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Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics

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Abstract
We investigate the uncertainty dynamics surrounding extreme weather events through the lens of option and stock markets by identifying market responses to both the uncertainty regarding potential hurricane landfall and subsequent economic impact. Stock options on firms with establishments exposed to the landfall region exhibit increases in implied volatility of 5-10 per- cent, reflecting impact uncertainty. Using hurricane forecasts, we show that landfall uncertainty and potential impact uncertainty are reflected in prices before landfall. We find no evidence that markets incorporate better hurricane forecasts than those from NOAA. Improvements to hurricane forecasts could have economically significant effects in financial markets.

Keywords: extreme weather events, uncertainty, implied volatility, stock returns, hurricanes, climate finance

JEL Classification Number: G12, G14, Q54

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1 Introduction

Extreme weather events can have devastating effects and were responsible for over $300 billion in damages in the United States in 2017 alone.[1] Despite significant research on extreme weather effects on real economic activity and household, firm, and financial institution decision making, little is known about uncertainty surrounding extreme weather.[2] Given that uncertainty affects real economic activity and decision making (see, for example, Bernanke (1983); Bloom, Bond, and van Reenen (2007); Bloom (2009)), a comprehensive assessment of the economic effects of extreme weather events requires understanding the uncertainty dynamics surrounding them.

This paper examines extreme weather uncertainty resulting from hurricanes through the lens of financial markets. Asset prices are an ideal instrument to assess the dynamics and magnitude of extreme weather uncertainty because of the frequency and scale at which financial data are available and the fact that the investor behavior underlying the asset prices is guided by financial incentives. We distinguish between two components of extreme weather uncertainty: (a) the "landfall uncertainty" regarding where, when, and whether a hurricane will make landfall, and (b) the "impact uncertainty" about a hurricane's effect conditional on it making landfall.[3]

We combine firm establishment and sales data at the county level with hurricane forecast and damage data in order to identify firms that operate within regions (potentially) exposed to a particular hurricane. We use these data to test two hypotheses regarding how financial markets price a hurricane's landfall and impact uncertainty.

Our first hypothesis is that immediately after a hurricane has made landfall, implied volatilities of options of firms in the disaster region are elevated due to impact uncertainty. Implied volatility is a proxy for uncertainty (see, for example, Bloom (2009) and Kelly, Pastor, and Veronesi (2016)) as it captures the investors' expectation of volatility. Our results support this first hypothesis. Indicative of substantial impact uncertainty, we find that immediately after hurricane landfall the

[1]The damage estimate is from the National Oceanic and Atmospheric Administration (NOAA) and can be found here:
https://www.climate.gov/news-features/blogs/beyond-data/2017-us-billion-dollar-weather-and-climate-disasters-historic-year.

[2]For research on the real effects and decision making of extreme weather events, see, for example, Belasen and Polachek (2008); Imberman, Kugler, and Sacerdote (2012); Barrot and Sauvagnat (2016); Bernile, Bhagwat, and Rau (2017); Dessaint and Matray (2017); Brown, Gustafson, and Ivanov (2017); Hong, Li, and Xu (2019).

[3]We focus on hurricanes because they develop and resolve over fairly short but well-defined time frames, NOAA publishes a range of forecast data, and they are likely to garner investor attention due to significant impacts and extensive media coverage. However, our framework can be applied to other extreme weather events like snow storms and severe floods, which are also subject to landfall and impact uncertainty.

implied volatility of options of firms in the disaster region are between 5 and 10 percent higher than before the hurricane's inception. This finding is surprisingly robust across industries, holds within industries, and for different time periods. To analyze the resolution of impact uncertainty, we examine the post-landfall stock price reactions of firms with a physical presence in a hurricane disaster region. In the short-term, the abnormal returns of firms in the disaster region are not significantly different from the control firms' abnormal returns, but the differences are substantial in the long-term. Further, the long-term differences are more pronounced for the underperforming stocks. Over the 120 trading days after hurricane landfall, the 10^{th} percentile of the abnormal return distribution for firms in disaster regions is 12 to 14 percentage points lower than the 10^{th} percentile of the abnormal return distribution of the control firms. Our results are consistent with a slow resolution of impact uncertainty, in line with investors only learning over time the effects of a particular hurricane and which firms were most affected by it.

Our second hypothesis is that investors pay attention to hurricane forecasts before landfall and demand compensation for the landfall uncertainty and the potential impact uncertainty. This hypothesis implies that hurricane forecasts contain valuable information for investors and, if financial markets are efficient, this information should be reflected in asset prices. Using NOAA forecasts issued in the days or weeks leading up to a hurricane's landfall or dissipation (in the case of a hurricane that "missed") to measure landfall uncertainty, we find implied volatilities increase and stock returns decrease consistent with Pastor and Veronesi (2012, 2013) even at low landfall probabilities of 10 percent and below.[4] Further, consistent with our framework, the combined landfall uncertainty and expected impact uncertainty can cause implied volatility to be higher before landfall compared to shortly after landfall, when landfall uncertainty is fully resolved and only impact uncertainty remains.

We build on our main results with several key extensions. First, given anecdotal evidence that hedge funds obtain information on hurricane forecasts from sources other than the NOAA,[5] we test whether financial markets can improve upon NOAA hurricane forecasts by estimating if firms that are *not* in the forecasted path of a hurricane but end up in the disaster region also see increases

[4]Unlike at the aggregate market level, stock returns and volatility at the firm level generally exhibit positive contemporaneous correlation as shown in Duffee (1995); Albuquerque (2012); Grullon, Lyandres, and Zhdanov (2012). As such, the negative return-volatility relationship documented at the aggregate levelis unlikely to drive our results.

[5]See, for example, the discussion of the hedge fund with the name Nephila by Michael Lewis here: https://www.nytimes.com/2007/08/26/magazine/26neworleans-t.html?pagewanted=all.

in the implied volatility of their options. We fail to reject the null hypothesis that markets do not reflect superior information to NOAA forecasts on hurricanes.

In light of recent improvements in hurricane forecast accuracy[6] and ongoing developments that could actually reduce the forecast accuracy going forward,[7] for our second extension, we examine the potential benefits of improving NOAA forecast accuracy in this context. We estimate the additional change in implied volatility due to forecast errors for firms for which the forecasted exposure was larger (smaller) than the eventual exposure to the disaster region. We find large average effects of up to 150 basis points for thousands of firms over the sample period from 2007 to 2017. This result speaks to the outsized importance of NOAA's hurricane forecasts for financial markets and is valuable information for legislators who make budgetary decisions.

Third, although we have focused our main results on the broad universe of US public firms (excluding financial firms), we conduct a separate analysis on insurance firms. Despite limitations due to the fairly small number of public property and casualty insurance firms with liquid options and stocks, and regional exposure (fraction of written premiums) data being at the state rather than county level, we find that single stock options of property and casualty insurance firms reflect substantial impact uncertainty immediately following a hurricane landfall, increasing implied volatilities by as much as 40 percent.

Our paper makes several contributions that build upon each other. We begin by presenting a novel framework to think about the uncertainty before and after extreme weather events. Second, our results show that investors are attentive to firm exposures to hurricanes even before landfall.[8] Third, our estimates imply that extreme weather uncertainty impose significant financial costs that should be taken into account when assessing the aggregate damage of extreme weather events. Fourth, given that research has shown that other types of uncertainty can affect a firm's decision making and that major events like elections yield similar magnitudes of uncertainty,[9] the

[6]Alley, Emanuel, and Zhang (2019) show that hurricane forecasts have indeed improved dramatically in recent decades. In particular, they find that "modern 72-hour predictions of hurricane tracks are more accurate than 24-hour forecasts were 40 years ago."

[7]Spectrum auctions for the 5G network may overlap with the frequency range in which water vapor emits, thereby limiting the ability of forecasters to collect an important source of data for current forecast models (see this discussion in The Guardian: https://www.theguardian.com/world/2019/may/04/5g-mobile-networks-threat-to-world-weather-forecasting.)

[8]Investor attention to extreme weather risk is important for correctly pricing assets with extreme weather and climate change exposure and reduces the risks of sudden large price corrections that could disrupt financial stability (see, for example, Carney (2015)).

[9]Uncertainty has been shown to reduce firm investments by Bernanke (1983), Bloom, Bond, and van Reenen

large economic magnitudes of our estimated responses together with the slow resolution of impact uncertainty suggest that extreme weather uncertainty is an important factor for real outcomes.

The remainder of this paper is structured as follows. We begin with a discussion of related literature in Section 2. Then we describe our empirical design and datasets in Sections 3 and 4, respectively. We present our main results in Section 5, followed by extension in Section 6. We conclude in Section 7.

2 Related literature

Our paper ties in to several diverse bodies of literature. By analyzing extreme weather uncertainty, our paper contributes to the uncertainty literature, in which several papers have focused on economic policy uncertainty and its effects on firms (see, for example, Bloom, Bond, and van Reenen (2007) and Bloom (2009)). Other researchers have focused on political uncertainty proxied by elections and how they affect firm investments and financial markets (see, for example, Julio and Yook (2012); Kelly, Pastor, and Veronesi (2016); Jens (2017)). Our paper complements this body of work by showing that extreme weather uncertainty is a different but important source of uncertainty that affects prices in financial markets. Moreover, in the case of elections, there is uncertainty about outcomes, but generally not about when and whether the elections themselves will occur because they are scheduled in advance.[10] Our analysis introduces an additional layer of complexity as we separately examine the effects of the uncertainty about the landfall of a hurricane and the uncertainty about the impact of the event itself. Our paper differs from the research on macroeconomic uncertainty and economic growth (see, for example, Jurado, Ludvigson, and Ng (2015); Baker, Bloom, and Davis (2016); Baker, Bloom, and Terry (2018); Dew-Becker, Giglio, and Kelly (2018)) in that our analysis is at the firm level and more granular than the macroeconomy as a whole, which is important as extreme weather events are generally local phenomena. Also, the uncertainty shock in our case, the hurricane, is exactly determined.

(2007), and Julio and Yook (2012). Our on average 5 to 10 percent increase in implied volatility is of a similar magnitude to the increase in implied volatility found by Kelly, Pastor, and Veronesi (2016) around major political elections.

[10] Empirical work on political uncertainty focuses on scheduled elections in order to isolate political uncertainty from economic uncertainty. Unscheduled elections and regime changes can be precipitated by economic conditions. In contrast, hurricanes are exogenous to economic uncertainty (economic conditions do not make hurricanes more likely), so we do not face this identification issue.

Further, by showing that extreme weather events cause substantial uncertainty in economic regions before and after landfall, our work proposes an additional factor that should be considered by the literature that examines extreme weather events' real effects and their impact on economic agents' decision making. This growing literature includes work that examines the effects of extreme weather on labor markets and schooling (see Belasen and Polachek (2008) and Imberman, Kugler, and Sacerdote (2012)). Barrot and Sauvagnat (2016) find that shocks of extreme weather events propagate in customer-supplier firm networks. Bernile, Bhagwat, and Rau (2017) analyze the relationship between risk taking behavior and the early-life disaster experiences of CEOs. Dessaint and Matray (2017) show that managers overreact to hurricane risks after experiencing a hurricane. Brown, Gustafson, and Ivanov (2017) report that firms experience decreased cash flows after extreme snowfall events and that they respond by increasing their use of credit lines. Looking at storm-level total damages, Martinez (2018) finds that damages increase with forecast error of landfall location 12 hours before landfall. Roth Tran and Wilson (2018) find that hurricanes have a wide range of impacts on local economic activity, including on employment, population, and home prices.

Finally, this paper introduces a novel topic to an emerging literature on climate finance that includes early empirical work on how Florida temperature fluctuations affect orange juice futures prices (see Roll (1984) and Boudoukh, Richardson, Shen, and Whitelaw (2007)) and how the use of a time series forecasting approach is useful for pricing weather derivatives (see Campbell and Diebold (2005)). Our research contributes to three branches of the climate finance literature.

First, by examining hurricane effects, this paper builds on recent papers in the finance literature focused on extreme weather events and investor attention. Hong, Li, and Xu (2019) show that drought indices are predictive of food company stock returns, indicating that investors are inattentive to droughts' impacts on food companies. Choi, Gao, and Jiang (2018) examine how investors' climate change beliefs when temperatures are warmer than usual and find evidence of a positive relationship. Addoum, Ng, and Ortiz-Bobea (2019) examine whether firm earnings are affected by high temperatures and how analysts and investors react to temperature shocks.

Second, our paper adds to climate finance papers that develop hedging strategies. While Baker, Hollifield, and Osambela (2018) and Roth Tran (2018) present theoretical models in which green or emission-oriented investors can hedge risks by investing in polluters, Andersson, Bolton, and

Samama (2016) show empirically that investors can hedge against potential future prices on carbon emissions by investing in a decarbonized index. Engle, Giglio, Kelly, Lee, and Stroebel (2018) develop a climate change news index and assess strategies that can hedge an investor against such news. In contrast to these papers, we focus on market dynamics that reflect investor behavior around specific disaster events that occur at a local level.

Third, by using daily hurricane forecasts from NOAA, this paper adds to recent climate finance research that analyzes how NOAA forecasts are reflected in asset prices. Drawing mixed conclusions, several papers (see Bernstein, Gustafson, and Lewis (2018); Giglio, Maggiori, Rao, Stroebel, and Weber (2018); Murfin and Spiegel (2018)) use NOAA sea level rise predictions to examine whether residential real estate prices reflect sea level rise risks. Our use of NOAA forecasts is substantially different, because for hurricanes we can observe multiple isolated events from inception to resolution, whereas NOAA's forecasts for sea level rise are long-term and cannot yet be compared to realizations. We are thus able to show not only that price reactions in options and stocks are consistent with investors paying attention to NOAA's hurricane forecasts, but also assess whether this attention is in line with the realized outcomes.

3 Empirical design

3.1 Landfall uncertainty and impact uncertainty

Our framework distinguishes between two types of uncertainty that surround a hurricane: impact uncertainty and landfall uncertainty. While this paper focuses on hurricanes as an example for an extreme weather event due to the availability of high quality data, the framework of landfall and impact uncertainty can also be applied to other types of extreme weather events. The impact uncertainty is the uncertainty about a hurricane's impact on firms with exposure to the landfall area. More formally, if hurricane h is expected to make landfall at time $t+1$ and an all-equity firm i's stock return at $t+1$ is given by

$$r_{i,t+1} = \epsilon_{i,t+1} + \theta_{h,t+1} g_{i,h,t+1}, \tag{1}$$

where $\epsilon \sim N(0, \sigma^2)$ represents a random shock to the firm's return at time $t + 1$ with a mean of zero and variance of σ^2. The random variable $g_{i,h,t+1} \sim N(\mu_g, \sigma_g^2)$ is independent of ϵ and captures the impact of the hurricane on the value of firm i, conditional on hurricane landfall in the firm's geographic region. The random variable θ captures whether or not the firm is hit by the hurricane and has a Bernoulli distribution or, equivalently, a binomial distribution with one draw, $\theta \sim B(1, \phi)$, where $Pr(\theta = 1) = 1 - Pr(\theta = 0) = \phi$ and $0 \leq \phi \leq 1$. The product of the two random variables, $\theta_{h,t+1} g_{i,h,t+1}$, is the component of the return attributable to the hurricane.

Conditional on hurricane landfall at time $t + 1$, σ_g^2 represents the *impact uncertainty*. Defining uncertainty as the variance of an unpredictable disturbance is in line with Pastor and Veronesi (2012 and 2013) and Jurado, Ludvigson, and Ng (2015). In this framework, a hurricane landfall introduces uncertainty for the local economy and firms. Predicting at the time of landfall which firms will be most affected could be challenging for several reasons. First, the number of hurricane landfalls for a given local economy are not sufficient to predict the exact economic effect. For example, Houston, TX, had not experienced a hurricane for more than two decades before Hurricane Harvey hit in 2017. Second, a hurricane's impact on individual firms operating within a disaster region is to a large extent unpredictable. Knowing ex-ante exactly which areas will actually flood in a particular storm, the extent of power outages, or whether a levy will break, is challenging if not impossible.

Prior to the potential hurricane landfall, there is a second source of uncertainty which we call *landfall uncertainty* about whether the hurricane will make landfall. More generally, in other contexts, this corresponds to the uncertainty of the incidence or occurrence of an event or the uncertainty on the extensive margin. Similarly, impact uncertainty can be thought of as uncertainty on the intensive margin. At time t, we can decompose the uncertainty generated for the firm from the hurricane into *expected* impact uncertainty and landfall uncertainty as follows.

The expected return conditional on whether or not landfall occurs is, intuitively, $E_t[r_{i,t+1}|\theta = 1] = \mu_g$ and $E_t[r_{i,t+1}|\theta = 0] = 0$. The conditional variance of firm i's return is,

$$Var_t(r_{i,t+1}|\theta = 0) = \sigma^2, \tag{2}$$

$$Var_t(r_{i,t+1}|\theta = 1) = \sigma^2 + \sigma_g^2. \tag{3}$$

Then, we can find the expected conditional variance[11] and the variance of the conditional expectation,[12]

$$E[Var_t(r_{i,t+1}|\theta)] = \sigma^2 + \phi\sigma_g^2, \tag{4}$$

$$Var(E_t[r_{i,t+1}|\theta]) = \phi(1-\phi)\mu_g^2. \tag{5}$$

Applying the law of total variance, we can derive $Var_t(r_{i,t+1})$ using (4) and (5),

$$\begin{aligned} Var_t(r_{i,t+1}) &= E[Var_t(r_{i,t+1}|\theta)] + Var(E_t[r_{i,t+1}|\theta]), \\ &= \sigma^2 + \phi\sigma_g^2 + \phi(1-\phi)\mu_g^2. \end{aligned} \tag{6}$$

Landfall uncertainty is captured in the total variance by the third term in equation (6), $\phi(1-\phi)\mu_g^2$. For a given $\mu_g \neq 0$, landfall uncertainty is highest when the probability of landfall, $\phi = 0.5$. When $\mu_g = 0$, there is no contribution from landfall uncertainty to total variance at time t. In this case, $Var_t(r_{i,t+1})$ varies with ϕ purely due to the expected impact uncertainty, $\phi\sigma_g^2$.

Figure 1 depicts how the total variance prior to landfall ($Var_t(r_{i,t+1})$) varies with the probability of hurricane landfall (ϕ). The figure has parameters $\sigma = 0.4$ and $\sigma_g = 0.05$. The four dashed lines have μ_g absolute values of 0.1, 0.07, 0.05, and 0, respectively. The solid line shows the level of variance following hurricane landfall, $Var_t(r_{i,t+1}|\theta = 1) = \sigma^2 + \sigma_g^2$.

Depending on the the parameter values of μ_g and σ_g^2, as ϕ varies from 0 to 1, prior to landfall, the relative contribution to total variance from the landfall uncertainty and the expected impact uncertainty will vary. All else equal, as μ_g increases, the contribution of landfall uncertainty to total variance increases. In Figure 1, landfall uncertainty at a given ϕ is the vertical distance between a curve and the dot-dash (red) straight line depicting $Var_t(r_{i,t+1})$ when $\mu_g = 0$. $Var_t(r_{i,t+1})$ will in fact be greater than $Var_t(r_{i,t+1}|\theta = 1)$ when $|\mu_g| > \frac{1}{\sqrt{\phi}}\sigma_g$. In the figure, this is the case where the dashed lines are above the solid black line. When $\phi > 0$ and at least one of μ_g or σ_g is non-zero, $Var_t(r_{i,t+1})$ is greater than $Var_t(r_{i,t+1}|\theta = 0) = \sigma^2$.

[11] $E[Var_t(r_{i,t+1}|\theta)] = (1-\phi)\sigma^2 + \phi(\sigma^2 + \sigma_g^2) = \sigma^2 + \phi\sigma_g^2$

[12] $E[E_t[r_{i,t+1}|\theta]] = \phi\mu_g$,
$Var(E_t[r_{i,t+1}|\theta]) = E[(E_t[r_{i,t+1}|\theta] - \phi\mu_g)^2] = \phi(\mu_g - \phi\mu_g)^2 + (1-\phi)(0-\phi\mu_g)^2 = \phi(1-\phi)\mu_g^2$.

3.2 Identification strategy

Changes to the expected volatility of stock returns due to a hurricane event can be measured by the changes to the implied volatility of the stock's options. In our analysis, we use single stock options of firms that are in the damage region or forecasted path of a hurricane to estimate treatment effects, while using single stock options of firms unaffected by a hurricane as controls.

Because an extreme weather event like a hurricane is generally a local phenomenon, our identification strategy is based on selecting counties where a hurricane has made (or is predicted to make) landfall. For each hurricane, we have data on which counties were damaged and which counties lay in the forecasted path of the hurricane on a given day. A firm's exposure to these counties are then measured through the share of establishments or sales located in such counties. For firm i on day T_h, the landfall day of hurricane h, the exposure to counties damaged by hurricane h is given by

$$HurricaneDamageExposure_{i,T_h} = \sum_c (FirmCountyExposure_{i,T_h,c} \times I_{c \in D_{T_h}}), \tag{7}$$

where $FirmCountyExposure_{i,T_h,c}$ is the share of firm i's establishments (sales) located in county c, and D_{T_h} is the set of counties damaged by hurricane h. Therefore, a firm's exposure to a hurricane is a continuous variable that can range from 0 percent to 100 percent. To measure a firm's exposure to a forecasted hurricane path, we can use the set of counties in the forecasted path of a hurricane Γ days before the landfall or dissipation of the hurricane, denoted $F_{T_h-\Gamma}$, in place of D_{T_h}:

$$HurricaneForecastExposure_{i,T_h-\Gamma} = \sum_c (FirmCountyExposure_{i,T_h-\Gamma,c} \times I_{c \in F_{T_h-\Gamma}}). \tag{8}$$

For each hurricane, there are two groups of firms, those with and without exposure, with the degree of exposure being heterogeneous. Therefore, our analysis can be thought of as a differences-in-differences setting, where each hurricane represents a treatment, and we jointly estimate the treatment effect across all the hurricanes.

Because a hurricane has an identified inception date, we can isolate and estimate a hurricane's impact uncertainty, described in Section 3.1 by comparing the implied volatility of firms exposed to the landfall area shortly after landfall to the implied volatility before the inception of the hurricane. The implied volatility dynamics of the options of firms with zero exposure over the same time window comprise the control set. To measure landfall uncertainty, we rely on hurricane forecasts from NOAA. NOAA releases forecasts for the path of a hurricane starting from the hurricane's inception. For each hurricane, these forecasts provide a landfall probability for each county and each day since the inception of the hurricane. The landfall uncertainty defined in Section 3.1, can be computed based on the probabilities issued by NOAA.

4 Data and summary statistics

We combine data from a range of sources. We use data both from the Federal Emergency Management Agency (FEMA) and the Spatial Hazard Events and Losses Database for the United States (SHELDUS) when determining which counties are affected by hurricanes. We identify county level pre-landfall hurricane risk levels using archived forecasts from the NOAA. We combine these data sources with National Establishment Time-Series (NETS) data on locations of firm establishments and sales to identify firm exposure to hurricanes. And finally, our stock and option outcome data come from CRSP-Compustat and OptionMetrics, respectively. We describe each of these data sources below.

4.1 Hurricane damages

We use FEMA Disaster Declarations Summary data in combination with Spatial Hazard Events and Losses Database for the United States (SHELDUS) data to identify counties that experienced significant hurricane damages. We create an indicator that equals 1 if a county received a FEMA disaster declaration qualifying residents for individual and household program (IHP) assistance due to a hurricane. Counties are only eligible for IHP aid if they sustain significant damage on a per capita basis.

We build on the basic disaster indicator based solely on FEMA declarations by combining it with SHELDUS data in order to allow for the possibility that there are areas with significant damages which do not receive IHP aid.[13] SHELDUS data draw upon National Centers for Environmental Information (formerly National Climatic Data Center) Storm Data and Unusual Weather Phenom-

[13] A reason for why we may see SHELDUS damages in excess of reported FEMA declaration thresholds without seeing FEMA declarations could be because of measurement errors and disagreements or if FEMA chooses to diverge from its reported guidelines.

ena for hurricanes to provide county level per capita estimates of damages for named hurricane events. We set our second disaster indicator variable equal to 1 if there was a FEMA declaration for IHP aid or if the SHELDUS-reported per capita damages exceeded the published threshold for FEMA to provide IHP aid. Summary statistics are provided in Table 1. Figure 2 shows the number of times each county received an IHP declaration from FEMA for a hurricane between 2007 and 2017, while Figure 3 shows which counties received IHP aid or met the threshold according to SHELDUS in the case of Hurricane Sandy.

4.2 Hurricane forecasts

We use NOAA's National Hurricane Center (NHC) wind speed probability forecasts to develop our measure of a hurricane's landfall uncertainty prior to landfall. In particular, we use text files containing probabilities that particular locations will experience winds in excess of 64 knots (KT), which is the lower bound windspeed for hurricanes. Because NOAA does not issue forecasts for the damage that counties could experience, the hurricane windspeed forecasted for a county acts as a proxy for the amount of damage, with higher windspeed implying larger damage.

The windspeed probabilities are presented cumulatively for 12-hour windows up to five days out from the time of each forecast. The NHC reports these wind speeds for cities, towns, and military bases along the coast as well as some major cities that are more inland (including Birmingham, AL, Savannah, GA, and Washington, DC.) There are three wind speed thresholds included in these reports, the lowest and highest of which are the cutoffs for tropical storm-force and hurricane-force winds, respectively. These windspeed data are derived from the same underlying data of the hurricane forecast charts published by the NHC in real time and used by news outlets in the run-up to hurricanes. Figure 4 shows an example of the forecast chart of cumulative probability bands for hurricane force winds, as presented by the NHC, over a five day period in the case of Hurricane Sandy in 2012.

We have taken two steps to deal with the fact that the wind speed probabilities in these text files are only reported for particular locations, most of which are coastal. First we define a set of criteria that counties with data must meet in order to be considered at risk. For example, we might define a location as being at risk if it has at least a 20 percent probability of experiencing hurricane-force winds, that is 64 KT and above, within the next five days. Second, we define as at-risk any county within a 75-mile radius of a county with data that has been defined as being at-risk in the first step. For each day, we only use the last available forecast before close of trading, as forecasted hurricane paths can change meaningfully over the course of a day. Figure 5 illustrates a sample of processed wind speed data at different probability thresholds for Hurricane Sandy over a period four days.

One benefit of using the wind speed probability data is that it provides us information not only on where the eye of the storm is expected to be but also on how intense the winds will likely be and how wide the impact will be geographically. A hurricane that technically never makes landfall because the eye of the storm never passes over land can still pass close enough to a coastline to generate significant damage through strong winds, heavy rainfall, and storm surge. The wind speed forecast would show strong winds in the coastal areas closest to this hurricane. We will be referring to locations with forecasted windspeeds of 64 KT or more as the locations where the hurricane is predicted to make landfall. These windspeed forecasts are available from 2007 to 2017.

Table 2 reports summary statistics on the hurricane forecast data used in our empirical analysis. The number of storms for which we observe forecasts decreases as probability threshold or days to event resolution (hurricane landfall or, in the case of "misses", dissipation) increases. Panel A reports the mean, median, and standard deviation of the number of county-dates observations for which we have hurricane forecasts for each storm at a given probability threshold. Panel B presents the observation count by days to resolution at a given probability threshold.

4.3 Firm data

We use data on locations of firm establishments and sales in order to precisely estimate firm exposure to specific hurricanes. In particular, we use NETS data (see, for example, Neumark, Wall, and Zhang (2011) and Barnatchez, Crane, and Decker (2017)) to compute the geographic footprint of a firm. The NETS data contain establishment locations of public and private firms at the county level at an annual frequency. The data also include sales data for each establishment. For each hurricane season, we use the firms' geographic footprints from the previous year. Because the NETS data end in 2014, we use the geographic footprint from 2014 for hurricanes in 2015-2017.

To obtain financial data for the firms in NETS, we map them to OptionMetrics and CRSP-Compustat, both data sources are described below. The start of our sample is in 2002, which corresponds to the first year for which we have OptionMetrics data. The mapping is conducted based on the name of the firm and the address of the headquarters. We exclude all financial firms with SIC numbers from 6000 to 6799 from our analysis.[14] Summary statistics for the NETS data are reported in Table 3. From 2002 to 2014, we have 4,197 (4,187) firms in our sample with establishment (sales) data. On average, a county has 69 establishments and 525 million in sales. For counties that have experienced hurricane damage the number is higher with an average of 88 establishments and 675 million in sales. Figure 6 shows counties sorted into deciles based on the number of establishments for the years 2010 and 2014. The economic activity as measured by firm establishments is high in the hurricane prone areas along the Atlantic and the Gulf Coast.

We obtain daily frequency stock data from CRSP-Compustat and single-name stock options from OptionMetrics. Similar to previous studies we use the data from out-of-the-money traded options with valid pricing information,[15] and we restrict the set of options to slightly out-of-the-money options. These are more liquid and have a relatively smaller effect from any potential early-exercise premium for American options over European options for the time horizons that we consider.

Accordingly, we include single-stock options with: (i) standard settlement, (ii) a positive open interest, (iii) a positive bid price and bid-ask spread, (iv) a valid implied volatility estimate, (v) greater than 7 days and at most 200 days to expiry, and (vi) an option delta, δ, that satisfies $0.2 \leq |\delta| \leq 0.5$. The estimate for the average implied volatility of firm i at date t is, $IV_{i,t} = \frac{1}{N}\sum_{j=1}^{N} IV_{i,j,t,M}$, where M is the nearest-to-maturity expiration at time t with valid options which satisfy the above criteria and N is the number of valid stock options for firm i with that expiry. Using this methodology for the period from 2002 to 2017, we obtain 10,152,776 firm-date observations of implied volatility from OptionMetrics. We merge these data with CRSP-Compustat on firm CUSIP, which yields 9,420,182 observations covering 5,691 firms and 4,028 dates. Of these 3,866,672 observations are from 2,198 firms that appear at least once in the firm establishment data from NETS. The summary statistics for these data are in Table 4.

[14]We provide a separate analysis on insurance firms in Section 6.3.
[15]See, among others, Carr and Wu (2009); Kelly, Pastor, and Veronesi (2016); Martin and Wagner (2018).

5 Results

In this section, we describe the regression specifications that we employ to test our hypotheses and the corresponding results. The three hypotheses are: (i) stock options of firms in hurricane disaster regions exhibit a higher implied volatility right after a hurricane has hit, in line with investors perceiving uncertainty about the firms in the disaster region of the hurricane; (ii) abnormal stock returns of firms with a physical presence in a hurricane disaster region show a large dispersion that is negatively skewed in the long-run after a hurricane has hit, consistent with a slow resolution of impact uncertainty; and (iii) pre-landfall, stock and option prices react to hurricane forecasts, with implied volatility increasing and stock prices decreasing for firms located in the forecasted hurricane paths, consistent with investors paying attention to hurricane forecasts.

5.1 Impact uncertainty estimation

We begin with testing the hypothesis that stock options of firms in disaster regions have higher implied volatilities. The implied volatility is an estimate of expected future volatility and is commonly used as a measure of uncertainty. If a hurricane landfall leads to impact uncertainty for firms in the disaster region, the implied volatilities of these firms should increase. The impact uncertainty can be isolated and estimated by looking at the implied volatilities shortly after landfall, when investors know where the hurricane hit, that is all the landfall uncertainty has disappeared, but do not know what the eventual impact on the firms located in the damage region will be. To test this first hypothesis, we estimate the following panel regression model,

$$log\left(\frac{IV_{i,T_h+\tau}}{IV_{i,T_h^*}}\right) = \lambda HurricaneDamageExposure_{i,T_h} + \theta_h + \psi_{Ind} + \epsilon_{i,h,\tau}, \tag{9}$$

where τ is the number of trading days since the hurricane made landfall on day T_h.[16] The last trading day before the *inception* of the hurricane is T_h^* and IV_i is the implied volatility of firm i. $HurricaneDamageExposure_{i,T_h}$ is a measure of firm i's exposure to the counties with hurricane damage, as defined in equation (7).[17] This measure can vary from 0 percent, for firms with no

[16] If a hurricane makes multiple landfalls, the first landfall date is used as T_h in the analysis.

[17] The inception day of a hurricane is defined as the first day on which the hurricane is predicted to make landfall with at least a 1% probability. For hurricanes before 2007, we do not have hurricane forecast data available and choose as inception day the first day that the hurricane appeared as a tropical depression.

exposure to the hurricane disaster region, to 100 percent, for firms with all of their establishments (or sales) located within the disaster region. The NETS data allow us to use different variables to measure the county exposure of a firm, namely, the amount of establishments or sales in a specific county as a percent of the firm's total establishments and sales, respectively, throughout the U.S. We include hurricane fixed effects (θ_h), which is equivalent to including time fixed effects because there is one time period per hurricane. We include industry fixed effects (ψ_{Ind}) based on the firms' two-digit SIC numbers. Only firms for which we have implied volatility measures for each trading day from inception to τ days after landfall are included in our sample. As our treatment selection is at a geographic level, we cluster the standard errors based on the county where the headquarters of a firm are located (see, for example, Dessaint and Matray (2017) and Abadie, Athey, Imbens, and Wooldridge (2017)).[18]

The regression model in equation (9) can also be seen as a differences-in-differences estimation where each hurricane acts as a treatment, that is firms with exposure to the disaster zone are considered treated and firms with no exposure to the disaster zone act as controls. Following the recommendation of Bertrand, Duflo, and Mullainathan (2004), for each hurricane, we collapse the time series information into a pre- and post-period, where the pre-period is T_h^*, the day before the inception, and the post-period is $T_h + \tau$, τ days after the landfall.

The coefficient estimate of λ is expected to be significant and positive if investors perceive that hurricane landfall leads to impact uncertainty surrounding the local firms. A hurricane making landfall could introduce severe uncertainty for the local economy and firms. Knowing ex-ante which firms will be most affected is likely impossible because of several factors. First, the number of hurricane landfalls for a given local economy are mostly insufficient to predict the exact economic effect. Second, the hurricane's impact on individual firms in the disaster zone is to a large extent random, as described in Section 3.1.

The estimation results of the model given in equation (9) are reported in Table 5. Panel A shows the results when the exposure of a firm to the hurricane disaster region is based on establishments. We consider selecting counties in the disaster region solely based on FEMA damage data and FEMA damage data enhanced with SHELDUS data. The value τ, trading days after landfall, is set to 5

[18] We use the headquarters location for clustering instead of a firm's geographic footprint as a firm's geographic footprint is unique in the great majority of the cases, which would leave us with clusters that are not sufficiently large to ensure conservative standard error estimates.

days, but our results are robust to choosing a different τ close to landfall. We have high quality option data available from 2002. We also show the results for the time period from 2007 to 2017, as the hurricane forecast data used in the subsequent analysis start in 2007.

The estimate of λ is significant and positive for all specifications, which is in line with our first hypothesis that hurricane landfall causes impact uncertainty for local firms. In particular, we find that a firm with 100 percent of its establishments located in the disaster region experiences a 5 to 10% percent increase in its implied volatility relative to before inception of the hurricane. This economic magnitude is considerable and comparable to Kelly, Pastor, and Veronesi (2016), who show that political uncertainty leads to implied volatilities of index options increasing on average around 5 percent around major political elections compared to non-election periods. These results are robust to including industry times time fixed effects, which implies that the effects are present within industry.

These results are robust to measuring the geographic footprint of a firm by sales at the county level instead of establishments, as shown in Panel B. The estimates of λ in Panel B are also strongly significant for all the specifications. The largest coefficient estimates for five days after the landfall are 0.06, implying that a firm with a 100 percent of its sales in the disaster region has an implied volatility that is 6 percent higher than before the inception of the hurricane. The fact that the magnitudes of the coefficients based on exposure of sales (Panel B) are smaller than those based on exposure of establishments (Panel A) could be explained by investors being more concerned about damages to production facilities or our data on locations of firm establishments being better than on the sales.

Importantly, our results are not driven by small firms. The average market capitalization of a firm with exposure to disaster region counties of at least 20% is \$6.0 billion and \$8.2 billion when measuring the exposure by establishments and sales, respectively. The average market capitalization of a firm with less than 20% exposure to the disaster region is similar in magnitude with \$6.8 billion and \$6.7 billion, respectively. Firms with coastal exposure can differ from other firms based on unobserved characteristics, and it is possible that firms that would be more vulnerable to hurricanes because of their particular line of business avoid being exposed to the Atlantic or Gulf Coast. However, such sorting would bias us against finding evidence of impact uncertainty.

We also test if these results are driven by a particular industry but find that the impact uncertainty of hurricanes is similar across industries. Table A.1 in the appendix shows the results when an industry dummy is interacted with $HurricaneDamageExposure_{i,T_h}$ in equation (9).[19] The coefficient estimate of the interaction term is insignificant for almost all specifications, which suggests that the reported effect is not driven by one particular industry. Only the construction industry shows a consistent pattern of facing less uncertainty surrounding a hurricane than the other industries, with the caveat that the number of construction firms in our sample is small. A potential explanation for this finding is that these firms can profit from a hurricane due to a boom in reconstruction.

5.2 Impact uncertainty resolution

The large impact uncertainty measured in the previous section suggests that firms in the disaster region face uncertain outcomes. The resolution of this impact uncertainty should be reflected in the firms' stock prices in the months following a hurricane landfall. In particular, we test if the abnormal stock returns of firms with exposure to a hurricane disaster region show a large dispersion in the long-run, in line with investors learning over time how devastating a hurricane was and which firms were most adversely affected.

To isolate the resolution of impact uncertainty, we estimate how a hurricane affects firms' stock returns *after* landfall, we first estimate daily abnormal returns relative to the Fama-French three-factor model (see Fama and French (1993)). For each firm and each hurricane in our sample, the following model is estimated:

$$r_{i,d} = \alpha_i + \beta_{1,i} r_{m,d} + \beta_{2,i} r_{smb,d} + \beta_{3,i} r_{hml,d} + \epsilon_{i,d}, \tag{10}$$

where $r_{m,d}$ is the daily market return on day d minus the risk-free rate, $r_{smb,d}$ and $r_{hml,d}$ are the daily returns of the small-minus-big and high-minus-low portfolios, respectively. We estimate this model using 200 trading days before the day of hurricane landfall. We then use the coefficient estimates from this first stage regression to compute abnormal returns for each firm and hurricane as follows:

$$r^a_{i,d} = r_{i,d} - (\hat{\alpha}_i + \hat{\beta}_{1,i} r_{m,d} + \hat{\beta}_{2,i} r_{smb,d} + \hat{\beta}_{3,i} r_{hml,d}). \tag{11}$$

[19]The industry dummy is based on the two-digit SIC numbers of the firms. We exclude the agriculture and the non-classified categories because of the small number of firms.

We next aggregate the abnormal returns to a cumulative abnormal return, denoted $r^{ac}_{i,T_h:T_h+\tau}$, for each firm and hurricane over the time period T_h to $T_h+\tau$, where T_h is again the day of the landfall and τ is the number of trading days.[20] The time period starts in 2002 and ends in 2017, which corresponds to the time period used in Table 5. To ensure that stocks with stale prices are excluded from our analysis, a stock is required to have return data for all trading days from 200 trading days before landfall to τ trading days after landfall.

We compute the differences in the mean and nine percentiles between the cumulative abnormal return distributions of firms with (treated) and without (control) exposure to a hurricane damage region. The results are reported in Table 6 along with the corresponding t-stats. We estimate the standard errors using a bootstrap that clusters by county based on firm headquarters. Because we want to compare the returns in the short- and long-run after hurricane landfall, the cumulative abnormal returns are computed from the day of landfall for up to 5 and 120 trading days after landfall.[21] For Panel A, we consider firms to be in the disaster region if at least 50 percent of the establishments are in the disaster region. For Panel B, the threshold is 50 percent of the sales. Table A.2 in the Appendix shows that the results are robust to lowering the threshold to 25%.

Panel A shows that the cumulative abnormal returns from the landfall day to five days after yield a negative difference for all percentiles except the top one. These differences are generally between -10 and -50 basis points, and they are not significant. However, when looking at the cumulative abnormal returns from landfall day to 120 trading days after the landfall, the differences in cumulative abnormal returns are strongly negatively skewed. For the 10$^{\text{th}}$ and 20$^{\text{th}}$ percentiles, the difference in cumulative abnormal returns between control and treated firms is around -14 percent and strongly statistically significant, but for the 80$^{\text{th}}$ and 90$^{\text{th}}$ percentiles, the difference is only around -5 percent and statistically insignificant. In Panel B, firm exposure to hurricane disaster regions is measured based on a firm's sales in a county. The cumulative abnormal return distribution of the treated firms is again negatively skewed and comparable to Panel A in magnitude and statistical significance for the long horizon. For the period from landfall to 5 trading days after, the differences between percentiles of the control and treated firms' return distributions are again

[20] If a hurricane makes landfall on a non-trading day, we take the next trading day as T_h.

[21] We choose 120 trading days as they correspond to half a calendar year. The hurricane season lasts half a calendar year, and thus, we avoid overlaps with the following year's hurricane season. The results are robust to a different benchmark of trading days.

insignificant.

These findings are in line with a slow resolution of impact uncertainty in the aftermath of a hurricane. Investors appear to learn over time how devastating a hurricane was and which firms were most adversely affected.

5.3 Uncertainty before landfall

In Table 5 we show that days after landfall, options price in substantial impact uncertainty in hurricane disaster regions. However, over the course of the days or weeks while a hurricane makes its approach toward the Atlantic or the Gulf Coast, NOAA issues hurricane forecasts that contain the probabilities of the hurricane making landfall in a particular region. Such forecasts are often highly publicized through news outlets. For example, the forecasted path of Hurricane Sandy in 2012 shown in Figure 4 likely looks familiar to people who tend to follow the news during hurricane season. Based on the efficient market hypothesis, investors should pay attention to these forecasts, and the forecasts should be priced in. If investors pay attention to hurricane forecasts before landfall, then the impact uncertainty will increasingly be priced into options as the likelihood of a hurricane making landfall in a specific region increases, which is represented by the term $\phi\sigma^2$ in equation (6). In addition, investor attention to hurricane forecasts will also lead to landfall uncertainty, given by the term $\phi(1-\phi)\mu_g$ in equation (6), being reflected in option prices through higher implied volatilities.

We use the NOAA forecasts described in Section 4.2 to examine how hurricane forecasts affect implied volatilities of firms located in the path of a hurricane and estimate the following panel regression model

$$log\left(\frac{IV_{i,T_h-\Gamma}}{IV_{i,T_h^*}}\right) = \lambda HurricaneForecastExposure_{i,T_h-\Gamma} + \theta_h + \psi_{Ind} + \epsilon_{i,h,\Gamma}, \tag{12}$$

where Γ represents the number of calendar days before the landfall or dissipation of the hurricane and we estimate the regression separately for each $\Gamma \in \{1,2,3,4,5\}$, as NOAA forecasts hurricane paths up to five days out.[22] Firm i's exposure to hurricane h's forecasted path, $HurricaneForecastExposure_{T_h-\Gamma}$, is as defined in equation (8). The remaining parameters are as described for regression equation

[22]If a hurricane makes landfall on multiple days, we only consider the first landfall day.

(9). Only hurricanes for which the day $T_h - \Gamma$ is a trading day are included in the regression. The time series starts in 2007, because we have high quality hurricane forecast data from 2007 onwards, and ends in 2017. As described in detail in Section 4.2, the hurricane forecasts provide a probability that a county will experience windspeeds of at least 64 KT within five days. A storm's windspeed has to be at least 64 KT to be classified as a hurricane by NOAA.

If investors pay attention to hurricane forecasts, the estimate of λ is expected to be positive and significant. Particularly, the change in a firms' implied volatilities should depend on the probability that a hurricane will make landfall in counties in which the firm operates. In our framework presented in Section 3.1, we show in Figure 1 that for any probability of landfall greater than zero, given by the term ϕ, the implied volatility will be higher than before the inception of the hurricane. Further, the total uncertainty given in equation (6) can be higher before landfall, when landfall and impact uncertainty are present, then right after landfall when there is no uncertainty about landfall but only uncertainty about the impact of a hurricane. Figure 1 shows that depending on the parametrization, the total variance (uncertainty) can be higher before landfall, when ϕ is smaller than 1, than at landfall, that is when ϕ equals 1. Whether total uncertainty is higher before landfall than right after landfall is ultimately an empirical question.

We report the estimation results of the model in equation (12) in Table 7. The parameter Γ is between 1 and 5 days, and the probabilities of hurricane-level windspeeds that we require to designate a county as at-risk ranges from 1 to 50 percent. Figure 7 plots the λ coefficient estimates and confidence interval bands for Γ=1 and Γ=2. For each Γ and probability, we require that at least three hurricanes and 25 firms that have an exposure of 20 percent or more of their establishments or sales in counties in the path of a hurricane. Because the days before the landfall or dissipation of a hurricane can fall on non-trading days and different hurricanes reach probability thresholds of making landfall on different days, the hurricanes included in the estimation can vary across the table's columns.

The results are in line with investors paying attention to hurricane forecasts and the uncertainty surrounding a hurricane being reflected in the implied volatilities of firms located in the forecasted path of a hurricane. The estimates of λ are always positive, regardless of whether a firm's exposure to a hurricane is based on establishments (Panel A) or sales (Panel B). The λ estimates are also significant with the exception of the estimates five days before landfall/dissipation. For each day, the magnitude of λ increases with higher landfall probabilities. It is clear from Figure 7 that the λ estimates are significant higher at as landfall probability increases. In fact, for high probabilities, the increase in implied volatilities is in some cases larger than the increase in implied volatilities right after landfall reported in Table 5.[23] This result suggests that the landfall uncertainty is strongly reflected in option prices and can push the total uncertainty before landfall above the impact uncertainty measured at landfall, as suggested by our framework in Section 3.1. Overall, these results are consistent with hurricane forecasts containing valuable information and investors paying attention to them.

An interesting observation is that the estimated magnitude of λ for the same probability is sometimes lower for days closer to the landfall or dissipation of the hurricane, although not significantly so. A possible explanation for this is that hurricanes that reach a specific probability of making landfall when they are still far off the coast are simply stronger hurricanes that can lead to more devastating effects.

5.3.1 Alternative specification for forecasts and implied volatilities

The estimates of the regression model shown in equation (12) support the hypothesis that investors pay attention to hurricane forecasts and the uncertainty surrounding a hurricane is reflected in option prices before landfall. To further test the robustness of this result, we use an alternative estimation where we allow for the fact that firms can reach an exposure threshold to a specific hurricane, for example, 10 percent of establishments are located in the forecasted path of a hurricane, on different days. In the regression model in equation (12), it is not possible to jointly estimate the change in implied volatilities for these firms. The model specification below allows for a joint estimation, but the hurricane exposure variable is an indicator variable instead of a continuous variable as in equation (12). We compute the measure given by

$$IVD_{i,h} = log\left(\frac{IV_{i,t_{i,h}}}{IV_{i,T_h^*}}\right) - \frac{1}{|J_h|}\sum_{J_h} log\left(\frac{IV_{j,t_{i,h}}}{IV_{j,T_h^*}}\right), \tag{13}$$

[23]A caveat is that the sample of hurricanes in the two tables can differ. In particular, while in Table 5 we include only the hurricanes that make landfall, in Table 7 we also consider hurricanes that dissipate without making landfall. Also, for some hurricanes included in Table 5, a specific day before landfall can be a non-trading day, and thus, the hurricane would not be included for that day in Table 7. However, the result of higher total uncertainty before the landfall than right after landfall holds when comparing the same hurricanes.

where $t_{i,h}$ is the first trading day when the number of establishments (sales) of firm i in the path of hurricane h exceed a certain threshold, and T_h^* is again the last trading day before the inception of hurricane h. The set of control firms, J_h, for hurricane h are the firms with zero exposure to the forecasted path of the hurricane. We exclude from this analysis the days on which a hurricane makes landfall. We compute $IVD_{i,h}$ for all hurricanes and firms and estimate the mean, $\overline{IVD}$, for the sample from 2007 to 2017. A positive and significant $\overline{IVD}$ would be consistent with the results shown in Table 7.

The results for this specification are presented in Table 8. Here we use five probability thresholds ranging from 1 to 50 percent to designate which counties lie within the forecasted path of a hurricane. A 1 percent probability threshold implies that a county has at least a 1 percent chance of experiencing hurricane-force winds in the next 5 days. We consider three thresholds for a firm's exposure to a hurricane wherein 10, 25, and 50 percent of a firm's establishments (sales) are located in counties that we have designated as being in the hurricane's forecasted path. For a 10 percent threshold, we compute the difference in the implied volatility of firm i on the first trading day that 10 percent of firm i establishments (sales) are located in the hurricane's forecasted path and the implied volatility on the last trading day before the inception of the hurricane.

Panel A reports the estimates of $\overline{IVD}$ when the firm geographic footprints are computed based on the share of establishments in a county. The estimates of $\overline{IVD}$ are positive and significant for the great majority of the specifications. The only two exceptions are for the probability threshold of 1 percent. As in Table 7, the magnitude of the estimates is monotonically increasing with the probability of the firms being hit by a hurricane. Further, when selecting only firms with at least 25 or 50 percent of their establishments or sales in at-risk counties, the estimates are substantially larger than for the firms with an exposure of at least 10 percent. These results further support the hypotheses that investors pay attention to hurricane forecasts which leads to uncertainty landfall and expected impact being reflected in the implied volatilities of firms located in the forecasted path of a hurricane.

5.3.2 Forecasts and stock returns

The results in the previous sections show that hurricane forecasts lead to price effects in option markets. Consequently, hurricane forecasts should also affect the underlying stock prices. We expect that a higher likelihood of a hurricane strike should cause negative stock returns. First, the stock returns can be depressed because investors require a premium to hold stocks during a time period of high uncertainty, as, for example, discussed by Pastor and Veronesi (2012, 2013) in the context of political uncertainty.[24] Second, the possibility of a hurricane strike can decrease stock returns because of lower expected cash flows.

To test if hurricane forecasts affect the stock returns, we estimate the regression model in equation (12), but with cumulative stock returns as the dependent variable:

$$r_{i,T_h^*:T_h-\Gamma} = \lambda HurricaneForecastExposure_{i,T_h-\Gamma} + \theta_h + \psi_{Ind} + \epsilon_{i,h,\Gamma}, \tag{14}$$

where $r_{i,T_h^*:T_h-\Gamma}$ is the cumulative return of firm i from the inception of hurricane h to Γ calendar days before the landfall or dissipation of the hurricane.[25] An estimate of λ that is significant and negative would support the hypothesis that the uncertainty surrounding firms in a hurricane's path leads to negative stocks returns.

The results are reported in Table 9, which is structured the same as Table 7. The estimates of λ are negative in all cases except for the last column that examines effects five days before landfall/dissipation with a probability of a hurricane hit of 10 percent. The estimates are strongly significant for the majority of the specifications. The estimates are also economically significant. The smallest estimate is -0.09, which implies that a firm with a 100 percent exposure to the forecasted path of a hurricane experiences a negative return of 9 percent from the inception of the hurricane to a few days before the landfall/dissipation. The estimates are similar when the geographic footprint of a company is based on establishments, as in Panel A, or on sales, as in Panel B. These results are consistent with our analysis on implied volatilities and support the hypothesis that the uncertainty associated with a hurricane leads to negative stock returns.

[24] Pastor and Veronesi (2012, 2013) look at market effects, which cannot be diversified. The uncertainty surrounding a hurricane affects individual firms, but the presence of market frictions, for example, limited access to information as in Merton (1987), can lead to investors demanding a premium for idiosyncratic volatility.

[25] We use non-adjusted returns in this analysis, but the results are qualitatively the same when using risk-adjusted returns.

6 Extensions

Having examined how markets broadly price in impact and landfall uncertainty both before and after hurricane landfall, we now turn our attention to three key extensions. We ask whether markets beat NOAA forecasts, what the potential benefit of improving hurricane forecast accuracy is, and how extreme weather uncertainty affects insurance firms (which are excluded from our baseline results together with other financial firms).

6.1 Can the market forecast better than NOAA?

The previous results show that market prices react to hurricane forecasts by pricing in the impact uncertainty caused by a potential hurricane strike. The hurricane forecasts in our analysis are taken from NOAA. NOAA's hurricane forecasts are arguably the most prominent as they are widely publicized through the media. However, it is possible that large institutional investors like hedge funds, which often act as marginal investors in asset markets and move asset prices, could outperform the publicly available NOAA hurricane forecasts by trading on proprietary hurricane forecast information. In this case, markets would predict hurricane damages more precisely than NOAA forecasts. There are a few of reasons to believe that markets could predict damages more precisely. First, there is anecdotal evidence that hedge funds buy information on hurricane forecasts from private companies.[26] Second, the budget of NOAA's subdivision responsible for hurricane forecasts, the National Weather Service, is minuscule compared to the value of assets managed by large institutional investors.[27] Therefore, a firm that produces proprietary hurricane forecasts and sells them to institutional investors could potentially generate sufficient revenues to rival NOAA. Third, because the NOAA forecasts are public and available in real-time, investors can use the information in the NOAA forecasts and improve upon them with proprietary information.

We test this hypothesis by estimating the panel regression model in equation (12) with an additional term that measures whether option markets can predict which firms end up more exposed

[26] See, for example, the discussion of the hedge fund with the name Nephila by Michael Lewis here: https://www.nytimes.com/2007/08/26/magazine/26neworleans-t.html?pagewanted=all.

[27] The total budget of the National Weather Service, a subdivision of NOAA, was around $1 billion in 2017. However, this budget also includes funds appropriated for weather forecasts other than hurricane forecasts. The budget of the National Weather Service for 2017 can be found here: https://www.corporateservices.noaa.gov/nbo/.

to the hurricane than predicted by the NOAA forecasts:

$$\begin{aligned} log\left(\frac{IV_{i,T_h-\Gamma}}{IV_{i,T_h^*}}\right) =& \lambda HurricaneForecastExposure_{i,T_h-\Gamma} \\ &+ \gamma UnderPrediction_{i,T_h-\Gamma} + \theta_h + \psi_{Ind} + \epsilon_{i,h,\Gamma}. \end{aligned} \tag{15}$$

Here $UnderPrediction_{i,T_h-\Gamma}$ is defined as the difference between a firm's exposure to counties that eventually experience hurricane related damages and the exposure to counties in a hurricane's forecasted path:

$$\begin{aligned} UnderPrediction_{i,T_h-\Gamma} =& (HurricaneDamageExposure_{i,T_h} \\ &- HurricaneForecastExposure_{i,T_h-\Gamma}) \\ &\times I_{(HurricaneDamageExposure_{i,T_h} - HurricaneForecastExposure_{i,T_h-\Gamma})>0}. \end{aligned} \tag{16}$$

Firm i will have a positive value for $UnderPrediction_{i,T_h-\Gamma}$ if the share of its establishments or sales in counties that experience hurricane damages is greater than the share of its establishments or sales predicted to be affected based on NOAA forecasts made Γ days before landfall. Otherwise, $UnderPrediction_{i,T_h-\Gamma}$ will assume a value of zero. If the market can forecast which counties will experience hurricane damage more accurately than NOAA, the estimate of γ in equation (15) would be significant and positive.[28] The underprediction measure can also be thought of as a measure of false negatives, and we test if markets can detect them.

We look at underpredicted firms rather than overpredicted firms, because a smaller than average increase in implied volatility for overpredicted firms (firms that end up with less exposure to the damage region than forecasted) could be explained by markets being less attentive to low probability forecasts, which include many firms in the forecasted path that end up with no or little exposure to the damage region. Therefore, analyzing underpredicted firms allows us to better isolate and estimate the forecast ability of financial markets.

The results are shown in Table 10, which has the same structure as Table 7. While the estimates

[28]Suppose, for example, that the NOAA forecast implies zero exposure for a firm four days before a hurricane's actual landfall. If the firm ends up with significant exposure to counties affected by the hurricane four days later, $UnderPrediction_{i,T_h-4}$ would equal the exposure of the firm to the actual hurricane damage region. If the markets are able to predict the final exposure four days ahead when the NOAA forecast did not, γ would reflect this by being significant and positive.

of γ are positive, in line with the market forecasting better than NOAA, they are insignificant for all but one weakly significant coefficient estimate. Therefore, we do not find support for the hypothesis that markets can forecast hurricanes better than NOAA. This null result could be caused by a lack of statistical power. However, given that the number of firms with a non-zero $UnderPrediction_{i,T_h-\Gamma}$ measure is quite large with an average of around 1,200 across the specifications, we should have sufficient power to detect the market's ability, if any, to beat NOAA forecasts. In contrast, the coefficient estimates on $HurricaneForecastExposure_{i,T_h-\Gamma}$ are positive and strongly significant for most specifications as in Table 7.[29]

6.2 The economic effect of improved forecasts

The previous findings show that markets price in NOAA's hurricane forecasts and furthermore do not appear to be able to outperform NOAA forecasts. These findings lead to the question: what economic effect would improved hurricane forecasts have? In other words, how much of the price variation in options around hurricanes were caused by mispredictions, that is over- and underpredictions.[30] This price variation could potentially be reduced by more accurate forecasts.[31]

To answer this question, we compute by how much implied volatilities are too high or low on average due to an overprediction or underprediction. To estimate by how much implied volatilities are too high due to an overprediction, we compute the average overprediction (for the day before landfall or dissipation) for the probability thresholds shown in Table 7. We then multiply this average overprediction by the coefficient estimate on $HurricaneForecastExposure_{i,T_h-\Gamma}$ of the corresponding probability threshold given in Panel A of Table 7. To estimate by how much implied volatilities are too low due to an underprediction, we multiply the average underprediction by the equation (9) coefficient on $HurricaneDamageExposure_{i,T_h}$ estimated for the respective hurricanes

[29] We also test if our results change when we focus on options for which the underlying stocks have a large institutional ownership, because institutional investors are more likely than retail investors to have the means to obtain hurricane forecasts that are not generated by NOAA. However, we do not find evidence of the market outperforming NOAA.

[30] While the measure of underprediction is described in equation 16, the overprediction measure is defined as $OverPrediction_{i,T_h-\Gamma} = (HurricaneDamageExposure_{i,T_h} - HurricaneForecastExposure_{i,T_h-\Gamma}) \times I_{(HurricaneDamageExposure_{i,T_h}-HurricaneForecastExposure_{i,T_h-\Gamma})<0}$. The overprediction measure can be thought of as a measure of false positives.

[31] Alley, Emanuel, and Zhang (2019) show that hurricane forecasts have indeed improved dramatically in recent decades. In particular, they find that "modern 72-hour predictions of hurricane tracks are more accurate than 24-hour forecasts were 40 years ago."

in the sample using five days post-landfall.[32]

Figure 8 presents the results of this analysis. Panel A shows the average over- and underreactions in implied volatilities resulting from over- and underpredictions. The magnitudes are large, reaching 75 basis points for the overpredictions and -150 basis points for the underpredictions. To provide more intuition on the economic significance, we multiply the over- and underreactions in the implied volatilities with the average market capitalization of the respective firms and show the results in Panel B.[33] The resulting product tells us by how much the expected fluctuations of the market capitalization changes due to the over- and underpredictions. The overpredictions reach values of above \$60 millions, and the underpredictions lead to values of below -\$80 millions. Considering that the number of firms affected by over- and underpredictions is large as reported in Panel C, these results imply that improvements to hurricane forecasts could have large economic effects on pricing of hurricane related uncertainty in option markets.

6.3 Insurance firms

The analysis and discussion so far in this paper has been focused on the universe of firms excluding financial firms as common in the asset pricing literature. One contribution of this paper is to show that the uncertainty around extreme weather events affects a wide range of firms and not only insurance firms which are often thought of in the context of natural disasters. However, we also want to investigate if extreme weather uncertainty is reflected in the asset prices of insurance firms. The challenge that we face is that the number of publicly traded insurance firms with liquid options is relatively limited and we only have the exposure of an insurance firm at the state level, not at the county level.

We use data on insurance statutory financials from S&P Global Market Intelligence, which provides us with the share of total premiums written by state for property and casualty insurance firms in the US. We estimate the regression in equation (9) for these property and casualty insurance firms, with $HurricaneDamageExposure_{i,T_h}$ being replaced by a variable that measures the share of total premiums, lagged by one year, written in states that experienced damage by hurricane h.

[32] The damage exposure of a firm is based on the combined FEMA and SHELDUS dataset, and the number of establishments act as the geographic footprint measure.

[33] For example, for the underprediction of the 50% or more probability threshold, we multiply the average underreaction of -1.54% with 0.44, which is the average implied volatility level in our sample, and then multiply the resulting product with the average market capitalization.

The results are reported in Table 11. Panel A (B) considers a state to have experienced hurricane damage if at least 10% (25%) of the counties experienced hurricane damage as measured by FEMA data and FEMA data enhanced with SHELDUS.

The coefficient estimate is positive and significant for all specifications implying that the impact uncertainty for property and casualty insurance firms is substantial in the aftermath of a hurricane. The magnitude of the coefficient estimates are economically significant, with the implied volatility being up to 40% higher for insurance firms with a 100% exposure to the damage region of the hurricane. The statistical significance is slightly weaker than for the universe of firms in Table 5 as the number of insurance firms in our sample is relatively small. We have on average 20 to 30 insurance firms per hurricane depending on the specification.

7 Conclusion

This paper studies extreme weather uncertainty through prices in option and stock markets by analyzing the uncertainty surrounding hurricanes. Our framework distinguishes between landfall uncertainty (on where the hurricane will hit, if at all) and impact uncertainty (on the consequences to the local firms and economy following landfall).

We find that options of firms operating in regions affected by hurricanes have considerably higher implied volatilities, between 5 to 10 percent, in the immediate aftermaths of those hurricanes. The higher implied volatilities are in line with investors being concerned about substantial impact uncertainty right after a hurricane has hit. The stock returns of firms in damage regions show a strong negative skewness in the long-run consistent with a slow resolution of impact uncertainty. Using daily hurricane forecasts from NOAA, we find that landfall uncertainty combined with potential impact uncertainty are both priced before a hurricane makes landfall.

Our novel analysis and framework contribute to a burgeoning climate finance literature. Further, we add to the existing uncertainty literature by showing that extreme weather uncertainty is important and reflected in the prices of options and stock markets. Future research can build on the results in this paper by linking extreme weather uncertainty to real economic activity. Extreme weather uncertainty potentially affects firm production networks, commodity and agricultural markets, and decisions by various economic agents.

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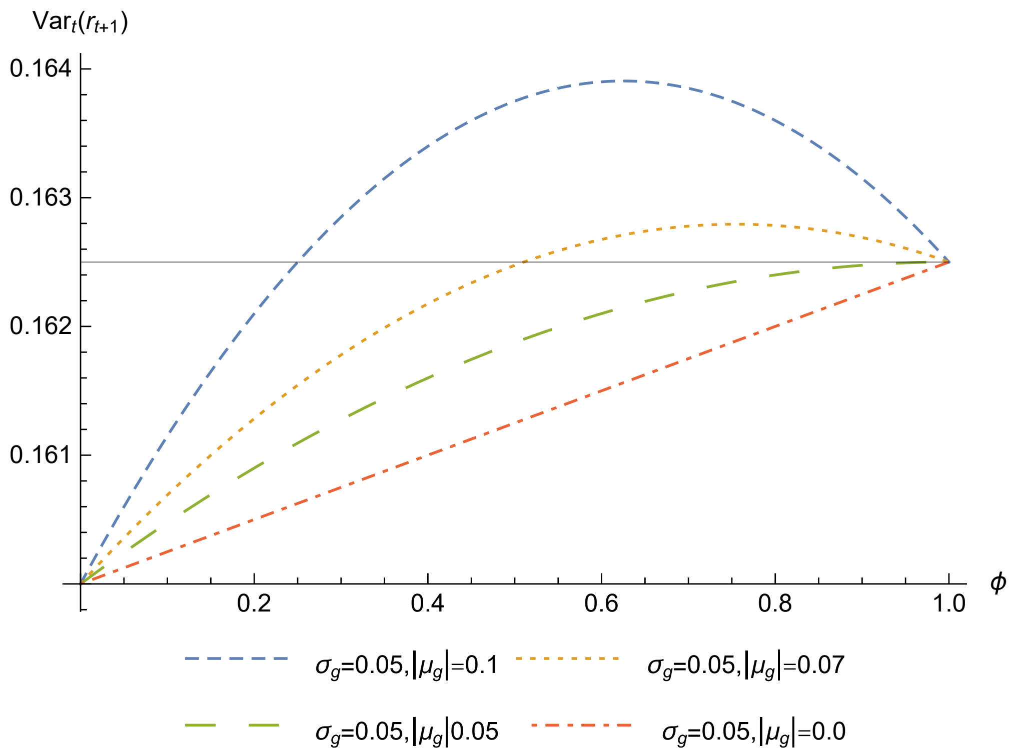
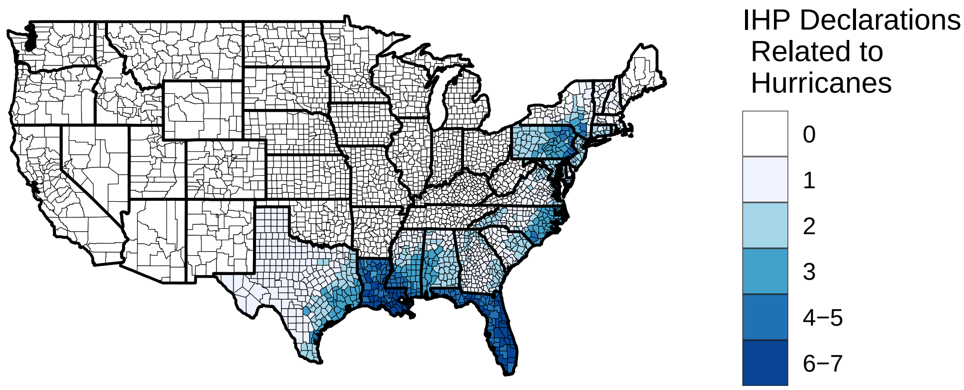
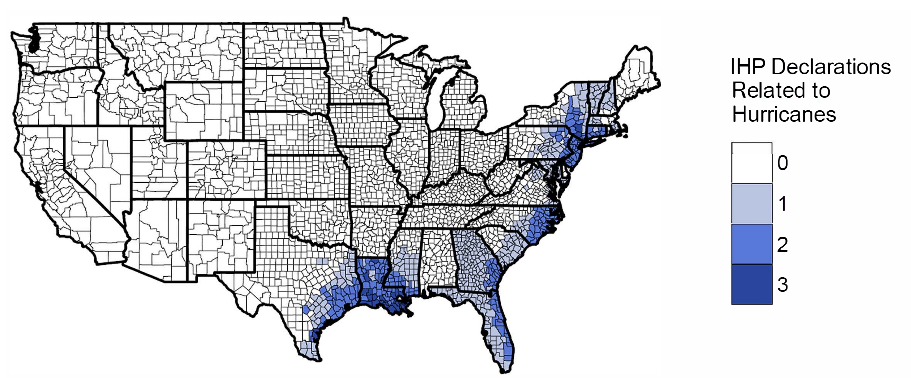


Figure 1: Variance as a function of the probability of hurricane landfall

This figure shows the total variance prior to landfall, $Var_t(r_{i,t+1})$ derived in equation (6), as the probability of landfall, ϕ, varies from 0 to 1. In this figure, $\sigma = 0.4$ and $\sigma_g = 0.05$. The four dashed lines have absolute values of 0.1, 0.07, 0.05, and 0 for μ_g. The solid line shows the level of variance conditional on hurricane landfall, $Var_t(r_{i,t+1}|\theta = 1) = \sigma^2 + \sigma_g^2$, as defined in equation (3).



(a) From 2002 to 2017



(b) From 2007 to 2017

Figure 2: US counties with hurricane damage

This figure highlights the counties with at least one hurricane related IHP declaration during the sample period from 2002 to 2017 (Panel A) and the sample period from 2007 to 2017 (Panel B). The map is constructed using data from FEMA.

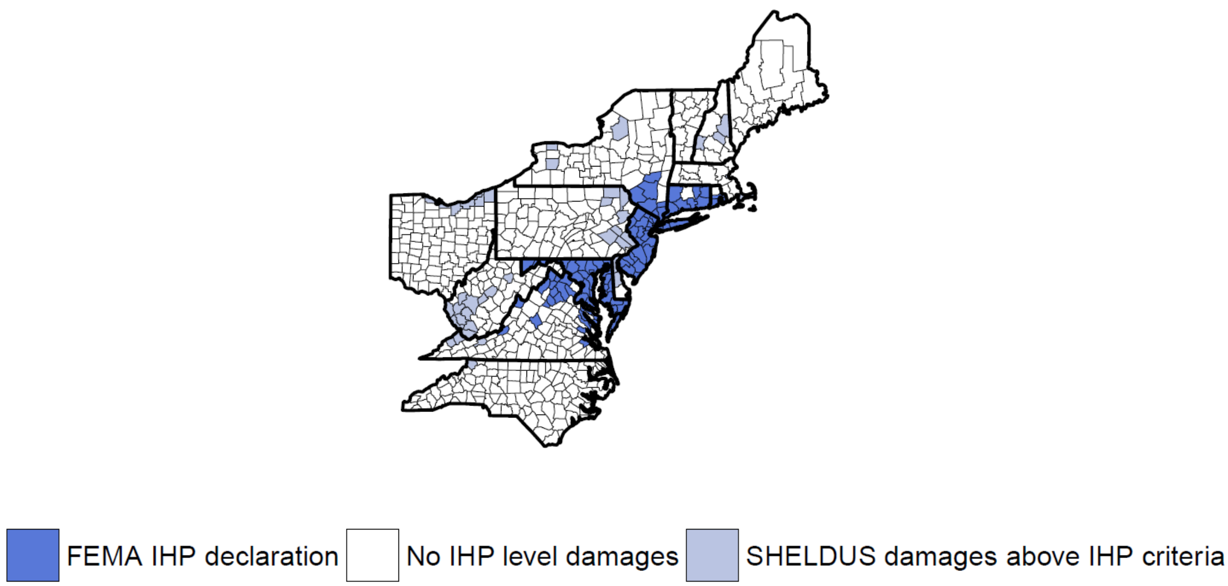


Figure 3: Counties with damage from Hurricane Sandy.

This figure highlights the counties with IHP-level damages from Hurricane Sandy in 2012. The map is constructed using data from FEMA and SHELDUS.

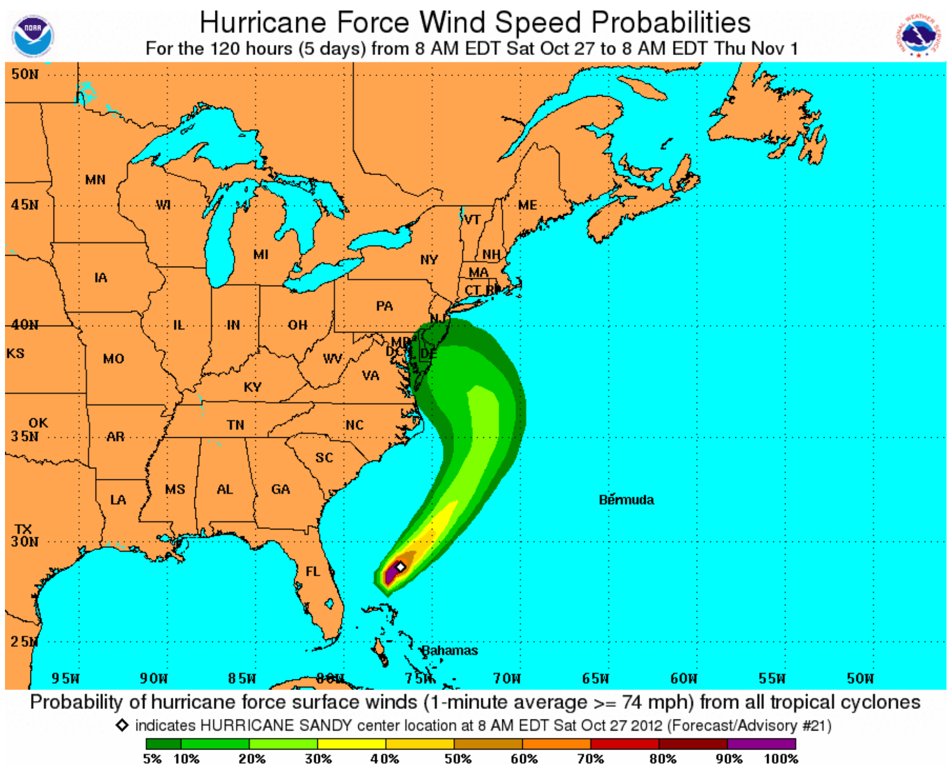


Figure 4: Example of a five-day forecast of a hurricane.

This figure from NOAA illustrates the five-day forecast for Hurricane Sandy on October 27, 2012. We obtain the raw data underpinning such hurricane forecast visualizations for our analysis.

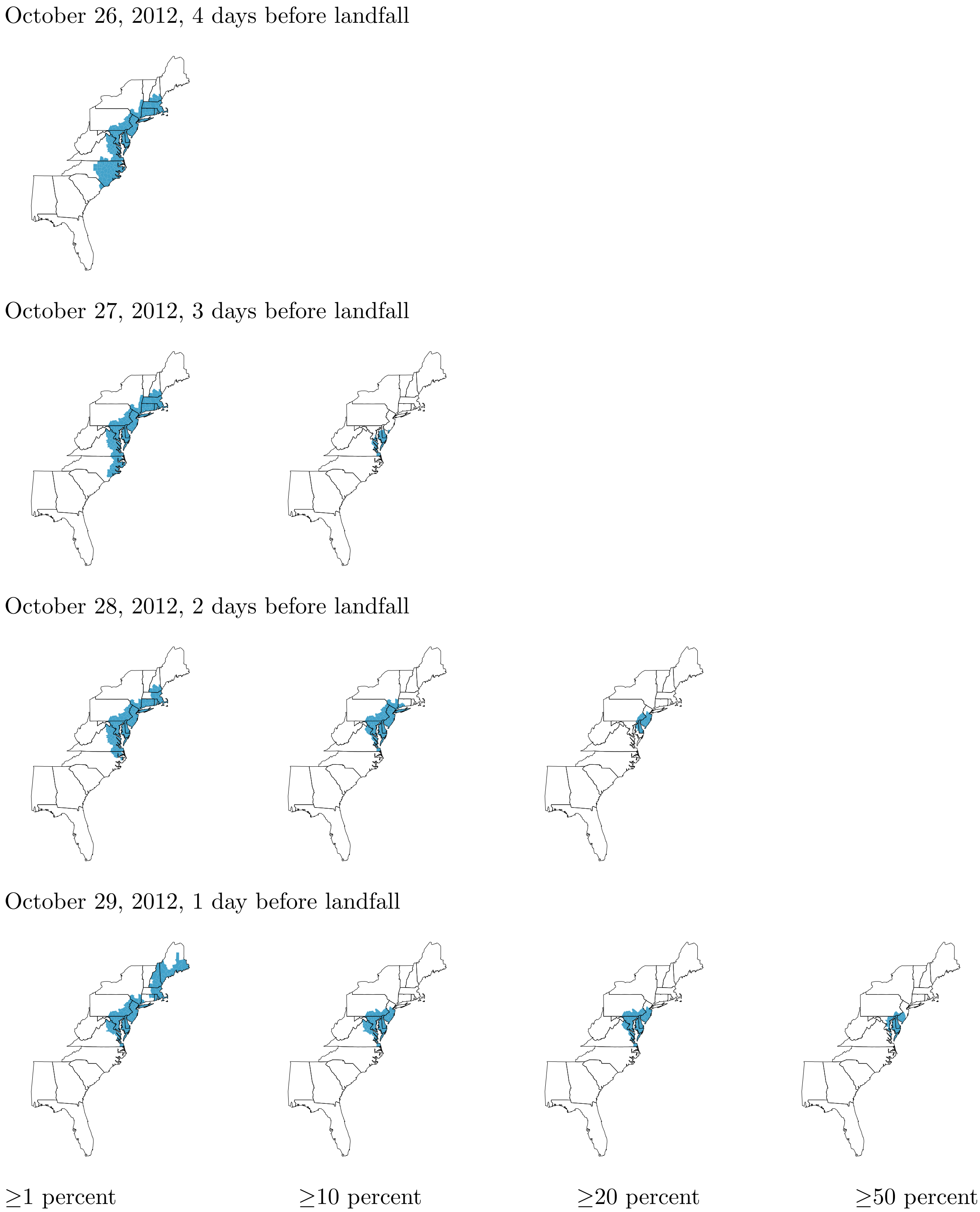
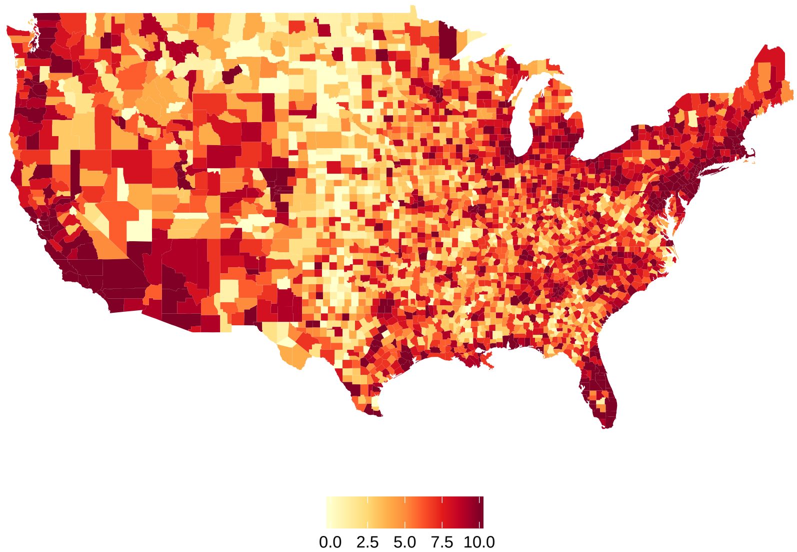
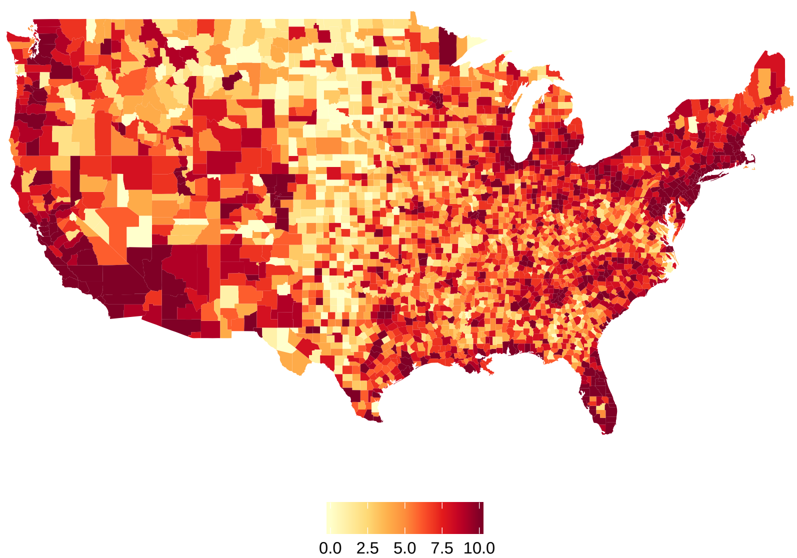


Figure 5: Hurricane Forecasts At Different Time Frames and Windspeed Probability Thresholds

Each map shows the counties indicated as being at-risk for Hurricane Sandy given the number of days before landfall in each row and the wind speed probability threshold shown in each column. Note that the 5-day ahead forecast was excluded due to space constraints. Source: NOAA.



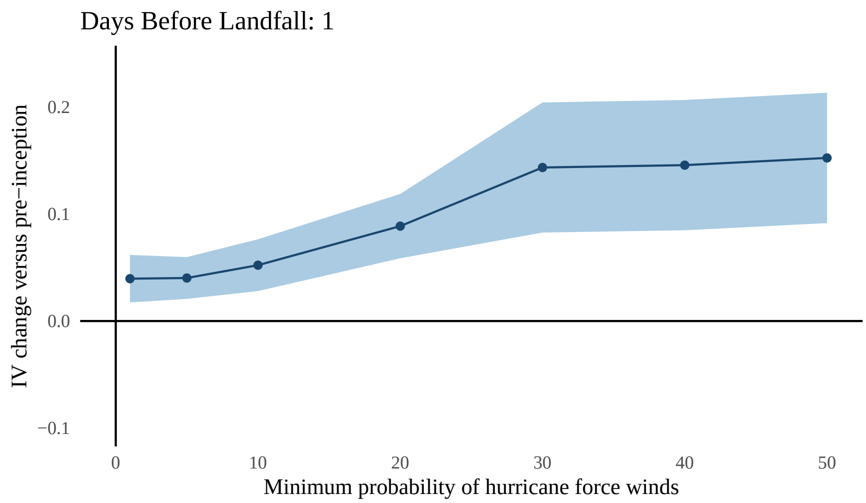
(a) Year 2010



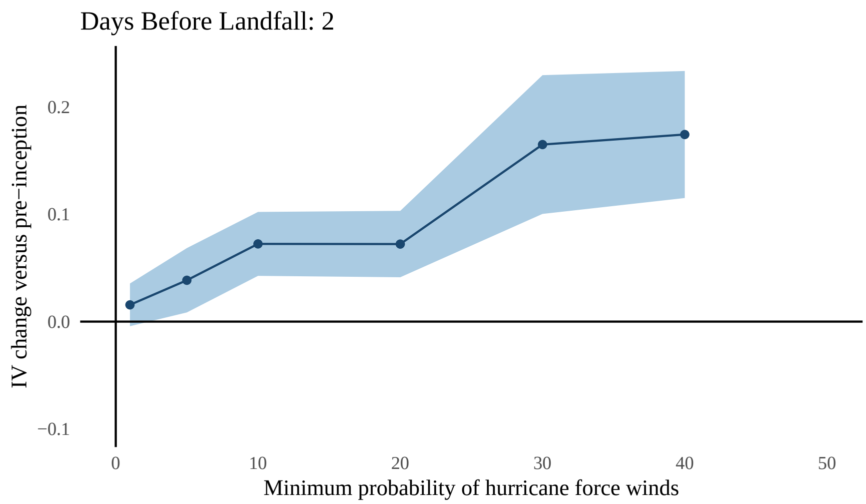
(b) Year 2014

Figure 6: Firm establishments by county

This chart plots counties based on the number of establishments located in that county for the years 2010 (Panel A) and 2014 (Panel B). The data are from NETS. Only firms that could be mapped to CRSP-Compustat are included. The counties are sorted into deciles based on the number of establishments.



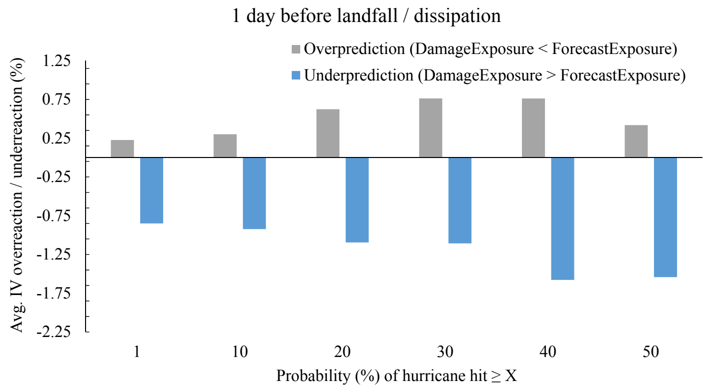
(a) One day before hurricane landfall/dissipation



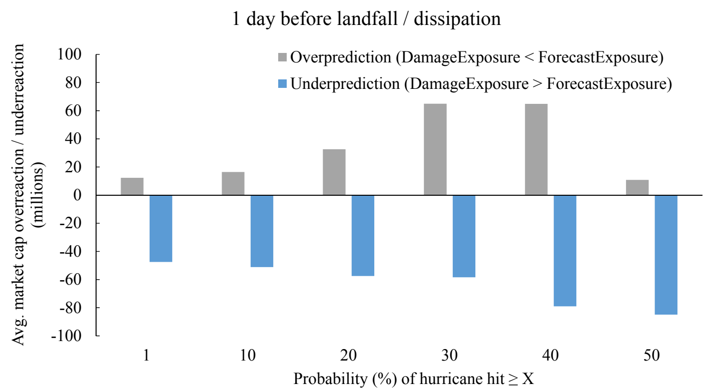
(b) Two days before hurricane landfall/dissipation

Figure 7: Implied volatility difference for firms exposed to a hurricane forecast path

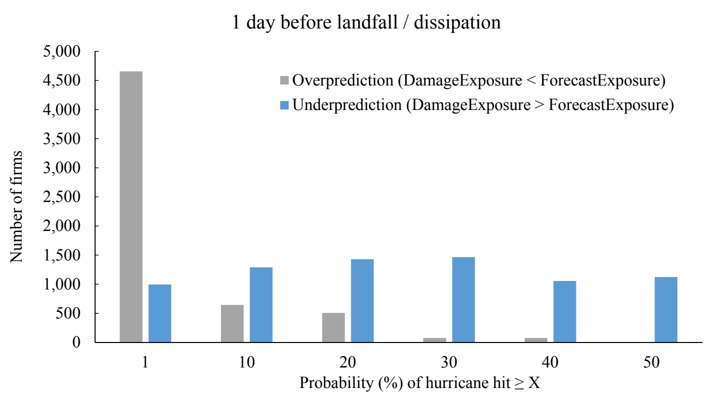
This chart plots the implied volatility difference for firms exposed to hurricane forecast path one and two days before hurricane landfall/dissipation. This corresponds to the λ coefficient estimate in regression equation (12) by probability threshold. The complete results of the regressions are presented in Table 7. The blue shaded region above and below the plotted line depicts the confidence interval of the estimates.



(a) Implied volatility overreaction / underreaction



(b) Market cap overreaction / underreaction



(c) Number of firms overpredicted / underpredicted

Figure 8: Economic effects of differences in forecast and damage exposure

Panel A plots by how much the implied volatility is on average overreacting (underreacting) due to an overprediction (underprediction), i.e., the firm's forecast exposure to a hurricane is greater (smaller) than the firm's eventual damage exposure. Panel B, depicts the average implied volatility overreaction (underreaction) multiplied with the average market capitalization of the respective firms. Panel C plots the number of firms for which the forecast exposure to a hurricane is greater (smaller) than the firm's eventual damage exposure summed across all the hurricanes from 2007 to 2017. The analysis is based on hurricane forecasts one day before landfall or dissipation. The geographic footprint of firms is based on the number of establishments in counties. The damage exposure is measured with FEMA and SHELDUS data.

Table 1: Summary statistics of hurricane damage data

This table reports summary statistics on the damage data for each hurricane from 2002 to 2017 based on FEMA and SHELDUS. Counties are eligible for individual and household program (IHP) assistance if there is a FEMA disaster declaration due to significant damage from a hurricane on a per capita basis.

	Mean	Median	Std Dev	Min	Max	Obs
FEMA Counties with IHP declarations	80	72	53	16	254	20
SHELDUS Counties with property damage	175	137	126	24	466	20
SHELDUS Counties with IHP-worthy damages	100	77	88	5	345	20
SHELDUS Property damages estimate ($millions)	12,158	2,808	24,613	32	89,432	20

Table 2: Summary statistics of hurricane forecast data

This table reports summary statistics of NOAA windspeed forecasts from 2007 to 2017 for storms that are forecasted to make landfall within five days with windspeeds of at least 64KT with a given minimum probability. Panel A reports the mean, median, and standard deviation of the number of county-dates observations for which we have hurricane forecasts for each storm at a given probability threshold. Panel B presents the observation count by days to resolution (hurricane landfall or, in the case of "misses", dissipation) at a given probability threshold.

Panel A: Summary statistics of county date forecast observations per storm

	Probability $\geq$				
	1	10	20	40	50
N Storms	49	17	14	9	9
N County Days	14,988	2,093	913	414	335
Mean	305.878	42.714	18.633	8.449	6.837
Median	124.000	0.000	0.000	0.000	0.000
Std. Dev.	402.974	91.761	43.723	20.857	18.004

Panel B: Number of county date forecast observations

Days to dissipation or landfall	Probability $\geq$				
	1	10	20	40	50
1	2,251	536	371	239	199
2	3,131	678	320	149	122
3	3,198	545	159	14	14
4	2,431	187	37	12	0
5	1,929	101	21	0	0

Table 3: Firm establishment and sales summary statistics

This table reports the summary statistics on the number of establishments and amount of sales (in USD) in the NETS dataset from 2002 to 2017 for the firms that were matched to equity data from CRSP-Compustat.

Number of firms with establishment/sales data					
Establishments	4,197				
Sales	4,187				
Statistics by firm-year					
	Avg	SD	10% percentile	50% percentile	90% percentile
Establishments	69.397	323.093	1.000	4.000	110.000
Sales (in millions)	524.601	2,465.746	0.310	31.642	959.216
Statistics by county-year					
	Avg	SD	10% percentile	50% percentile	90% percentile
Establishments	66.659	207.904	2.000	14.000	143.000
Sales (in millions)	503.377	2,088.409	2.408	58.780	894.028
Statistics by county-year for hurricane damaged counties					
	Avg	SD	10% percentile	50% percentile	90% percentile
Establishments	88.054	241.813	3.000	21.000	214.000
Sales (in millions)	675.404	2,831.049	2.923	87.663	1,260.017

Table 4: Summary statistics of implied volatility

This table reports the summary statistics on the single-stock options data from January 1, 2002 to December 31, 2017 from OptionMetrics including the number of observations (N), mean, median, standard deviation, 25^{th}, 75^{th}, 10^{th}, and 90^{th} percentiles. Panel A includes the options dataset once merged with CRSP-Compustat. Panel B further restricts the sample to firms appearing at least once in the NETS firm establishment data.

Panel A: Firms matched to CRSP-Compustat

	N	Mean	Median	Stdev	25th	75th	10th	90th
$IV_{i,t}$	9,420,182	0.453	0.384	0.273	0.272	0.551	0.205	0.778
$log\left(\frac{IV_{i,t}}{IV_{i,t-1}}\right)$	9,420,182	0.001	0.000	0.124	-0.042	0.045	-0.105	0.110
Days to expiry$_{i,t}$	9,420,182	38.852	29.000	35.427	17.000	40.000	11.000	93.000
Total open interest$_{i,t}$	9,420,182	2,396.119	267.000	11,321.761	54.000	1,347.000	13.000	5,106.000

Panel B: Firms matched to CRSP-Compustat and NETS

	N	Mean	Median	Stdev	25th	75th	10th	90th
$IV_{i,t}$	3,866,672	0.440	0.372	0.265	0.267	0.530	0.202	0.750
$log\left(\frac{IV_{i,t}}{IV_{i,t-1}}\right)$	3,866,672	0.001	0.000	0.126	-0.043	0.045	-0.106	0.112
Days to expiry$_{i,t}$	3,866,672	39.243	29.000	35.577	17.000	40.000	11.000	93.000
Total open interest$_{i,t}$	3,866,672	2,080.397	234.000	7,681.694	50.000	1,194.000	12.000	4,584.000

Table 5: Hurricane effects on implied volatility

This table reports the coefficients and test statistics when estimating the panel model in equation (9). The dependent variable is the change (in percent) in the implied volatility of firm i from the day before the inception day of the hurricane T_h^* until 5 trading days after the landfall T_h. The independent variable measures how much of the geographic footprint of a firm is exposed to the disaster area. For Panel A, the geographic footprint used to measure the exposure to a hurricane of a firm is based on establishments per county, and for Panel B, the geographic footprint is based on sales per county. To identify counties that have been damaged by a hurricane we use FEMA data and FEMA data enhanced with SHELDUS data. The data are from 2002 to 2017. Results are also shown for the subsample from 2007 to 2017, which corresponds to the time period for which we have hurricane forecast data used in the subsequent analysis. The values in parentheses are the t-stats. The standard errors are clustered by county (headquarter location). Industry and time fixed effects are used. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Firms' hurricane exposure based on establishments

Dependent variable: Change in IV, $log\left(IV_{i,T_h+5}/IV_{i,T_h^*}\right)$

	2002-2017				2007-2017			
	FEMA		FEMA+SHELDUS		FEMA		FEMA+SHELDUS	
$DamageExposure_{i,T_h}$	0.072***	0.053***	0.071***	0.057***	0.085***	0.065***	0.086***	0.071***
	(4.345)	(3.222)	(4.316)	(3.428)	(4.250)	(2.933)	(4.181)	(3.225)
Adjusted R^2 (%)	13.379	14.128	13.574	14.336	14.841	15.793	14.862	15.824
Obs. total	12,156	12,156	12,621	12,621	7,204	7,204	7,204	7,204
Obs. firm exposure $> 0\%$	5,387	5,387	5,938	5,938	3,020	3,020	3,261	3,261
Obs. firm exposure $\geq 20\%$	805	805	974	974	479	479	593	593
Obs. firm exposure $\geq 50\%$	286	286	317	317	175	175	199	199
Hurricanes	19	19	20	20	10	10	10	10
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry $\times$ Time FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Firms' hurricane exposure based on sales

Dependent variable: Change in IV, $log\left(IV_{i,T_h+5}/IV_{i,T_h^*}\right)$

	2002-2017				2007-2017			
	FEMA		FEMA+SHELDUS		FEMA		FEMA+SHELDUS	
$DamageExposure_{i,T_h}$	0.051***	0.038***	0.050***	0.039***	0.063***	0.048***	0.063***	0.052***
	(3.554)	(2.738)	(3.726)	(3.084)	(3.810)	(2.771)	(3.964)	(3.155)
Adjusted R^2 (%)	13.368	14.139	13.556	14.337	14.829	15.797	14.845	15.821
Obs. total	12,126	12,126	12,590	12,590	7,194	7,194	7,194	7,194
Obs. firm exposure $> 0\%$	5,365	5,365	5,916	5,916	3,006	3,006	3,249	3,249
Obs. firm exposure $\geq 20\%$	808	808	953	953	488	488	595	595
Obs. firm exposure $\geq 50\%$	391	391	447	447	235	235	279	279
Hurricanes	19	19	20	20	10	10	10	10
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry $\times$ Time FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 6: Abnormal returns post hurricane landfall

This table reports differences in cumulative abnormal returns post landfall between firms with exposure (treated) and firms without exposure (control) to the hurricane disaster region. The differences are reported for the mean and nine percentiles of the return distributions of the treated and control firms. The differences are estimated for two time periods: from landfall to 5 trading days and 120 trading days after landfall, respectively. The abnormal returns are estimated based on the Fama-French three factor model. FEMA and SHELDUS data are used to identify counties that have been hit by a hurricane. For Panel A, the hit firms are defined as firms that have 50 percent or more of their establishments in the counties of the disaster region, and for Panel B, 50 percent or more of the sales have to be located in the disaster area counties. We exclude hurricanes that affected less than 25 firms. The data are from 2002 to 2017. The standard errors are bootstrapped and clustered by county (headquarter location). The significance of the difference in abnormal returns is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Hit firms selected based on exposure in disaster region $\geq 50\%$

	From 0 to 5 days post landfall		From 0 to 120 days post landfall	
	Cumulative r difference	T-stat	Cumulative r difference	T-stat
Mean	0.103	0.197	-6.489	-1.562
Percentiles				
10%	-0.315	-0.637	-13.754***	-3.556
20%	-0.479	-0.801	-14.781***	-3.550
30%	-0.214	-0.681	-10.241**	-2.310
40%	-0.241	-1.003	-7.871**	-2.213
50%	-0.500*	-1.858	-7.491***	-3.402
60%	-0.357	-1.215	-8.262***	-2.734
70%	-0.143	-0.327	-4.529	-1.395
80%	-0.199	-0.423	-3.795	-1.061
90%	0.927	0.523	-5.708	-0.910
Hit firms	415		382	
Control firms	8,376		7,027	

Panel B: Hit firms selected based on sales in disaster region $\geq 50\%$

	From 0 to 5 days post landfall		From 0 to 120 days post landfall	
	Cumulative r difference	T-stat	Cumulative r difference	T-stat
Mean	0.131	0.248	-6.501**	-1.968
Percentiles				
10%	-0.661	-1.139	-12.215***	-2.577
20%	-0.438	-0.823	-10.233**	-2.502
30%	-0.313	-0.967	-6.862**	-2.528
40%	-0.314	-0.947	-5.394**	-2.195
50%	-0.318	-0.848	-5.697***	-2.693
60%	-0.054	-0.144	-5.633***	-2.923
70%	0.278	0.439	-4.838**	-2.127
80%	0.251	0.382	-3.559	-1.215
90%	0.948	0.828	-6.667	-1.120
Hit firms	641		622	
Control firms	10,115		9,795	

Table 7: Forecasted hurricane path and implied volatility

This table reports the coefficients and test statistics when estimating the panel model in equation (12). The dependent variable is the change (in percent) in the implied volatility of firm i from inception of the hurricane to Γ days before landfall or dissipation, T_h, of the hurricane. The independent variable measures how much (in percent) of the geographic footprint of a firm is exposed to the forecasted path of a hurricane Γ days before the landfall or dissipation of the hurricane. The geographic footprint used to measure the exposure to a hurricane of a firm is based on establishments per county for Panel A and based on sales per county for Panel B. The forecasted path of the hurricane is from NOAA and gives a probability of being hit by a specific hurricane for each county. The included probability thresholds have at least three hurricanes and 25 firms with an exposure of over 20% in establishments or sales to the counties in the forecasted path. The data are from 2007 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county (headquarter location). Industry and time fixed effects are used. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Firms' hurricane exposure based on establishments

Dependent variable: Change in IV from hurricane inception to Γ days before landfall/dissipation, $log\left(IV_{i,T_h-\Gamma}/IV_{i,T_h^*}\right)$

Γ	1 Day					2 Days				3 Days			4 Days		5 Days	
Probability of hurricane hit $\geq$	1%	10%	20%	40%	50%	1%	10%	20%	40%	1%	10%	20%	1%	10%	1%	10%
$ForecastExposure_{i,T_h-\Gamma}$	0.043***	0.047***	0.082***	0.137***	0.144***	0.017*	0.071***	0.067***	0.171***	0.014**	0.100***	0.139***	0.014*	0.127***	0.009	0.006
	(4.164)	(4.155)	(4.776)	(3.714)	(4.077)	(1.798)	(4.644)	(4.381)	(5.448)	(2.123)	(3.588)	(5.672)	(1.723)	(3.259)	(0.944)	(0.131)
Adjusted R^2	16.083	21.278	19.926	23.303	23.305	11.977	14.795	16.655	18.976	10.748	14.236	15.330	15.709	25.102	10.048	9.182
Obs. Total	21,160	6,070	5,358	2,345	2,345	16,008	7,075	5,463	3,974	14,239	7,046	4,752	11,871	4,005	10,320	2,373
Obs. ForecastExposure > 0%	5,731	1,717	1,437	704	647	6,209	1,871	1,315	928	6,645	1,957	1,283	6,029	1,109	4,550	670
Obs. ForecastExposure $\geq$ 20%	408	175	126	70	61	1,244	163	116	66	1,929	144	88	1,853	86	1,106	34
Number of hurricanes	27	8	7	3	3	20	9	7	5	18	9	6	15	5	13	3
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Firms' hurricane exposure based on sales

Dependent variable: Change in IV from hurricane inception to Γ days before landfall/dissipation, $log\left(IV_{i,T_h-\Gamma}/IV_{i,T_h^*}\right)$

Γ	1 Day					2 Days				3 Days			4 Days		5 Days	
Probability of hurricane hit $\geq$	1%	10%	20%	40%	50%	1%	10%	20%	40%	1%	10%	20%	1%	10%	1%	10%
$ForecastExposure_{i,T_h-\Gamma}$	0.036***	0.044***	0.074***	0.134***	0.150***	0.018**	0.070***	0.080***	0.164***	0.015**	0.087**	0.133***	0.014*	0.121***	0.006	0.020
	(3.430)	(4.623)	(4.141)	(3.917)	(4.890)	(2.111)	(5.389)	(5.277)	(5.081)	(2.525)	(2.524)	(4.559)	(1.952)	(3.145)	(0.824)	(0.652)
Adjusted R^2	16.134	21.345	20.037	23.541	23.584	11.996	14.838	16.735	19.105	10.776	14.280	15.466	15.777	25.201	10.032	9.154
Obs. total	21,132	6,061	5,350	2,342	2,342	15,988	7,066	5,456	3,969	14,220	7,037	4,746	11,855	4,000	10,307	2,370
Obs. ForecastExposure > 0%	5,660	1,706	1,426	700	641	6,177	1,855	1,304	918	6,619	1,939	1,275	6,000	1,100	4,529	663
Obs. ForecastExposure $\geq$ 20%	459	189	143	76	66	1,186	172	123	74	1,746	144	95	1,647	96	983	39
Number of hurricanes	27	8	7	3	3	20	9	7	5	18	9	6	15	5	13	3
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Alternative specification for forecasted hurricane path and implied volatility

This table reports the sample mean, denoted $\overline{IVD}$, and t-stat for $IVD_{i,h}$ described in equation (13). For each hurricane and firm i, we subtract the implied volatility (IV) on the day before the inception of the hurricane from the IV on the day when the firm's exposure to counties in the hurricane's path exceeds a threshold of X percent. Landfall days are excluded. The log difference in IV is then demeaned by the mean log difference in IV of firms that are not exposed to the hurricane. The geographic footprint used to measure the exposure to a hurricane of a firm is based on establishments per county for Panel A and based on sales per county for Panel B. The forecasted path of the hurricane is from NOAA and gives a probability of being hit by a specific hurricane for each county. The data are from 2007 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county (headquarter location). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Firms' hurricane exposure based on establishments

Exposure to hurricane path ≥	10%					25%					50%				
Probability of hurricane hit ≥	1%	10%	20%	40%	50%	1%	10%	20%	40%	50%	1%	10%	20%	40%	50%
$\overline{IVD}$	-0.348	1.738**	2.450**	6.519*	8.529**	0.279	3.489***	4.656***	11.122***	12.495***	0.985**	2.178**	3.376***	9.404***	11.311***
	(-1.475)	(2.213)	(2.293)	(1.715)	(2.538)	(0.728)	(3.130)	(4.135)	(3.045)	(3.606)	(2.065)	(2.094)	(2.836)	(3.269)	(5.835)
Number of firms	6,088	649	414	178	145	2,775	244	165	68	61	1,282	118	81	32	27
Number of hurricanes	40	13	9	5	5	39	11	7	5	5	37	11	7	4	4

Panel B: Firms' hurricane exposure based on sales

Exposure to hurricane path ≥	10%					25%					50%				
Probability of hurricane hit ≥	1%	10%	20%	40%	50%	1%	10%	20%	40%	50%	1%	10%	20%	40%	50%
$\overline{IVD}$	-0.135	1.887**	2.877**	7.494*	12.217***	0.199	2.466**	4.783***	10.633***	11.634***	0.440	2.721**	3.882***	9.096**	11.348***
	(-0.499)	(1.996)	(2.282)	(1.827)	(3.740)	(0.610)	(1.961)	(7.899)	(2.892)	(4.276)	(1.204)	(2.545)	(5.498)	(2.418)	(3.499)
Firms	4,788	538	354	160	132	2,792	279	193	84	73	1,706	174	122	57	48
Number of hurricanes	39	14	10	6	6	37	12	9	5	5	37	12	8	5	5

Table 9: Forecasted hurricane path and stock returns

This table reports the coefficients and test statistics when estimating the panel model in equation (14). The dependent variable is the stock return (in percent) of firm i from inception of the hurricane to Γ days before landfall or dissipation of the hurricane. The independent variable measures how much (in percent) of the geographic footprint of a firm is exposed to the forecasted path of a hurricane Γ days before the landfall or disappearance of the hurricane. The geographic footprint used to measure the exposure to a hurricane of a firm is based on establishments per county for Panel A and based on sales per county for Panel B. The forecasted path of the hurricane is from NOAA and gives a probability of being hit by a specific hurricane for each county. The included probability thresholds have at least three hurricanes and 25 firms with an exposure of over 20 percent in establishments or sales to the counties in the forecasted path. The data are from 2007 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county (headquarter location). Industry and time fixed effects are used. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Firms' hurricane exposure based on establishments

Dependent variable: Cumulative return from hurricane inception to Γ days before landfall/dissipation, $r_{i,T_h^*:T_h-\Gamma}$

Γ	1 Day					2 Days				3 Days			4 Days		5 Days	
Probability of hurricane hit $\geq$	1%	10%	20%	40%	50%	1%	10%	20%	40%	1%	10%	20%	1%	10%	1%	10%
$ForecastExposure_{i,T_h-\Gamma}$	-0.015	-0.030***	-0.032***	-0.066***	-0.072***	-0.015	-0.040***	-0.047***	-0.091***	-0.005	-0.048**	-0.056**	-0.007	-0.088***	-0.002	0.004
	(-1.103)	(-3.378)	(-3.715)	(-3.418)	(-3.763)	(-1.419)	(-3.806)	(-6.199)	(-4.468)	(-1.018)	(-2.561)	(-2.540)	(-1.625)	(-3.171)	(-0.500)	(0.492)
Adjusted R^2	3.614	2.005	1.597	1.023	1.025	0.964	8.935	8.897	20.839	0.725	5.390	12.313	2.368	2.814	4.502	19.775
Obs. total	25,062	7,235	6,314	2,448	2,448	17,507	7,716	6,096	4,153	16,109	8,128	5,072	14,082	4,343	11,371	2,500
Obs. ForecastExposure > 0%	6,583	1,846	1,553	747	686	6,663	1,937	1,361	944	7,345	2,088	1,324	6,890	1,138	5,132	671
Obs. ForecastExposure $\geq$ 20%	563	174	132	70	63	1,402	165	115	67	2,159	155	93	2,008	87	1,367	35
Number of hurricanes	28	8	7	3	3	20	9	7	5	18	9	6	16	5	13	3
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Firms' hurricane exposure based on sales

Dependent variable: Cumulative return from hurricane inception to Γ days before landfall/dissipation, $r_{i,T_h^*:T_h-\Gamma}$

Γ	1 Day					2 Days				3 Days			4 Days		5 Days	
Probability of hurricane hit $\geq$	1%	10%	20%	40%	50%	1%	10%	20%	40%	1%	10%	20%	1%	10%	1%	10%
$ForecastExposure_{i,T_h-\Gamma}$	-0.011	-0.024***	-0.025***	-0.053***	-0.057***	-0.011	-0.032***	-0.041***	-0.078***	-0.004	-0.039***	-0.048***	-0.008**	-0.073***	-0.003	-0.004
	(-1.054)	(-3.715)	(-4.021)	(-3.401)	(-3.622)	(-1.371)	(-3.230)	(-6.933)	(-5.464)	(-1.016)	(-2.621)	(-2.883)	(-2.383)	(-4.172)	(-1.035)	(-0.545)
Adjusted R^2	3.612	2.005	1.596	1.021	1.022	0.962	8.925	8.908	20.916	0.724	5.380	12.349	2.376	2.821	4.510	19.789
Obs. total	25,053	7,234	6,314	2,448	2,448	17,499	7,714	6,095	4,153	16,100	8,126	5,071	14,076	4,342	11,365	2,498
Obs. ForecastExposure > 0%	6,511	1,834	1,542	744	681	6,631	1,921	1,350	935	7,321	2,072	1,317	6,862	1,130	5,112	664
Obs. ForecastExposure $\geq$ 20%	637	201	156	87	73	1,371	177	126	79	2,007	164	111	1,865	104	1,263	41
Number of hurricanes	28	8	7	3	3	20	9	7	5	18	9	6	16	5	13	3
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Market and NOAA forecasts comparison

This table reports the coefficients and test statistics when estimating the panel model in equation (15). The dependent variable is the change (in percent) in the implied volatility of firm i from inception of the hurricane to Γ days before landfall or dissipation, T_h, of the hurricane. The independent variable $HurricaneForecastExposure_{i,T_h-\Gamma}$ measures how much (in percent) of the geographic footprint of a firm is exposed to the forecasted path of a hurricane Γ days before the landfall or dissipation of the hurricane. The independent variable $UnderPrediction_{i,T_h-\Gamma}$ measures the difference between the firm's exposure to the eventual hurricane damage region and the firm's exposure to the forecasted path of a hurricane, as shown in equation (16). The geographic footprint used to measure the exposure to a hurricane of a firm is based on establishments per county for Panel A and based on sales per county for Panel B. The forecasted path of the hurricane is from NOAA and gives a probability of being hit by a specific hurricane for each county. The included probability thresholds have at least three hurricanes and 25 firms with an exposure of over 20% in establishments or sales to the counties in the forecasted path. The data are from 2007 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county (headquarter location). Industry and time fixed effects are used. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Firms' hurricane exposure based on establishments

Dependent variable: Change in IV from hurricane inception to Γ days before landfall/dissipation, $log\left(IV_{i,T_h-\Gamma}/IV_{i,T_h^*}\right)$

Γ	1 Day					2 Days				3 Days			4 Days		5 Days	
Probability of hurricane hit $\geq$	1%	10%	20%	40%	50%	1%	10%	20%	40%	1%	10%	20%	1%	10%	1%	10%
$ForecastExposure_{i,T_h-\Gamma}$	0.043***	0.048***	0.082***	0.138***	0.145***	0.017*	0.071***	0.068***	0.171***	0.014**	0.100***	0.138***	0.014*	0.126***	0.009	0.006
	(4.172)	(4.236)	(4.698)	(3.709)	(4.045)	(1.773)	(4.619)	(4.389)	(5.374)	(2.067)	(3.578)	(5.651)	(1.732)	(3.198)	(0.993)	(0.132)
$UnderPrediction_{i,T_h-\Gamma}$	0.036	0.066*	0.025	0.018	0.020	-0.016	0.021	0.031	0.012	-0.039	0.016	0.021	0.013	0.046	0.023	0.001
	(1.001)	(1.926)	(0.811)	(0.549)	(0.588)	(-0.262)	(0.684)	(0.974)	(0.444)	(-1.150)	(0.672)	(0.832)	(0.256)	(1.590)	(0.908)	(0.062)
Adjusted R^2 (%)	16.085	21.327	19.927	23.282	23.286	11.973	14.792	16.666	18.962	10.753	14.229	15.324	15.703	25.152	10.051	9.143
Obs. total	21,160	6,070	5,358	2,345	2,345	16,008	7,075	5,463	3,974	14,239	7,046	4,752	11,871	4,005	10,320	2,373
Obs. ForecastExposure > 0%	5,731	1,717	1,437	704	647	6,209	1,871	1,315	928	6,645	1,957	1,283	6,029	1,109	4,550	670
Obs. ForecastExposure $\geq$ 20%	408	175	126	70	61	1,244	163	116	66	1,929	144	88	1,853	86	1,106	34
Obs. ForecastExposure $\geq$ 50%	157	68	46	25	22	442	62	47	23	687	48	33	670	30	363	13
Obs. UnderPrediction	995	1,290	1,429	1,055	1,123	757	1,444	1,614	1,538	924	1,539	1,408	651	1,159	1,035	738
Obs. UnderPrediction $\geq$ 20%	78	117	173	165	171	64	207	234	294	98	208	223	76	220	151	150
Obs. UnderPrediction $\geq$ 50%	24	36	58	53	53	20	69	76	97	28	68	71	22	69	64	50
Number of hurricanes	27	8	7	3	3	20	9	7	5	18	9	6	15	5	13	3
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Market and NOAA forecasts comparison (continued)

Panel B: Firms' hurricane exposure based on sales

Dependent variable: Change in IV from hurricane inception to Γ days before landfall/dissipation, $log\left(IV_{i,T_h-\Gamma}/IV_{i,T_h^*}\right)$

Γ	1 Day					2 Days				3 Days			4 Days		5 Days	
Probability of hurricane hit ≥	1%	10%	20%	40%	50%	1%	10%	20%	40%	1%	10%	20%	1%	10%	1%	10%
$ForecastExposure_{i,T_h-\Gamma}$	0.037***	0.045***	0.074***	0.134***	0.150***	0.017**	0.070***	0.080***	0.164***	0.014**	0.087**	0.133***	0.014**	0.121***	0.007	0.020
	(3.431)	(4.554)	(4.163)	(3.959)	(4.924)	(2.077)	(5.332)	(5.264)	(5.105)	(2.461)	(2.522)	(4.547)	(1.961)	(3.124)	(0.889)	(0.651)
$UnderPrediction_{i,T_h-\Gamma}$	0.012	0.029	0.006	0.000	0.002	-0.047	0.001	0.005	-0.003	-0.041	0.012	0.010	0.003	0.030	0.022	0.001
	(0.422)	(1.290)	(0.282)	(0.016)	(0.085)	(-0.991)	(0.050)	(0.182)	(-0.130)	(-1.250)	(0.586)	(0.425)	(0.072)	(1.303)	(1.216)	(0.029)
Adjusted R^2 (%)	0.161	0.214	0.200	0.235	0.236	0.120	0.148	0.167	0.191	0.108	0.143	0.155	0.158	0.252	0.100	0.091
Obs. total	21,132	6,061	5,350	2,342	2,342	15,988	7,066	5,456	3,969	14,220	7,037	4,746	11,855	4,000	10,307	2,370
Obs. ForecastExposure > 0%	5,660	1,706	1,426	700	641	6,177	1,855	1,304	918	6,619	1,939	1,275	6,000	1,100	4,529	663
Obs. ForecastExposure ≥ 20%	459	189	143	76	66	1,186	172	123	74	1,746	144	95	1,647	96	983	39
Obs. ForecastExposure ≥ 50%	237	101	74	41	35	602	89	70	40	905	73	56	889	50	488	21
Obs. UnderPrediction	1,023	1,291	1,426	1,055	1,122	812	1,452	1,606	1,531	951	1,553	1,403	718	1,157	1,086	736
Obs. UnderPrediction ≥ 20%	113	158	205	203	206	97	234	264	311	137	221	233	97	221	195	136
Obs. UnderPrediction ≥ 50%	45	61	92	87	90	41	106	114	144	53	96	97	40	96	88	63
Number of hurricanes	27	8	7	3	3	20	9	7	5	18	9	6	15	5	13	3
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Hurricane effects on implied volatility of insurance firms

This table reports the coefficients and test statistics when estimating the panel model in equation (9) for insurance firms. The dependent variable is the change (in percent) in the implied volatility of firm i from the day before the inception day of the hurricane T_h^* until 5 trading days after the landfall T_h. The independent variable measures the share of total premiums written by an insurance firm in states that experienced damage by a hurricane. For Panel A, a state is considered to have experienced hurricane damage if at least 10% of the counties experienced damage, and for Panel B, the threshold is 25% of the counties. To identify counties that have been damaged by a hurricane we use FEMA data and FEMA data enhanced with SHELDUS data. The data are from 2002 to 2017. Results are also shown for the subsample from 2007 to 2017 as in Table 5. The values in parentheses are the t-stats. The standard errors are clustered by insurance firm. Time fixed effects are used. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: State considered hit if 10% or more of the counties were damaged

Dependent variable: Change in IV, $log\left(IV_{i,T_h+5}/IV_{i,T_h^*}\right)$

	2002-2017		2007-2017	
	FEMA	FEMA+SHELDUS	FEMA	FEMA+SHELDUS
$StateDamageExposure_{i,T_h}$	0.348**	0.328*	0.357*	0.360**
	1.985	1.963	1.850	1.995
Adjusted R^2 (%)	36.894	34.790	33.399	33.597
Obs. total	400	418	238	238
Obs. insurance firm exposure $> 0\%$	356	374	207	207
Obs. insurance firm exposure $\geq 20\%$	49	88	30	53
Obs. insurance firm exposure $\geq 50\%$	11	11	11	11
Hurricanes	18	19	9	9
Time FE	Yes	Yes	Yes	Yes

Panel B: State considered hit if 25% or more of the counties were damaged

Dependent variable: Change in IV, $log\left(IV_{i,T_h+5}/IV_{i,T_h^*}\right)$

	2002-2017		2007-2017	
	FEMA	FEMA+SHELDUS	FEMA	FEMA+SHELDUS
$StateDamageExposure_{i,T_h}$	0.426*	0.400**	0.424*	0.413**
	1.922	2.329	1.733	2.251
Adjusted R^2 (%)	38.482	36.595	37.328	38.254
Obs. total	367	385	205	205
Obs. insurance firm exposure $> 0\%$	326	345	177	179
Obs. insurance firm exposure $\geq 20\%$	22	43	14	27
Obs. insurance firm exposure $\geq 50\%$	7	11	7	11
Hurricanes	17	18	8	8
Time FE	Yes	Yes	Yes	Yes

Appendix A Additional tables

Table A.1: Hurricane effects on implied volatility with industry interactions

This table reports the coefficients and test statistics when estimating the panel model in equation (9) but including an industry interaction term. The dependent variable is the change (in percent) in the implied volatility of firm i from the day before the inception of the hurricane until 5 trading days after the landfall. The first independent variable measures how much of the geographic footprint of a firm is exposed to the disaster area. The second independent variable interacts the exposure to the disaster area with an industry indicator variable for industry g. The industry classification is based on two-digit SIC numbers. For Panel A, the geographic footprint used to measure the exposure to a hurricane of a firm is based on establishments per county, and for Panel B, the geographic footprint is based on sales per county. The analysis is based on damage data from FEMA and FEMA enhanced with SHELDUS data. The data are from 2002 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county (headquarter location). Industry and time fixed effects are used. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Firms' hurricane exposure based on establishments

Dependent variable: Change in IV, $log\left(IV_{i,T_h+5}/IV_{i,T_h^*}\right)$

	Damage based on FEMA						
Interaction industry	Construct.	Manufact.	Mining	Retail	Services	Transport.	Wholesale
$DamageExposure_{i,T_h}$	0.072***	0.086***	0.072***	0.073***	0.073***	0.060***	0.067***
	(4.359)	(4.643)	(3.403)	(4.492)	(4.078)	(3.100)	(3.840)
$DamageExposure_{i,T_h} \times I_{i \in Industry_g}$	-0.125	-0.043	-0.002	-0.039	-0.009	0.068	0.078
	(-1.528)	(-1.385)	(-0.048)	(-0.367)	(-0.196)	(1.294)	(1.242)
Adjusted R^2 (%)	13.375	13.384	13.372	13.374	13.373	13.392	13.381
Obs. total	12,156	12,156	12,156	12,156	12,156	12,156	12,156
Obs. exposure $>$ 0%	5,387	5,387	5,387	5,387	5,387	5,387	5,387
Obs. exposure $\geq$ 20%	805	805	805	805	805	805	805
Obs. exposure $\geq$ 50%	286	286	286	286	286	286	286
Obs. $i \in Industry_g$	212	5,356	1,146	1,218	2,221	1,512	383
Number of hurricanes	19	19	19	19	19	19	19

	Damage based on FEMA+SHELDUS						
Interaction industry	Construct.	Manufact.	Mining	Retail	Services	Transport.	Wholesale
$DamageExposure_{i,T_h}$	0.072***	0.080***	0.071***	0.075***	0.074***	0.059***	0.067***
	(4.359)	(4.226)	(3.597)	(4.484)	(4.223)	(3.022)	(3.915)
$DamageExposure_{i,T_h} \times I_{i \in Industry_g}$	-0.216***	-0.027	0.001	-0.084	-0.018	0.075	0.086
	(-3.137)	(-0.902)	(0.032)	(-0.953)	(-0.383)	(1.433)	(1.417)
Adjusted R^2 (%)	13.576	13.572	13.567	13.577	13.568	13.591	13.578
Obs. total	12,621	12,621	12,621	12,621	12,621	12,621	12,621
Obs. exposure $>$ 0%	5,938	5,938	5,938	5,938	5,938	5,938	5,938
Obs. exposure *geq* 20%	974	974	974	974	974	974	974
Obs. exposure *geq* 50%	317	317	317	317	317	317	317
Obs. $i \in Industry_g$	221	5,562	1,174	1,273	2,317	1,569	394
Number of hurricanes	20	20	20	20	20	20	20
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.1: Hurricane effects on implied volatility with industry interactions (continued)

Panel B: Firms' hurricane exposure based on sales

Dependent variable: Change in IV, $log\left(IV_{i,T_h+5}/IV_{i,T_h^*}\right)$

	Damage based on FEMA						
Interaction industry	Construct.	Manufact.	Mining	Retail	Services	Transport.	Wholesale
$DamageExposure_{i,T_h}$	0.052***	0.063***	0.047***	0.053***	0.058***	0.041***	0.047***
	(3.621)	(3.699)	(2.874)	(3.944)	(3.633)	(2.588)	(3.156)
$DamageExposure_{i,T_h} \times I_{i \in Industry_g}$	-0.129**	-0.034	0.019	-0.037	-0.037	0.057	0.068
	(-2.028)	(-1.428)	(0.561)	(-0.438)	(-1.039)	(1.560)	(1.517)
Adjusted R^2 (%)	13.367	13.372	13.364	13.363	13.369	13.381	13.372
Obs. total	12,126	12,126	12,126	12,126	12,126	12,126	12,126
Obs. exposure $> 0\%$	5,365	5,365	5,365	5,365	5,365	5,365	5,365
Obs. exposure $\geq 20\%$	808	808	808	808	808	808	808
Obs. exposure $\geq 50\%$	391	391	391	391	391	391	391
Obs. $i \in Industry_g$	212	5,333	1,146	1,211	2,221	1,512	383
Number of hurricanes	19	19	19	19	19	19	19
	Damage based on FEMA+SHELDUS						
Interaction industry	Construct.	Manufact.	Mining	Retail	Services	Transport.	Wholesale
$DamageExposure_{i,T_h}$	0.051***	0.056***	0.047***	0.052***	0.058***	0.038**	0.047***
	(3.777)	(3.378)	(3.168)	(4.053)	(3.996)	(2.500)	(3.473)
$DamageExposure_{i,T_h} \times I_{i \in Industry_g}$	-0.119**	-0.019	0.016	-0.050	-0.049	0.070*	0.041
	(-2.327)	(-0.808)	(0.516)	(-0.665)	(-1.457)	(1.823)	(0.908)
Adjusted R$2̂$ (%)	0.136	0.136	0.136	0.136	0.136	0.136	0.136
Obs. total	12,590	12,590	12,590	12,590	12,590	12,590	12,590
Obs. exposure $¿$ 0%	5,916	5,916	5,916	5,916	5,916	5,916	5,916
Obs. exposure $\geq 20\%$	953	953	953	953	953	953	953
Obs. exposure *geq* 50%	447	447	447	447	447	447	447
Obs. $i \in Industry_g$	221	5,538	1,174	1,266	2,317	1,569	394
Number of hurricanes	20	20	20	20	20	20	20
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.2: Abnormal returns post hurricane landfall (alternative threshold)

This table reports differences in cumulative abnormal returns post landfall between firms with exposure (treated) and firms without exposure (control) to the hurricane disaster region. Compared to Table 6, the exposure threshold for a firm to be characterized as treated is reduced from 50% to 25%. The differences are reported for the mean and nine percentiles of the return distributions of the treated and control firms. The differences are estimated for two time periods: from landfall to 5 days and 120 days after landfall, respectively. The abnormal returns are estimated based on the Fama-French three factor model. FEMA and SHELDUS data are used to identify counties that have been hit by a hurricane. For Panel A, the hit firms are defined as firms that have 25 percent or more of their establishments in the counties of the disaster region, and for Panel B, 25 percent or more of the sales have to be located in the disaster area counties. We exclude hurricanes that affected less than 25 firms. The data are from 2002 to 2017. The standard errors are bootstrapped and clustered by county (headquarter location). The significance of the difference in abnormal returns is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Hit firms selected based on establishments in disaster region $\geq$ 25%

	From 0 to 5 days post landfall		From 0 to 120 days post landfall	
	Cumulative r difference	T-stat	Cumulative r difference	T-stat
Mean	0.049	0.120	-4.997**	-1.980
Percentiles				
10%	-0.476	-1.038	-12.693***	-3.103
20%	-0.657	-1.924	-7.216**	-2.283
30%	-0.251	-0.980	-6.168***	-2.661
40%	-0.268	-1.195	-4.392**	-2.211
50%	-0.224	-0.980	-4.672***	-2.944
60%	-0.276	-1.210	-4.427**	-2.243
70%	-0.079	-0.170	-3.727**	-2.395
80%	-0.066	-0.154	-3.553	-1.556
90%	1.223	1.264	-2.197	-0.483
Hit firms	1,131		1,096	
Control firms	9,977		9,665	

Panel B: Hit firms selected based on sales in disaster region $\geq$ 25%

	Cumulative r difference (0 to 5 days)	T-stat	Cumulative r difference (0 to 120 days)	T-stat
Mean	0.037	0.086	-4.113	-1.640
Percentiles				
10%	-0.085	-0.221	-8.691**	-2.129
20%	-0.452	-1.221	-4.930*	-1.658
30%	-0.201	-0.752	-4.622*	-1.763
40%	-0.193	-0.712	-3.738**	-1.984
50%	-0.237	-0.931	-3.501*	-1.935
60%	-0.132	-0.469	-3.366*	-1.855
70%	0.020	0.046	-2.478*	-1.653
80%	-0.022	-0.051	-2.897	-1.353
90%	0.268	0.289	-4.740	-1.194
Hit firms	1,164		1,131	
Control firms	9,898		9,583	