Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics*

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Abstract

This paper investigates the uncertainty dynamics surrounding extreme weather events through the lens of financial markets. Our framework identifies market responses to the uncertainty regarding both potential hurricane landfall and subsequent economic impact. Stock options on firms with establishments exposed to the landfall region exhibit large increases in implied volatility of up to 30 percent, reflecting impact uncertainty. Impact uncertainty persists for several months after landfall. Using hurricane forecasts, we show both landfall uncertainty and potential impact uncertainty are reflected in option prices before landfall. Our findings have important implications for assessing the economic costs of extreme weather events.

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1 Introduction

Extreme weather can be devastating and was 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,[2] little is known about the uncertainty surrounding extreme weather both in terms of the magnitude of this uncertainty and its dynamics. Given that uncertainty can affect 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 and costs 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. The frequency and scale of financial data and the financial incentives underlying investor behavior make asset prices an ideal instrument to assess the dynamics and magnitude of extreme weather uncertainty. We use implied volatility from stock options to proxy for uncertainty as it captures investor expectations of volatility (see, for example, Bloom (2009) and Kelly, Pastor, and Veronesi (2016)). 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 data at the county level with hurricane forecast and landfall data in order to identify firms that operate within regions (potentially) exposed to a particular hurricane. We use these granular data to conduct an in-depth analysis on extreme weather uncertainty using a difference-in-differences approach.

Our first hypothesis is that while a hurricane is out in the ocean and making its way towards the coast, the associated landfall and potential impact uncertainty will be reflected in the stock options of exposed firms. Using NOAA forecasts issued in the days leading up to a hurricane's landfall or

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

[2] 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, which allows for an isolated estimation of the effects, and NOAA publishes a range of relevant data on hurricanes. However, our framework can also be applied to other extreme weather events like snow storms and severe floods that are also subject to landfall and impact uncertainty.

dissipation (in the case of a hurricane that "missed"), we find implied volatilities increase even at low landfall probabilities of 10 percent and below. Implied volatility increases up to 21 percent, implying substantial uncertainty about the hurricane.[4] This result also implies that investors pay attention to hurricane forecasts. Such attention to climatic events is by no means a given. Other papers in the climate finance literature assessing informational efficiency have found that investors are inattentive to climatic events as they unfold (see, for example, Hong, Li, and Xu (2019) and Murfin and Spiegel (2019)). Furthermore, investor attention to extreme weather risk is important for correctly pricing assets with exposure to extreme weather and climate change and reduces the risks of sudden large price corrections that could disrupt financial stability (see, for example, Carney (2015)).

Our second hypothesis is that immediately after a hurricane has made landfall, implied volatilities of options of firms in the landfall region are elevated due to impact uncertainty, and that this impact uncertainty gradually resolves following landfall. Our results strongly support this second hypothesis. Indicative of substantial impact uncertainty, we find that immediately after hurricane landfall the implied volatility of options of firms with establishments in the landfall region are up to 30 percent higher than before the hurricane's inception. Implied volatilities remain elevated for several months after hurricane landfall indicating that the resolution of the impact uncertainty is slow.

The economic magnitude of these uncertainty estimates is large. The increase in implied volatilities in the aftermath of a hurricane translate into additional hedging costs of up to \$91 billion summed over our sample period from 1996 to 2017. This magnitude is substantial considering that the total damages estimated by NOAA over the same period were \$583 billion.[5] Our estimates show that uncertainty can lead to substantial costs associated with hurricanes, and such costs are not included in conventional damage estimates.

We build on these baseline results with several key extensions and robustness checks. Our findings are robust across industries and also hold within industries. We show that the stocks of the the worst performing firms exposed to hurricane landfall regions dramatically underperform the

[4] We note here that 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 for market index volatility is not driving our results, which concern firm-level volatility.

[5] The dollar values are in 2017 inflation adjusted US dollars.

worst performing firms in the control set. The cumulative abnormal return difference is as much as 26 percent. This underperformance takes several months after landfall to manifest and supports the notion that investors price in significant uncertainty because it takes time to determine the full effects of a hurricane and resolve which firms were most adversely affected. We further show that our baseline results are robust to the exclusion of the most damaging hurricanes (Katrina, Sandy, and Harvey).[6] Having excluded financial firms in our baseline results, we find that single stock options of property and casualty insurance firms reflect substantial impact uncertainty immediately following a hurricane landfall, exhibiting implied volatility increases of as much as 70 percent. While our results show that investors are attentive to short-term forecasts and price in landfall and potential impact uncertainty, we find no evidence that they react to NOAA's medium-term seasonal forecasts. The reason is likely that these seasonal forecasts are much less accurate than the forecasts for individual hurricanes.

This paper makes several key contributions. First, we present a novel framework of landfall and impact uncertainty to formalize uncertainty before and after extreme weather events. Second, our estimates imply that extreme weather uncertainty imposes significant financial costs that should be taken into account when assessing the aggregate impact of extreme weather events. Not only do hurricanes impose large costs due to damage to property and infrastructure, but if investors have to hedge themselves against the uncertainty surrounding a hurricane, then this is an additional cost that has to been taken into account. Third, given that research has shown that other types of uncertainty can affect household and firm decision making—for example political uncertainty around elections has been shown to reduce firm investments (see Julio and Yook (2012) and Jens (2017))—the large economic magnitudes of our extreme weather uncertainty estimates together with the slow resolution of impact uncertainty suggest that extreme weather uncertainty could be an important factor for such real outcomes. Fourth, we show that in the case of hurricanes, unlike other climatic events, investors are attentive to forecasts as a hurricane unfolds.

The remainder of this paper is structured as follows. We begin with a discussion of related literature in Section 2. We describe our empirical strategy and data in Sections and 3 and 4, respectively. Section 5 presents our main results, followed by extensions and robustness tests in

[6]We show additional robustness checks, for example, to alternative firm exposure measures and clustering of standard errors, in the Online Appendix.

Section 6. We conclude in Section 7.

2 Related literature

In showing that extreme weather events cause substantial uncertainty that is costly to investors, our work is relevant to the literature examining extreme weather events and its effects. This growing body of work has shown, for example, how extreme weather affects labor markets, schooling, household finance, and income (see Belasen and Polachek (2008), Imberman, Kugler, and Sacerdote (2012), Gallagher and Hartley (2017), and Deryugina, Kawano, and Levitt (2018)). 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 (2019) find that natural disasters have a wide range of impacts on local economic activity, including on employment, population, and home prices. Addoum, Ng, and Ortiz-Bobea (2019) examine high temperatures and find little evidence that US firms' sales are affected.

Further, 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 two branches of the climate finance literature.

First, by examining hurricane effects, this paper builds on recent papers in the finance literature focused on climatic 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) find evidence of a positive relationship between investors' beliefs about climate change and warmer-than-usual temperatures.

Alok, Kumar, and Wermers (2019) show that fund managers that are hit by a natural disasters misestimate the risk of such disasters subsequently. Drawing mixed conclusions, several papers (see Bernstein, Gustafson, and Lewis (2018); Giglio, Maggiori, Rao, Stroebel, and Weber (2018); Murfin and Spiegel (2019)) use NOAA sea level rise predictions to examine whether residential real estate prices reflect sea level rise risks.

Second, our analysis complements climate finance papers that develop hedging strategies. While Baker, Hollifield, and Osambela (2018) and Roth Tran (2019) 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 (2019) 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.

Finally, by analyzing extreme weather uncertainty, our paper adds a novel type of uncertainty to the uncertainty literature. Several papers have shown that policy uncertainty dampens firm investment (see, for example, Bloom, Bond, and van Reenen (2007); Bloom (2009); Kim and Kung (2017); Fried, Novan, and Peterman (2019)). Other researchers have examined political uncertainty as 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 an important source of uncertainty that affects prices in financial markets. Our analysis introduces a new layer of complexity as we separately examine the effects of the uncertainty not only about the impact of a hurricane that occurs but also about when, whether, and where the hurricane will make landfall. This contrasts with the case of elections, where there is uncertainty about outcomes, but generally not about when and whether the elections themselves will occur because they are scheduled in advance.[7]

Our paper differs from the research on macroeconomic uncertainty and economic growth (see,

[7] 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.

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 firm-level analysis is more granular than examinations of the macroeconomy as a whole. This distinction matters because extreme weather events are generally local phenomena.

3 Empirical design

3.1 Landfall and impact uncertainty framework

Our framework distinguishes between two types of uncertainty that surround a hurricane: impact uncertainty and landfall uncertainty. Intuitively, one can think of impact uncertainty as uncertainty about the intensive margin of an extreme weather event and landfall uncertainty as uncertainty regarding the extensive margin. While this paper focuses on hurricanes, our framework is general enough that it can be applied to other types of extreme weather events.

Impact uncertainty is the uncertainty about how a hurricane will impact 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

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

where $\epsilon \sim N(0, \sigma^2)$ represents a random shock to the firm's return at time $t+1$. The random variable $g_{i,h,t+1} \sim N(\mu_g, \sigma_g^2)$ is independent of $\epsilon_{i,t+1}$ 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 $\theta_{i,h,t+1}$ indicates whether firm i is hit by hurricane h. $\theta_{i,h,t+1}$ has a Bernoulli distribution which can equivalently be thought of as a binomial distribution with one draw, $\theta_{i,h,t+1} \sim B(1, \phi)$, where $Pr(\theta_{i,h,t+1} = 1) = 1 - Pr(\theta_{i,h,t+1} = 0) = \phi$ 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*.[8] In our framework, 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.

[8] This definition of uncertainty as the variance of an unpredictable disturbance is in line with Pastor and Veronesi (2012 and 2013) and Jurado, Ludvigson, and Ng (2015).

First, hurricane landfall in a particular location is a rare event, making it difficult to predict the exact economic effect based on past experience. 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 largely extent unpredictable. Knowing ex-ante exactly which areas will actually flood in a particular storm, the extent and duration of power outages, whether a levy will break, or how long infrastructure repairs will take, is challenging if not impossible.

Prior to (potential) landfall, there is additional uncertainty about whether and where a hurricane will make landfall. We call this *landfall uncertainty.* More generally, this uncertainty is about the incidence or occurence of an event.

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 $E_t[r_{i,t+1}|\theta = 1] = \mu_g$ and $E_t[r_{i,t+1}|\theta = 0] = 0$. The conditional variance of firm i's return is,

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

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

It follows that the expected conditional variance[9] and the variance of the conditional expectation are[10]

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

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

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), $\phi(1 -$

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

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

$\phi)\mu_g^2$. For a given $\mu_g \neq 0$, landfall uncertainty is highest when the probability of landfall, $\phi = 0.5$. When $\mu_g = 0$, meaning that a hurricane is expected to have no impact, 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) when $\sigma = 0.4$ and $\sigma_g = 0.05$. The four dashed lines have μ_g absolute values of 0.1, 0.07, 0.05, and 0. 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 parameter values of μ_g and σ_g^2, as ϕ varies from 0 to 1, the relative contribution to total variance from landfall uncertainty and expected impact uncertainty will vary prior to landfall. 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 red dot-dash 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 $Var_t(r_{i,t+1}|\theta = 0) = \sigma^2$.

3.2 Firm exposure to hurricanes

We separately determine firm exposure to a hurricane forecast and a hurricane that has made landfall. In both cases, we first determine which counties are in the forecast path or the landfall region of a hurricane, and then measure a firm's exposure to these counties based on firm establishment locations.

For the forecasts, we use hurricane wind speed probabilities to develop firm- and day-specific exposures to hurricanes before landfall. NOAA issues hurricane forecasts that show which counties have a probability of at least P to experience hurricane force winds for a given hurricane. This set of counties is denoted $F_{P,t}$, where t is a trading day. NOAA updates these forecasts multiple times a day, so for each trading day, we use the last forecast made before market close. Importantly, counties in a forecast hurricane path include both counties later hit by hurricanes and those spared by evolving hurricane paths. More detail on the hurricane forecast data is presented in Section 4.1.

We compute firm i's exposure to the forecast path of hurricane h as the share of its establishments located in the set of counties in the forecast path $F_{P,T_h-\Gamma}$, where $T_h - \Gamma$ is a trading day which is Γ days before hurricane landfall or dissipation. This forecast exposure, a continuous variable ranging from 0 to 1, is given by

$$ForecastExposure_{i,P,T_h-\Gamma} = \sum_c (FirmCountyExposure_{i,T_h-\Gamma,c} \times I_{c \in F_{P,T_h-\Gamma}}). \tag{7}$$

We take a similar approach for our post-landfall analyses by determining the set L_{R,T_h} of counties exposed to hurricane impacts due to landfall. Using the landfall data described in section 4.2, we determine a county c to be in the landfall region of a hurricane, if the counties centroid is within a given radius R of the eye of the storm at landfall. We then calculate the share of firm i's establishments in the landfall region counties. Formally, on landfall day T_h, firm i's exposure to the landfall region of hurricane h is given by

$$LandfallRegionExposure_{i,R,T_h} = \sum_c (FirmCountyExposure_{i,T_h,c} \times I_{c \in L_{R,T_h}}). \tag{8}$$

A firm's exposure to a hurricane landfall region is again a continuous variable ranging from 0 to 1. Similarly to the analyses prior to landfall that are performed on a series of probability thresholds, we perform the landfall analyses for several radii around the eye of the storm. As the diameter grows, the average intensity of impact on firms decreases but the number of hit firms increases.

3.3 Baseline estimation strategy

To estimate the uncertainty dynamics surrounding hurricanes, we employ a differences-in-differences framework. Each hurricane or forecast yields a separate treatment, and the treatment effects are jointly estimated across all hurricanes. The treatment intensity varies, because treatment is defined continuously as exposure to the forecast path or landfall region, shown in equations 7 and 8, respectively. Firms with zero exposure to particular events serve as the controls. We follow the recommendation of Bertrand, Duflo, and Mullainathan (2004) by collapsing the time series information into a pre- and post-treatment period for each difference-in-difference, that is each hurricane. For both the pre-and post-landfall analyses described below, the pre-treatment period is T_h^*, the day before hurricane inception. For pre-landfall analyses, the post-treatment period comes

Γ days before landfall, while it comes τ days after landfall for the post-landfall analysis.

We examine how hurricane forecasts affect implied volatilities of firms located in the path of a hurricane by estimating the following panel regression model

$$log\left(\frac{IV_{i,T_h-\Gamma}}{IV_{i,T_h^*}}\right) = \lambda_{F,P,\Gamma} ForecastExposure_{i,P,T_h-\Gamma} + \pi_h + \psi_{Ind} + \epsilon_{i,h,\Gamma}. \tag{9}$$

The dependent variable is the change in implied volatility $IV_{i,t}$ of firm i from the last trading day before hurricane h inception, T_h^*, to Γ calendar days before hurricane landfall or dissipation on T_h.[11] $ForecastExposure_{i,P,T_h-\Gamma}$ is our continuous treatment variable defined in equation (7). We include hurricane fixed effects (π_h), which is equivalent to a time fixed effects because each hurricane has a separate time period. We include industry fixed effects (ψ_{Ind}) based on firm two-digit SIC numbers. We exclude from the control group for a hurricane any firm that has been hit for another hurricane within 180 calendar days.[12] Given the geographic nature of our treatment, we cluster standard errors by the county to which the firm has the largest exposure (see, for example, Dessaint and Matray (2017) and Abadie, Athey, Imbens, and Wooldridge (2017)).[13]

We estimate the regression separately for each combination of $\Gamma \in \{1, 2, 3, 4, 5\}$ and probability threshold $P \in \{1, 10, 20, 30, 40, 50\}$. Only hurricanes for which the day $T_h - \Gamma$ is a trading day are included in a regression for a given Γ. This means that the set of hurricanes included in the regression sample depends on Γ and P. We exclude firms that do not have implied volatility measures for at least half of the trading days from inception to $T_h - \Gamma$ days before landfall/dissipation. The time series starts in 2007, because we have hurricane wind speed forecast data from 2007 onwards, and ends in 2017.

In terms of interpreting results, a positive and significant $\lambda_{F,P,\Gamma}$ is consistent with firms in the forecast path of a hurricane facing substantial landfall and expected impact uncertainty. 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. Figure 1 shows that depending on the parametrization (depending on the expected impact (μ_g), impact uncertainty (σ_g), and probability of landfall (ϕ)),

[11] 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 percent 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.

[12] For this purpose, we consider a firm as being hit if at least 10 percent of its establishments are located in the landfall region. Varying this threshold leads to qualitatively similar results.

[13] In the Online Appendix, we show that the results are robust when using alternatively clustered standard errors.

the total variance (uncertainty) can be higher before landfall, (when ϕ is less than 1) than at landfall (when ϕ equals 1). Whether total uncertainty is higher before landfall than right after landfall is ultimately an empirical question.

While the higher implied volatilities for firms in the forecasted path of a hurricane can result from expected impact uncertainty as well as landfall uncertainty (as shown in equation (6)), after landfall–when the landfall uncertainty has been resolved–options should only price impact uncertainty. We isolate and estimate impact uncertainty by looking at the implied volatilities shortly after landfall, when investors know where the hurricane has hit, but do not know what the eventual impact on exposed firms will be.

We estimate impact uncertainty using the following panel regression model,

$$log\left(\frac{IV_{i,T_h+\tau}}{IV_{i,T_h^*}}\right) = \lambda_{L,R,\tau} LandfallRegionExposure_{i,R,T_h} + \pi_h + \psi_{Ind} + \epsilon_{i,h,\tau}, \tag{10}$$

where τ is the number of trading days since hurricane h made landfall on day T_h and T_h^* designates the last trading day before hurricane inception. $LandfallRegionExposure_{i,R,T_h}$ is the measure defined in equation (8) of firm i's exposure to counties within the landfall region, which can vary from 0 to 1. A positive and significant $\lambda_{L,R,\tau}$ reflects impact uncertainty in the aftermath of a hurricane.

4 Data and summary statistics

Our analysis combines data from a range of sources. We combine NOAA data on wind speed forecasts and realized storm tracks from NOAA with firm establishment data from the National Establishment Time-Series (NETS) database to determine firm-by-storm specific treatment levels. We use CRSP-Compustat and OptionMetrics data for our stock and option outcome variables. We describe each of these data sources below. Additional information on the hurricane data can be found in the Online Appendix.

4.1 Hurricane forecasts

We use NOAA's National Hurricane Center (NHC) wind speed probability forecasts to measure uncertainty prior to hurricane landfall. The underlying text files of the hurricane forecast charts published by the NHC in real-time and used by news outlets in the run-up to hurricanes, are stored in NOAA's hurricane archives.[14] Figure 2 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 use these text files from the NOAA website that contain probabilities of particular locations, for example Norfolk, VA, experiencing winds in excess of 34, 50, and 64 knots for a particular hurricane. These forecast data are updated every 6 hours and available from 2007 to 2017. Our analysis is based on the 64 knots forecasts because a tropical storm is considered a hurricane, when the storm causes wind speeds of at least 64 knots. The wind speed probabilities are presented up to five days out from the time of each forecast. We translate the reported location-specific wind speed forecasts to county specific forecasts in two steps. First, we determine which selected locations have reported probabilities of hurricane force winds above a given *probability threshold*, such as a 10 percent, and match these locations to counties. Second, we add counties that are within a 75 mile radius of the counties from the first step. Figure 3 illustrates a sample of processed wind speed data at different probability thresholds for Hurricane Sandy over a four day period. Panel A of Table 1 lists the hurricanes included in our forecast sample. More information on how we process the hurricane forecast data can be found in the Online Appendix.

4.2 Hurricane landfall regions

We use hurricane track data collated from forecast advisory files from the NOAA hurricane archives to develop firm-specific exposure to hurricane landfall regions. These data show the intensity and location of the hurricane's eye at various points of time. To account for the fact that hurricanes can impact counties that are not located in immediate proximity to the eye of the storm, we consider all counties to be in the hurricane landfall region if they are located within a given radius of the

[14]The NOAA hurricane archives can be found here https://www.nhc.noaa.gov/archive.

hurricane's eye within 24 hours before and after the hurricane making landfall.[15,16] We use county centroids to generate the sets of counties that lie within 50, 100, 150, 200 miles of the eye of each hurricane. Figure 4 shows which counties fall into each set for hurricanes Katrina (2005), Sandy (2012), Matthew (2016), and Harvey (2017). Having this time window around the landfall time ensures that we capture counties that lie more inland and counties that were close to the eye of the hurricane before the actual landfall for hurricanes that move along the coast. Panel B of Table 1 lists the hurricanes included in our landfall region sample. Additional details are discussed in the Online Appendix.

Importantly, these data are published by NOAA in real-time. Therefore, investors had access to these data on the landfall region of a hurricane as soon as the hurricane made landfall. Some other papers use damaged counties to discern which firms were affected by natural disasters (for example, Barrot and Sauvagnat (2016) and Dessaint and Matray (2017).) In our context, doing so could bias estimates because investors do not know at the time of the landfall which counties experienced damage from a hurricane. Damage data become available with a substantial lag.

4.3 Firm data

We use NETS firm establishment location data to precisely estimate firm exposure to specific hurricanes. These data has been used in several other studies. For example, Neumark, Wall, and Zhang (2011) investigate the job creation of small businesses based on NETS. Addoum, Ng, and Ortiz-Bobea (2019) use NETS to analyze the effect of temperature fluctuations on firms' sales. The NETS data contain establishment information at the county level and are updated annually.[17] For each hurricane season, we use firm geographic footprints from the previous year to avoid the possibility that we will miss establishments closed due to hurricanes. Because our NETS data extend only through 2014, we use the 2014 geographic footprint for hurricanes in 2015-2017. Plotting 2010 and 2014 deciles of county establishment numbers, Figure 5 shows that economic activity as measured by firm establishments is high in areas prone to hurricanes along the Atlantic

[15] We also consider other time windows, for example, 12, 36, and 48 hours, and the results are qualitatively similar.

[16] Two hurricanes in the sample, Charley 2004 and Katrina 2005, make two landfalls. We use as the landfall date the landfall when the hurricane was of the higher storm strength on the Saffir-Simpson scale.

[17] Our baseline results rely on the establishment location data. NETS also contains establishment level sales data, but these data are often imputed. An analysis using sales data yield qualitatively similar results shown in Section 6.1.

and the Gulf Coast.

We use firm name and headquarter address to link the firms in NETS to those in OptionMetrics and CRSP-Compustat. Our linked sample starts in 1996, the first year in our OptionMetrics data. Because financial firms' geographical exposure to natural disasters may not be reflected by their establishment locations and financial firms are often excluded in asset pricing studies, our baseline results exclude all financial firms by dropping firms with SIC numbers from 6000 to 6799 from our analysis. We provide a separate analysis on insurance firms in Section 6.3.

We obtain daily data on stocks from CRSP-Compustat and single-name stock options from OptionMetrics. Consistent with previous studies (see, among others, Carr and Wu (2009); Kelly, Pastor, and Veronesi (2016); Martin and Wagner (2018)), we use data from traded options with non-missing pricing information that are slightly out-of-the-money. These options are more liquid and have a relatively small difference due to any potential early-exercise premium between American options and European options.

We apply standard filters to the options data consistent with the existing literature. In our sample, we include single-stock options which meet the following criteria: (i) standard settlement, (ii) a positive open interest, (iii) a positive bid price and bid-ask spread (valid prices), (iv) the implied volatility estimate is not missing, (v) greater than 7 days and at most 200 calendar 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 options which satisfy the above criteria and N is the number of valid options for firm i with that expiry.[18]

We report summary statistics on our sample of firms in Table 2. We have 1,645 unique firms in our sample. On average, a firm has 107 establishments in a given year. When only considering the subsample of firms that had 25 percent of their establishment in a hurricane landfall region at least once during our sample period, that is they were "hit" at least once, then the average number of establishments is 116. Interestingly, these hit firms are also comparable to the non-hit firms in terms of market capitalization. In fact, the average market capitalization of hit firms is 5.3 billion US$ compared to 4.5 billion US$ of the total sample. The slightly higher market capitalization

[18] In additional analysis examining "seasonal effects," to capture uncertainty effects in options spanning the full hurricane season, we use options available in late May whose calendar days-to-expiry range from 120 to 180.

might be caused by the higher economic activity in coastal regions. The summary statistics on option measures are nearly identical between the total sample and the subsample of "hit" firms.

5 Baseline Results

5.1 Uncertainty before landfall

We first test whether option prices react to hurricane forecasts before storm landfall (or dissipation) and price in landfall and expected impact uncertainty. In Table 3, we report results of estimating equation (9) for each combination of days before landfall (Γ) and hurricane-force wind probability threshold (P) for which we have sufficient observations.[19] Each column presents results from a separate regression performed for the specified Γ (1-5 days before landfall) and P (1 to 50 percent). Because the location-specific NOAA wind speed probabilities rarely get high when a hurricane is far from the coast, the maximum P for which we estimate equation (9) declines as we increase the number of days prior to landfall or dissipation. Also, because for a given hurricane Γ might be a non-trading day, the sample of hurricanes differs across the columns of Table 3. For example, not all of the 12 hurricanes for 1% probability and 5 days before landfall are included in the the regression for 1% probability and 4 days before landfall. The total sample of hurricanes used in the analysis is listed in Panel A of Table 1. The table reports for each regression the total number of firm observations with an establishment share in the forecast path of greater than 0% and at least 20%. The higher the probabilities, the smaller the number of firms with a certain exposure to the forecast path because the region covered by the forecast path becomes smaller as the probability increases.

The results in Table 3 show that substantial uncertainty arises from the forecast path of a hurricane. The estimates of $\lambda_{F,P,\Gamma}$ are always positive, regardless of whether time and industry fixed effects are included separately (Panel A) or interacted with each other (Panel B). In Panel A, the $\lambda_{F,P,\Gamma}$ estimates are generally significant with the exception of the estimates at the 1% probability threshold more than one day prior to landfall which is insignificant in two specifications. For a given Γ, the magnitude of $\lambda_{F,P,\Gamma}$ generally increases with higher landfall probabilities, reaching up

[19] We require a $\Gamma - P$ sample to include at least three hurricanes and 30 firm-storm observations with $ForecastExposure_{i,P,T_h-\Gamma}$ greater than or equal to 20 percent.

21. This implies that a firm with 100 percent (50 percent) of its establishments being located in the path of the hurricane sees an increase in the implied volatility of 21 percent (10.5 percent). The results in Panel B are based on interacting time and industry fixed effects with each other and show somewhat lower coefficient but qualitatively similar estimates. The coefficients are always positive, increasing in the probability thresholds, and mostly significant. A more detailed discussion on the economic magnitude of these changes in implied volatility can be found in Section 5.3.

These results show that option markets price in substantial uncertainty before hurricane landfall, in line with the framework presented in Section 3.1 that shows landfall uncertainty and expected impact uncertainty should be priced in before hurricane landfall. The empirical estimates confirm that uncertainty generally increases with probability of landfall as predicted in Figure 1. These estimates of uncertainty before landfall are implicitly also a test of investor attention to hurricane forecasts. If investors did not pay attention to NOAA's hurricane forecasts, then we would not observe an option price reaction. The emerging climate finance literature investigates investor attention to other climatic events. For example, Hong, Li, and Xu (2019) show that investors are inattentive to droughts. Also, there exists mixed evidence whether or not residential real estate owners pay attention to sea-level rise forecasts (see, for example, Bernstein, Gustafson, and Lewis (2018); Giglio, Maggiori, Rao, Stroebel, and Weber (2018); Murfin and Spiegel (2019)). Therefore, the strong evidence of investors paying attention to hurricane forecasts shown in this paper is not necessarily expected. Arguably, these climatic events are different from one another in terms of, for example, intensity and duration, and it might be these differences that capture investors' attention in distinct ways.

5.2 Uncertainty after landfall

We now turn to our estimates of uncertainty post landfall. After the hurricane has made landfall, landfall uncertainty is resolved and only impact uncertainty remains. In Table 4, we present results from the estimation of equation (10) for 5 trading days (1 week) after landfall in Panel A and for 30 trading days (1.5 months) after landfall in Panel B. We show results from regressions for which the landfall region is based on different radii around the eye of the storm, ranging from 50 to 200 miles. The specifications include separate industry and time fixed effects (as shown in equation (10)) as well as results based on interacted industry and time fixed effects. The table reports for each regression the total number of firm observations with an establishment share in the landfall region of greater than 0%, at least 20%, and at least 50%. As the radius around the eye of the hurricane increases, that is the landfall region becomes larger, the number of firms with a certain exposure to the landfall region also increases. Panel B of Table 1 lists the hurricanes included the sample.

All of our $\lambda_{L,R,\tau}$ estimates in Table 4 are positive regardless of radii or fixed effect choices and significant for all but one specification. The magnitude of the effect we estimate reaches up to 30 for the 50 mile radius and 30 trading days post landfall. This implies that relative to its pre-inception IV level, a firm with a 100 percent (50 percent) exposure to the landfall region will see its implied volatility increase by 30 percent (15 percent). These are substantial magnitudes of impact uncertainty. Section 5.3 describes the economic context of these magnitudes in detail.

When analyzing the within industry effect by including industry fixed effects interacted with time fixed effects, the magnitude of the estimates are slightly lower but the estimates remain significant for all but one specification. A more detailed industry analysis is presented in Section 6.1. The magnitude of the effect decreases with larger radii, which implies that firms with establishments located further away from the epicenter of the storm face less impact uncertainty. Also, while the statistical significance is stronger 5 trading days post landfall, the coefficient estimates are often higher 30 trading days after landfall. This result points to a slightly delayed reaction of investors to the hurricane landfall, with the caveat that the differences between the 5 and 30 trading days estimates are mostly insignificant (not shown).

In Figure 6, we build on the Table 4 results by showing how affected firms' implied volatilities evolve over the 90 trading days (4.5 months) after landfall. Each point in the figure shows the coefficient estimate from a separate regression estimating equation (10) for a combination of τ and R. In Panel A, which uses a 50 mile radius (R) around the eye of the hurricane to determine a firm's landfall region exposure, our estimate of $\lambda_{L,R,\tau}$ increases up to 30 trading days post landfall at which point it reaches about 30. Thereafter the implied volatility effect gradually decrease until it becomes insignificant around 80 trading days (4 months) after landfall. When in Panel B we apply a 200 mile radius to determine the hurricane landfall region, we similarly observe that the increase in implied volatility rises for sometime before peaking and falling back to baseline. However, the peak happens earlier at 20 trading days after landfall, falls back sooner (becoming insignificant 60 trading days or 3 months after landfall), and has a smaller magnitude peaking around 10.

One potential concern with our specification is that our results could be driven by small firms. However, Table 2 reports that the subsample of firms that were hit by hurricanes at least once during our sample period, where we define a hit as having at least 25 percent of establishments in a landfall region, has on average a slightly higher market capitalization than the total sample. 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 landfall and impact uncertainty.

5.3 Economic significance

We have shown that the implied volatilities of firms in the forecast path or landfall region of a hurricane increase substantially, indicating high uncertainty. What are the economic implications of these implied volatility changes?

Investors often use options to hedge exposure to risks of stock price changes. When the implied volatility of an option increases, the option premium (the price of the option) increases as well, and hedging becomes more expensive. We use our previous results to compute how much hedging costs in the aftermath of a hurricane increase for investors of firms with exposure to the landfall region. After hurricane landfall the total additional cost of hedging the impact uncertainty over our sample period would have been as high as 50 to 91 billion U.S. dollars in 2017 inflation-adjusted terms.[20] This magnitude is considerable, representing up to 16 percent of the $583 billion (also inflation-adjusted to 2017) in total hurricane damages estimated by NOAA for the same time period (see Table 1.)[21] Our estimates show that uncertainty itself can lead to substantial costs associated with hurricanes. Conventional damage estimates that exclude these types of costs may significantly understate the true damages of extreme weather events.

[20]These values are based on a landfall region radius of 200 miles around the eye of the storm. We compute the average percentage point increase in implied volatilities of the firms with exposure to the landfall region (0.55 and 1.04 percentage points for 5 and 30 trading days post landfall, respectively.) To obtain the increase in the option premium, we multiply this average increase in implied volatilities by the average vega (0.034) of the same firms, where the vega is a measure of how option prices respond to changes in implied volatilities. Finally, we multiply the increase in the option premium by the total number of shares outstanding (2,237.6 billion) of the exposed firms to obtain the increase in total hedging costs in dollars. The values are inflation-adjusted to 2017 dollars.

[21]Further, we likely underestimate the total hedging costs caused by a hurricane as we drop some firms from our sample due to insufficient data, as described in Section 4.

While the changes in implied volatilities and consequently option premia directly affect investors, the large extreme weather uncertainty estimates that we document can also have other wide-ranging consequences. Other types of uncertainty have been shown to affect decision making of economic agents. For example, uncertainty around political elections and events causes firms to reduce investments as shown in Julio and Yook (2012), Jens (2017), and Kim and Kung (2017). The large and persistent estimates of extreme weather uncertainty can have similar effects, particularly as the magnitudes of our estimates are larger than the increase in implied volatilities around major political events (see Kelly, Pastor, and Veronesi (2016)). While an examination of how extreme weather uncertainty affects decisions of economic agents is beyond the scope of this paper, it is straightforward to develop scenarios in which extreme weather uncertainty has real consequences. For example, firms whose suppliers or customers are located in hurricane landfall regions could be affected by uncertainty about their supply chain. Similarly, firms may delay or backtrack on decisions on where to expand if there is significant uncertainty regarding a hurricane that has made or will make landfall in regions of interest.

6 Extensions and robustness

Having examined how markets price in impact and landfall uncertainty both before and after hurricane landfall, we now turn our attention to robustness and extension analyses.

6.1 Robustness

This section contains robustness tests for the main results. Additional robustness tests can be found in the Online Appendix. First, One question is whether the uncertainty caused by hurricanes affects varies across industries. To get at this question, we test whether our baseline post-landfall results are driven by a particular industry.[22] Building on equation (10), an industry-specific interaction

[22] We choose the post-landfall analysis for this purpose, because the larger number of hit firms provides a more representative sample of firms for each industry.

term is added as follows

$$log\left(\frac{IV_{i,T_h+\tau}}{IV_{i,T_h^*}}\right) = \lambda_{L,R,\tau} LandfallRegionExposure_{i,R,T_h} + \omega_{L,R,\tau} LandfallRegionExposure_{i,R,T_h} \times I_{i\in Industry_g} + \pi_h + \psi_{Ind} + \epsilon_{i,h,\tau}, \tag{11}$$

where $I_{i\in Industry_g}$ indicates whether firm i is in $Industry_g$, the industry being examined. We estimate this equation separately for the construction, manufacturing, mining, retail, services, transportation, and wholesale industries based on firm two-digit SIC numbers.[23] If our baseline effects were driven primarily by one industry, then we would expect $\lambda_{L,R,\tau}$ to be statistically indistinguishable from zero in the regression for that industry.

In Table 5, we present our results for the 200 miles radius to ensure that we have a considerable number of firms with a large exposure to hurricane landfall regions in each industry. However, the results are qualitatively similar when using smaller radii. The parameter τ is set to five trading days. The estimates of $\lambda_{L,R,\tau}$ are positive and significant in every industry specification, suggesting that our baseline results are not driven primarily by one sector. Also, the magnitude of the estimate is similar to the magnitude of the coefficients for the 200 mile radius around the eye of the hurricane shown in Table 4. The estimate of $\omega_{R,\tau}$, the coefficient on the interaction term, is insignificant for most specifications, suggesting limited industry-specific heterogeneity. The only industry for which the estimates of $\omega_{R,\tau}$ are significant is construction. The negative sum $\lambda_{L,R} + \omega_{R,\tau}$ for the construction industry suggests that investors believe that hurricanes reduce uncertainty for construction firms. This result could be prompted by the expected boost from rebuilding activity.

A second robustness test estimates the regression in equation (10) but excludes hurricane Katrina (2005), Sandy (2012), and Harvey (2017) from the analysis. These three hurricanes were the most devastating hurricanes in our sample in terms of total damage as shown in Table 1. We want to test if our results are solely driven by these hurricanes. The results are presented in Table 6. The magnitude and significance of the coefficient estimates are similar to the estimates shown in Table 4. A higher exposure to the landfall region increases the implied volatilities of the firms, and this effect is weaker the larger the radius around the eye of the hurricane used to define the landfall

[23] We exclude the agriculture and non-classified categories because of the small number of firms.

region.

Additional robustness tests are presented in the Online Appendix. Our baseline measure of geographic location of a firm are the location of establishments. Alternatively, we can also use establishment level sales data from NETS. These data allow us to measure the exposure of a firm to a hurricane by the share of sales that were generated in counties affected by the hurricane. The baseline results on uncertainty before and after landfall are robust to measuring geographic footprint based on sales. Further, we show that our baseline results are robust to alternative standard error clustering choices.

6.2 Long-run impact on firm value

The large uncertainty estimates surrounding a hurricane imply that firms in the landfall region face uncertain outcomes. The resolution of this uncertainty should be reflected in the firms' stock prices in the months following a hurricane landfall. In particular, the higher expected volatility of the hit firms' returns should lead to a large cross-sectional dispersion of cumulative abnormal returns in the long-run.

We first estimate daily abnormal returns relative to the Fama-French five-factor model (see Fama and French (1993)). For each firm and each hurricane in our sample, the following model is estimated:

$$r_{i,d} = \alpha_i + \beta_{1,i} r_{m,d} + \beta_{2,i} r_{smb,d} + \beta_{3,i} r_{hml,d} + \beta_{4,i} r_{rmw,d} + \beta_{5,i} r_{cma,d} + \epsilon_{i,d}, \tag{12}$$

where $r_{m,d}$ is the daily market return on day d minus the risk-free rate, $r_{smb,d}$, $r_{hml,d}$, $r_{rmw,d}$, and $r_{cma,d}$ are the daily returns of the small-minus-big, high-minus-low, robust-minus-weak, and conservative-minus-aggressive portfolios, respectively. We estimate this model using 250 trading days (roughly one calendar year) before the inception day of the hurricane. We then use the coefficient estimates from this first stage regression to compute abnormal returns for each firm and hurricane as follows:

$$r^a_{i,d} = r_{i,d} - (\hat{\alpha}_i + \hat{\beta}_{1,i} r_{m,d} + \hat{\beta}_{2,i} r_{smb,d} + \hat{\beta}_{3,i} r_{hml,d} + \hat{\beta}_{4,i} r_{rmw,d} + \hat{\beta}_{5,i} r_{cma,d}). \tag{13}$$

We next aggregate the abnormal simple 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 again T^*_h is the inception day, T_h is the day of the landfall, and τ is the number of trading days. The time period starts in 1996 and ends in 2017 to correspond to the option sample used previously. To ensure that stocks with stale prices are excluded from our analysis, a stock is required to have return data for at least half of all trading days for a given period. Further, we exclude stocks with share prices below $5 from our analysis (see Amihud (2002)).

We take the cumulative abnormal return from inception to a 120 trading days (6 months) after landfall for all the firms and a given hurricane and subtract the mean cumulative abnormal return to account for correlated shocks across firms that are independent of the hurricane. We choose a horizon of 120 trading days as that corresponds 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 as a hurricane season last six months (from June to November). One group contains the cumulative abnormal returns of the hit firms, that is the firms with at least 25% of their establishments in the hurricane landfall region. The other group contains the cumulative abnormal returns of the control firms, that is the firms with less than 25% of their establishments in the hurricane landfall region. Then, we compute the differences in the mean and nine percentiles between the cumulative abnormal return distributions of the hit and the control firms.

The results are reported in Table 7 along with the corresponding t-stats.[24] For the landfall region based on the 50 mile radius around the eye of the hurricane, the bottom two percentiles of the treated firms underperform the control firms by 21 to 26 percent. However, it is also notable that significant differences are only found for the bottom percentiles. The top percentiles show differences between the treated and control firms that while mostly negative are generally insignificant. This result holds also for wider radii. In the aftermath of a hurricane, there are some firms with exposure to the landfall region that severely underperform, but other firms appear to be unaffected in the long-run. Interestingly, the differences in mean effects are insignificant regardless of the radii.

These results are in line with the substantial estimates of impact uncertainty that are presented in the previous section. Investors appear to be uncertain about the impact of a hurricane on the

[24] For the differences between the percentiles, the standard errors are cluster bootstrapped.

firms in the landfall region and this manifests itself in the large increases in implied volatilities. In the long-run, the implied volatilities come back down as the effect on the firms becomes clearer, and some firms will be severely negatively affected.

Figure 7 shows the difference in cumulative abnormal returns between firms hit by a hurricane and control firms also for the 10 and 60 trading days (2 weeks and 3 months) post landfall horizon. These plots show that the lower percentiles of the hit firms underperform more in the long-run, that is after 60 or 120 trading days, then in the short-run, that is after 10 trading days. These plots are in line with investors needing time to assess the impact on the firms in the landfall region. The Online Appendix contains two tables that are structured as Table 7 but present the estimates for 5 and 60 trading days post landfall instead of a 120 trading days.

6.3 Insurance firms

The analysis and discussion so far 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 data on the exposure of an insurance firm at the state level, not at the county level.[25]

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 (10) for these property and casualty insurance firms, with $LandfallRegionExposure_{i,R,T_h}$ being replaced by a variable that measures the share of total premiums, lagged by one year, written in states that experienced landfall by hurricane h. The results are reported in Table 8. Panel A (B) considers a state to have experienced hurricane landfall if at least 10% (25%) of the counties were within a given radius of the hurricane's eye.

[25]For insurance firms, the establishment level data from NETS is likely not a precise measure of their exposure to a certain region because an insurance firm that, for example, insures a homeowner in Louisiana does not need an establishment close by.

The coefficient estimates are positive 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 70 percent (35 percent) higher for insurance firms with a 100 percent (50 percent) exposure to the landfall region of the hurricane. The magnitude of the coefficient tends to decrease for larger radii's around the eye of the hurricane. The statistical significance is weaker than for the non-financial firms in Table 4 as the number of insurance firms in our sample is relatively small, but most of the specifications yield a significant coefficient estimate.

6.4 Hurricane season effects

Hurricanes off the US Atlantic and Gulf coasts occur during the hurricane season which starts in June and ends in November. Because the timing of the hurricane season does not vary from year-to-year, it is challenging to disentangle hurricane season effects from other season effects that are unrelated to hurricanes but also affect firms with establishments in coastal locations. To obtain an additional source of variation, we rely on hurricane season outlooks issued by NOAA.

In addition to forecasts for individual hurricanes, NOAA also releases hurricane season outlooks in May of each year. Dating back to 2001, each seasonal outlook reports the probability that the season will be above-normal, near-normal, or below-normal.[26] Panel A of Figure 8 shows that there is significant variation in the probabilities reported in these pre-season outlooks.

We test if options with long expiry, 120 to 210 calendar days to expiry, of firms that have establishments located in counties historically affected by hurricanes exhibit higher implied volatilities after NOAA issues a forecast of a hurricane season with above average activity. Options with long expiry are chosen because they cover the majority of the hurricane season. We use two methods to determine counties that could be hit by a hurricane during the hurricane season. The first method simply uses coastal counties from the Atlantic and Gulf coasts as counties that could reasonably be exposed to a hurricane in any given hurricane season. The second method relies on historical landfall regions over the preceding 30 years and computes the annual probability with which a county c ends up in the landfall region of a hurricane. In the Online Appendix we provide more

[26] See National Weather Service "NOAA 2012 Atlantic Hurricane Season Outlook" https://www.cpc.ncep.noaa.gov/products/outlooks/hurricane2012/May/hurricane.shtml

detail on the counties included in each method.

For the first approach, the regression specification is then given by

$$log\left(\frac{IV_{i,T_{s+5}}}{IV_{i,T_{s-1}}}\right) = \lambda_{S,1} CoastalExposure_{i,T_s} + \lambda_{S,2} CoastalExposure_{i,T_s} \times AboveAvgSeasonForecast_{T_s} + \pi_{T_s} + \psi_{Ind} + \epsilon_{i,T_s}, \tag{14}$$

where T_{s-1} is the last trading day before NOAA's hurricane season outlook is announced in May, and T_{s+5} occurs 5 trading days later.[27] Following the methodology in equations (7) and (8), the variable $CoastalExposure_{i,s}$ is a variable that ranges from 0 to 1 and measures the share of establishments of firm i located in counties along the Atlantic and Gulf coast. We can replace this variable with $HistoricalHurricaneExposure_{i,s}$, which measures the share of a firm's establishments located in counties with an elevated probability of being hit during a hurricane season. $AboveAvgSeasonForecast_s$ reflects the probability for an above average hurricane season that NOAA issues. A positive estimate of $\lambda_{S,2}$ would be consistent with investor attention to medium-term seasonal forecasts and imply heightened uncertainty if the probability of an above average season is high.[28]

Table 9 presents the estimates of equation (14). In Panel A the independent variable is $CoastalExposure_{i,s}$, and in Panel B it is replaced with $HistoricalHurricaneExposure_{i,s}$. In both panels, none of the estimates of $\lambda_{S,2}$ are statistically significant, and all of the point estimates have a negative sign. Thus, we find no support for the hypothesis that implied volatility increases for exposed firms when NOAA's hurricane season outlook reports a high probability of an above normal season. The coefficient estimate of $\lambda_{S,1}$ is positive and significant for some specifications. A possible explanation is that the saliency of the upcoming hurricane season leads to a general increase in uncertainty in May for firms with establishments located along the Atlantic and Gulf coasts. However, the significance of the $\lambda_{S,1}$ estimate is weak and not robust to alternative specifications.

The results in Section 5.1 have shown that investors pay close attention to NOAA's forecast of hurricane paths. What is the reason behind investors not paying attention to seasonal forecasts?

[27] Varying the window length leads to qualitatively similar results.

[28] The expected sign of $\lambda_{S,1}$ is unclear. Firms with exposure to coastal counties are at risk of being hit by a hurricane during the hurricane season, but firms with exposure to coastal counties are likely also subject to other unobservable risks that are unrelated to hurricanes.

The reason is potentially that these seasonal forecasts are not as accurate. The scatter plots in Panel B of Figure 8 show only a weak positive relationship between these seasonal outlooks and the number of hurricanes making landfall in a given year (Panel A) or the total damages resulting from those hurricanes (Panel B). There is an emerging debate in the climate finance literature about investor attention to climatic events. In the case of hurricanes, investors behave fairly rational. They pay attention to the short-term hurricane forecasts that contain valuable information but appear to ignore medium-term forecasts that are less accurate.

7 Conclusion

Little is known about extreme weather uncertainty. 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).

Using daily hurricane forecasts from NOAA, we find that landfall uncertainty combined with potential impact uncertainty are both priced before a hurricane makes landfall, consistent with investors paying attention to the unfolding of a hurricane. We find that options of firms operating in regions affected by hurricanes have considerably higher implied volatilities after hurricanes hit. The higher implied volatilities are in line with investors being concerned about substantial impact uncertainty. The impact uncertainty resolves slowly, and the implied volatilities return back to pre-hurricane levels several months after 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 stylized facts discovered in this paper by, for example, 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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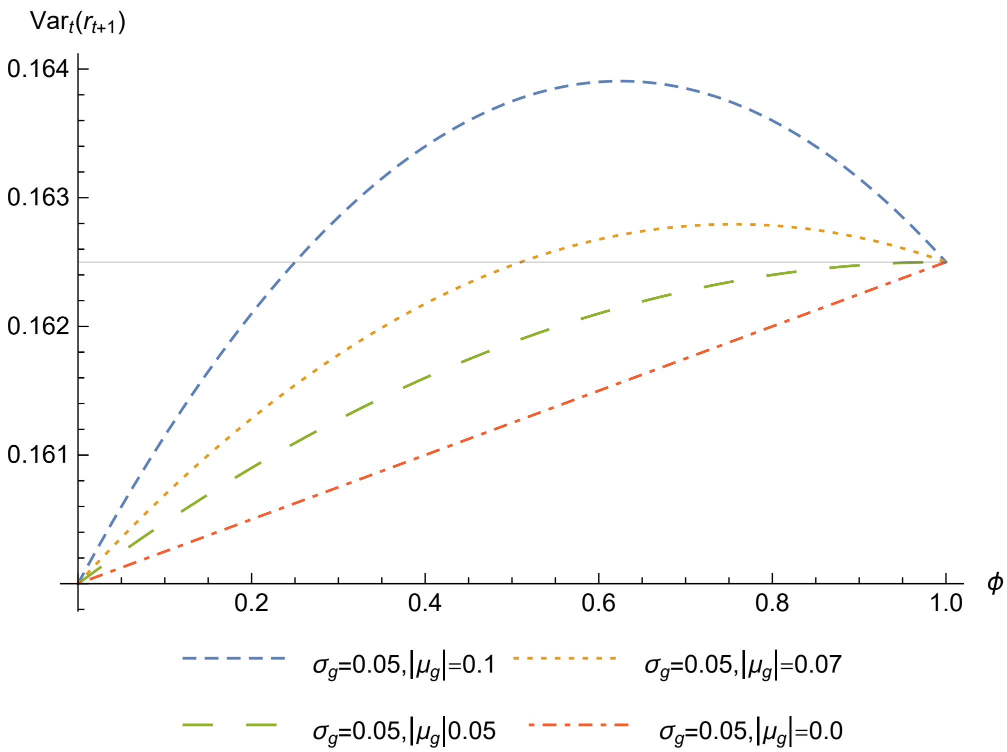


Figure 1: Variance as a function of the probability of hurricane landfall

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).

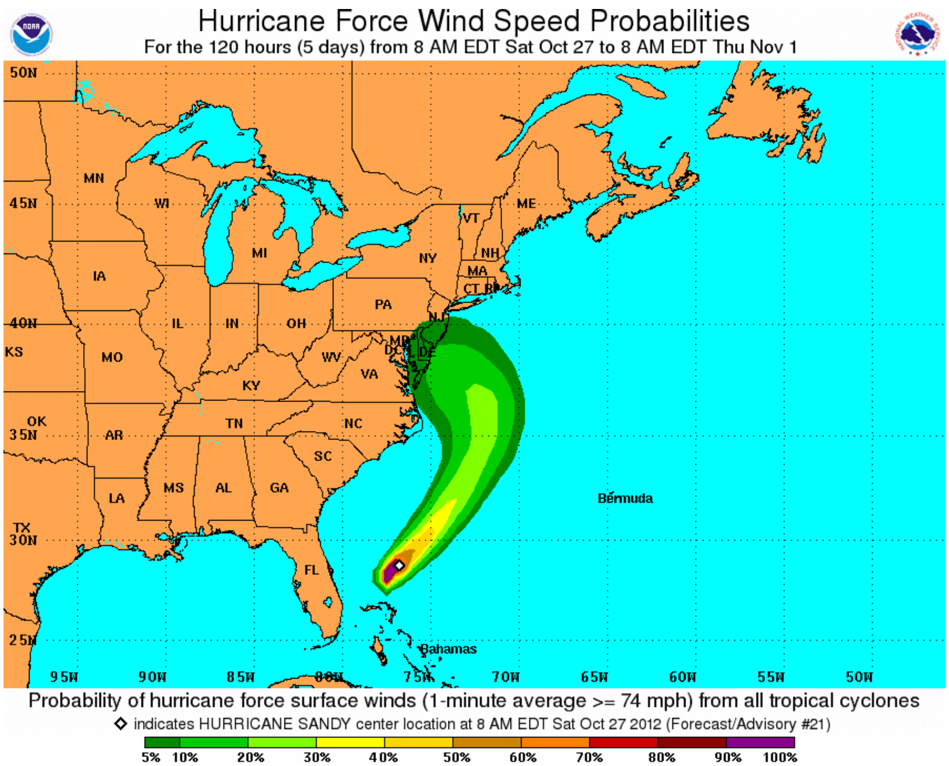


Figure 2: Example of a hurricane forecast

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.

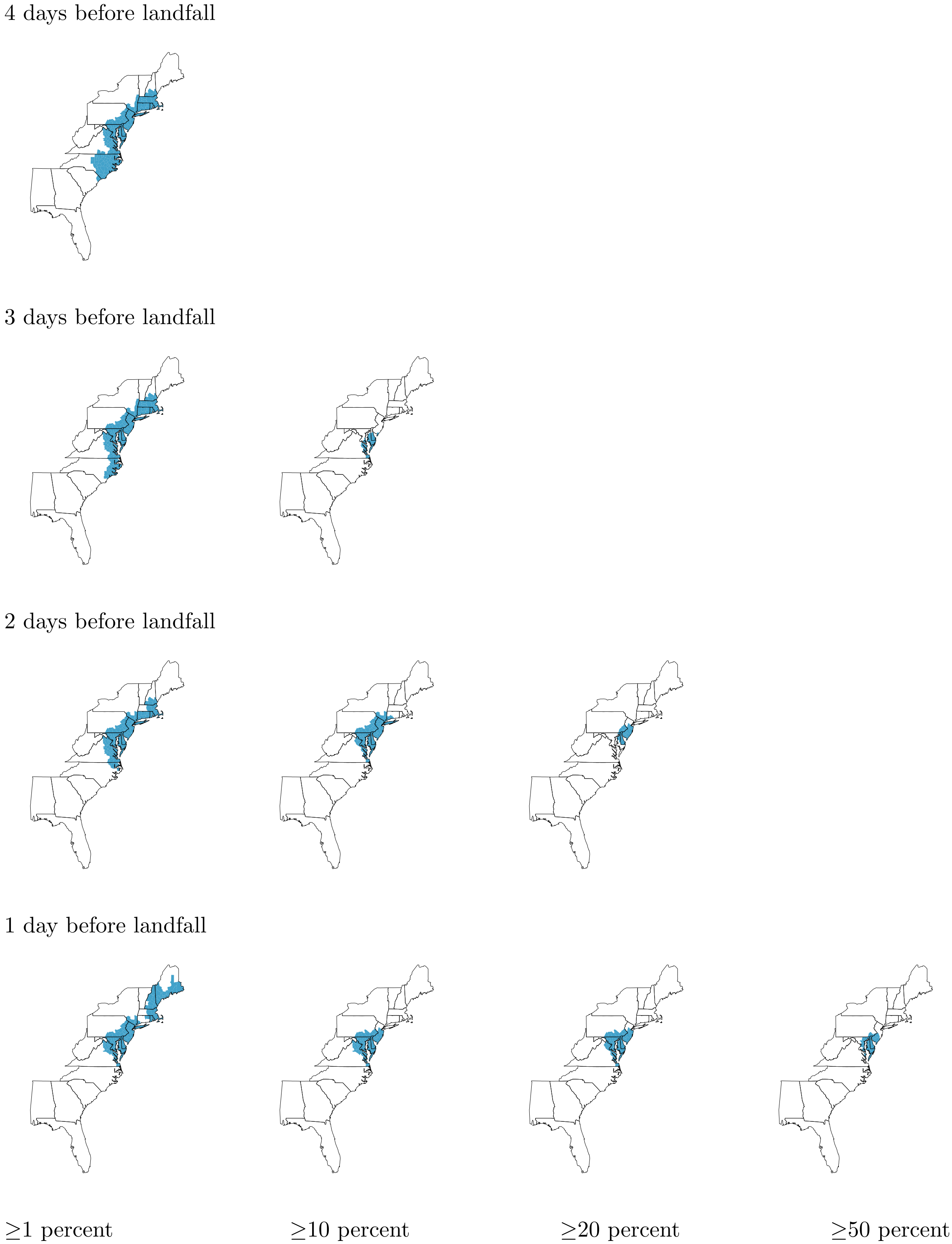
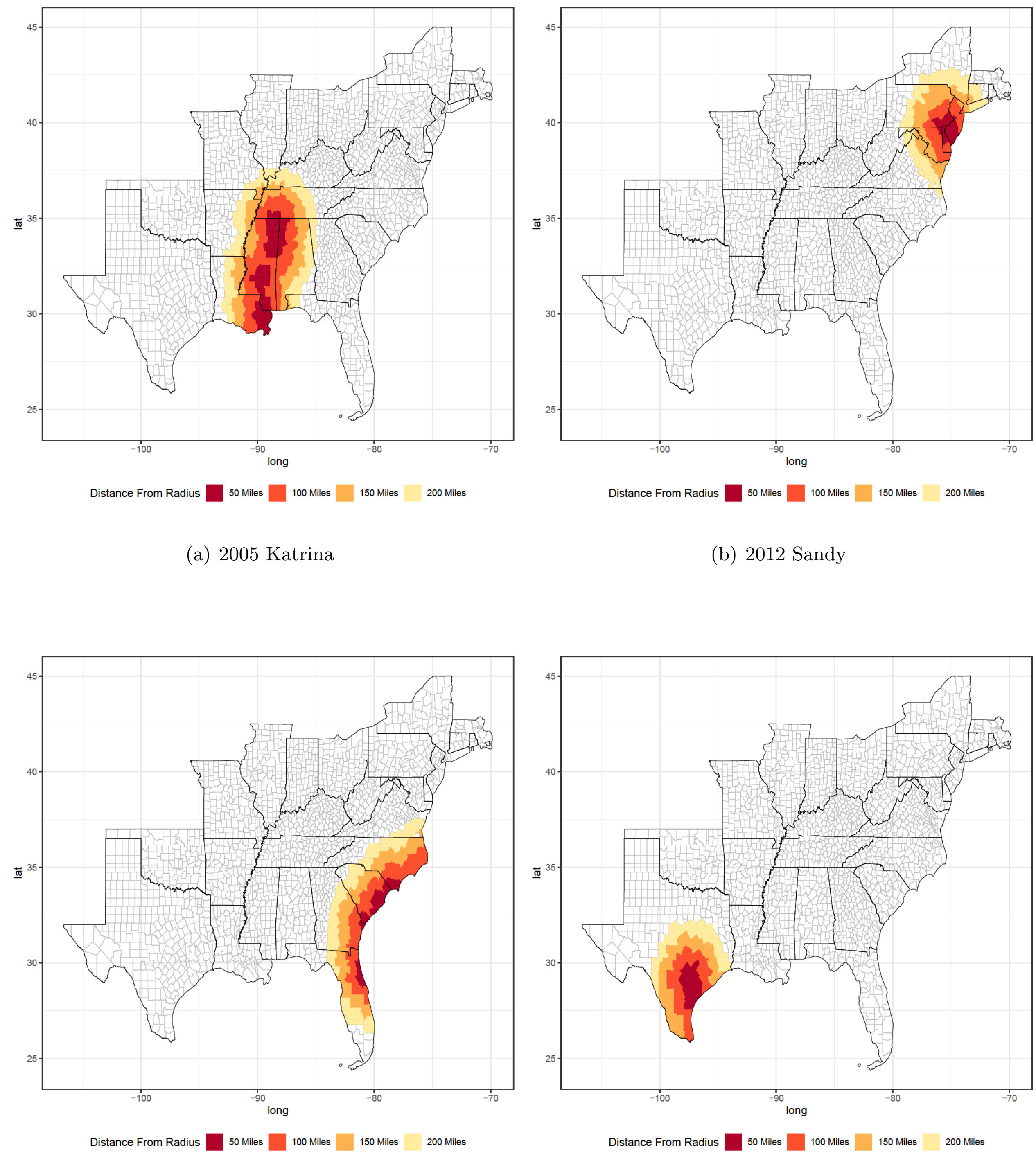


Figure 3: Hurricane forecasts at different time frames and wind speed probability thresholds

Each map shows the counties indicated as being in the forecast path for Hurricane Sandy given the number of days before landfall in each row and the wind speed probability threshold in each column. For each day, the last available forecast before 4pm (market close) is shown.



(a) 2005 Katrina

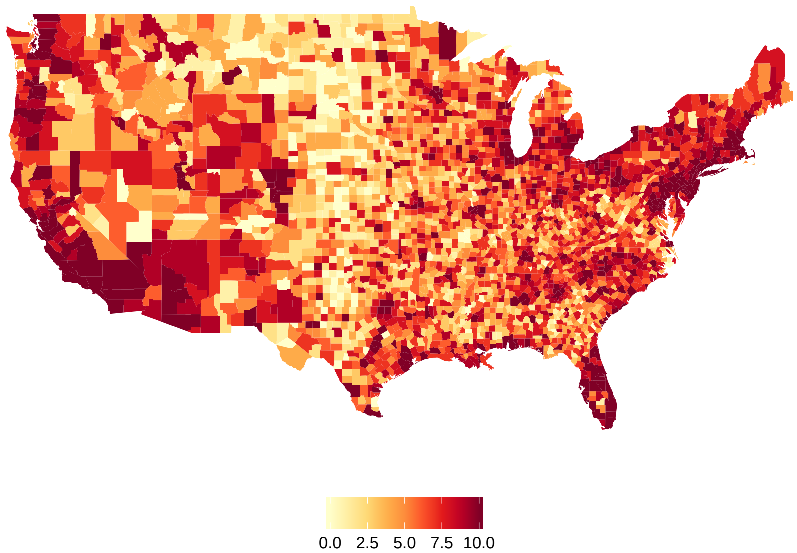
(b) 2012 Sandy

(c) 2016 Matthew

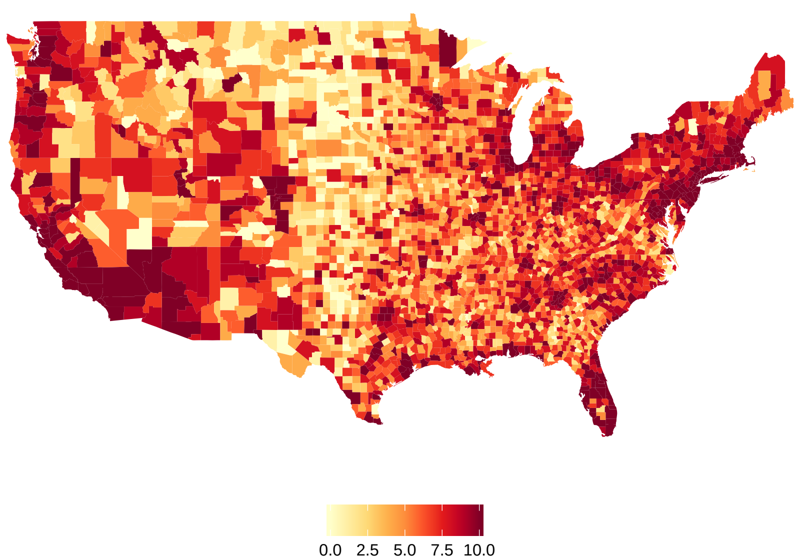
(d) 2017 Harvey

Figure 4: Counties in a hurricane landfall area

This figure highlights the counties that are within 50, 100, 150, and 200 miles of the eye of the hurricane at landfall.



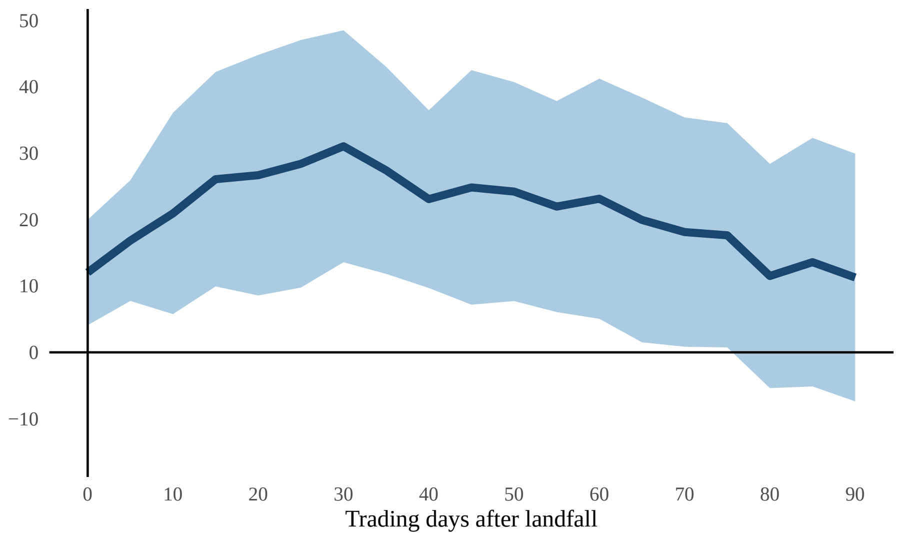
(a) Year 2010



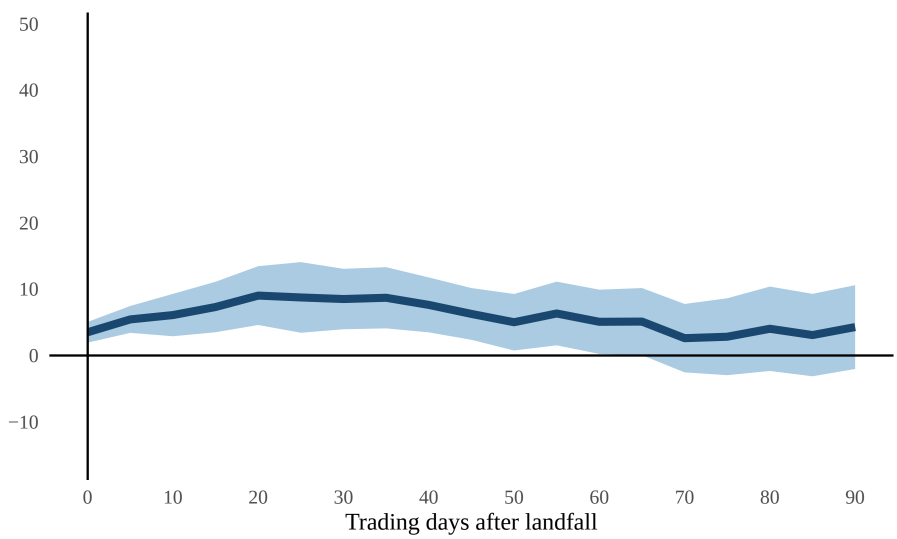
(b) Year 2014

Figure 5: 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). Only firms that could be mapped to CRSP-Compustat are included. The counties are sorted into deciles based on the number of establishments.



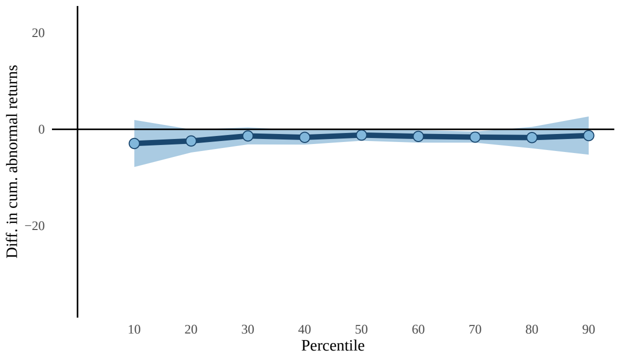
(a) 50 mile radius around eye of hurricane



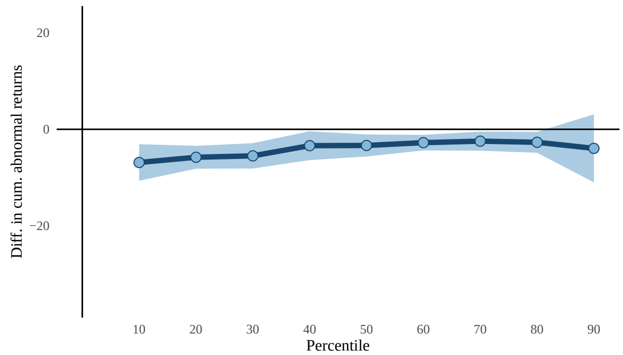
(b) 200 mile radius around eye of hurricane

Figure 6: Changes in implied volatilities post hurricane landfall

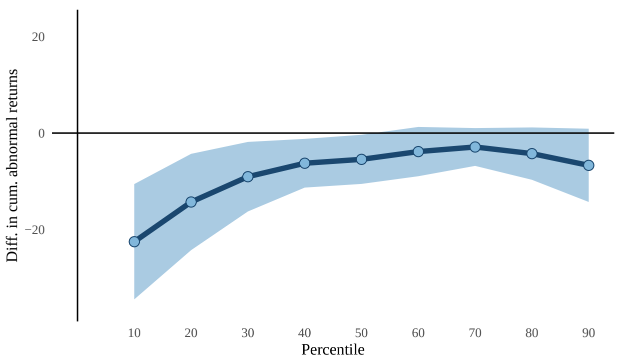
This figure plots coefficient estimates from the regression model given in equation (10). Changes in implied volatilities from inception of the hurricane up to 90 trading days (4.5 months) post hurricane landfall are regressed on the landfall region establishment share of firms. An coefficient estimate of, for example, 30 means that a firm with all of its establishments in the landfall region is estimated to experience a 30% increase in the implied volatility. The landfall region is based on a 50 mile radius around the eye of the hurricane (a) and 200 mile radius around the eye of the hurricane (b). Confidence bands of 95 percent are shown.



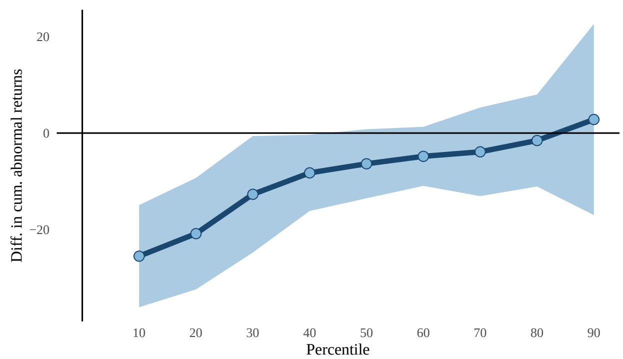
(a) 5 trading days (1 week) post landfall



(b) 10 trading days (2 weeks) post landfall



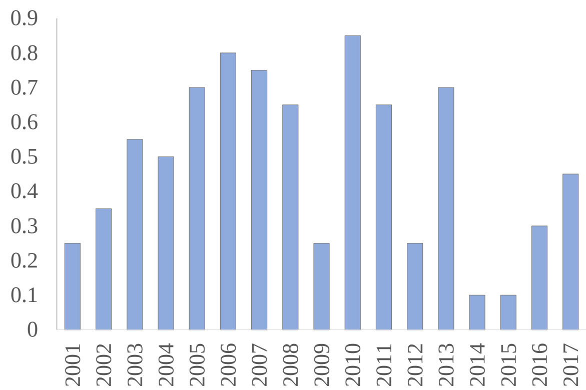
(c) 60 trading days (3 months) post landfall



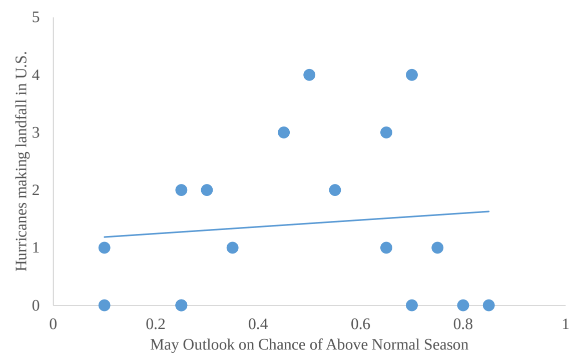
(d) 120 trading days (6 months) post landfall

Figure 7: Differences in cumulative abnormal returns between hit and control firms

This chart plots the difference in cumulative abnormal returns between firms with at least 25% of their establishments in the landfall region of a hurricane, that is hit firms, and firms with less than 25% of their establishments in the landfall region, that is control firms. The difference is shown for nine percentiles of the return distribution. The cumulative abnormal returns are computed since hurricane inception up to 5, 10, 60, and 120 trading days post landfall. The landfall region is based on 50 miles around the eye of the hurricane. The data are from 1996 to 2017. Confidence bands of 95 percent are shown.



(a) Probability of above average hurricane season



(b) Hurricane landfall count per year

Figure 8: NOAA's Atlantic Hurricane Season Outlook

Panel A shows the May Outlook for the Atlantic Hurricane season that NOAA issues each year. This outlook represents a projection of the number of hurricanes that will form in the Atlantic and the Gulf. Panel B depicts the relationship between the season outlook and realized hurricane outcomes for that season.

Table 1: Hurricane sample

The tables below show the hurricanes included in our analyses. Panel A, showing the sample for the forecast analyses, includes storms with wind speed forecasts reporting at least 1 percent probability of hurricane force winds. Because the forecasts include storms that never make landfall in the U.S., we indicate storms that make landfall with asterisks (*). Panel B shows the landfall and inception dates for storms that are included in the post-landfall analyses. The damage estimates shown here come from the National Hurricane Center's Tropical Cyclone Reports and have been inflated to 2017 values using the consumer price index from the U.S. Census Bureau. We show the revised estimates when applicable. Landfall dates come from the Tropical Cyclone Reports. In the event that a storm made multiple landfalls, we use the date of landfall that occurred with the higher Saffir-Simpson Hurricane Wind Scale category. For storms with forecast data (post-2007), the inception date reflects the first date for which there is at least a 1 percent probability of hurricane force winds in a U.S. location. For storms without forecast data (pre-2007), the inception date reflects the date that the tropical depression formed, as per the Tropical Cyclone Reports.

Panel A: Storms included in forecast analyses

2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Dean	Dolly*	Ana	Alex	Don	Debby	Andrea	Arthur*	Ana	Colin	Harvey*
Humberto*	Edouard	Bill	Bonnie	Emily	Isaac*	Karen		Erika	Hermine*	Irma*
Noel	Fay	Danny	Earl	Irene*	Leslie			Joaquin	Matthew*	Jose
	Gustav*	Ida	Paula	Nate	Sandy*					Maria
	Hanna									Nate*
	Ike*									
	Kyle									
	Paloma									

Panel B: Storms included in post-landfall analyses

Post-Landfall Analysis Only				Forecast and Post-Landfall Analyses			
Storm	Landfall date	Inception date	Damages 2017 $mn	Storm	Landfall date	Inception date	Damages 2017 $mn
Bertha	Jul. 12, 1996	Jul. 5, 1996	421	Humberto	Sep. 13, 2007	Sep. 12, 2007	N/A
Fran	Sep. 6, 1996	Aug. 23, 1996	4,994	Dolly	Jul. 23, 2008	Jul. 20, 2008	1,198
Danny	Jul. 18, 1997	Jul. 16, 1997	153	Gustav	Sep. 1, 2008	Aug. 25, 2008	5,271
Bonnie	Aug. 27, 1998	Aug. 19, 1998	1,085	Ike	Sep. 13, 2008	Sep. 1, 2008	33,692
Earl	Sep. 3, 1998	Aug. 31, 1998	119	Irene	Aug. 27, 2011	Aug. 21, 2011	17,258
Georges	Sep. 28, 1998	Sep. 15, 1998	9,594	Isaac	Aug. 29, 2012	Aug. 21, 2012	2,514
Bret	Aug. 23, 1999	Aug. 18, 1999	89	Sandy	Oct. 30, 2012	Oct. 22, 2012	53,481
Floyd	Sep. 16, 1999	Sep. 7, 1999	10,184	Arthur	Jul. 4, 2014	Jul. 1, 2014	2
Irene	Oct. 15, 1999	Oct. 13, 1999	1,181	Hermine	Sep. 2, 2016	Aug. 28, 2016	562
Lili	Oct. 3, 2002	Sep. 21, 2002	1,264	Matthew	Oct. 8, 2016	Sep. 28, 2016	10,215
Claudette	Jul. 15, 2003	Jul. 8, 2003	240	Harvey	Aug. 26, 2017	Aug. 17, 2017	125,000
Isabel	Sep. 18, 2003	Sep. 6, 2003	7,175	Irma	Sep. 10, 2017	Aug. 30, 2017	50,000
Charley	Aug. 13, 2004	Aug. 9, 2004	19,661	Nate	Oct. 8, 2017	Oct. 4, 2017	225
Frances	Sep. 5, 2004	Aug. 25, 2004	12,368				
Ivan	Sep. 16, 2004	Sep. 2, 2004	24,483				
Jeanne	Sep. 26, 2004	Sep. 13, 2004	9,965				
Dennis	Jul. 10, 2005	Jul. 4, 2005	3,202				
Katrina	Aug. 29, 2005	Aug. 23, 2005	135,894				
Rita	Sep. 24, 2005	Sep. 18, 2005	15,146				
Wilma	Oct. 24, 2005	Oct. 15, 2005	26,433				

Table 2: Firm establishment and option summary statistics

This table reports the summary statistics on the firms included in our sample. The sample is from 1996 to 2017. Statistics are reported for all firms and a subsample of "hit" firms. Hit firms had at least once 25% or more of their establishments in a hurricane landfall region (200 mile radius around the eye of the hurricane).

Number of unique firms	1,645						
Number of unique hit firms	744						
	Avg.	Std. dev.	10% percentile	25% percentile	50% percentile	75% percentile	90% percentile
Establishments (annually)	106.847	411.645	1.000	2.000	9.000	49.000	199.000
Establishments hit firms (annually)	115.958	419.809	1.000	3.000	11.000	55.000	216.000
Market cap. (quarterly in billion $)	4.524	19.588	0.076	0.217	0.684	2.244	7.617
Market cap. hit firms (quarterly in billion $)	5.341	22.741	0.092	0.265	0.839	2.673	9.065
$IV_{i,t}$ (daily)	0.485	0.276	0.223	0.300	0.417	0.595	0.827
$IV_{i,t}$ hit firms (daily)	0.477	0.268	0.222	0.298	0.412	0.585	0.808
$log(IV_{i,t}/IV_{i,t-1})$ (daily in %)	0.136	11.511	-9.862	-3.953	0.038	4.201	10.424
$log(IV_{i,t}/IV_{i,t-1})$ hit firms (daily in %)	0.129	11.198	-9.667	-3.905	0.024	4.116	10.222
Days to expiry$_{i,t}$ (daily)	36.598	32.665	11.000	17.000	28.000	39.000	82.000
Days to expiry$_{i,t}$ hit firms (daily)	35.374	31.217	10.000	17.000	26.000	38.000	75.000
Total open interest$_{i,t}$ (daily)	1,920.052	6,869.582	13.000	50.000	233.000	1,134.000	4,270.000
Total open interest$_{i,t}$ hit firms (daily)	2,015.321	7,266.748	14.000	53.000	248.000	1,193.000	4,425.000

Table 3: Forecast hurricane path and 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 inception of the hurricane to Γ days before landfall or dissipation, T_h, of the hurricane. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, that is establishments, is in counties located in the forecast path of a hurricane. The forecast path of the hurricane is from NOAA and gives a probability of being hit by a specific hurricane for each county. For each regression, the total number of firm observations with an establishment share in the forecast path of greater than 0% and at least 20% are reported. The data are from 2007 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are used separately in Panel A and are interacted in Panel B. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (9). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: With time (hurricane) and industry fixed effects

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

Γ	1 Day					2 Days				3 Days			4 Days		5 Days
Prob. of hurricane hit $\geq$	1%	10%	20%	40%	50%	1%	10%	20%	40%	1%	10%	20%	1%	10%	1%
$ForecastExposure_{i,P,T_h-\Gamma}$	4.467***	8.691***	18.303***	20.984***	19.100***	1.415	7.412***	8.164***	15.559***	1.287*	9.772***	13.699***	1.319	11.329***	1.895**
	(4.074)	(5.651)	(6.615)	(7.999)	(6.584)	(1.331)	(4.652)	(5.066)	(4.596)	(1.734)	(3.435)	(4.881)	(1.467)	(3.073)	(2.069)
Adjusted R^2	12.807	15.734	15.014	15.891	20.146	10.056	11.994	13.271	18.222	10.938	15.446	14.337	14.152	18.792	10.381
Total obs.	22,623	7,064	6,324	4,079	3,211	17,544	8,808	6,470	3,317	13,339	6,312	3,189	10,099	3,985	9,212
Total obs. ForecastExpos. $> 0\%$	6,564	1,757	1,393	829	686	7,532	2,551	1,864	1,041	6,319	1,860	1,060	5,352	1,383	4,242
Total obs. ForecastExpos. $\geq 20\%$	585	126	74	57	56	1,622	221	163	90	1,585	150	85	1,821	112	1,017
Hurricanes	29	9	8	5	4	22	11	8	4	17	8	4	13	5	12
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: With industry × time (hurricane) fixed effects

Γ	1 Day					2 Days				3 Days			4 Days		5 Days
Prob. of hurricane hit $\geq$	1%	10%	20%	40%	50%	1%	10%	20%	40%	1%	10%	20%	1%	10%	1%
$ForecastExposure_{i,P,T_h-\Gamma}$	2.347**	4.332**	11.478***	12.924***	11.817***	1.077	3.801**	4.043**	8.558***	0.710	4.016	5.703*	0.503	5.147*	1.800*
	(2.092)	(2.139)	(3.781)	(3.876)	(3.598)	(0.942)	(2.003)	(2.047)	(2.882)	(0.968)	(1.557)	(1.813)	(0.541)	(1.777)	(1.750)
Adjusted R^2	13.435	16.281	15.525	16.606	21.074	10.824	12.715	13.991	19.352	11.823	16.535	15.693	15.651	20.556	11.308
Total obs.	23,522	7,333	6,563	4,221	3,332	18,197	9,117	6,697	3,418	13,839	6,550	3,293	10,498	4,125	9,575
Total obs. ForecastExpos. $> 0\%$	6,564	1,757	1,393	829	686	7,532	2,551	1,864	1,041	6,319	1,860	1,060	5,352	1,383	4,242
Total obs. ForecastExpos. $\geq 20\%$	585	126	74	57	56	1,622	221	163	90	1,585	150	85	1,821	112	1,017
Hurricanes	29	9	8	5	4	22	11	8	4	17	8	4	13	5	12
Industry × Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Hurricane effects on implied volatility post landfall

This table reports the coefficients and test statistics when estimating the panel model in equation (10). 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 (1 week) and 30 trading days (1.5 months) after the landfall T_h in Panel A and B, respectively. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, that is establishments, is in counties located in the landfall region of a hurricane. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 50, 100, 150, and 200 miles surrounding the eye. For each regression, the total number of firm observations with an establishment share in the landfall region of greater than 0%, at least 20%, and at least 50%, are reported. The data are from 1996 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are used. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (10). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Inception to 5 trading days (1 week) after landfall

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

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,R,T_h}$	16.833***	11.946**	8.741***	7.191***	5.185***	4.251***	5.444***	4.074***
	(3.629)	(2.549)	(4.206)	(3.355)	(3.639)	(2.901)	(5.258)	(3.683)
Adjusted R^2 (%)	12.077	12.587	12.214	12.715	12.173	12.701	12.238	12.779
Total firm obs.	20,240	20,240	19,987	19,987	20,052	20,052	20,184	20,184
Total firm obs. with exposure > 0%	4,634	4,634	7,285	7,285	8,974	8,974	10,249	10,249
Total firm obs. with exposure ≥ 20%	157	157	633	633	1,302	1,302	2,133	2,133
Total firm obs. with exposure ≥ 50%	44	44	212	212	435	435	685	685
Hurricanes	33	33	33	33	33	33	33	33
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry × Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Inception to 30 trading days (1.5 months) after landfall

Dependent variable: Change in IV (in %), $log\left(IV_{i,T_h+30}/IV_{i,T_h^*}\right)$

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,R,T_h}$	31.049***	21.539***	8.302**	4.778	6.369***	4.368*	8.515***	6.575***
	(3.483)	(2.827)	(2.380)	(1.552)	(2.710)	(1.884)	(3.661)	(2.925)
Adjusted R^2 (%)	35.642	35.922	36.309	36.625	36.294	36.589	36.404	36.693
Total firm obs.	20,298	20,298	20,049	20,049	20,109	20,109	20,237	20,237
Total firm obs. with exposure > 0%	4,629	4,629	7,291	7,291	8,990	8,990	10,263	10,263
Total firm obs. with exposure ≥ 20%	158	158	640	640	1,309	1,309	2,141	2,141
Total firm obs. with exposure ≥ 50%	44	44	215	215	441	441	691	691
Hurricanes	33	33	33	33	33	33	33	33
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry × Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 5: Hurricane effects on implied volatility post landfall with industry interactions

This table reports the coefficients and test statistics when estimating the panel model in equation (10) 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 day of the hurricane T_h^* until 5 trading days after the landfall T_h. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, that is establishments, is in counties located in the landfall region of a hurricane. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 200 miles surrounding the eye. For each regression, the total number of firm observations with an establishment share in the landfall region of greater than 0%, at least 20%, and at least 50%, are reported. The data are from 1996 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are used. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (10). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

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

	Manuf.	Manuf.	Wholesale	Wholesale	Services	Services	Transport	Transport	Retail	Retail	Mining	Mining	Construct.	Construct.
$LandfallRegionExposure_{i,R,T_h}$	6.531***	4.606***	5.265***	3.704***	5.873***	4.234***	5.000***	3.485***	5.725***	4.217***	3.992***	4.082***	5.697***	4.277***
	(5.015)	(3.108)	(4.894)	(3.209)	(5.521)	(3.739)	(4.545)	(2.814)	(5.432)	(3.631)	(3.264)	(3.117)	(5.446)	(3.862)
$LandfallRegionExposure_{i,R,T_h} \times I_{i\in Ind_g}$	-2.913	-1.328	3.584	7.135	-2.649	-0.987	2.942	3.535	-6.811	-3.126	6.961*	-0.046	-24.305***	-18.650**
	(-1.429)	(-0.603)	(1.031)	(1.588)	(-0.927)	(-0.300)	(0.837)	(0.952)	(-1.304)	(-0.515)	(1.768)	(-0.011)	(-3.103)	(-2.252)
Adjusted R^2 (%)	12.242	12.776	12.236	12.783	12.238	12.775	12.238	12.780	12.242	12.776	12.262	12.774	12.259	12.787
Total firm obs.	20,184	20,184	20,184	20,184	20,184	20,184	20,184	20,184	20,184	20,184	20,184	20,184	20,184	20,184
Total firm obs. interaction industry	8,789	8,789	640	640	3,837	3,837	2,642	2,642	2,005	2,005	1,770	1,770	360	360
Firm obs. with exposure > 0%	10,249	10,249	10,249	10,249	10,249	10,249	10,249	10,249	10,249	10,249	10,249	10,249	10,249	10,249
Firm obs. with exposure ≥ 20%	2,133	2,133	2,133	2,133	2,133	2,133	2,133	2,133	2,133	2,133	2,133	2,133	2,133	2,133
Firm obs. with exposure ≥ 50%	685	685	685	685	685	685	685	685	685	685	685	685	685	685
Hurricanes	33	33	33	33	33	33	33	33	33	33	33	33	33	33
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry X Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 6: Hurricane effects on implied volatility post landfall (excluding Katrina, Sandy, and Harvey)

This table reports the coefficients and test statistics when estimating the panel model in equation (10) but when excluding hurricanes Katrina (2005), Sandy (2012), and Harvey (2017), which are the hurricanes in our sample that caused most damage. 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 (1 week) and 30 (1.5 months) trading days after the landfall T_h in Panel A and B, respectively. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, that is establishments, is in counties located in the landfall region of a hurricane. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 50, 100, 150, and 200 miles surrounding the eye. For each regression, the total number of firm observations with an establishment share in the landfall region of greater than 0%, at least 20%, and at least 50%, are reported. The data are from 1996 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are used. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (10). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Inception to 5 trading days (1 week) after landfall

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

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,R,T_h}$	18.924***	12.709**	9.231***	7.150***	5.500***	3.909**	5.701***	3.835***
	(4.020)	(2.510)	(4.033)	(3.084)	(3.054)	(2.220)	(4.504)	(2.998)
Adjusted R^2 (%)	13.192	13.749	13.250	13.791	13.239	13.806	13.343	13.914
Total firm obs.	18,072	18,072	17,862	17,862	17,959	17,959	18,062	18,062
Firm obs. with exposure > 0%	4,057	4,057	6,405	6,405	7,847	7,847	9,076	9,076
Firm obs. with exposure ≥ 20%	129	129	538	538	1,053	1,053	1,841	1,841
Firm obs. with exposure ≥ 50%	37	37	182	182	345	345	587	587
Hurricanes	30	30	30	30	30	30	30	30
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry X Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Inception to 30 trading days (1.5 months) after landfall

Dependent variable: Change in IV (in %), $log\left(IV_{i,T_h+30}/IV_{i,T_h^*}\right)$

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,R,T_h}$	37.679***	26.806***	9.694**	5.154	8.532**	5.613*	9.943***	7.415***
	(4.150)	(3.215)	(2.416)	(1.436)	(2.534)	(1.875)	(3.197)	(2.631)
Adjusted R^2 (%)	37.355	37.628	37.923	38.245	37.900	38.191	38.038	38.323
Total firm obs.	18,129	18,129	17,924	17,924	18,019	18,019	18,123	18,123
Firm obs. with exposure > 0%	4,059	4,059	6,418	6,418	7,867	7,867	9,097	9,097
Firm obs. with exposure ≥ 20%	130	130	542	542	1,056	1,056	1,847	1,847
Firm obs. with exposure ≥ 50%	37	37	182	182	347	347	589	589
Hurricanes	30	30	30	30	30	30	30	30
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry X Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 7: Long-run cumulative abnormal return differences

This table reports differences in cumulative abnormal returns post landfall for the mean and nine percentiles between hit firms and control firms. For a firm to be characterized as hit at least 25% of its establishments have to be in the hurricane landfall region. The hurricane landfall region is defined as a 50, 100, 150, or 200 mile radius around the eye of the hurricane at landfall. The cumulative returns are from hurricane inception to 120 trading days (6 months) post hurricane landfall. The differences are reported for the mean and nine percentiles of the return distributions of the hit and control firms. The abnormal returns are estimated based on the Fama-French five factor model. The data are from 1996 to 2017. The standard errors are bootstrapped and clustered by county based on a firm's largest exposure. The significance of the difference in abnormal returns is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat
Mean	-0.498	(-0.949)	-2.584	(-1.557)	-3.016	(-1.093)	-2.288	(-0.634)
Percentiles								
10%	-25.546***	(-4.724)	-13.167 ***	(-4.729)	-10.549***	(-4.328)	-10.202***	(-6.672)
20%	-20.866***	(-3.535)	-6.859***	(-3.163)	-7.168***	(-4.432)	-5.253***	(-3.420)
30%	-12.703**	(-2.060)	-5.397***	(-3.029)	-4.047***	(-3.400)	-3.515***	(-3.829)
40%	-8.257**	(-2.047)	-3.553***	(-2.118)	-2.725***	(-2.658)	-2.607***	(-3.561)
50%	-6.372*	(-1.743)	-1.628	(-1.022)	-1.926*	(-1.702)	-1.846**	(-2.089)
60%	-4.829	(-1.545)	-2.098	(-1.569)	-2.203*	(-1.914)	-1.343*	(-1.654)
70%	-3.891	(-0.830)	-1.955	(-0.936)	-1.919*	(-1.726)	-0.712	(-0.685)
80%	-1.542	(-0.317)	-1.711	(-0.838)	0.093	(0.055)	-0.001	(-0.001)
90%	2.815	(0.278)	4.423	(0.762)	3.743	(0.995)	1.685	(0.568)
Hit firms (exposure $\geq$ 25%)		106		430		949		1,522
Control firms (exposure < 25%)		11,997		18,150		18,346		17,747
Hurricanes		20		31		33		33

Table 8: Hurricane effects on implied volatility of insurance firms post landfall

This table reports the coefficients and test statistics when estimating the panel model in equation (10) 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 were in the landfall region of a hurricane. For Panel A, if at least 10% of a state's counties lie in the hurricane landfall region, the state is considered to be hit by the hurricane. For Panel B, the threshold is 25% of the counties. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 50, 100, 150, and 200 miles surrounding the eye. For each regression, the total number of firm observations with an exposure to the states in the landfall region of greater than 0%, at least 20%, and at least 50%, are reported. The data are from 1996 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by the state to which the insurance firm has the largest exposure. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (10). 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 (in %), $log\left(IV_{i,T_h+5}/IV_{i,T_h^*}\right)$

	Radius around eye of the hurricane			
	50 miles	100 miles	150 miles	200 miles
$LandfallRegionExposure_{i,R,T_h}$	38.615***	20.978*	18.232	6.779
	(6.882)	(1.902)	(1.571)	(1.060)
Adjusted R^2 (%)	22.625	18.391	18.958	18.525
Total firm obs.	557	693	731	731
Firm obs. with exposure > 0%	518	660	707	711
Firm obs. with exposure ≥ 20%	17	50	107	149
Firm obs. with exposure ≥ 50%	7	12	24	34
Hurricanes	25	31	33	33
Time (Hurricane) FE	Yes	Yes	Yes	Yes

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

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

	Radius around eye of the hurricane			
	50 miles	100 miles	150 miles	200 miles
$LandfallRegionExposure_{i,R,T_h}$	70.207***	41.892***	19.887*	23.934**
	(4.332)	(6.850)	(1.757)	(2.266)
Adjusted R^2 (%)	8.407	19.700	18.341	18.699
Total firm obs.	301	601	693	693
Firm obs. with exposure > 0%	277	561	662	672
Firm obs. with exposure ≥ 20%	6	22	55	93
Firm obs. with exposure ≥ 50%	3	7	13	21
Hurricanes	13	27	31	31
Time (Hurricane) FE	Yes	Yes	Yes	Yes

Table 9: Hurricane season outlook effects on implied volatility

This table reports the coefficients and test statistics when estimating the panel model in equation (14). The dependent variable is the change (in percent) in the implied volatility of firm i from the last trading day before the May Outlook for the hurricane season is released (T_{s-1}) to 5 trading days thereafter. Options that cover the majority of the hurricane season (120 to 210 days to expiry) are used. The independent variable $AboveAvgSeasonForecast_s$ is the probability which NOAA assigns to an above average hurricane season in terms of number of storms. In Panel A, the independent variable $CoastalExposure_{i,s}$ measures the share of a firm's establishments that are located in Atlantic and Gulf coastal counties. For columns 4 and 5, the counties on the Atlantic coast north of Florida are excluded. In Panel B, the independent variable $HistoricalHurricaneExposure_{i,s}$ measures the share of a firm's establishments that are located in counties that over the previous 30 years had a probability of being hit by a hurricane in a given season of at least 0.05 and 0.1, respectively. For each regression, the total number of firm observations with an establishment share in the coastal counties (or the counties with an elevated probability of getting hit) of greater than 0%, at least 20%, and at least 50%, are reported. The data range from 2001 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are used separately and interacted. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Atlantic and Gulf coast counties

Dependent variable: Change in IV (in %), $log\left(\frac{IV_{i,T_{s+5}}}{IV_{i,T_{s-1}}}\right)$

	All coastal counties		Excl. counties north of FL	
$CoastalExposure_{i,s}$	1.315*	1.364*	0.998	0.956
	(1.850)	(1.857)	(1.309)	(1.194)
$CoastalExposure_{i,s}$ $\times AboveAvgSeasonForecast_s$	-1.335	-1.415	-0.998	-0.799
	(-1.028)	(-1.067)	(-0.752)	(-0.560)
Adjusted R^2 (%)	3.463	3.853	3.411	3.799
Total firm obs.	11,531	11,531	11,531	11,531
Total firm obs. with exposure $> 0\%$	9,393	9,393	7,589	7,589
Total firm obs. with exposure $\geq 20\%$	7,583	7,583	2,441	2,441
Total firm obs. with exposure $\geq 50\%$	2,663	2,663	759	759
Industry FE	Yes	No	Yes	No
Time FE	Yes	No	Yes	No
Industry X Time FE	No	Yes	No	Yes

Panel B: Counties selected based on historical probability of being hit

	Counties with prob. ≥ 0.05		Counties with prob. ≥ 0.1	
$HistoricalHurricaneExposure_{i,s}$	1.533**	1.457**	1.138	1.097
	(2.105)	(2.021)	(1.436)	(1.294)
$HistoricalHurricaneExposure_{i,s}$ $\times AboveAvgSeasonForecast_s$	-1.988	-1.843	-1.143	-0.931
	(-1.464)	(-1.346)	(-0.798)	(-0.595)
Adjusted R^2 (%)	3.440	3.822	3.415	3.803
Total firm obs.	11,531	11,531	11,531	11,531
Total firm obs. with exposure $> 0\%$	8,179	8,179	7,186	7,186
Total firm obs. with exposure $\geq 20\%$	3,997	3,997	2,073	2,073
Total firm obs. with exposure $\geq 50\%$	1,131	1,131	706	706
Industry FE	Yes	No	Yes	No
Time FE	Yes	No	Yes	No
Industry X Time FE	No	Yes	No	Yes

Online Appendix for "Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics"

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1 Hurricane data

The paper uses data on the forecast path and landfall regions of hurricanes. This section describes how we gather the data from the National Oceanic and Atmospheric Administration (NOAA) and process them.

1.1 Details on hurricane forecast data

In our paper, we use the wind speed forecasts from NOAA. This wind speed forecasts can be found in NOAA's hurricane archives here https://www.nhc.noaa.gov/archive. For each tropical storm, NOAA issues text files in real-time that contain wind speed forecasts for five days out for selected locations along the coast. Figure A1 provides an example of such a text file. The file shows the coastal locations in the first column, and then provides for each location and three different wind speeds (34 knots (KT), 50 KT, and 64 KT) a probability and a cumulative probability (in parentheses) for the location reaching these wind thresholds 12 to a 120 hours out.

We translate these wind speed forecasts into counties that are located in the forecast path of a hurricane in two steps. First, we apply a series of probability thresholds — a minimum reported cumulative probability 5 days (120 hours) out for a 64 KT wind speed — ranging from 1 to 50 percent to select locations in the text files. For example, when we apply a probability threshold of 1 percent for 64 KT wind, Surf City, NC, is the only location on this list that is selected. We then

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map these selected locations to specific counties. In a second step, we add counties that are within a 75 mile radius of the counties from the first step.[1] We only focus on the 64 KT wind speed, because this is the minimum hurricane level wind speed.

Table A1 reports summary statistics on the hurricane forecast data. The number of storms for which we observe forecasts decreases as probability threshold or days to event resolution (hurricane landfall or dissipation) increases. Panel A reports the mean, median, and standard deviation of the number of county-date observations for which we have hurricane forecasts for each storm at a given probability threshold. When using a probability threshold of 1 percent, we include 49 storms, with the average storm having 306 county-day observations. At a probability threshold of 50 percent, our sample includes only nine storms with an average of just 7 county-day observations. Panel B presents the observation count by days to resolution at a given probability threshold.

1.2 Details on hurricane landfall region data

We use hurricane track data collated from forecast advisory files from the NOAA hurricane archives to determine which counties were located in the hurricane landfall regions. For each hurricane, NOAA publishes forecast advisory text files from the inception of the storm until the storm dissolves. Every six hours a new file is published with information on the location, that is the coordinates, of the storm eye. The file also contains information on the storm category, for example, was the storm a tropical depression or a hurricane at a given point in time. A lot of storms in NOAA's hurricane archive never get close to landfall. We select all the storms for which the eye gets within 50 miles of at least one county while being of hurricane level strength.

To determine the landfall region of each of the selected hurricanes, we first hand collect the landfall time of the hurricanes from NOAA's tropical cyclone reports, which can also be found in the hurricane archives. Then we include all counties in the landfall region that were at one point within a radius R of the storm eye 24 hours before or after the landfall time.[2] Having this time window around the landfall time ensures that we capture counties that lie more inland and counties that were close to the eye of the hurricane before the actual landfall for hurricanes that move along

[1] We use Census county centroids for this purpose, which can be found here https://www2.census.gov/geo/tiger/TIGER2017/COUNTY/.

[2] We use Census county centroids that can be found here https://www2.census.gov/geo/tiger/TIGER2017/COUNTY/.

the coast. Also, because we only require the storm to be of hurricane level strength at landfall, as described previously, this methodology captures counties that are affected by strong rainfall even when the storm windspeeds fall below hurricane level after landfall. While 24 hours is our baseline time window, we try additional time windows, namely 12, 36, and 48 hours, and the results are qualitatively similar. The values used for the radius R around the storm eye are 50, 100, 150, and 200 miles.

```
 - - - - WIND SPEED PROBABILITIES FOR SELECTED LOCATIONS - - - -

                FROM    FROM    FROM    FROM    FROM    FROM    FROM
  TIME        18Z THU 06Z FRI 18Z FRI 06Z SAT 18Z SAT 18Z SUN 18Z MON
PERIODS         TO      TO      TO      TO      TO      TO      TO
              06Z FRI 18Z FRI 06Z SAT 18Z SAT 18Z SUN 18Z MON 18Z TUE

FORECAST HOUR    (12)   (24)    (36)    (48)    (72)    (96)   (120)
- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
LOCATION       KT

DANVILLE VA    34  X   X( X)   1( 1)   2( 3)   2( 5)   1( 6)   X( 6)

NORFOLK NAS    34  X   X( X)   X( X)   X( X)   3( 3)   1( 4)   X( 4)

NORFOLK VA     34  X   X( X)   X( X)   1( 1)   2( 3)   1( 4)   X( 4)

OCEANA NAS VA  34  X   X( X)   X( X)   1( 1)   3( 4)   1( 5)   X( 5)

ELIZABETH CTY  34  X   X( X)   X( X)   2( 2)   4( 6)   2( 8)   X( 8)

GREENSBORO NC  34  X   X( X)   1( 1)   3( 4)   4( 8)   X( 8)   X( 8)

RALEIGH NC     34  X   X( X)   1( 1)   4( 5)   5(10)   X(10)   X(10)

ROCKY MT NC    34  X   X( X)   1( 1)   4( 5)   5(10)   X(10)   1(11)

CAPE HATTERAS  34  X   X( X)   X( X)   4( 4)   8(12)   2(14)   X(14)

FAYETTEVILLE   34  X   X( X)   5( 5)   9(14)   7(21)   1(22)   X(22)

CHARLOTTE NC   34  X   X( X)   5( 5)   4( 9)   3(12)   1(13)   X(13)

CHERRY PT NC   34  X   X( X)   2( 2)   8(10)  10(20)   3(23)   X(23)
CHERRY PT NC   50  X   X( X)   X( X)   1( 1)   2( 3)   X( 3)   X( 3)

NEW RIVER NC   34  X   X( X)   2( 2)   7( 9)  12(21)   4(25)   X(25)
NEW RIVER NC   50  X   X( X)   X( X)   1( 1)   2( 3)   1( 4)   X( 4)

MOREHEAD CITY  34  X   X( X)   2( 2)   8(10)  12(22)   4(26)   X(26)
MOREHEAD CITY  50  X   X( X)   X( X)   1( 1)   2( 3)   1( 4)   X( 4)

SURF CITY NC   34  X   1( 1)   5( 6)  11(17)  15(32)   3(35)   X(35)
SURF CITY NC   50  X   X( X)   X( X)   2( 2)   4( 6)   X( 6)   X( 6)
SURF CITY NC   64  X   X( X)   X( X)   X( X)   1( 1)   1( 2)   X( 2)
```

Figure A1: Partial sample raw text file for windspeed forecast data

This figure shows a portion of a NOAA wind speed forecast text file for Hurricane Matthew on October 6, 2016. The left column shows selected locations with wind speed probabilities of at least one percent at the speed of at least 34 knots (KT) within the 120 hours following the time of the forecast. The next column shows which wind speed the probabilities for a given row pertain to. When a location has probability of at least 1% of achieving 64 KT wind, then it will also show rows for 34 and 50 KT winds. In each of the following columns, the first number is the probability of the wind speed within that time frame while the number in parentheses reflects the cumulative probability of experiencing that wind speed at some point by the end of that period. For example, Surf City, NC, has an 11 percent probability of experiencing 34 KT winds during the 12-hour window occurring 36-48 hours from the time of the forecast. The cumulative probability that Surf City, NC will have experienced 34 KT winds within the next 48 hours is 17 percent.

Table A1: Summary statistics of hurricane forecast data

This table reports summary statistics of NOAA wind speed forecasts from 2007 to 2017 for storms that are forecast to make landfall within five days with wind speeds of at least 64KT with a given minimum probability. Panel A reports the mean, median, and standard deviation of the number of county-date 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-days forecast observations per storm

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

Panel B: Number of county-days 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

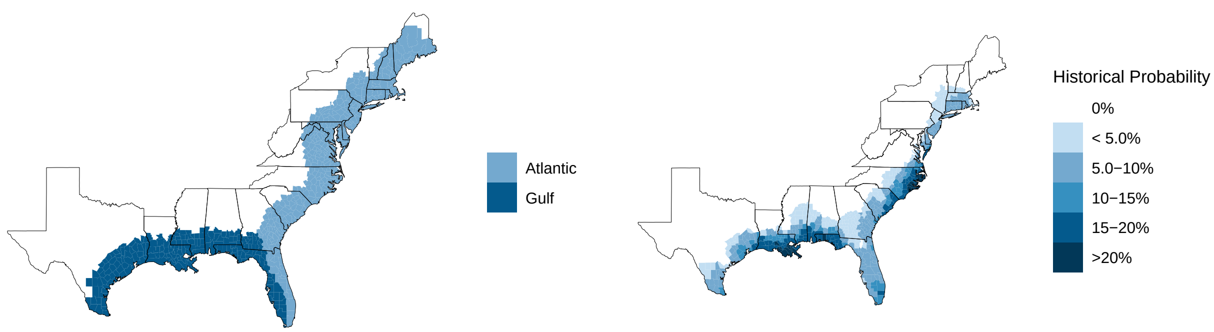
Table A2: Summary statistics of hurricane landfall region data

This table reports summary statistics on the hurricane landfall regions derived from NOAA data as described in Section 1.2 of this Online Appendix. Reported are statistics on the number of counties located in hurricane landfall regions from 1996 to 2017. Landfall regions are based on a range of radii around the eye of the hurricane.

	Across all hurricanes			By hurricane		
Radius around eye of the hurricane	Hurricanes	Total counties	Unique counties	Avg. counties	SD counties	Median counties
50 miles	33.000	832.000	537.000	25.212	15.299	24.000
100 miles	33.000	2,431.000	973.000	73.667	44.020	64.000
150 miles	33.000	4,370.000	1,246.000	132.424	74.903	123.000
200 miles	33.000	6,705.000	1,471.000	203.182	108.634	194.000

2 Additional figures and tables

This section provides additional figures and tables. Figure A2 plots the counties used for the seasonal outlook analysis in Section 4.2 of the paper. Tables A3 and A4 present the results of our baseline regressions that estimate the uncertainty before and after hurricane landfall when measuring the firms' geographic footprint with county level sales instead of establishments. In Table A5, we show that our baseline results are robust when double clustering standard errors by county and time (hurricane). In the paper, our baseline estimations cluster the standard errors by county to which the firm has the largest exposure. This choice is motivated by geographic location determining whether a firm is hit or not (see Abadie, Athey, Imbens, and Wooldridge (2017)). Also, for none of the regressions do we have a sufficient number of hurricanes to cluster by hurricane, as the recommended minimum number of clusters is 50 (see Bertrand, Duflo, and Mullainathan (2004)), and using fewer clusters leads to overly conservative standard errors. The sample with the largest number of hurricanes (33) is used to estimate changes in implied volatility post landfall, as done in Table A5. Tables A6 and A7 show long-run cumulative abnormal return differences between hit and control firms 5 trading days (1 week) and 60 trading days (3 months) after landfall. The two tables are structured as Table 7 in the paper, which shows the cumulative abnormal return differences up to 120 trading days (6 months) after landfall.



(a) Atlantic and Gulf counties

(b) Historical probability of hurricane landfall

Figure A2: Coastal counties and hurricanes

This figure plots the coastal counties used for the analysis in Section 6.4. Panel A shows all the counties that are either directly bordering the Atlantic/Gulf coast or are within a 100 mile distance of a county that does. Panel B shows the counties' historical probabilities of being in the landfall region of a hurricane at least once in a given year. The plotted probabilities are as of 2001 and computed based on a window of 30 years. The landfall regions are based on a 100 mile radius around the eye of the hurricane.

Table A3: Forecasted hurricane path and implied volatility (firms' geographic footprints based on sales)

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 inception of the hurricane to Γ days before landfall or dissipation, T_h, of the hurricane. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, that is establishments, is in counties located in the landfall region of a hurricane. The forecasted path of the hurricane is from NOAA and gives a probability of being hit by a specific hurricane for each county. For each regression, the total number of firm observations with a sales share in the forecast path of greater than 0% and at least 20% are reported. The data are from 2007 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are used separately in Panel A and are interacted in Panel B. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (9). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: With time (hurricane) and industry fixed effects

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

Γ	1 Day					2 Days				3 Days			4 Days		5 Days
Prob. of hurricane hit $\geq$	1%	10%	20%	40%	50%	1%	10%	20%	40%	1%	10%	20%	1%	10%	1%
$ForecastExposure_{i,P,T_h-\Gamma}$	3.663***	8.165***	15.302***	19.084***	18.082***	1.408	6.399***	8.099***	13.627***	1.432**	9.571***	14.415***	1.652**	9.329***	1.303*
	(3.139)	(5.679)	(5.622)	(7.246)	(6.994)	(1.594)	(4.087)	(7.009)	(4.548)	(2.011)	(2.976)	(5.930)	(1.994)	(2.963)	(1.944)
Adjusted R^2	12.813	15.765	15.042	15.964	20.256	10.063	12.004	13.32	18.304	10.947	15.51	14.564	14.185	18.826	10.354
Total obs.	22,611	7,060	6,320	4,076	3,209	17,532	8,802	6,465	3,314	13,332	6,309	3,187	10,094	3,983	9,207
Total obs. ForecastExpos. $> 0\%$	6,485	1,739	1,375	818	677	7,497	2,531	1,853	1,036	6,297	1,844	1,056	5,326	1,377	4,223
Total obs. ForecastExpos. $\geq 20\%$	605	138	85	65	64	1,521	227	169	97	1,476	143	89	1,582	122	903
Hurricanes	29	9	8	5	4	22	11	8	4	17	8	4	13	5	12
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: With industry × time (hurricane) fixed effects

Γ	1 Day					2 Days				3 Days			4 Days		5 Days
Prob. of hurricane hit $\geq$	1%	10%	20%	40%	50%	1%	10%	20%	40%	1%	10%	20%	1%	10%	1%
$ForecastExposure_{i,P,T_h-\Gamma}$	1.985*	4.372**	9.919***	12.552***	12.237***	1.188	3.421**	4.612***	7.933***	0.996	5.217*	8.816***	1.105	4.636**	1.218
	(1.864)	(2.261)	(3.672)	(3.666)	(3.637)	(1.283)	(2.126)	(2.883)	(3.346)	(1.545)	(1.957)	(3.335)	(1.388)	(2.237)	(1.623)
Adjusted R^2	13.432	16.193	15.414	16.447	20.969	10.713	12.615	13.9	19.241	11.66	16.269	15.366	15.508	20.251	11.084
Total obs.	22,611	7,060	6,320	4,076	3,209	17,532	8,802	6,465	3,314	13,332	6,309	3,187	10,094	3,983	9,207
Total obs. ForecastExpos. $> 0\%$	6,485	1,739	1,375	818	677	7,497	2,531	1,853	1,036	6,297	1,844	1,056	5,326	1,377	4,223
Total obs. ForecastExpos. $\geq 20\%$	605	138	85	65	64	1,521	227	169	97	1,476	143	89	1,582	122	903
Hurricanes	29	9	8	5	4	22	11	8	4	17	8	4	13	5	12
Industry × Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A4: Hurricane effects on implied volatility post landfall (firms' geographic footprints based on sales)

This table reports the coefficients and test statistics when estimating the panel model in equation (10). 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 (1 week) and 30 trading days (1.5 months) after the landfall T_h in Panel A and B, respectively. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, that is sales, is in counties located in the landfall region of a hurricane. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 50, 100, 150, and 200 miles surrounding the eye. For each regression, the total number of firm observations with a sales share in the landfall region of greater than 0%, at least 20%, and at least 50%, are reported. The data are from 1996 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are used. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (10). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Inception to 5 trading days (1 week) after landfall

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

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,T_h}$	11.647***	8.067**	7.133***	5.986***	3.096**	2.263*	4.133***	3.101***
	(3.413)	(2.438)	(3.753)	(3.159)	(2.255)	(1.694)	(4.005)	(3.128)
Adjusted R^2 (%)	12.073	12.59	12.188	12.722	12.166	12.706	12.238	12.792
Total firm obs.	20,201	20,201	20,046	20,046	20,061	20,061	20,126	20,126
Total firm obs. with exposure $>$ 0%	4,529	4,529	7,245	7,245	8,928	8,928	10,174	10,174
Total firm obs. with exposure $\geq$ 20%	168	168	635	635	1,247	1,247	1,960	1,960
Total firm obs. with exposure $\geq$ 50%	81	81	320	320	620	620	979	979
Hurricanes	33	33	33	33	33	33	33	33
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry $\times$ Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Inception to 30 trading days (1.5 months) after landfall

Dependent variable: Change in IV (in %), $log\left(IV_{i,T_h+30}/IV_{i,T_h^*}\right)$

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,R,T_h}$	24.591***	16.827***	7.912**	5.180*	5.403**	3.783*	7.595***	6.141***
	(3.107)	(2.676)	(2.234)	(1.736)	(2.349)	(1.845)	(3.266)	(2.966)
Adjusted R^2 (%)	35.623	35.952	36.341	36.664	36.481	36.779	36.423	36.698
Total firm obs.	20,267	20,267	20,097	20,097	20,121	20,121	20,184	20,184
Total firm obs. with exposure $>$ 0%	4,525	4,525	7,248	7,248	8,946	8,946	10,190	10,190
Total firm obs. with exposure $\geq$ 20%	169	169	640	640	1,252	1,252	1,967	1,967
Total firm obs. with exposure $\geq$ 50%	81	81	325	325	624	624	986	986
Hurricanes	33	33	33	33	33	33	33	33
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry $\times$ Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A5: Hurricane effects on implied volatility post landfall (double clustered standard errors)

This table reports the coefficients and test statistics when estimating the panel model in equation (10). 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 (1 week) and 30 trading days (1.5 months) after the landfall T_h in Panel A and B, respectively. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, that is sales, is in counties located in the landfall region of a hurricane. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 50, 100, 150, and 200 miles surrounding the eye. For each regression, the total number of firm observations with an establishment share in the landfall region of greater than 0%, at least 20%, and at least 50%, are reported. The data are from 1996 to 2017. The values in parentheses are the t-stats. Industry and time fixed effects are used. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (10). The standard errors are double clustered by county based on a firm's largest exposure and by time period (hurricane). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Inception to 5 trading days (1 week) after landfall

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

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,R,T_h}$	16.833***	11.946**	8.741**	7.191*	5.185*	4.251*	5.444***	4.074**
	(2.724)	(2.215)	(2.302)	(2.036)	(2.102)	(1.898)	(2.797)	(2.463)
Adjusted R^2 (%)	12.077	12.587	12.214	12.715	12.173	12.701	12.238	12.779
Total firm obs.	20,240	20,240	19,987	19,987	20,052	20,052	20,184	20,184
Firm obs. with exposure > 0%	4,634	4,634	7,285	7,285	8,974	8,974	10,249	10,249
Firm obs. with exposure ≥ 20%	157	157	633	633	1,302	1,302	2,133	2,133
Firm obs. with exposure ≥ 50%	44	44	212	212	435	435	685	685
Hurricanes	33	33	33	33	33	33	33	33
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry X Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Inception to 30 trading days (1.5 months) after landfall

Dependent variable: Change in IV (in %), $log\left(IV_{i,T_h+30}/IV_{i,T_h^*}\right)$

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,R,T_h}$	31.049**	21.539*	8.302	4.778	6.369	4.368	8.515**	6.575*
	(2.086)	(1.660)	(1.121)	(0.741)	(1.318)	(1.042)	(1.963)	(1.778)
Adjusted R^2 (%)	35.642	35.922	36.309	36.625	36.294	36.589	36.404	36.693
Total firm obs.	20,298	20,298	20,049	20,049	20,109	20,109	20,237	20,237
Firm obs. with exposure > 0%	4,629	4,629	7,291	7,291	8,990	8,990	10,263	10,263
Firm obs. with exposure ≥ 20%	158	158	640	640	1,309	1,309	2,141	2,141
Firm obs. with exposure ≥ 50%	44	44	215	215	441	441	691	691
Hurricanes	33	33	33	33	33	33	33	33
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry X Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A6: Cumulative abnormal return differences - 5 trading days post landfall

This table reports differences in cumulative abnormal returns post landfall for the mean and nine percentiles between hit firms and control firms. For a firm to be characterized as hit at least 25% of its establishments have to be in the hurricane landfall region. The hurricane landfall region is defined as a 50, 100, 150, or 200 mile radius around the eye of the hurricane at landfall. The cumulative returns are from hurricane inception to 5 trading days (1 week) post hurricane landfall. The differences are reported for the mean and nine percentiles of the return distributions of the hit and control firms. The abnormal returns are estimated based on the Fama-French five factor model. The data are from 1996 to 2017. The standard errors are bootstrapped and clustered by county based on a firm's largest exposure. The significance of the difference in abnormal returns is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat
Mean	-2.311**	(-2.180)	-0.498	(-0.949)	-0.241	(-0.622)	-0.369	(-1.181)
Percentiles								
10%	-2.940	(-1.181)	-1.452*	(-1.781)	-0.595	(-1.065)	-0.463	(-1.263)
20%	-2.416**	(-1.976)	-0.688	(-1.510)	-0.250	(-0.876)	-0.308	(-1.232)
30%	-1.371	(-1.525)	-0.624*	(-1.645)	-0.565**	(-2.158)	-0.476**	(-2.076)
40%	-1.666**	(-2.163)	-0.222	(-0.679)	-0.280	(-1.173)	-0.278*	(-1.675)
50%	-1.196**	(-1.988)	-0.418	(-1.167)	-0.307	(-1.514)	-0.286**	(-1.973)
60%	-1.466**	(-2.208)	0.027	(0.069)	-0.077	(-0.318)	-0.106	(-0.548)
70%	-1.618***	(-2.761)	0.106	(0.288)	0.008	(0.031)	-0.201	(-1.039)
80%	-1.718	(-1.516)	0.197	(0.316)	0.255	(0.600)	-0.156	(-0.516)
90%	-1.297	(-0.642)	0.542	(0.614)	0.989	(1.660)	0.577	(1.231)
Hit firms (exposure $\geq$ 25%)		115		469		1,015		1,624
Control firms (exposure < 25%)		12,844		19,317		19,599		18,954
Hurricanes		20		31		33		33

Table A7: Long-run cumulative abnormal return differences - 60 trading days post landfall

This table reports differences in cumulative abnormal returns post landfall for the mean and nine percentiles between hit firms and control firms. For a firm to be characterized as hit at least 25% of its establishments have to be in the hurricane landfall region. The hurricane landfall region is defined as a 50, 100, 150, or 200 mile radius around the eye of the hurricane at landfall. The cumulative returns are from hurricane inception to 60 trading days (3 months) post hurricane landfall. The differences are reported for the mean and nine percentiles of the return distributions of the hit and control firms. The abnormal returns are estimated based on the Fama-French five factor model. The data are from 1996 to 2017. The standard errors are bootstrapped and clustered by county based on a firm's largest exposure. The significance of the difference in abnormal returns is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat
Mean	-9.402	(-1.455)	-3.016	(-1.093)	-1.973	(-0.999)	-2.446	(-1.422)
Percentiles								
10%	-22.539***	(-3.693)	-8.852***	(-3.224)	-5.480***	(-3.633)	-5.636***	(-4.478)
20%	-14.302***	(-2.805)	-4.448**	(-2.264)	-2.279**	(-2.109)	-2.382***	(-3.122)
30%	-9.051**	(-2.458)	-2.802**	(-1.970)	-2.204***	(-2.828)	-2.175***	(-3.788)
40%	-6.261**	(-2.428)	-2.963***	(-3.521)	-2.077***	(-3.170)	-1.862***	(-4.052)
50%	-5.454**	(-2.097)	-1.691	(-1.477)	-1.593**	(-1.960)	-1.392**	(-2.262)
60%	-3.842	(-1.473)	-1.098	(-1.094)	-0.821	(-1.262)	-1.126*	(-1.859)
70%	-2.887	(-1.442)	-1.672	(-1.307)	-1.531**	(-2.170)	-1.444***	(-2.770)
80%	-4.263	(-1.538)	0.284	(0.219)	-0.039	(-0.040)	-0.842	(-0.984)
90%	-6.699*	(-1.728)	-3.355	(-1.136)	-1.660	(-0.833)	-1.815	(-1.065)
Hit firms (exposure $\geq$ 25%)		111		448		982		1,570
Control firms (exposure $<$ 25%)		12,312		18,631		18,876		18,262
Hurricanes		20		31		33		33