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The memory of Katrina and the stock market response to hurricane-related news and events

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Abstract: This paper examines the relationship between hurricane news coverage and U.S stock market returns focusing on the costliest hurricanes following Katrina (Ike, Irene and Sandy) and Patricia, which was one of the strongest hurricanes on record worldwide. In particular, we investigate the reaction of the market to hurricane news coverage and the way the memory of Katrina affected the investors' decisions during hurricanes Ike, Irene, Sandy and Patricia. Using an event study methodology, we find that the event of a hurricane generates a significant positive reaction on the stock returns, in the short-term, that fades away over a 20 day period. The empirical evidence shown here suggests that hurricane related news coverage has a negative effect on stock returns for all events excluding hurricane Irene. Moreover, Katrina related news still have a significant effect during each event even 10 years after it took place. The memory of Katrina has a positive correction effect over the initial negative reaction of investors to the hurricane related news-coverage.

Key words: Event study, Hurricanes, Stock market, News coverage

1 Introduction

Hurricanes cause substantial damage to life, limb and property. The literature on the economic effects of extreme events is growing rapidly, but is hampered by the low frequency of economic data collection and reporting. In this paper, we study the effect of hurricanes and hurricane forecasts on the daily returns of the stock market. Stock market returns is a timely and real-time indicator of the economic disruption caused by hurricanes. Using a series of hurricanes, we also show that the memory of a hurricane can affect stock markets many years after it occurred.

Since 1970, there are 29 documented tropical cyclones and tropical storms that affected the United States with more than $1 billion in damages (see Table A.4). The total estimated damages of the costliest 32 hurricanes is around $400 billion. Hurricanes Katrina, Sandy and Ike, between 2005 and 2012, account for more than 50% of that total estimated damages. 27% of the total estimated damages comes from hurricane Katrina alone that was also responsible for 1200 deaths, making Katrina the costliest and 3rd deadliest hurricane to hit the United States [Blake et al. (2011)]. In addition, the 2005 hurricane period including Katrina, Rita and Wilma (see Tables 1 and A.4) caused almost $52 billion in insured losses i.e. approximately 93% of the domestic insured losses of 2005. The concern about the future major landfalling hurricanes is growing due to the increasing coastal populations and economic activity associated with these areas as well as due to climate change.

Knutson et al. (2010) estimate that the intensity of tropical cyclones will increase by 2-11%. Climate models also predict a future decrease in the numbers of tropical cyclones. Walsh et al. (2016), reach the same conclusion indicating that that projected increase in intensity is more prominent for the strongest storms with an additional increase in rainfall rates. Bender et al. (2010) found that the maximum intensity of Atlantic hurricanes will increase by almost 5% and this increase outweighs the estimated reduction in hurricane frequency, giving a rough estimate of a 30% increase in damages for the Atlantic basin by 2100. Even though, the aforementioned are projections with a certain level of uncertainty, what is important for the present paper is the expectation of future hurricane damages and the memory of past hurricanes. On that,*"[S]ociologists estimate, however, that people only remember the worst effects of a hurricane for about seven years.[Blake et al. (2011)]"*

General perception of catastrophic events and more specifically hurricanes could potentially be altered by the news-coverage each event gets, by influencing the importance people attach to disasters. Additionally, news media can extend the period people remember a devastating event.

Eisensee and Strömberg (2007) show that decisions on relief following a natural disaster are driven by the news-coverage each disaster gets. This indicates that news creates a mechanism of signalling when an event is significant and requires attention either in the form of relief, additional investments and others. Bourdeau-Brien and Kryzanowski (2017) show that even though the stock market is affected by natural disasters and that location of each event plays a role on the firm-level effects of disasters, news-coverage of the disasters has either no or a weak influence on returns. Griffin et al. (2015), show that news related to unburnable carbon[1] news have a significant effect on abnormal returns. This suggests that there might be a mechanism through which environment- and weather-related news, concerning events that might affect the firms' value, could be translated into abnormal returns. Similarly, Mitchell and Mulherin (1994) show a significant change in return and trading volume as a direct result of publicly available news. Considering firm-specific news releases and macro-economic announcements, Nofsinger (2001) finds that trading patterns of investors change around news releases, with a differentiation between institutions and individual investors. Looking at the effects of news-coverage on net investor flows into a mutual fund, Kaniel et al. (2007) show that there is a significant effect that is consistent with investor attention to news and learning from them.

There is more literature on the effects of natural disasters on the stock market. Lamb (1998), finds that the market reacts differently to each hurricane, dependent on the magnitude and the firms' loss exposure for hurricanes Hugo and Andrew. Ewing et al. (2006) look at the effects of hurricane Floyd on insurance firms by making a connection with the available media releases of the market value of such firms. They find that the markets respond to the time sensitive information provided by the National Weather Service (NWS), the National Hurricane Center (NHC), and media outlets. Blau et al. (2008), looking at hurricanes Katrina and Rita, find that there is abnormal short selling but only after 2 days following landfall of Katrina and that these effects are more prominent during hurricane Rita. There, the market incorporated the information about hurricane Rita before landfall indicating that short sellers tried to profit from stock price changes during hurricane Rita based on the

[1] Based on Griffin et al. (2015), unburnable carbon refers to the economic value of the excess of a firm's prove economically recoverable oil, gas, and coal reserves over those reserves consistent with stabilizing global temperature increases less than 2°C.

information available from Katrina. Feria-Domínguez et al. (2017) analyse the impact of hurricanes on the P&C Insurance Firms for seven major hurricanes between 2005 and 2012. They find that there are significantly abnormal returns during hurricanes Rita, Felix, Ike, Igor and Ophelia but not during Katrina or Sandy.

This paper is the first to address the memory effect of hurricane Katrina on the reaction of the U.S. stock exchange returns around the costliest hurricanes that followed Katrina. The analysis focuses on the hurricane-related news-coverage and their effects on stock returns not only as a simple event study, as is normally done, but by controlling for the amount of news each event generated. Our goal is to identify changes in the stock returns of *all sectors listed in the S&P 500 SPX index* in the years that hurricanes Katrina, Ike, Irene, Sandy and Patricia took place. There, we focus on the way news coming from the NHC and all major news outlets affect the investors' reaction to hurricanes. We focus on the changes in those reactions whenever the news make a comparison of every hurricane with Katrina. Additionally, we explore the effects of spatial differentiation by looking at the effects of hurricanes on the stock market given the states affected by each hurricane when taking into account the concentration of S&P 500 firms' headquarters. Furthermore, we test the hypothesis that hurricane-related news affect the market even in the absence of actual significant damages; if there is a strong *expectation of damages* as a result of media news-coverage and scientific reports. Last, we discuss the effect of hurricanes in all the SIC defined divisions (see Table A.1 in the appendix), separately, as indicated by the Standard Industrial Classification (SIC) code of each firm in the S&P 500 index.[2]

Section 2 discusses the data we used for our assessment and our hypotheses. Section 3 presents the results and Section 4 concludes.

2 Hypotheses and data

In order to identify the effect of hurricane-related news-coverage on stock returns and the effect hurricane Katrina has on the perception on the following events, we look at the costliest mainland United States tropical cyclones following hurricane Katrina (i.e., from 2005). Based on the National Oceanic and Atmospheric Administration's (NOAA) data [Blake et al. (2011)], we look at hurricane Katrina in 2005 which caused circa \$108 billion in damages. Next, we focus on hurricanes Sandy in 2012, Irene in 2011 and Ike in 2008 which caused \$71.4 billion, \$15.8 billion, \$29.5 billion in damages, respectively (see Tables 1 and A.4). Since we are interested in the response of the market to the hurricane-related news but also on the role hurricane Katrina plays in the memory of investors when evaluating hurricanes, we only consider hurricanes that have caused substantial damages (i.e., more than \$10 billion).

Our main assumption is that under *significant expected damages*, investors will correct their initial negative response to hurricane news when a comparison with Katrina is made, as no hurricane was expected to do as much damage. Additionally to Ike, Irene and Sandy, we discuss hurricanes Rita and Wilma which made landfall in the U.S. mainland between the period August-October 2005 just after Katrina hit. Due to the intensity of all three events (Katrina, Wilma and Rita) and their temporal proximity, separating the news coverage signal on stock returns for each event is difficult if not impossible. We assume that in the weeks following Katrina, when Rita and Wilma hit, the news treated the events as a continuous story making the direct distinction between them difficult.

Additionally, we look at the effect of news around hurricane Patricia in 2015. Even though the actual damages of hurricane Patricia where minimal (circa \$325 million), *"Patricia is the strongest hurricane on record in either the eastern North Pacific or North Atlantic basins"* [Kimberlain et al. (2016)]. As such, we include hurricane Patricia as a control case. The *expected damages*, based on the projected intensity and path, where very high, yet the end result of Patricia was minimal damage. A similar phenomenon was observed during hurricane Irene, were the expectation of damages was much higher than the actual damages of \$15.8 billion. The inclusion of these hurricanes, will allow as to examine the hypothesis that hurricane news affect the market *negatively* even in the absence of significant damage, if there is a strong *expectation of damages* as a result of such media coverage and scientific reports.

The analysis of late 2008 requires special attention. During the last day of hurricane Ike on Monday, September 15, 2008 Lehman Brothers Holdings Inc. declared bankruptcy with \$639 billion in assets and \$619 billion in debt forcing Standard & Poor's to remove Lehman Brothers Holdings Inc. (LEH.N) from S&P 500 SPX stock index, and replace it with Harris Corp. (HRS.N). On that day,

[2] From now on the 9 divisions define by the SIC codes in our dataset are referred to as Industries.

S&P 500 SPX index lost 4.7% and the Dow Jones Industrial Average (INDU) index lost 504 points (i.e., 4.4%). Later the same day, another firm listed on the S&P 500 SPX stock index, American International Group, Inc. (AIG) sees its credit rating lowered from A- to AA- due to reduced flexibility. Only a day later on September 16, the Fed announces the bailing-out of the insurance company with a $85 billion loan in return of the 79.9% of AIG's equity. The announcement of a bank bailout package on September 18, lifted the index by 4.3% only to lose 8.8% on September 29 when the US Senate voted against the bailout bill. Thus, due to this volatile situation, separating the signal from hurricane Ike is challenging. Another year in which important financial shocks occurred is 2011. On August 8, 2011, following the downgrade of the U.S. credit rating from AAA to AA+ by Standard & Poor's and the fears of a further debt crisis in Europe, the S&P 500 stock index dropped by 6.7% with all industry groups of the index falling. Nonetheless, by August 21, 2011 when Irene hit the U.S., the effects of these shocks on the market seem to have dissipated (see fig. 1).

Tables 1 and A.4 describe the dates, damages, and intensities as measured by the Saffir-Simpson scale for each hurricane and the warning/intensity variable.[3] Additionally, figure 1 shows the market returns on the S&P 500 stock index around the days of the selected hurricanes separate.

2.1 Hypotheses regarding the effects of news coverage on the stock market

This section describes the working hypotheses regarding the effects of news coverage on the stock market that will be empirically tested in the following sections.

2.1.1 Hurricanes and news-coverage

Bourdeau-Brien and Kryzanowski (2017) argue that news-coverage of disasters (not restricted to hurricanes) has either no or a weak influence on the abnormal returns but the events themselves generate abnormal returns. In this paper, we investigate the relationship between news and abnormal returns when focusing on the costliest hurricanes. Investors' perception of firms' future value can be affected by hurricane-related news. Hurricanes distort supply chains and destroy capital and infrastructure, but also create opportunities. One example is Carnival Corp.[4] The initial effect of hurricane Katrina on Carnival was a huge drop in revenues that was counteracted shortly after by a $236 million government contract to provide temporary housing to people affected by Katrina on three of its ships. Thus, hurricanes can create two opposing forces, downwards due to damages caused and upwards due to opportunities generated.

Nevertheless, the effects of hurricanes on the stock market are not the same for all types of investors. We assume that buy-and-hold investors will be less interested in making changes in their investing strategy because in the long-run, the effects of a hurricane will be averaged out. This is not the same though for the day-trading or short-term outlook investors who try to make a profit by exploiting changes in prices of stocks during the course of a day. The changes in returns produced by hurricane related news we look to identify are mostly created by the latter types of investors and by the contrasting effects hurricanes can have on the firms' values.

Hurricanes' impacts on the stock market are expected to be found and to be of a very small magnitude as argued by Mitchell and Mulherin (1994). Additionally, as we will discuss in detail below, we hypothesise that the sign of the effect is dependent on the Industry of interest. Considering all of the above, we assume that the news coverage of a hurricane creates a signalling mechanism. If there is an effect of hurricanes on abnormal returns, this effect is triggered by the investors being informed about the unfolding of the disaster. This information is passed to the investors either through the news-coverage of the event or through other sources. What we explore with this paper is exactly this mechanism, how the hurricanes' news coverage affects the investors perspective on the value of a firm.

2.1.2 The Katrina memory effect

One of the main assumptions of this paper is that, under significant expected damages from the hurricanes after Katrina, which turned out to be lower than the ones caused by Katrina, investors correct their initial response to hurricane news when a comparison with Katrina is made. A simple example

[3] As described below in section 2.2§1.

[4] CCL, that is part on the S&P 500 index for all years considered in our study.

comes from the *Insurance* sector and hurricane Irene with a total of around $7 billion in insured losses [Avila and Cangialosi (2011)]. Day traders or short-term outlook investors may consider selling the insurance stocks they hold due to losses caused by payments of insurance claims. Although, when a direct comparison with Katrina, Wilma and Rita, and the $52 billion in insured losses caused (i.e., approximately 93% of all domestic insured losses of 2005), investors may re-evaluate their reaction to the news about the $7 billion in insured losses which are a fifth of the Katrina related losses. This assumption here connects additionally to the quote by B. Morrow on the [Blake et al. (2011)] report that people only remember the worst effects of a hurricane for about seven years. All of the hurricanes considered in this paper fall within a seven-year period and, given the arguments above, the Katrina related news can be expected to have an opposite sign effect to those of the original hurricane's news. We call this the *Katrina memory effect*. We test the empirical validity of this assumption in the following section. Patricia occurred 10 years later than Katrina. This larger distance between Patricia and Katrina provides the opportunity to test if the seven-year memory claim also holds for investors. If this were the case, we should expect to see no Katrina memory effect there.[5]

2.1.3 Industries

Our analysis does not focus on one industry or one aggregate index. We are interested in the industry specific responses to hurricanes and hurricane-related news. The testable assumption here is that the returns of different industries are affected in different ways by the hurricanes and hurricane-related news, whether in sign, magnitude and significance. The *Insurance* firms for example, may experience a downwards pressure on their value caused by payments to cover damages caused by the hurricane, resulting in a depletion of their cash and cash equivalents.[6] *Mining* firms are expected to react negatively, as the insurance firms above, to hurricanes and hurricane-related news due to capital destruction and disruption of operations caused, for example, by flooding.

After a hurricane hits, the damages on, for example, infrastructure and buildings need to be repaired as soon as possible. Thus, the expectation of future revenues could be enough to drive the value of *Construction* firms upwards following a hurricane. Shortly before a hurricane, grocery stores near the potentially affected areas could see an increase in their revenues due to the peoples' reaction to stocking-up food and other supplies in case of an emergency. This influx of revenue might be enough to affect the firms' values positively. Even though the positive effects seen by the *Retail Trade* firms are only on the short-term, for the period during or directly after the hurricane, it could be possible to detect a slight increase in the firms' values.

2.1.4 Damages and expected damages

We are interested in the effect of the news, not only during hurricanes that actually caused significant damages, but also during hurricanes that were expected to cause such damages but did not. In particular, hurricane Patricia, which was projected to be one of the strongest hurricanes ever recorded and was expected to hit the U.S., at the end did not make landfall in that country. However, due to the high-risk perception created by the news-coverage, investors may have reacted in the short-run similarly as they did during hurricanes that did cause large damages due to fear.

2.1.5 Intensity

Data on the projected intensity and the warnings made by the NHC and NWS are publicly available and broadcast by the media before and during each event. We start from a simple assumption that hurricanes indeed affect the stock market. A logical extension would be that as the intensity of an event increases so does the (positive or negative) effect on the stock market. Now remember the two conflicting forces discussed above. Assuming that a hurricane can indeed create opportunities for profit, we believe that there must be a tipping point. Effectively, an intensity point where investors stop seeing opportunities any more but rather the size of the disaster. This could generate a fear of losses which in turn can create a downwards pressure on the firms' values. This implies a non-linear reaction to hurricane's intensity, meaning that, as intensity increase returns increase up to a point where they start decreasing. This is consistent with Fink and Fink (2013) who found that the increasing intensity

[5] In the section 4.2 we also look at the effects of the second costliest hurricane i.e Sandy similarly to Katrina.

[6] Of course in reality the effects are not so straight forward. Here there might be an opposite force at play that might although take place a bit after a hurricane has passed. As indicated by Shelor et al. (1992), the insurance sector might profit from a hurricane by additional premium earnings by people re-evaluate their own insurance needs or government required coverage.

of major tropical storms' warnings by the NHC is associated with increases in the returns of large petroleum refining firms.

2.1.6 Latent response

As indicated by Bourdeau-Brien and Kryzanowski (2017), the effects on a firm's value resulting from a hurricane come from indirect channels such as production and supply-chain disruptions rather than direct damages. As such, the full effect of a hurricane on profits and hence the stock market may require some time to materialise. Another example of a latent response to hurricanes was described above for the Insurance firms. There can be a negative effect in the short-run resulting from payments to the policyholders, that can be counteracted by a positive effect resulting from higher premium or greater coverage. In this case, the negative effects can materialize close to the hurricane event due to investors' expectations. Contrary, the positive effects may require some additional time to take place. Consequently, differences in effects are expected between the days of the hurricane event and a relatively longer period of time.

2.1.7 Regional effect and past costs

The location of damages can be a very important determinant of the hurricanes' impacts on stock market returns. Our assumption is that the relationship between hurricanes and hurricane-related news, and the stock market returns might be dependent on the U.S. states each hurricane affected. One reason for this difference could be the concentration of firms' operations within one region. We propose a *spatial proximity hypothesis* which states that the effect of a hurricane on the stock market is going to be stronger when U.S. states with higher concentration of economic activity are hit, by taking into account the significance each region has in the operations of different firms. Based on that assumption, we would expect that different affected regions show different signs, magnitudes and significance levels. For simplicity, we suppose that states that concentrate more headquarters are more important for the firms' operations. This is an oversimplification but it is necessary due to complexity of the firms' operations and the data availability. Apart from the production side of the *spatial proximity hypothesis*, by including the hurricane affected regions in our analysis we are able to answer a more relevant question: *"Do investors react differently to hurricane news when the hurricanes affect the U.S stock exchange operations directly such as during hurricane Sandy in 2012?"*. What we expect is that, due to the closure of the stock exchange, the effects of the hurricanes would become more prominent to investors and thus, the effects larger in magnitude.

Regarding the news coverage itself, we examine the memory of hurricane Katrina when the subsequent hurricanes took place. However, there may be a short-term memory effect as well. Examining the news articles, an apparent trend can be found: news tends to mention the damages of the previous significant hurricane. As a result, it could be expected that the significance of the hurricane with which a direct comparison is made plays a role in the reaction of investors. A way to measure the severity is through the damages caused by each hurricane. We assume that, if a comparison with a past hurricane is made, the damages caused of such hurricane will be also mentioned. Thus, this reminder could potentially affect the investors' reaction to the hurricane news.

In our model, we also use past costs as an attempt to capture *forecast fatigue*. We define *forecast fatigue* as the reaction caused by an unsuccessful hurricane forecast in time t for region j, during the following hurricane forecast in time $t{+}1$ for the same region j. A clear example is given by hurricanes Irene and Sandy that hit approximately the same region with only one year difference. The forecasts about Irene generated a lot of media attention but the final effects of Irene on the coastal areas were far from the ones predicted. This might have affected the way coastal residents dealt with the information about Sandy. Another example of *forecast fatigue* might explain why some people chose not to evacuate New Orleans before Katrina. Hurricane Ivan was forecast to strike the city the year before, thus residents evacuated. Nevertheless, Ivan turned more to the east and hit Pensacola, Florida. Simply, *forecast fatigue*, in a more generalised setting, can be more easily understood based on Aesop's fable, *The Boy Who Cried Wolf*. Based on the moral of the story, a series of wrong predictions will generate mistrust that can hamper stakeholders' reactions to a threat. So, based on our *past costs* assumption and the *forecast fatigue* hypothesis, we expect that, the damages of the past hurricanes affect the investors reaction negatively today. What we mean is that if the costs of the previous hurricane were small, investors may be more confident to invest during a hurricane compared to investing during a hurricane that follows a very costly one.

2.2 Data

Table 2 shows the data used in our analysis. Data on the daily holding period returns of the S&P 500 firms were downloaded from the Center for Research in Security Prices (CRSP) for the whole calendar year in which an event took place. The S&P 500 Composition Changes was downloaded for every year from Compustat - Capital IQ, Compustat Monthly Updates and compared with a dataset from Siblis Research.[7] The five Fama-French factors of the Fama-French-Carhart model [Fama and French (1993), Carhart (1997)] was accessed through WARDS (Wharton Research Data Services) database. The price of crude oil (West Texas Intermediate) was obtained, from the U.S Energy and Information Administration [EIA (2017)]. The frequency of the data is daily. Quarterly data on earnings and analysts' recommendation from WARDS are also included in our analysis. Data on the dates of the hurricanes, the warnings issued and the intensity measured by the Saffir-Simpson scale were extracted from the NOAA report of each hurricane [Knobb et al. (2005), Berg (2009), Avila and Cangialosi (2011), Blake et al. (2013), Kimberlain et al. (2016)]. In our analysis, expected intensity is represented by the highest warning issued by the NOAA at day t within the U.S. Based on the coastal watch-and-warning system, the Hurricane/Tropical Storm alerts are translated in a 0-5 scale representing expected intensity; Tropical Storm discontinued(1), Tropical Storm Watch issued(2), Tropical Storm Warning(3), Hurricane Watch(4), Hurricane Warning(5) and when no warnings were issued it is zero. Table 1, contains the highest warning issued by hurricane in order to give an idea on the expected damages that can be compared with the actual damages on the previous column.

The news coverage of each separate hurricane was downloaded, with daily frequency, from LexisNexis Academic NL.[8,9,10] We considered news data staring from three calendar days before each event started [Knobb et al. (2005), Berg (2009), Avila and Cangialosi (2011), Blake et al. (2013), Kimberlain et al. (2016)])] and for 50 calendar days after that. News count is assumed zero after this period. The reason is that, approximately one month after the occurrence of the hurricane the news-coverage is very small with the exception for hurricane Katrina when Wilma and Rita were happening at almost the same time, thus generating more news-coverage. We have also obtained the news coverage of all the hurricanes of interest that happened before the ongoing one. For example, during the days of hurricane Sandy we collected the news headlines mentioning hurricanes Katrina, Ike and Irene, and tried to exclude, as much as possible, the overlap between them.

Figure 1 shows the days when the event occurred, the news-coverage during and after each hurricane, and the returns on the S&P 500 stock index. As expected, the Katrina related news peaked after the event was over, when the size of the damages became apparent. It is worth noting that hurricane Sandy generated more headlines than Katrina did during the days of the event. Katrina received approximately the same amount of attention during hurricanes Ike and Irene but much less attention during Sandy and Patricia (see Figure A.2).

Figure A.1 shows the headquarters' location of each of the S&P 500 firms included in our analysis (Derived from Compustat - Capital IQ) and the U.S. states that were affected by each hurricane (damages linked to each hurricane). Furthermore, we have aggregated the affected states in five groups which are similar to that of the Census Bureau Regions and Divisions with the following exceptions: Division 5: South Atlantic and Division 6: East South Central were merged together as well as the two Midwest Divisions 3 and 4 [US-Census-Bureau (2010)] (see Table 2 for more information). As discussed above, the regional variables are included in the analysis to capture the the hurricanes' spatial proximity effect given the importance of every state measure in the concentration of headquarters.

3 Methodology

3.1 Model specification

We conduct an event study type analysis. With this aproach, we can explore the relationship between the S&P 500 firms' daily excess stock returns including the news about hurricanes. We follow Griffin

[7] http://siblisresearch.com/data/

[8] https://academic.lexisnexis.nl/

[9] The query terms used for the search are: [(("hurricane HHH" OR "storm HHH" AND HEADLINE(HHH)) and ((#GC342#) OR (#GC343#)) and Date(geq("DATE") and leq("DATE")))], where HHH is the name of each hurricane and DATE is one day of interest for all the Major Publications in the U.S.

[10] In addition to the daily count of headlines containing the hurricanes of interest, we downloaded the daily count of the major news outlets' coverage mentioning the hurricanes in the main body with no constrain on the headline to contain the name of the hurricane. Even though this search gave obviously more results in general, we refrain from using it in our analysis for two reasons. First, LexisNexis Academic NL truncates the maximum number of results to 3000 without giving an indication of the true search result. Second, we assume that the headline has a higher impact since they are not restricted by pay-walls as the main body of some news articles is.

et al. (2015) who use daily data on energy firms to examine the relation between the stock market returns and news about unburnable carbon coming from the literature and other news sources.

Our analysis is based on the Calendar-Time Abnormal Returns model (the Fama-French-Carhart model [Fama and French (1993), Carhart (1997)]). The model estimates the *abnormal returns* by regressing the daily stock returns of each firm (R_{it}) on the daily one-month treasury bill rate (R_{tf}), the returns on the US market minus weighted equity index in excess returns of free risk rate ($R_{mk} - R_{tf}$), the size factor of Fema-French model (SMB), the Earnings growth rate of Fema-French model (HML) and Momentum (UMD).[11]

$$R_{it} = \beta_0 + \beta_1 R_{ft} + \beta_2(R_{mk} - R_{ft}) + \beta_3(SMB_t) + \beta_4(HML_t) + \beta_5(UMD_t) + \varepsilon_{it} \quad (1)$$

This model specification (Eq.1) is extended to include the news-coverage of each hurricane, a dummy variable for the days the hurricanes took place, the price of crude oil plus some firm specific information such as reported earnings per share, earnings announcements and analysts' recommendations. The final model has the following form:[12]

$$\begin{aligned} R_{it} = {} & \beta_0 + \beta_1 R_{ft} + \beta_2(R_{mk} - R_{ft}) + \beta_3(SMB_{it}) + \beta_4(HML_{it}) + \beta_5(UMD_{it}) + \\ & \beta_6(Event_t) + \beta_7(Katrina\_headlines_t) + \beta_8(Ike\_headlines_t) + \beta_9(Katrina{*}Ike\_headlines_t) + \beta_{10}(Irene\_headlines_t) + \\ & \beta_{11}(Katrina{*}Irene\_headlines_t) + \beta_{12}(Sandy\_headlines_t) + \beta_{13}(Katrina{*}Sandy\_headlines_t) + \beta_{14}(Patricia\_headlines_t) + \\ & \beta_{15}(Katrina{*}Patricia\_headlines_t) + \beta_{16}(Analyst_{it}) + \beta_{17}(EPSAR_{it}) + \beta_{18}(Earnings_{it}) + \varepsilon_{it} \end{aligned} \quad (2)$$

The intercept β_0 is the estimated daily average abnormal return of the S&P 500 firms (i.e., the amount the firms outperform/under-perform the market). This should be statistically insignificant, otherwise it might be an indication of missing factors affecting the stock returns or of potentially ignored structural breaks occurring in the U.S. market.

In contrast with the even-time model, this model specification allows not only to look at a longer time period where more information concerning the events in question is available, but also to account for within-industry cross-firm correlation of returns [Lyon et al. (1999)]. Furthermore, it allows to control for several other firm level variables such as additional recommendations from analysts (*Analyst*), and the earnings per share as reported (*EPSAR*). This information is available for longer periods (quarterly). In order to test the hypothesis that Katrina had long-term effects, we create an interaction term between the Katrina related news and the news-coverage of each hurricane. For example, this interaction term for Ike equals to zero during the years 2005, 2011, 2012 and 2015 but during 2008 it is equal to the product of the hurricane Katrina related news appearing during Ike times the Ike related news-coverage. This allows to test the Katrina memory hypothesis, which consists in that when news about a current hurricane are accompanied by Katrina comparisons in the news, investors re-evaluate their original reactions.

Based on our basic model structure (Eq.2), we are able to test longer time-window responses to hurricane news. Basically, by expanding the time-window of the *Event* variable we can test the delayed response hypothesis. In this version of our model (see Eq.4 in the appendix) we have included an additional variable ($Event_{+20}$) which is equal to 1 for the days of each event and for 20 days after the event has finished and zero otherwise. Similarly, we test out hurricane intensity hypotheses by substituting the *Event* variable by our *Intensity* variable. These two variables (i.e. *Event* and *Intensity*) are not included together in the same model because of multicollinearity. The variable *Intensity* takes values different from 0 only during the days of an event, exactly as the variable *Event*, thus, measuring a similar effect.

Both of these variables, capture the response of the market during the days of hurricanes. The only difference between them is the additional variation coming from changes in hurricane intensity. As a result, we adjust our basic model as presented in Eq.5. As described above, hurricane intensity enters our model here in a quadratic form.

We enrich our model in Eq.2 by including two new pieces of information: first, regional variables are added (as described in 2.2§4) in order to test the spatial proximity hypothesis, and second, the magnitude of total costs of the previous hurricane is included (e.g., in 2012 these are the costs of the previous significant hurricane which was Irene).This extension of our basic model is described by Eq.6 in the appendix.

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[11] An interesting and in depth description on the event study methodology can be found in Sorescu et al. (2017).

[12] Table 2 contains the description of all the variables used in the model.

Based on the first two digits of the SIC code of each of the S&P 500 firms, we group the firms into 9 SIC defined divisions: 1) Agriculture, Forestry and Fishing; 2) Construction; 3) Finance, Insurance and Real Estate; 4) Manufacturing; 5) Mining; 6) Retail Trade; 7) Services 8) Transportation, Communications, Electric, Gas and Sanitary service; 9) Wholesale Trade.

In order to identify the effects of hurricane-related news coverage on the stock returns of each industry group we estimate Eq.2 for each sector separately. This provides an estimate on how different industries react to hurricanes and their related news.

We also look at the effects of each hurricane separately. A simple way of looking at the individual effects could be to split the regression into five groups by year of event (i.e., 2005, 2008, 2011, 2012 and 2015) but this could cause specification errors. The problem occurs due to the existence of possible high multicollinearity among each year between our news covariates. Imagine the following example, we are estimating the effects of Ike related news on stock returns between two years 2008 and 2011. We hypothesise that the interaction of Katrina related news with Ike related news affects stock returns too but the interaction term is highly collinear during 2008. Thus in the split regression Ike related news will be probably insignificant in 2008 due to the potential high multicollinearity despite having an actual impact on stock returns. Considering the aforementioned, we use a year based interacted regression model (see Eq.7), that is analogous to the split year regressions, but does not suffer from the same shortcomings.

3.2 Standard errors and clustering

Following Thompson (2011), we note that standard errors (SEs) are consistently estimated if the residuals are not correlated across the two dimensions of the panel (here firms and time). With that in mind, consider the case of the hurricane as a market-wide shock. This will create correlation among the firms of the dataset at time *t*. Additionally, due to the recurrent nature of the hurricanes, they can induce correlation between different firms in different years. Based on that information, computing the SEs requires some additional attention. *"[...]If one clusters by firm, observations may be correlated within each firm, but must be independent across firms. If one clusters by time, observations may be correlated within each time period, but correlation across time periods is ruled out[...]"*[Thompson (2011)]. Thus, in our analysis we employ a double clustering method that computes the SEs such that they are robust to correlations amongst both the dimensions of our data (i.e firm and time).

In the simplest, case the variance estimate for an OLS estimator $\widehat{\beta}$ is:

$$\widehat{V}[\widehat{\beta}] = \widehat{V}_{firm} + \widehat{V}_{time} - \widehat{V}_{white} \tag{3}$$

where $\widehat{V}_{firm}$ is the variance estimate when clustering by firm, $\widehat{V}_{time}$ is the variance estimate when clustering by time, and $\widehat{V}_{white}$ is the heteroskedasticity-robust OLS estimate. Eq.3 is valid in the absence of persistent common shocks. In the methodology discussed by Thompson (2011), the problem of persistent common shocks can be solved by estimating autocovariances between residuals. Based on Thompson (2011), we know that autocovariance estimates that correct for persistent common shocks are biased downward resulting in estimated standard errors that are biased downward. Thus, eliminating the bias requires a large number of time periods. Unfortunately, the hurricanes considered in our analysis constrained by hurricane Katrina, are nearly not enough to eliminate this bias. Thus, in this paper we employ the simple double clustering technique described in Eq.3 by firm-year.

4 Results

4.1 Main results

The discussion of our results follows the hypotheses made above in 2.1 and are based on equations 2, 4, 5, 6 and 7 and Table 3. It is important to note that the intercepts in the regressions (Eq. 2, 6, 4 and 5) are insignificant, which indicates the absence of unexplained abnormal returns.

4.1.1 The news effect

The main interest of this paper is to evaluate the effect of hurricane news-coverage on the stock market returns. Table 3 Eq.2 shows a clear pattern. *Hurricane news has a significant negative effect* *on the stock market returns,* with an exception in hurricane Irene, ranging from -5.5e-5pp (SE 5e-6) in Patricia to -2.1e-7pp (SE 5.1e-8) for Katrina. Even the effects of Patricia related news are negative and significant indicating that in absence of actual damages, the fear generated by news is enough to have an actual impact on the stock returns. This pattern indicates that there is a mechanism, similar to the one described by Eisensee and Strömberg (2007) but on the side of the investors. News coverage here acts as a signalling mechanism for the investors on the importance of a hurricane and the damages it might cause.

As a hurricane gets more and more attention, the expected damages rise and the opportunities for profit due to the disaster are minimised. Additionally, what we see is that following very costly hurricanes such as Katrina and Sandy, the negative news effect on the returns of the next hurricane, Ike and Patricia, respectively, becomes stronger. In general though, news has a small effect on the stock returns.

The positive and highly significant effect of Irene related news is of interest. As shown in Figure 1, in all cases except Irene, the returns of the S&P 500 index (dashed line) decrease immediately after the hurricane has passed. Risk aversion explains this, as the realisation of the hurricane forecast resolves most the uncertainty about its impact. In contrast, in the case of Irene, the returns kept increasing from mid-hurricane and for two days afterwards up to the 29th of August when the index started correcting. Insurance firms saw very positive returns during Irene such as Hartford Financial, of 12%. On the Energy sector, O'Connell (2011) wrote that *"**[U]tility companies are glowing**. While widespread power outages were reported along the eastern seaboard this weekend, the consensus seems to be that utility companies handled the storm effectively, and that's being reflected in share prices this morning"*. To sum up, as the effects of the hurricane became clear (i.e., the insurance payments will be of far less magnitude than the ones expected and the effective way which the energy companies handled the situation) the mechanism of news, as indicated in the paragraph above, reverses. More news is additional information on the opportunities that arose from hurricane Irene thus additionally feeding this increase in returns.

Next, we discuss our *Katrina memory* hypothesis. Contrary to the negative and significant effects of news on the stock returns, the interaction terms including Katrina are all positive and significant but very small in magnitude. The existence of these positive effects can be interpreted as a correction effect supporting our *Katrina memory* hypothesis. Given the news of a hurricane, once the news outlets start making a direct comparison with Katrina, by mentioning how much more disastrous Katrina was, the investors seem to respond to that information positively correcting their negative reaction to the hurricane news. Finally, the positive and significant coefficient for the interaction term of Katrina*Patricia indicates that even if people remember the worst effects of a hurricane only for seven years, a direct comparison made by the news can still affect the perception of investors.

In contrast to the other memory coefficients, the Katrina*Irene coefficient is negative and significant, but much smaller in magnitude. In this case Katrina can be seen as a reminder that kept some investors from valuing the firms higher.

4.1.2 The effect of hurricanes

The binary variable *Event* captures the change in returns created by the hurricanes. As it seems from Table 3 Eq.2, the hurricanes in question increase the market returns by 0.032 (SE 1.2e-4) percentage points. The positive and significant result of *Event* indicates that, during the short period the hurricanes were taking place, investors viewed the events as a profit opportunity and re-evaluated their perception of the firms' value higher than in the absence of the hurricanes. We begin our interpretation of the results from the binary variable *Event* that captures the change in returns created by the hurricanes as events. As it seems from Table 3 Eq.2, the hurricanes in question *increase* the market returns by 0.032 percentage points. Based on the analysis in section 2.1.1, the positive and significant result of *Event* indicates that, during the short period the hurricanes were taking place, investors viewed the events as a profit opportunity and re-evaluated their perception of the firms' value higher than in the absence of the hurricanes. Most probably, this small effect we see here is a result of the changes in the perception of short-term outlook investors that do make adjustments trying to make a profit by exploiting changes in prices of stocks during the course of a day. So, what we see is a short-term positive reaction of investors, in the presence of a hurricane.

In Table 3 Eq.6, which includes past costs and locality, show that *Event* is no longer significant. *Event* is also insignificant if extended to include twenty working days after a hurricane (see Eq.4). This connects to our *latent response* hypothesis. The insignificant result here indicates that as more information about the actual effects of the hurricanes became available, the market sees no change in the value of firms resulting from the hurricanes. Thus, there is indeed a difference between the direct repose of the market to the hurricanes and the reaction based on a relatively longer period of time where more information is available. The lack of statistical significance of the extended *Event* variable contradicts the results of Lanfear et al. (2017), who found that extreme weather events in the form of hurricanes in the 30 post-event period generate a price depreciation for most of the industries excluding gold-related stocks. More on the industry specific effects is discussed below.

However, not all events create the same response. As shown by the estimates produced by Eq.7 (Table 3), which separates the variable *Event*, the short-term market's reaction was positive (and highly significant) during hurricanes Katrina, Ike and Sandy (i.e., the three most costly hurricanes; see table A.4 in the appendix) and negative during Irene and Patricia (i.e., the least costly hurricanes included in our analysis). This negative reaction (-0.062pp, SE 2.2e-4) during hurricane Patricia is not surprising. Even though the final damages were minimal due to the path followed, Patricia is the strongest hurricane on record and the expectation of damages was very high. This can be interpreted as a negative response of the stock market to the *expectation of damages*, (in the absence of actual damages) created by the news and the NHC warnings for hurricane Patricia. This supports our hypothesis 2.1.4 that even though Patricia did not make landfall in the U.S. nor generated extreme damages, the fear of a change in path of the hurricane Patricia generated significant abnormal returns as was the case during the disastrous hurricanes such as Katrina and Ike.

The positive reactions during Ike and Sandy suggest that this positive reaction is caused by *forecast fatigue*. In the case of Irene and Sandy, *forecast fatigue* may be more prominent as both hurricanes hit roughly the same area, New Jersey and New York, with only one year difference. As the media coverage of Irene overstated the potential damages investors might have felt comfortable when Sandy was announced maybe expecting a similar outcome. The final results of Sandy though, were completely different and comparable with Katrina in magnitude of damages.

4.1.3 The intensity effect

Based on Eq.5 we test the hypothesis that the intensity enters stock returns in quadratic form. The two intensity coefficients in table 3 Eq.5 are jointly significant at 1% with with α negative and β positive. As such, for small intensity values, returns increase up to an inflection point where they start decreasing. If we look at intensity in a linear form the coefficient is positive and significant similar to *Event* in Eq.2, a finding that is line with the results of Fink and Fink (2013).

4.1.4 The past costs and locality effect

The past cost coefficient is insignificant thus our past costs hypothesis is not supported here. By including past costs and locality, *Event* is no longer significant.[13] Assuming that past costs can capture *forecast fatigue*, the inclusion of forecast fatigue has minimal effects on our results.

The locality coefficients *NEd1, NEd2, MWd3_4, Sd5_6, Sd7*, are all significant (except for *Sd7* that includes Texas, Louisiana and Arkansas (see Figure A.1) but with mixed signs, as expected. Keeping the number of headquarters constant in New Jersey, New York and Pennsylvania (*NEd2*), when this region is affected by a hurricane, the market drops by 5.5e-6pp (SE 1.2e-6). Interestingly, Indiana, Illinois, Michigan, Ohio and Missouri (*MWd3_4*) generate larger negative effects than the states of *NEd2*, (-8.4e-6pp, SE 4.8e-6) but with the same order of magnitude. This may be caused by the concentration of firms' specific production or other important infrastructure in those states. Next, looking at the positive locality coefficients *NEd1* and *Sd5_6* we see that they are an order of magnitude larger than the negative ones, 1.9e-5pp (SE 3.7e-6 and 5.6e-6 respectively) for both. Thus, these results support our hypothesis that the spatial proximity of hurricanes generate different reactions to investors not only in magnitude but also in sign.

4.1.5 The industries specific effect

Based on the divisions of the SIC codes (see Table A.1 in the appendix), we have defined 9 industries and we discuss the results of each industry separately based on Eq.2 as presented on Tables 4 and A.3.

[13] Some further investigation revealed that the significance of *Event* only goes after the inclusion of localities and not past coats.

Table 4 shows that hurricanes generate different reactions in different industries. Division E, *Transportation, Communications, Electric, Gas, and Sanitary Services* is characterized by the same general results described above: *Event* is positive (1.1e-3, SE 5e-4), news related coefficients are negative (including Irene related news) and, without exceptions, memory interactions are negative. Similar results are found for *Services* (1.2e-3, SE 6.4e-4) and *Manufacturing* (1.1e-3, SE 3.2e-4) but not all news related coefficients are significant in these cases.

Finance, Insurance and Real Estate and *Mining* are the only two industry groups with a negative coefficient for *Event* (-2.3e-3, SE 7.9e-4 and -3.1e-3, SE 1.2e-3 respectively). In general, these negative results are not surprising. Mining and oil-gas extraction firms are expected to be affected by the hurricanes either due to production disturbance due to damages or flooding, or due to supply-chain breakdowns. Similarly, this negative result for *Finance, Insurance and Real Estate* can be due to the expected payments to policy holders from the side of the insurance firms. Real Estate can also be negatively affected by hurricanes probably due to the *"Citizens hurricane or tropical storm binding suspension rule"*. This rule restricts application for new coverage or endorsement for increased coverage when a tropical storm or hurricane watch or warning has been issued by the NWS. Thus, if new insurance will not be issued due to the hurricanes' NWS warnings, Real Estate closing cannot take place if insurance is required. This is also in line with the results of Saginor and Ge (2017) who find a significant and negative effect on housing sales values from 1984 to 2007, which can directly be attributed to the hurricanes impacting the area of study.

Wholesale Trade is the industry that seems completely unaffected by the hurricanes. What is surprising, though, is the non-significant coefficient for *Event* in *Construction* and *Retail Trade*. Based on our assumptions, we expected these two industries to show a positive reaction during the days of the hurricane. These insignificant coefficients may be due to the fact that the news variables absorb the variation of the event.[14]

4.2 Sensitivity analysis

A.2 in the appendix presents some sensitivity analyses. The interaction terms of hurricane Katrina related news and the news of the event in question imply a potentially complex relation between the dependent and the independent variables and may need control for confounding effects. S.2 of Table A.2 excludes all interaction terms related to hurricane news. The sign and the significance of the remaining variables compared to the full model remain mostly unaffected except for hurricane Ike related news which is now insignificant. Ike coincided with the beginning of the financial crisis, so separating the signal resulting from hurricane Ike is challenging.

Based on that finding we go further by excluding hurricane Ike and 2008 from our analysis in S.5 of Table A.2. Excluding the period of high volatility (i.e., 2008) the coefficients of the remaining covariates do not change much. Therefore, our model is broadly robust to these exclusions with some small changes in the magnitude which are expected.[15]

Our analysis is based on the 4-factor model of Fama and French (1993) and Carhart (1997). Even though the inclusion of Carhart momentum in the 3-factor Fama-French model is common in the asset pricing literature [Blitz et al. (2016)], it is somewhat arbitrary. We compare the 4-factor with the 3-factor based model in S.3. If momentum is excluded from the analysis the significance levels between the single firm level (see S.3) and the double firm-time clustering are the same.[16] Even though the standard errors are slightly different, variables retain their significances. The significant Intercept here indicates that the 3-factor model is probably incomplete and that more factors are needed to describe stock returns.

Hurricanes Rita and Wilma struck the U.S. mainland between the period August-October 2005, days after Katrina hit. Due to difficulties in separating the signal coming from three events so close to each other, Rita and Wilma related news were omitted from our main model. Variable Event is changed to include also the days during Rita and Wilma as indicated by the NOAA/NHC [Blake et al. (2011)] report. Comparing S.4 with S.1 we see practically no changes in significance and magnitude of the results apart from quarterly earnings per share as reported (*EPSAR*) which is now insignificant.

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14 If we run these two regressions excluding all news related variables, *Event* becomes significant (positive) in Construction but not in Retail Trade.

15 Even though it has not been included in the paper we have also explored the effect of news only during the days of the hurricanes. In that case, *Event* is still positive and significant so are the Katrina interactions with Ike and Patricia. Katrina and Patricia related news are negative and significant but the Ike, Irene and Sandy are not.

16 Results are available upon request.

We assume that the intensity enters the model in a quadratic form. If we look at returns as a linear function of intensity a positive and highly significant coefficient as in Table A.2, S.6, implying that no matter how severe an event is, more destructive hurricanes would produce higher returns.

Looking beyond the effects of the Katrina memory effect, we include the memory of the second costliest hurricane also, Sandy. The result of the new interaction term Sandy*Patricia is highly significant, positive (1.1e-5, SE 2.1e-6) and the same order of magnitude as the Katrina*Patricia coefficient (5.4e-5, SE 8.4e-6). Thus the memory of Sandy had the same effect as the memory of Katrina, correcting the initial negative response to the Patricia related news. The signs and significance of the other covariates compared to S.1 (main model) are the same and the magnitudes are slightly different.

4.3 Effect size

We predict, ceteris paribus, the impact on stock returns of a hurricane based on the average number of headlines during a twenty day interval since a hurricane first appears. Figure 2 and Table 5 show the predicted returns. Table 5 directly compares the predicted returns with the largest gains in the S&P 500 index (11.6% on the 13th October 2008), if the prediction is positive, and the lowest percentage change between 2005 and 2015 (-9% on the 15th October 2008) if the prediction is negative.[17] Hurricane Ike is worst (-0.14%). This is 1.5% of the largest losses of the S&P 500 index between 2005-2015; or 0.007% of Black Monday.[18] Ike is followed by Patricia (-0.11% or 1.2% of the S&P largest losses), Sandy (-0.04% or 0.4% of the S&P largest losses) and Katrina (-0.03% or 0.3% of the S&P largest losses). The interaction of Katrina and Ike has the largest positive effect size (0.10% or 0.8% of the S&P largest gains) almost equivalent to the positive Ike effect followed by Irene (0.03% or 0.3% of the S&P largest gains). Clearly, the average effect of hurricane-related news is very small in comparison with other changes of the index.

5 Conclusion

This paper investigates the effects on the S&P 500 firms' value of the four costliest hurricanes: Katrina, Ike, Irene and Sandy, plus Patricia which is strongest hurricane on record. We look at the reaction of the stock market to the hurricane-related news-coverage in order to identify how much of the hurricanes' effect on the stock market is actually caused by the media. Moreover, we test the hypothesis that a direct comparison with the costliest hurricane (i.e., Katrina) would have a calming effect counteracting the potentially negative effects of hurricane-related news during Ike, Irene, Sandy and Patricia. We define this comparison with Katrina as the *Katrina memory* effect. By looking at all divisions based on the SIC codes, featured in the S&P 500 during the years 2005, 2008, 2011, 2012 and 2015 we are able to identify differences in responses based on the specific characteristics of each industry. Furthermore, we explore the effect of hurricane-related news on the stock market given the expected intensity of each event as measured on a daily basis by the warnings made by the National Weather Service (NWS). Last but not least, we further broaden our research by trying to capture the effects of forecast fatigue on our results, and the changes the hurricanes' spatial proximity causes to the stock market.

Results indicate that investors react positively (significant positive abnormal returns) to hurricanes as events but negatively to the amount of news associated with the hurricanes. This positive reaction though, seems to fade away once a longer event period of 20 days following the event is considered. Same positive effect is also shown for intensity, indicating that, as warnings become more severe, there are additional significant positive abnormal returns. Nevertheless, the relationship between intensity and returns is more complex as shown by the results. We show that the memory of hurricane Katrina still has an effect on the reaction of investors during hurricanes Ike, Irene, and Sandy that fall within the seven-year interval that the memory of the worst effects of a hurricane remain, but also during Patricia, 10 years after Katrina took place. This effect is positive for all hurricanes except Irene where is negative. Additional to the news, we explore the effect of a hurricane's spatial proximity effect on the stock returns. We found that when a hurricane affects (i.e., generates damages) the states belonging to North East division 2 and Mid-West divisions 3 and 4, the market reacts negatively compared to the positive reaction to hurricanes affecting states belonging to North East division 1 and

[17] See Table A.5 for the highest and lowest returns of the index.

[18] 19th of October 1987, were the index dropped by 20.47%.

South divisions 5, 6 and 7. These results are in line with Bourdeau-Brien and Kryzanowski (2017) who find significant positive abnormal returns resulting from natural disaster in the states where the disaster hits but also in the neighbouring states. Last, our sensitivity analysis shows that our model is robust, thus our main results are not affected by changes in model specifications.

There are some issues that call for further research. The way news enters our model is in the form of amount of coverage without making a distinction between the "language" and terms used in every article. Further research is needed regarding the effect of specific terms in the texts such as "disaster", "damages" and "flood" relating to hurricane news (i.e., sentiment analysis). Another potential use of sentiment analysis in our setting could be the analysis of the SEC filings[19] relating to hurricanes. Last, concerning the news, more attention is needed in the future in the way forecast fatigue affects the perception of investors during hurricanes beyond past costs, maybe in the form of an experiment. A point of further research relates additionally to when hurricane news coverage is collected. Here we only follow the news for 50 days following an event. Instead, a longer period could be considered until all hurricane-related news went down to zero. Although we do not expect the extended news to have a substantial effect, because two months after the hurricane the event can just be considered as old news and no new information is to be obtained. On the modelling side, when looking at the effects of news on each industry separately, we base our results on a split sample analysis. Another potential way of looking at the industry specific effect without assuming that the decisions of investors in every industry are independent of the rest is probably a model based on Seemingly Unrelated Regressions (SUR) or based on Multi-level models.

Finally, after a long hurricane drought without any landfall in mainland USA, we observed two such events (Harvey, Irma) at the start of the hurricane season of 2017, a close call (Maria) and the prospect of more to come. These events provide an excellent out-of-sample test for our models, and additional data for re-estimation.[20] The academic excitement about recent events is outweighed by their human loss and suffering.

6 Tables and Figures

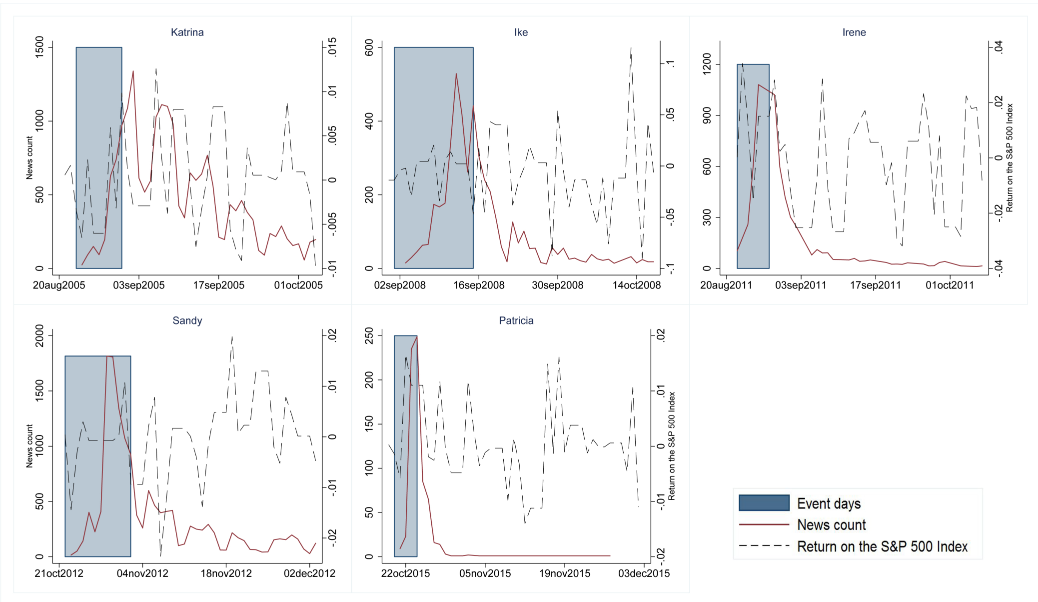

Fig. 1 Amount of news coverage for each event and S&P 500 returns by day around the days of each event

[19] SEC filings are financial statements submitted to the U.S. Securities and Exchange Commission (SEC).

[20] At the time of writing, these data are not yet available.

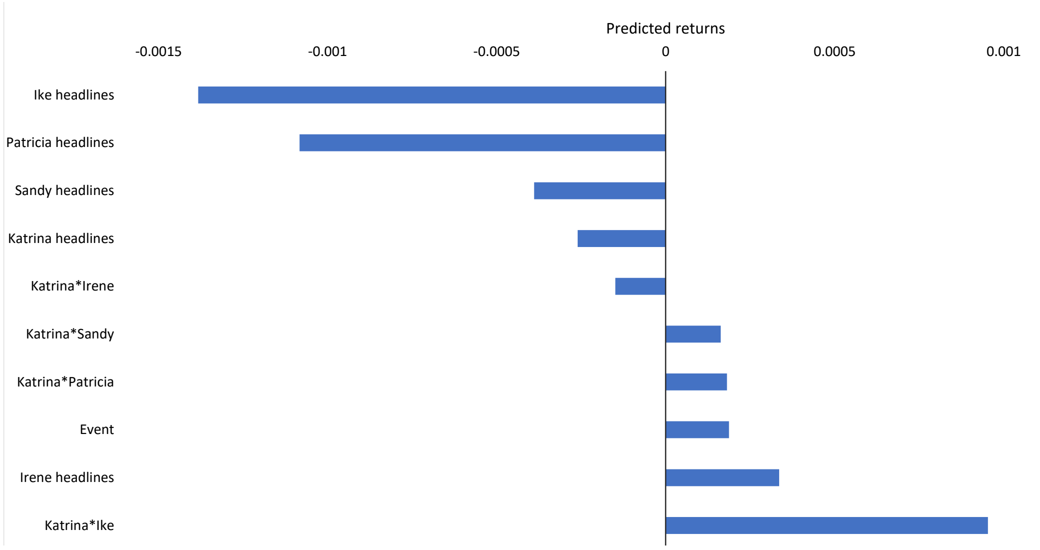

Fig. 2 Predicted returns for the mean headlines during a twenty day interval since a hurricane has started (see Table 5)

Table 1 Events' days, costs and intensity

Hurricane	Dates	Damage	Intensity[a]
Patricia	20 - 24 October 2015	$325 million	0[b]
Sandy	22 - 29 October 2012	$71.4 billion	3
Irene	21 - 28 August 2011	$15.8 billion	4
Ike	1 - 15 September 2008	$29.5 billion	5
Wilma	15 - 25 October 2005	$20.6 billion	5
Rita	18 - 26 September 2005	$12 billion	5
Katrina	23 - 30 August 2005	$108 billion	5

The *damage costs* are based on the NOAA report for each event.

[a] See section 2.2§1.

[b] No warning for the U.S 5 including the warnings in Mexico.

Table 2 Definition of variables

Variable name	Definition
rf	Daily one-month treasury bill rate.
Rmk-Rft	Returns on the US market minus weighted equity index in excess returns of free risk rate.
smb	Size factor of Fema-French model.
hml	Earnings growth rate of Fema-French model.
umd	Momentum; average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.
Oil price	$(P_t - P_{t-1})/P_{t-1}$ where P is the price of West Texas Intermediate (WTI) crude oil.
Event	1 during the days of all Hurricanes as reported by the NOAA reports and 0 otherwise.
Event 2005	1 during the days of Hurricane Katrina as reported by the NOAA reports and 0 otherwise.
Event 2008	1 during the days of Hurricane Ike as reported by the NOAA reports and 0 otherwise.
Event 2011	1 during the days of Hurricane Irene reported by the NOAA reports and 0 otherwise.
Event 2012	1 during the days of Hurricane Sandy as reported by the NOAA reports and 0 otherwise.
Event 2015	1 during the days of Hurricane Patricia as reported by the NOAA reports and 0 otherwise.
Intensity	Saffir-Simpson Hurricane Wind Scale from 1 to 5 during the days of each events and 0 otherwise.
Event+20	1 during days -1 plus 20 working days after each event has past and 0 otherwise.
Katrina_headlines	Count of hurricane Katrina related headlines in major news platforms.
Ike_headlines	Count of hurricane Ike related headlines in major news platforms.
Katrina*Ike	Interaction of Katrina related headlines times the Ike related headlines during Ike and 0 otherwise.
Irene_headlines	Count of hurricane Irene related headlines in major news platforms.
Katrina*Irene	Interaction of Katrina related headlines times the Irene related headlines at time t.
Sandy_headlines	Count of hurricane Sandy related headlines in major news platforms.
Katrina*Sandy	Interaction of Katrina related headlines times the Sandy related headlines at time t.
Patricia_headlines	Count of hurricane Patricia related headlines in major news platforms.
Katrina*Patricia	Interaction of Katrina related headlines times the Patricia related headlines at time t.
Past costs	Indicates the total damages of the previous significant hurricane and 0 for the days without hurricane news.
NEd1	Sum of S&P 500 headquarters of the states affected by each event in Northeast Division 1[a].
NEd2	Sum of S&P 500 headquarters of the states affected by each event in Northeast Division 2[a].
MWd3_4	Sum of S&P 500 headquarters of the states affected by each event in Midwest Divisions 3 and 4[a].
Sd5_6	Sum of S&P 500 headquarters of the states affected by each event in South Divisions 5 and 6[a].
Sd7	Sum of S&P 500 headquarters of the states affected by each event in South division 7[a].
Analyst	1 if analysts made a recommendation on day t for firm j and 0 otherwise.
EPSAR	Quarterly earnings per share as reported.
Earnings	1 during days of earnings announcements for firm j and 0 otherwise.

a. See Fig. A.1

Table 3 Basic results on daily returns based on Eq. 2 to 6[b].

	Basic model (Eq.2)	Including past costs and locality (Eq.6)	20 days window ($Event_{+20}$) (Eq.4)	Event intensity (Eq.5)	Decomposing events (Eq.7)
Event	3.2e-04***	2.7e-04[c]	1.0e-04		3.1e-04***
Event 2008					5.0e-04***
Event 2011					-2.4e-04**
Event 2012					9.1e-05
Event 2015					-6.2e-04***
Intensity				1.5e-04+	
$Intensity^2$				-1.5e-05+	
Katrina_headlines	-2.1e-07***	-7.2e-07***	-2.9e-07	-2.0e-07***	-6.4e-08
Ike_headlines	-8.0e-06***	-7.6e-06[a]	-7.8e-06[a]	-8.1e-06***	-9.6e-06***
Katrina*Ike	1.3e-06***	1.3e-06***	1.3e-06***	1.3e-06***	1.4e-06***
Irene_headlines	1.8e-06***	2.4e-06***	1.9e-06***	1.7e-06***	2.0e-06***
Katrina*Irene	-1.5e-08**	-2.0e-08**	-1.4e-08	-1.2e-08	-1.6e-08*
Sandy_headlines	-7.0e-07***	-6.7e-07[a]	-8.6e-07***	-7.2e-07***	-5.0e-07***
Katrina*Sandy	3.1e-07***	3.0e-07***	3.2e-07***	3.1e-07***	2.9e-07***
Patricia_headlines	-5.5e-05***	-6.6e-05***	-5.4e-05***	-5.7e-05***	-4.0e-05***
Katrina*Patricia	7.3e-06***	9.3e-06***	7.2e-06***	7.6e-06***	4.7e-06***
Past costs		-1.4e-06			
NEd2		-5.5e-06***			
NEd1		1.9e-05***			
MWd3_4		-8.4e-06*			
Sd5_6		1.9e-05***			
Sd7		4.6e-06			
Intercept	-5.2e-05	-4.4e-05	-5.5e-05	-5.2e-05	4.7e-04***
N	645843	645843	645843	645843	645843
R^2	0.354	0.354	0.354	0.354	0.354

[*] $p < 0.1$, [**] $p < 0.05$, [***] $p < 0.01$,

[+] jointly significant with p<0.001,

[a] SEs are omitted because the two-way robust estimator results in variance estimates $\hat{V}[\hat{\beta}]$ that have negative elements on the diagonal so a reported error occurs , even though inference is appropriate for the parameters of interest Cameron et. al (2009).

[b] Full representation of the results that includes all variables used in the models is included in the appendix Table A.2.

[c] $p = 0.110$ and $SE = 1.715e-4$

Table 4 Industry lever regression basic results based on Eq.2

	Construction	FIRe	Manufacturing	Mining	Retail Trade	Services	Transportation	Wholesale Trade
Event	NS	-2.3e-03***	1.1e-03***	-3.1e-03***	NS	1.2e-03**	1.1e-03**	NS
Katrina_headlines	NS	NS		2.7e-06***	NS	NS	NS	NS
Ike_headlines	4.2e-05*	NS	-1.2e-05***	8.2e-05***	-4.7e-05***	-2.3e-05***	-3.5e-05***	-2.3e-05*
Katrina*Ike	NS	NS	1.9e-06***	-1.1e-05***	6.6e-06***	2.9e-06***	4.9e-06***	NS
Irene_headlines	2.9e-05**	7.1e-06***	NS	3.2e-06*	NS	2.8e-06*	-5.5e-06***	NS
Katrina*Irene	-6.8e-07**	-9.9e-08**	NS	NS	NS	NS	9.8e-08***	NS
Sandy_headlines	-1.9e-05*	-3.7e-06***	3.8e-06***	NS	NS	NS	-6.0e-06***	NS
Katrina*Sandy	5.0e-06**	6.6e-07**	-5.2e-07**	NS	1.5e-06***	NS	9.8e-07**	NS
Patricia_headlines	-8.8e-04***	NS	NS	-5.3e-04***	NS	NS	-3.4e-04***	NS
Katrina*Patricia	1.8e-04***	NS	NS	8.2e-05**	NS	NS	5.2e-05***	NS

[*] $p < 0.1$, [**] $p < 0.05$, [***] $p < 0.01$,

-Each column represents one separate regression with daily returns as the dependent variable. **FIRe**: Finance, Insurance and Real Estate, **NS**: Not significant, **NA**: No coefficient because Agriculture appears in our dataset only after 2012.

Transportation represents Division E: Transportation, Communications, Electric, Gas, And Sanitary Services.

Table A.3 in the appendix includes all coefficients of model Eq.2 by industry.

Table 5 Predicted returns (Effect size) of the mean headlines during a twenty day interval since a hurricane has started.

Variable	Coefficient (Eq.2)	Mean headlines	Effect size	Comparison[a]
Ike headlines	-8.0e-06	161	-0.138%	1.5% of the 15th October 2008 decrease[b]
Patricia headlines	-5.5e-05	18	-0.108%	1.2% of the 15th October 2008 decrease
Sandy headlines	-7.1e-07	384	-0.039%	0.4% of the 15th October 2008 decrease
Katrina headlines	-2.1e-07	655	-0.026%	0.3% of the 15th October 2008 decrease
Katrina*Irene	-1.5e-08	7	-0.015%	0.2% of the 15th October 2008 decrease
Katrina*Sandy	3.1e-07	3	0.016%	0.1% of the 13th October 2008 increase
Katrina*Patricia	7.3e-06	3	0.018%	0.2% of the 13th October 2008 increase
Event	3.2e-04	-	0.019%	0.2% of the 13th October 2008 increase
Irene headlines	1.8e-06	260	0.034%	0.3% of the 13th October 2008 increase
Katrina*Ike	1.3e-06	5	0.095%	0.8% of the 13th October 2008 increase

[a] See Table A.5 for returns on the 13th and 15th of October 2008. [b] or 0.07‰ of Black Monday 19/10/1987.

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A Appendix

Table A.1 SIC Division Structure[a]

A. Division A	**Agriculture, Forestry, And Fishing**
Major Group 01	Agricultural Production Crops
Major Group 02	Agriculture production livestock and animal specialties
Major Group 07	Agricultural Services
Major Group 08	Forestry
Major Group 09	Fishing, hunting, and trapping
B. Division B	**Mining**
Major Group 10	Metal Mining
Major Group 12	Coal Mining
Major Group 13	Oil And Gas Extraction
Major Group 14	Mining And Quarrying Of Nonmetallic Minerals, Except Fuels
C. Division C	**Construction**
Major Group 15	Building Construction General Contractors And Operative Builders
Major Group 16	Heavy Construction Other Than Building Construction Contractors
Major Group 17	Construction Special Trade Contractors
D. Division D	**Manufacturing**
Major Group 20	Food And Kindred Products
Major Group 21	Tobacco Products
Major Group 22	Textile Mill Products
Major Group 23	Apparel And Other Finished Products Made From Fabrics And Similar Materials
Major Group 24	Lumber And Wood Products, Except Furniture
Major Group 25	Furniture And Fixtures
Major Group 26	Paper And Allied Products
Major Group 27	Printing, Publishing, And Allied Industries
Major Group 28	Chemicals And Allied Products
Major Group 29	Petroleum Refining And Related Industries
Major Group 30	Rubber And Miscellaneous Plastics Products
Major Group 31	Leather And Leather Products
Major Group 32	Stone, Clay, Glass, And Concrete Products
Major Group 33	Primary Metal Industries
Major Group 34	Fabricated Metal Products, Except Machinery And Transportation Equipment
Major Group 35	Industrial And Commercial Machinery And Computer Equipment
Major Group 36	Electronic And Other Electrical Equipment And Components, Except Computer Equipment
Major Group 37	Transportation Equipment
Major Group 38	Measuring, Analyzing, And Controlling Instruments; Photographic, Medical And Optical Goods; Watches And Clocks
Major Group 39	Miscellaneous Manufacturing Industries
E. Division E	**Transportation, Communications, Electric, Gas, And Sanitary Services. (Transportation)**
Major Group 40	Railroad Transportation
Major Group 41	Local And Suburban Transit And Interurban Highway Passenger Transportation
Major Group 42	Motor Freight Transportation And Warehousing
Major Group 43	United States Postal Service
Major Group 44	Water Transportation
Major Group 45	Transportation By Air
Major Group 46	Pipelines, Except Natural Gas
Major Group 47	Transportation Services
Major Group 48	Communications
Major Group 49	Electric, Gas, And Sanitary Services
F. Division F	**Wholesale Trade**
Major Group 50	Wholesale Trade-durable Goods
Major Group 51	Wholesale Trade-non-durable Goods
G. Division G	**Retail Trade**
Major Group 52	Building Materials, Hardware, Garden Supply, And Mobile Home Dealers
Major Group 53	General Merchandise Stores
Major Group 54	Food Stores
Major Group 55	Automotive Dealers And Gasoline Service Stations
Major Group 56	Apparel And Accessory Stores
Major Group 57	Home Furniture, Furnishings, And Equipment Stores
Major Group 58	Eating And Drinking Places
Major Group 59	Miscellaneous Retail
H. Division H	**Finance, Insurance, And Real Estate. (FIRe)**
Major Group 60	Depository Institutions
Major Group 61	Non-depository Credit Institutions
Major Group 62	Security And Commodity Brokers, Dealers, Exchanges, And Services
Major Group 63	Insurance Carriers
Major Group 64	Insurance Agents, Brokers, And Service
Major Group 65	Real Estate
Major Group 67	Holding And Other Investment Offices
I. Division I	**Services**
Major Group 70	Hotels, Rooming Houses, Camps, And Other Lodging Places
Major Group 72	Personal Services
Major Group 73	Business Services
Major Group 75	Automotive Repair, Services, And Parking
Major Group 76	Miscellaneous Repair Services
Major Group 78	Motion Pictures
Major Group 79	Amusement And Recreation Services
Major Group 80	Health Services
Major Group 81	Legal Services
Major Group 82	Educational Services
Major Group 83	Social Services
Major Group 84	Museums, Art Galleries, And Botanical And Zoological Gardens
Major Group 86	Membership Organizations
Major Group 87	Engineering, Accounting, Research, Management, And Related Services
Major Group 88	Private Households
Major Group 89	Miscellaneous Services

[a] Table derived from the Occupational Safety and Health Administration of the US department of labor.

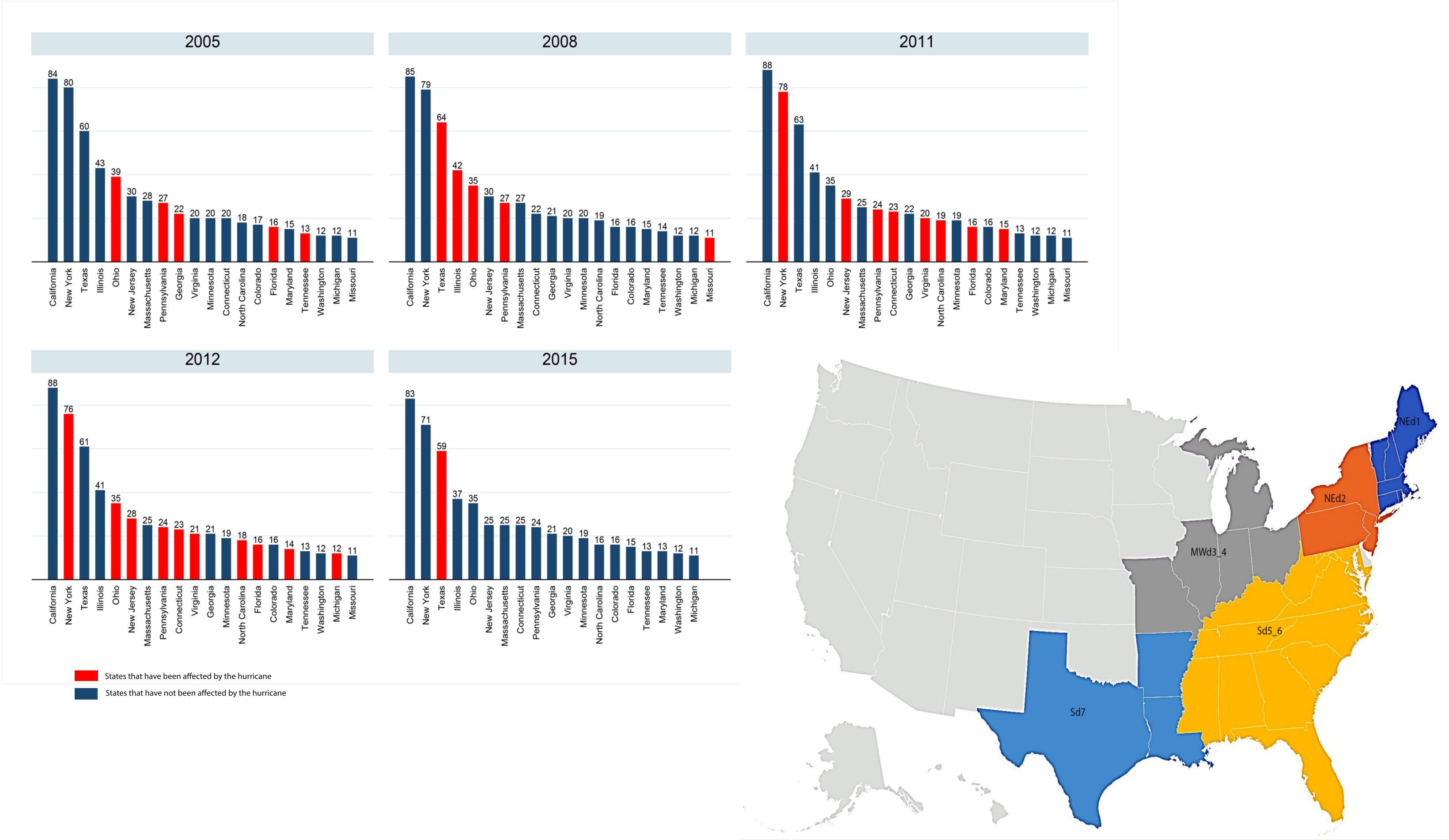

Fig. A.1 S&P 500 headquarters by state and regional grouping of U.S states

A.1 Additional model representations

$$
\begin{aligned}
R_{it} =& \beta_0 + \beta_1 R_{ft} + \beta_2 (R_{mk} - R_{ft}) + \beta_3 (SMB_{it}) + \beta_4 (HML_{it}) + \beta_5 (UMD_{it}) + \\
& \beta_6 (Event_{+20t}) + \beta_7 (Katrina\_headlines_t) + \beta_8 (Ike\_headlines_t) + \beta_9 (Katrina{*}Ike\_headlines_t) + \beta_{10} (Irene\_headlines_t) + \\
& \beta_{11} (Katrina{*}Irene\_headlines_t) + \beta_{12} (Sandy\_headlines_t) + \beta_{13} (Katrina{*}Sandy\_headlines_t) + \beta_{14} (Patricia\_headlines_t) + \\
& \beta_{15} (Katrina{*}Patricia\_headlines_t) + \beta_{16} (Analyst_{it}) + \beta_{17} (EPSAR_{it}) + \beta_{18} (Earnings_{it}) + \varepsilon_{it}
\end{aligned} \tag{4}
$$

$$
\begin{aligned}
R_{it} =& \beta_0 + \beta_1 R_{ft} + \beta_2 (R_{mk} - R_{ft}) + \beta_3 (SMB_{it}) + \beta_4 (HML_{it}) + \beta_5 (UMD_{it}) + \beta_6 (Intensity_t) + \beta_7 (Intensity_t^2) + \\
& \beta_8 (Katrina\_headlines_t) + \beta_9 (Ike\_headlines_t) + \beta_{10} (Katrina{*}Ike\_headlines_t) + \beta_{11} (Irene\_headlines_t) + \\
& \beta_{12} (Katrina{*}Irene\_headlines_t) + \beta_{13} (Sandy\_headlines_t) + \beta_{14} (Katrina{*}Sandy\_headlines_t) + \beta_{15} (Patricia\_headlines_t) + \\
& \beta_{16} (Katrina{*}Patricia\_headlines_t) + \beta_{17} (Analyst_{it}) + \beta_{18} (EPSAR_{it}) + \beta_{19} (Earnings_{it}) + \varepsilon_{it}
\end{aligned} \tag{5}
$$

$$
\begin{aligned}
R_{it} =& \beta_0 + \beta_1 R_{ft} + \beta_2 (R_{mk} - R_{ft}) + \beta_3 (SMB_{it}) + \beta_4 (HML_{it}) + \beta_5 (UMD_{it}) + \\
& \beta_6 (Event_t) + \beta_7 (Katrina\_headlines_t) + \beta_8 (Ike\_headlines_t) + \beta_9 (Katrina{*}Ike\_headlines_t) + \beta_{10} (Irene\_headlines_t) + \\
& \beta_{11} (Katrina{*}Irene\_headlines_t) + \beta_{12} (Sandy\_headlines_t) + \beta_{13} (Katrina{*}Sandy\_headlines_t) + \beta_{14} (Patricia\_headlines_t) + \\
& \beta_{15} (Katrina{*}Patricia\_headlines_t) + \beta_{16} (Analyst_{it}) + \beta_{17} (EPSAR_{it}) + \beta_{18} (Earnings_{it}) + \\
& \beta_{19} (NEd1) + \beta_{20} (NEd2) + \beta_{21} (MWd3_4) + \beta_{22} (Sd5_6) + \beta_{23} (Sd7) + \beta_{24} (PastCosts) + \varepsilon_{it}
\end{aligned} \tag{6}
$$

$$
\begin{aligned}
R_{it} =& \beta_0 + \beta_1 R_{ft} + \beta_2 (R_{mk} - R_{ft}) + \beta_3 (SMB_{it}) + \beta_4 (HML_{it}) + \beta_5 (UMD_{it}) + \\
& \beta_6 (Event_t) + \beta_7 (Katrina\_headlines_t) + \beta_8 (Ike\_headlines_t) + \beta_9 (Katrina{*}Ike\_headlines_t) + \beta_{10} (Irene\_headlines_t) + \\
& \beta_{11} (Katrina{*}Irene\_headlines_t) + \beta_{12} (Sandy\_headlines_t) + \beta_{13} (Katrina{*}Sandy\_headlines_t) + \beta_{14} (Patricia\_headlines_t) + \\
& \beta_{15} (Katrina{*}Patricia\_headlines_t) + \beta_{16} (Analyst_{it}) + \beta_{17} (EPSAR_{it}) + \beta_{18} (Earnings_{it}) + \beta_{19} (Year_{2008}) + + \beta_{19} (Year_{2011}) + \\
& \beta_{20} (Year_{2012}) + + \beta_{21} (Year_{2013}) + \beta_{22} (Event2008_t) + \beta_{23} (Event2011_t) + \beta_{24} (Event2012_t) + \beta_{25} (Event2015_t) + \varepsilon_{it}
\end{aligned} \tag{7}
$$

Table A.2 Sensitivity analysis[c].

	Main model (Eq.2, S.1)	Excluding news interactions (S.2)	Excluding momentum(umd[b]) (S.3)	Including Wilma and Rita (S.4)	Excluding 2008 (S.5)	Linear intensity (S.6)	Fully interacted model (S.7)	Including Sandy interaction (S.8)
rf	3.4***	3.5***	3.0***	3.4***	3.5***	3.4***	-1.2	3.4***
Rmk-Rft	1.0***	1.0***	1.1***	1.0***	1.0***	1.0***	1.0***	1.0***
smb	8.0e-02***	8.1e-02***	8.2e-02***	8.0e-02***	6.1e-02***	8.0e-02***	8.0e-02***	8.1e-02***
hml	5.4e-02**	5.2e-02**	1.7e-01***	5.4e-02**	3.4e-02	5.4e-02**	5.4e-02**	5.4e-02**
umd	-1.4e-01***	-1.4e-01***		-1.4e-01***	-6.9e-02***	-1.4e-01***	-1.4e-01***	-1.4e-01***
Oil price	1.5e-04	-8.6e-05	-5.7e-04	1.6e-04	1.8e-04	1.6e-04	3.3e-04	3.8e-05
Event	3.2e-04***	2.1e-04*	1.5e-04	2.0e-04*	2.2e-04***		3.1e-04***	4.9e-04***
Intensity						7.8e-05***		
Katrina_headlines	-2.1e-07***	-2.0e-07***	-5.0e-07**	-2.2e-07*	-3.1e-07***	-1.9e-07***	-6.4e-08	-2.3e-07***
Ike_headlines	-8.0e-06***	6.0e-08	-1.2e-05***	-7.7e-06[a]		-8.0e-06***	-9.6e-06***	-8.4e-06[a]
Katrina*Ike	1.3e-06***		1.6e-06***	1.3e-06[a]		1.3e-06***	1.4e-06***	1.3e-06***
Irene_headlines	1.8e-06***	1.5e-06***	1.6e-06***	1.9e-06***	1.1e-06***	1.7e-06***	2.0e-06***	1.6e-06***
Katrina*Irene	-1.5e-08**		-3.5e-08**	-1.5e-08*	6.0e-09	-1.1e-08	-1.6e-08*	-1.6e-08**
Sandy_headlines	-7.0e-07***	5.0e-07***	-2.0e-06***	-6.7e-07***	-5.4e-07***	-7.2e-07***	-5.0e-07***	-7.5e-07***
Katrina*Sandy	3.1e-07***		7.1e-07***	3.0e-07***	3.3e-07***	3.1e-07***	2.9e-07***	3.2e-07***
Patricia_headlines	-5.5e-05***	-1.9e-05***	-7.5e-05**	-5.2e-05***	-5.7e-05***	-5.8e-05***	-4.0e-05***	-3.5e-04***
Katrina*Patricia	7.3e-06***		1.0e-05*	6.8e-06***	6.9e-06***	7.8e-06***	4.7e-06***	5.4e-05***
Sandy*Patricia								1.1e-05***
Analyst	-3.1e-04	-3.2e-04	-1.9e-04	-3.1e-04	-1.5e-04	-3.1e-04	-3.1e-04	-3.1e-04
EPSAR	2.4e-05***	2.4e-05***	2.5e-05***	2.4e-05	2.5e-05**	2.4e-05***	2.6e-05***	2.4e-05***
Earnings	4.0e-04	3.9e-04	5.6e-04	4.0e-04	1.8e-04	4.0e-04	4.1e-04	4.0e-04
2008							-1.2e-04**	
2011							-5.3e-04***	
2012							-6.2e-04***	
2015							-5.3e-04***	
Event 2008							5.0e-04***	
Event 2011							-2.4e-04**	
Event 2012							9.1e-05	
Event 2015							-6.2e-04***	
Intercept	-5.2e-05	-5.5e-05	-1.0e-04***	-5.0e-05	-1.2e-04***	-5.2e-05	4.7e-04***	-5.3e-05
N	645843	645843	645843	645843	515541	645843	645843	645843
R^2	0.354	0.354	0.353	0.354	0.322	0.354	0.354	0.354

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$,

[a] SEs are omitted because the two-way robust estimator results in variance estimates $\widehat{V}[\widehat{\beta}]$ that have negative elements on the diagonal so a reported error occurs , even though inference is appropriate for the parameters of interest [Cameron et al. (2011)].

[b] SEs are calculated based on single firm level clustering.

[c] In every regression the dependent variable is daily returns.

Table A.3 Industry lever regression results based on Eq.2

	Construction	FIRe	Manufacturing	Mining	Retail Trade	Services	Transportation	Wholesale Trade
rf	-1.4	-2.7e-01	3.4***	2.4e+01***	5.5***	4.7***	9.7e-01	6.6e-01
Rmk-Rft	1.3***	1.2***	9.8e-01***	1.5***	8.9e-01***	1.0***	9.3e-01***	8.2e-01***
smb	9.9e-01***	4.9e-02	1.1e-01***	-1.7e-01***	2.6e-01***	1.6e-01***	-1.8e-01***	2.0e-01*
hml	8.9e-01***	9.6e-01***	-1.9e-01***	-5.2e-01***	-4.2e-02	-1.9e-01***	-2.8e-02	-6.7e-02
umd	-4.6e-01***	-2.6e-01***	-1.2e-01***	-6.9e-02	-2.4e-01***	-1.4e-01***	6.1e-02**	-1.7e-01**
Oil price	-3.6e-02*	1.8e-03	-4.2e-04	5.0e-03	-5.7e-03	-1.2e-03	2.8e-03	1.2e-02
Event	2.0e-03	-2.3e-03***	1.1e-03***	-3.1e-03***	4.3e-04	1.2e-03**	1.1e-03**	3.2e-03
Katrina_headlines	1.8e-06	3.6e-07	-4.4e-07	2.7e-06***	-1.4e-06	-7.2e-07	2.2e-07	-7.7e-07
Ike_headlines	4.2e-05*	1.6e-05	-1.2e-05***	8.2e-05***	-4.7e-05***	-2.3e-05***	-3.5e-05***	-2.3e-05*
Katrina*Ike	-3.3e-06	-1.8e-06	1.9e-06***	-1.1e-05***	6.6e-06***	2.9e-06***	4.9e-06***	1.0e-06
Irene_headlines	2.9e-05**	7.1e-06***	3.6e-07	3.2e-06*	2.4e-06	2.8e-06*	-5.5e-06***	3.3e-06
Katrina*Irene	-6.8e-07**	-9.9e-08**	2.6e-08	-6.3e-08	-4.6e-08	-3.3e-08	9.8e-08***	-9.9e-09
Sandy_headlines	-1.9e-05*	-3.7e-06***	3.8e-06***	2.0e-06	-4.0e-06	-1.0e-06	-6.0e-06***	-1.6e-06
Katrina*Sandy	5.0e-06**	6.6e-07**	-5.2e-07**	-9.4e-07	1.5e-06***	6.4e-07	9.8e-07**	1.2e-06
Patricia_headlines	-8.8e-04***	6.4e-05	5.2e-05	-5.3e-04***	7.3e-05	-7.9e-05	-3.4e-04***	6.3e-06
Katrina*Patricia	1.8e-04***	-6.8e-06	-1.4e-05	8.2e-05**	-2.7e-05	2.1e-05	5.2e-05***	-1.5e-06
Analyst	-1.9e-03***	1.4e-03***	-6.3e-04***	-3.2e-03***	-4.4e-04	-3.7e-04	-3.6e-04	-7.6e-04
EPSAR	4.3e-05	-3.6e-06	2.9e-05***	6.0e-06	2.0e-05	2.1e-05	8.8e-05	5.9e-05
Earnings	8.2e-03**	4.0e-04	7.0e-04	-3.1e-03	4.9e-05	1.9e-03	-2.2e-03**	3.7e-03*
Intercept	1.2e-03**	1.5e-04	-1.5e-04***	-4.0e-04**	7.6e-05	1.9e-05	-1.1e-04	-2.4e-04
N	7440	115137	264531	31576	53391	73809	83813	14870
R^2	0.490	0.410	0.369	0.412	0.356	0.377	0.369	0.273

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

FIRe: Finance, Insurance and Real Estate. **Transportation** represents Division E: Transportation, Communications, Electric, Gas, And Sanitary Services.

In every regression the dependent variable is daily returns.

Table A.4 The costliest mainland United States tropical cyclones, 1900-2016, (not adjusted for inflation) [Blake et al. (2011)].

Rank	Tropical Cyclone	Year	Category[d]	Damages[c]
1	KATRINA (SE FL, LA, MS)	2005	3	$108,000
2	SANDY (Eastern U.S.)[a]	2012	3	$71,400
3	IKE (TX, LA)	2008	2	$29,520
4	ANDREW (SE FL/LA)	1992	5	$26,500
5	WILMA (S FL)	2005	3	$21,007
6	IVAN (AL/NW FL)	2004	3	$18,820
7	IRENE (NC, NJ, NY, VT)[a]	2011	3	$15,800
8	CHARLEY (SW FL)	2004	4	$15,113
9	RITA (SW LA, N TX)	2005	3	$12,037
10	FRANCES (FL)	2004	2	$9,507
11	ALLISON (N TX)	2001	TS[b]	$9,000
12	JEANNE (FL)	2004	3	$7,660
13	HUGO (SC)	1989	4	$7,000
14	FLOYD (Mid-Atlantic & NE U.S.)	1999	2	$6,900
15	ISABEL (Mid-Atlantic)	2003	2	$5,370
16	OPAL (NW FL/AL)	1995	3	$5,142
17	GUSTAV (LA)	2008	2	$4,618
18	FRAN (NC)	1996	3	$4,160
19	GEORGES (FL Keys, MS, AL)	1998	2	$2,765
20	DENNIS (NW FL)	2005	3	$2,545
21	FREDERIC (AL/MS)	1979	3	$2,300
22	AGNES (FL/NE U.S.)	1972	1	$2,100
23	ALICIA (N TX)	1983	3	$2,000
24	BOB (NC, NE U.S)	1991	2	$1,500
25	JUAN (LA)	1985	1	$1,500
26	CAMILLE (MS/SE LA/VA)	1969	5	$1,421
27	BETSY (SE FL/SE LA)	1965	3	$1,421
28	ELENA (MS/AL/NW FL)	1985	3	$1,250
29	DOLLY (S TX)	2008	1	$1,050
30	CELIA (S TX)	1970	3	$930
31	LILI (SC LA)	2002	1	$925
32	GLORIA (Eastern U.S.)	1985	3	$900
	Total damages			**$400,160**

[a] added by the authors. [b] TS: Tropical Storm. [c] Damages in million US$.

[d] Hurricane category is based on the Saffir-Simpson Hurricane Wind Scale. It takes values from 1 to 5 based on the level of *sustained* winds. For more info see Schott et al. (2012).

Table A.5 The 10 largest daily gains and 10 lowest daily percentage losses of S&P 500 index between 2005 and 2015.

Date	S&P 500 returns
15 October 2008	-9.0%
1 December 2008	-8.9%
29 September 2008	-8.8%
9 October 2008	-7.6%
20 November 2008	-6.7%
19 November 2008	-6.1%
22 October 2008	-6.1%
7 October 2008	-5.7%
5 November 2008	-5.3%
12 November 2008	-5.2%
11 August 2011	4.6%
9 August 2011	4.7%
20 October 2008	4.8%
16 December 2008	5.1%
30 September 2008	5.4%
21 November 2008	6.3%
24 November 2008	6.5%
13 November 2008	6.9%
28 October 2008	10.8%
13 October 2008	11.6%

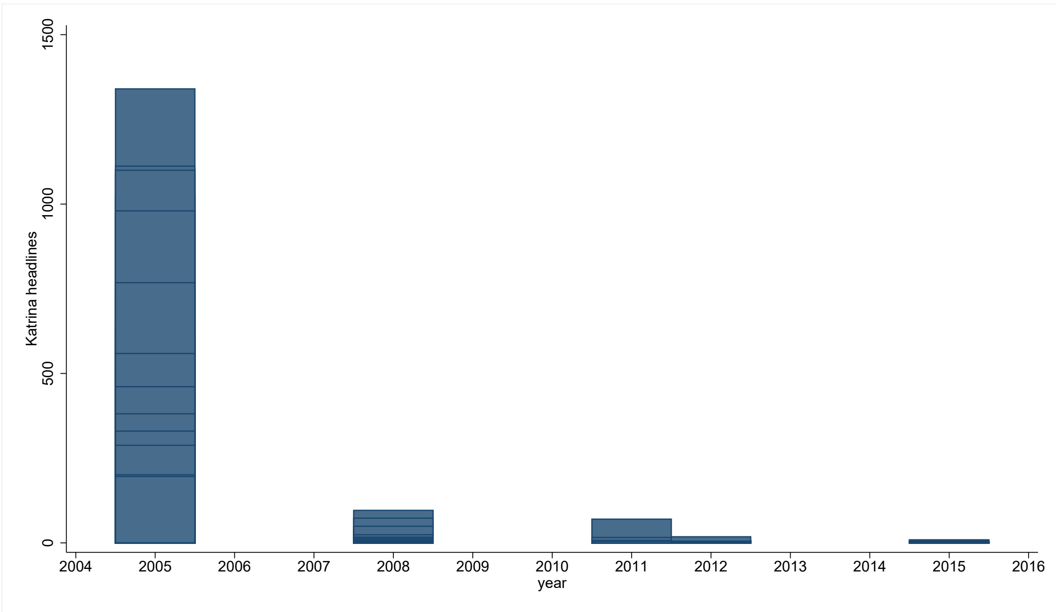

Fig. A.2 Katrina related headlines by year

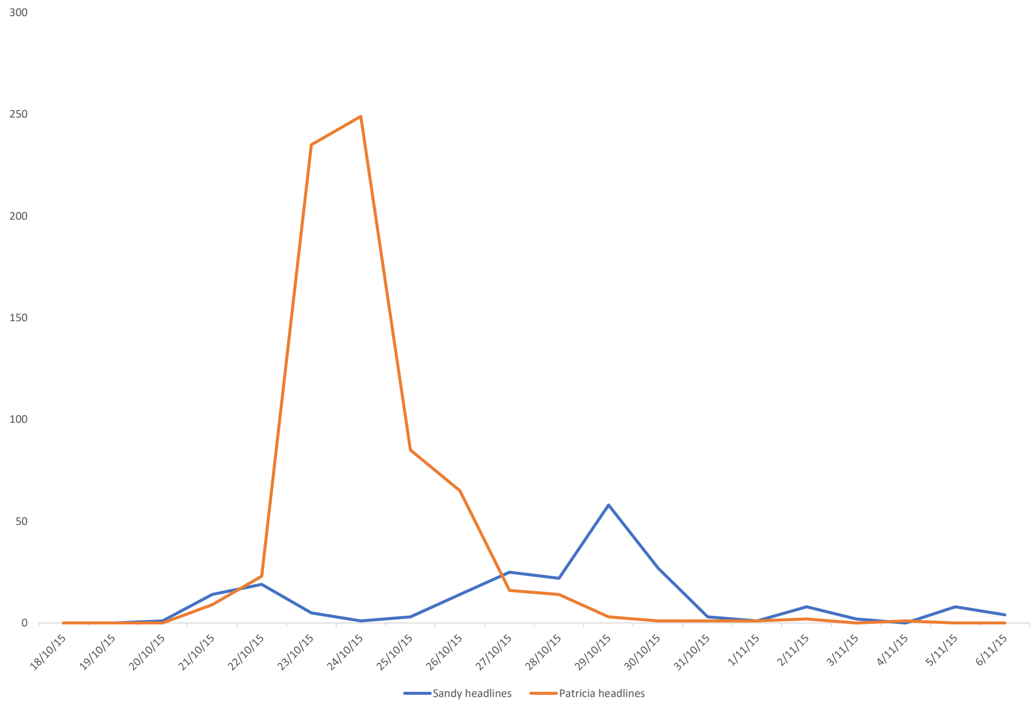

Fig. A.3 Sandy and Patricia related headline count during Patricia