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Impact of hurricanes on US insurance stocks

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Abstract

This paper analyzes the impact of hurricanes on insurance stock returns in the United States. The objective is to assess the reaction of insurance stock prices caused by hurricanes using an extensive data sample consisting of the costliest hurricanes since 2004. We aim to understand the insurance stock price reactions and provide possible explanations for the observed results. The main outcome is a negative abnormal return for all examined time windows. Analyses of impact factors show that high-category hurricanes have more negative abnormal returns in comparison to low-category hurricanes. The latter category is even positively correlated with the cumulative abnormal return. The regression model indicates a statistically significant negative correlation between the cumulative abnormal return and the damage caused by the hurricane.

1 | INTRODUCTION

1.1 | Background

One of the most threatening extreme weather phenomena is hurricanes, tropical cyclones that typically threaten the US east coast and the Caribbean (World Economic Forum, 2019, p. 5). Hurricanes are also among the costliest catastrophic events. Hurricane Katrina, one of the worst hurricanes in history, caused more than 100 billion USD of damage (Howerton & Bacon, 2017,

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p. 12). For individuals and companies, insurance might be salvation after hurricanes, whereas the requirement to pay resulting claims might turn into a challenge for insurers. Claim requests after natural disasters especially affect property and liability (P&L) insurers as homeowner's insurance policies typically include the coverage of wind as one type of peril (Insurance Information Institute, 2021). In the case of Hurricane Katrina: about 62 billion USD of its damage was insured (Munich Re, 2021).

Throughout the last decades, both the severity and frequency of natural disasters increased significantly. The risk of extreme weather events interconnects with the failure of climate change adaptation and mitigation (World Economic Forum, 2019, p. 15). Climate change leads to a higher likelihood of hurricanes (Holland & Bruyère, 2014, p. 625). The coastal development, especially an increased population living in these areas, enables hurricanes to cause more damage (Congressional Budget Office, 2016, pp. 5–6). These increases in frequency and severity could evolve into a major negative financial impact on insurance companies. Although the hurricane season is recurring and predictable, the occurrence and impact of individual hurricanes are still not fully predictable. There is a great concern among investors about whether insurance companies will be able to cope with catastrophic weather events in the future (Born & Viscusi, 2006, p. 56). Insurance firms should be able to effectively and efficiently absorb losses after catastrophes to sustain their long-term value. Therefore, understanding the implications of hurricanes and possible impact factors is of great importance for insurance companies and investors. At first glance, it seems obvious that severe hurricane events are a threat to insurers and should therefore also have a clear negative influence on the stock value of insurance companies. But diving deeper into the topic, reinsurance solutions and demand effects linked to the foreseeable damages of a hurricane could also have positive effects on insurance stocks.

1.2 | Research objective

Previous studies focus either on stock market implications of individual hurricanes, such as hurricane Katrina or Andrew (Angbazo & Narayanan, 1996, p. 622; Howerton & Bacon, 2017, p. 13) or on the effects that a data sample with diverse catastrophe types imply (Born & Viscusi, 2006, p. 57; Hagedorff et al., 2015, p. 159). An identified research gap is how insurance companies react to a group of hurricanes as one type of natural disaster because most previous studies focus on discrete analyses of single events or various catastrophe types. This paper focuses on hurricanes solely and includes a more extensive data sample, consisting of the costliest and most recent hurricanes¹ in the United States. Our goal is to answer the following research question:

1.2.1 | How do stock prices of US insurers react to the costliest hurricanes since 2004?

We aim to ascertain the general reaction of insurance stock prices triggered by hurricanes. Additionally, the goal is to better understand the drivers of abnormal returns. Thus, the

¹This paper includes hurricanes since 2004 as most previous literature focused on earlier hurricanes. Additionally, adjusted costs (based on the 2020 Consumer price index) from the database with the costliest tropical cyclones in the United States (National Centers for Environmental Information [NCEI] & National Hurricane Center [NHC], 2020, p. 2) have to be over 10 billion USD.

cross-sectional regression model of this paper investigates the impact of various independent variables, namely, the hurricane category, hurricane damage, and S&P 500 (Standard & Poor's index) membership, on the observed cumulative abnormal return. To sum up, this paper contributes to understanding the insurance stock price reactions due to hurricanes and provides possible explanations for the observed results.

1.3 | Paper structure

The remainder of this paper is organized as follows: Section 2 discusses the theoretical foundations of the implications of hurricanes on insurance companies before hypotheses concerning the corresponding stock price reactions are derived. Next, Section 3 describes the underlying data set before Section 4 outlines the applied event study methodology and linear regression model. Section 5 illustrates our event study and regression results. Section 6 discusses the empirical findings and possible explanations. The last section gives a short conclusion and outlines limitations, implications, and suggestions for further research.

2 | LITERATURE REVIEW AND HYPOTHESES

The following literature review focuses on existing studies that investigate the financial impact of hurricanes. Angbazo and Narayanan (1996, p. 628) identify a statistically significant negative reaction of P&L insurers on and after the day of hurricane Andrew's landfall. Their observation shows that the negative reaction includes a positive and counteracting effect for an anticipated premium increase (Angbazo & Narayanan, 1996, p. 628).

Hurricane Katrina made landfall in August 2005 and caused more than 100 billion USD of damage (Howerton & Bacon, 2017, p. 12). The study of 10 P&L insurers with coverage in the affected areas shows a semistrong market efficiency as the stock prices react fast to public information around the event. Statistically significant negative risk-adjusted returns of -0.02% prevail in the $[-30; +30]$ day period around the event (Howerton & Bacon, 2017, p. 14, p. 16).

The data set of Born and Viscusi (2006, p. 71) comprises natural catastrophic events (floods, storms, fires, earthquakes) and every firm that writes homeowners' insurance coverage in the United States from 1984 to 2004 classified by state. They examine the 20 most devastating events, including 12 hurricanes, with the conjecture that the insurers did not fully anticipate these catastrophes and their severity (Born & Viscusi, 2006, pp. 57–59). The regression analysis includes (among others) three independent variables regarding unexpected catastrophes,² which have a statistically significant positive effect on the probability of insurance firms terminating business after catastrophes (Born & Viscusi, 2006, p. 69). The paper clarifies that catastrophic events hit insurers hard and lead to an increase in losses as a response to catastrophic events (Born & Viscusi, 2006, pp. 69–71).

Lamb (1995, p. 116) demonstrates that investors efficiently access the information generated by Hurricane Andrew in 1992, as the market response is concentrated on Days 0 and +1 after the hurricane struck Florida's coast. Additionally, investors can distinguish P&L insurers

²The variable "unexpected catastrophe" is defined by Born and Viscusi (2006, p. 61) as "the difference between the number of actual catastrophic events in a given year and the average number of catastrophic events in that state over the 1984–2004 period." The regression model includes this variable not only in the year of the dependent variable, but also for the two previous years.

according to their number and volume of written insurance policies. Firms with business in the most exposed states (Florida and Louisiana) obtain significant negative returns (-0.05%) over the 2 days on and after landfall (Lamb, 1995, p. 117, p. 120). Three years later, Lamb again examines hurricane Andrew to compare it with hurricane Hugo, concluding that Andrew caused approximately three times the damage of Hugo. Hurricane Hugo and Andrew led to different market reactions for P&L firms, providing evidence that the market can discriminate by hurricane magnitude (Lamb, 1998, p. 168, p. 171).

The study of Hagendorff et al. (2015, pp. 159–160) investigates the effect of megacatastrophes in the United States on 57 publicly traded P&L insurers in the period from 1996 to 2010. Nine of the 19 catastrophes in the sample are hurricanes. The analysis from Hagendorff et al. (2015, p. 162) reveals negative performance implications of -0.28% (1% significance level) for the time window $[0;+1]$. The researchers conducted a multivariate regression analysis to identify factors that determine the observed market reactions of insurers in the $[0;+15]$ period. A significant negative relationship exists between catastrophe size, measured as total insured loss in constant 2010 USD terms and insurers' stock price reaction, as anticipated by the researchers. As an additional dummy variable, Hagendorff et al. (2015, p. 167) study the relationship between the insurance company's Standard and Poor's rating and abnormal returns. They find a positive (between 0.014 and 0.034) correlation. Insurers with a rating of AA or better would have less negative abnormal returns. However, this result is nonsignificant.

Lanfeer et al. (2017) investigate how stock price reactions after hurricanes vary for different decile portfolios. They use a sample of 34 hurricanes making landfall between 1990 and 2014 in the United States. The database includes stock data of NYSE and NASDAQ listed companies, sorted into decile portfolios regarding market equity (Panel A) and book-to-market equity (Panel B). The main finding of Panel A is that abnormal returns due to hurricanes are negatively related to firms' size. Firms of smaller size face more negative abnormal returns than firms of a bigger size. The magnitude of the negative effect is generally decreasing when moving from smaller to larger stock-size portfolios (Lanfeer et al., 2017, p. 15). Results for the book-to-market equity ratio (Panel B) indicate that growth stocks (low book equity/market equity) and value stocks (high book equity/market equity) suffer larger negative abnormal returns compared to portfolios in the middle of the decile range.

Likewise, Gangopadhyay et al. (2010, p. 147) find empirical evidence for an efficient adjustment of stock prices concerning the new information from hurricanes Katrina and Rita. The observed negative abnormal returns of hurricane Katrina align closely with the press releases (Gangopadhyay et al., 2010, p. 142). Both exposed and unexposed insurers react in the same direction, indicating that contagion effects on unexposed firms exist (Gangopadhyay et al., 2010, p. 148). Nevertheless, for the $[0;+1]$ time window on and after landfall, exposed insurers react more severely with a stock price reaction of -1.55% compared to unexposed insurers with -0.98% , both at a 5% significance level (Gangopadhyay et al., 2010, p. 145). The regression indicates that market capitalization has no significant impact on the cumulated abnormal return in the $[-1;+1]$ window (Gangopadhyay et al., 2010, p. 143).

The evaluation of US insurance stock reactions after individual catastrophes reveals manifold insights. First, hurricanes mostly lead to negative stock price reactions. Second, when examining various hurricanes, the magnitude and timing of the reactions differ, although a tendency to observe negative stock price reactions persists. In this paper, several hypotheses are set up to analyze the research question of how stock prices of US insurers react to the costliest hurricanes since 2004. The goal is to extend knowledge of the empirically varying results in previous literature with a more extensive data set.

Shelor et al. (1992, p. 477) published one of the first papers that refers to the “damage” and “revenue” hypothesis³ to explain the impact of catastrophes on insurance firms’ value. Further studies that examine the effect of catastrophes on stock prices, for example, Gangopadhyay et al. (2010, p. 143), similarly refer to the opposing damage and revenue hypotheses. The “damage” hypothesis represents the theory that catastrophes have a negative impact on the firm value of insurers because insurers need to handle claim payments for damages to policyholders. This expectation of losses can lead to a decline in insurance stock prices. Contrary, the “revenue” hypothesis states that catastrophes lead to an increase in stock prices because insurance firms may benefit from catastrophes via demand effects or premium increases.⁴ The positive effect of the revenue hypothesis counterbalances the negative effect of the damage hypothesis (Shelor et al., 1992, p. 477). Although previous literature is consistent with the two hypotheses, the results about the dominating effect after disasters are still inconsistent. Our first hypothesis investigates which of the counteracting effects dominates and leads to positive/negative abnormal returns.

H1: Hurricanes generate a negative abnormal return for insurance stocks.

In this study, hurricanes are differentiated into five categories according to their strength.⁵ The second hypothesis investigates whether a difference in abnormal return generation occurs depending on the respective hurricane category. To test this hypothesis, hurricanes from the two highest categories (4 or 5), the middle (3) and the two lowest categories (1 or 2), are compared. One would expect that hurricanes from a higher category, thus with higher wind speeds, lead to more negative stock returns due to possibly higher resulting claims. This expectation is in line with the damage hypothesis. More negative abnormal returns for higher-category hurricanes can result if either the damage hypothesis increases or the revenue hypothesis decreases. The analysis of the hurricane category helps to achieve the goal to shed light on the influencing factors for stock price reactions to anticipated hurricanes, as the hurricane category is observable before the event date. To understand this effect, the following hypothesis is tested:

H2: High-category hurricanes have more negative abnormal returns than low-category hurricanes.

A related question to the hurricane category (Hypothesis 2) is whether the financial damage a hurricane causes correlates with abnormal returns. For this examination, firstly, the three most impactful hurricanes with respect to their damage (measured in billion USD based on the 2020 consumer price index) are compared with the remaining hurricanes in the sample. Second, the regression analysis investigates the prevalence of a correlation between hurricane damage and cumulative abnormal return. In contrast to Hypothesis 2, the damage caused by the hurricane is only observable after the hurricane event. Hagedorff et al. (2015, p. 167) study

³This paper defines the hypotheses from Shelor et al. (1992) as “revenue” and “damage” hypothesis.

⁴In early 2007, Florida enacted legislation that sought to increase regulatory control over insurance rates and claims adjustment. This pressures insurers to lower their prices, which reduces the effect of premium increases. At the same time, especially relevant in the context of catastrophe risk, regulators may pressure insurers to make more generous claims payments and pay claims more quickly, which increases the demand effect (Grace & Klein, 2009; pp. 107–109).

⁵The hurricane category is derived from the Saffir–Simpson Hurricane Wind Scale. A hurricane is classified in the respective category based on the sustained winds (see section “hurricane data”).

the impact of the catastrophe size, measured by the total insured loss. This paper seizes that suggestion and wants to fill the gap of missing research regarding the overall hurricane damage costs. Insured as well as uninsured costs are considered in the damage estimate. The tested hypothesis is:

H3: More damaging hurricanes have more negative abnormal returns.

Lanfear et al. (2017, p. 15) and Gangopadhyay et al. (2010, p. 146) investigate the impact of extreme weather events on stocks, controlled by various capitalization and income variables. Lanfear et al. (2017, p. 15) state that microstocks have more negative abnormal returns on hurricanes compared to larger stocks. This paper uses the S&P 500 index membership during the assessed period of this event study as a market capitalization indicator. The following hypothesis has the goal to clarify the controversial findings from previous studies regarding the significance level of a capitalization approximation on abnormal returns:

H4: The S&P 500 membership has a positive impact on abnormal returns after hurricanes.

3 | DATA

3.1 | Hurricane data

This paper restricts the sample of hurricanes to the United States as a geographic region because this country is susceptible to hurricanes. Hurricanes occur not only frequently but also devastatingly (National Hurricane Center [NHC] & Central Pacific Hurricane Center [CPHC], n.d.). Additionally, this paper narrows down the scope to the costliest hurricanes with adjusted costs of over 10 billion USD. The database of “costliest tropical cyclones to impact the United States” from the National Oceanic and Atmospheric Administration (NCEI & NHC, 2020) provides hurricane data. In this sample, 16 out of the 21 costliest US hurricanes occurred between 2004 and 2018 (NCEI & NHC, 2020, p. 2). Thus, the focus of this paper is set on the 16 most recent and costliest hurricanes from the initial database. Table 1 shows the selected hurricanes with their date of landfall, hurricane category, and adjusted costs based on the 2020 consumer price index. The date of landfall is retrieved from the National Weather Service website (<https://www.weather.gov>) and sets the day when the hurricane made its first continental landfall in the United States (Puerto Rico for hurricane Maria).

As hurricane Ike occurred during the financial crisis in 2008, a time of unique market conditions, it is reasonable to exclude this hurricane from the analysis to prevent distortion of the results. Due to partly overlapping event windows, hurricanes Ivan and Irma are eliminated to ensure a spread of more than 10 trading days between the events. Thus, the final sample consists of 13 hurricanes since 2004.

To accomplish a precise analysis, the event date (day of landfall) has to be adjusted for hurricanes Katrina, Harvey, and Sandy to the day after the actual landfall. This is necessary as hurricane landfall occurred in the late evening when the stock market was already closed (trading hours: 9:30 a.m. until 4:00 p.m. ET). Furthermore, if the day of landfall falls on a

TABLE 1 List of the costliest hurricanes since 2004

Hurricane	Adjusted damage costs (based on 2020 Consumer Price Index)	Date of landfall (as reported by https://www.weather.gov)	Hurricane category
Katrina	170.0 bn USD	25.08.2005	3
Harvey	131.3 bn USD	25.08.2017	4
Maria	94.5 bn USD	20.09.2017	4
Sandy	74.1 bn USD	29.10.2012	1
Irma	52.5 bn USD	10.09.2017	4
Ike	36.9 bn USD	13.09.2008	2
Ivan	28.7 bn USD	16.09.2004	3
Wilma	25.8 bn USD	24.10.2005	3
Michael	25.5 bn USD	10.10.2018	5
Rita	25.2 bn USD	24.09.2005	3
Florence	24.5 bn USD	14.09.2018	1
Charley	22.4 bn USD	13.08.2004	4
Irene	15.8 bn USD	27.08.2011	1
Frances	13.7 bn USD	05.09.2004	2
Matthew	10.9 bn USD	08.10.2016	1
Jeanne	10.5 bn USD	26.09.2004	3

Source: Based on NCEI and NHC (2020, p. 2).

TABLE 2 Hurricane category

Category	Sustained Winds	Hurricane damage
1	119–153 km/h	Very dangerous winds produce some damage
2	154–177 km/h	Extremely dangerous wind causes extensive damage
3	178–208 km/h	Devastating damage occurs
4	209–251 km/h	Catastrophic damage occurs
5	252 km/h or higher	Catastrophic damage occurs

Source: Based on NHC and CPHC (n.d.).

nontrading day (e.g., weekend or public holiday), the event date is shifted to the first following trading day after the actual (reported) day of landfall.

A further distinction between the events is the hurricane category, which is derived from the Saffir–Simpson Hurricane Wind Scale. The categories range from 1 to 5, based on a hurricane's sustained wind speed (NHC & CPHC, n.d.). Table 2 presents the categories and their respective potential property damage. For the regression model, hurricanes of Categories 1 and 2 are summarized as an independent variable *Category_low*. Catastrophic hurricanes of Categories 4 and 5 are summarized as variable *Category_high*.

3.2 | Stock data

Besides event data, the second pillar to conduct an event study analysis is the daily prices of the sample stocks and chosen index. Stock and index prices are extracted from Thomson Reuters Datastream. The selection of insurance companies is based on the sample from Hagendorff et al. (2015, p. 170), including 57 publicly traded P&L insurers that earned positive premiums in the homeowners' business line from 1996 until 2010. From the original sample, 34 insurers provide stock data for the assessed period of this event study (end of 2003 until 2018). Two more companies are excluded due to their illiquid stocks. To ensure that all firms from the final sample are potentially exposed to the hurricanes in our analysis, the annual report of each company was reviewed with the finding that generally all considered firms include hurricane damages in their portfolio. Thirty-two firms represent the final company sample of this paper (see Table A1).⁶

4 | EMPIRICAL MODEL AND METHODOLOGY

4.1 | Event study methodology

This paper uses the event study methodology to empirically assess the effect of hurricanes on US insurance stock prices. The event's impact is measured with abnormal stock market returns that are attributable to the hurricane events. The impact of an event can be quantified as the delta of the expected stock price that would have been realized without any unanticipated events and the actual stock price after the event's appearance.

MacKinlay (1997, p. 37) states that an "important characteristic of a successful event study is the ability to identify the date of the event precisely." This clear event date definition is especially important for hurricanes as investor stock price expectations adjust as the hurricane evolves and approaches landfall. Likewise, Lamb (1998, p. 171) shows that investors incorporate the produced new information about hurricanes quickly in the market, as abnormal returns are concentrated on the 2 days after hurricane Andrew's landfall. Generally, hurricanes are not unexpected events as the existence of the storm is already known before landfall (Cagle, 1996, p. 60). The hurricane category can be observed before landfall. Nevertheless, the realized magnitude of the damage through the hurricane may be unexpected and different from the anticipated value. The actual damage will be revealed after landfall when the actual magnitude becomes observable and reports of damage are available (Cagle, 1996, p. 60). Thus, the date of landfall is relevant for the damage event that includes some uncertainty. This paper sets the event date t_0 (Day 0) as the date of hurricane landfall in the United States, which is defined by the National Hurricane Center as the date when the center of a hurricane hits the coastline (NHC & CPHC, n.d.). To isolate the effect of hurricanes the event window covers two trading days, $[0; +1]$, the day of and the day after landfall. This time window does not only capture immediate responses on the day of hurricane landfall but also incorporates slightly delayed information. This is beneficial, as costs of damage are not

⁶Berkshire Hathaway and Donegal Group list class A and B stocks. Berkshire Hathaway class A stocks are excluded. Due to the ongoing high price (Datastream, 2020) they could react differently to the events. For Donegal Group, Class B stocks are excluded because Donegal Mutual held approximately 85% of the outstanding Class B common stocks, but only 40% of the outstanding Class A common stocks (Donegal Group Inc., 2020, p. 1). Thus, due to the higher free float percentage, Class A is more suitable for an analysis as they better represent the market and can react to external influences.

necessarily fully transparent on the day of landfall. At the same time, this window minimizes the amount of time in which other factors may influence the results. To include possible further delayed reactions, the regression analysis is performed with the $[0;+5]$ time window. Additionally, the event window lengths $[-5;+5]$, $[-2;+2]$, and $[0;+10]$ extend the analysis of this paper to cross-check findings with event windows besides the typical periods.

There is no clear consensus regarding the optimal length of the estimation window when conducting an event study with daily stock data. For example, Lamb (1995, p. 114; 1998, p. 166) uses a 150-day trading period as an estimation window, ending 10 days before landfall to avoid contamination through anticipation of the hurricane's impact. Angbazo and Narayanan (1996, p. 623) use an estimation period of 110 days (Days -120 to -11) for their calculation. Lanfear et al. (2017, p. 12) define the estimation window based on the Atlantic hurricane season. This method is especially suitable when multiple hurricanes occur in the same year to avoid a confounding influence of other hurricanes in the estimation window. The Atlantic hurricane season lasts from June 1st until November 30th (NHC & CPHC, n.d.). Thus, the period outside and before the hurricane season, December 1st until May 31st, determines the estimation window.

This paper uses the framework from Lanfear et al. (2017) and determines its applicability. The general US hurricane season will be adjusted to ensure that all estimation windows are outside the hurricane season. Therefore, the latest landfall date of the event data set (October 29) determines the adjusted hurricane season end date. Whereas the earliest date of the data sample (August 13) sets the start date of the adjusted hurricane season. To ensure that all estimation windows are before and outside the adjusted hurricane season, the nonhurricane season is extended from mid-November until mid-July. As a result, the estimation window $[-188;-77]$ includes 110 trading days. The window starts 78 days before the event date to avoid abnormal return contaminations of other hurricanes.

The normal return in the estimation window is calculated as the theoretically appropriate required rate of return in the absence of the event. The comparison of the actual stock return with the expected normal stock return presents the abnormal return (MacKinlay, 1997, p.15). To measure the expected normal return, several approaches based on economic and statistical assumptions are available. This paper uses the market model event study methodology which requires stock prices for all firms and the (daily) market portfolio returns. In this study, the S&P 500 composite index represents the US stock market as it is the most widely used measure of overall stock market performance in the United States.

All actual returns are computed with daily stock returns as short-term daily data can be advantageous over longer periods (Brown & Warner, 1985, p. 25). Day-end prices of stocks are based on the official day-end prices from NYSE, NASDAQ, or non-NASDAQ OTC (over-the-counter). Stock prices and market portfolio data are extracted from Thomson Reuters Datastream as all sample firms are publicly traded. As recommended by Corrado and Truong (2008, p. 518), this paper uses logarithmic returns as they generally produce better test specifications compared to simple compounded returns. Moreover, this paper follows the approach of continuously compounded returns as mostly used in event studies (Henderson, 1990, p. 287).

To draw an overall conclusion, abnormal returns are aggregated over time and across securities (MacKinlay, 1997, p. 21). Abnormal returns are aggregated over the event window. Aggregating abnormal returns across all firms on Day t leads to the average abnormal return (AAR). By combining aggregation for AARs through time, cumulative AAR (CAAR) represents the mean abnormal returns for all companies in the event window.

4.2 | Regression analysis methodology

An event study identifies significant abnormal returns for subsamples with certain characteristics, but it does not explain the causes of abnormal returns. Whereas a multivariate regression model determines the impact of different characteristics on the cumulative abnormal return (CAR). In this paper, the dependent variable of the cross-sectional regression is CAR [0;+5] to evaluate a longer period than in the subsample analyses. *Category_low*, *Category_high*, *Hurricane_Damage*, and *S&P_Member* are explanatory variables to model the relationship with CAR. Model I investigates the influence of the hurricane category, which is identifiable before the final realization of the damage of the hurricane, on insurance stocks. The first dummy variable *Category_low* is set to 1 for hurricanes defined as Category 1 or 2 hurricanes and thus belong to the lower end of the hurricane category classification. Whereas *Category_high* refers to the upper end of the classification and is set to 1 for hurricanes of Category 4 or 5. In Model II, the influence of the hurricane damage, which is realized after the event, on insurance stocks is analyzed. *Hurricane_Damage* states the damage costs of a hurricane in billion USD. Data for the hurricane category and damage are provided by NCEI and NHC (2020, p. 2), illustrated in Table 2. In Model III, we investigate the influence of market capitalization on the stock reaction to hurricanes. We use the insurer's membership in the S&P 500 index as a dummy variable for high market capitalization. *S&P_Member* is set to 1 if the company has been part of the S&P 500 index during the assessed period of this event study. Model IV combines all variables.

A series of variables is used as control factors. The control variable *Net_income* is a variable regarding the average net income of the investigated insurance companies from 2004 until 2018. It is used to check for size effects based on actuarial income. If the average net income was above 200 million USD, the dummy variable is set to 1; otherwise, it is set to 0. *Debt_Equity* depends on the capital structure of the investigated companies as it is set to 1 if the debt-to-equity ratio is higher than 25% on average during the period from 2004 until 2018. With an average debt-to-equity ratio below 25%, the dummy variable *Debt_Equity* is set to 0. The cumulated average return of the S&P 500 index is used as an indicator to constitute the overall stock market reactions around the event date. If the cumulated S&P 500 return in the period starting 5 days before and ending 5 days after the event day was positive, the dummy variable *Market* is set to 1. For a cumulated negative return, the variable is set to 0.

The significance of the multiple linear regression is tested with the standard two-sided *t*-test. Estimated parameters in combination with the test statistic help to infer a correlation between a respective variable of interest and the CAR [0;+5].

5 | EMPIRICAL RESULTS

5.1 | Event study

The following section outlines the empirical results of the conducted event study that investigates changes in stock prices as a reaction to hurricanes. First, results for the full sample are shown, including abnormal and cumulated abnormal returns for different periods around the day of landfall. Second, this paper evaluates subsamples, regarding the hurricane category, damage impact, and S&P 500 membership. Last, the findings of the regression analysis are

presented to explain the identified CAR effects. Statistical significance is tested at levels of 1%, 5%, and 10%, respectively.

5.1.1 | Entire sample

This first section examines the changes in stock prices when considering the full sample set, including 13 events and 32 companies.

Figure 1 represents the AAR results linked to the hurricanes in the $[-5; +5]$ period around the day of landfall. A statistically significant (1% level) positive AAR of +0.28% is identified on the day before the event, but no statistically significant AAR prevails on the day of hurricane landfall (t_0). A negative and statistically significant AAR is observed before hurricane landfall on Day t_{-2} with a mean of -0.18% . Additionally, the 2 days after landfall reveal statistically significant negative AARs. The AAR on t_1 with a mean of -0.28% exactly offsets the positive AAR on the day before landfall. AAR on t_2 is -0.41% , the most negative value within the examined 2-week period around landfall.

Generally, observable patterns are decreasing AARs in the $[-1; +2]$ time window and negative AARs for the $[-5; -2]$ and $[+1; +5]$ time windows before and after hurricane landfall. However, the second time frame has a slightly positive (but insignificant) AAR on Day 4. Detailed daily AARs and the respective test statistics (t -test and Wilcoxon's signed-rank test) for the $[-10; +10]$ period are presented in Table B1.

As negative abnormal return patterns predominate, this paper analyzes additional test statistics for different time windows around the day of hurricane landfall. Table 3 represents the observed mean CAARs for different time windows and their respective significance tests (t -test and Wilcoxon's signed-rank test). Each tested period shows statistically significant CAARs with a significance level of at least 5% for both conducted test methods. All mean CAARs are negative and range between -0.2% for the $[0; +1]$ time window and -1.06% for the $[-5; +5]$ time window. Even the longest postevent window, including 10 trading days after hurricane landfall, shows a negative CAAR of -0.78% at a statistical significance level of 1% for the t -test and 5% for Wilcoxon's signed-rank test.

To summarize, hurricanes generate statistically significant negative CAARs for each analyzed time window, ranging between -0.2% and -1.06% . The AAR analysis shows the pattern of decreasing AARs, starting on the day before hurricane landfall. After hurricane landfall, mainly negative AARs prevail. These outcomes help to evaluate Hypothesis 1, which assumes that hurricanes generate negative abnormal returns for insurance stocks.

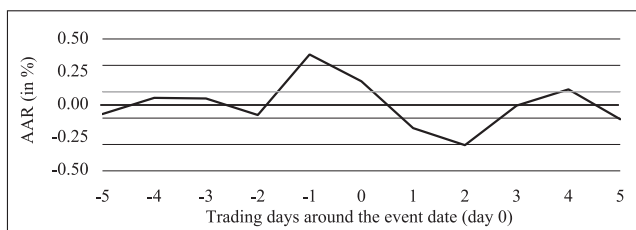


FIGURE 1 Average abnormal returns (AARs) for the whole sample in $[-5; +5]$ days period. The figure depicts the AARs for the whole data sample ($N = 416$) around the event date (day of hurricane landfall).

TABLE 3 Value effects for different periods

Time window	Sample size	Mean (CAAR) (%)	t-Test	Wilcoxon's signed-rank test
[0;+1]	416	−0.20	−1.69** (0.046)	−2.96*** (0.003)
[−5;+5]	416	−1.06	−4.04*** (0.000)	−3.77*** (0.000)
[−2;+2]	416	−0.50	−2.73*** (0.003)	−2.31** (0.021)
[0;+5]	416	−0.90	−4.21*** (0.000)	−3.37*** (0.001)
[0;+10]	416	−0.78	−3.19*** (0.001)	−2.57** (0.010)

Abbreviation: CAAR, cumulative average abnormal return.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

TABLE 4 Value effects for Panel A: Hurricane category

Criteria specification	Sample size	CAAR [0;+1] mean (%)	t-Test	Wilcoxon's signed-rank test
Category low	160	0.37	2.28** (0.012)	3.20*** (0.001)
Category middle	128	−0.44	−1.81** (0.037)	−4.48*** (0.000)
Category high	128	−0.66	−3.40*** (0.001)	−4.53*** (0.000)

Note: “Category low” includes hurricanes with the indicated Category 1 or 2, “Category middle” includes hurricanes of Category 3, and “Category high” includes hurricanes of Category 4 or 5.

Abbreviation: CAAR, cumulative average abnormal return.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.1.2 | Subsamples by the hurricane or firm criteria

This article presents results from different subsamples to extend the full sample analysis ($N = 416$) and examine the additional hypotheses. Therefore, the following analyses include subsamples regarding the hurricane category, resulting damage, and the S&P 500 membership. Subsample analyses are based on the [0;+1] time window as this period includes the most direct effects related to the hurricane landfall.

Panel A: Hurricane category

To test hypothesis 2, the sample of events is split up into various subsamples. The first subsample analysis refers to the hurricane category. “Category low” subsumes hurricanes with an indicated Category 1 or 2 according to the Saffir–Simpson Hurricane Wind Scale. Hurricanes of Category 3 represent “Category middle” and “Category high” subsumes hurricanes with Category 4 or 5. This subsample is evaluated in Table 4.

The results indicate that for the [0;+1] time window, the mean CAAR has a more negative value for category high hurricanes compared to category middle hurricanes. Additionally, category middle hurricanes have a more negative mean CAAR than category low hurricanes. All identified abnormal returns are statistically significant at the 5% level at least. At the same time, the CAAR associated with category low hurricanes is positive at 0.37%, whereas category middle hurricanes lead to a negative CAAR of −0.44% and category high hurricanes result in a

TABLE 5 Welch's *t*-test for Panels B and C

Criteria specification	Sample size	CAAR [0;+1] mean (%)	SD	Welch's <i>t</i> -test	<i>p</i> Value
Panel B: Hurricane damage					
Non-Top 3	320	−0.09	2.47		
Top 3	96	−0.56	1.95		
Difference		0.47		1.95**	0.027
Panel C: S&P 500					
Non-S&P 500	299	−0.10	2.58		
S&P 500	117	−0.44	1.69		
		0.34		1.57*	0.059

Note: Panel B refers to the adjusted damage costs based on the 2020 consumer price index in billion USD (Table 1). The three most damaging hurricanes are subsumed and compared to the remaining hurricanes in the data sample. The dummy variable in Panel C is set to 1 if a sample firm has been part of the S&P 500 index during the assessed period of this event study.

Abbreviations: CAAR, cumulative average abnormal return; S&P, Standard & Poor's index.

****p* < 0.01; **p* < 0.1; ***p* < 0.05.

CAAR of −0.66%. This leads to an overall mean CAAR difference of approximately 1%-point between hurricanes from category low and category high.

Panel B: Hurricane damage

Hypothesis 3 aims to find out whether the actual hurricane impact, measured in adjusted damage costs based on the 2020 Consumer Price Index, makes a difference in the observed abnormal returns. As Welch's *t*-test requires a dummy variable, this paper constructs a subsample with the three most damaging hurricanes, which are hurricanes Katrina, Harvey, and Maria. These three hurricanes are compared to the remaining 10 hurricanes in the sample. Table 5 represents the results of the hurricane damage study. The CAAR of both, the top three and the remaining hurricanes, is negative. To be more precise, the CAAR of the three most damaging hurricanes amounts to −0.56% and is thus 0.47%-point more negative than the CAAR of the remaining hurricanes in the sample. This difference in CAAR is confirmed with Welch's *t*-test at a 5% significance level.

Panel C: S&P 500

The last panel refers to the dummy variable *S&P_Member*, which is set to 1 for companies that have been part of the S&P 500 index during the assessed period of this event study. Otherwise, the variable is set to 0. Welch's *t*-test (Table 5) shows a positive difference in CAAR (10% significance level) whether a company belongs to the S&P 500 subset or not. Thus, companies that belong to the S&P 500 have a 0.34%-point more negative CAAR than companies that did not belong to the index during the assessed period of this event study. This observation helps to evaluate Hypothesis 4.

To summarize, hurricanes generate significant negative CAARs, ranging for different periods between −0.2% and −1.06%, at least with a 5% significance level. A decreasing AAR pattern starts on the day before landfall until two days after landfall. The first subsample investigates different hurricane categories. Hurricanes classified with a high hurricane category reveal more negative CAARs compared to middle-category hurricanes. The same applies to hurricanes from the middle

and low hurricane classifications. Hurricanes with a middle category reveal a (more) negative CAAR, as low-category hurricanes even lead to a positive CAAR. Next, the top three hurricanes in terms of damage indicate more negative CAARs than the remaining hurricanes. Lastly, Welch's t-test results show a more negative CAAR for companies that have been part of the S&P 500 index during the assessed period, however at a significance level of 10%.

5.2 | Regression analysis

As the preceding step for valid multiple regression analysis, it must be ensured that all necessary assumptions are met. Eventually, the assumptions for the ordinary least squares (OLS) regression are tested and adjusted before the presentation of regression results. Regression Models I–IV analyze different constellations of predictor variables of interest: *Category_low*, *Category_high*, *Hurricane_Damage*, *S&P_Member*, *Net_income*, *Debt_Equity*, and *Market*. Table C1 shows descriptive statistics for all variables in the conducted regression model with the dependent variable CAR of the [0;+5] time window.

5.2.1 | Regression assumptions

As a prerequisite to obtaining valid results from the regression analysis, several assumptions have to be fulfilled. As the first pretest, outliers are identified and afterward excluded. Figure C1 provides a graphical overview of all variables in a scatterplot to identify outliers and hence exclude data point number 386. Following, pairwise correlation is calculated for all variables, presented in Table C2. Although the variables indicate further correlations, none of the variables of interest has to be dropped, as values from 0.3 to 0.7 indicate a moderate linear relationship (Ratner, 2009, p. 140). Next, the normality of residuals is both numerically and graphically checked. Although the calculated results from the Shapiro–Wilk test (Table C3) reject the null hypothesis of normal distribution, residuals illustrated in Figure C2 appear to be close enough to the straight line to justify a normal distribution. In conclusion, the normality assumption is confirmed, however, with reservations.

The next prerequisite for a valid multiple regression is heteroscedasticity (“same variance”). The evaluation in Figure C3 indicates that the assumption of heteroscedasticity is not violated as the absolute variance of error terms tends to be constant and no systematic effects are identifiable. Additionally, the regression model requires no multicollinearity among predictor variables. This is examined by the variance inflation factor analysis (Figure C4), which reveals only values below 3. Thus, one can expect uncorrelated independent variables (Hoffmann, 2016, p. 15). Partial residual plots in Figure C5 are used to test linearity for variables of the regression models. The graphs show that the independent variables fulfill the assumptions of linearity sufficiently as the regression lines fit the data adequately. Hence, all necessary assumptions are met at a satisfactory level.

5.2.2 | Regression results

The results of regression Models I–IV are shown in Table 6. Models I, II, and IV have an *F*-significance at a 1% level; however, Model III reveals no significance. Thus, we can conclude

TABLE 6 Linear regression results

Independent variable	Dependent variable: CAR [0;+5]			
	I	II	III	IV
Category_low	0.95** (0.046)			0.37 (0.442)
Category_high	−1.29** (0.011)			−0.96* (0.054)
Hurricane_Damage		−0.03*** (0.000)		−0.02*** (0.000)
S&P_Member			−0.02 (0.971)	−0.02 (0.967)
Net_income	0.21 (0.585)	0.21 (0.586)	0.22 (0.631)	0.22 (0.618)
Debt_Equity	−0.04 (0.926)	−0.03 (0.933)	−0.03 (0.934)	−0.03 (0.938)
Market	1.28*** (0.002)	0.56 (0.163)	1.03** (0.013)	0.81** (0.048)
Constant	−1.67*** (0.001)	−0.03 (0.944)	−1.54*** (0.001)	−0.23 (0.688)
N	415	415	415	415
Significance F	0.0000	0.0000	0.1659	0.0000
R ²	0.0663	0.1031	0.0157	0.1192
Adjusted R ²	0.0549	0.0944	0.0060	0.1041

Note: Reported results are OLS regression coefficients, *p* values are stated within parenthesis. The independent variables are *Category_low* (dummy variable), which is set to 1 for hurricanes of Categories 1 and 2, the dummy variable *Category_high* is set to 1 for hurricanes of Categories 4 and 5, *Hurricane_Damage* refers to the adjusted damage costs in billion USD, the dummy variable *S&P_Member* is 1 for firms that have been part of the S&P 500 index during the assessed period of this event study. The control variable *Net_income* is a dummy variable that is set to 1 if the average net income of the firm from 2004 to 2018 was above 200 million USD. The control variable *Debt_Equity* (dummy variable) is set to 1 if the average debt-to-equity ratio of a firm from 2004 to 2018 is higher than 25%. The dummy control variable *Market* is set to 1 if the cumulated S&P 500 return was positive in the period 5 days before and 5 days after the event day.

Abbreviations: CAR, cumulative abnormal return; OLS, ordinary least squares; S&P, Standard & Poor's index.

p* < 0.1; *p* < 0.05; ****p* < 0.01.

that Models I, II, and IV offer useful insights. The coefficient of determination, adjusted *R*², suggests that between 0.60% (Model III) and 10.41% (Model IV) of the variance of the dependent variable CAR [0;+5] can be explained to a certain extent by the investigated models.

Model I illustrates the impact analysis of the hurricane category and reveals that the dummy variable *Category_low* is positively correlated with abnormal returns due to hurricanes. Whereas *Category_high* (dummy variable) correlates negatively with abnormal returns. Thus, the dependent variable CAR [0;+5] increases for low-category hurricanes, whereas decreases for high-category hurricanes. Model IV confirms the sign of correlation for these independent variables at different significance levels.

Model II analyzes the independent variable *Hurricane_Damage*. It reveals a negative and statistically significant (1% level) correlation with CAR [0;+5]. Model III focuses on the independent dummy variable *S&P_Member*, which is set to 1 if a company has been part of the S&P 500 index during the assessed period of this event study. The model reveals a slightly negative, however statistically insignificant, correlation between the S&P membership and CAR [0;+5]. Model IV combines all the independent variables and confirms the sign of correlation in Models I–III, which analyses the input factors individually. To summarize, the regression analysis confirms a positive correlation between low-category hurricanes and abnormal returns. Whereas high-category hurricanes are negatively correlated with

CAR. The caused hurricane damage similarly reveals a negative correlation with abnormal stock returns. The correlation between the S&P 500 membership and CAR is not statistically significant.

6 | DISCUSSION

The goal of this paper is to analyze how stock prices of US insurers react to the costliest hurricanes since 2004. Overall, the event study results reveal statistically significant negative returns as a reaction to hurricanes. The full sample analysis indicates for the $[0;+1]$ time window a mean CAAR of -0.2% and a mean CAAR of -0.9% for the week after landfall, $[0;+5]$. Both results are statistically significant, at a 5% level. Table 7 provides a summarized overview of the findings for all hypotheses.

Overall, the results indicate slightly negative and statistically significant, abnormal returns of insurance stocks for all examined event windows, $[0;+1]$, $[-5;+5]$, $[-2;+2]$, $[0;+5]$, and $[0;+10]$, with a CAAR between -0.2% and -1.06% (Table 3). This confirms Hypothesis 1 that hurricanes can create statistically significant negative abnormal returns. The daily AARs in the 2 weeks around hurricane landfall reveal the most negative mean of -0.41% 2 days after the day of landfall. This observation might prove that the occurred damage is not immediately observable on the day of hurricane landfall. Rather, the actual damage becomes entirely revealed through damage reports on the days following landfall. This publicly available new information about the extent of destruction might then result in negative abnormal returns. Considering the theoretical explanations, the expected negative abnormal return from the damage hypothesis exceeds the expected positive abnormal return from the revenue hypothesis.

Nevertheless, the observed abnormal returns are not disruptive as most of the assessed event windows report a CAAR of less than -1% . These rather low negative abnormal returns are in line with the findings of Hagedorff et al. (2015, p. 162). The market seems to react efficiently to new information provided by a hurricane and its landfall, as abnormal returns are quickly incorporated. Also, the relatively low level of negative abnormal returns shows that insurance companies can cope with hurricanes efficiently because investors incorporate hurricane impacts continuously in the fair price assessment. Therefore, the concerns of investors about whether insurance companies can manage hurricane risks in the future are historically not given.

Different subsamples are studied to meet the second objective of this paper and provide possible drivers for the observed abnormal returns. The following Hypotheses H_2 – H_4 analyze

TABLE 7 Hypotheses results overview

Hypotheses	Test
H_1 : Negative abnormal returns for insurance stocks due to hurricanes	✓
H_2 : More negative abnormal returns for higher hurricane category	✓
H_3 : More negative abnormal returns for more damaging hurricanes	✓
H_4 : S&P 500 membership has a positive impact on abnormal returns	✗

Note: ✓, confirmed; ✗, rejected.

Abbreviation: S&P, Standard & Poor's index.

the underlying reasons for the observed negative abnormal returns. Empirical findings support Hypothesis 2 that hurricanes with a higher category have more negative abnormal returns. Subsamples of the event study compare resulting abnormal returns after high-category hurricanes (Category 4 or 5) with middle- (Category 3) and low-category hurricanes (Category 1 or 2). The analysis shows that hurricanes with a high category have a more negative impact on insurance stock prices than middle-category hurricanes. Furthermore, middle-category hurricanes have a negative impact on stock returns, whereas low-category hurricanes show a positive cumulative abnormal return for the $[0;+1]$ period. Overall, hurricanes in the test sample of a high category lead to an approximately 1%-point more negative abnormal return than hurricanes of a low category. The linear regression model confirms these results and similarly reveals that the dummy variable for hurricanes of a low category is positively correlated with CAR $[0;+5]$, whereas hurricanes with a high category negatively correlate with CAR. These results show that the hurricane category is a potential driver for the sign and strength of abnormal returns on insurance stocks. The stock price reaction is especially strong for high-category hurricanes, which is important for investors as the hurricane category can be anticipated by the market before landfall.

The damage and revenue hypotheses illustrate the main impact factors for positive or negative reactions of insurance firms after catastrophes. The damage hypothesis emphasizes claim payments having a negative impact on insureds' firm value. Whereas the revenue hypothesis mentions the demand increase for insurance coverage and an increase in premiums as beneficial for insurance companies after catastrophes. Concerning these drivers, positive abnormal returns for insurers after low-category hurricanes might imply that either the claim payments are lower than expected or the increase in demand or premiums is higher than anticipated by the stock market. The same reasoning applies to negative abnormal returns after high-category hurricanes. The resulting claim obligations for insurance companies could be higher than expected, or the demand or premium increase might be lower than anticipated. The net abnormal return of insurance stocks on hurricanes depends on the strength of these opposing factors.

The next hypothesis examines the relationship between hurricane damage and its financial effect on insurance stock returns. Both the results from Welch's *t*-test and the regression model confirm Hypothesis 3, stating that more damaging hurricanes generate more negative abnormal returns. Welch's *t*-test confirms that the three most damaging hurricanes generate a statistically significant more negative CAAR for the $[0;+1]$ time window compared to the remaining less damaging hurricanes of the sample. Similarly, regression results confirm a negative correlation ($-0.02/-0.03$) between hurricane damage (measured in billion USD) and the CAR $[0;+5]$ at a 1% significance level. The observed abnormal returns might arise from unpredicted damages or unexpectedly severe damages that become observable just after hurricane landfall. These results are in line with the assumption that hurricanes with especially high damage generate higher loss claims for insurance companies. Claim handling is (according to the damage hypothesis) a reason to explain the negative impact of catastrophes on insurance firms' value. Comparing these results with previous research, Hagendorff et al. (2015, p. 168) similarly find a significant negative correlation between the variable catastrophe size, measured by insured losses, and CAR $[0;+15]$. Lamb (1998, p. 171) also concludes that the market discriminates against hurricanes Hugo and Andrew by their magnitude. The subsample demonstrates that the top three hurricanes in terms of damage have an almost 0.5%-point more negative abnormal return compared to the remaining hurricanes of the sample, which is confirmed by a negative correlation in the regression analysis. This verifies that investors incorporate information regarding the incurred hurricane damage in the stock prices

of insurance companies. It assumes that the hurricane impact is not fully foreseeable by the hurricane category.

Hypothesis 4 which states that the S&P 500 membership has a positive impact on abnormal returns is rejected. Empirical findings are ambiguous. The findings are also not or only at a level of 10% significant. Welch's *t*-test provides evidence that the S&P 500 membership has a negative impact on the $[0;+1]$ abnormal return at a 10% significance level. However, the regression model shows a slightly negative, but insignificant correlation for the S&P 500 membership with CAR $[0;+5]$. Generally, the S&P 500 membership variable can be assessed as an approximation for capital strength, because of the required market capitalization to get listed in this index (S&P Dow Jones Indices LLC, 2020). In previous literature and this paper, market capitalization approximations, such as the S&P 500 index membership in this study, are not proven as a significant factor to predict the amplitude of abnormal returns after hurricanes. Lanfear et al. (2017, p. 27) reveal that market equity is related negatively to abnormal returns. Gangopadhyay (2010, p. 146) utilizes the logarithm of market capitalization and finds a negative, but not statistically significant impact on CAR $[-1;+1]$. Therefore, the S&P 500 membership is most likely no significant variable to predict abnormal returns after hurricanes.

Overall, we can subsume, that US insurance stock prices react significantly negatively to the costliest hurricanes since 2004. Still, the negative abnormal returns seem not too severe as the CAAR is mostly less than 1%. Negative abnormal returns are concentrated on Days 1 and 2 after hurricane landfall. Additionally, the results verify that hurricanes classified with a high category come along with more negative abnormal returns compared to low-category hurricanes. The hurricane damage has a negative correlation with abnormal returns, whereas the S&P 500 membership correlation with CAR is rejected.

7 | CONCLUSION

This paper provides a broad overview of how insurance stock prices react to hurricanes. It is based on an extensive data sample, including the costliest and most recent hurricanes, whereas previous literature mainly investigates the reaction of insurance stock returns for a single or only a few individual events. Research about hurricanes is of high importance because their severity and frequency increased significantly throughout the last decades. This comes along with the increasing concern of investors about whether insurance companies are and will still be able to cope with environmental risks in the future. Thus, this paper aims to explain the implications of hurricanes for the stock returns of insurance companies. Therefore, this paper conducts an event study to answer the research question of how stock prices of US insurers reacted to the costliest hurricanes since 2004. The data sample consists of the 13 costliest hurricanes that have made landfall since 2004 and 32 P&L insurance companies listed on the US stock market. Additionally, the variables hurricane category (low, middle, and high), hurricane damage, and S&P 500 membership are investigated. The goal of the regression model is to find possible drivers of abnormal returns due to hurricanes.

To conclude, this paper confirms that hurricanes lead to negative, but not disruptive abnormal returns of P&L insurance stocks. Additionally, this paper attempts to understand which factors explain the strength of negative abnormal returns after hurricanes. Thereby, the regression model of this paper explains up to 10.41% of the variance of CAR $[0;+5]$. The event study and regression results reveal that hurricanes with a higher category lead to more negative abnormal returns. Additionally, the occurred hurricane damage is negatively correlated with abnormal returns. The

hypothesis that the S&P 500 membership has a significant impact on abnormal returns cannot be confirmed. Although statistically significant negative abnormal returns prevail, the mean AARs are moderate with a maximum of -0.41% in the 2 weeks around the event. The insurance sector seems to be capable to cope with the uncertainty of hurricane risks as the market does not indicate extreme price jumps in price assessment. As negative abnormal returns are mainly concentrated on Days 1 and 2 after hurricane landfall, we conclude that the insurance market reacts efficiently to new information generated by hurricanes.

This paper has some limitations: We utilize a subsample of listed companies that might have a self-selection bias. Thus, a generalization of findings on nonlisted companies is not generally given. As many hurricanes occur within a short period, it is difficult to avoid spillover effects completely. This limitation is known as calendar clustering where events occur at or near the same time. This paper attempts to minimize this limitation by excluding hurricanes Ivan and Irma with partly overlapping event windows. Additionally, the influence of the overall political atmosphere concerning catastrophe relief and regulation, for example, the consensus over federal disaster relief or the state of the National Flood Insurance Program, should be investigated more closely.

Overall, this paper provides further insights into the impact factors on abnormal returns after hurricanes. It can be used as a starting point for additional research. Further analyses can expand the data set of insurance firms, for example, with smaller insurance companies, having the goal of further verifying and generalizing the outcomes of this study. Further coefficients that differentiate the insurance firms could be used as additional explanatory variables. A promising approach would be the utilization of exposure-weighted indicators such as, for example, the proportion of homeowner's insurance premiums written in hurricane-exposed states.

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APPENDIX A: DATA

TABLE A1 Final sample of 32 P&L insurance firms

Allstate Ordinary	Hanover Insurance Group
American Financial Group	Hartford Financial Services Group
American International Group	Horace Mann Educators
Argo Group International Holdings	Kemper
Aspen Insurance Holdings	Markel
Axis Capital Holdings	Mercury General
Berkshire Hathaway “B”	Old Republic International
Chubb	Progressive Corporation
Cincinnati Financial	RenaissanceRe Holdings
CAN Financial	Safety Insurance Group
Donegal Group “A”	Selective Insurance Group
EMC Insurance Group	Travelers Companies
Erie Indemnity “A”	United Fire Group
Everest Re Group	Universal Insurance Holding
First Acceptance	W. R. Berkley
Hallmark Financial Services	White Mountains Insurance Group

Note: The selection of insurance companies is based on the sample from Hagendorff et al. (2015, p. 170), including publicly traded P&L insurers that earned premiums in the homeowners’ business line.

Abbreviation: P&L, property and liability.

APPENDIX B: EVENT STUDY

TABLE B1 Overview of AAR from -10 to +10 including significance test

[t]	Mean (AAR _t) (%)	Median (%)	t-Test	p Value (t-test)	Wilcoxon's signed-rank test	p Value (Wilcoxon)
-10	0.12	0.03	1.69*	(0.092)	1.89*	0.059
-9	-0.29	-0.07	-3.59***	(0.000)	-3.18***	0.002
-8	0.49	0.34	6.73***	(0.000)	6.71***	0.000
-7	0.14	0.02	1.33	(0.184)	2.64***	0.008
-6	0.10	0.03	1.50	(0.135)	1.69*	0.091
-5	-0.17	-0.14	-1.45	(0.148)	-3.77***	0.000
-4	-0.05	-0.06	-0.56	(0.577)	-1.20	0.231
-3	-0.05	0.01	-0.75	(0.455)	-0.42	0.674
-2	-0.18	-0.18	-2.12**	(0.035)	-3.31***	0.001
-1	0.28	0.30	2.36**	(0.019)	5.19***	0.000
0	0.08	-0.02	0.99	(0.321)	0.79	0.430
1	-0.28	-0.28	-3.08***	(0.002)	-5.64***	0.000
2	-0.41	-0.22	-3.60***	(0.000)	-4.42***	0.000
3	-0.11	0.01	-1.53	(0.127)	-0.77	0.443
4	0.02	0.08	0.27	(0.785)	1.35	0.176
5	-0.21	-0.03	-2.27**	(0.023)	-0.51	0.610
6	0.19	0.12	2.32**	(0.021)	2.18**	0.030
7	-0.22	-0.06	-2.67***	(0.008)	-1.80*	0.073
8	0.05	-0.17	0.55	(0.581)	-1.62	0.105
9	-0.08	-0.10	-1.00	(0.316)	-1.72*	0.086
10	0.18	0.90	3.09***	(0.002)	3.64***	0.000

Note: This table indicates the AARs and median abnormal return for the whole data sample ($N = 416$) around the event date (day of hurricane landfall, $t = 0$). The statistical significance is tested with the t -test and Wilcoxon's signed-rank test.

Abbreviation: AAR, average abnormal return.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

APPENDIX C: REGRESSION ANALYSIS

TABLE C1 Summary statistics of sample characteristics

Variable	Mean	SD	Median	5th percentile	95th percentile
CAR05	−0.90	4.35	−0.4	−7.35	4.76
Category_low	0.38	0.49	0.0	0.0	1.0
Category_high	0.31	0.46	0.0	0.0	1.0
Damage	49.55	49.95	25.2	10.5	170.0
S&P_Member	0.28	0.45	0.0	0.0	1.0
Net_income	0.50	0.5	0.5	0.0	1.0
Debt_Equity	0.56	0.5	1.0	0.0	1.0
Market	0.62	0.49	1.0	0.0	1.0

Note: N = 416.
Abbreviation: S&P, Standard & Poor's index.

TABLE C2 Correlation matrix (correlation test)

CAR05	CAR05	Category_low	Category_high	Hurricane_Damage	S&P_Member	Net_income	Debt_Equity	Market
CAR05	1.000							
Category_low	0.188*	1.000						
Category_high	-0.155*	-0.527*	1.000					
Hurricane_Damage	-0.285*	-0.345*	0.252*	1.000				
S&P_Member	0.020	0.000	0.000	0.000	1.000			
Net_income	0.041	0.000	0.000	0.000	0.487*	1.000		
Debt_Equity	-0.019	0.000	0.000	0.000	0.131*	0.000	1.000	
Market	0.136*	-0.025	0.185*	-0.184*	0.000	0.000	0.000	1.000

Note: N = 416.
Abbreviation: S&P, Standard & Poor's index.
*Significance at 1% level.

TABLE C3 Shapiro–Wilk test for Models I–IV (normality test)

Variable	Obs	W	V	z	Prob > z
Res_Mod_1	415	0.94627	15.289	6.500	0.000
Res_Mod_2	415	0.95197	13.666	6.233	0.000
Res_Mod_3	415	0.94361	16.043	6.615	0.000
Res_Mod_4	415	0.95014	14.187	6.322	0.000

Note: The dependent variable is CAR [0;+5] for all regression models. The independent variables are: Model 1: Category_low, Category_high, Net_income, Debt_Equity, Market; Model 2: Hurricane_Damage, Net_income, Debt_Equity, Market; Model 3: S&P_Member, Net_income, Debt_Equity, Market; Model 4: Category_low, Category_high, Hurricane_Damage, S&P_Member, Net_income, Debt_Equity, Market.

Abbreviations: CAR, cumulative abnormal return; Obs, observed; Prob, probability.

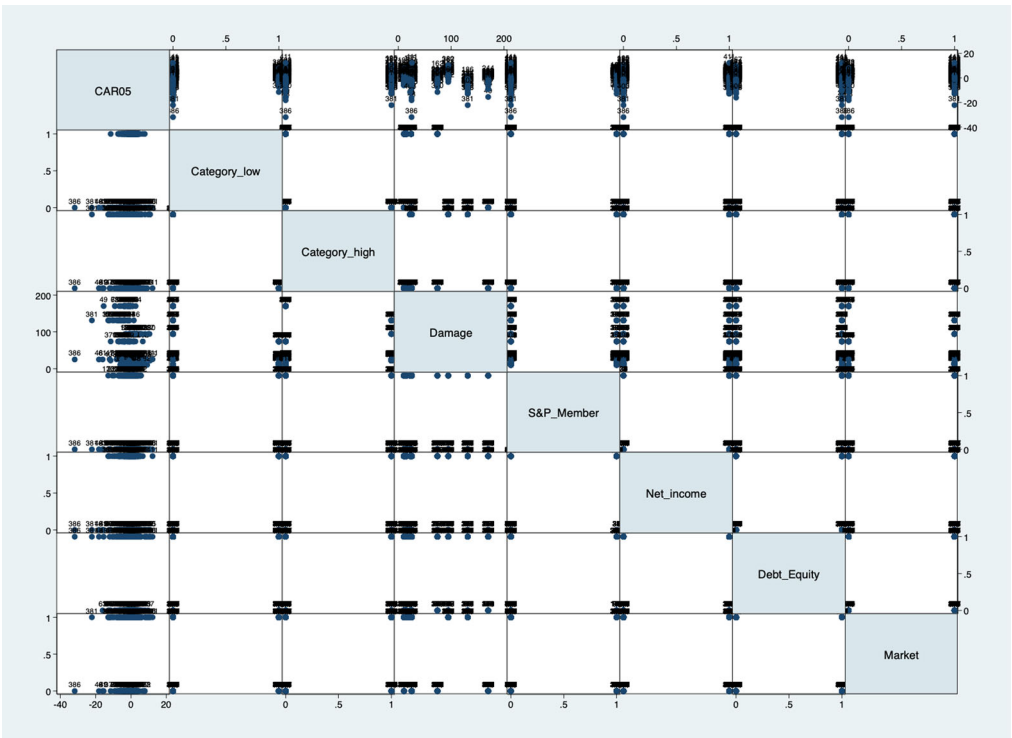
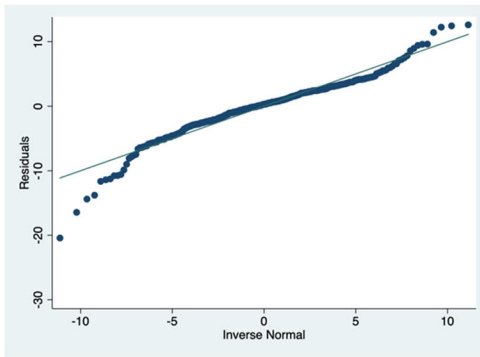
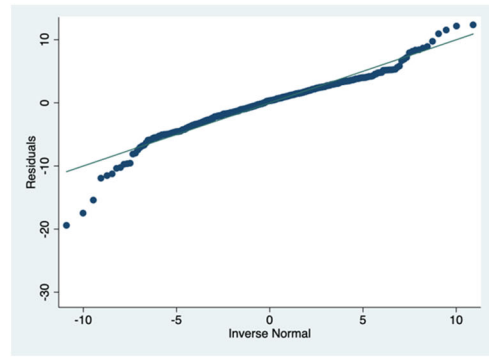


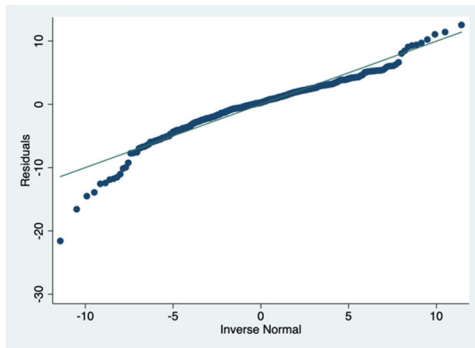
FIGURE C1 Correlation of coefficients (outliers test). $N = 415$ (id 386 excluded, the number represents sample firm Universal Insurance Holding).



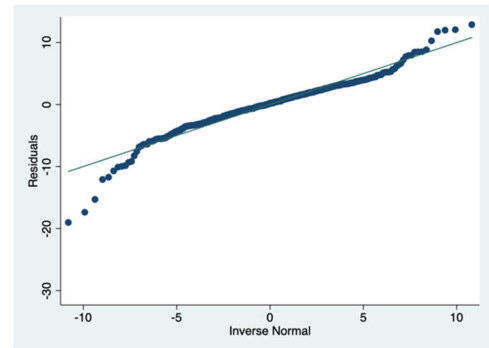
(Model I)



(Model II)



(Model III)



(Model IV)

FIGURE C2 QQ-Plot: Plots of quantiles against quantiles of the normal distribution (normality test). The dependent variable is CAR [0;+5] for all regression models. The independent variables are: Model 1: Category_low, Category_high, Net_income, Debt_Equity, Market; Model 2: Hurricane_Damage, Net_income, Debt_Equity, Market; Model 3: S&P_Member, Net_income, Debt_Equity, Market; Model 4: Category_low, Category_high, Hurricane_Damage, S&P_Member, Net_income, Debt_Equity, Market. CAR, cumulative abnormal return; S&P, Standard & Poor's index.

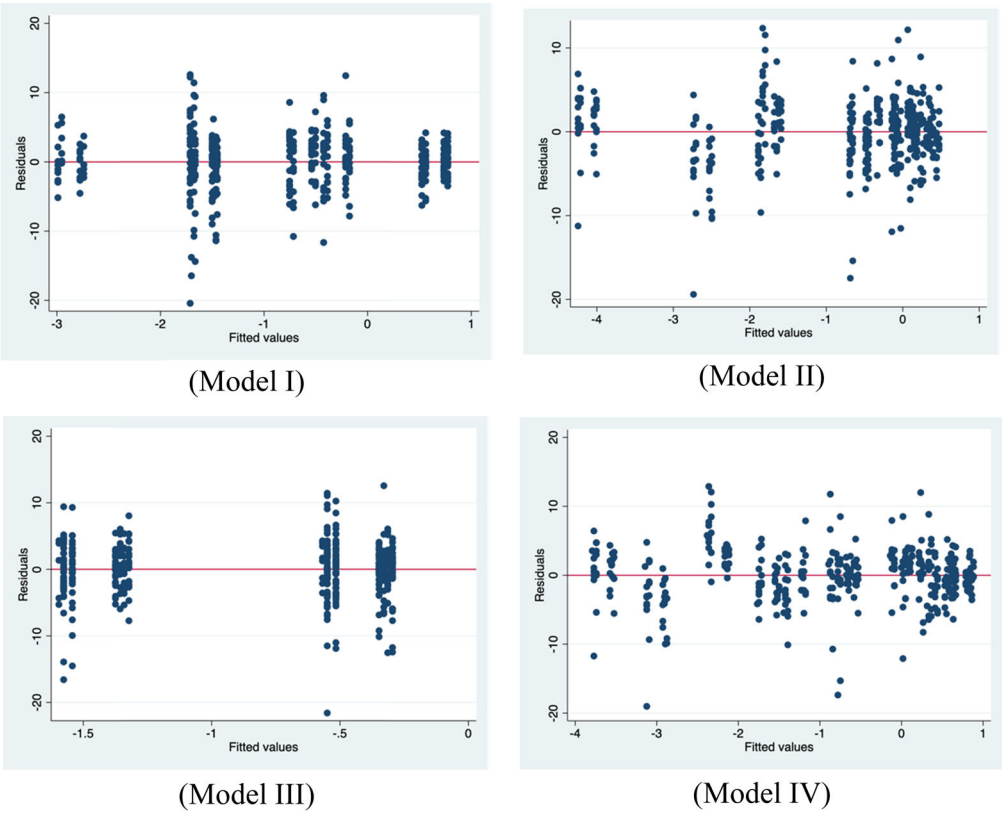


FIGURE C3 Residual-versus-fitted plot (homoscedasticity test). The dependent variable is CAR [0;+5] for all regression models. The independent variables are: Model 1: Category_low, Category_high, Net_income, Debt_Equity, Market; Model 2: Hurricane_Damage, Net_income, Debt_Equity, Market; Model 3: S&P_Member, Net_income, Debt_Equity, Market; Model 4: Category_low, Category_high, Hurricane_Damage, S&P_Member, Net_income, Debt_Equity, Market. CAR, cumulative abnormal return; S&P, Standard & Poor's index.

Variable	VIF	1/VIF
Category_low	1.40	0.7152
Category_high	1.45	0.6918
Net_income	1.00	1.0000
Market	1.04	0.9599
Debt_Equity	1.00	1.0000
Mean VIF	1.18	

(Model I)

Variable	VIF	1/VIF
S&P_Member	1.34	0.7466
Net_income	1.32	0.7600
Market	1.00	1.0000
Debt_Equity	1.02	0.9772
Mean VIF	1.17	

(Model III)

Variable	VIF	1/VIF
Damage	1.04	0.9656
Net_income	1.00	1.0000
Market	1.04	0.9656
Debt_Equity	1.00	1.0000
Mean VIF	1.02	

(Model II)

Variable	VIF	1/VIF
Category_low	1.49	0.6715
Category_high	1.47	0.6796
Damage	1.21	0.8274
S&P_Member	1.34	0.7466
Net_income	1.32	0.7600
Market	1.10	0.9089
Debt_Equity	1.02	0.9772
Mean VIF	1.28	

(Model IV)

FIGURE C4 VIFs (multicollinearity test). The dependent variable is CAR [0;+5] for all regression models. The independent variables are: Model 1: Category_low, Category_high, Net_income, Debt_Equity, Market; Model 2: Hurricane_Damage, Net_income, Debt_Equity, Market; Model 3: S&P_Member, Net_income, Debt_Equity, Market; Model 4: Category_low, Category_high, Hurricane_Damage, S&P_Member, Net_income, Debt_Equity, Market. CAR, cumulative abnormal return; S&P, Standard & Poor's index; VIF, variance inflation factor.

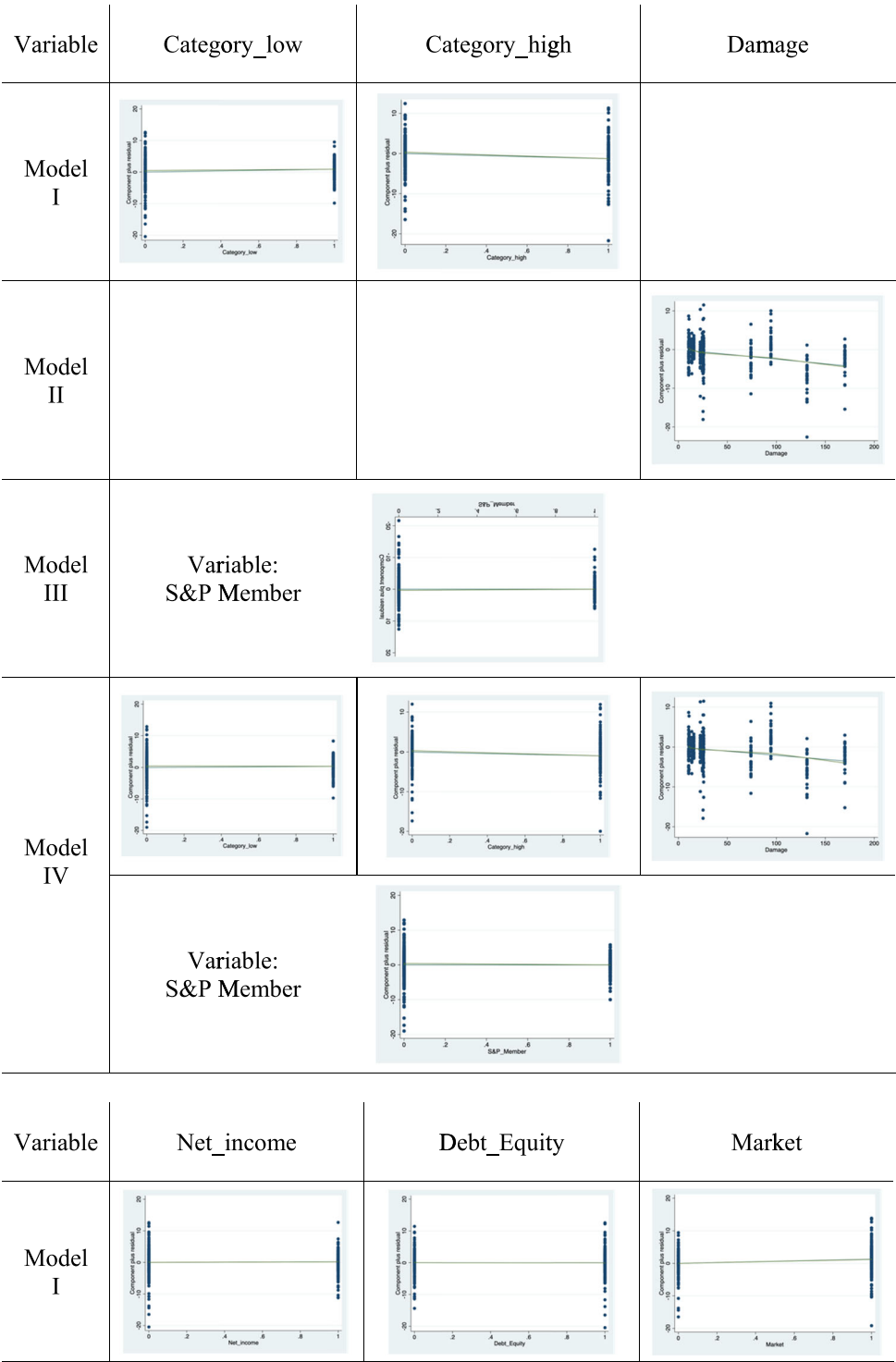


FIGURE C5 Component-plus-residual plot (linearity of variables test). The dependent variable is CAR [0;+5] for all regression models. The independent variables are: Model 1: Category_low, Category_high, Net_income, Debt_Equity, Market; Model 2: Hurricane_Damage, Net_income, Debt_Equity, Market; Model 3: S&P_Member, Net_income, Debt_Equity, Market; Model 4: Category_low, Category_high, Hurricane_Damage, S&P_Member, Net_income, Debt_Equity, Market. CAR, cumulative abnormal return; S&P, Standard & Poor's index.

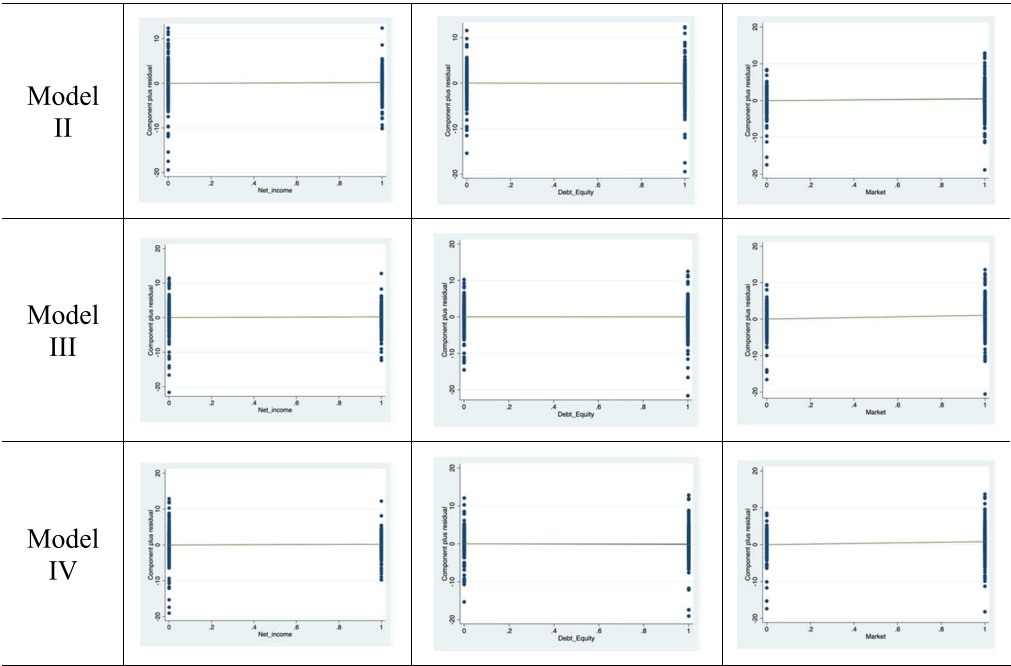


FIGURE C5 Continued