutional demand" (see Shelor, Anderson, and Cross, 1992). Their results support the second hypothesis. After an earthquake, property-liability insurers' stock values tend to increase.

The negative impact is easy to understand; insurers are responsible for paying a large amount of money to policyholders due to natural disasters. As a result, insurance companies' stocks are likely to do poorly after a hurricane. However, the empirical literature also provides other findings. According to Cagle and Harrington (1995), the supply of insurance is an increasing function of the insurer's capital. Higher costs of capital and solvency requirements limit the ability of insurers to provide insurance, including policy renewals and insurance for new coverage (see Winter, 1991, 1994; Gron, 1994; Cummins and Danzon, 1997; Cummins and Lewis, 2003; Chen, Doerpinhaus, Lin, and Yu, 2008). After natural disasters, the capital of insurance firms could decrease, thus the supply of insurance may decrease. Consequently, the relation between supply and demand could increase premiums. From another point of view, due to natural disasters, the demand for insurance from previously uninsured customers could increase, which would increase premiums. Furthermore, these two effects are likely to be influenced by regulations. For example, regulators may allow insurance firms to raise premiums but control the magnitude of the increase. Thus, the net effect should depend on the strengths of the two opposite effects.

Similarly, Chen, Doerpinghaus, Lin, and Yu (2008) propose two effects: a claim effect and a growth effect. The claim effect is defined as the impact of unexpected losses on insurers' short-run profitability. The authors argue that the growth effect, on the other hand, is a growth opportunity. If price increases dominate quantity reductions of issued coverage, insurers' profitability increases. The claim effect could be a short-term phenomenon, resulting from insufficient premiums before catastrophic losses, while the growth effect could be a long-term effect, because of insurance supply reductions and risk updating. Their results suggest evidence of a claim effect after catastrophic losses. The growth effect, however, is less obvious.

Unlike Shelor, Anderson, and Cross (1992), Angbazo and Narayanan (1996) find that Hurricane Andrew had a large negative effect on insurance stocks, which was ameliorated to some extent by a small positive effect. Furthermore, the hurricane affected the industry as a whole, whether or not the respective firms had any claim exposure in the hurricane-affected states. Approximately two weeks after Andrew, on September 9, 1992, the Florida insurance commission issued a warning that regulators would not permit any unjustified rate increases in the wake of Hurricane Andrew. Given this warning, the authors find that this regulatory event also had industry-wide contagion effects.

However, Lamb's (1995) results show that the market efficiently interprets the information generated by hurricanes and distinguishes property-liability insurers based on the existence and magnitude of insurance policies written. Indeed, Andrew had a significant negative effect on the stock prices of property-liability insurers with direct premiums written in Florida or Louisiana, while unexposed firms sustained no significant price response.

The type of natural disaster itself may be at the root of the differing results reported in the prior empirical literature. Earthquakes, for example, cannot be anticipated in the same way as hurricanes. Therefore, anticipation itself may cause different results regarding hurricanes. The extent of loss is a further consideration. Under the Saffir-Simpson Hurricane Scale, Andrew was the second most costly hurricane in the U.S., based on the estimated insured losses and damages for a category five hurricane.

Three years later, Lamb's (1998) findings show that results vary, even when focusing on only one type of catastrophe. Hurricane Hugo and Hurricane Andrew produced dramatically different market reactions for property and causality insurance companies. Insurers were unaffected by Hurricane Hugo, despite the existence of exposure and their degree of exposure in North and South Carolina. Hurricane Andrew, however, only had a significant negative impact for insurers with premium business in Florida or Louisiana. The market also discriminates based on the magnitude of a hurricane. Furthermore, in the case of Andrew, the market discriminated among insurers according to their degree of exposure. It is worth noting that the significant negative response produced by Hurricane Andrew was concentrated during the two days after the hurricane hit, demonstrating that the information produced by Andrew was quickly digested by the market.

Hagendorff, Hagendorff, and Keasey (2015) examine whether mega-catastrophes significantly affect the performance of insurers and whether different types of mega-catastrophes have different impacts. Their sample consists of fifty-seven publicly traded property and liability (P&L) insurers in the U.S. and nineteen mega-catastrophes that are broken down into 191 state-level catastrophes during the period from 1996 to 2010. By studying the share price responses of insurance firms to catastrophic events, they conclude that the impact of mega-catastrophes on insurers has not been too damaging. To be specific, the exact impact of a catastrophe depends on the nature of the event and the degree of competition within the insurance market, because less competition allows insurers to reimburse catastrophe losses through adjustments to premiums. Overall, they conclude that insurance firms in the U.S. can manage the risks and costs of mega-catastrophes.

Cummins, Doherty, and Lo (2002) suggest that the property-liability industry could sustain a mega-catastrophe with damages of up to $100 billion. Similarly, Chen, Doerpinghaus, Lin, and Yu (2008) find that insurers can thrive by providing risk transfers for catastrophic losses.

However, the results from Born and Viscusi (2006) are not as optimistic. They argue that insurance companies suffered serious losses as a result of some catastrophes and did not manage their risk well. They thus conclude that catastrophic risks can lead to considerable problems for the insurance industry. Both the incurred losses and the loss ratios rise in response to catastrophic events. Catastrophes reduce total premiums earned in the affected states. In addition, catastrophes lead to a reduction in the net number of firms writing insurance coverage in the states as well as to an increase in the probability of exit from the state.

In our research, we examine the influence of natural disasters on insurers; thus, we compare firms' pre-event and post-event performance. However, despite the interesting insights our results offer, our study can not address the question whether individuals and companies have taken sufficient protective measures before a natural disaster. Serious consequences from catastrophes do not only arise from the damage itself. Natural disasters have serious consequences besides those covered by insurance; there continue to be physical problems and damage after natural disasters in hazard-prone areas. Our discussion below briefly reviews the related literature in this area.

Sadowski and Sutter (2005) take the perspective of residents and illustrate that there is an offsetting behavior in hazardous areas (see also Peltzman, 1975). Technology and regulations reduce the full cost of risky behaviors, thus people will engage in more risky behaviors. Improvements in technology can help reduce fatalities over time. If hurricanes are less likely to produce fatalities and injuries, living in an exposed area becomes more attractive (see Sadowski and Sutter, 2005). Consequently, hurricanes will kill fewer people but will produce more property damage. They offer evidence via an analysis of land-falling hurricanes in the United States between 1940 and 1999. Their results suggest that reductions in hurricane mortality have a significantly and quantitatively large effect on damage in portions of the coast most prone to hurricanes.

Analogously, Kunreuther (1996) and Kunreuther (2006) provide extensive evidence that indicates that residents in hazardous areas do not undertake loss prevention measures voluntarily. They propose several reasons for this such as underestimating the probability of the disaster occurring, budget constraints, myopic behavior by individuals, short time horizons for benefits, and interdependencies with neighbors' decisions. The author suggests providing incentives – such as premium reductions, lower deductibles, and higher limits of coverage – to individuals in hazardous areas to encourage them to voluntarily adopt cost effective measures.

In addition, Fronstin and Holtmann (1994) hypothesize that consumers may not pay attention to whether a home is structurally sound – built to undergo hurricanes – because of the rising cost of construction.

From the perspective of regulations, Fronstin and Holtmann (1994) illustrate that building codes appear to have eroded over time. Their results indicate that newer houses (those built after the 1960s) sustained a greater amount of damage from Hurricane Andrew than houses built earlier, ceteris paribus. Burby (2006) advises that appropriate land-use regulations and well-enforced building codes should be developed in hazard-prone areas.

Similarly, Kunreuther (1996, 2006) point out that building codes are not always enforced in hazard-prone areas. Insurance experts have indicated that twenty-five percent of the insured losses from Hurricane Andrew could have been prevented through better building code compliance and enforcement (see Insurance Research Council and Insurance Institute of Property Loss Reduction, 1995). A comprehensive insurance system ought to comprise separate programs that include insurance coverage, other policy tools, and non-insurance industry parties such as banks and financial institutions, builders and contractors, and government agencies.

Regarding the role of government in catastrophes, Grace, Klein, and Liu (2005) discuss whether a national plan is better than a private system for the insurance market. They mention that the supply and price of reinsurance and related financial instruments will be important factors because they can influence the supply and price of homeowners' insurance. Some insurers prefer to seek assistance from the federal government in providing "less expensive" catastrophe reinsurance.

Regulators and legislators are motivated to explore other measures to expand the supply of insurance and reduce its cost. People hold different views about the feasibility of a national plan, or of state, regional, and national catastrophe reinsurance systems. Advocates think that the federal government has the ability to provide a more stable, reliable, and less expensive source of catastrophe reinsurance over time and geographically. However, opponents believe that private reinsurance and financial markets can provide adequate and efficient financing of catastrophe risks if they are allowed to do so. The authors express concern that a government program could be unfair. Because it would benefit from taxpayer-funded subsidies, it could crowd out private reinsurance and keep financial markets from covering catastrophe risks.

Natural disasters affect many industries, not only the insurance industry. There is previous literature that examines the impact of natural vulnerabilities in other industries as well; many, such as the real estate industry, are affected by catastrophes. Furthermore, some prior literature has compared the different consequences of natural disasters among industries.

Shelor, Anderson, and Cross (1990) investigate the effects of the California earthquake of October 17, 1989 on the stock value of firms in the real estate industry. They find that the California earthquake produced relevant new information that was transmitted to the market and which was reflected in significant negative stock returns among real estate firms operating around San Francisco. However, in other areas of California, real estate-related firms were generally unaffected by the earthquake. This suggests that the market discriminates among firms based on their geographic risk exposure.

In comparison with the real estate industry, Shelor, Anderson, and Cross (1992) also examine the market response of property-liability insurers operating in the California earthquake zone. In contrast, the property-liability industry illustrates a significant positive response to the California earthquake. Similarly, Aiuppa, Carney, and Krueger (1993) find a positive response when examining the impact of the Loma Prieta earthquake on property-liability firms' stock values.

Furthermore, certain researchers devote themselves to finding a better catastrophe risk model or conduct research on post-catastrophe consequences in order to improve risk management mechanisms.

Cossette, Duchesne, and Marceau (2003) propose a general individual catastrophe risk model that allows damage ratios to be random functions of the catastrophe intensity. Yang, Wang, and Chen (2008) examine the correlation between catastrophe risk securities and portfolios of other equities by analyzing catastrophe effects in the Japanese stock market. They find that there is no significant catastrophe effect regarding the Japanese stock market as a whole. The results indicate a significant negative correlation between catastrophe losses and the insurance industry's equity returns or abnormal returns. A significant positive correlation exists in the construction industry, but there is no significant correlation in the real estate industry. In addition, Cole, Macpherson, and McCullough (2010) analyze the impact of housing, insurance, and mitigation characteristics on average annual losses using four hurricane loss models.

3. Hypothesis Development

The extant literature offers two opposing hypotheses that have not been resolved; although much of the previous literature has investigated them, the results are inconsistent. Some studies, such as Angbazo and Narayanan (1996), conclude that hurricanes have a large negative effect on insurance stocks. They investigate Hurricane Andrew, the second costliest hurricane in the United States. In contrast, Shelor, Anderson, and Cross (1992) find that insurers benefit from isolated catastrophic events. Most recently, Hagendorff, Hagendorff, and Keasey (2015) conclude that the impact of mega-catastrophes on insurers has not been too damaging.

Do natural disasters bring benefits or heavy losses to insurance companies? When a catastrophe occurs, how do investors expect the insurers' stock to act in the future? Some hold that disasters have definite negative influences because of the large claims and reduced confidence that may follow catastrophes. On the other hand, insurance policies for homeowners could attract more interest after natural catastrophes. The demand for insurance policies could increase, especially in areas where natural disasters are more frequent. In addition, subject to regulatory controls, insurance companies may increase premiums for specific insurance contracts, which could help increase firm values as well. Thus, our first hypothesis is that natural disasters will have a negative effect on insurers.

Second, we investigate whether the existence and degree of exposure affects insurers. Exposed insurers are defined as companies providing a large proportion of homeowner insurance in the affected areas. Unexposed insurers, on the other hand, represent insurance firms that draw their insurance premiums from other states. Does the market demonstrate an ability to discriminate based on the existence of exposure or the degree of exposure of property-liability insurers under severe catastrophes? If the market has the ability to discriminate, then it may be reasonable to expect that insurance companies with more business in hazardous areas will be more severely influenced than insurers that conduct their business in other states. Insurance companies supply different services according to their geographic area and business line. In addition, different types of natural disasters occur in relatively fixed areas. Some insurers supply property-liability contracts concentrated in Florida and Louisiana, for example, as the probability of hurricanes in these two states is higher than in the central United States.

Conversely, if the magnitude of exposure is not significant, there may no difference among the different types of areas. Facing a catastrophe, all insurance companies – no matter whose business is in the seriously affected states – could be influenced at the same time. Investors view them as a whole industry. For example, Angbazo and Narayanan (1996) find that Hurricane Andrew and subsequent regulations significantly affected most insurers, regardless of whether these firms had any claims exposure in the hurricane-affected states. This means that there were industry-wide contagion effects.

Although some insurance companies supply insurance policies in the affected areas, not all of them provide property-liability insurance, which may also alter results. Similarly, the proportion of homeowner's incomes to total insurance incomes may influence the results.

Therefore, our second hypothesis is that hurricane effects may be influenced by the existence of exposure and the magnitude of exposure. In other words, insurers in affected areas and with a large property-liability exposure could suffer more from hurricanes than other insurers. Unlike bank industry failures (Aharony and Swary, 1983; Swary, 1986) and airline crashes (Barrett, Heuson, Kolb, and Schropp, 1987; Davidson, Chandy, and Cross, 1987), there is no contagion effect in the insurance industry.

Third, we want to investigate the possible factors that influence the abnormal performance of insurers' stocks. These factors include the insurers' characteristics and the catastrophe characteristics. Regarding the characteristics of catastrophes, and in addition the exposure magnitude, we examine the relation between hurricane damages and the insurers' performance in the stock market. Included in the firms' characteristics are variables such as firm size, Tobin's Q, ROA, the loss ratio related to the homeowner's line of business, the degree of diversity of the insurance lines, and the financial rating of the insurer.

We expect that large firms, firms with higher ROA and Tobin's Q, and firms with higher ratings may manage their risk better and may benefit from in the stock market because they have more resources, higher profitability, better investor expectations, and a better financial structure.

Conversely, the loss ratio may negatively influence the stock return of insurers because they bear larger amounts of payments to policyholders.

In light of the diversification of insurance lines, the relationship between abnormal performance and diversification is not easy to estimate. More insurance lines may help insurers diversify their risk when facing hurricanes because we generally believe that the line of insurance most influenced by natural disasters is homeowner coverage and property-liability insurance. On the other hand, investors may regard the insurance company as a whole no matter how much business is in the homeowner line, or how many lines of business it has. In addition, there might be interaction among the different kinds of insurance coverage held by one policyholder such as an owner of a small furniture factory. After a serious hurricane, both his home and the factory could be damaged. His employees could be injured while working in the factory. Several insurance policies could be involved simultaneously in this event. However, there may be a combination effect from these two possibilities because there is a joint impact produced by the positive and negative effects. Hagendorff, Hagendorff, and Keasey (2015) examine the relationship between the diversification of lines and cumulative abnormal returns (CARs). However, they find no clear result. We will examine this factor by calculating a 1-Herfindahl index.

4. Data and Methodology

First, we select the target hurricanes as the events. According to the National Centers for Environmental Information of the National Oceanic and Atmospheric Administration, all of the billion-dollar hurricanes affecting the U.S. occurred during the period from 2006 to 2014. We choose three top hurricanes whose adjusted cost is higher than $10 billion including Sandy (2012), Irene (2011), and Ike (2008). They have caused estimated costs of 67, 14 and 33 billion USD, respectively. Detailed information on these three hurricanes is found in Table 1.Table 1also shows the state classifications. The three hurricanes are broken down into 150 state-level hazards, including twenty-seven states that were directly affected by the disasters, twenty-seven states that were close-by, and ninety-six states that were unaffected.

We then define the insurers used in this research. We obtain the names of the top one hundred insurance companies in the United States from Bloomberg. It provides premiums detailed for each state in the U.S. and in each insurance line. We use direct premiums written, defined as the aggregate amount of recorded originated premiums, other than reinsurance, written during the year, whether collected or not, at the close of the year, plus retrospective audit premium collections, after deducting all return premiums (defined by A.M. Bests). We use the premium to identify the geographic areas of the insurers' businesses and to observe the changes in premiums due to the events. Bloomberg also supplies the losses incurred in the homeowner line of business.

We check all firms through Bloomberg, Google Financial, and on each company's website to verify whether the companies are private or not. Sample firms are required to have accounting and share price information on CRSP and Compustat, respectively. Some of the insurance companies are listed in Europe and Australia. After eliminating the firms with missing data and those listed outside of the U.S., 49 insurers were left. We also double checked the SIC codes for the remainder of the companies. Based on the SIC codes from Compustat, two companies were eliminated. They are Berkshire Hathaway with SIC code 9997, and Wells Fargo & Co with SIC code 6020. These two companies do have insurance businesses; however, considering that their businesses are very comprehensive, it would not be possible to assess the repercussions of these events on their property-liability insurance lines. Therefore, we eliminated them from the sample. Finally, 47 publicly traded insurance firms in the U.S. make up the sample. The full list of companies can be found in the APPENDIX, Table 2.

We will run the cross sectional analysis based on daily return of the event study using market model, which is widely used in the studies by Shelor, Anderson, and Cross (1992), and Angbazo and Narayanan (1996), etc.

The market model is used to indicate the reaction of a stock price to catastrophic events. Assume that stock returns follow a single factor market model,

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt},$$

where R_{jt} is the rate of return of the common stock of firm j on day t. R_{mt} is the rate of return on the CRSP equally-weighted index return on day t. Many previous studies on the implications of catastrophic events for insurers have employed the CRSP equally-weighted index. ε_{jt} is a random variable which has an expected value of zero and is assumed to be uncorrelated with R_{mt}, not autocorrelated and homoscedastic.

β_j is a parameter that measures the change in R_{jt} given a change in R_{mt}, and indicates sensitivity of R_{jt} to the market index. α_j represents the market independent rate of return on firm j. The coefficients $\widehat{\alpha_j}$ and $\widehat{\beta_j}$are estimated based on ordinary least squares.

Abnormal return for the common stock of firm j on day t is defined as:

$$AR_{jt} = R_{jt} - \left(\widehat{\alpha_j} + \widehat{\beta_j} R_{mt}\right).$$

We merge the abnormal return over the event windows to obtain the cumulative abnormal return:

$$CAR_{t_1 t_2} = \sum_{t_1}^{t_2} AR_{jt},$$

where t_1 is the start day of one of the specific event window and t_2 is the end of the specific event window. We define six event windows, window (-5, -1), window (-1, 1), window (0, 1), window (0, 5), window (0, 10), and window (0, 20). We include the pre-windows and post-windows.

We define the minimum and maximum estimation lengths at 3 days and 255 days, respectively. The estimation period ends 10 days before the event date. Then, we set the whole event period from 7 days before to 30 days after the event.

We regard the landfall day of the hurricane as the event date, as shown in Table 1. If the event occurs on a weekend day, we use the next trading day as the event day instead. In particular, on Monday, October 29, 2012, Hurricane Sandy made landfall near Brigantine, New Jersey, with winds of approximately 80 mph (130km/h). Because of its severity, the stock market closed on Monday and Tuesday. Therefore, we use Wednesday, October 31 as the event date.

By running the event study, we get a preliminary image of the abnormal performance of insurers due to serious hurricanes and investigate the net effect of catastrophes on insurers. The question therefore is: Will the overall outcome favor the positive or the negative hypothesis?

We define the affected areas, close-by areas, and unaffected areas for each firm by matching the homeowner insurance premiums of each company with the states affected by each hurricane. For example, for one insurer (ACE LTD) under one hurricane (Sandy 2012), if there was a positive premium in the homeowner line in one specific state (NY) in 2012, it means that the insurer (ACE LTD) had homeowner business in that state (NY) in 2012. Then, we check which area the specific state (NY) belongs to for that hurricane (Sandy 2012): an affected, close-by, or unaffected area. If Hurricane Sandy struck the state (NY) in 2012, then the state (NY) is defined as one of the affected areas for the insurer (ACE LTD).

After matching all hurricane areas with all insurers, we calculate the magnitude of exposure for each insurer. Premium income information is from Bloomberg. We use direct premiums written, defined as the aggregate amount of recorded originated premiums, other than reinsurance, written during the year, whether collected or not, at the close of the year, plus retrospective audit premium collections, after deducting all return premiums. Exposure_affected_H is the ratio of homeowner premiums earned in the affected state(s) to total homeowner premiums earned. Exposure_affected_T is measured as the ratio of homeowner premiums earned in the affected state(s) to total premiums earned. Similarly, we calculate the exposure for close-by states.

Proportion_Home is the ratio of total homeowner premiums earned to total premiums earned. In other words, Exposure_T is the interaction item (X_1X_2), calculated as the product of Exposure_H (X_1) and Proportion_Home (X_2). Estimated cost caused, representing the total estimated damage (in billions USD) caused by a given hurricane, is from the National Centers for Environmental Information of the National Oceanic and Atmospheric Administration.

All accounting data are from Compustat. We use the log of total assets to measure the size of the insurer. Tobin's Q is measured as the market value of equity plus the book value of liabilities divided by the book value of assets. ROA is the ratio of pretax profits to total assets. To define loss ratio, we apply the log of loss ratio defined as total losses incurred in the homeowner line of business. Linedivers, a measure of line diversification, is calculated as the sum of the squared percentage of insurance premiums earned in each business line to the total premiums earned in all property-liability lines. Finally, we use the rating assigned by Standard & Poor's to measure the financial situation of insurers: a dummy variable that equals 1 if the insurer's financial rating assigned by Standard & Poor's is A or better; otherwise, it is 0. Detailed definitions of all variables are shown in the APPENDIX, Table 3.

In the following analysis section, we first run the univariate analysis to make sure whether the premium changes in homeowner lines are different from zero in the event year, 1 year after the event year, and 2 years after the event year. By doing so, we can investigate whether or not hurricanes bring serious influences to insurers as well as whether those influences are short or long term.

Then, in order to do a preliminary investigation to determine whether there is discrimination among different types of states, we run mean and median tests for premium changes in the event year, 1 year after the event year, and 2 years after the event year. If there are significant differences between the three kinds of areas, it means there is recognition among the various areas after hurricanes. Alternately, if there are no significant differences, it may suggest that a contagion effect exists in the insurance industry when facing hurricanes. Furthermore, if there is a contagion effect, how long will it last? We can also get a basic answer from this test. At least, we would have a look at whether there is a difference in results by year. We may imagine that there is a significant difference in the event year, after which the significance may decrease.

In addition, we go further with ordinary least squares (OLS) regression to examine the relations between several factors and CARs.

Based on Hagendorff, Hagendorff, and Keasey (2015), we estimate the model as the following:

$$CAR[x\,,y] = \alpha + \beta'\boldsymbol{IC} + \boldsymbol{\gamma}'\boldsymbol{HC} + \boldsymbol{\varepsilon},$$

where CAR[x, y] is the market-adjusted mean cumulative abnormal return over different event windows. **IC** is a vector of the insurers' characteristics in the year before the event, including firm size, Tobin's Q, ROA, loss ratio, lines diversification, and financial rating. **HC** is a vector of the hurricanes' characteristics, including exposure variables and hurricane losses. We include insurer characteristics and hurricane characteristics separately first, and then run the whole model with both of them.

To be more specific, we construct three sub-models. First, we look at each hurricane's characteristics:

$$\mathrm{CAR}[x, y] = \alpha + \beta_1 \times \mathrm{Exposure\_affected\_T} + \beta_2 \times \mathrm{Exposure\_closeby\_T} + \beta_3 \times \mathrm{Loss} + \varepsilon.$$

The variable exposure links the insurance policies of insurers to the hurricane's landfall characteristics. We include two variables, Exposure_affected_T and Exposure_closeby_T, to represent the three types of areas during hurricanes (affected, close-by, and unaffected). In this model, we examine how hurricanes' characteristics relate to insurers' stock performance.

Second, we look at the insurers' characteristics:

$$\mathrm{CAR}[x, y] = \alpha + \beta_1 \times \mathrm{FirmSize} + \beta_2 \times \mathrm{TOBQ} + \beta_3 \times \mathrm{ROA} + \beta_4 \times \mathrm{Lossratio} + \beta_5 \times \mathrm{Linedivers} + \beta_6 \times \mathrm{HighRating} + \varepsilon.$$

Last, we include all characteristics in one model:

$$\mathrm{CAR}[x, y] = \alpha + \beta_1 \times \mathrm{Exposure\_affected\_T} + \beta_2 \times \mathrm{Exposure\_closeby\_T} + \beta_3 \times \mathrm{Loss} + \beta_4 \times \mathrm{Firm\ Size} + \beta_5 \times \mathrm{TOBQ} + \beta_6 \times \mathrm{ROA} + \beta_7 \times \mathrm{Lossratio} + \beta_8 \times \mathrm{Linedivers} + \beta_9 \times \mathrm{High\ Rating} + \varepsilon.$$

In the basic regression section, we run three sub-models for the six event windows.

Based on these results, we run additional analyses. For example, we add year and firm fixed effects and consider the problem of residuals and outliers in the additional analysis section.

OLS regression assumes that the residuals are independent. However, our dataset includes data for 47 publicly traded insurance firms in the U.S. and for three years: 2008, 2011 and 2012. It is possible that the firm performance in each year may not be independent, and this could lead to residuals that are not independent over years. On the other hand, all companies in the insurance industry may interact, no matter in which year. Therefore, in our additional analyses, we use the cluster option in SAS to control for the fact that the observations are clustered by year and insurer. We further estimate heteroscedasticity consistent with p-values, in order to get a better understanding of the relationship between hurricanes and insurers' firm performance.

Furthermore, robust regressions are an alternative to least squares regressions when data are contaminated with outliers or influential observations. Therefore, in our additional analyses, we also employ robust regressions to treat outliers. The robust regression method most commonly used today is Huber M estimation, which we also use in this research. Huber's (1973) M estimation is the simplest approach both computationally and theoretically.

As there are interaction variables (X_1X_2) which have been introduced, we will conduct robustness tests to assess whether the results are consistent by including the interaction items (X_1X_2) in the models. The detailed model is shown as the following:

$$\begin{aligned} \text{CAR}\,[x,y] = {} & \alpha + \beta_1 \times \text{Exposure\_affected\_T} + \beta_2 \times \text{Exposure\_affected\_H} + \beta_3 \\ & \times\ \text{Proportion\_Home} \times \text{Exposure\_closeby\_T} + \beta_5 \times \text{Exposure\_closeby\_H} + \beta_6 \\ & \times \text{Loss} + \beta_7 \times \text{Firm Size} + \beta_8 \times \text{TOBQ} + \beta_9 \times \text{ROA} + \beta_{10} \times \text{Lossratio} + \beta_{11} \\ & \times \text{Linedivers} + \beta_{12} \times \text{High Rating} + \varepsilon. \end{aligned}$$

5. Empirical Results

In this section, we will check the results of univariate and multivariate analysis that were introduced in the methodology section.

5.1 Univariate Analysis

In this subsection, we examine the effect of hurricanes on premium income and shareholder wealth, respectively.

5.1.1 Effect of hurricanes on premium income

We calculate the premium changes and combine our three sample events by year: the event year (year 0), and 1 and 2 years pre-event and post-event. The values in pre-event years are calculated as $100/(1 + \text{premium change } (\%)_{t-1,t})$.Similarly, the values for the post-event years (year 1 and year 2) are calculated as $100 \times (1 + \text{premium change } (\%)_{t-1,t})$. After these calculations, we set the premiums in the event year as the base point (100) for the three types of areas in order to get a better comparison.

Figure 1 shows the trend of premium changes from 2 years before to 2 years after hurricanes, with the datum equals to 100 in the event year. Before the event year (year 0), property and casualty premium income does not change much, especially in the years (-2) and (-1). After hurricanes, the premiums written have increased at different levels for the three types of areas. The result supports the hypothesis that insurers could benefit from serious hurricanes. However, there is no obvious discrimination among different types of states.

Among the three types of areas, the premiums in the close-by area have jumped most obviously, from 100 to 109. We can understand that the residents who live in close-by areas have witnessed the serious consequences of the catastrophic events. They prefer more insurance to guarantee their property and casualties, therefore the demand for insurance will increase and insurers would benefit a great deal. However, the premiums in the affected areas are not as high as those in the close-by areas, because both insurers and policyholders need time to recover. That is, they need time to make claims, reconstruct, and buy insurance for new properties. The insurers also need time to manage a considerable number of claims. The net increase of premiums could not be as much as it is in close-by areas.

In year 1, the premiums in affected and unaffected states are very close, with a value of 103. Over time, the premiums indifferent areas converge to the same amount. The value for the unaffected states has grown higher than it is in the affected states. However, that is just a general and simple result that could be disordered. We will statistically analyze this further in the following sections.

First, we test whether the premium changes during and after the event year are different from zero for the three areas, based on their exposure. Table 4 provides all the premium changes that are significantly different from zero. After hurricanes, insurers in all areas have a significant premium increase. In the event year, the differences in the three types of areas are above 8% and significant. The year after the event, the difference in close-by states remains greater than 8% at a highly significant level. In addition, Table 4 shows a downward trend in the magnitude of differences. After a long period of recovery, premium incomes tend to stabilize. The result is consistent with Chen, Doerpinghaus, Lin, and Yu (2008): After hurricanes, there are growth opportunities because price increases could dominate quantity reductions of issued coverage. Insurers' profitability increases, leading to better growth opportunities.

Subsequently, we perform pairwise comparisons of premium changes between areas. As shown in Table 5, Panel A provides a comparison between affected and close-by states, Panel B compares affected and unaffected states, and Panel C provides a comparison between close-by and unaffected states. Premium changes are significantly different between any two areas in the event year but only a few of them are significant in the following year. Therefore, the hurricanes may not bring many influences or distinguish results over a long period. In Panel A, we compare affected and close-by areas and get results similar to Figure 1. Premiums in close-by areas have a larger increase than those in affected areas. For example, in the event year, the mean premium change in close-by states is more than 2% higher than it is in affected states. In addition, premiums in affected areas have the smallest growth. Unexpectedly, premiums in the unaffected states have the largest increase. In the event year, premium changes in the unaffected states are 1% higher than in close-by states.

5.1.2 Effect of hurricanes on shareholder wealth

In this subsection, we examine changes in the market values of insurers in response to catastrophes. Table 6 reposts abnormal stock price performance with our samples in the various event windows. Only in the pre-event window (window (-5, -1)) is there a negative mean cumulative abnormal return. After that, for the post-event windows, all the mean CARs are significantly positive, ranging from 1.45% on day 1 to 5.55% twenty days after the event date. Furthermore, the degree of increase becomes bigger and bigger over time. Based on these results, we can conclude that the expected benefits of potential premium increases after catastrophes could outweigh the substantial loss of reimbursements to policyholders. Moreover, from Table 6, we can see that, in general, more insurers enjoy positive CARs instead of negative CARs. For instance, in window (0, 10), only 50 out of 137 insurers suffer negative abnormal performance, significant at the 1% significance level. In the following sections, we will continue to seek the factors related to the market's reaction to serious natural disasters.

This result is consistent with Shelor, Anderson, and Cross (1992). They conclude that insurers benefit from an isolated catastrophic event because of subsequent increased consumer or institutional demand. As mentioned in our section on the literature review, according to Cagle and Harrington (1995), the supply of insurance is an increasing function of the insurer's capital. Higher costs of capital and solvency requirements limit the ability of insurers to provide insurance, including policy renewals and issuance of new coverage (see Winter, 1991, 1994; Gron, 1994; Cummins and Danzon, 1997; Cummins and Lewis, 2003; Chen, Doerpinhaus, Lin, and Yu, 2008).After natural disasters, the capital of insurance firms could decrease, so the supply of insurance could decrease. Then, premiums could increase because of the relation between supply and demand. Similarly, Hagendorff, Hagendorff, and Keasey (2015) illustrate that the impact of mega-catastrophes on insurers has not been too damaging. However, this is opposite to the findings of Angbazo and Narayanan (1996). They find that Hurricane Andrew had a large negative effect on insurance stocks that was ameliorated to some extent by a smaller positive effect. In addition, Born and Viscusi (2006) illustrate that insurance companies suffer seriously from the catastrophic event rather than manage risk well.

Figure 2 depicts the trend in CARs from one week before to one week after the event. We can see that, between 2 days and 1 day before the event, there is an obvious decrease in CARs. After the event, CARs exhibit a generally positive trend. This could be because of the weather forecast. Before landfall, a hurricane forms in the ocean. It may always change over time. The direction, intensity, power or any other factors may change. As Lamb (1998) explains, the actual path that a hurricane will take remains largely an unpredictable event, despite the existence of sophisticated technology. Although the technology has improved over time (for example, hurricanes are tracked by satellites), the ultimate path and resulting damage are still uncertain. Additionally, in our research, we define the event date as the landfall date. However, landfall could be forecast when a hurricane comes close. Thus, this estimation could be the reason that the turning point of CARs is on day (-1) instead of day 0. Furthermore, Figure 2 shows that the positive effects surpass the negative effects of hurricanes; insurers could gain advantages from catastrophes. Another explanation could be the quick market reaction. This result is similar to Lamb's (1998) investigation of market efficiency around Hurricane Hugo and Hurricane Andrew. He finds that the significant negative response produced by Hurricane Andrew was concentrated during the two days after landfall, illustrating that the information produced by Hurricane Andrew was quickly incorporated by the market.

5.2 Multivariate Analysis

We apply multivariate regression analyses to assess the findings in the univariate analysis and examine the factors affecting market reactions of insurers.

Table 7 in the APPENDIX shows the correlation between independent variables to check the correlation between explanation variables. Only between firm size and high financial rating is there a significant positive relation with coefficient 0.58. For the others, there is no substantial multicollinearity problem among the independent variables.

5.2.1 Basic regression results

In this subsection, we report the results of basic OLS regressions of CARs in different event windows, shown in Table 8, in order to find the relationships between insurers' abnormal performance due to hurricanes and insurers characteristics. First, for the exposure variables, there are not many significant results. This may illustrate that there is no distinguishing impact on insurers in types of areas when facing serious hurricanes. Angbazo and Narayanan (1996), find that Hurricane Andrew had a large negative effect on insurance stocks. More important, it is an industry-wide contagion effect since it significantly affected most insurers, whether or not these firms have any claims exposure in the hurricane-affected states.

However, the severity of the hurricanes massively affects abnormal performance. There is a negative relationship between loss caused by hurricanes and stock price reactions. Similarly, Chen, Doerpinghaus, Lin, and Yu (2008) demonstrate that loss estimates are an important determinant of the short-term position. Catastrophic claims have a negative effect on the short-term, which is the claim effect. We understand that the more severe the hurricanes are the more hesitant investors could remain. A more serious hurricane probably brings more damage to property, which could potentially lead to more reimbursement payments.

Regarding insurance companies, in the pre-event and in the very short period of the post-event window (1 day after the event date), firm size is negatively related to abnormal returns, which is the opposite of our expectation. Big companies do not gain more confidence from investors; they may need to pay large amounts to their policyholders quickly, thereby decreasing their assets, which is not good for financial liquidity, new investment, or growth in the future. In addition, firm size does not represent all the operation circumstances of insurers. They may not obtain a good standard that would allow them to raise capital at low cost. However, this relationship is not very significant in the post-event windows.

ROA is positively connected to abnormal returns, which supports our expectation. ROA indicates the percentage of how profitable a company's assets are in generating revenue. After hurricanes, indeed, insurers would face more claims. The ability to get more profit with a certain level of asset would make investors have more confidence in the insurer in the future. Last, lines diversity is negatively in relation to abnormal returns in the post-event windows. If an insurer has various lines of insurance, it may face more problems when natural disasters occur. There might be interaction between different lines of insurance, especially for the same client, as seen in the previous example of home insurance and business insurance. Alternately, resources as a whole such as assets, capital, or knowledge could be divided into other lines of insurance that are not as influenced by disasters. However, the results are not significant in all event windows.

5.2.2 Additional analysis

In the first subsection of additional analysis, we fix the year and insurer effects. We fix both effects for the year, the firm, and then both combined. We fix both effects for the year, the firm, and then both combined. The results are shown in Table 9. Consistent with our findings regarding regression, ROA has a significantly positive relationship with abnormal returns. It supports that investors could have good expectations for the future, depending on a high ROA. They trust the ability of such insurance companies to be profitable. Continually, big companies have difficulties gaining more confidence from investors. Firm size has a negative relationship to stock market reactions. Furthermore, in terms of hurricane losses, it is negatively related to CARs.

As a whole, the degrees of significance decrease over time. There are no long time influences on abnormal performance due to hurricanes. Especially in the pre-event window (-5, -1), Exposure_closeby_T is significantly and positively related to CARs. This supports the hypothesis that insurers in nearby states could benefit from hurricanes. Individuals and companies have experience based on consequences. They prefer to protect and insure their properties more. The demand for insurance increases, premiums could potentially increase, and expectations may become promising. However, this is not significant during post-event windows and we will continue to examine that in the following analysis. Still, in the pre-event window (-5, -1), high financial rating is positively related to CARs. It illustrates that just a few days before hurricanes, investors could expect that more highly rated insurers are likely to manage risk well and benefit from it. They have better financial situations with which to face a hurricane's attacks. However, the result is no longer clear in the post-event windows.

Considering the possible problem of residuals, Table 10 exhibits the results of a series of CAR regressions in different event windows relative to insurer and hurricane characteristics under cluster year and cluster firm. Heteroscedasticity consistent p-value for the coefficients is reported in parentheses. In pre-event windows, Exposure_affected_T negatively influences CARs. Exposure_closeby_T, however, positively influences CARs. In affected states, investors devalue those insurers in the aftermath of catastrophic events because the insurers need to face potential reimbursement payments to policyholders. Higher loss exposures lead to less favorable stock price performance (see Hagendorff, Hagendorff, and Keasey, 2015). This is also consistent with Angbazo and Narayanan (1996). They illustrate that Hurricane Andrew had a large negative effect on insurance stocks that was ameliorated to some extent by a smaller positive effect. Furthermore, the result shows discrimination among exposure states to a certain extent. However, this is not clear in the post-event windows.

In the last subsection of additional analysis, we run robust regressions in order to tolerate the outliers in our dataset. We can see from Table 11 that more significant results show in the variables of exposures, which support the findings in the previous subsections. Exposure_affected_T negatively affects CARs while Exposure_closeby_T positively influences CARs. In the affected states, the negative influence from hurricanes outweighs the positive effect; in contrast, insurers benefit from hurricanes in the close-by states. Consistent with the results in earlier sections, loss has a negative relationship with CARs. The more serious a hurricane is, the more damage it brings to property, which potentially could lead to more reimbursement payments.

Tobin’s Q is positively related to CARs. High Tobin’s Q encourages companies to invest more in capital because the companies are “worth” more than the price paid for them, which reflects the confidence of investors. Therefore, higher Tobin’s Q leads to higher abnormal returns. However, Hagendorff, Hagendorff, and Keasey (2015) find an opposite result. They argue that loss events leading to internal capital depletion are more severe for firms with strong growth prospects than for firms whose market value is more dependent on assets in place. That is because capital for new investments is more important for growth-orientated firms.

6. Robustness Tests

As introduced in the data and methodology section, we define Exposure_affected_T as the ratio of homeowner premiums earned in the affected state(s) to total premiums earned, and Exposure_closeby_T as the ratio of homeowner premiums earned in the close-by state(s) to total premiums earned. These two variables are the interaction items (X_1X_2). Exposure_affected_T is the product of Exposure_affected_H (the ratio of homeowner premiums earned in the affected state(s) to total homeowner premiums earned) and Proportion_Home (the ratio of total homeowner premiums earned to total premiums earned). Exposure_closeby_T is the product of Exposure_closeby_H (the ratio of homeowner premiums earned in the close-by state(s) to total homeowner premiums earned) and Proportion_Home.

In the robustness test, we ran the regression with the interaction variables (X_1X_2) and the composition variables (X_1 and X_2) at the same time. In general, Table 12 shows that the results are consistent with the findings in the previous sections. Among different types of states, there is not a large difference. Only the pre-event window (-5, -1) distinguishes the exposures of insurers. Loss from hurricanes always has a negative influence on insurers' stock prices. Similarly, big companies do not attract more confidence from investors. In contrast, the ability to make profits from assets can help insurers gain more from hurricane events.

In order to confirm the yearly differences, we ran the regressions by year as well. There are indeed big differences in sensitivity to insurers' and hurricanes' characteristics among the years 2008, 2011, and 2012. In 2008, CARs have more significant relationships with insurers' characteristics.

The signs of the coefficients of the variables are consistent with the findings above. Alternately, CARs are more sensitive to hurricane characteristics in 2011, and even more soin 2012. Insurers with higher exposure in the affected states are hit by hurricanes more seriously. The considerable differences among years may be one of the reasons that we cannot get better and more significant results and conclusions from our analysis. Consequently, we have a general picture but cannot make a definitive conclusion. With a limited sample size, there are not enough observations for each model when running the regressions by year. Therefore, we do not report the table showing regression by year.

However, based on Lamb (1998), there is support indicating big variances among hurricanes. He finds that Hurricane Hugo and Hurricane Andrew produced dramatically different market reactions for property and causality insurance companies. Insurers were unaffected by Hurricane Hugo, in spite of exposure in North or South Carolina. Hurricane Andrew, however, generated a significant negative impact only on insurers with premium business in Florida or Louisiana.

7. Conclusions and Discussion

Our results show that insurers in all areas (i.e. insurers that operate in affected, close-by, and unaffected states) experience a significant premium increase after hurricanes. Premium changes are significantly different between any two types of areas in an event year, but only a few of them are significant in the following year. Consequently, while hurricanes appear to affect the short-term premium income of insurance companies, they may not influence premium income in the long term. In addition, we find that insurers in close-by areas appear to benefit more than those in affected areas, possibly as a result of a wake-up call stemming from having closely avoided a disaster.

In light of shareholder wealth, we conclude that the increase in expected benefits from potential premiums after catastrophes outweighs the substantial losses insurers incur due to reimbursements to policyholders. However, while there are no obvious distinguishing results among areas when facing serious hurricanes, there is a certain degree of discrimination due to differing magnitudes of exposure. Insurers with business in close-by states benefit from hurricanes. In contrast, insurers in affected states suffer negative consequences. This is not significant in all event windows, especially in the long term, but is fairly consistent in the short term.

The severity of hurricanes greatly affects the abnormal stock price performance of insurance companies. There is a negative relationship between the losses caused by hurricanes and stock price reactions. We understand that the more severe the hurricane is, the more hesitant investors tend to remain. A more serious hurricane likely causes higher property damages, which potentially lead to higher reimbursement payments.

Large companies do benefit from potential investor confidence and even suffer negative consequences due to hurricanes. ROA has a significantly positive effect on abnormal returns. Line diversity is negatively related to CARs while Tobin's Q is positively related to CARs.

As Kunreuther (1996) and Kunreuther (2006) argue, residents in hazard-prone areas do not undertake loss-prevention measures voluntarily. Individuals and companies take insufficient protective measures. This might weaken the significance of our results.

Future researchers who plan to work in this area are thus encouraged to use more events during a longer period to obtain more comprehensive results. However, these efforts may be hindered by the fact that data collection is difficult because, at the state level, premium writing is very detailed; furthermore, the information is not commonly available.

In order to construct a more comprehensive insurance mechanism that allows for better management of catastrophic risks, more efforts ought to be made. We should involve not only private insurance firms, but should also improve industry regulations. We need the participation of both private insurers and other parties, including banks and financial institutions, builders and contractors, and the government. Even property owners should participate and be encouraged to take efficient measures in order to bear natural hazards.

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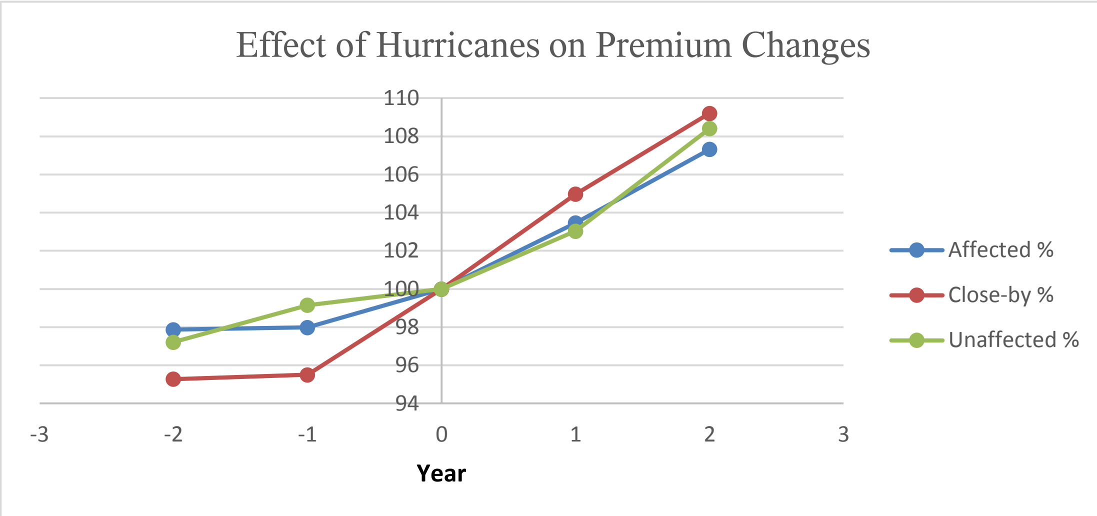
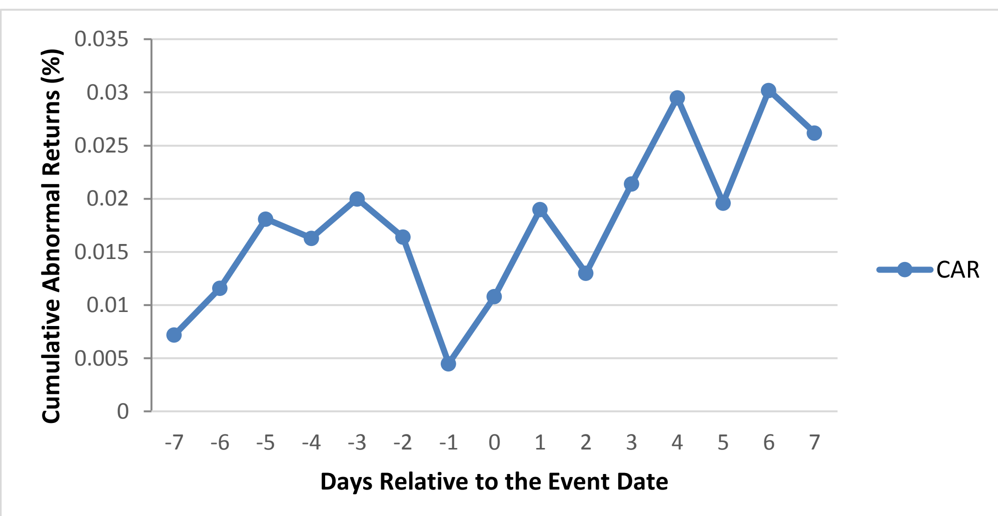
Appendices

Figure 1 Effect of Hurricanes on Premium Changes



Note: The figure shows premium changes for states, categorized based on their exposure to a given hurricane. Before the event year (year 0), the property and casualty premium income does not change a lot, especially in the years (-2) and (-1). After the hurricanes, the premium income exhibits a big increase in all three types of areas. Among them, the premium for the close-by area has jumped most obviously. Premium incomes are from Bloomberg. We use direct premiums written, defined as the aggregate amount of recorded originated premiums, other than reinsurance, written during the year, whether collected or not, at the close of the year, plus retrospective audit premium collections, after deducting all return premiums.

Figure 2 Cumulative Abnormal Returns of Insurers



Note: Figure 2 depicts the trend in CARs from one week before to one week after the event. We can see that, between 2 days and 1 day before the event, there is an obvious decrease in CARs. After the event, CARs exhibit a generally positive trend.

Table 1 The Top 3 Hurricanes between 2006 and 2014

Date	Hurricanes	States affected	States Close-by	States Unaffected	Deaths	CPI-Adjusted estimated cost (Billions $)
29.10.2012	Sandy	MD, DE, NJ, NY, CT, MA, RI	NC, VA, WV, OH, PA, NH, VT	WA, OR, CA, NV, AZ, ID, UT, MT, WY, CO, NM, ND, SD, NE, KS, TX, OK, MN, IA, MO, AR, LA, WI, IL, KY, TN, MS, AL, MI, IN, GA, FL, SC, ME, AK, HI	159	$67
27.08.2011	Irene	NC, VA, MD, NJ, NY, CT, RI, MA, VT	PA, WV, SC, NH, DE	WA, OR, CA, NV, AZ, ID, UT, MT, WY, CO, NM, ND, SD, NE, KS, TX, OK, MN, IA, MO, AR, LA, WI, IL, MS, AL, MI, IN, OH, GA, FL, ME, AK, HI, KY, TN	45	$14
13.09.2008	Ike	TX, LA, AR, TN, IL, IN, KY, MO, OH, MI, PA	MS, AL, GA, SC, NC, VA, WV, MD, DE, NJ, NY, OK, KS, IA, WI	WA, OR, CA, NV, AZ, ID, UT, MT, WY, CO, NM, ND, SD, NE, MN, FL, VT, NH, ME, MA, CT, RI, AK, HI	112	$33

Note: The sample consists of the top hurricanes whose adjusted cost is higher than $ 10 billion.

Data source: National Centers for Environmental Information of National Oceanic and Atmospheric Administration

Table 2 Sample Firms

Table 2: Sample Firms (N=47)		
ACE LTD	EMC INSURANCE GROUP INC	OLD REPUBLIC INTL CORP
ALLEGHANY CORP	EMPLOYERS HOLDINGS INC	PROASSURANCE CORP
ALLIANZ SE	ENDURANCE SPECIALTY HOLDINGS	PROGRESSIVE CORP-OHIO
ALLIED WORLD ASSURANCE CO AG	ERIE INDEMNITY CO - CL A	RLI CORP
ALLSTATE CORP	EVEREST RE GROUP LTD	SAFETY INSURANCE GROUP INC
AMERICAN INTERNATIONAL GROUP	FAIRFAX FINANCIAL HOLDINGS	SELECTIVE INS GROUP INC
AMERICAN NATIONAL INSURANCE	AMERICAN FINANCIAL GROUP INC	STATE AUTO FINANCIAL CORP
AMERIPRISE FINANCIAL INC	HARTFORD FINANCIAL SERVICES	HANOVER INSURANCE GROUP INC
AMTRUST FINANCIAL SERVICES	HCC INSURANCE HOLDINGS INC	TOWER GROUP INTL LTD
ARCH CAPITAL GROUP LTD	HALLMARK FINANCIAL SERVICES	TRAVELERS COS INC
ARGO GROUP INTL HOLDINGS LTD	HORACE MANN EDUCATORS CORP	KEMPER CORP/DE
ASSURANT INC	INFINITY PROPERTY & CAS CORP	UNIVERSAL INSURANCE HLDGS
AXIS CAPITAL HOLDINGS LTD	MARKEL CORP	BERKLEY (W R) CORP
CHUBB CORP	MERCURY GENERAL CORP	WHITE MTNS INS GROUP LTD
CINCINNATI FINANCIAL CORP	METLIFE INC	XL GROUP PLC
CNA FINANCIAL CORP	NAVIGATORS GROUP INC	

Note: The sample consists of 47 insurance firms that are publicly traded in the U.S. and that have complete information on direct premiums written in various insurance lines on Bloomberg as well historical accounting and stock price information on Compustat and CRSP, respectively.

Table 3 Variable Definition

Table 3: Variable Definition		
	Variable	Definition
Dependent variables	CAR(x, y)	Market-adjusted mean cumulative abnormal returns over different event windows
Independent variables	Exposure_affected_H	The ratio of homeowner' premiums earned in affected state(s) to total homeowners' premiums earned (%)
	Exposure_affected_T	The ratio of homeowners' premiums earned in affected state(s) to total premiums earned (%)
	Exposure_closeby_H	The ratio of homeowners' premiums earned in close-by state(s) to total homeowners' premiums earned (%)
	Exposure_closeby_T	The ratio of homeowners' premiums earned in close-by state(s) to total premiums earned (%)
	Proportion_Home	The ratio of total homeowners' insurance premiums earned to total premiums earned (%)
	Loss	Estimated total damage caused by a given hurricane, adjusted by 2014 CPI ($ billion)
	Firm Size	Log of total assets
	TOBQ	Tobins's Q measured as the market value of equity plus the book value of liabilities, divided by the book value of assets
	ROA	The ratio of pretax profits to total assets (%)
	Lossratio	Log of the loss ratio, defined as the total loss incurred in the homeowners' line of business.
	Linedivers	A measure of line diversification, calculated as the sum of the squared percentage of insurance premiums earned in each business line to the total premiums earned in all property-liability lines (%)
	High Rating	Dummy variable that equals 1 if the insurer's financial rating assigned by Standard & Poor's is A or better (and 0 otherwise)

Note: All accounting data are from Compustat. Premium income is from Bloomberg. We use direct premiums written, the aggregate amount of recorded originated premiums, other than reinsurance, written during the year, whether collected or not, at the close of the year, plus retrospective audit premium collections, after deducting all return premiums. The estimated losses caused by each hurricane are from the National Centers for Environmental Information of National Oceanic and Atmospheric Administration.

Table 4 T-tests to examine whether premium changes are different from zero

Table 4: T-tests to examine whether premium changes are different from zero

	Affected	N	Close-by	N	Unaffected	N
Event year	0.0848***	400	0.0821***	387	0.0884***	1088
	(<.0001)		(<.0001)		(<.0001)	
1 Year after	0.0616***	529	0.0832***	515	0.0799***	1729
	(<.0001)		(<.0001)		(<.0001)	
2 Years after	0.0293***	522	0.0541***	520	0.0626***	1735
	(<.0001)		(<.0001)		(<.0001)	

Note: The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1%level, respectively. We test whether the premium changes during and after the event year are different from zero for the three areas based on their exposure. All premium changes are significantly different from zero. Premium income is from Bloomberg. We use direct premiums written, defined as the aggregate amount of recorded originated premiums, other than reinsurance, written during the year, whether collected or not, at the close of the year, plus retrospective audit premium collections, after deducting all return premiums.

Table 5 Difference Tests of Premium Changes by Region

Table 5: Difference Tests of Premium Changes by Region					
Panel A: Affected vs. Close-by					
		Affected	Close-by	Test of differences	
				Difference	p-value
Event year	N	522	520		
	Mean	0.0293	0.0541	-0.0248***	(<.0001)
	Median	0.0239	0.0373	-0.0133***	(0.0098)
1 year after	N	529	515		
	Mean	0.0616	0.0832	-0.0216*	(0.0528)
	Median	0.0428	0.0454	-0.0027	(0.4216)
2 years after	N	400	387		
	Mean	0.0848	0.0821	0.0027	(0.8553)
	Median	0.0461	0.0431	0.0029	(0.7170)
Panel B: Affected vs. Unaffected					
		Affected	Unaffected	Test of differences	
				Difference	p-value
Event year	N	522	1735		
	Mean	0.0293	0.0695	-0.0402***	(<.0001)
	Median	0.0239	0.0425	-0.0185***	(<.0001)
1 year after	N	529	1729		
	Mean	0.0616	0.0799	-0.0183**	(0.0309)
	Median	0.0428	0.0477	-0.0049	(0.1103)
2 years after	N	400	1088		
	Mean	0.0848	0.0884	-0.0036	(0.7664)
	Median	0.0461	0.0495	-0.0034	(0.9632)
Panel C: Close-by vs. Unaffected					
		Close-by	Unaffected	Test of differences	
				Difference	p-value
Event year	N	520	1735		
	Mean	0.0541	0.0695	-0.0154***	(<.0001)
	Median	0.0373	0.0425	-0.0052*	(0.0833)
1 year after	N	515	1729		
	Mean	0.0832	0.0799	0.0033	(0.7319)
	Median	0.0454	0.0477	-0.0022	(0.5508)
2 years after	N	387	1088		
	Mean	0.0821	0.0884	-0.0063	(0.6251)
	Median	0.0431	0.0495	-0.0064	(0.6146)

Note: The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1%level, respectively. We perform pairwise comparisons of premium changes between areas. Panel A provides a comparison between affected and close-by states, panel B compares affected and unaffected states, panel C provides a comparison between close-by and unaffected states. The premium changes are significantly different between any two areas in the event year but only few of them are significant in the following year. Premium income is from Bloomberg. We use Direct Premiums Written, defined as the aggregate amount of recorded originated premiums, other than reinsurance, written during the year, whether collected or not, at the close of the year, plus retrospective audit premium collections, after deducting all return premiums.

Table 6 Abnormal Stock Price Performance

Table 6: Abnormal Stock Price Performance					
Event Window (Days)	N	Mean Cumulative Abnormal Return	Mean (t-test)	CAR<0%	
				N	Percentage
(-5,-1)	137	-0.70%	-2.895***	77	56.20%
(-1,+1)	137	0.26%	0.735	62	45.26%*
(0,+1)	137	1.45%	7.424****	54	39.42%**
(0,+5)	137	1.52%	3.347****	63	45.99%
(0,+10)	137	2.45%	5.05****	50	36.5%***
(0,+20)	137	5.55%	8.426****	52	37.96%***

Note: The symbols *,**,***, and **** denote statistical significance at the 10%, 5%, 1%, and 0.1% level, respectively, using a one-tailed test. We examine changes in the market value of insurers in response to catastrophes. The table reports the abnormal performance to our sample firms during various event windows. In the pre-event window, i.e. when the hurricane approached the mainland, there is a negative mean cumulative abnormal return. Afterwards, in the post-event windows, all mean CARs are significantly positive.

Table 7 Pearson Correlation Coefficients

Table 7: Pearson Correlation Coefficients

This table reports the Pearson correlation coefficients between our dependent variables. P-values are reported in parentheses.

	High Rating	Exposure_affected_T	Exposure_closeby_T	Firm Size	TOBQ	ROA	Loss	Lossratio
Exposure_affected_T	0.2411***							
	(0.0091)							
Exposure_closeby_T	0.1819*	0.4457***						
	(0.0507)	(<.0001)						
Firm Size	0.5809***	0.1998**	0.1114					
	(<.0001)	(0.0175)	(0.1886)					
TOBQ	-0.0450	-0.0774	0.0112	-0.4705***				
	(0.6376)	(0.3685)	(0.8967)	(<.0001)				
ROA	-0.1204	-0.1124	0.0228	-0.2457***	0.2349***			
	(0.1979)	(0.1843)	(0.7884)	(0.0033)	(0.0057)			
Loss	-0.0137	-0.0463	-0.1460*	0.0597	-0.3113***	0.1795**		
	(0.8838)	(0.5855)	(0.0841)	(0.4816)	(0.0002)	(0.0332)		
Lossratio	0.2930***	0.4696***	0.4019***	0.3792***	-0.1398	-0.1615*	-0.0003	
	(0.0018)	(<.0001)	(<.0001)	(<0.0001)	(0.1112)	(0.0614)	(0.9976)	
Linedivers	-0.0399	-0.1658*	-0.1121	-0.2511***	0.2211**	0.2350***	0.0449	-0.4445***
	(0.6719)	(0.0520)	(0.1906)	(0.003)	(0.0102)	(0.0055)	(0.6011)	(<.0001)

Note: The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8 Basic Regressions of Insurers' Cumulative Abnormal Returns

Table 8 Basic Regressions of Insurers' Cumulative Abnormal Returns

	CAR(-5,-1)			CAR(-1, 1)			CAR(0, 1)		
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Intercept	0.0093	0.1009*	0.2366*	0.3827**	0.2051*	0.9028***	0.4811***	0.1498*	0.8625***
	(0.9128)	(0.0983)	(0.0920)	(0.0221)	(0.0839)	(0.0011)	(0.0002)	(0.0984)	(<.0001)
Exposure_affected_T	-0.1672		-0.2336	-0.2365		0.0434	-0.0882		0.1921
	(0.2566)		(0.3495)	(0.4094)		(0.9281)	(0.6834)		(0.5838)
Exposure_closeby_T	0.4440**		0.9391***	0.3165		0.6435	0.1782		0.3980
	(0.0169)		(0.0068)	(0.3774)		(0.3285)	(0.5100)		(0.4065)
Loss	-0.0019		-0.0131	-0.0374**		-0.0633***	-0.0460***		-0.0646***
	(0.8195)		(0.2406)	(0.0224)		(0.0039)	(0.0002)		(<.0001)
Firm Size		-0.0305**	-0.0294**		-0.0525**	-0.0615**		-0.0362*	-0.0458**
		(0.0254)	(0.0293)		(0.0467)	(0.0185)		(0.0719)	(0.0162)
TOBQ		-0.0043	-0.0046		0.0009	-0.0071		0.0033	-0.0050
		(0.3491)	(0.3646)		(0.9228)	(0.4609)		(0.6295)	(0.4793)
ROA		0.5528***	0.6536***		1.2214***	1.6044***		0.8356***	1.2209***
		(0.0016)	(0.0003)		(0.0004)	(<.0001)		(0.0013)	(<.0001)
Lossratio		0.0024	0.0005		0.0019	0.0001		0.0015	-0.0002
		(0.1955)	(0.8169)		(0.5835)	(0.9720)		(0.5740)	(0.9539)
Linedivers		0.0119	0.0006		-0.0451	-0.0509		-0.0381	-0.0424
		(0.6693)	(0.9817)		(0.4044)	(0.3385)		(0.3571)	(0.2736)
High Rating		0.0229	0.0218		0.0206	0.0257		0.0092	0.0145
		(0.1105)	(0.1214)		(0.4590)	(0.3424)		(0.6636)	(0.4616)
Observations	137	106	106	137	106	106	137	106	106
Adjusted R^2	0.0228	0.0983	0.1738	0.0282	0.1383	0.2203	0.0847	0.1242	0.2801
Pr > F	0.1089	0.0118	0.0010	0.0785	0.0019	0.0001	0.0020	0.0036	<.0001

	CAR(0, 5)			CAR(0, 10)			CAR(0,20)		
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Intercept	0.6464***	-0.0096	0.8917***	0.4811***	0.1039	0.9396***	1.0621***	0.0903	1.2234***
	(<.0001)	(0.9087)	(<.0001)	(0.0013)	(0.2732)	(<.0001)	(<.0001)	(0.4913)	(<.0001)
Exposure_affected_T	-0.2910		-0.1041	-0.3638		0.2384	-0.4691		0.1207
	(0.1368)		(0.7377)	(0.1517)		(0.5252)	(0.1507)		(0.8171)
Exposure_closeby_T	0.1216		-0.0977	0.2249		-0.8076	0.3157		-0.5539
	(0.6178)		(0.8181)	(0.4772)		(0.1171)	(0.4380)		(0.4379)
Loss	-0.0618***		-0.0799***	-0.0446***		-0.0737***	-0.0987***		-0.1004***
	(<.0001)		(<.0001)	(0.0022)		(<.0001)	(<.0001)		(<.0001)
Firm Size		0.0075	-0.0105		-0.0210	-0.0393*		-0.0158	-0.0390
		(0.6836)	(0.5273)		(0.3182)	(0.0526)		(0.5878)	(0.1645)
TOBQ		0.0186***	0.0048		0.0068	-0.0066		0.0276***	0.0102
		(0.0041)	(0.4415)		(0.3438)	(0.3830)		(0.0065)	(0.3344)
ROA		0.4900**	0.9385***		0.9131***	1.3103***		-0.2841	0.2706
		(0.0390)	(<.0001)		(0.0009)	(<.0001)		(0.4427)	(0.4602)
Lossratio		-0.0030	-0.0014		0.0003	0.0025		-0.0006	0.0015
		(0.2336)	(0.5871)		(0.9135)	(0.4359)		(0.8754)	(0.7300)
Linedivers		-0.1091***	-0.0948***		-0.0740*	-0.0547		-0.1199**	-0.0994*
		(0.0051)	(0.0067)		(0.0898)	(0.1876)		(0.0481)	(0.0865)
High Rating		-0.0133	-0.0002		-0.0043	0.0085		0.0140	0.0304
		(0.4995)	(0.9890)		(0.8468)	(0.6849)		(0.6506)	(0.3014)
Observations	137	106	106	137	106	106	137	106	106
Adjusted R^2	0.1879	0.1311	0.3437	0.0639	0.1203	0.2495	0.1762	0.0911	0.2178
Pr > F	<.0001	0.0026	<.0001	0.0081	0.0044	<.0001	<.0001	0.0162	0.0001

Notes: The table reports the results of basic OLS regressions of CARs in different event windows, with insurer and hurricane characteristics as the independent variables. Specifically, the independent variables include Exposure (Exposure_affected_T and Exposure_closeby_T), measured as the ratio of homeowners' premiums earned in the affected state(s) and close-by state(s) to total premiums earned, respectively; Loss, which represents the total estimated damages (in $billion) caused by a given hurricane, adjusted by CPI; Firm Size, measured as the log of total assets; Tobin's Q (TOBQ), measured as the market value of equity plus the book value of liabilities divided by the book value of assets; ROA, i.e. the ratio of pretax profits to total assets; the log of the loss ratio (Lossratio), defined as the total losses incurred in the homeowners' line of business; Linedivers, a measure of line diversification, calculated as the sum of the squared percentage of insurance premiums earned in each business line to the total premiums earned in all property-liability lines; and High Rating, a dummy variable that equals 1 if the insurer's financial rating assigned by Standard & Poor's is A or better (and 0 otherwise). P-values are reported in parentheses below each coefficient. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1%level, respectively.

Table 9 Regressions of Insurers' Cumulative Abnormal Returns with Year and Insurer Fixed Effects

	Table 9 Regressions of Insurers' Cumulative Abnormal Returns with Year and Insurer Fixed Effects								
	CAR(-5,-1)								
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Intercept	-0.0828	0.1274**	0.2310	-0.0515	0.4342	0.4793	-0.0960	0.5962	0.1441
	(0.8130)	(0.0326)	(0.6086)	(0.5949)	(0.3910)	(0.3231)	(0.7889)	(0.2455)	(0.9053)
Exposure_affected_T	-0.1265		-0.1584	0.2681		-0.0949	0.1880		-0.0933
	(0.3923)		(0.5340)	(0.4024)		(0.7972)	(0.5635)		(0.8007)
Exposure_closeby_T	0.3566*		0.7114*	0.9682***		1.2342***	0.7586*		1.0352**
	(0.0599)		(0.0606)	(0.0086)		(0.0042)	(0.0557)		(0.0287)
Loss	0.0072		-0.0111	0.0039		0.0012	0.0083		0.0395
	(0.8249)		(0.7852)	(0.6696)		(0.9286)	(0.8022)		(0.6567)
Firm Size		-0.0370***	-0.0323**		-0.1481	-0.1461		-0.1623	-0.1564
		(0.0056)	(0.0185)		(0.1711)	(0.1705)		(0.1404)	(0.1451)
TOBQ		-0.0094*	-0.0062		0.0104	0.0025		-0.0043	-0.0026
		(0.0524)	(0.2284)		(0.3903)	(0.8449)		(0.7648)	(0.8512)
ROA		0.7165***	0.6850***		1.3247***	1.2023***		1.3152***	1.2093***
		(<.0001)	(0.0002)		(<.0001)	(0.0002)		(<.0001)	(0.0001)
Lossratio		0.0027	0.0010		0.0301	0.0438*		0.0395	0.0461*
		(0.1282)	(0.6378)		(0.2219)	(0.0700)		(0.1089)	(0.0583)
Linedivers		0.0181	0.0055		0.1332	0.0733		0.0335	0.0372
		(0.5005)	(0.8429)		(0.5121)	(0.7071)		(0.8694)	(0.8514)
High Rating		0.0265*	0.0233*		0.1100***	0.0920**		0.0928**	0.0865**
		(0.0569)	(0.0999)		(0.0055)	(0.0152)		(0.0181)	(0.0237)
Year fixed effects	Yes	Yes	Yes				Yes	Yes	Yes
Insurer fixed effects				Yes	Yes	Yes	Yes	Yes	Yes
Observations	137	106	106	137	106	106	137	106	106

Adjusted R^2	0.0707	0.2309	0.2611	0.3596	0.5716	0.6324	0.3737	0.6044	0.6384
Pr > F	0.0839	0.0010	0.0017	0.4954	0.0131	0.0033	0.5006	0.0076	0.0038
					CAR(-1, 1)				
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Intercept	-0.1476	0.2342**	0.5688	0.3257*	2.1224**	2.3254**	-0.1591	1.8623*	3.0679
	(0.8305)	(0.0409)	(0.5180)	(0.0867)	(0.0451)	(0.0291)	(0.8210)	(0.0843)	(0.2478)
Exposure_affected_T	-0.2408		0.0580	0.3366		-0.1414	0.3709		-0.1405
	(0.4083)		(0.9070)	(0.5890)		(0.8593)	(0.5611)		(0.8613)
Exposure_closeby_T	0.3220		0.5675	1.0133		0.5492	1.1244		0.4419
	(0.3860)		(0.4391)	(0.1521)		(0.5413)	(0.1463)		(0.6617)
Loss	0.0114		-0.0324	-0.0314*		-0.0488*	0.0130		-0.1134
	(0.8583)		(0.6844)	(0.0772)		(0.0994)	(0.8408)		(0.5581)
Firm Size		-0.0660***	-0.0615**		-0.5318**	-0.4301*		-0.4400*	-0.4357*
		(0.0100)	(0.0214)		(0.0190)	(0.0637)		(0.0569)	(0.0638)
TOBQ		-0.0115	-0.0079		0.0142	-0.0077		-0.0119	-0.0105
		(0.2136)	(0.4320)		(0.5709)	(0.7825)		(0.6890)	(0.7305)
ROA		1.6465***	1.6197***		2.1027***	2.3251***		2.3677***	2.3289***
		(<.0001)	(<.0001)		(0.0011)	(0.0006)		(0.0004)	(0.0007)
Lossratio		0.0024	0.0003		0.0113	0.0234		0.0209	0.0246
		(0.4738)	(0.9508)		(0.8237)	(0.6505)		(0.6806)	(0.6379)
Linedivers		-0.0327	-0.0480		-0.0861	-0.1845		-0.2086	-0.2039
		(0.5253)	(0.3755)		(0.8372)	(0.6618)		(0.6242)	(0.6376)
High Rating		0.0285	0.0251		0.0747	0.0651		0.0651	0.0621
		(0.2836)	(0.3615)		(0.3473)	(0.4163)		(0.4167)	(0.4468)
Year fixed effects	Yes	Yes	Yes				Yes	Yes	Yes
Insurer fixed effects				Yes	Yes	Yes	Yes	Yes	Yes
Observations	137	106	106	137	106	106	137	106	106

Adjusted R^2	0.0544	0.2801	0.2886	0.3628	0.5377	0.5652	0.3685	0.5638	0.5657
Pr > F	0.1915	<.0001	0.0004	0.4738	0.0419	0.0435	0.5358	0.0337	0.0573
					CAR(0, 1)				
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Intercept	-0.1893	0.1789**	0.4345	0.4397***	1.6420**	1.8758**	-0.1942	1.3409*	2.2946
	(0.7151)	(0.0321)	(0.4968)	(0.0026)	(0.0415)	(0.0168)	(0.7135)	(0.0882)	(0.2369)
Exposure_affected_T	-0.0805		0.2227	0.3291		-0.0481	0.3178		-0.0463
	(0.7126)		(0.5371)	(0.4847)		(0.9345)	(0.5079)		(0.9372)
Exposure_closeby_T	0.1573		0.2647	0.7561		0.3028	0.7532		0.0884
	(0.5727)		(0.6190)	(0.1572)		(0.6457)	(0.1949)		(0.9046)
Loss	0.0159		-0.0247	-0.0416***		-0.0579***	0.0168		-0.0887
	(0.7410)		(0.6695)	(0.0024)		(0.0088)	(0.7306)		(0.5308)
Firm Size		-0.0498***	-0.0462**		-0.4152**	-0.2966*		-0.3089*	-0.3077*
		(0.0077)	(0.0174)		(0.0161)	(0.0805)		(0.0665)	(0.0730)
TOBQ		-0.0091	-0.0063		0.0196	-0.0047		-0.0107	-0.0103
		(0.1759)	(0.3930)		(0.3047)	(0.8185)		(0.6218)	(0.6451)
ROA		1.2623***	1.2456***		1.5107***	1.8037***		1.8179***	1.8113***
		(<.0001)	(<.0001)		(0.0019)	(0.0003)		(0.0002)	(0.0003)
Lossratio		0.0020	0.0001		0.0008	0.0104		0.0120	0.0129
		(0.4159)	(0.9850)		(0.9840)	(0.7831)		(0.7465)	(0.7361)
Linedivers		-0.0257	-0.0380		-0.0622	-0.1641		-0.2045	-0.2030
		(0.4935)	(0.3344)		(0.8450)	(0.5957)		(0.5104)	(0.5214)
High Rating		0.0172	0.0140		0.0499	0.0440		0.0387	0.0381
		(0.3740)	(0.4836)		(0.4087)	(0.4534)		(0.5075)	(0.5232)
Year fixed effects	Yes	Yes	Yes				Yes	Yes	Yes
Insurer fixed effects				Yes	Yes	Yes	Yes	Yes	Yes
Observations	137	106	106	137	106	106	137	106	106

Adjusted R^2	0.1171	0.3366	0.3469	0.3988	0.5355	0.5936	0.4099	0.5965	0.5967
Pr > F	0.0056	<.0001	<.0001	0.2505	0.0448	0.0166	0.2721	0.0104	0.0209
					CAR(0, 5)				
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Intercept	-0.0956	0.0299	0.1463	0.5388***	0.9943	1.1969**	-0.1343	0.7524	0.3362
	(0.8364)	(0.6751)	(0.7904)	(<.0001)	(0.1265)	(0.0469)	(0.7335)	(0.2097)	(0.8177)
Exposure_affected_T	-0.2524		0.0175	-0.0888		-0.5202	-0.1688		-0.5167
	(0.1975)		(0.9550)	(0.8026)		(0.2530)	(0.6370)		(0.2479)
Exposure_closeby_T	0.0342		-0.5364	0.5671		0.0315	0.3844		-0.4025
	(0.8907)		(0.2439)	(0.1601)		(0.9507)	(0.3739)		(0.4715)
Loss	0.0072		-0.0091	-0.0532***		-0.0621***	0.0091		0.0333
	(0.8672)		(0.8550)	(<.0001)		(0.0004)	(0.8026)		(0.7551)
Firm Size		-0.0086	-0.0139		-0.2313*	-0.1006		-0.1310	-0.1230
		(0.5889)	(0.4020)		(0.0952)	(0.4387)		(0.3055)	(0.3384)
TOBQ		0.0042	0.0011		0.0323**	0.0116		-0.0027	0.0003
		(0.4735)	(0.8641)		(0.0397)	(0.4387)		(0.8720)	(0.9864)
ROA		0.9803***	1.0099***		0.3297	0.6913*		0.6303*	0.7067*
		(<.0001)	(<.0001)		(0.3876)	(0.0628)		(0.0770)	(0.0533)
Lossratio		-0.0024	-0.0006		0.0027	0.0141		0.0171	0.0190
		(0.2606)	(0.8301)		(0.9301)	(0.6311)		(0.5489)	(0.5103)
Linedivers		-0.0943***	-0.0827**		-0.2223	-0.3035		-0.3976*	-0.3822
		(0.0043)	(0.0162)		(0.3922)	(0.2074)		(0.0987)	(0.1138)
High Rating		-0.0039	0.0003		0.0127	0.0083		-0.0043	-0.0037
		(0.8129)	(0.9876)		(0.7951)	(0.8553)		(0.9239)	(0.9337)
Year fixed effects	Yes	Yes	Yes				Yes	Yes	Yes
Insurer fixed effects				Yes	Yes	Yes	Yes	Yes	Yes
Observations	137	106	106	137	106	106	137	106	106

Adjusted R^2	0.2309	0.4264	0.4375	0.6253	0.6436	0.7181	0.6413	0.7248	0.7327
Pr > F	<.0001	<.0001	<.0001	<.0001	0.0005	<.0001	<.0001	<.0001	<.0001
					CAR(0,10)				
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Intercept	-0.2552	0.1263	0.4007	0.4177***	1.5866*	1.7782**	-0.2433	1.3036	1.0613
	(0.6741)	(0.1572)	(0.5556)	(0.0072)	(0.0501)	(0.0269)	(0.6667)	(0.1101)	(0.5926)
Exposure_affected_T	-0.3506		0.3171	-0.1305		0.3903	-0.1300		0.3921
	(0.1721)		(0.4089)	(0.7950)		(0.5169)	(0.7995)		(0.5170)
Exposure_closeby_T	0.1916		-1.0969*	0.7876		-0.4097	0.8168		-0.6333
	(0.5571)		(0.0549)	(0.1675)		(0.5453)	(0.1881)		(0.4046)
Loss	0.0235		-0.0227	-0.0348**		-0.0470**	0.0260		0.0274
	(0.6761)		(0.7126)	(0.0161)		(0.0363)	(0.6177)		(0.8503)
Firm Size		-0.0331*	-0.0413**		-0.3642**	-0.2736		-0.2752	-0.2851
		(0.0967)	(0.0446)		(0.0349)	(0.1158)		(0.1142)	(0.1049)
TOBQ		-0.0045	-0.0091		0.0109	-0.0069		-0.0096	-0.0128
		(0.5322)	(0.2444)		(0.5686)	(0.7428)		(0.6702)	(0.5790)
ROA		1.3050***	1.3580***		0.8296*	1.1138**		1.0783**	1.1218**
		(<.0001)	(<.0001)		(0.0817)	(0.0250)		(0.0267)	(0.0248)
Lossratio		0.0007	0.0030		0.0445	0.0417		0.0511	0.0443
		(0.7880)	(0.3462)		(0.2528)	(0.2851)		(0.1875)	(0.2614)
Linedivers		-0.0631	-0.0466		-0.2180	-0.2784		-0.3065	-0.3190
		(0.1205)	(0.2666)		(0.4970)	(0.3821)		(0.3434)	(0.3280)
High Rating		0.0029	0.0087		-0.0142	-0.0076		-0.0188	-0.0138
		(0.8905)	(0.6811)		(0.8142)	(0.8997)		(0.7568)	(0.8220)
Year fixed effects	Yes	Yes	Yes				Yes	Yes	Yes
Insurer fixed effects				Yes	Yes	Yes	Yes	Yes	Yes
Observations	137	106	106	137	106	106	137	106	106

Adjusted R^2	0.0958	0.2988	0.3273	0.4875	0.5714	0.6091	0.4969	0.6032	0.6121
Pr > F	0.0203	<.0001	<.0001	0.0166	0.0132	0.0091	0.0209	0.0079	0.0117

	CAR(0,20)								
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Intercept	-0.4641	0.1192	0.3726	0.9347***	1.1037	1.4310	-0.4814	0.6174	-1.2524
	(0.5482)	(0.3312)	(0.6948)	(<.0001)	(0.3458)	(0.2133)	(0.5243)	(0.5967)	(0.6648)
Exposure_affected_T	-0.4403		0.1672	0.0711		0.2052	0.0310		0.2055
	(0.1780)		(0.7550)	(0.9168)		(0.8142)	(0.9639)		(0.8155)
Exposure_closeby_T	0.2438		-0.7758	1.3460*		0.5067	1.3004		0.4704
	(0.5575)		(0.3279)	(0.0827)		(0.6063)	(0.1181)		(0.6705)
Loss	0.0424		-0.0213	-0.0847***		-0.0748**	0.0457		0.1744
	(0.5533)		(0.8043)	(<.0001)		(0.0223)	(0.5124)		(0.4114)
Firm Size		-0.0327	-0.0393		-0.3005	-0.1494		-0.1493	-0.1513
		(0.2315)	(0.1693)		(0.2285)	(0.5507)		(0.5493)	(0.5512)
TOBQ		0.0116	0.0080		0.0392	0.0052		0.0051	0.0043
		(0.2482)	(0.4649)		(0.1640)	(0.8655)		(0.8746)	(0.8989)
ROA		0.2736	0.3137		-1.0246	-0.6679		-0.6027	-0.6666
		(0.4543)	(0.3986)		(0.1403)	(0.3460)		(0.3825)	(0.3512)
Lossratio		-0.0001	0.0019		0.0808	0.0921		0.0916	0.0925
		(0.9843)	(0.6763)		(0.1573)	(0.1062)		(0.1033)	(0.1093)
Linedivers		-0.1046*	-0.0916		0.0539	-0.0911		-0.0919	-0.0977
		(0.0622)	(0.1192)		(0.9085)	(0.8433)		(0.8435)	(0.8365)
High Rating		0.0241	0.0290		-0.1050	-0.1130		-0.1120	-0.1140
		(0.4006)	(0.3284)		(0.2390)	(0.1989)		(0.2037)	(0.2041)
Year fixed effects	Yes	Yes	Yes				Yes	Yes	Yes
Insurer fixed effects				Yes	Yes	Yes	Yes	Yes	Yes
Observations	137	106	106	137	106	106	137	106	106

Adjusted R^2	0.2203	0.2854	0.2936	0.4993	0.5067	0.5570	0.5211	0.5553	0.5570
Pr > F	<.0001	<.0001	0.0003	0.0101	0.1000	0.0559	0.0075	0.0440	0.0733

Notes: The table reports the results of a series of CAR regression in different event windows, with insurer and hurricane characteristics under year fixed effect, insurer fixed effect and both of the fixed effects, respectively. Specifically, the independent variables include Exposure (Exposure_affected_T and Exposure_closeby_T), measured as the ratio of homeowners' premiums earned in the affected state(s) and close-by state(s) to total premiums earned, respectively; Loss, which represents the total estimated damages (in $billion) caused by a given hurricane, adjusted by CPI; Firm Size, measured as the log of total assets; Tobin's Q (TOBQ), measured as the market value of equity plus the book value of liabilities divided by the book value of assets; ROA, i.e. the ratio of pretax profits to total assets; the log of the loss ratio (Lossratio), defined as the total losses incurred in the homeowners' line of business; Linedivers, a measure of line diversification, calculated as the sum of the squared percentage of insurance premiums earned in each business line to the total premiums earned in all property-liability lines; and High Rating, a dummy variable that equals 1 if the insurer's financial rating assigned by Standard & Poor's is A or better (and 0 otherwise). P-values are reported in parentheses below each coefficient. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1%level, respectively.

Table 10 Regressions of Insurers' Cumulative Abnormal Returns Clustered by Year and Firm

Table 10 Regressions of Insurers' Cumulative Abnormal Returns Clustered by Year and Firm

	CAR(-5,-1)	CAR(-1,1)	CAR(0, 1)	CAR(0, 5)	CAR(0,10)	CAR(0,20)
Intercept	0.0093	0.3827*	0.4811***	0.6464***	0.4811***	1.0621***
	(0.9268)	(0.0703)	(0.0025)	(<.0001)	(0.0059)	(<.0001)
Exposure_affected_T	-0.1672*	-0.2365*	-0.0882	-0.2910*	-0.3638	-0.4691
	(0.0739)	(0.0846)	(0.4360)	(0.0660)	(0.1282)	(0.1053)
Exposure_closeby_T	0.4440***	0.3165*	0.1782	0.1216	0.2249	0.3157
	(0.0036)	(0.0615)	(0.1811)	(0.6056)	(0.5722)	(0.4467)
Loss	-0.0019	-0.0374*	-0.0460***	-0.0618***	-0.0446***	-0.0987***
	(0.8412)	(0.0575)	(0.0020)	(<.0001)	(0.0066)	(<.0001)
Observations	137	137	137	137	137	137
Adjusted R^2	0.02280	0.02820	0.08470	0.18790	0.06390	0.17620
Pr > F	0.10890	0.07850	0.00200	<.0001	0.00810	<.0001

Notes: The table reports the results of a series of CARs regressions in different event windows, with insurer and hurricane characteristics clustered by year and firm as the independent variables. Specifically, the independent variables include Exposure (Exposure_affected_T and Exposure_closeby_T), measured as the ratio of homeowners' premiums earned in the affected state(s) and close-by state(s) to total premiums earned, respectively; and loss, which represents the total estimated damage caused by a given hurricane, adjusted by CPI. Heteroscedasticity consistent p-values are reported in parentheses below each coefficient. The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1%levels respectively.

Table 11 Robust Regressions of Insurers' Cumulative Abnormal Returns

Table 11 Robust Regressions of Insurers' Cumulative Abnormal Returns

	CAR(-5,-1)			CAR(-1, 1)			CAR(0, 1)		
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Intercept	0.0718	-0.0276	0.0391	0.5651***	-0.0098	0.5877***	0.5991***	-0.0110	0.6340***
	(0.1263)	(0.4627)	(0.5677)	(<.0001)	(0.8308)	(<.0001)	(<.0001)	(0.8149)	(<.0001)
Exposure_affected_T	-0.2410***		-0.3682***	-0.2906***		-0.2957*	-0.1535*		-0.1066
	(0.003)		(0.0026)	(0.0017)		(0.0682)	(0.0783)		(0.4676)
Exposure_closeby_T	0.4670***		0.9854***	0.1052		0.3952*	0.0659		0.3038
	(<.0001)		(<.0001)	(0.3630)		(0.0744)	(0.5453)		(0.1296)
Loss	-0.0074		-0.0066	-0.0542***		-0.0564***	-0.0570***		-0.0600***
	(0.1059)		(0.2288)	(<.0001)		(<.0001)	(<.0001)		(<.0001)
Firm Size		0.0027	0.0056		0.0045	0.0017		0.0058	0.0007
		(0.7500)	(0.3894)		(0.6581)	(0.8458)		(0.5743)	(0.9251)
TOBQ		0.0015	-0.0003		0.0103***	0.0038		0.0105***	0.0029
		(0.5982)	(0.9182)		(0.0034)	(0.2426)		(0.0031)	(0.3313)
ROA		-0.0633	0.2561***		-0.3634***	0.0952		-0.2919**	0.1727*
		(0.5497)	(0.0028)		(0.0051)	(0.4023)		(0.0270)	(0.0933)
Lossratio		0.0007	-0.0008		-0.0020	-0.0017		-0.0013	-0.0016
		(0.5260)	(0.4269)		(0.1519)	(0.2112)		(0.3454)	(0.2093)
Linedivers		0.0151	-0.0076		-0.0268	-0.0356**		-0.0276	-0.0314*
		(0.3817)	(0.5725)		(0.2032)	(0.0462)		(0.1990)	(0.0520)
High Rating		0.0043	-0.0015		-0.0067	0.0045		-0.0101	-0.0012
		(0.6293)	(0.8223)		(0.5395)	(0.6203)		(0.3583)	(0.8885)
Observations	137	106	106	137	106	106	137	106	106

Adjusted R^2	0.1044	0.0156	0.2402	0.3426	0.1308	0.3920	0.3980	0.1168	0.4630

	CAR(0, 5)			CAR(0,10)			CAR(0,20)		
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Intercept	0.5565***	-0.0512	0.5643***	0.4698***	-0.0166	0.5416***	0.8446***	-0.0980	0.9649***
	(<.0001)	(0.3669)	(<.0001)	(<.0001)	(0.7726)	(<.0001)	(<.0001)	(0.3292)	(<.0001)
Exposure_affected_T	-0.2261**		-0.0044	-0.1025		0.0364	-0.3352		0.0122
	(0.0449)		(0.9819)	(0.4581)		(0.8654)	(0.1413)		(0.9694)
Exposure_closeby_T	0.2088		0.0033	-0.4170**		-0.4580	0.3579		-0.0089
	(0.1384)		(0.9902)	(0.0157)		(0.1187)	(0.2091)		(0.9836)
Loss	-0.0536***		-0.0554***	-0.0437***		-0.0488***	-0.0787***		-0.0947***
	(<.0001)		(<.0001)	(<.0001)		(<.0001)	(<.0001)		(<.0001)
Firm Size		0.0149	0.0056		0.0079	-0.0044		0.0214	0.0079
		(0.2360)	(0.5921)		(0.5331)	(0.7003)		(0.3365)	(0.6396)
TOBQ		0.0188***	0.0085**		0.0136***	0.0051		0.0299***	0.0048
		(<.0001)	(0.0306)		(0.0018)	(0.2374)		(<.0001)	(0.4497)
ROA		-0.4030**	0.0982		-0.5359***	-0.1408		-0.4306	0.9557***
		(0.0117)	(0.4738)		(0.0009)	(0.3500)		(0.1285)	(<.0001)
Lossratio		-0.0033**	-0.0024		-0.0015	0.0008		-0.0017	-0.0008
		(0.0497)	(0.1477)		(0.3660)	(0.6411)		(0.5620)	(0.7722)
Linedivers		-0.0605**	-0.0535**		-0.0365	-0.0371		-0.0509	-0.0565
		(0.0198)	(0.0132)		(0.1637)	(0.1176)		(0.2693)	(0.1058)
High Rating		-0.0159	-0.0141		-0.0119	-0.0087		-0.0094	-0.0128
		(0.2332)	(0.2008)		(0.3791)	(0.4731)		(0.6902)	(0.4728)
Observations	137	106	106	137	106	106	137	106	106
Adjusted R^2	0.2099	0.1295	0.2672	0.1238	0.0905	0.2222	0.1253	0.0801	0.2361

Notes: The table reports the results of a series of CAR robust regression in different event windows, with insurer and hurricane characteristics as the independent variables. Specifically, the independent variables include Exposure (Exposure_affected_T and Exposure_closeby_T), measured as the ratio of homeowners' premiums earned in the affected state(s) and close-by state(s) to total premiums earned, respectively; Loss, which represents the total estimated damages (in $billion) caused by a given hurricane, adjusted by CPI; Firm Size, measured as the log of total assets; Tobin's Q (TOBQ), measured as the market value of equity plus the book value of liabilities divided by the book value of assets; ROA, i.e. the ratio of pretax profits to total assets; the log of the loss ratio (Lossratio), defined as the total losses incurred in the homeowners' line of business; Linedivers, a measure of line diversification, calculated as the sum of the squared percentage of insurance premiums earned in each business line to the total premiums earned in all property-liability lines; and High Rating, a dummy variable that equals 1 if the insurer's financial rating assigned by Standard & Poor's is A or better (and 0 otherwise). P-values are reported in parentheses below each coefficient. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1%level, respectively.

Table 12 Regressions of Insurers' Cumulative Abnormal Returns with Interaction Terms

Table 12 Regressions of Insurers' Cumulative Abnormal Returns with Interaction Terms

	CAR(-5, 1)		CAR(-1, 1)		CAR(0, 1)	
	(A)	(C)	(A)	(C)	(A)	(C)
Intercept	0.0422	0.2455*	0.4225**	0.8805***	0.4998***	0.8364***
	(0.6562)	(0.0898)	(0.0270)	(0.0022)	(0.0006)	(<.0001)
Exposure_affected_T	-0.3585	-0.7487*	-0.3934	-0.6980	-0.1184	-0.2008
	(0.1095)	(0.0673)	(0.3777)	(0.3785)	(0.7246)	(0.7283)
Exposure_affected_H	0.0295	0.0689*	0.0252	0.0932	0.0061	0.0552
	(0.3592)	(0.0720)	(0.6940)	(0.2104)	(0.8992)	(0.3095)
Proportion_Home	0.0179	0.1626	-0.0011	0.2850	-0.0159	0.1576
	(0.6511)	(0.2791)	(0.9893)	(0.3307)	(0.7896)	(0.4611)
Exposure_closeby_T	0.7463**	0.8627*	0.6198	0.3250	0.3331	0.1509
	(0.0146)	(0.0866)	(0.3050)	(0.7388)	(0.4645)	(0.8321)
Exposure_closeby_H	-0.0655	-0.0041	-0.0635	0.0264	-0.0294	0.0324
	(0.1615)	(0.9405)	(0.4955)	(0.8038)	(0.6755)	(0.6771)
Loss	-0.0051	-0.0161	-0.0410**	-0.0639***	-0.0476***	-0.0635***
	(0.5810)	(0.1765)	(0.0272)	(0.0068)	(0.0008)	(0.0003)
Firm Size		-0.0254*		-0.0547**		-0.0423**
		(0.0704)		(0.0462)		(0.0352)
TOBQ		-0.0026		-0.0042		-0.0037
		(0.6337)		(0.6944)		(0.6352)
ROA		0.7152***		1.6925***		1.2760***
		(0.0002)		(<.0001)		(<.0001)
Lossratio		-0.0016		-0.0043		-0.0029
		(0.5580)		(0.4308)		(0.4573)
Linedivers		-0.0043		-0.0622		-0.0462
		(0.8880)		(0.3005)		(0.2922)
High Rating		0.0192		0.0206		0.0118

		(0.1817)		(0.4622)		(0.5627)
Observations	130	104	130	104	130	104
Adjusted R^2	0.0193	0.1808	0.0059	0.2077	0.0599	0.2620
Pr > F	0.2111	0.0020	0.3509	0.0006	0.0335	<.0001

	CAR(0, 5)		CAR(0,10)		CAR(0,20)	
	(A)	(C)	(A)	(C)	(A)	(C)
Intercept	0.62010***	0.8709***	0.4699***	0.9375***	0.9095***	1.0681***
	(<.0001)	(<.0001)	(0.0056)	(<.0001)	(<.0001)	(0.0005)
Exposure_affected_T	-0.1223	-0.2399	-0.4027	-0.0321	-0.5132	0.6509
	(0.6824)	(0.6407)	(0.3062)	(0.9588)	(0.2929)	(0.4365)
Exposure_affected_H	-0.0179	-0.0005	0.0181	0.0263	0.0306	0.0034
	(0.6771)	(0.9910)	(0.7497)	(0.6525)	(0.6629)	(0.9652)
Proportion_Home	-0.0542	0.1507	-0.0358	0.1177	0.0181	-0.0476
	(0.3079)	(0.4280)	(0.6073)	(0.6091)	(0.8337)	(0.8775)
Exposure_closeby_T	-0.0547	-0.5908	0.3657	-0.9477	-0.7682	-1.7561*
	(0.8925)	(0.3516)	(0.4921)	(0.2184)	(0.2453)	(0.0903)
Exposure_closeby_H	0.0485	0.0616	-0.0159	0.0066	0.2292	0.2809**
	(0.4381)	(0.3741)	(0.8461)	(0.9374)	(0.0258)	(0.0140)
Loss	-0.0590***	-0.0789***	-0.0433***	-0.0745***	-0.0851***	-0.0834***
	(<.0001)	(<.0001)	(0.0085)	(<.0001)	(<.0001)	(0.0009)
Firm Size		-0.0076		-0.0363*		-0.0452
		(0.6661)		(0.0917)		(0.1173)
TOBQ		0.0062		-0.0052		0.0050
		(0.3713)		(0.5417)		(0.6562)
ROA		0.9912***		1.3422***		0.3849
		(<.0001)		(<.0001)		(0.3057)
Lossratio		-0.0035		0.0010		-0.0014

		(0.3239)		(0.8214)		(0.8029)
Linedivers		-0.1039***		-0.0610		-0.0689
		(0.0087)		(0.1976)		(0.2772)
High Rating		-0.0020		0.0064		0.0362
		(0.9115)		(0.7720)		(0.2213)
Observations	130	104	130	104	130	104
Adjusted R^2	0.1865	0.3223	0.0403	0.2218	0.2069	0.2434
Pr > F	<.0001	<.0001	0.0856	0.0003	<.0001	0.0001

Notes: The table reports the results of a series of CAR regression with interaction item in different event windows, with insurer and hurricane characteristics as the independent variables. Specifically, the independent variables include Exposure (Exposure_affected_T and Exposure_closeby_T), measured as the ratio of homeowners' premiums earned in the affected state(s) and close-by state(s) to total premiums earned, respectively; Exposre (Exposure_affected_H and Exposure_closeby_H), measured as the ratio of homeowner' premiums earned in affected state(s) and close-by state(s) to total homeowners' premiums earned, respectively; Proportion_Home, measured as the ratio of total homeowners' insurance premiums earned to total premiums earned; Loss, which represents the total estimated damages (in $billion) caused by a given hurricane, adjusted by CPI; Firm Size, measured as the log of total assets; Tobin's Q (TOBQ), measured as the market value of equity plus the book value of liabilities divided by the book value of assets; ROA, i.e. the ratio of pretax profits to total assets; the log of the loss ratio (Lossratio), defined as the total losses incurred in the homeowners' line of business; Linedivers, a measure of line diversification, calculated as the sum of the squared percentage of insurance premiums earned in each business line to the total premiums earned in all property-liability lines; and High Rating, a dummy variable that equals 1 if the insurer's financial rating assigned by Standard & Poor's is A or better (and 0 otherwise). P-values are reported in parentheses below each coefficient. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1%level, respectively.