THE EFFECT OF CYCLONES ON P&C INSURANCE COMPANY STOCKS

The effect of the 30 costliest recent cyclones (1985-2018) on the stock returns of the 30 biggest current Property and Casualty insurance companies are analyzed using an event study methodology. The analysis is conducted on multiple levels: for the whole sample, per cyclone, per company, and per state. Additionally, the effects of cyclone characteristics (strength, costs, event density, and state location) on individual returns per cyclone/firm match are analyzed.

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Introduction

Residents of the southern US states surely remember the devastation that followed the 2017 hurricane Harvey, and 12 years prior to that hurricane Katrina. With both Harvey and Katrina resulting in approximately 125 billion USD in damages, and respectively claiming 107 and a staggering 1836 lives, immense economic and social damage occurred. In addition to the sheer numbers, the increased recent attention to climate change caused the emergence of hurricanes as a multidisciplinary topic of study in academic literature (Feria-Domínguez, Paneque, & Gil-Hurtado, 2017) (Francis & Vavrus, 2012). Similarly, researchers from Oxford University and the Met Office predict that due to global warming, the frequency of occurrence and magnitude of natural disasters worldwide will increase in the coming decade (Koerniadi, Krishnamurti, & Tourani-Rad, 2011)

Most economic studies regarding natural disasters analyze the short- and long-run impact on macroeconomic indicators like Gross Domestic Product (GDP) and its annual growth (Ferreira & Karali, 2015), yet relatively few papers analyze the effect on stocks. The research that has been conducted concerning stock returns mainly focuses on a single (or a few) isolated cyclones. The goal of this paper is to build on existing research on an aggregate level; there has been very little research conducted on the financial effects these hurricanes have in common, or on a "larger scale". This leads to the research question: "*On an aggregate level, how do hurricane characteristics interact with Property and Casualty Insurance companies' stock returns?*"

To answer this question, a number of separate hypotheses are tested:

1. *Different cyclones have different effects on the abnormal returns of P&C insurance companies.*
2. *Individual P&C companies are affected by the cyclones.*
3. *The effect on the abnormal returns of P&C companies for individual affected states is different*
4. *The Saffir-Simpson category, amount of damage, and amount of cyclones in succession affects the abnormal returns of the P&C companies*

In the literature review section, a comprehensive overview of existing literature regarding financial research on cyclone stock returns is given. The hypotheses and research question are answered using a sample of 30 costliest cyclones in recent history (after 1985) and 30 biggest Property and Casualty (P&C) insurance companies listed on the NYSE and NASDAQ as of mid-July. The CAARs (Cumulative Average Abnormal Returns) of the whole dataset, individual cyclones, individual companies, and individual states are analyzed, and CARs (Cumulative Abnormal Returns) per cyclones/company match are regressed on cyclone characteristics and states of occurrence. The CAAR findings indicate that most individual companies are not significantly affected by cyclones, some states show a stronger reaction in terms of abnormal stock returns, and certain cyclones have a significantly stronger effect than others do. The CAR regression findings demonstrate that certain characteristics significantly affect the abnormal returns of individual company/cyclone matches (each observation); the strength of the hurricane on the Saffir-Simpson Scale, the state location, and the follow-up variable (for cyclones in rapid succession). These findings add to existing literature on aggregate level; whereas previous research presents findings concerning single events, this research finds some patterns common to cyclones, like the increased positive or negative abnormal returns in certain states, and an increase in abnormal returns in later years.

Literature review

Academic literature on the effect of hurricanes on stock markets exists but is far from extensive. In most currently existing research, different types of natural disaster are combined under the label "catastrophic events". A lot of these studies are inconclusive or contradicting as to the effect on the general economy and stock markets. Nakamura, Steinsson, Barro and Ursúa (2013) find a steep decline in consumption following (natural) disasters. Hochrainer (2009), Raddatz (2009) and Noy and Nualsri's (2011) findings report a general decline in economic growth following natural disasters, but contrary to this many researchers find an increase in economic productivity (Baker & Bloom, 2013) (Bernile, Delikouras, Korniotis, & Kumar, 2015) (Skidmore & Toya, 2002).

When looking specifically at the effects on the stock market, Worthington (2008) found no significant differences in returns on the stock market following natural disasters in Australia, and similarly Wang and Kutan (2013) found no effects of natural disasters on the Japanese and US stock markets. However, in an earlier publication prior to 2008, Wortington and Valadkhani (2004) found significant abnormal returns as a result of natural disasters in Australia. Moreover, out of all the included natural disasters (earthquakes, bushfires, floods, storms and cyclones), cyclones and bushfires were found to have the most significant effects on the stock market.

Some minor research has been conducted with the specific aim of analyzing the effects of cyclones and hurricanes on stock returns. This has mostly been limited to insurance stocks and real estate, as these stocks are most likely to be affected. Lamb (1995) used a sample of 34 insurance companies to test for discrimination effects in the stock market after hurricane Andrew in 1992, based on the amount of loss exposure of the included firms. Indeed, he found that insurance companies with premium value in

Florida and Louisiana had negative abnormal returns following hurricane Andrew, and unexposed companies experienced no significant abnormal returns, indicating that the market efficiently interpreted the information (for insurance companies). The research was conducted using event study methodology. Lamb defines 24 August, which is the day Andrew struck the Florida coast, as the event date (0). This is an interesting point of debate that will be discussed later in this paper, because unlike financial events like earnings announcements, stock splits, etc. the event date for cyclones and hurricanes is quite subjective.

Ewing and Kruse (2006) conducted a similar study regarding hurricane Floyd, but used the defining characteristics of the hurricane that were transmitted to the market through news as separate day-by-day events for their event study. This unique methodology enabled them to analyze the stock market's response to the development of the hurricane. They found that specific news during the progress of hurricane indeed affected the returns of insurance companies differently. Especially a change in direction towards the US coast was found to have a significant effect.

Feria-Dominguez, Paneque and Gil-Hurtado (2017) also conducted research analyzing the effects of 7 hurricanes (2005-2012) in the US on the stock returns of the 7 main Property and Casualty insurance companies on the NYSE. They found different reactions of the market to different hurricanes. For most hurricanes (Rita, Felix, Ike, Igor and Ophelia) they found a significant impact on the insurer stock market; in short term around the hurricanes the cumulative abnormal returns of the insurance companies' stocks were significantly different from 0. Hurricane Katrina and Sandy displayed no significant abnormal returns, indicating that investors did not panic and did not overreact to short-term developments. For hurricane Sandy, the forecast for the storm track proved to be accurate, providing enough time for preparations to be instigated.

Weiderman and Bacon (2008) analyzed the effect hurricane Katrina had on stock returns of oil companies that eighter operated in the Gulf of Mexico or imported oil to the refineries in the Gulf using an event study. They too found significant negative abnormal returns as far as 25 days prior to the defined event date (30 August).

Data

The data concerning the hurricanes and their characteristics in this study is collected from the National Hurricane Centre (NHC), which is a division of the National Weather Service in the US tasked with the prediction and tracking of weather systems within the Gulf of Mexico, Caribbean Sea and the North

Atlantic Ocean. As stated on their website (https://www.nhc.noaa.gov/mission.shtml), their mission is to "To save lives, mitigate property loss, and improve economic efficiency by issuing the best watches, warnings, forecasts and analyses of hazardous tropical weather, and by increasing understanding of these hazards".

Specifically, the hurricanes used in this study come from a report written in August 2011 that lists the deadliest, costliest and most intense hurricanes from 1851 to 2010 (Blake, Landsea, & Gibney, 2011). Because of recent devastating events like hurricane Harvey, Irma and Sandy, the list was updated on January 26, 2018. In this research, attention is focused on the costliest hurricanes listed because these are most likely to affect the stock market, and the economy in general. The updated report consists of two tables documenting the costliest hurricanes; one lists the 41 costliest hurricanes without adjusting for inflation, and one lists the 41 costliest hurricanes when adjusting for inflation to 2017 dollars. Some of the hurricanes in the list accounting for inflation are not present in the one without, and vice versa. In these cases, the cost with/without inflation is calculated using the *U.S. census bureau price deflator* for construction, as was done in the original report. The damage estimates prior to, and after 1995 are obtained differently; before 1995, damages are obtained from the Monthly Weather review, an estimate based on losses from the American Red Cross, the U.S. Office of Emergency Preparedness, insurance companies and press reports. After 1995 damages are obtained by doubling private insurance losses reported by the Property Claim Service and the American Insurance Institute. In addition to these dollar amounts, the report lists the category of the hurricanes on the *Saffir-Simpson scale*, and the states affected by the hurricane.

The Saffir-Simpson Hurricane Wind Scale classifies hurricanes according to their sustained wind speeds on a scale from 1 to 5. The scale indicates the potential damage to property and expected flooding along the coast. Categories 3-5 are considered to be major hurricanes. Starting at hurricanes classified as category 3, evacuation of low-lying residences several blocks of the shoreline may be required, no water or electricity services are available, significant damage to housing occurs, and trees are uprooted. At category 4, terrain under 10ft (3m) above sea level may be flooded and require a massive evacuation of residential areas up to 10km inland. Power poles go down and electricity is out for weeks/months. At category 5, evacuation of low residences as far at 16km inland and residences below 15ft (4,5m) above sea level may be required. A high percentage of homes is completely destroyed, and residential areas become isolated from outside help (Feria-Domínguez, Paneque, & Gil-Hurtado, 2017) (Blake, Landsea, & Gibney, 2011) When wind speeds are under 119 km/h, the storm is not considered a hurricane but a regular cyclone or tropical storm (TS). Table 1 presents the wind speeds associated with each category.

Table 1. Saffir-Simpson Hurricane Wind Scale (SSHWC)

Category nr.	Sustained Wind Speeds (km/h)
1	119–153
2	154–177
3 (major)	178-209
4 (major)	210-249
5 (major)	>249

Source: National Weather Service, National Hurricane Centre

In addition to the Saffir-Simpson scale, the report documents the states affected by each hurricane. In some cases it specifies in what part of the state the hurricane struck (north, east, south, west and intercardinal directions). For the sake of this research however, this is not taken into account; what counties can be categorized as north/east/south/west in each state is not discussed in the report, and extensive knowledge about each individual hurricane's path through the US would be needed to provide any meaningful insights into their effect on each county.

The first time the hurricane makes landfall is also listed. "Landfall" refers to the moment the eye (center) of a cyclone or hurricane moves from sea to land. Table 2 gives an overview of the hurricanes used in this paper. Cyclones dating back later than 1985 are not included for the purpose of this research, as the available data on stock returns for the companies used becomes increasingly more limited from this point on. A full list of state abbreviations is included in the appendix (A). *Mid-Atlc & NE U.S.* are special cases. These are not states but collections of states. They are densely concentrated, and distinguishing what specific states are affected would be very hard. The Mid-Atlantic Area consists of New York, New Jersey, Pennsylvania, Delaware, Maryland, Washington D.C., Virginia and West Virginia (Virginia is listed separately in the dataset as it was specifically impacted). The New England area consists of the states Maine, Vermont, New Hampshire, Massachusetts, Rhone Island and Conneticut. In image 1. New England states are shown in red and Mid-Atlantic states in pink. Hurricane Matthew is a special case and is indicated by SE U.S. (Southeastern United Stated), which are all states in the dataset excluding the regions New England and Mid-Atlantic.

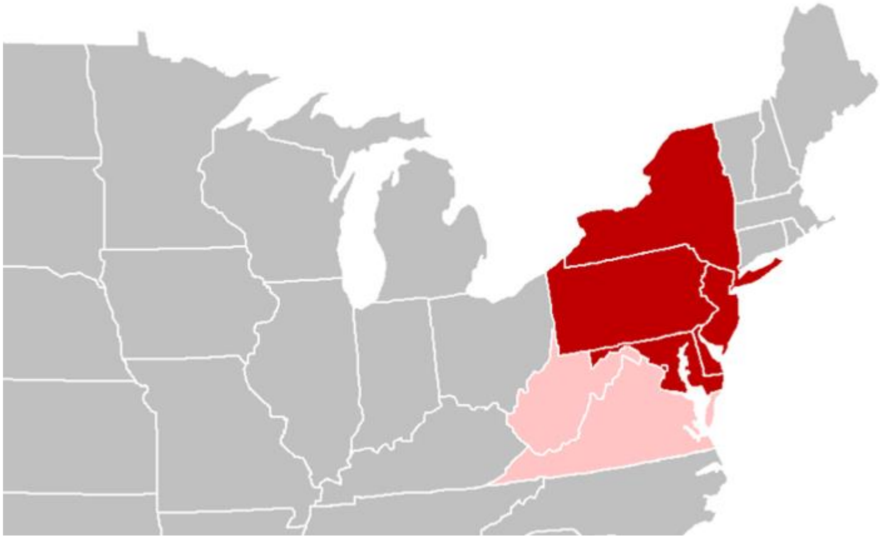

Image 1. Mid-Atlantic & New England regions

Table 2. Costlieset hurricanes US 1985-2017

Hurricane	Start Date	End Date	Highest Category (Saffir-Simpson scale)	Damage in mil US$ (inflation corrected)	Damage in mil US$ (no inflation)	State
Katrina	23/8/2005	30/8/2005	3	$160,000.00	$125,000.00	FL, LA, MS
Harvey	17/8/2017	1/9/2017	4	$125,000.00	$125,000.00	TX, LA
Sandy	22/10/2012	2/11/2012	1	$70,200.00	$65,000.00	Mid-Atlc & NE U.S.
Irma	30/8/2017	13/9/2017	4	$50,000.00	$50,000.00	FL
Andrew	16/8/1992	28/8/1992	5	$47,790.00	$27,000.00	FL, LA
Ike	1/9/2008	14/9/2008	2	$34,800.00	$30,000.00	TX, LA
Wilma	15/10/2005	25/10/2005	3	$24,320.00	$24,320.00	FL
Ivan	2/9/2004	24/9/2004	3	$17,832.00	$20,500.00	FL, AL
Irene	21/8/2011	30/8/2011	1	$14,985.00	$13,500.00	Mid-Atlc & NE U.S.
Matthew	28/9/2016	10/10/2016	1	$10,300.00	$10,000.00	SE US
Charley	9/8/2004	14/8/2004	4	$21,120.00	$16,000.00	FL
Hugo	10/9/1989	22/9/1989	4	$14,070.00	$7,000.00	SC
Rita	18/9/2005	26/9/2005	3	$23,680.00	$18,500.00	LA, TX, FL
Allison	5/6/2001	17/6/2001	TS	$11,815.00	$8,500.00	TX
Frances	25/8/2004	8/9/2004	2	$12,936.00	$9,800.00	FL
Floyd	7/9/1999	17/9/1999	2	$9,620.00	$6,500.00	Mid-Atlc & NE U.S.
Jeanne	13/9/2004	28/9/2004	3	$9,900.00	$7,500.00	FL
Opal	27/9/1995	6/10/1995	3	$7,614.00	$4,700.00	FL, AL
Fran	23/8/1996	8/9/1996	3	$7,900.00	$5,000.00	NC
Isabel	6/9/2003	19/9/2003	2	$7,370.00	$5,500.00	NC, VA
Alicia	15/8/1983	21/8/1983	3	$7,470.00	$3,000.00	TX
Gustav	25/8/2008	4/9/2008	2	$6,960.00	$6,000.00	LA
Georges	15/9/1998	1/10/1998	2	$3,775.00	$2,500.00	FL, LA, MS
Juan	24/9/2003	29/9/2003	1	$1,996.68(*)	$1,500.00	LA

Bob	16/8/1991	29/8/1991	2	$2,707.07(*)	$1,500.00	NC, NE U.S.
Lili	21/9/2002	4/10/2002	1	$1,498.21(*)	$1,100.00	SC, LA
Dolly	20/7/2008	25/7/2008	1	$1,456.97(*)	$1,300.00	TX
Bonnie	19/8/1998	30/8/1998	2	$1,508.71(*)	$1,000.00	Mid-Atlc
Dennis	4/7/2005	18/7/2005	3	$3,200.00	$2,500.00	FL
Elena	28/8/1985	4/9/1985	3	$3,003.00	$1,300.00	AL, FL

(*) theses values were manually calculated using the 2017 price deflator for inflation ($)

The companies used in this research are the largest 30 Property and Casualty insurance companies listed on either the NYSE or the NASDAQ. Largest in this research is defined as their current market capitalization, which is the shares outstanding multiplied by the current stock price as of July 20,2018. For each company the year in which it was founded is shown. Some are relatively new to the market, while others have been around for as long as since 1839. The *Ticker*- and *ISIN*-codes are both identifiers for their respective stocks. The well-known Ticker is an abbreviation used to uniquely identify a specific stock on a specific exchange. NASDAQ tickers have four letters whereas NYSE tickers consist of three (and other variations for other exchanges). For the purpose of this research ISIN-codes are used; these consist of 12 letters and numbers, and are generally better suited for quantitative purposes as more programs and services used for analysis tend to recognize them. A full list of used companies is shown below in table 3.

Table 3. Largest P/C insurance Companies

ISIN	**Ticker**	**Stock**	**Market Cap.**	**Exchange**	**Founded**
US0846707026	BRK-A	Berkshire Hathaway Inc.	490.238B	NYSE	1839
CH0044328745	CB	Chubb Limited	62.059B	NYSE	1985
US0268747849	AIG	American International Group, Inc.	47.864B	NYSE	1919
	PGR	The Progressive Corporation	34.844B	NYSE	1937
US89417E1091	TRV	The Travelers Companies, Inc.	33.837B	NYSE	1853
US0200021014	ALL	The Allstate Corporation	32.836B	NYSE	1931
CA8667961053	SLF	Sun Life Financial Inc.	24.901B	NYSE	1865
US4165151048	HIG	The Hartford Financial Services Group, Inc.	18.745B	NYSE	1810
US5705351048	MKL	Markel Corporation	15.946B	NYSE	1930
US5404241086	L	Loews Corporation	15.845B	NYSE	1946
BMG982941046	XL	XL Group Ltd	14.531B	NYSE	1998
US1261171003	CNA	CNA Financial Corporation	12.977B	NYSE	1967
BMG0450A1053	ACGL	Arch Capital Group Ltd.	11.833B	NASDAQ	1995
US1720621010	CINF	Cincinnati Financial Corporation	11.549B	NASDAQ	1950
US0259321042	AFG	American Financial Group, Inc.	9.793B	NYSE	1959
US0171751003	Y	Alleghany Corporation	9.294B	NYSE	1929
BMG3223R1088	RE	Everest Re Group, Ltd.	9.213B	NYSE	1973

US0844231029	WRB	W. R. Berkley Corporation	9.081B	NYSE	1967
US6802231042	ORI	Old Republic International Corporation	6.136B	NYSE	1887
US31847R1023	FAF	First American Financial Corporation	6.077B	NYSE	1889
BMG9319H1025	VR	Validus Holdings, Ltd.	5.584B	NYSE	2005
US4108671052	THG	The Hanover Insurance Group, Inc.	5.275B	NYSE	1852
BMG7496G1033	RNR	RenaissanceRe Holdings Ltd.	4.996B	NYSE	1993
BMG0692U1099	AXS	AXIS Capital Holdings Limited	4.836B	NYSE	2001
BMG3075P1014	ESGR	Enstar Group Limited	4.603B	NASDAQ	2001
US5528481030	MTG	MGIC Investment Corporation	4.56B	NYSE	1957
US7502361014	RDN	Radian Group Inc.	3.848B	NYSE	1977
	KMPR	Kemper Corporation	3.824B	NYSE	1990
US8163001071	SIGI	Selective Insurance Group, Inc.	3.422B	NASDAQ	1926
US0285911055	ANAT	American National Insurance Company	3.358B	NASDAQ	1973

Methodology

In this paper an event study analyzing possible abnormal returns to firm's stock resulting from cyclones and hurricanes will be conducted. The methodology for event studies consists of two periods; the estimation window and the event window. Firstly, the estimation window is used to calculate the normal return during the event window (MacKinlay, 1997). "Normal return" is defined as the expected return in absence of the event of interest of the study. After this, the abnormal is measures by taking the difference of the realized return and the normal return. In general, the formula form this looks like (I).

(I) $$\boldsymbol{AR_{iT} = R_{iT} - E(R_{iT}|X_T)}$$

AR_{iT} is the abnormal return, R_{iT} the realized return, and $E(R_{iT}|X_T)$ the normal return, in which X_T is the conditioning information for the normal return. i and T are respectively the firm in question and the time period.

Various models are, or have been used to condition normal returns in event studies; The Market Model, the Constant Mean Return Model, CAPM and APT-model (MacKinlay, 1997). In the Constant Mean Return Model the expected return is assumed to be normally distributed with constant variance and mean, but despite the simple setup often yields results similar to more sophisticated models. The CAPM measures the normal return in accordance to its beta (β), and the risk free rate of return on the market. The beta indicates how a stock moves relative to the market portfolio including all securities. The APT-model is an extension of the CAPM model, utilizing more than one risk-factor (the β in CAPM) to predict returns. The CAPM & APT are models based on economic theory, as opposed to statistical models (Market Model & Constant Mean Return Model)

In this research, the Market Model will be used, which is displayed in formula-form in (II).

(II)
$$\boldsymbol{R_{it} = \alpha_i + \beta_i RM_{it} + \varepsilon_{it}}$$

with

$$\boldsymbol{E(\varepsilon_{it} = 0)} \;\&\; \boldsymbol{var(\varepsilon_{it}) = \sigma_i^2}$$

This model relates the return of any security to the market portfolio RM_{it}. The model linear specification follows from the assumed joint normality of assets (MacKinlay, 1997). α_i, β_i & σ_i^2 are the parameters of the market model. They are estimated using OLS (ordinary least squares) during the estimation window of the event study. The index for the construction of the market model in the estimation period is the Standard & Poor's 500 (S&P500). The Market model is an improvement over CAPM as a measure of normal returns, because deviations from the CAPM have been discovered, which makes the validity of CAPM's restrictions on the market model questionable (MacKinlay, 1997). The main explanatory factor in the APT-model has been found to follow the market factor, with little additional explanatory power provided by additional factors. This makes it an unnecessarily complicated model compared to the market model.

As stated before, two parameters need to be chosen to conduct an event study; the event window and the estimation window to determine the normal return using equation (II). In standard finance and economics event studies, the event window is usually defined larger than the period of interest around the actual event date specified (MacKinlay, 1997). Ewing and Kruse's (2006) methodology is not feasible here, because accurately identifying all the news concerning hurricanes during their progress for 30+ hurricanes is a very complicated task, and additionally, news services have evolved throughout the years. In Lamb's (1995) methodology, the event date of the hurricane for his event study is defined as the moment the hurricane makes landfall, because at that moment 'the possibility becomes a certainty'. Some hurricanes make landfall multiple times; they keep moving from sea to land and back repeatedly. In these cases, for the sake of consistency, I will define the actual event date as the first time the cyclone makes landfall (on US soil), even though this might not necessarily be the most 'devastating' landfall in its' lifecycle. An event window of (-5, 5) is used for the purpose of this research, which is considerably smaller than used in either Lamb's (1995) or Ewing and Kruse's (2006) methodology. The reason for this is the close proximity in time of some cyclones to one another; the event windows of separate cyclones should not overlap. Using a (-5, 5) event window, the cyclones' event date (first landfall) must be at least 10 working days separated from each other (5 days forward and 5 backward for each respective cyclone) which is approximately 14 days (7/5*10). As a result of the (-5, 5) window, the windows in the selected sample do not overlap.

For the estimation window, existing literature suggests 120-200 days (Feria-Domínguez, Paneque, & Gil-Hurtado, 2017). Longer estimation windows increase the accuracy of the measurement of normal returns. The estimation window should not cover the landfall of another hurricane, as this can affect the alpha and beta generated in the market model. Like Feria-Dominguez, Paneque and Gil-Hurtado (2017) and Lamb (1995), a 150-day estimation window is used. However, the estimation window is not allowed to overlap with the event window of another cyclone. For this reason, some cyclones use a delayed estimation window. For instance, Hurricane Irma's would measure a part of its market model during Hurricane Harvey's event window. The delayed estimation window means cyclones in succession of each other use the first cyclone's estimation window, in this case Harvey's.

After calculating the abnormal returns using the market model parameters from the estimation window and the realized return, three more return types can be derived; the Cumulative Abnormal Return (CAR), the Average Abnormal Return (AAR) and the Cumulative Average Abnormal Return (CAAR).

The CAR is simply the sum of the Abnormal Returns for a selected stock as displayed in formula (III).

$$\textbf{(III)} \qquad CAR_i = \sum AR_{iT}$$

The CAR indicates the cumulative return of a single stock i. T is the time period. To test the significance of the CAR's found, two hypotheses are tested:

$$H_0: the\ mean\ of\ CAR = 0$$

$$H_1: the\ mean\ of\ CAR \neq 0$$

The t-statistic to test these hypotheses is displayed in formula (IV).

(IV) $$t = CAR_i/(SD_{cari}/\sqrt{T})$$

SD_{cari} here is the standard deviation of the CAR of stock i. T is number of trading day in the event window. On a 5% significance level, H_0 can be rejected when $|t| \geq t_{0.05,dof}$. The value of $t_{0.05,dof}$ can be found in a t-table using the appropriate degrees of freedom (dof).

After finding the CAR-values, the CAAR is obtained using formula (V).

(V) $$CAAR = 1/N \sum CAR_i$$

The CAAR is the average of the CAR's over all firms in the sample. i indicates a specific stock, and N the amount of stocks in the sample. To test if the CAAR's are significantly different from zero the following two hypotheses are tested:

$$H_0: CAAR = 0$$
$$H_1: CAAR \neq 0$$

To test these hypotheses, the following t-value is calculated:

(VI) $$t = \frac{CAAR}{SD_{CAAR}}\sqrt{N}$$

In formula VI, N equals the number of firms in the sample, and SD_{CAAR} the standard deviation of the cumulative abnormal returns. On a 5% significance level, when $|t| \geq t_{0.05,dof}$ using the appropriate degrees of freedom (dof), H_0 can be rejected.

For the purpose of this research, Average Abnormal Returns (AAR) will not be used (aside from a general analysis of the whole sample), as it relates to specific days in the event window. Because the exact event date of a cyclone is very subjective (especially on and aggregate level), this would not provide much valuable information.

Using the steps to calculate CAR and CAAR, the CAAR's for the various categories, including cyclones, companies, and states, are tested for significance.

Additionally, a model is estimated to try explain individual CAR's for each company/cyclone match. This model looks as follows:

(VII) $$\boldsymbol{CAR = \alpha + \beta_i SSM + \beta_j FU + \beta_k STATE + \beta_z DamageINF + \varepsilon}$$

With i= 1, 2, 3, 4, 5 where 1 = Maximum Saffir-Simpson of 1, 2 = Maximum Saffir-Simpson of 2, 3 = Maximum Saffir-Simpson of 3, 4 = Maximum Saffir-Simpson of 4 and 5 = Maximum Saffir-Simpson of 5. j = 6, 7, 8 where 6 = following 1 hurricane, 7 = following 2 hurricanes and 8 = following 3 hurricanes. Here "following" means that a cyclone already occurred at most 1,5 month before the one in question. This way the (possible) effect of rapid succession of hurricanes is analyzed. $\beta_k STATE$ are dummies for each state affected. DamageINF is the amount of damage caused adjusted for 2017 inflation.

Results

Full Sample

The AAR's and CAAR's for the complete sample (all 680 observations) for every day ranging from -5 to 5 in the event window are displayed in the graph 1, and the t-values corresponding to each day's AAR in the table below.

Graph 1. AAR & CAAR Full Sample

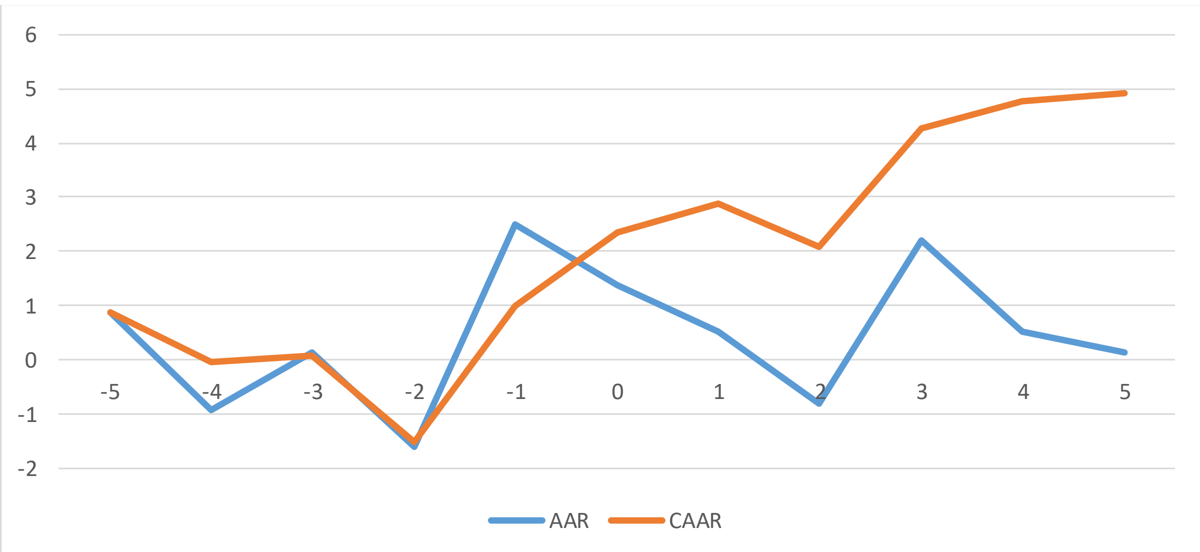

Table 4. AAR t-stats (t-crit: 2.246)

-5	-4	-3	-2	-1	0	1	2	3	4	5
1.69	-1.31	0.25	-3.03(*)	4.32(*)	1.51	0.88	-1.24	2.37(*)	0.71	0.17

Overall, both the CAAR and the AAR fluctuate around 0 prior to the event date (the cyclone landfall). After date -2, every date reflects a positive AAR with the exception of date 2. Additionally, after date -2 the CAAR never drops below 0, indicating positive abnormal returns. The AAR's -2, -1 and 3 are significant on a 5% level. The CAAR's t-value for the full event window is 0.66, so the dataset taken as a whole does not display (significant) abnormal returns within the event window selected. The AAR results should be interpreted with caution, as the use of landfall dates as event dates is quite subjective.

Cyclones

Table 5. provides an overview of the significance and magnitude of the effect of each cyclone, sorted by the date of occurrence.

Table 5. Cyclone CAAR's

Cyclone	CAAR	SDCAAR	t-stat	t-critical	p-value	#Companies
Harvey	-0.03865	0.031495	-6.7215	-2.04523(*)	<0.0001	30
Irma	-0.01429	0.027714	-2.8245	-2.04523(*)	0.0085	30
Matthew	0.037195	0.019358	10.524	-2.04523(*)	<0.0001	30
Sandy	0.018416	0.044433	2.27016	-2.04523(**)	0.0308	30
Irene	-0.00667	0.067012	-0.545	-2.04523	0.5899	30
Dolly	0.115309	0.171634	3.61793	-2.04841(*)	0.0011	29
Gustav	0.093193	0.101812	4.92931	-2.04841(*)	<0.0001	29
Ike	0.050979	0.101812	2.69644	-2.04841(**)	0.0115	29
Dennis	-0.00103	0.002422	-2.1728	-2.05954(**)	0.0395	26
Katrina	-0.00183	0.002939	-3.1704	-2.05954(*)	0.0040	26
Rita	-0.00165	0.029933	-0.2804	-2.05954	0.7815	26
Wilma	0.016919	0.170616	0.50563	-2.05954	0.6174	26
Jeanne	0.0045	0.036744	0.62453	-2.05954	0.5377	26
Charley	-0.00549	0.029583	-0.9283	-2.0639	0.3625	25
Frances	-0.00213	0.034366	-0.3033	-2.06866	0.7644	24
Ivan	0.00201	0.029525	0.35369	-2.05553	0.7263	27
Isabel	-0.00758	0.024173	-1.4714	-2.07961	0.1560	22
Lili	-0.00874	0.104988	-0.3991	-2.07387	0.6937	23
Allison	0.012863	0.037214	1.72828	-2.0639(***)	0.0968	25

Floyd	-0.01857	0.051999	-1.7855	-2.0639(***)	0.0868	25
Georges	-0.04349	0.072914	-2.9218	-2.06866(*)	0.0077	24
Bonnie	-0.00857	0.044787	-0.9375	-2.06866	0.3582	24
Fran	0.00666	0.026451	1.20762	-2.07387	0.2400	23
Opal	0.003816	0.05022	0.32238	-2.10982	0.7511	18
Andrew	-0.02655	0.029512	-3.4837	-2.14479(*)	0.0037	15
Bob	-0.00034	0.00356	-0.3574	-2.16037	0.7265	14
Hugo	0.004011	0.051088	0.28312	-2.17881	0.7819	13
Elena	-0.01143	0.033193	-1.1422	-2.22814	0.2800	11

(*) significant at 1% (**) significant at 5% (***) significant at 10%

Out of the 28 cyclones 11 are found to have significant CAAR's (5% significance). Harvey, Matthew and Gustav have incredibly high t-stats, respectively -6.7215, 10.524 and 4.92931, resulting in a p-value < 0.0001. The only cyclone found to have an insignificant CAAR in the range of the first 10 cyclones is Irene. The sign (positive of negative abnormal return) differs between cyclones; Harvey, Irma, Dennis and Katrina seem to have a negative effect on returns of P&C insurance companies, while Matthew, Sandy, Dolly, Gustav and Ike indicate positive returns. This is according to existing theory, as increased premiums can have a positive effect, and large claims a negative effect (Angbazo & Narayanan, 1996). As we move further down the list (and in time), only Georges and Andrew show significant CAAR's on a 5% significance level (t-stats of -2.9218 and -3,4837). Allison and Floyd are still significant on 10% significance level. Two observations are interesting to note; a) All hurricanes listed on the "most casualties list" of the National Hurricane Centre report (Blake, Landsea, & Gibney, 2011) are at least significant on a 10% level (Katrina: 1200 deaths, Floyd: 56 deaths and Allison: 41 deaths). b) Andrew is the only Hurricane reaching magnitude 5 on the Saffir-Simpson scale (as it is one of the few hurricanes still showing significant CAAR's this far back in time. Georges, not having any distinguishing characteristics, is a surprising find. The coefficients of the CAAR's found vary in size; most are around 1% (Irma: 1.42%, Sandy: 1.84%, Allison: 1.28%, Floyd: -1.85%). Dolly and Gustav have the strongest reactions to the cyclones with respective coefficients of 11.53% and 9.32%. Katrina and Dennis have the weakest responses, respectively 0.18% and 0.10%. Katrina's weak response is an interesting find, considering it was one of the most devastating hurricanes in recent history.

Companies

Very little finding are done regarding the company CAAR's. Only two companies appear to show significant CAAR's on a 5% significance level; Cincinnati Financial (t=2.39635) and Old Republic International (t= 2.17528). the CAAR's for both companies are positive, indicating that effect of increased premium is (estimated to be by investors) larger than the effect of claims made caused by the cyclones (Angbazo & Narayanan, 1996). MGIC investment and Radian Group's CAAR's are found significant on a 10% level. The full table of company CAAR's is listed in the appendix.

States

Table 6. shows the results for individual state (and Mid-Atlantic and New England regions) CAAR's;

Table 6. State CAAR's

State	CAAR	SDCAAR	t-stat	t-critical	p-value	#Obs
Florida	-0.00374	0.041351	-1.65366	-1.96711(***)	0.0991	334
Texas	0.029926	0.115269	3.375036	-1.97419(*)	0.0009	169
Louisiana	0.008315	0.096095	1.317967	-1.97029	0.1888	232
Alabama	0.012942	0.036995	3.244335	-1.98827(**)	0.017	86
Mississippi	-0.00563	0.056718	-0.88799	-1.99045	0.3772	80
South-Carolina	0.014652	0.069501	1.712685	-1.99714(***)	0.0915	66
North-Carolina	0.011796	0.031992	3.478445	-1.98729(*)	0.0008	89
Virginia	0.01825	0.030866	4.263749	-2.00758(*)	<0.0001	52
Georgia	0.037195	0.019358	10.52397	-2.04523(*)	<0.0001	30
New-England	-0.00166	0.05462	-0.30198	-1.98447	0.7633	99
Mid-Atlantic	-0.00291	0.054389	-0.55905	-1.98217	0.5773	109

(*) significant at 1% (**) significant at 5% (***) significant at 10%

The states of Texas, Alabama, North Carolina, Virginia and Georgia all show very significant CAAR's respectively with t-values 3.375, 3,244, 3,478, 4,263 and 10,523, all indicating positive abnormal returns. For Georgia and Virginia this significance does not provide much information, as only one cyclone in the dataset affected Georgia and two Virginia raising the question whether it's just the effects of the cyclones that are reflected in this result. Texas, Alabama and North Carolina have slightly larger pools, respectively 6, 5 and 4 hurricanes, with mainly Texas having a respectable 169 observations. For these three states the argument can be made that premiums (positive Abnormal Returns) outweigh the effect of claims (Angbazo & Narayanan, 1996), but this should be taken with caution. For most of these significant states the coefficients are just above 1% (Alabama 1.29%, South Carolina 1.46%, North-Carolina 1.17%, Virginia 1.85%). Florida (only significant on 10% level) has the only negative coefficient for the abnormal returns in the set of significant effect states, but has by far the lowest coefficient (-0.37%)

CAR Regression

The regression results (equation VII) are displayed in table 7. below;

Table 7. CAR (-5,5) regression

CAR(-5,5)	Coefficient	Std. Error	t	P>t	95% Confidence Interval	
SSM2	0.1029	0.0189	5.43	0.000	0.0656	0.1401
SSM3	0.0946	0.0242	3.91	0.000	0.0471	0.1421
SSM4	0.1194	0.0239	5.00	0.000	0.0725	0.1663
SSM5	0.0173	0.0224	0.77	0.439	-0.0266	0.0613
SSM6	0.1661	0.0383	4.33	0.000	0.0909	0.2413
FU2	0.0950	0.0177	5.36	0.000	0.0602	0.1298
FU3	0.0234	0.0188	1.24	0.215	-0.0136	0.0604
FU4	0.0123	0.0124	0.99	0.322	-0.0121	0.0367
FloridaD	-0.0913	0.0230	-3.96	0.000	-0.1366	-0.0461
TexasD	0.0417	0.0234	1.78	0.075	-0.0043	0.0877
LouisianaD	-0.0741	0.0143	-5.17	0.000	-0.1023	-0.0459
AlabamaD	-0.0052	0.0126	-0.43	0.671	-0.0192	0.0188
MississippiD	-0.0429	0.0258	-1.66	0.097	-0.0937	0.0078
SouthCarolinaD	0.0003	0.0301	0.01	0.991	-0.0587	0.0594
NorthCarolinaD	-0.0799	0.0245	-3.25	0.001	-0.1282	-0.0316
VirginiaD	-0.0882	0.0293	-3.01	0.003	-0.1458	-0.0306
GeorgiaD	0.3028	0.0484	6.26	0.000	0.2079	0.3978
NewEnglandD	0.0046	0.0153	0.30	0.763	-0.0253	0.0345
MidAtlanticD	-0.0774	0.0204	-3.79	0.000	-0.1176	-0.0373
DamageINF	4.64e-08	1.53e-07	0.30	0.763	-2.55e-07	3.48e-07
constant	-0.0294	0.0281	-1.05	0.295	-0.0845	0.0257

All Saffir-Simpson Scale categories, except for Saffir-Simpson scale 4 (SSM5) are significant on a 5% significance level (with reference category TS), with t-stats 5.43, 3.91, 5.00 and 4.33. Aside from Saffir-Simpson category 1 (SSM2), the categories display an upward trend on the abnormal returns, with coefficients of respectively 9.46% for Saffir-Simpson 2, 11.94% for 3, and 16.61% for 5. Their confidence intervals are all fully negative, meaning they have a negative effect on abnormal returns with 95% certainty in this set. For the follow-up (cyclone succeeding another cyclone within a 1.5 month timeframe) only the second cyclone in a row (FU2) has a significant effect on the abnormal returns, with t-stat 5.36 and a 9.50% coefficient. Again, the confidence interval is fully positive, so the sign (+/-) of the effect in the set can be determined with 95% certainty. The significant state dummies include; Florida (-3.96), Louisiana (-5.17), North-Carolina (-3.25), Virginia (-3.01), Georgia (6.26) and the Mid-Atlantic (-3.79). The signs of the coefficients are negative for the most part; Florida -9.13%, Louisiana -7.41%, North-Carolina -7.99%, Virginia -8.82% and Mid-Atlantic -7.74%. The only positive value for the coefficient is found in Georgia (30.28%) which is surprisingly about 4 times as high as most other states (in the opposite direction), indicating that higher future premiums in Georgia outweigh the downside of damage claim payments (Angbazo & Narayanan, 1996). Damage with adjustment for inflation has a very small t-value of 0.30, and furthermore a very small coefficient of 4.46e-08. This may however be strongly influenced by hurricanes Harvey and Katarina, as these present heavy outliers in damage costs (160.000.000.000$ and 125.000.000.000$ adjusted for inflation). After removing these (56 observations dropped), and running the regression again (found in the appendix B), the t-stat of DamageINF remains insignificant (1.07).

Conclusion, Recommendations & Limitations

In this research existing academic literature regarding the effects of cyclones on stocks was presented, mainly focusing on Lamb (1995), Feria-Dominguez, Paneque and Gil-Hurtado (2017). A similar methodology was adopted, but on an aggregate level, including cyclones and hurricanes with sufficient economic impact dating back to 1985. Results on four different levels were analyzed: overall abnormal returns of the dataset, abnormal returns per cyclones/hurricane, abnormal returns per company, and abnormal returns per state.

The overall dataset displays an upward trend in abnormal returns starting two days prior to the event data (landfall), but most of the Average Abnormal Returns are insignificant, so no clear conclusions can be drawn regarding general effects on abnormal returns from the utilized sample. The same can be said for the analysis on company level; most companies display insignificant abnormal returns in the selected event window (-5,5), with a few exceptions (Cincinnati Financial and Old Republic). Both present (minor) positive returns.

"Individual P&C companies are affected by the cyclones."

The hypothesis is rejected, as there is too little proof aside from the few exceptions.

On the cyclone level of analysis very significant results are found (both positive and negative abnormal returns), mostly for recent hurricanes, indicating that a) generally put, the effects of cyclones on stock returns of the P&C companies have increased over the years and b) the effect on abnormal returns is not solely in one direction (positive or negative), but depends on various characteristics. Casualties seem to have an effect on abnormal returns, as all heavy-casualty cyclones (Blake, Landsea, & Gibney, 2011) show at least 10% significance. Further research regarding the effect of cyclone casualties on abnormal returns of P&C companies is therefore recommended.

"Different cyclones have different effects on the abnormal returns of P&C insurance companies."

The hypothesis is accepted, some cyclones clearly have more (and different) effect on the abnormal return of P&C companies

On state level analysis, multiple state locations affect abnormal returns, almost exclusively in the positive direction (except Florida). The amount of cyclones in most of the states with significant returns is limited though, so it is unclear whether the location or the hurricane is the actual cause of the effect (as is also indicated by the regression for Alabama and North-Carolina) For Texas (N=169), a case can be made that overall abnormal returns tend to be positive. The same counts for Florida, but only on 10% significance level.

"The effect on the abnormal returns of P&C companies for individual affected states is different"

The hypothesis is accepted (cautiously), as the coefficients of the returns differ, and Florida solely presents negative abnormal returns.

The regression clearly reflects that some variables have a significant effect on individual CAR's per firm/cyclone match. The 95% confidence intervals of the significant variables are all on either the positive or negative spectrum, so with 95% certainty at least the sign (+/-) is correct. Follow-up (1), the Saffir-Simpson scale, and state location has a mixed effect. Damage costs incurred do not seem to affect the abnormal returns.

"The Saffir-Simpson category, amount of damage, amount of cyclones in succession, and the state location affects the individual abnormal returns of the P&C companies"

The hypothesis is accepted.

In summary, and answering the research question "*On an aggregate level, how do hurricane characteristics interact with Property and Casualty Insurance companies' stock returns.":* Most individual companies are not significantly affected, some states show different reactions, but with limited proof, certain hurricanes significantly have a stronger effect then others, and cyclone characteristics (Saffir-Simpson, follow-up (1) and state) significantly affect individual CAR's (firm/cyclone matches).

There are a number of limitations to the conducted research; the cyclones occur in specific months in the US, mostly around August/September. If there are other events in these months that occur every year, these events would seriously and consistently influence the outcome of this research.

The definition of the event date, as has been mentioned many times throughout the paper, is somewhat vague. The landfall is not the actual event date, but rather the perception of the event becoming certain. For future research, a possible approach would be to define the event date as *reaching a 100% probability that landfall will occur.* However, this in turn raises the question if investors actually have access to this information (or interpret it correctly). In any case, the definition of the event date is an interesting point of study for such research.

As mentioned in the data section, damage estimates before and after 1995 are obtained from different sources (Monthly Weather Review & Property Claim Service/American Insurance Institute), which might cause some inconsistencies for the conducted regression.

As mentioned multiple times previously, the effect on the abnormal returns consist of a positive (increased future premiums) and negative (damage claims) (Angbazo & Narayanan, 1996) (Ewing, Hein, & Kruse, 2006). This research offers no explanation as to how the effect is obtained. For instance, a strong positive return could just be caused by increased future premiums, or a combination of damage claims with an even stronger effect on perceived increased future premiums. A recommendation for future research is to distinguish between the two, and analyze the strength of these two factors.

At the cyclone level of analysis and interesting observation was made; all cyclones that resulted in a lot of human casualties (that were present on "deadliest hurricanes list") experienced significant abnormal returns. The variable "casualties" was not included for the purpose of this research, and could be useful for future research regarding the effect of cyclones on P&C stocks. But this may present problems; the issue with using the casualties variable is that most of the "deadly" cyclones occurred before 1950, making it hard to use for stock analysis, especially for the purpose of this research (all data used is from the period 1985-present).

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Appendix

Appendix Table 1. Company CAAR's

Company	CAAR	SDCAAR	t-stat	t-critical	p-value	#Hurricanes
Alleghany	0.008453663	0.060603	0.68337	-2.06866	0.5012	24
Allstate	0.001557659	0.032085	0.23784	-2.06866	0.8141	24
AMER.NAT.IN	-0.001929755	0.03972	-0.233	-2.07387	0.8179	23
AMERICAN FINL.GP.OHIO	0.004498474	0.034701	0.67361	-2.05553	0.5065	27
AMERICAN INTL.GP.	-0.018319179	0.160428	-0.6042	-2.05183	0.5507	28
ARCH CAP.GP.	-0.003341636	0.045173	-0.3844	-2.05553	0.7038	27
AXIS CAPITAL HDG.	-0.002012722	0.056958	-0.1369	-2.14479	0.8931	15
BERKSHIRE HATHAWAY 'B'	-0.000778385	0.040137	-0.0889	-2.08596	0.9301	21
CHUBB	0.009184626	0.046769	1.03916	-2.05183	0.3079	28
CINCINNATI FINL.	0.025699331	0.056748	2.39635(*)	-2.05183	0.0238	28
CNA FINANCIAL	0.010316116	0.055271	0.91438	-2.06866	0.37	24
ENSTAR GROUP	0.020693855	0.039927	1.55488	-2.306	0.1586	9
EVEREST RE GP.	-0.005249133	0.062345	-0.4375	-2.05553	0.6654	27
FIRST AMER.FINL.	-0.010200467	0.038261	-0.5961	-2.77645	0.5832	5
HANOVER INSURANCE GROUP	-0.035707476	0.106424	-1.6091	-2.07387	0.1219	23
HARTFORD FINL.SVS.GP.	0.00154303	0.057931	0.13581	-2.05954	0.8931	26
KEMPER	-3.61342E-05	0.05406	-0.0035	-2.05553	0.9973	27
LOEWS	-0.000700411	0.034195	-0.1003	-2.06866	0.9209	24
MARKELL	0.009832592	0.050509	1.0301	-2.05183	0.3121	28
MGIC INVESTMENT	0.081689249	0.174394	1.87368(**)	-2.13145	0.0806	16

OLD REPUBLIC INTL.	0.030736886	0.069223	2.17528(*)	-2.06866	0.0401	24
PROGRESSIVE OHIO	-0.004250047	0.037101	-0.6062	-2.05183	0.5495	28
RADIAN GP.	0.084560661	0.20324	1.99537(**)	-2.07387	0.0585	23
RENAISSANCERE HDG.	0.003060138	0.058649	0.24473	-2.07961	0.809	22
SELECTIVE IN.GP.	0.007233884	0.052853	0.6979	-2.05954	0.4917	26
SUN LIFE FINL.	0.007494398	0.035739	0.91405	-2.10092	0.3728	19
TRAVELERS COS.	0.005692469	0.04457	0.6257	-2.06866	0.5377	24
VALIDUS HOLDINGS	-0.016758256	0.046017	-1.03	-2.36462	0.3373	8
W R BERKLEY	0.001424428	0.04163	0.18106	-2.05183	0.8577	28
XL GROUP	0.009682658	0.055459	0.85532	-2.06866	0.4012	24

(*) significant at 5% (**) significant at 10%

Appendix table 2. CAR regression 2

Car(-5,5)	Coefficient	Std. Error	T	P>t	95% confidence interval	
SSM2	0.1024	0.0196	5.21	0.000	0.0639	0.1310
SSM3	0.0926	0.0244	3.79	0.000	0.0447	0.1406
SSM4	0.1288	0.0335	3.85	0.000	0.0631	0.1945
SSM5	0.0126	0.0383	0.33	0.742	-0.0626	0.0878
SSM6	0.1876	0.0731	2.57	0.010	0.0442	0.3311
FU2	0.1097	0.0568	1.93	0.054	-0.0019	0.2212
FU3	0.0351	0.0286	1.23	0.221	-0.0211	0.0913
FU4	0.0130	0.0129	1.01	0.311	-0.0122	0.0383
FloridaD	-0.0999	0.0232	-4.30	0.000	-0.1455	-0.0542
TexasD	0.0428	0.0305	1.40	0.161	-0.0171	0.1027
LouisianaD	-0.0844	0.0398	-2.12	0.035	-0.1626	-0.0061
AlabamaD	-0.0053	0.0128	-0.42	0.675	-0.0304	0.0197
MississippiD	-0.0316	0.0271	-1.17	0.244	-0.0848	0.0216
SouthCarolinaD	0.0097	0.0608	0.16	0.873	-0.1097	-0.1291
NorthCarolinaD	0.0856	0.0250	-3.43	0.001	-0.1347	-0.0366
VirginiaD	-0.0943	0.0508	-1.86	0.064	-0.1941	0.0055
GeorgiaD	0.3133	0.0541	5.79	0.000	0.2070	0.4195
NewEnglandD	0.0084	0.0171	0.49	0.622	-0.0251	0.0419
MidAtlanticD	-0.0775	0.0237	-3.27	0.001	-0.1241	-0.0310
Constant	-0.0230	0.0337	-0.89	0.375	-0.0962	0.0363

Regression damageINF<100.000.000.000$

Appendix table 3. State abbreviations

Abbreviation	**State**
TX	Texas
FL	Florida
LA	Louisiana
MS	Mississippi
AL	Alabama
NC	North-Carolina
SC	South-Carolina
VA	Virginia
Mid-Atlc	Mid-Atlantic
NE US	New-England