Exploring the Impact of Natural Disasters on U.S. Insurance Companies:
An Empirical Analysis

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ABSTRACT

Exploring the Impact of Natural Disasters on U.S. Insurance Companies:
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In this study, we investigate the impact of natural disasters on the stock prices of U.S. insurance companies from 2010 to 2022. Using a sample of hurricanes, wildfires, and tornadoes, we conduct an event study to analyze the market reactions to these events and examine why some insurance firms are more affected than others. Our findings indicate that natural disasters tend to result in negative abnormal returns for insurance firms, with stock prices dropping significantly around the events. Yet, the price declines are followed by a brief recovery period after the disaster has ended. The study highlights key factors affecting insurers' market performance during such events: firms with higher leverage, lower net income, and a lower market valuation perform worse than their respective counterparts. Additionally, we find that disasters with large insured damage amounts as well as hurricanes invoke larger negative market reactions. Furthermore, we observe that natural disasters have a significant impact on an insurer's accounting performance. Specifically, disasters cause a significant decline in an insurer's Return on Assets (ROA), with variations based on the insured damages stemming from a disaster and the insurer's ex-ante financial performance.

Keywords: Natural disasters, Insurance companies, Cumulative abnormal returns (CAR)s, Event Study, Market reactions

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1. Introduction

Climate change increases environmental risks, contributing to economic and financial instability (Tol, 2009). A joint study by the OECD, World Bank, and United Nations estimates that meeting climate and development objectives up to the year 2030 will cost the global economy nearly US$6.9 trillion annually, equivalent to 8% of global GDP (OECD et al., 2018). In addition, the World Bank (2013) documents that economic losses from natural disasters attributable to climate change totaled US$3.8 trillion between 1980 and 2012, largely due to extreme weather events. In a later report, the World Bank (2016) further reports that natural disasters caused approximately $520 billion in annual consumption losses and drove 26 million people into poverty (see also Walker et al., 2023). Following a natural disaster, the affected country faces substantial costs for rebuilding infrastructure, offering employment and medical aid, providing temporary housing if needed, restoring utilities, and covering other related expenses (Newkirk, 2001; Walker et al., 2023).

The increasing frequency and severity of natural disasters results in significant economic losses, prompting insurance companies to take proactive measures and rethink their risk modeling and pricing. Insurers play a vital role in managing these risks by spreading the associated costs among policyholders and using their expertise to tackle challenges, e.g., by predicting disasters and reducing future losses (Bouwer & Vellinga, 2005; Mills, 2009). Governments also rely on insurers to protect citizens from the financial aftermath of natural catastrophes, thereby preventing severe economic hardship and declines in living standards (Hagendorff et al., 2015; Kalfin et al., 2022). In some countries such as the U.S., Mexico, Chile, France, Germany, Japan, and the U.K., governments often share responsibility for high-risk catastrophe areas, providing partial reimbursement to underinsured individuals (Botzen & Van Den Bergh, 2008). However, this can strain public finances if major disasters occur. Consequently, catastrophe insurance serves a dual purpose: safeguarding citizens and mitigating financial impacts on governments (Hagendorff et al., 2015).

To further enhance disaster preparedness, Kunreuther & Pauly (2006) propose the adoption of mandatory disaster insurance for all homeowners, emphasizing that many individuals tend not to take precautions against natural disasters. This leads to costly and less effective reliance on public assistance after a catastrophe. This highlights the critical role of insurance not only in spreading and mitigating risks, but also in fortifying both individual and governmental resilience against the financial burdens of catastrophic events—a crucial component of public policy.

Climate change affects the insurance industry in two main ways: insurers help communities adapt by sharing risks, but face an increasing risk exposure from climate events, requiring them to adjust their premiums and risk management strategies accordingly (Mills, 2005; Gupta et al., 2023; Smolka, 2006). In typical insurance markets such as auto insurance, insurers handle many independent risks that generally follow a predictable annual pattern. They charge premiums that can be invested to generate returns before paying out losses, ensuring profitability. However, catastrophic losses from natural disasters present a challenge. Unlike the foreseeable spread of risks in auto insurance, these losses are unpredictable and can affect all policies simultaneously, posing significant financial risks for insurers (Born & Viscusi, 2006). These catastrophic risks strain insurers by causing unpredictable, large-scale losses that can exceed premiums, potentially leading to financial instability or market exits. To confront these challenges, insurers now focus on leveraging their skills in data collection, catastrophe modeling, and risk analysis to monitor trends and address issues arising from natural disasters, seeking solutions beneficial for both the industry and society (Kousky, 2019; Mills, 2009).

Therefore, understanding the profound impact of natural disasters on the insurance industry, alongside the factors influencing this impact, is paramount. In this study, we examine the abnormal stock price performance of insurers around natural disasters and investigate the underlying drivers of differential stock price reactions among investors. By analyzing these dynamics, our study enhances our understanding of how insurers respond to and mitigate the financial consequences of natural catastrophes. Such insights are crucial for policymakers, insurance companies, and stakeholders alike, as they navigate the complexities of disaster risk management and try to enhance resilience.

In this study, we examine how natural disasters affect the financial performance of U.S. insurance companies, focusing on stock market reactions from 2010 to 2022. Through an event study, we assess the impact of these events on the stock prices of insurers, identifying key factors that influence these market responses. Our findings reveal that natural disasters lead to significant drops in stock prices, particularly for firms with higher leverage, lower profitability, and lower market valuations. However, these initial declines are often followed by a period of recovery as more information becomes available. Additionally, we observe that larger insured damages and high-category hurricanes exacerbate these negative effects. The study also highlights a decline in insurers' return on assets (ROA) post-disaster, further illustrating the financial strain imposed by such events on the industry. These insights suggest the need for insurance firms to closely monitor their leverage, adopt robust risk management strategies, and refine their pricing and reinsurance practices. Policymakers can use these findings to develop regulations that ensure adequate capital buffers and support the stability of the insurance market, including potential public-private partnerships that enhance resilience during and after natural disasters.

The remainder of this paper is structured as follows: Chapter 2 reviews the existing literature on insurance companies and natural disasters, introducing our hypotheses and research questions. Chapter 3 provides a detailed description of our sample, data sources, and the variables employed in our study, alongside descriptive statistics. In Chapter 4, we explain the methodology employed to investigate the impact of natural disasters on insurance companies. Chapter 5 presents the empirical findings derived from our analysis, while Chapter 6 encompasses robustness checks and supplementary analyses. Finally, in Chapter 7, we draw our conclusions.

2. Literature Review and Hypothesis Development

The rising frequency of catastrophic natural disasters lead to significant economic losses, amplifying insured damages. Insurers respond by implementing diverse strategies to stabilize their operational performance, showcasing their pivotal role in disaster risk management.

2.1. Literature Review

2.1.1. The Impact of Natural Disasters on Financial Institutions

Natural disasters can have significant long-term and short-term impacts on the economy, negatively affecting growth, development, and GDP, and causing a rise in poverty (Benson and Clay, 2003; Noy, 2009; Noy & duPont, 2016). Severe weather-related natural disasters can cause financial instability and a macroeconomic downturn by damaging the balance sheets of households, businesses, banks, and insurers. However, this effect can be mitigated if risks are efficiently distributed through insurance and reinsurance (Batten et al., 2016; Von Peter et al., 2012).

Several studies have examined the impact of natural disasters on financial institutions and have documented a significant effect on operational stability and financial performance (Andrew et al., 2015; Duqi, 2023; Keerthiratne & Tol, 2017). In particular, natural disasters have been shown to pose a substantial risk to banks and other financial intermediaries, resulting in higher rates of non-performing loans, defaults, reduced lending capacity, unexpected deposit withdrawals, financial market stresses, and increased vulnerability to bankruptcy (Alexander, 2014; Brahmana et al., 2016; Collier et al., 2013; Klomp, 2014; Steindl & Weinrobe, 1983). Cortés and Strahan (2017) demonstrate that US banks tend to reduce lending in non-core markets following natural disasters to mitigate economic shocks. Additionally, Noth and Schüwer (2018) find that these disasters have a detrimental impact on banks' performance, reflected in declines in z-scores and increases in non-performing assets.

Gramlich et al. (2023) study the impact of natural disasters on bank solvency, investigating how these events affect bank liquidity. Analyzing data from 9,928 banks in 149 countries, their study shows that natural disasters have a detrimental effect, influencing traditional accounting measures of solvency more than regulatory ones.

In another study, Walker et al. (2023) further investigate the impact of natural disasters on the financial performance and stability of U.S. banks from 2000 to 2014. Their findings show that these disasters affect various aspects of profitability, including net-income-to-assets, net-income-to-equity ratio, impaired loans, and the return on average assets. Additionally, solvency measures like the equity ratio and tier-1 capital ratio are also influenced. Notably, regional banks demonstrate a proactive approach by increasing their capital reserves in response to disasters, whereas local and national banks often face significant negative repercussions.

Overall, these studies indicate that natural disasters negatively affect financial institutions, financial stability, and the broader economy. They underscore the broader implications of catastrophic events on the financial sector, providing a foundation for examining similar impacts on insurance firms.

2.1.2. The Effect of Natural Disasters on the Insurance Market

Insurance companies confront significant challenges in managing and mitigating the risks associated with natural disasters (Sturm & Oh, 2010; Wang & Kutan, 2013). Multiple major insurers have withdrawn themselves from high-risk zones due to their inability to effectively manage associated risks (Von Ungern-Sternberg, 2009). In response, to reduce their exposure, these insurers stopped underwriting policies and terminated contracts. Initiatives such as the "Florida Hurricane Catastrophe Fund" have been established to reimburse insurers for part of their losses during severe hurricanes and incentivizing them to maintain coverage in these high-risk areas (Benali & Feki, 2017; Kunreuther & Michel-Kerjan, 2007; Stechemesser et al., 2015).

Born and Viscusi (2006) document that natural disasters have a significant impact on both insurance companies and policyholders. They argue that in response to unexpected and severe catastrophes, insurers often increase their premiums to manage heightened risks and cover potential losses. This initial adjustment aims to stabilize loss ratios, which can spike immediately after disasters. In the long-term, as the market adjusts, competition among insurers and changes in consumer demand may lead insurers to revert back to lower premiums for their policyholders. Insurers pursue these adjustments to maintain competitiveness and attract customers in a potentially smaller market with fewer participants. Additionally, in response to frequent and unexpected disasters, insurers' capacity to provide coverage for unforeseen losses diminishes (Born & Klimaszewski-Blettner, 2013), further influencing market dynamics and insurers' strategic responses. These factors collectively contribute to a landscape where fewer insurers remain, and financially vulnerable firms exit the market.

In their study, Hagendorff et al. (2015) explore the impact of mega-catastrophes on U.S. property-liability insurance firms, revealing moderate wealth losses for shareholders. However, these losses are not devastating, indicating the insurers' ability to effectively manage the risks and costs associated with such events. Additionally, their results indicate that hurricanes have a less negative impact on insurers compared to other types of catastrophes. Moreover, they find that post-Hurricane Katrina, insurers are able to better anticipate and account for potential losses in their premium income, highlighting the industry's resilience in sharing catastrophic losses.

Natural disasters can have profound effects on the profitability and financial stability of insurance companies. Profitability is vital for insurance companies to sustain their operations and prepare for potential losses. Benali and Feki (2017) analyze thirty property and casualty (P&C) insurance companies in the U.S. from 2008 to 2012, and find that higher capital volumes and favorable premium-to-surplus ratios are key factors in guaranteeing the profitability of P&C insurance firms. Conversely, factors such as an insurer's loss ratio, unexpected event frequency, and severity of disasters have a negative effect on the insurer's financial performance, emphasizing the need for adaptive strategies to maintain profitability.

2.2. Hypothesis Development

The existing literature highlights the significant economic repercussions of natural catastrophes, and the strategic responses insurers adopt to manage these risks effectively. However, there is a notable gap of empirical research on how natural disasters affect insurers' performance. To close this gap, our study aims to investigate the impact of natural disasters on the market reactions of publicly traded U.S. insurance companies. Our analysis utilizes a panel dataset that includes various insurance firms across multiple disaster events. This structure allows us to examine the behavior of these firms across multiple events and over time. Specifically, we seek to determine whether natural disasters lead to declines in share prices and adversely affect insurers' accounting performance. Additionally, we analyze various factors that may shape and modify these effects on insurers' financial performance and market valuations. We hypothesize that:

1- The cumulative abnormal returns (CARs) of an insurance company is negative around the occurrence of a natural disaster in the area in which the insurance firm is headquartered.

This hypothesis is based on the premise that natural disasters lead to substantial financial losses and increased liabilities for insurers, prompting immediate adverse market reactions. A positive alternative hypothesis could be that insurance benefit from the increased demand for policies following a disaster and from their ability to reprice existing policies. This could lead to a *positive* stock price reaction for insurance firms. We explore this issue further in our results section.

2- High leverage exacerbates an insurance firm's stock price decline around a natural disaster.

This hypothesis is based on the premised that highly leveraged insurance companies are more vulnerable to financial distress when faced with large, unexpected claims resulting from natural disasters. This can lead to a more pronounced negative reaction in their stock prices.

Additional hypotheses:

3- Similar hypotheses are also proposed for an insurer's ex-ante profitability and size: we expect less profitable and smaller (less diversified) insurers to be more affected by a disaster than their more profitable and larger counterparts as their ability to tolerate the associated losses is smaller.

4- Higher market valuation (as measured by Tobin's Q) has a positive impact on insurers' CARs. Insurers with higher market valuation are perceived to have better growth prospects and financial health, leading to better market performance post-disaster.

By analyzing these dynamics, we aim to contribute valuable insights that enhance our understanding of how insurers' stock prices respond to natural disasters over different time horizons and under varying circumstances. This research is crucial for enhancing the resilience of insurance companies and informing stakeholders, policymakers, and investors about the factors that drive market reactions during and after catastrophic events. By filling this gap in the literature, we seek to provide actionable knowledge that supports informed decision-making in disaster risk management and enhances the overall stability of the insurance industry.

3. Data

3.1. Sample Construction

Our study employs detailed data on publicly traded U.S. insurance companies. Our sample comprises 223 insurers from 2010 to 2022. To form our sample, we first identify all fire, marine, and casualty insurance companies (SIC code 6331), life insurance companies (SIC code 6311), insurance agents, brokers and service firms (SIC code 6411), and accident and health insurance firms (SIC code 6321) on the Center for Research in Security Prices (CRSP). Next, we obtain stock price data for these firms from CRSP and financial data from Compustat. Both datasets are accessible through the Wharton Research Data Service (WRDS) website. Table 1 presents the Standard Industrial Classification (SIC) codes alongside the number of companies in each segment that are included in our analysis.

Insert Table 1 about here

Our sample for the event study includes natural disasters with damages exceeding $10 billion between 2010 and 2022. We collect specific disaster data from the International Disaster Database (EM-DAT) and supplement it with public information available from the National Oceanic and Atmospheric Administration (NOAA) database. EM-DAT is managed by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Leuven (CRED, 2016). Our sample includes hurricanes, wildfires, and tornadoes. Table 2 details the natural disasters included in our study, presenting the disaster type, event name, year, affected states, and total estimated damage. In addition, we obtain economic data (e.g. GDP per capita) from the Federal Reserve Economic Data (FRED) database.

Insert Table 2 about here

3.2. Variables

We outline the variables used in this study in Table 3. The dependent variable in our regression analysis are the cumulative abnormal returns (CARs) of insurance firms around natural disasters, derived from an event study. The CARs measure deviations in stock prices during specific windows surrounding disasters, enabling an analysis of investor sentiment and market volatility in response to a given event.

A critical independent variable is Leverage, defined as total debt to total assets. It indicates how insurers finance operations through debt, influencing their financial stability and sensitivity to external shocks such as natural disasters. Higher leverage can exacerbate financial impacts, potentially amplifying negative market reactions.

Other independent variables include profitability measures such as the Return on Assets (ROA), which assesses how effectively insurers generate earnings from their asset base. In addition, Net Income (Loss) provides insights into the magnitude and direction of financial performance changes attributable to disasters. Firm size is measured by total assets captures the scale of the insurer's operations, with larger firms potentially having more diversified risk and resources to absorb the impacts of natural disasters. Net Income to Equity, which is obtained by dividing Net Income (Loss) by Stockholders' Equity, measures profitability relative to the equity base, indicating the firm's ability to generate profit from its equity. Market valuation metrics such as the Price-to-Book ratio reflect market perceptions of insurer value relative to their book value of equity. Moreover, Tobin's Q, which compares market value to asset replacement value, further informs us about investor expectations and valuation dynamics around disaster events.

Insured damages, accounting for inflation through CPI adjustments, quantify the economic losses covered by insurers, directly linking disaster impacts to financial outcomes.

We introduce a hurricane dummy variable to distinguish hurricanes from other disasters, assigning a value of 1 for hurricanes and 0 otherwise. Furthermore, an interaction term between hurricanes and leverage allows us to explore whether leverage has a differential effect for often stylized and broadly disruptive hurricanes and other disasters. Additionally, we include a dummy variable for affected states, which takes on a value of 1 if the headquarters of the insurance firm is located in the states affected by the events and 0 otherwise. This variable helps us determine whether being headquartered in an affected state has any significant impact on the firm's stock market reaction to the disaster.

GDP per Capita is included as a control variable to account for the overall economic context in the US during the years of the natural disasters. This variable helps us understand the broader economic environment's role in influencing the stock performance of insurance companies, with the expectation that a stronger economy may enhance firms' resilience to the financial impacts of such events.

Insert Table 3 about here

4. Methodology

4.1. Event Study

We conduct our empirical analysis by performing a series of event studies around natural disasters. The key goals of the event studies are to measure the sample securities' cumulative mean abnormal returns (CARs) around the time of the event (Kothari & Warner, 2007). An abnormal return (residual) is defined as the actual return (determined using arithmetic percentages) minus the return predicted by the firm's beta, given the market return. The residual or abnormal return represents the part of the return that is not predicted and is, therefore, an estimate of the change in firm value caused by the event (natural disaster). The predicted return represents the return that would be expected if no event took place (Liargovas & Repousis, 2011).

For hurricanes, we define the event date as the day they made landfall, typically coinciding with their classification into the highest categories based on the Saffir-Simpson Hurricane Wind Scale. For wildfires and tornadoes, we consider the event date based on their peak intensity or the period when they reached their maximum strength. We hypothesize that stocks that are affected by the event will experience negative CARs. In this study, we choose an event window of -10 to +10 trading days around the event (day 0). For the estimation period, we consider the end to be 46 days before the event date, with minimum and maximum estimation lengths being 3 and 255 days, respectively. To calculate predicted returns, we use the market-adjusted returns model which involves regressing a stock's returns against a market index (here, we use the equally weighted market index return).

Each abnormal security return is calculated and then normalized by its estimation period standard deviation, which helps standardize the returns and allows for comparison across different securities and time periods. Specifically, the abnormal return (AR) for the jth stock on day t, AR_{jt} is first obtained by subtracting the normal or expected returns in the absence of the event, $E(R_{jt})$, from the actual return in the event period, (R_{jt}), as per the following equation:

$$AR_{jt} = R_{jt} - E(R_{jt}) \tag{1}$$

The abnormal return is then normalized by dividing it by the standard deviation of the estimation period returns for that stock. This normalization process ensures that the ARs are measured on a consistent scale, accounting for differences in the volatility of individual stocks.

The market model relates the return of a security to the return of the market portfolio as per the following equation:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt'} \quad (2)$$

where, α_j is a constant term for the jth stock, β_j is the beta of the jth stock, R_{mt} is the market return, and $\varepsilon_{jt'}$ is an error term.

We use the estimated parameters to calculate abnormal returns (ARs) for each day in the event window. Afterwards, we match the estimated parameters with the actual returns in the event period. We calculate the daily excess return, denoted as AR_{jt} for day t, using actual returns during the event period and the estimated coefficients from the estimation period as per the following equation:

$$AR_{jt} = R_{jt} - \left(\hat{\alpha} + \hat{\beta} R_{mt}\right) \qquad \text{Where t = -10, …., +10} \quad (3)$$

Next, we calculate the average abnormal return (AAR_t) for each day in the event window as per the following equation:

$$AAR_t = \frac{1}{N} \sum_{j=1}^{N} AR_{jt'} \quad \text{, where N is the number of firms.} \quad (4)$$

The cumulative abnormal return (CAR) for a given security is the sum of daily ARs over the event window.

$$CAR_{(T_1,T_2)} = \sum_{t=T_1}^{T_2} AR_t \quad (5)$$

Over an interval of two or more trading days beginning with day T1 and ending with day T2, the cumulative average abnormal return (CAAR) for N securities is then calculated as per the following equation:

$$CAAR_{T_1T_2} = \frac{1}{N}\sum_{j=1}^{N}\sum_{t=T_1}^{T_2} AR_{jt} \tag{6}$$

We conduct the event study analysis across six different windows: [-10,-5], [-5,0], [-1,1], [0,1], [0,5], and [5,10]. This approach enables us to investigate both the short-term and relatively longer-term effects of the events studied.

4.2. Cross-sectional Regression Analyses

Having estimated the abnormal stock price performance of insurance firms around natural disasters, we use a multivariate OLS regression to examine the drivers of the cumulative abnormal returns for each insurance company. The regression model is specified as follows:

$$\begin{aligned} \mathrm{CAR}_{j,k} = {} & \alpha + \beta_1(\text{Leverage}) + \beta_2(\text{ROA}) + \beta_3(\text{Net Income (Loss)}) + \beta_4(\text{Firm Size}) + \beta_5(\text{Net} \\ & \text{Income to Equity}) + \beta_6(\text{Price to Book}) + \beta_7(\text{Tobin's Q}) + \beta_8(\text{Insured Damage}) + \\ & \beta_9(\text{Hurricane Dummy}) + \beta_{10}(\text{Hurricane}\times\text{Leverage}) + \beta_{11}(\text{GDP per capita}) + \\ & \beta_{12}(\text{Affected State dummy (} + \varepsilon_j \end{aligned} \tag{7}$$

where $\mathrm{CAR}_{j,k}$ is insurance company j's CAR in window k. Leverage is insurance j's total debt divided by total assets. ROA is the return on assets measured as net income(loss) divided by total assets. Net Income (Loss) is transformed using the natural logarithm after adding a constant of 6,085 million dollars to each value. We add this constant, which represents the minimum net income in our sample, to ensure all values are positive before applying the logarithmic transformation. Firm Size is the natural logarithm of total assets (in millions of US dollars) plus 1. Net Income to Equity is calculated as net income (loss) divided by stockholders' equity. The Price to Book Ratio is the market value of equity divided by the stockholders' equity. Tobin's Q is the market value of equity plus the book value of liabilities divided by the book value of assets. Insured damage measures the economic damage covered by insurance companies and is adjusted for inflation using the Consumer Price Index (CPI).

Hurricane Dummy is a dummy variable that takes on a value of 1 if the event is a hurricane and 0 otherwise. Hurricane×Leverage is the interaction term between the hurricane dummy variable and the leverage ratio. GDP per Capita is the natural logarithm of the gross domestic product per capita of the U.S., measured annually in US dollars. Affected State takes on a value of 1 when the headquarters of the insurance firm is located in a state affected by the event and 0 otherwise.

We utilize financial data from the fiscal year immediately preceding each natural disaster event in our regression analysis. This approach enables us to examine the company's financial situation at the time of the disaster, providing insights into how each factor influences a firm’s response to a natural disaster. For instance, using fiscal year 2016 data for Hurricane Harvey in 2017 helps us understand the company's financial position leading up to the event.

Our regression is based on a panel dataset that includes multiple insurance companies for each event. Each event year comprises a different number of firms, with many firms being common across multiple years. This structure allows us to capture both cross-sectional and temporal variations in the data. By utilizing panel regression, we can effectively control for unobserved heterogeneity and account for the dynamic effects of natural disasters on insurers over time.

5. Empirical Results

5.1. Event Study Results

Table 4 represents the event study results for the sample of natural disasters. Column 1 displays the number of observations (abnormal returns) in each window. Column 2 reports the mean CARs of insurance firms in each window, z-statistics in parentheses, and Column 3 shows the percentage of negative CARs. The purpose is to examine the stock price effects associated with natural disasters in the entire sample.

Table 4 shows that the mean cumulative abnormal returns (CARs) for insurance firms around natural disasters are predominantly negative across most event windows, except for the [+5,+10] window, which shows a positive mean CAR. For the negative CARs, the mean ranges from -0.47% in the [-5,0] window to -0.18% in the [-10,-5] window. All of these are significant at the 1% level. This indicates that, on average, the stock prices of insurance companies decrease significantly in the days leading up to and immediately following natural disasters. This finding is consistent with the results of Hagendorff et al. (2015), who also find that CARs are significantly negative during various windows before and after a mega-catastrophe.

Moreover, the positive and significant CAR in the [+5,+10] window suggests a rebound in stock prices after the initial negative impact. This pattern can be interpreted as an initial investor over-reaction, possibly driven by concerns about claims and financial losses, followed by a subsequent correction as more information becomes available and the initial uncertainty diminishes.

While the analysis primarily considers the event date as the day a hurricane made landfall or when a wildfire reached peak intensity, it is important to recognize that insurer stock prices may react even earlier. Investors often anticipate the potential impact of these events in the days leading up to landfall or peak intensity, as hurricanes typically take several days to develop, and wildfires can escalate gradually. Additionally, the onset of the hurricane season itself may prompt market reactions as investors assess the likelihood of significant storms. This anticipatory behavior suggests that stock price movements could begin before the actual event.

Insert Table 4 about here

Figure 1 displays the cumulative abnormal returns (CARs) for the days -10 to +10 relative to the event date for our sample. The horizontal axis represents the days relative to the event, while the vertical axis shows the cumulative abnormal returns. From the figure, we observe that the CARs are mostly negative leading up to the event day (day 0), reflecting the market's anticipation of the event's potential negative impact. Notably, there is a significant dip in CARs around day 1, indicating a pronounced abnormal return immediately following the event. This could be attributed to the immediate reaction of the market as the impact of the event becomes apparent.

However, starting from day 4 onwards, the CARs show a positive trend, indicating a recovery. By day 10, the CARs have increased substantially, suggesting that the market's perception of the event's impact becomes more positive or stabilizes as more information becomes available and the initial shock wears off. This gradual recovery could be due to the market's adjustment to the event's actual impact, as opposed to the anticipated impact. Overall, the figure highlights the market's initial negative reaction to the event, followed by a gradual recovery in the days following the event.

Insert Figure 1 about here

To analyze the effect of each individual event on insurers, we conduct a separate event study for each natural disaster in our sample. We report the CARs of insurers in Table 5. The findings indicate that hurricanes such as Harvey, Irma, Matthew, Michael, and Sandy exhibit markedly negative CARs across multiple event windows, indicating a significant market reaction. These negative CARs reflect investor sensitivity to the impacts of such events on insurance firms. Additionally, hurricanes such as Florence and Laura, as well as events such as the Tornado Super Outbreak, show initial negative CARs followed by significant positive CARs in later event windows (e.g., [+5,+10]), implying a subsequent market recovery or reassessment. Notably, the majority of events demonstrate positive CARs in the [+5,+10] window, consistent with the trends observed in the overall sample. The window [0,+5] exhibits the most negative CARs, indicating heightened investor concern or immediate market reaction following the natural disasters

Events such as Hurricane Ian and Hurricane Maria, and wildfires such as the Californian Complex Fire and Camp Fire exhibit mixed reactions in CARs across different event windows. This variability underscores the diverse market responses and financial impacts of such disasters on insurance companies.

Overall, our findings indicate that natural disasters tend to initially depress insurance firm stock prices. However, subsequent positive CARs suggest that markets adjust as more information regarding damages and potential claims becomes available, alleviating initial investor concerns.

Insert Table 5 about here

5.2. Descriptive Statistics

Table 6 provides descriptive statistics for the variables we use in our regression model. The [0,5] CAR shows a negative mean of -0.2%, indicating that, on average, insurers experience a decline in abnormal returns in the immediate aftermath of natural disasters. Leverage averages 0.087, reflecting moderate financial leverage among insurers. Net Income (Loss) exhibits a mean of $0.539 billion, with a notable standard deviation of $1.312 billion, indicating variability in profitability. The Price to Book ratio averages 1.467. These metrics provide insights into the financial dynamics impacting insurers during the studied period.

Insert Table 6 about here

5.3. Multi-collinearity

We assess the presence of multicollinearity among our independent variables. To do so, we compute the variance inflation factor (VIF) for each predictor in our model. The VIF values (Table 7), all below the threshold of 10, indicate no significant multicollinearity issues among our independent variables. Additionally, when we examine the correlation matrix in Table 8, we observe low and moderate correlations among the predictors, further supporting the absence of multicollinearity. These steps assure that our regression estimates are stable and not unduly influenced by multi-collinearity among the explanatory variables.

Insert Table 7 about here

Insert Table 8 about here

5.4. Heteroskedasticity

To ensure the reliability of our regression results, we further test for the presence of heteroskedasticity using the Breusch-Pagan test. The test results significant evidence of heteroskedasticity, suggesting that the variance of the error terms is not constant across the observations. To address this issue, we implement robust standard errors in our regression analysis. Robust standard errors provide consistent estimates of the standard errors in the presence of heteroskedasticity, ensuring that our statistical inferences are robust and unbiased by the varying error variance.

5.5. Regression Results

Table 9 presents the OLS regression results examining the cumulative abnormal returns (CAR) in the [0,5] window. We select this window to capture the immediate impact of natural disasters on insurers, effectively highlighting the short-term effects following a disaster. Model (1) reports the results with robust standard errors. Model (2) includes year-fixed effects to control for temporal variations, while Model (3) adds firm-fixed effects to account for unobserved heterogeneity across firms. Model (4) shows results with both year and industry fixed effects. By including dummy variables for the different SIC codes in our model, we control for industry-specific effects, ensuring that any observed impacts on CAR are not confounded by differences between industries.

Leverage, defined as total debt divided by total assets, shows a significant negative relationship with the CARs across all models. Aligned with our hypothesis, this finding indicates that firms with greater leverage face a more pronounced decline in stock prices in the aftermath of such events. The increased financial obligations associated with higher debt levels likely heighten investor concerns about the firm's capacity to manage the additional financial stress caused by the natural disaster. Consequently, highly leveraged insurance companies are more adversely impacted in terms of market performance compared to those with lower leverage.

Net income and the price-to-book ratio are positively correlated with CAR following natural disasters, both showing statistical significance. This suggests that firms with higher net income experience a smaller drop in stock prices around a disaster, implying that profitability helps cushion the negative market impact of such events. Similarly, the positive coefficient for the Price-to-Book Ratio, indicates that firms with a higher market valuation tend to perform better in terms of CAR post-disaster. This finding suggests that market participants view these firms as having better growth prospects or financial health, thereby mitigating the adverse effects of natural disasters on their stock performance.

Interestingly, the significant negative coefficient for Net Income to Equity indicates that firms with higher net income relative to their stockholders' equity experience more negative CAR following natural disasters. This suggests that while higher net income is viewed positively, a high Net Income to Equity ratio might signal a smaller equity base, making these firms appear riskier and vulnerable to investors, leading to a greater decline in stock prices.

Tobin's Q, representing market valuation relative to asset value, is significantly positive in the robust standard error model (1) and fixed year effect model (2) with coefficients of 0.007 and 0.008, respectively, but not in the other models. This indicates that relative firm value has a weakly positive impact on CARs, possibly because more highly valued firms are more resilient to natural disasters. The positive and significant coefficient for Firm Size indicates that larger firms, as measured by their total assets, experience better CAR following natural disasters. Specifically, the coefficients for this variable are 0.002 in Model 1, 0.003 in Model 2, and 0.003 in Model 4, significant at the 1%, 5%, and 5% levels respectively. This suggests that larger firms tend to be more resilient to the financial impacts of natural disasters, possibly due to their greater resources, diversified operations, and stronger market presence, which help mitigate the adverse effects on their stock performance. We did not observe significant results in model 3.

The hurricane dummy variable has a significant negative effect on CARs at the 1% level, reflecting a more profound impact of hurricanes on the stock price performance of insurance companies compared to the other natural disasters. However, the interaction term between hurricane and leverage is positive and highly significant (at the 1% level), indicating that the negative effect of leverage is mitigated for hurricane events. This could be due to expected higher premium income or increased government support following these often geographically disastrous events. The results also indicate that insured damages, adjusted for inflation, have a highly significant negative impact on CARs, highlighting, not surprisingly, that greater economic damages lead to poorer stock performance.

The coefficient for GDP per Capita as a control variable is positive and significant across the fixed effect models (2, 3, and 4), indicating that higher economic wealth in the US during the years of the natural disasters is associated with better CAR for insurance companies. This suggests that a stronger overall economy may help firms better absorb and mitigate the adverse effects of such events on their stock performance.

The Affected State Dummy variable, which takes on a value of 1 when the headquarters of the insurance firm are located in a state affected by the event and 0 otherwise, is not significant across the models. This indicates that the location of a firm's headquarters in an affected state does not necessarily translate to a different stock market reaction compared to firms headquartered elsewhere. One possible reason for this could be that investors consider the overall financial health and resilience of insurance firms in general rather than their geographic location in their investment decisions, possibly because, e.g., large insurance companies often have diversified operations and risk management strategies that mitigate the localized impacts of a natural disaster.

We observe no significant relationship between ROA and abnormal returns in our sample.

Overall, the results of our regressions models suggest that while leverage and economic damage adversely affect insurers' abnormal returns, higher net income and market valuation provide a buffer.

Insert Table 9 about here

5.6. The Impact of Natural Disasters on the Profitability of Insurance Firms

To examine the broader implications of natural disasters on the financial health of insurance firms, this section analyzes whether these events affect the profitability by examining the changes in their Return on Assets (ROA). To investigate this, we perform a paired t-test comparing the Return on Assets (ROA) before (T-1) and after (T+1) the natural disasters. The results in Table 10 suggest a significant decrease in ROA post-disaster (Mean Difference = 0.0049, t-value = 2.15, p-value = 0.0335). This indicates that natural disasters have a negative impact on the profitability of insurance firms. The statistically significant decrease in ROA implies that these firms tend to experience reduced profitability following a natural disaster.

Insert Table 10 about here

Following the t-test, we conduct OLS regression to examine the impact of various factors on the change in ROA. The dependent variable is ΔROA, which is calculated as the difference between ROA of the year after the natural disaster (T+1) and the year preceding the natural disaster (T-1). Our main independent variables include Δ Insurance Premium and Insured Damage. Control variables include Leverage, Firm Size, Net Income to Equity, Price to Book, Asset Turnover, Cash Flow to Debt, and an interaction term between Leverage and Insured Damage.

Table 11 displays the regression results. The coefficient for Δ Insurance Premium, calculated as the natural logarithm of one plus the percentage change in premiums from the year before to the year after the disaster, is positive and significant across all models. This indicates that an increase in insurance premiums after a disaster is associated with an increase in ROA. Specifically, Model (1) shows a coefficient of 0.008 (significant at the 1% level), Model (2) a coefficient of 0.010 (significant at the 5% level), Model (3) a coefficient of 0.008 (significant at the 10% level), and Model (4) a coefficient of 0.011 (significant at the 1% level). These results suggest that insurance firms benefit from increased premium income following natural disasters, positively affecting their profitability.

The coefficient for Insured Damage is negative and significant across all models, suggesting that higher insured damages from natural disasters are associated with a decrease in ROA. Specifically, Model (1) shows a coefficient of -0.012 (significant at the 1% level), while Models (2), (3), and (4) show coefficients of -0.006, -0.005, and -0.005, respectively, all significant at the 5% level. This finding indicates that the financial burden of insured damages negatively impacts the profitability of insurance firms.

The regression results support the findings from the paired t-test, indicating that natural disasters significantly impact the profitability of insurance firms. The positive and significant coefficients for Δ Insurance Premium suggest that increased premium income post-disaster helps mitigate the negative effects on profitability. However, the negative coefficients for insured damage highlight the financial burden these events impose on insurance firms, reducing their ROA.

The control variables show mixed results, with firm size, price-to-book ratio, and asset turnover having a positive impact on ROA changes, while leverage, net income to equity, and cash flow to debt ratios are associated with negative impacts. The interaction term between leverage and insured damage indicates that higher leverage mitigates some of the negative effects of insured damage on profitability, possibly because more leveraged firms might expect higher premium income post-disaster, providing a buffer against financial losses.

Insert Table 11 about here

6. Further Analysis

6.1. Cumulative Abnormal Returns Using the Fama-French Model

As a robustness check, we also estimate the cumulative abnormal returns (CARs) for the sample of natural disasters using the Fama-French model. We present the results in Table 12. Our findings replicate our main results, showing statistically significant negative CARs at the

1% level in the first five windows. Additionally, consistent with our primary analysis, we observe significant and positive CARs in the [+5,+10] window.

Insert Table 12 about here

6.2. Differences among Hurricanes of Different Strength

We categorize hurricanes into "low" (Category 1, 2, and 3) and "high" (Category 4 and 5) based on the Saffir-Simpson Hurricane Wind Scale using data from the National Oceanic and Atmospheric Administration (NOAA). As shown in Table 13, Hurricanes Sandy, Florence, Laura, and Irene are low-category hurricanes, while the rest of the hurricanes in our sample fall into the high-category group. We conduct separate event studies for these groups to analyze the cumulative abnormal returns (CARs) as shown in Table 14.

Insert Table 13 about here

Comparing the CARs between high and low category hurricanes reveals significant differences. In the initial [-10,-5] day window, both groups show negative CARs, with relatively similar percentages. However, as we approach the event date, the CARs for high category hurricanes become markedly more negative compared to those for low category hurricanes across all subsequent windows. This suggests that uncertainties surrounding hurricane severity in the days leading up to the event date result in relatively minor differences in CARs between high- and low-category hurricanes. As the event nears and more accurate predictions emerge, the market response intensifies, Culminating in larger abnormal returns.

In addition, we analyze non-hurricane events, revealing that CARs for wildfires and tornadoes are generally less negative compared to hurricanes. This may be due to two factors: (1) the geographically more limited impact of these disasters, and (2) the somewhat vague event date for wildfires which may have been building for weeks before reaching their peak strength. Moreover, in the [5,10] day window, all event studies demonstrate significantly positive CARs for both types of hurricanes (low and high category) and non-hurricane events, indicating potential market recovery post-event. Interestingly, the CARs are more positive for low category hurricanes (1.04%) than for high category hurricanes (0.22%) in this window, highlighting a nuanced market reaction influenced by hurricane severity.

These findings suggest that the severity of hurricanes significantly influences the financial outcomes for insurance companies, highlighting varied market responses within the insurance sector.

Insert Table 14 about here

6.3. The Stock Price Performance of Affected Insurance Firms

Our primary objective in this paper is to investigate the effects of major natural disasters on the entire insurance industry. To ensure the robustness of our findings, we also examine the impact on the most affected firms. We classify an insurance firm as 'affected' if its headquarters is located in a state struck by a disaster. This classification allows us to focus on firms that are likely to experience the most direct operational and financial disruptions.

Table 15 displays the mean cumulative abnormal returns (CARs) for affected insurance firms around natural disasters. The results confirm our main findings, showing significantly negative CARs around the disaster events. The negative CARs for affected firms are more pronounced compared to the overall sample of firms. This suggests that market reactions are more severe for firms directly impacted by the disasters, reflecting investors' heightened concerns about their immediate financial stability and future profitability. The CARs in the [5,10] window are positive, similar to our main results. This indicates a recovery period a few days after the events, as initial panic subsides, and investors reassess the firms' resilience and recovery prospects.

Insert Table 15 about here

7. Conclusions

Our study investigates the impact of natural disasters on the stock performance of U.S. insurance companies. The results reveal that natural disasters have a significant negative impact on the stock prices of insurance firms. This finding remains consistent across multiple event windows, with the [-5,0] window showing the most substantial negative mean CAR. These results suggest an efficient adverse market reaction as investors anticipate the financial repercussions of predictable events such as hurricanes on insurance companies.

In addition, we observe a positive and significant mean CAR in the [+5,+10] window, suggesting a market correction following the initial negative reaction. This rebound indicates that as more information about the actual damages and potential claims becomes available, investor sentiment improves, reflecting reduced uncertainty and the market's reassessment of the insurers' financial health. This pattern of initial negative effects followed by a positive correction highlights the dynamic nature of market responses to natural disasters.

Our analysis of individual events shows that hurricanes such as Harvey, Irma, Matthew, Michael, and Sandy caused significantly negative CARs across multiple windows, indicating a strong market reaction to these severe events. Events like Florence and Laura, and the 2011 Super Outbreak, exhibit a recovery in CARs in later windows, suggesting that initial market concerns alleviate as more accurate damage assessments emerge.

Our regression analysis indicates that higher leverage is associated with lower CARs, while profitability measures such as net income correlate positively with CARs, suggesting an increased resilience among profitable companies. Market valuation measures, such as the price-to-book ratio and Tobin's Q, which are positive in our results, indicate that firms with higher market valuations relative to their book values tend to experience a mitigating effect on CARs following natural disasters, suggesting that better market valuation helps buffer against adverse market reactions.

The interaction term between hurricanes and leverage suggests that leverage has a somewhat differential effect for different types of disasters, possibly due to expected higher premiums across a broad geographical area or increased government support. Not surprisingly, higher insured damages cause larger stock price declines, highlighting the financial burden of higher economic losses. Finally, categorizing hurricanes by severity shows that high-category hurricanes have a more pronounced negative impact on CARs compared to low-category hurricanes, emphasizing the importance of considering hurricane severity when assessing the financial outcomes for insurance companies.

We also find that natural disasters negatively affect the profitability of insurance firms, as evidenced by a significant decrease in their Return on Assets (ROA) post-disaster. The financial burden of insured damages contributes to this decline, although increased premium income post-disaster can help mitigate some of the negative effects.

Our research focuses on the US and natural disasters of hurricanes and wildfires. Future research could expand the scope by including a more diverse range of natural disasters and analyzing the impacts on insurance companies in different countries. Additionally, further studies could investigate the long-term effects of natural disasters on insurance firms' financial health and market performance.

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Tables and Figures

Table 1. Insurance Firm Sample

Insurance	SIC	Count
Fire, Marine, and Casualty Insurance	6331	113
Life Insurance	6311	58
Insurance Agents, Brokers and Service	6411	42
Accident and Health Insurance	6321	10
Total		223

Table 2. Sample of Natural Disasters from 2010 to 2022

Disaster	Event	Year	Affected States	Total Damage (Million USD)
Hurricane	Hurricane Harvey	2017	TX, LA	118,092
Hurricane	Hurricane Ian	2022	FL, NC	104,116
Hurricane	Hurricane Maria	2017	NJ, FL	91,619
Hurricane	Hurricane Ida	2021	LA, NY, NJ, MD, CT, VA, PA, DE	73,092
Hurricane	Hurricane Irma	2017	FL, SC, GA	70,855
Hurricane	Hurricane Sandy	2012	NY, NJ, PA, CT, OH, DE, RI, MD, MA, ME, NH, NC, VT, VA, DC, WV	66,357
Wildfire	Camp Fire	2018	CA	20,022
Hurricane	Hurricane Michael	2018	FL, GA, AL, NC, VA, MD	19,415
Hurricane	Hurricane Florence	2018	SC, NC, VA	16,988
Hurricane	Hurricane Laura	2020	LA, TX, AR, MS	15,305
Tornado	2011 Super Outbreak	2011	AL, AR, KY, MS, MO, TN, OK	14,901
Wildfire	Complex Fire	2020	CA, WA, OR, CO	12,950
Hurricane	Hurricane Matthew	2016	FL, GA, SC, NC, VA	12,696
Hurricane	Hurricane Irene	2011	NY, NJ, PA, NC, VA, MD, DC, CT, FL	10,889

The table presents the natural disasters between 2010 and 2022 that caused total damages exceeding $10,000 million, based on the EM-DAT database. It displays the event name, the year these events occurred, and the affected states in the U.S.

Table 3. Variable Definitions

Variable	Definition	Source
CAR	Cumulative abnormal return of an insurer during a specific window	EVENTUS
Leverage	Debt/asset ratio	Compustat
ROA	Net income(loss)/total asset ratio	Compustat
Net Income (Loss)	The natural logarithm of the net income (in millions of US dollars) plus a constant (6,085 million dollars), where the constant is the minimum amount for this variable in our sample, added to ensure all values are positive before transformation	Compustat
Firm Size	The natural logarithm of total assets (in millions of US dollars) plus 1	Compustat
Net Income to Equity	Net income (loss)/ stockholders' equity	Compustat
Price-to-Book	Market value of equity/stockholders' equity	Compustat
Tobin's Q	Market value of equity plus book value of liabilities divided by the book value of assets	Compustat
Insured Damage	Economic damage covered by insurance companies, in millions of US dollars, adjusted for inflation using the Consumer Price Index (CPI).	EM-DAT
Hurricane Dummy	Dummy variable that takes on a value of 1 if the event is a hurricane, and 0 otherwise	-
GDP per Capita	The natural logarithm of the gross domestic product per capita of the U.S., measured annually in US dollars	FRED
Affected State Dummy	Dummy variable that takes on a value of 1 when the headquarters of the insurance firm is located in a state affected by the event and 0 otherwise	Compustat

Table 4. Abnormal Stock Market Performance of Insurance Companies around Natural Disasters

Event Window	(1) N	(2) Mean CAR (%) (z-statistics)	(3) Negative CAR (%)
[-10,-5]	1,524	-0.18 (-3.74)***	57.55
[-5,0]	1,524	-0.47 (-4.80)***	55.91
[-1,+1]	1,524	-0.43 (-6.45)***	57.74
[0,+1]	1,524	-0.39 (-6.93)***	57.41
[0,+5]	1,524	-0.25 (-3.49)***	52.76
[+5,+10]	1,524	0.51 (5.47)***	44.16

The table presents the cumulative abnormal returns (CARs) during multiple event windows before and after natural disasters during the period 2010-2022. The results are based on a market model with an equally weighted market index. Column (1) shows the number of observations, Column (2) reports the mean CARs and the associated z-statistics in parentheses. Column (3) presents the percentage of negative CARs. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Table 5. Abnormal Stock Market Performance of Insurance Companies for each Individual Natural Disaster

		Event Window					
Event	N	[-10,-5]	[-5,0]	[-1,+1]	[0,+1]	[0,+5]	[+5,+10]
Hurricane Florence	105	-1.18 ***	0.37	0.98***	0.65***	-0.04	1.26***
		(-4.593)	(1.478)	(5.221)	(6.298)	(-0.459)	(3.817)
		71.43	34.29	25.71	24.76	53.33	31.43
Hurricane Harvey	108	-0.71***	-1.28***	-1.14***	-0.78***	-2.24***	-2.16***
		(-4.26)	(-6.35)	(-6.23)	(-4.99)	(-8.18)	(-4.93)
		62.04	82.41	82.41	78.70	84.26	68.52
Hurricane Ian	107	1.90*	-2.43***	1.90*	2.93**	2.97**	-2.23*
		(-2.21)	(3.76)	(4.59)	(2.21)	(4.16)	(1.86)
		50.2	45.8	45.8	48.8	44.6	47.0
Hurricane Ida	109	0.09	-2.49***	0.92	0.54	-0.80**	-0.36
		(1.54)	(-5.98)	(0.77)	(-0.27)	(-2.72)	(-0.29)
		42.20	78.90	61.47	65.14	71.56	48.62
Hurricane Irene	118	-0.21	1.99***	0.11	-0.14	-0.05	-0.43
		(0.46)	(6.61)	(0.01)	(-0.69)	(0.13)	(-1.09)
		49.15	26.27	51.69	55.93	43.22	54.24
Hurricane Irma	108	-1.92***	-5.26***	-3.39***	-2.92***	-1.59**	0.30
		(-7.96)	(-10.62)	(-9.56)	(-8.86)	(-2.76)	(-0.56)
		89.81	87.96	87.96	85.19	62.04	50.93
Hurricane Laura	106	-1.49***	-0.39	0.04*	0.60***	0.33*	2.32***
		(-4.10)	(0.95)	(2.22)	(4.53)	(1.81)	(3.48)
		68.87	38.68	39.62	31.13	48.11	33.02
Hurricane Maria	108	-2.12***	1.65***	0.35	-0.05	0.62**	-0.09
		(-4.69)	(3.34)	(0.69)	(-0.78)	(2.36)	(1.30)
		68.52	38.89	41.67	48.15	38.89	43.52
Hurricane Matthew	108	-0.29*	-0.86***	-0.91***	-0.31**	-1.64**	3.52***
		(-2.05)	(-4.98)	(-5.51)	(-2.78)	(3.06)	(11.96)
		59.26	70.37	75.00	67.43	67.59	11.11
Hurricane Michael	105	-0.36*	2.90***	-0.70***	-1.46***	-2.60***	1.21***
		(10.74)	(2.78)	(0.68)	(-5.95)	(-0.58)	(1.44)
		56.19	17.14	66.67	73.33	81.90	35.24
Hurricane Sandy	113	0.70***	-0.17	-1.72***	-1.18***	-1.35***	1.20***
		(3.173)	(-0.66)	(-5.38)	(-4.95)	(-4.47)	(4.14)
		41.59	46.02	75.22	73.45	69.91	30.97
Super Outbreak	117	-0.29***	-1.68***	-0.26	-0.04	0.26	0.03
		(-3.21)	(-7.40)	(-1.19)	(-0.43)	(1.62)	(0.08)
		64.10	76.07	56.41	55.56	42.74	49.57
Complex Fire	107	2.14**	0.17*	-0.93***	-0.87***	0.08	0.51**
		(2.38)	(-1.80)	(-4.38)	(-4.70)	(0.82)	(2.65)
		41.12	68.22	62.62	70.09	45.79	35.51
Camp Fire	105	1.16**	0.86**	0.66***	0.34***	-0.29	0.82**
		(2.45)	(2.48)	(3.44)	(3.25)	(1.33)	(2.33)
		47.62	43.81	35.24	33.33	33.33	38.10

This table presents the event study results for each individual natural disaster in our sample. It displays the cumulative abnormal returns (CARs) across six different windows, accompanied by their respective z-statistics in parentheses. The percentage of negative CARs is also noted below the z-statistics. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Table 6. Summary Statistics

Variables	N	Mean	Median	Min	Max	Standard deviation
[0,5] CAR	1,496	-0.002	-0.002	-0.521	2.065	0.076
Leverage	1,496	0.087	0.054	0.001	2.912	0.163
ROA	1,496	0.017	0.017	-0.962	0.519	0.073
Net Income (Loss) (US$ billion)	1,496	0.539	0.106	-6.084	17.798	1.312
Firm Size (US$ billion)	1,496	62.988	6.454	0.009	940.722	155.382
Net Income to Equity	1,496	0.056	0.080	-2.870	2.414	0.216
Price to Book	1,496	1.691	1.126	0.101	55.751	2.278
Tobin's Q	1,496	1.286	1.022	0.556	13.494	0.921
Insured Damage (US$ billion)	1,496	20.473	11.773	4.300	62.469	16.943
GDP per Capita (US$ thousands)	1,496	59.676	58.636	49.256	74.082	6.903

The table displays the summary statistics for all dependent and independent variables used in our study.

Table 7. Variance Inflation Factors

Variable	VIF	1/VIF
Leverage	3.93	0.25
ROA	1.76	0.56
Net Income (Loss)	1.02	0.97
Firm Size	1.14	0.87
Net Income to Equity	2.03	0.49
Price to Book	1.43	0.70
Tobin's Q	1.30	0.77
Insured Damage	1.51	0.66
Hurricane Dummy	1.31	0.76
Hurricane × Leverage	3.77	0.26
GDP per Capita	1.55	0.64
Affected State Dummy	1.08	0.92

Table 8. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Leverage	1.000										
(2) ROA	0.309**	1.000									
(3) Net Income	-0.003	0.053*	1.000								
(4) Firm Size	-0.188**	0.041	0.110**	1.000							
(5) Net income/Equity	-0.101**	0.482**	0.110**	0.159**	1.000						
(6) Price to Book	-0.075**	0.007**	0.017	-0.006	0.459**	1.000					
(7) Tobin's Q	0.382**	0.238**	-0.004	-0.246**	-0.033	-0.121**	1.000				
(8) Insured Damage	0.016	-0.032	0.020	0.007	-0.011	0.072**	0.071**	1.000			
(9) GDP	0.053*	-0.064*	0.010	0.024	-0.006	0.102**	0.128**	0.567**	1.000		
(10) Hurricane	-0.007	-0.023	0.005	-0.001	-0.020	0.017	0.000	0.168**	0.092**	1.000	
(11) Affected State	-0.002	-0.008	-0.003	-0.052*	-0.066*	-0.043	0.019	-0.099**	-0.159**	0.176**	1.000

Table 9. Regressions Results on CAR [0,5]

VARIABLES	(1)	(2)	(3)	(4)
Leverage	-0.140***	-0.137***	-0.236**	-0.140***
	(-4.384)	(-4.635)	(-2.196)	(-4.945)
ROA	0.157	0.152	0.172	0.149
	(1.161)	(1.198)	(1.013)	(1.167)
Net Income (Loss)	0.009***	0.007**	0.088**	0.007**
	(2.619)	(2.136)	(2.499)	(2.106)
Firm Size	0.002***	0.003**	-0.007	0.003**
	(2.827)	(2.445)	(-0.809)	(2.455)
Net Income to Equity	-0.155*	-0.157*	-0.225*	-0.156*
	(-1.748)	(-1.843)	(-1.682)	(-1.825)
Price to Book	0.004*	0.004*	0.007*	0.004*
	(1.879)	(1.868)	(1.661)	(1.692)
Tobin's Q	0.007**	0.008*	0.007	0.006
	(2.350)	(1.721)	(0.766)	(1.194)
Insured Damage	-0.005**	-0.015***	-0.016***	-0.015***
	(-2.059)	(-2.732)	(-2.848)	(-2.723)
Hurricane Dummy	-0.014***	-0.020***	-0.021***	-0.020***
	(-3.716)	(-4.330)	(-4.375)	(-4.269)
Hurricane × Leverage	0.117***	0.116***	0.119***	0.115***
	(5.339)	(8.385)	(8.114)	(8.356)
GDP per Capita	0.033	0.129**	0.127**	0.129**
	(1.368)	(2.282)	(2.118)	(2.283)
Affected State Dummy	-0.005	-0.005	-0.004	-0.005
	(-0.719)	(-0.699)	(-0.504)	(-0.710)
Constant	-0.404	-1.335**	-0.553	-1.329**
	(-1.431)	(-2.227)	(-1.643)	(-2.209)
Observations	1,496	1,496	1,496	1,496
Year fixed effects	No	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	No
Industry fixed effects	No	No	No	Yes
R-squared	0.120	0.140	0.185	0.142

The table presents OLS regression results for a regression of insurers' CARs on various explanatory factors. The dependent variable is the cumulative abnormal return (CAR) in the window [0,5]. **Leverage** is measured as total debt divided by total assets. **ROA** is calculated as the ratio of total net income (loss) to total assets. **Net income (loss)** is the natural logarithm of the net income (in millions of US dollars) plus a constant (6,085 million dollars), where the constant is the minimum amount for this variable in our sample, added to ensure all values are positive before transformation. **Firm Size** is the natural logarithm of total assets (in millions of US dollars) plus 1. **Net Income to Equity** is the net income (loss) divided by stockholders' equity. **Price to Book** is defined as the market value of equity divided by the stockholders' equity. **Tobin's Q** is measured as the market value of equity plus the book value of liabilities divided by the book value of assets. **Hurricane** is a dummy variable that takes on a value of 1 if the event is a hurricane, and 0 otherwise. **Hurricane × Leverage** represents the interaction between the hurricane dummy and the leverage ratio. **Insured Damage** represents the economic damage stemming from a given disaster that is covered by insurance companies, in millions of US dollars, adjusted for inflation using the consumer price index (CPI). **GDP per Capita** is calculated as the natural logarithm of the gross domestic product per capita of the U.S., measured annually in US dollars **Affected State** is a dummy variable that takes on a value of 1 when the headquarters of the insurance firm is located in a state affected by the event and 0 otherwise. Model (1) reports the results with robust standard errors. Model (2) displays the results with year-fixed effects and clustered standard errors. Model (3) represents the results using a fixed effects model with both firm and year-fixed effects. Model (4) shows the results considering both year and industry-fixed effects with clustered standard errors. T-statistics are shown in parentheses. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Table 10. Paired T-Test Results for ROA Before and After Natural Disasters

	obs	Mean1	Mean2	dif	St Err	t value	p value
ROA (ex) – ROA (post)	1394	.0185	0.0135	.0049	.00025	2.15	.0335

Table 11. Regressions Results on ROA Changes

VARIABLES	(1)	(2)	(3)	(4)
Δ Insurance Premium	0.008***	0.010**	0.008*	0.011***
	(2.897)	(2.555)	(1.768)	(3.109)
Insured Damage	-0.012***	-0.006**	-0.005**	-0.005**
	(-4.726)	(-2.524)	(-2.154)	(-2.369)
Leverage	-0.717***	-0.750***	-0.736***	-0.658***
	(-3.501)	(-4.384)	(-2.836)	(-3.830)
Firm Size	0.004***	0.004***	-0.022	0.004***
	(4.672)	(3.189)	(-1.290)	(3.201)
Net Income to Equity	-0.133***	-0.136***	-0.205**	-0.134***
	(-4.550)	(-3.493)	(-2.408)	(-3.311)
Price to Book	0.003***	0.003	0.006**	0.003
	(2.608)	(1.579)	(2.005)	(1.466)
Asset Turnover	0.036***	0.035***	-0.013	0.023*
	(3.401)	(3.019)	(-0.229)	(1.810)
Cash Flow to Debt	-0.084***	-0.084***	-0.070	-0.089***
	(-2.648)	(-3.608)	(-1.088)	(-3.899)
Leverage × Insured Damage	0.062***	0.066***	0.051*	0.055***
	(2.748)	(3.768)	(1.894)	(2.973)
Constant	0.081***	0.025	0.265*	0.019
	(3.606)	(1.010)	(1.701)	(0.839)
Observations	1,054	1,054	1,054	1,054
Year fixed effects	No	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	No
Industry fixed effects	No	No	No	Yes
R-squared	0.347	0.362	0.302	0.372

The table presents OLS regression results for a regression of changes of ROA on various explanatory factors. The dependent variable is **ΔROA** which is calculated as the difference between ROA of the year after the natural disaster (T+1) and the year preceding the natural disaster (T-1). ROA is calculated as the ratio of total net income (loss) to total assets. Independent variables: **Δ Insurance Premium** is defined as the natural logarithm of one plus the percentage change in premiums from the year before the disaster to the year after the disaster. **Insured Damage** represents the economic damage stemming from a given disaster that is covered by insurance companies, in millions of US dollars, adjusted for inflation using the consumer price index (CPI). **Leverage** is measured as total debt divided by total assets. **Firm Size** is measured as the natural logarithm of total assets (in millions of US dollars) plus 1. **Net Income to Equity** is the net income (loss) divided by stockholders' equity. **Price to Book** is defined as the market value of equity divided by the stockholders' equity. **Asset Turnover** is defined as net Sales divided by average total assets. **Cash Flow to Debt** is cash flow from operations divided by total debt. **Leverage × Insured Damage** represents the interaction between the leverage and insured damage. Model (1) reports the results with robust standard errors. Model (2) displays the results with year-fixed effects and clustered standard errors. Model (3) represents the results using a fixed effects model with both firm and year-fixed effects. Model (4) shows the results considering both year and industry-fixed effects with clustered standard errors. T-statistics are shown in parentheses. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Table 12. Abnormal Stock Market Performance of Insurance Companies Around Natural Disasters – Fama-French Model

Event Window	(1) N	(2) Mean CAR (%) (z-statistics)	(3) Negative CAR (%)
[-10,-5]	1,524	-0.21 (-4.06)***	58.53
[-5,0]	1,524	-0.47 (-5.02)***	56.10
[-1,+1]	1,524	-0.39 (-5.96)***	57.55
[0,+1]	1,524	-0.33 (-6.08)***	56.23
[0,+5]	1,524	-0.40 (-3.17)***	54.20
[+5,+10]	1,524	0.44 (5.58)***	43.10

The table represents the cumulative abnormal returns (CAR) during multiple event windows before and after a natural disaster during the period 2010-2022. The results are based on Fama-French model abnormal returns, using an equally weighted market index. Column (1) shows the number of observations, Column (2) reports the mean CARs with z-statistics in parentheses. Column (3) presents the percentage of negative CARs. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Table 13. Hurricane Categories

Event	Category
Hurricane Harvey	4
Hurricane Ian	4
Hurricane Maria	4
Hurricane Irma	4
Hurricane Ida	4
Hurricane Sandy	1
Hurricane Michael	4
Hurricane Florence	3
Hurricane Laura	3
Hurricane Matthew	5
Hurricane Irene	1

Table 14. Cumulative Abnormal Returns for High- and Low- Category Hurricanes and Non-Hurricane Events

		Event Window					
Event	N	[-10,-5]	[-5,0]	[-1,+1]	[0,+1]	[0,+5]	[+5,+10]
High-category hurricanes	753	-0.49***	-1.12***	-0.70***	-0.68***	-0.35**	0.22*
		(-6.382)	(-7.284)	(-8.394)	(-8.952)	(-2.854)	(2.147)
		60.42	64.28	65.74	65.34	57.50	22.34
Low-category hurricanes	442	-0.51	0.48***	-0.17	-0.04	-0.29*	1.04***
		(-0.950)	(4.826)	(-0.710)	(-0.209)	(-2.044)	(5.239)
		57.24	36.20	48.64	47.06	53.62	10.97
Non-hurricane events	329	0.96*	-0.27**	-0.18	-0.19	0.03**	0.44**
		(1.721)	(-2.698)	(0.400)	(-0.087)	(2.256)	(2.550)
		51.37	63.22	51.67	53.19	40.73	8.94

This table presents the event study results for different categories of hurricanes. The first group includes category 1, 2, and 3 hurricanes. The second group consists of category 4 and 5 hurricanes. The table displays the cumulative abnormal returns (CARs) across six different windows, accompanied by their respective z-statistics in parentheses. The percentage of negative CARs is also noted below the z-statistics. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Table 15. Abnormal Stock Market Performance of Affected Insurance Companies around Natural Disasters

Event Window	(1) N	(2) Mean CAR (%) (z-statistics)	(3) Negative CAR (%)
[-10,-5]	266	-0.16 (2.25)*	53.01
[-5,0]	266	-0.86 (-1.86)*	56.02
[-1,+1]	266	-1.30 (-7.26)***	64.66
[0,+1]	266	-0.94 (-7.17)***	63.53
[0,+5]	266	-0.52 (-3.84)***	62.78
[+5,+10]	266	0.67 (2.27)*	40.23

The table presents the cumulative abnormal returns (CARs) during multiple event windows before and after natural disasters during the period 2010-2022. The results are based on a market model with an equally weighted market index. Column (1) shows the number of observations, Column (2) reports the mean CARs and the associated z-statistics in parentheses. Column (3) presents the percentage of negative CARs. Significance levels are denoted by ***, **, and *, indicating 1%, 5%, and 10% significance, respectively.

Figures

Figure 1. Cumulative Abnormal Return from Day -10 to Day +10