Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics*

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Abstract

This paper isolates and estimates extreme weather uncertainty. Our framework identifies market responses to the uncertainty regarding both potential hurricane landfall and subsequent economic impact. Stock options of firms with establishments exposed to the landfall region exhibit large increases in implied volatility of up to 30 percent, reflecting impact uncertainty, which persists up to four months after landfall. Using hurricane forecasts, we find both landfall uncertainty and expected impact uncertainty are reflected in option prices before landfall. Our findings show the significant costs to hedging extreme weather uncertainty and have important implications for assessing the economic effects of extreme weather.

JEL classification: G12, G14, Q54.

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1 Introduction

From major hurricanes on the Atlantic and Gulf coasts, to droughts on the west coast, and flooding across the US, extreme weather has devastated a variety of communities in recent years. Despite an emerging climate finance literature that examines how investors can hedge climate risks (see, for example, Andersson, Bolton, and Samama (2016); Baker, Hollifield, and Osambela (2019); Engle, Giglio, Kelly, Lee, and Stroebel (2019); Krueger, Sautner, and Starks (2019); Roth Tran (2019)) and a growing literature on the impacts of extreme weather,[1] little is known about the magnitude and dynamics of extreme weather uncertainty. This gap in the literature is surprising, as uncertainty in other contexts is known to affect financial markets and real economic activity.[2] Researchers across disciplines are striving to assess the costs of extreme weather and better understand the mechanisms through which extreme weather affects local economies to improve their resilience.[3] Extreme weather uncertainty could lead to substantial costs that are currently ignored by conventional damage estimates and alter the decisions of economic agents, thereby affecting local economies. For example, uncertainty about how a firm will be affected by an extreme weather event can impact the hedging, insurance, financing, and investment decisions of the firm's managers, investors, customers, and suppliers. Thus, a comprehensive assessment of the costs and economic effects of extreme weather events requires understanding the uncertainty surrounding them.

In this paper, we use financial markets to isolate and quantify extreme weather uncertainty, analyze its dynamics and the costs to its hedging. 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.[4] We proxy for uncertainty using changes to the implied volatility of stock options, a measure that captures investor expectations of volatility.[5] We combine county-level firm establishment data with hurricane forecast and landfall data to identify firm exposure to regions

[1]See, for example, Barrot and Sauvagnat (2016); Bernile, Bhagwat, and Rau (2017); Dessaint and Matray (2017); Brown, Gustafson, and Ivanov (2017); Hong, Li, and Xu (2019).

[2]For example, political uncertainty is estimated to be high around elections (see Kelly, Pastor, and Veronesi (2016)) and has been shown to reduce firm investments (see Julio and Yook (2012); Jens (2017)).

[3]See, for example, Melillo, Richmond, and Yohe (2014).

[4]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 uncertainty about where they occur and what the eventual impact will be.

[5]See, for example, Bloom (2009) and Kelly, Pastor, and Veronesi (2016).

(potentially) affected by particular hurricanes. 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 toward the coast, the associated landfall and expected impact uncertainty will be reflected in the stock options of exposed firms. Using National Oceanographic and Atmospheric Administration (NOAA) forecasts issued in the days leading up to a hurricane's landfall or dissipation (in the case of a hurricane that "missed"), we find implied volatilities of firms with exposure to the forecast path increase even at low landfall probabilities and increase by up to 21 percent for high probabilities.[6] These results imply that hurricanes cause substantial uncertainty and that investors pay attention to hurricane forecasts. Such attention to climatic events is by no means a given, as some papers in the climate finance literature assessing informational efficiency have found that investors are inattentive to other climatic events as they unfold (see, for example, Hong, Li, and Xu (2019)). Furthermore, investor attention to extreme weather events is important for correctly pricing assets with exposure to extreme weather and other climate risks, thereby reducing 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, the implied volatility of options of firms in the landfall region are elevated due to impact uncertainty, which gradually resolves following landfall. 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 elevated, rising up to 30 percent higher than before the hurricane's inception. Implied volatilities remain elevated for several months after hurricane landfall indicating that resolution of impact uncertainty is slow.

These estimates are economically significant. If one were to hedge the shares outstanding of the affected firms in our sample, the increase in implied volatilities in the aftermath of a hurricane translates into hedging costs of up to \$53 billion. This value is substantial considering that NOAA estimates the total hurricane damages to be \$583 billion over the same sample period.[7]

We build on these baseline results with several robustness checks and extensions. For example,

[6] 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 impacting our results, which are on firm-level volatility.

[7] These values are reported in 2017 inflation-adjusted US dollars.

our findings are not driven by small firms, are robust across industries, hold within industries, and are also robust to the exclusion of the most damaging hurricanes according to NOAA (Katrina, Sandy, and Harvey). While financial firms are excluded from our baseline analyses, we show that single stock options of property and casualty insurance firms also reflect substantial impact uncertainty immediately following a hurricane landfall, exhibiting implied volatility increases of as much as 70 percent. We test if the large increases in implied volatilities from our baseline results are due to investor overreaction, but find no evidence for it. Further, 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, which are much less informative than the forecasts for individual hurricanes. Finally, we show that the stocks of the worst performing firms exposed to hurricane landfall regions dramatically underperform the worst performing firms in the control set. The cumulative abnormal return difference after 6 months is as much as 26 percent. This underperformance takes several months after landfall to manifest, supporting 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.

This paper makes several key contributions. First, we present a novel framework of landfall and impact uncertainty to formalize our notions of uncertainty before and after extreme weather events. Second, our estimates imply that extreme weather uncertainty can impose significant financial costs when hedging or insuring against extreme weather uncertainty, and these costs are currently ignored when assessing the aggregate impact of extreme weather events. 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 also be an important factor for such real outcomes. Fourth, we contribute to the literature that analyzes investor attention to extreme weather by showing that investors are attentive to short-term hurricane forecasts, but ignore medium-term seasonal forecasts possibly due to a lack of accuracy.

The remainder of this paper is structured as follows. We begin with a discussion of the related literature in Section 2. We describe our research design and data in Sections 3 and 4, respectively.

Section 5 presents our main results, followed by extensions and robustness tests in 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 the effects of extreme weather events. Barrot and Sauvagnat (2016) find that extreme weather event shocks 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. Addoum, Ng, and Ortiz-Bobea (2019), Aladangady, Aron-Dine, Dunn, Feiveson, Lengermann, and Sahm (2019), and Beatty, Shimshack, and Volpe (2019) examine how extreme weather events affect sales, finding significant impacts of hurricanes but not temperature deviations. Further research has shown how extreme weather affects local economies, labor markets, schooling, household finance, and income (see Belasen and Polachek (2008); Imberman, Kugler, and Sacerdote (2012); Gallagher and Hartley (2017); Deryugina, Kawano, and Levitt (2018); Martinez (2018); Roth Tran and Wilson (2019)).

Further, this paper introduces a novel topic to the emerging literature on climate finance that includes early work on how Florida temperature fluctuations affect orange juice futures prices (see Roll (1984); Boudoukh, Richardson, Shen, and Whitelaw (2007)); the pricing and usage of weather derivatives (see Campbell and Diebold (2005); Perez-Gonzalez and Yun (2013); Purnanandam and Weagley (2016); Weagley (2019)); how asset pricing theory can be used to calibrate the cost of carbon dioxide emissions (see Bansal, Kiku, and Ochoa (2017); Daniel, Litterman, and Wagner (2019); Barnett, Brock, and Hansen (2020)). Our research contributes to two branches of the climate finance literature.

First, our analysis complements climate finance papers that develop hedging strategies. While Baker, Hollifield, and Osambela (2019) 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, which focus largely on climate policy risk, we focus explicitly on extreme weather events which are physical realizations of climate risks.

Second, 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 warmer-than-usual temperatures and investors' beliefs about climate change. Alok, Kumar, and Wermers (2019) show that fund managers who are hit by a natural disaster subsequently misestimate the risk of such disasters. Krueger, Sautner, and Starks (2019) survey institutional investors and find these investors perceive that climate risks, especially regulatory risks, have already begun to materialize and will have impact on equity valuations. Drawing mixed conclusions, several papers (see Bernstein, Gustafson, and Lewis (2018); Giglio, Maggiori, Rao, Stroebel, and Weber (2018); Bakkensen and Barrage (2019); Baldauf, Garlappi, and Yannelis (2019); Murfin and Spiegel (2019)) use NOAA sea level rise predictions to examine whether residential real estate prices reflect sea level rise risks.

Finally, our paper investigates a novel type of uncertainty within the uncertainty literature. Our analysis that investigates uncertainty around specific events is comparable to research on political uncertainty. In this literature, scheduled elections are often used to isolate political uncertainty and investigate how financial markets and firm investments are affected (see, for example, Julio and Yook (2012); Pastor and Veronesi (2012, 2013); Kelly, Pastor, and Veronesi (2016); Jens (2017); Kim and Kung (2017); Fried, Novan, and Peterman (2019)). Our paper complements this body of work by showing that extreme weather events are an important source of uncertainty that affects prices in financial markets. Compared to predetermined political events, our analysis introduces a new layer of complexity as we separately examine the effects of the uncertainty about when, whether, and where the hurricane will make landfall.

Several papers have analyzed macroeconomic uncertainty (see, for example, Bloom, Bond, and van Reenen (2007); Bloom (2009); Jurado, Ludvigson, and Ng (2015); Baker, Bloom, and Davis

(2016); Dew-Becker, Giglio, Le, and Rodriguez (2017); Baker, Bloom, and Terry (2018); Dew-Becker, Giglio, and Kelly (2018)). Our paper differs from the research on macroeconomic uncertainty and economic growth 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 Research design

3.1 Theoretical framework on landfall and impact uncertainty

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. Impact uncertainty is the uncertainty about how a hurricane will impact firms with exposure to the landfall area. 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 occurrence of an event. While this paper focuses on hurricanes, our framework is general enough that it can be applied to other types of extreme weather events.

More formally, if hurricane h is expected to make landfall at time $t+1$, then 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 $\epsilon_{i,t+1} \sim N(0, \sigma^2)$ 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 (one draw of a binomial distribution), $\theta_{i,h,t+1} \sim B(1, \phi)$, 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, a hurricane landfall introduces uncertainty for the local economy and firms. Predicting at the time of landfall which firms will be most affected could be challenging for several reasons. First, 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 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.

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[10] are, respectively,

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

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

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

[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).

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

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

Landfall uncertainty is captured in the total variance by the third term in equation (6), $\phi(1-\phi)\mu_g^2$. For a given $\mu_g \neq 0$, landfall uncertainty is highest when the probability of landfall ϕ is 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 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 what the level of variance would be following hurricane landfall, $Var_t(r_{i,t+1}|\theta = 1) = \sigma^2 + \sigma_g^2$. The x-axis intersects the y-axis at the level of variance if hurricane landfall does not occur, $Var_t(r_{i,t+1}|\theta = 0) = \sigma^2$.

Prior to landfall, depending on the parameter values of μ_g and σ_g^2, as the probability of landfall, ϕ, varies from 0 to 1, the relative contribution to total variance from landfall uncertainty and expected impact uncertainty will vary. All else equal, as μ_g increases, the contribution of landfall uncertainty to total variance increases. In Figure 1, landfall uncertainty at a given ϕ is the vertical distance between a curve and the red dot-dash straight line depicting $Var_t(r_{i,t+1})$ when $\mu_g = 0$.[11]

3.2 Firm exposure to hurricanes

We separately determine firm exposure to a hurricane forecast and a hurricane landfall region. 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 based on the share of establishments located in these counties. Figure 2 shows a stylized example of how we measure a firm's exposure to a forecast path or a landfall region. We are agnostic on the channel through which the hurricane affects a firm. A firm could be negatively affected through, for example, damage to property, disruption to production process, or decrease in demand due to the wealth shock to the local population. On

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

the other hand, a firm could be positively affected because, for example, demand for its products increases in the rebuilding process or local competitors were more severely affected. Due to these range of possible channels, establishment locations seem to be the most natural way to capture firm exposure to hurricanes.[12]

We use hurricane wind speed forecasts to develop firm- and day-specific exposures to hurricanes before landfall. For our purpose, wind speed forecasts have the advantage that NOAA issues probabilities that a county will experience hurricane force winds for a given hurricane. These probabilities facilitate the connection between our framework from Section 3 and our empirical analysis. Forecasts on the hurricane eye or rainfall lack such granularity and exact probabilities.[13] Figure 3 shows an example of NOAA's wind speed forecasts. We denote the set of counties that have a probability of at least P to experience hurricane level wind speeds as $F_{P,t}$, 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, Γ days before hurricane landfall or dissipation, as the share of i's establishments located in the set of counties in the forecast path, $F_{P,T_h-\Gamma}$. This forecast exposure, a continuous variable ranging from 0 to 1, is given by

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

Figure 2(a) shows a stylized example of how the $ForecastExposure$ variable is computed, where the shaded blue squares represent the exposed counties in $F_{P,T_h-\Gamma}$.

We take a similar approach for our post-landfall analyses by determining the set L_{R,T_h} of counties located in the landfall region. 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 county's centroid is within a radius R of the eye of the storm at landfall. The radius accounts for the fact that hurricanes can impact counties that are not located in immediate proximity to the eye of the storm through wind and rain. Using

[12] County-firm level sales are used as robustness check in the Online Appendix.

[13] Also, which storm is considered a hurricane is based on wind speed and not rainfall. There is clearly a strong positive correlation between hurricane wind speed and rainfall. Therefore, the wind speed forecasts also proxy for rainfall.

data on the eye of the storm location to determine a hurricane's landfall region has the distinct advantage that these data are available to investors in real-time during a hurricane strike.[14] We then calculate the share of firm i's establishments in counties located in the hurricane's landfall region. 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. Similar to the forecast 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. With larger radii, the average intensity of impact on firms decreases but the number of treated firms and their exposure increases. Figure 2(b) depicts a stylized example of how the $LandfallRegionExposure$ variable is computed, with the shaded red squares being counties in L_{R,T_h}.

3.3 Baseline estimation strategy

We employ a differences-in-differences framework to estimate the uncertainty dynamics surrounding hurricanes. We jointly estimate the treatment effect across all hurricanes, where each hurricane landfall or forecast yields a separate treatment. 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 a hurricane serve as the controls for that event. 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. The pre-treatment period is T_h^*, the trading day before hurricane inception.[15] For the hurricane forecast analysis, the post-treatment period is Γ days before landfall or dissipation, while it is τ days after landfall for the hurricane landfall analysis.

We examine how hurricane forecasts affect implied volatilities of firms located in the path of a

[14] Alternative data that could be used to determine the landfall region of a hurricane, for example, county level damages, are only published by agencies like the Federal Emergency Management Agency with a substantial time lag of at least several months.

[15] 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, which are only used in the post-landfall analysis, we do not have hurricane forecast data available and choose as inception day the first day that the hurricane appeared as a tropical depression.

hurricane by estimating the following firm-hurricane panel regression model

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

Here, each hurricane enters the regression as a separate time period. 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. $ForecastExposure_{i,P,T_h-\Gamma}$ is our continuous treatment variable that ranges from 0 to 1, as defined in equation (7). We include hurricane fixed effects (π_h), which is equivalent to including time fixed effects because each hurricane has one distinct time period in each regression. We include industry fixed effects (ψ_{Ind}) based on firm two-digit SIC numbers. 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)).

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 have missing implied volatility estimates for more than 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.

Prior to landfall, the higher implied volatility of 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 reflect impact uncertainty. We isolate and estimate impact uncertainty by examining 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 firm-hurricane panel regression model, where again each hurricane enters the regression as a separate time period

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

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. Because this regression is estimated up to long periods post landfall (for large values of τ), we exclude firms that have been hit by a hurricane from the control set of other hurricanes that occur within 180 calendar days to avoid distortions due to overlapping.[16] A positive and significant $\lambda_{L,R,\tau}$ reflects impact uncertainty in the aftermath of a hurricane.

4 Data and summary statistics

Our analysis uses data from a range of sources. We combine NOAA data on wind speed forecasts and realized storm tracks 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. Figure 3 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. The NHC publishes hurricane forecast charts and text advisories, both produced from the same underlying hurricane forecast models, which are used in real-time by news outlets in the run-up to hurricanes and stored in NOAA's hurricane archives.[17]

We use these time-stamped text files from the NOAA website which contain the probabilities that a given set of locations, for example, Norfolk, VA, will experience winds in excess of 34, 50,

[16] 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.

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

and 64 knots for a particular hurricane over the subsequent days. These forecast data are updated every six hours and available from 2007 to 2017. We obtain the forecasts just before market close for each trading day in our analysis. Our analysis is based on the forecasts for 64 knots, the minimum wind speed at which a tropical storm is considered a hurricane. 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 the set of locations that have reported probabilities of hurricane force winds above each probability threshold $P \in \{1, 10, 20, 30, 40, 50\}$, and match these locations to counties. Second, we add counties that are within a 75 mile radius of the counties identified in the first step.[18] Figure 4 illustrates a sample of processed wind speed data at different probability thresholds for Hurricane Sandy over a four day period. Table 1 Panel A lists the hurricanes included in our forecast sample. Further details 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 collected from forecast advisory files from the NOAA hurricane archives to develop firm-specific exposure to hurricane landfall regions. These data show the actual location and intensity 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 a county to be in the hurricane landfall region if it is located within a given radius of the hurricane's eye within 24 hours before and after the hurricane makes landfall.[19,20] We use county centroids to generate the sets of counties that lie within 50, 100, 150, 200 miles of the eye of each hurricane. 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. Figure 5 shows which counties fall within each set for hurricanes Katrina (2005), Sandy (2012), Matthew (2016), and Harvey (2017). Table 1 Panel B lists the hurricanes included in our landfall region sample. Additional details are presented in the Online Appendix.

[18] The results presented in the paper are robust to using other radii.

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

[20] Two hurricanes in the sample, Charley 2004 and Katrina 2005, made two landfalls in the US. To avoid double-counting with these two hurricanes, we use as the landfall date, the date when the hurricane made landfall at a higher storm strength on the Saffir-Simpson scale.

Importantly, these data are published by NOAA in real-time. Therefore, investors have access to the information on the landfall region of a hurricane as soon as it makes landfall. Other papers have used damaged counties to discern which firms were affected by natural disasters (for example, Barrot and Sauvagnat (2016) and Dessaint and Matray (2017).) In our setting, doing so would introduce a forward-looking bias because investors do not know at the time of a hurricane landfall which counties will experience damage from a hurricane. County-specific damage data only become available with a substantial lag of at least several months.

4.3 Firm establishment, option, and stock data

We use NETS firm establishment location data to precisely estimate a firm's exposure to each hurricane. These data have 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.[21] For each hurricane season, we use firm geographic footprints from the previous year to avoid the possibility that we will miss establishments closed during the year. Because our NETS data extend only through 2014, we use the 2014 geographic footprint for 2016 and 2017, in addition to 2015. Figure 6 shows the number of establishments per county sorted into deciles using the NETS data for 2010 and 2014. This map illustrates that economic activity as measured by the density of firm establishments is high in areas prone to hurricanes along the Atlantic 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 generally 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,

[21] 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 and is shown in the Online Appendix.

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 for firm i stock, which satisfy the above six criteria and N is the number of valid options for firm i with that expiry.

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 7 percent of their establishments in a hurricane landfall region, with a large number of firms having zero exposure as indicated by the 25$^{\text{th}}$ percentile. On average, a firm has 107 establishments in a given year. For 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, the firms that were "hit" at least once, 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 compared to \$4.5 billion of the total sample. The summary statistics of the option measures are similar 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 landfall or dissipation and price in landfall and expected impact uncertainty, as predicted by our framework. 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. The total sample of hurricanes used in the analysis is listed in Table 1 Panel A. 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.[22] 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 in the sample for the regression for 1% probability and 4 days before landfall and vice versa. For each regression, the table reports the total number of firm observations with a forecast-exposed establishment share of greater than 0% and at least 20%. The higher the probability threshold, the smaller the number of firms with a given exposure to the forecast path because the region covered by the forecast path becomes smaller as the probability increases, as illustrated in Figure 4 using the forecast data for Hurricane Sandy.

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 to 21.[23] This implies that a firm with all its establishments located in the path of a hurricane sees an increase in its implied volatility of 21 percent. The results in Panel B, for specifications including time and industry fixed effects interacted with each other, show qualitatively similar estimates. The coefficients are positive and increases with the probability threshold. The changes to implied volatility represent substantial increases in hedging costs. 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

[22]We require a sample to include at least three hurricanes and 25 firm-storm observations with $ForecastExposure_{i,P,T_h-\Gamma}$ greater than or equal to 25 percent.

[23]The results for the 30% threshold are omitted to ensure readability of the table, but they are in line with the reported results.

impact uncertainty should be priced in before hurricane landfall. The empirical estimates confirm that uncertainty generally increases with the probability of landfall as predicted in Figure 1. Also, these increases in implied volatilities are not driven by the underlying stock pricing in expected damage. While at the *aggregate* stock index level, volatility is known to increase when returns decrease, the relationship changes at the *individual* stock level. At the individual stock level, contemporaneous returns and volatility are positively correlated (see Duffee (1995); Albuquerque (2012); Grullon, Lyandres, and Zhdanov (2012)).

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 on 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)). In this context, the strong evidence of investors paying attention to hurricane forecasts documented in this paper is not necessarily a given. Potentially, 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.[24] For each regression, the table reports 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

[24] A more detailed industry analysis is presented in Section 6.1.

increases, that is, as the landfall region becomes larger, the number of firms with a given exposure to the landfall region also increases. Table 1 Panel B lists the hurricanes included the sample.

Table 4 shows that the $\lambda_{L,R,\tau}$ estimates are positive and significant across a range of radii and fixed effect choices. 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 100 percent exposure to the landfall region will see its implied volatility increase by 31 percent. These are substantial magnitudes of impact uncertainty. Section 5.3 discusses the economic significance of these estimates in detail.

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. While this result points to a slightly delayed reaction of investors to the hurricane landfall, the differences between the 5 and 30 trading days estimates are mostly insignificant.

In Figure 7, 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 trading days after landfall, τ, and radius around the storm epicenter, 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, the estimate of $\lambda_{L,R,\tau}$ increases until 30 trading days post landfall at which point it reaches about 30. Thereafter, the implied volatility effect gradually decreases until it becomes insignificant around 80 trading days (4 months) after landfall based on 95% confidence bands. 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.

A potential concern with our specification is whether our results are driven by small firms. However, as reported in Table 2, relative to the total sample, 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 a comparable, if slightly higher, average market capitalization. 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 firm exposure to 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. The higher the implied volatility of an option, all else equal, the higher the option premium (the price of the option), reflecting increasing costs to hedging. We use our regression coefficient estimates to compute how much hedging costs increase in the aftermath of a hurricane for investors of firms with exposure to the landfall region, if investors were to hedge 100% of the equity of exposed firms. After hurricane landfall, the total additional cost of hedging the impact uncertainty over our sample period would have been as high as 34 to 53 billion U.S. dollars in 2017 inflation-adjusted terms.[25] This magnitude is considerable, representing up to 9 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). Importantly, we likely underestimate the total costs of hedging the uncertainty caused by a hurricane as we drop firms from our sample due to insufficient data, as described in Section 4. Our estimates show that uncertainty itself can lead to substantial costs associated with hurricanes. Conventional damage estimates, as those published by NOAA, that ignore these types of costs may significantly understate the true economic cost of extreme weather events.

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

[25] These values are based on IV change coefficient estimates for the landfall region of 200 mile radius around the eye of the storm, as shown in Table 4, of 5.444 and 8.515 for 5 and 30 trading days post landfall, respectively. These estimates are multiplied by the average IV level of the firms, 0.48, to obtain the percentage point change in IV for a fully exposed firm. This in turn is multiplied by the average $LandfallRegionExposure_{i,R,T_h}$ for a firm in the landfall region, 0.15. To obtain the increase in the option premium, we multiply this average increase in implied volatility by the average vega of the same options, $0.034, where the option vega is defined as the change in option premium for a 1% change in implied volatility. Finally, we multiply the average premium increase for one option of an exposed firm by the total number of shares outstanding of the exposed firms (2,237.6 billion in total for the period) to obtain the total increase in hedging costs in dollars. The values are inflation-adjusted to 2017 dollars.

consequences. Other types of uncertainty have been shown to affect decision making of economic agents. For example, uncertainty around political elections and events is estimated to be large (see Kelly, Pastor, and Veronesi (2016)) and causes firms to reduce investments as shown in Julio and Yook (2012), Jens (2017), and Kim and Kung (2017). Based on our estimates, which show that extreme weather uncertainty is large and long lasting, extreme weather uncertainty could have similar effects. 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 due to a hurricane that has made landfall in regions of interest.

6 Robustness and extensions

In this section, we present analyses on the robustness of our main results and several extensions.

6.1 Robustness

This section contains key robustness tests for the main results. Additional robustness tests can be found in the Online Appendix. One question that may arise is whether the uncertainty caused by hurricanes varies substantially across industries. To get at this question, we test whether our baseline post-landfall results are driven by a particular industry. 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. Building on equation (10), an industry-specific interaction term is added as follows

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

where $I_{i \in Industry_g}$ indicates whether firm i is in $Industry_g$, the industry being examined. We estimate this regression separately for each the industry, varying the interacted industry dummy. The analyzed industries are construction, manufacturing, mining, retail, services, transportation, and wholesale industries based on a firm's two-digit SIC number.[26] 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 where we include an interaction dummy variable for that industry.

In Table 5, we present our results for the 200 mile radius[27] 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 strongly 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 estimated by NOAA, as shown in Table 1. We want to test if our results are solely driven by these hurricanes. The results when these three hurricanes are excluded 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 gets weaker as the radius around the eye of the hurricane used to define the landfall region is increased.

We present additional robustness tests in the Online Appendix. In particular, we show that our baseline results on uncertainty before and after landfall are robust to measuring firm exposure to hurricanes based on county-level sales rather than locations of establishments. Further, we show the baseline results when excluding individual hurricanes other than Katrina (2005), Sandy (2012),

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

[27] This ensures that we have a reasonable number of firms in each industry with a large exposure to hurricane landfall regions. However, the results are qualitatively similar when using smaller radii.

and Harvey (2017).

6.2 The returns to trading options at landfall

A natural question arising from our results showing how option markets react to a firm's exposure to hurricanes is whether these price effects indicate investor overreaction or underreaction. If an investor trades a portfolio of options on hurricane-treated firms at landfall, would such a portfolio generate significant returns compared to a contemporaneous portfolio of options on a set of control firms with no exposure to the hurricane event? In this section, we present the difference-in-differences results to answer this question.

In principle, this is an event study with multiple observations (multiple hurricane landfalls) similar in spirit to studies that examine post-earnings announcement stock returns. However, the current setting has several distinctive features and challenges we address through our research design. Unlike stocks or even index options, most single-stock options do not necessarily have quoted prices daily. Options that are closer to at-the-money and nearer to maturity have greater open interest, are relatively more liquid and therefore have more reliable prices. We take this into account by trading the available options that are closest to at-the-money and maturity and holding them until expiration (similar to Hu and Jacobs (2019); Goyal and Saretto (2009)). This buy-and-hold strategy ensures that if, after trading, an option becomes deeper in-the-money or out-of-the-money due to price changes in the underlying stock, we are still able to measure the returns to such options in our portfolios without having to drop such observations due to a lack of quoted prices. We address the concern that option moneyness and time to maturity affect options returns (see, for example, Coval and Shumway (2001)) by comparing option returns within the same moneyness and time-to-maturity ranges in our difference-in-differences analysis. We address concerns regarding similar sources of potential noise or bias in option price and return data by estimating the *difference* between the returns of a treated and a control set of options. As long as a particular feature of option returns does not differentially affect options in the treated set versus those that are in the control set, i.e., as long as that data feature is not correlated with treatment selection, that data feature should not drive our results. Finally, we minimize the impact of noise (and thus attenuation bias) by filtering the option data inline with existing literature as described in section 4.3.

We calculate the returns to trading portfolios of delta-neutral straddles in the nearest-to-maturity expiry for each firm.[28] A delta-neutral straddle is commonly used to obtain a long position on the implied volatility of the underlying stock, with little directional exposure to underlying price movements.[29] The straddles are formed by trading the call that is nearest to at-the-money and the number of puts with the same maturity that make the portfolio delta neutral. As in Muravyev (2016), the number of puts in a straddle portfolio is $\delta_{call}/abs(\delta_{put})$. Trades are made at the mid prices available from OptionMetrics at the first market close after hurricane landfall.[30] The straddle payoff at expiration (*Payoff*) is calculated using the closing price of the underlying stock obtained from OptionMetrics. Options that expire out-of-the money have a payoff of 0.[31] We compute the returns to each straddle position using mid prices as $StraddleReturn = (Payoff - StraddlePrice)/StraddlePrice$. We estimate the difference between hit and control portfolio returns by estimating the regression jointly over all hurricanes in the sample,

$$StraddleReturn_{i,h} = \kappa IsHit_{i,h} + \pi_h + \psi_{Ind} + \epsilon_{i,h}, \tag{12}$$

where $IsHit_{i,h}$ is 1 if a firm is exposed to the hurricane, 0 otherwise. $IsHit_{i,h}$ is specified as a dummy variable in this regression rather than a continuous variable, so that the regression captures the return difference between buying option straddles on the treated versus control firms. We show results with different thresholds to including a firm in the hit set, varying both the radius around hurricane landfall and the exposed establishment share. A negative (positive) and significant κ would generally correspond to investors overreacting (underreacting) at hurricane landfall by overpricing (underpricing) stock options, yielding significantly lower (higher) returns compared to options on the control firms. In contrast, if κ is zero (insignificant) this would indicate that the treated option prices adjust to a level immediately following landfall such that the expected option returns between the treated and control firms are not significantly different and there is no

[28] The calendar days to expiry when an option is traded is greater than 7 and at most 45.

[29] See, for example, Coval and Shumway (2001); Goyal and Saretto (2009); Muravyev (2016); Hu and Jacobs (2019); Muravyev and Pearson (2019).

[30] We separately analyze the returns to a long (short) straddle position if one were to trade at the best ask (best bid), since the bid-ask spread can be significant for options. However, these return measures do not obtain significantly different results. For brevity, we show the regression results using bid-ask prices in the Online Appendix.

[31] As in Hu and Jacobs (2019), if the market is closed on the Friday of the expiration date, we use the closing price of the most recent prior trading date.

opportunity for investors to profit in expectation on a hurricane option trading strategy. As before, π_h is a hurricane fixed effect which is equivalent to a time fixed effect as there is at most one buy-and-hold return observation per firm per hurricane.

Table 7 shows the κ estimate for regressions with different thresholds at which a firm is considered "hit". We do not find any evidence of overreaction in option prices. The κ estimates show evidence of correct option price adjustments to the hurricane event and if anything, a slight underreaction in a few cases, as the coefficients are positive though mostly insignificant. The size of the coefficients generally increase as the conditions for inclusion in the treated set tighten: as the radius around hurricane landfall decreases and as the firms' exposed establishment share threshold increases.

6.3 Insurance firms

The analysis and discussion so far have 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. In this section, we also investigate if extreme weather uncertainty is indeed 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 by state and not by county.[32]

We use data on insurance statutory financials from S&P Global Market Intelligence, which provides us with the share of total premiums in each state written by property and casualty insurance firms in the US. We estimate the regression in equation (10) for these property and casualty insurance firms, with $LandfallRegionExposure_{i,R,T_h}$ 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. A state is considered to have experienced a hurricane landfall in Panel A (B), if at least 10% (25%) of the counties of that state were within a given radius of that hurricane's eye. For smaller radii, fewer hurricanes are included in the sample, because certain

[32]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.

hurricanes do not reach the required threshold of hit counties (10% or 25%) in any state.

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 higher for insurance firms with a 100 percent exposure to the landfall region of the hurricane. The magnitude of the coefficient tends to decrease for larger radii 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 and the economic exposure of insurance firms is observed at a lower state-level granularity, as opposed to county-level.

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 as they form and develop, 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.[33] Figure 8(a) shows that there is significant variation in the probabilities reported in these pre-season outlooks.

We test if the options with a longer time to expiration, 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 a longer expiry are chosen because they cover the majority of the hurricane season. We use two methods to the determine counties that could be hit by a hurricane during the hurricane season and construct firm-level variables capturing exposure to a hurricane season. The first method simply uses coastal counties from the Atlantic and Gulf coasts as the set of counties that could reasonably be exposed to a hurricane in any given hurricane season

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

($CoastalExposure_{i,T_s}$). The second method relies on historical landfall regions over the preceding 30 years and computes the annual probability with which a county ends up in the landfall region of a hurricane ($HistoricalHurricaneExposure_{i,T_s}$). In the Online Appendix, we provide further detail on the counties included in each method.

For the first method, the regression specification is given by

$$
\begin{aligned}
log\left(\frac{IV_{i,T_{s+5}}}{IV_{i,T_{s-1}}}\right) =& \lambda_{S,1} CoastalExposure_{i,T_s} + \lambda_{S,2} CoastalExposure_{i,T_s} \times AboveNormalSeasonProb_{T_s} \\
&+ \pi_{T_s} + \psi_{Ind} + \epsilon_{i,T_s}, \qquad (13)
\end{aligned}
$$

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.[34] The regression jointly estimates the effect of the seasonal outlooks for the years 2001 to 2017. Following the methodology in equations (7) and (8), $CoastalExposure_{i,s}$ 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. Under the second method of measuring seasonal exposure, we replace $CoastalExposure_{i,s}$ in equation (13) 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. The variable $AboveNormalSeasonProb_s$ is the probability NOAA issues in May of a given year for an above average hurricane season. 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.[35]

Table 9 presents the estimates of equation (13). Panel A shows the results for the specification using $CoastalExposure_{i,s}$, and Panel B uses $HistoricalHurricaneExposure_{i,s}$. 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

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

[35] 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.

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.

Our main results in Section 5.1 established that investors pay close attention to NOAA's forecast of hurricane paths. Then, what might explain investors not paying attention to seasonal forecasts? Potentially, this is because NOAA's seasonal forecasts are not as accurate. The scatter plots in Figure 8(b) show only a weakly positive relationship between the seasonal outlooks and the number of hurricanes making landfall in a given year. Another reason that we cannot rule out is that investors pay no attention to seasonal forecasts because they are medium term and lack the immediacy of the hurricane path forecasts. Investors being inattentive to medium term forecasts would question their ability to correctly price in other climate related long-term risks.

6.5 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 when this volatility is realized.

We first estimate daily abnormal returns relative to the Fama-French five-factor model (see Fama and French (1993) and Fama and French (2015)). For each firm and each hurricane in our sample, the following model is estimated:

$$r_{i,d} = \alpha_i + \beta_{1,i} r_{m,d} + \beta_{2,i} r_{smb,d} + \beta_{3,i} r_{hml,d} + \beta_{4,i} r_{rmw,d} + \beta_{5,i} r_{cma,d} + \epsilon_{i,d}, \tag{14}$$

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. The coefficient estimates from this first stage regression are then used to compute abnormal returns for each firm and hurricane as follows:

$$r_{i,d}^{a} = r_{i,d} - (\hat{\alpha}_i + \hat{\beta}_{1,i} r_{m,d} + \hat{\beta}_{2,i} r_{smb,d} + \hat{\beta}_{3,i} r_{hml,d} + \hat{\beta}_{4,i} r_{rmw,d} + \hat{\beta}_{5,i} r_{cma,d}). \tag{15}$$

We next aggregate the abnormal simple returns to a cumulative abnormal return, denoted $r_{i,T_h^*:T_h+\tau}^{ac}$, 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 post landfall. 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 up to 120 trading days (6 months) after landfall for all the firms and a given hurricane and subtract the contemporaneous mean cumulative abnormal return across all stocks to account for correlated shocks 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 (from June to November), and thus, we avoid overlaps with the subsequent year's hurricane season.

All the firm-hurricane observations are split into two groups. 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 10 along with the corresponding t-stats.[36] For the landfall region based on the 50 mile radius around the eye of the hurricane, the bottom two percentiles of the hit 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 hit and control firms that while mostly negative are generally insignificant. This result holds also for wider radii and imply that in the aftermath of a hurricane, there are some

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

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.

Figure 9 illustrates these results at 120 trading days graphically, and also shows the same difference in cumulative abnormal returns between firms hit by a hurricane and control firms at shorter post landfall horizons of 5, 10 and 60 trading days (1 week, 2 weeks and 3 months).[37] These plots show that as time passes, the cross-sectional dispersion increases for the hit firms compared to the control firms. The lower percentiles of the hit firms underperform more in the longer term, after 60 or 120 trading days, than in the near term, after 5 and 10 trading days.

These results are consistent with the substantial estimates of impact uncertainty presented in our baseline results. Investors appear to be uncertain about the impact of a hurricane on firms in the landfall region and this manifests itself in large increases in implied volatilities. In the long-run, the implied volatilities come back down as the effect on the firms becomes clearer, with some firms being severely negatively affected and others largely unaffected.

7 Conclusion

Little is currently known about extreme weather uncertainty. This paper isolates and estimates extreme weather uncertainty around hurricanes through the lens of financial markets. 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 our framework and 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 volatility 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. These increases in the implied volatility of option prices reflect large costs to hedging the uncertainty associated with hurricanes.

[37] The Online Appendix contains tables that are structured as Table 10 and presents the regression estimates for post landfall time horizons shorter than 120 trading days.

Our novel analysis and framework contribute to a burgeoning climate finance and uncertainty literatures by showing that extreme weather uncertainty is significant and reflected in the prices of options and stock markets. Future research could apply our framework and methodology to further examine extreme weather uncertainty and build on the findings 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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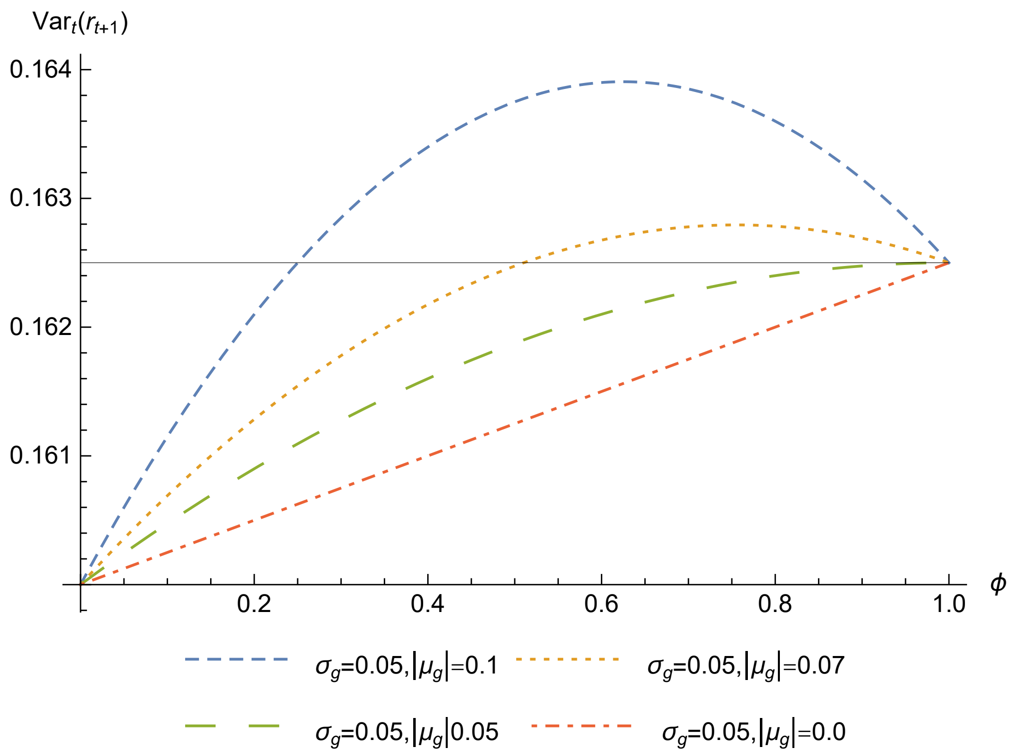
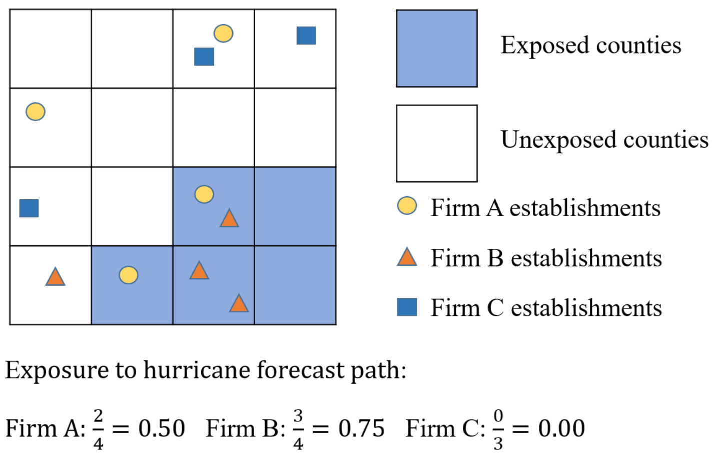
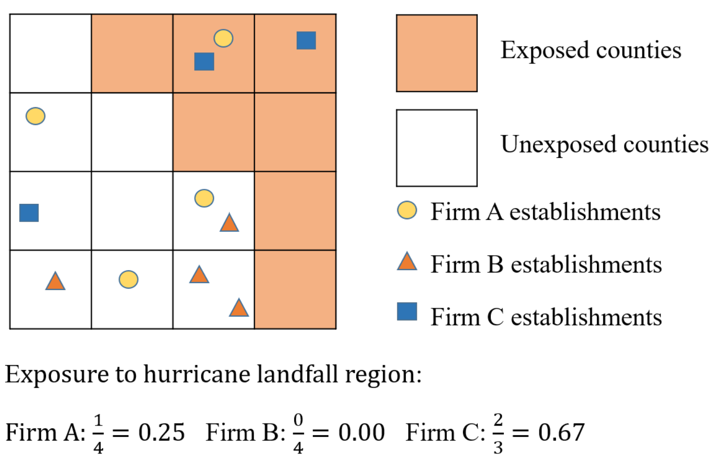


Figure 1: Expected variance as a function of the probability of hurricane landfall

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, respectively. The solid line shows the level of variance conditional on the firm being in the hurricane landfall region, $Var_t(r_{i,t+1}|\theta = 1) = \sigma^2 + \sigma_g^2$, as defined in equation (3).



(a) Hurricane forecast



(b) Hurricane landfall region

Figure 2: Stylized example of firm exposure to hurricanes

Panel A shows the stylized example of firm exposure to a hurricane forecast based on the share of establishments located in counties in the forecast path. The firm exposures reflect the variable $ForecastExposure$ in our analysis. Panel B shows the stylized example of firm exposure to a hurricane landfall region based on the share of establishments located in counties in the landfall region. The firm exposures reflect the variable $LandfallRegionExposure$ in our analysis.

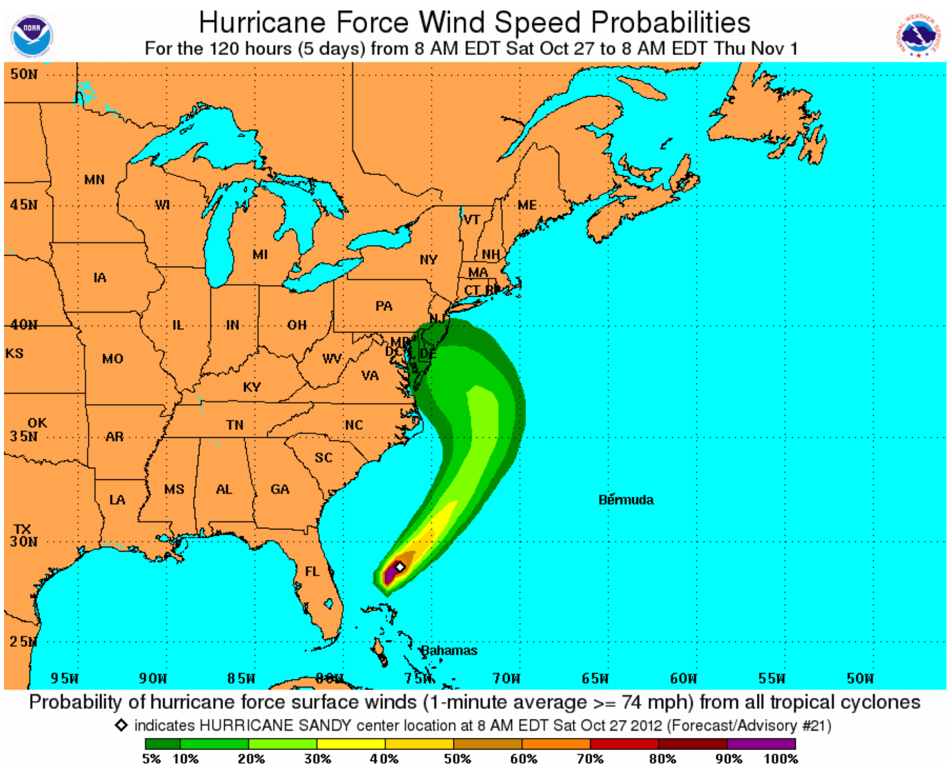


Figure 3: Example of a hurricane forecast

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.

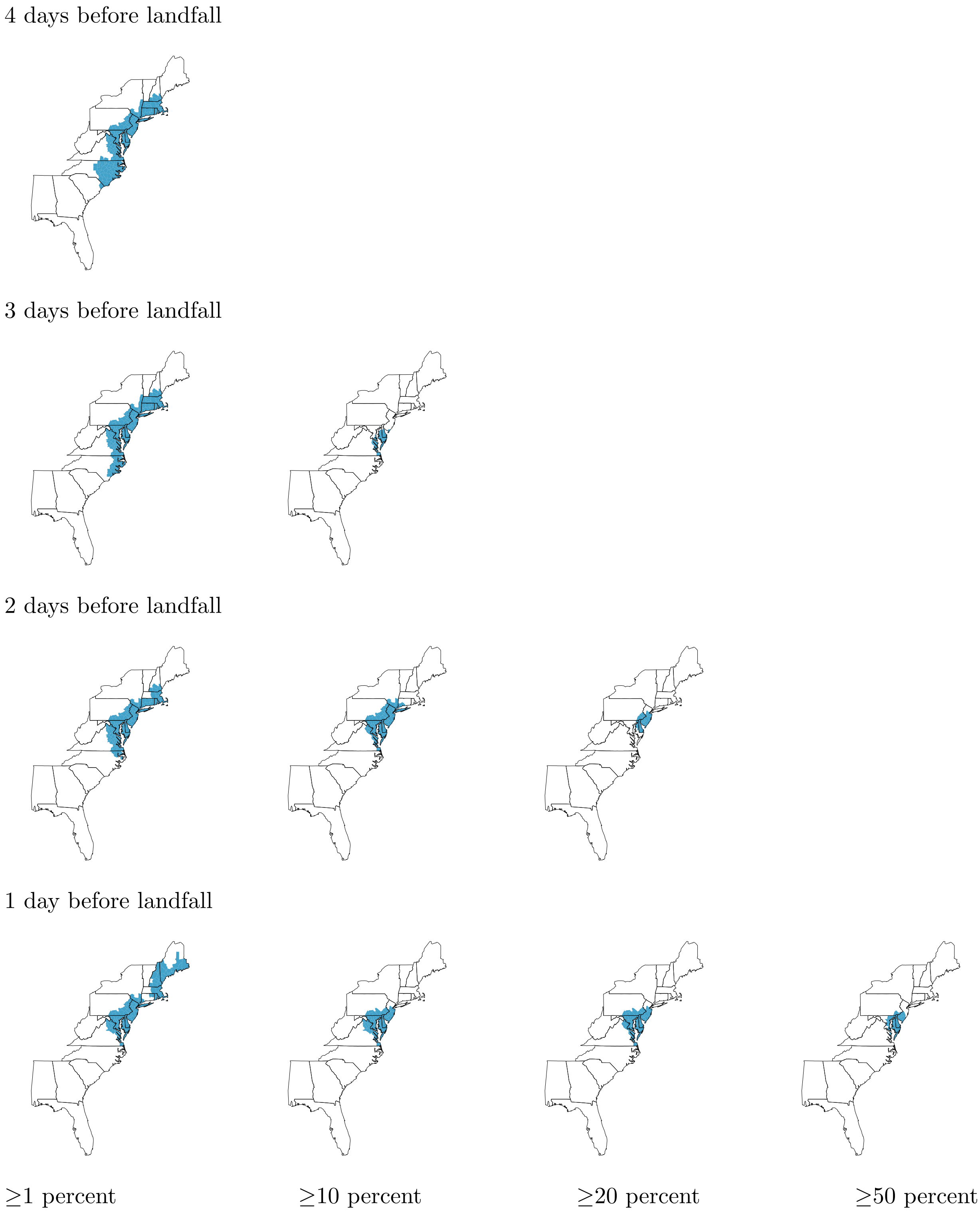
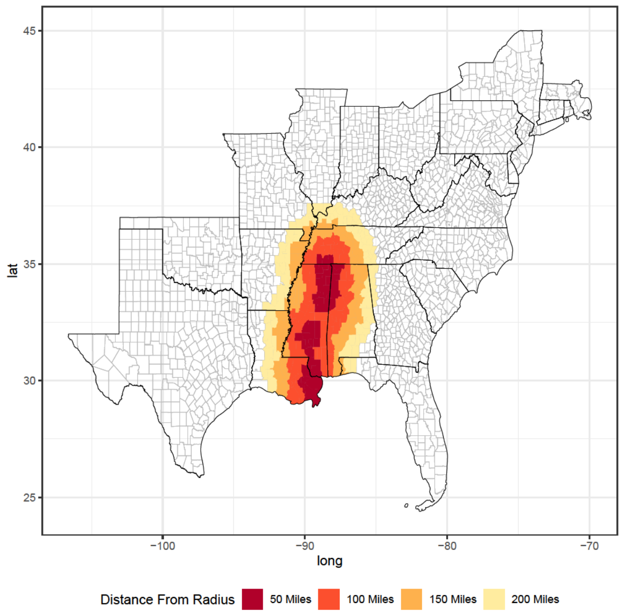
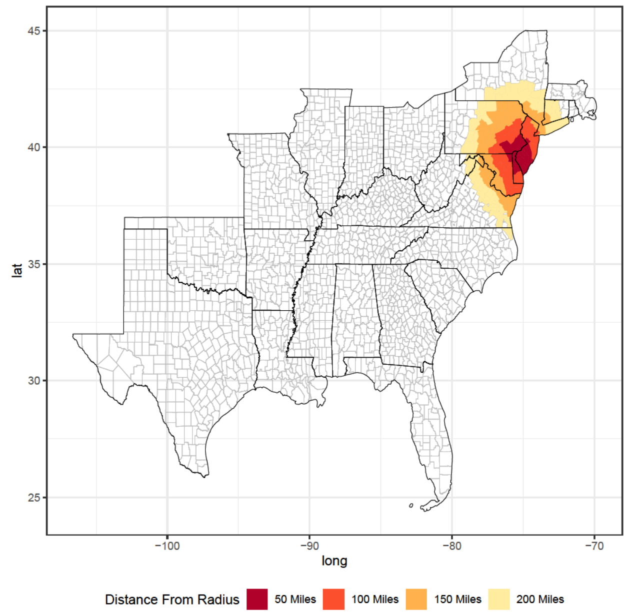


Figure 4: Hurricane forecasts at different time frames and wind speed probability thresholds

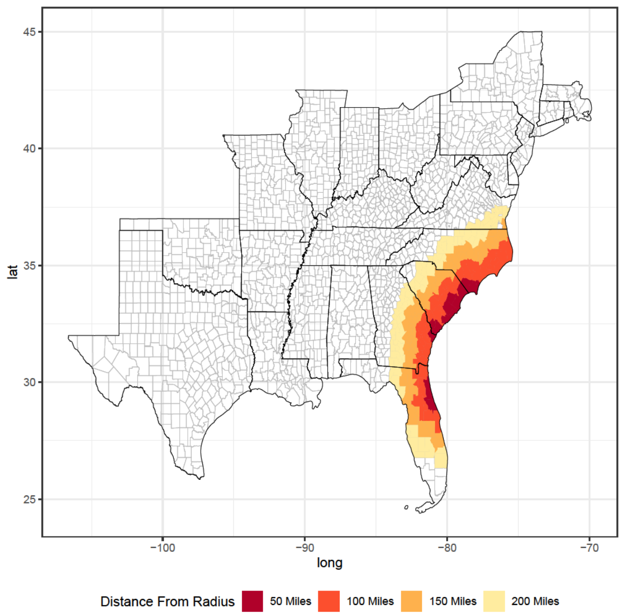
Each map shows the counties indicated as being in the forecast path for Hurricane Sandy given the number of days before landfall in each row and the wind speed probability threshold in each column. For each day, the last available forecast before 4pm (market close) is shown.



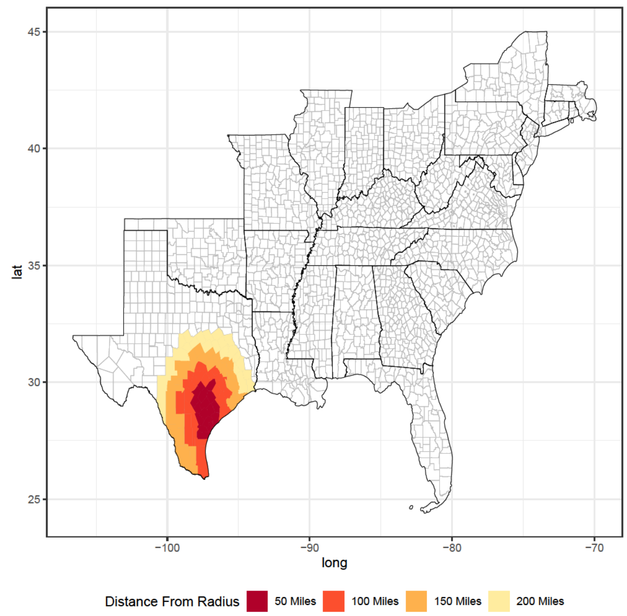
(a) 2005 Katrina



(b) 2012 Sandy



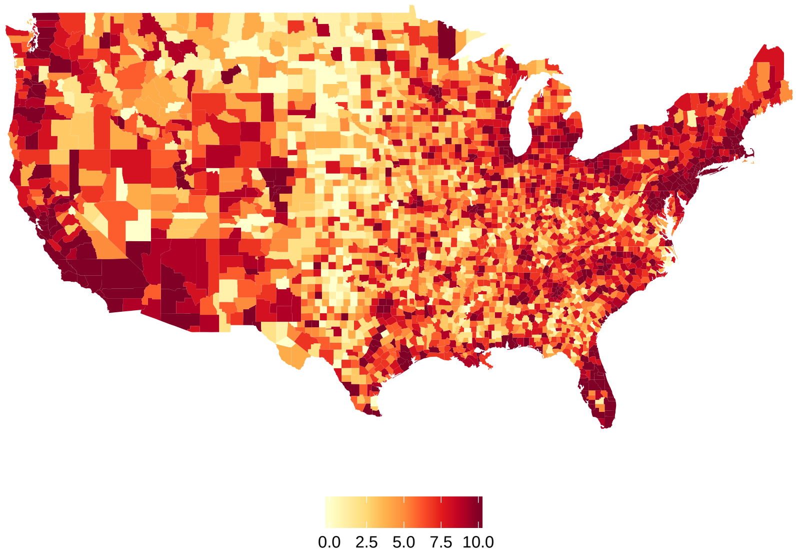
(c) 2016 Matthew



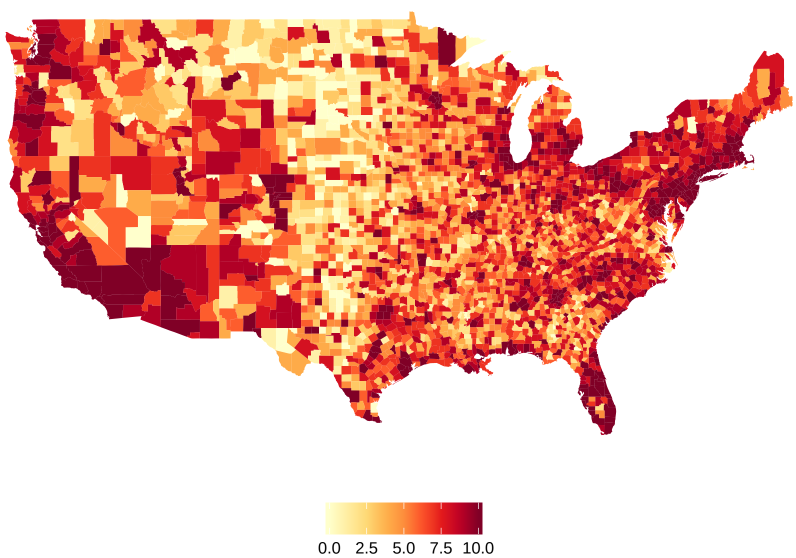
(d) 2017 Harvey

Figure 5: Counties in a hurricane landfall region

This figure highlights the counties that are within 50, 100, 150, and 200 miles of the eye of the hurricane at landfall for four hurricanes in our sample.



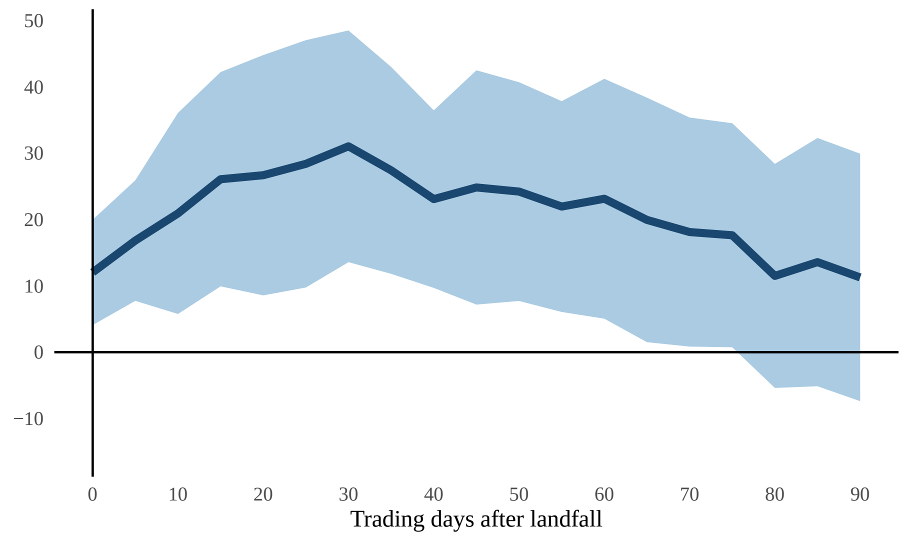
(a) Year 2010



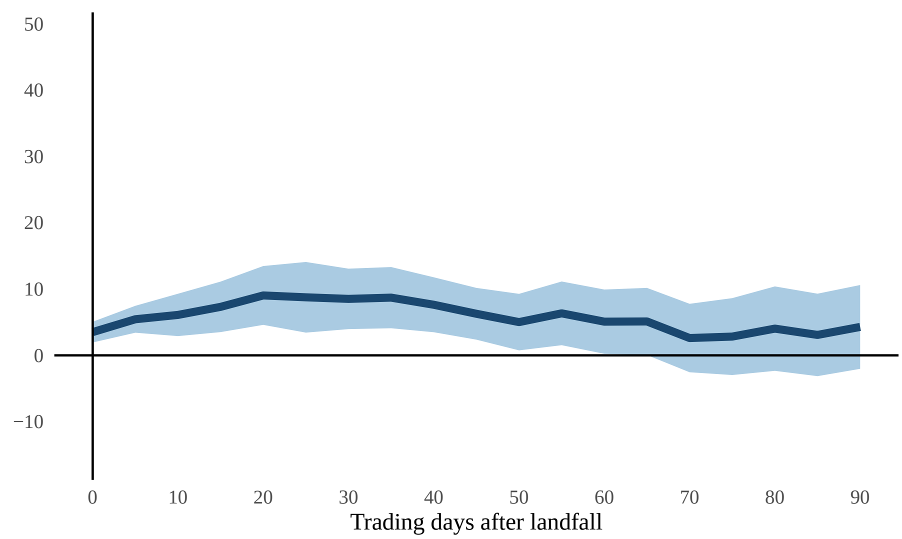
(b) Year 2014

Figure 6: Firm establishments by county

This figure plots counties based on the number of establishments located in that county for the years 2010 (Panel A) and 2014 (Panel B). Data are from the National Establishment Time Series and only firms in our sample included. The counties are sorted into deciles based on the number of establishments.



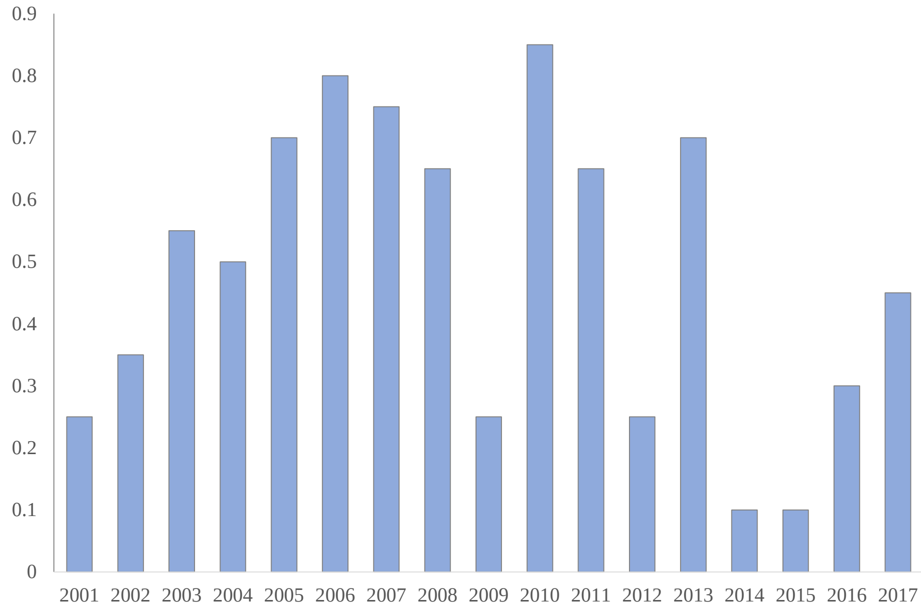
(a) 50 mile radius around eye of hurricane



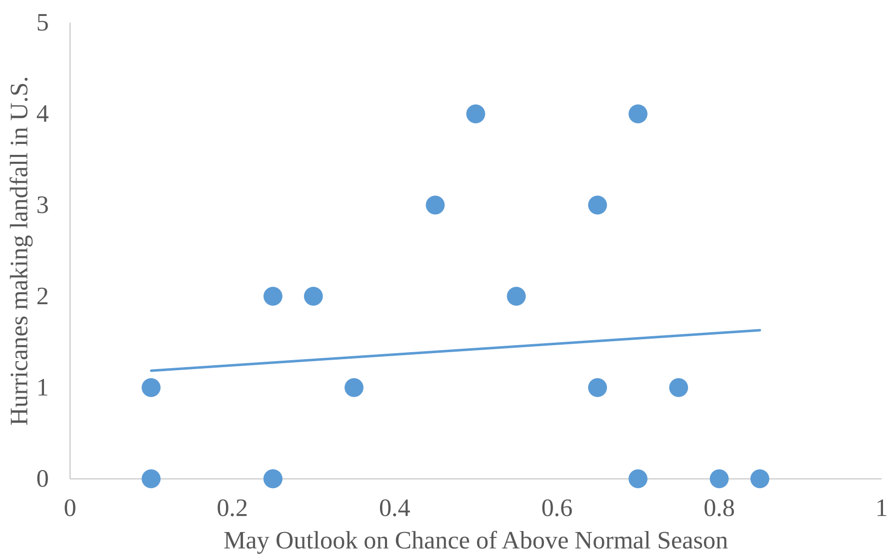
(b) 200 mile radius around eye of hurricane

Figure 7: 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. A 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 in Panel A and 200 mile radius around the eye of the hurricane in Panel B. Confidence bands of 95 percent are shown.



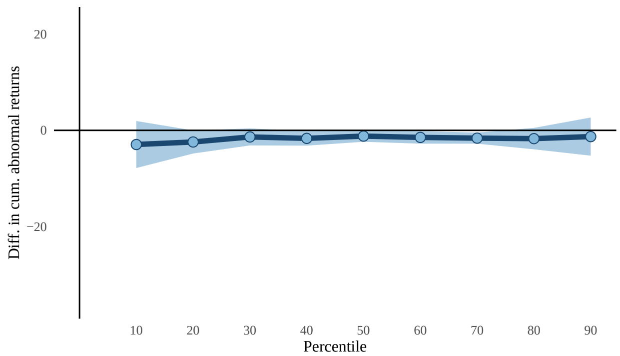
(a) Probability of above average hurricane season



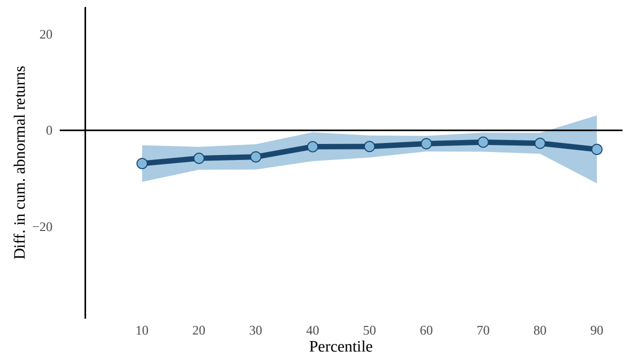
(b) Hurricane landfall count per year

Figure 8: NOAA's Atlantic and Gulf Hurricane Season Outlook

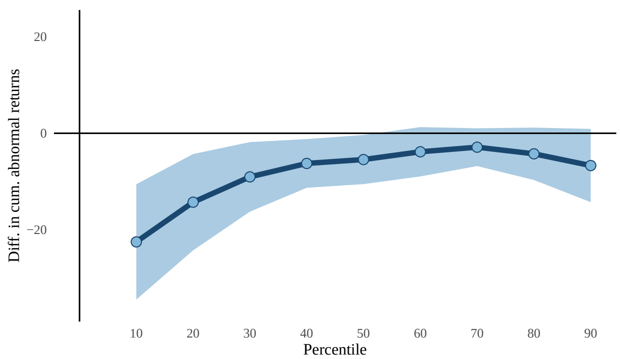
Panel A shows the probability of an above average hurricane season that NOAA issues each year in the May Outlook for the Atlantic and Gulf hurricane season. Whether a season is above average is based on the number of hurricanes that are predicted to form in the Atlantic Ocean and the Gulf. Panel B depicts the relationship between the season outlook and the number of hurricanes that make landfall for that season.



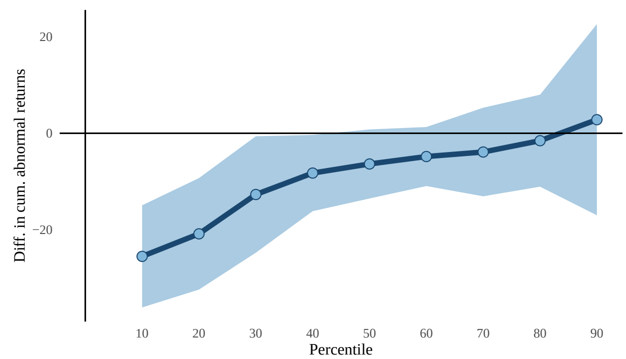
(a) 5 trading days (1 week) post landfall



(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 9: 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 (the hit firms) and firms with less than 25% of their establishments in the landfall region (the control firms). The difference between control and hit firms is shown for nine percentiles of the return distributions. 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.

Table 1: Hurricane sample

This table shows the hurricanes included in our analyses. Panel A, reporting the sample for the forecast analyses, includes storms that were at least once forecast to make landfall with hurricane force winds with a 1 percent probability or more. Because the forecasts include storms that never make landfall in the U.S., we indicate storms that make landfall with asterisks (*). The sample is from 2007 to 2017. Panel B shows the landfall and inception dates for storms that are included in the post-landfall analyses. The damage estimates shown 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. Landfall dates come from the Tropical Cyclone Reports. The sample is from 1996 to 2017.

Panel A: Hurricanes 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*
Humb.*	Edouard	Bill	Bonnie	Emily	Isaac*	Karen		Erika	Herm.*	Irma*
Noel	Fay	Danny	Earl	Irene*	Leslie			Joaquin	Matt.*	Jose
	Gustav*	Ida	Paula	Nate	Sandy*					Maria
	Hanna									Nate*
	Ike*									
	Kyle									
	Paloma									

Panel B: Hurricanes included in post-landfall analyses

Post-landfall analysis only				Forecast and post-landfall analyses			
Hurricane	Landfall	Inception	Damages 2017 $mn	Hurricane	Landfall	Inception	Damages 2017 $mn
Bertha	Jul. 12, 96	Jul. 5, 96	421	Humberto	Sep. 13, 07	Sep. 12, 07	N/A
Fran	Sep. 6, 96	Aug. 23, 96	4,994	Dolly	Jul. 23, 08	Jul. 20, 08	1,198
Danny	Jul. 18, 97	Jul. 16, 97	153	Gustav	Sep. 1, 08	Aug. 25, 08	5,271
Bonnie	Aug. 27, 98	Aug. 19, 98	1,085	Ike	Sep. 13, 08	Sep. 1, 08	33,692
Earl	Sep. 3, 98	Aug. 31, 98	119	Irene	Aug. 27, 11	Aug. 21, 11	17,258
Georges	Sep. 28, 98	Sep. 15, 98	9,594	Isaac	Aug. 29, 12	Aug. 21, 12	2,514
Bret	Aug. 23, 99	Aug. 18, 99	89	Sandy	Oct. 30, 12	Oct. 22, 12	53,481
Floyd	Sep. 16, 99	Sep. 7, 99	10,184	Arthur	Jul. 4, 14	Jul. 1, 14	2
Irene	Oct. 15, 99	Oct. 13, 99	1,181	Hermine	Sep. 2, 16	Aug. 28, 16	562
Lili	Oct. 3, 02	Sep. 21, 02	1,264	Matthew	Oct. 8, 16	Sep. 28, 16	10,215
Claudette	Jul. 15, 03	Jul. 8, 03	240	Harvey	Aug. 26, 17	Aug. 17, 17	125,000
Isabel	Sep. 18, 03	Sep. 6, 03	7,175	Irma	Sep. 10, 17	Aug. 30, 17	50,000
Charley	Aug. 13, 04	Aug. 9, 04	19,661	Nate	Oct. 8, 17	Oct. 4, 17	225
Frances	Sep. 5, 04	Aug. 25, 04	12,368				
Ivan	Sep. 16, 04	Sep. 2, 04	24,483				
Jeanne	Sep. 26, 04	Sep. 13, 04	9,965				
Dennis	Jul. 10, 05	Jul. 4, 05	3,202				
Katrina	Aug. 29, 05	Aug. 23, 05	135,894				
Rita	Sep. 24, 05	Sep. 18, 05	15,146				
Wilma	Oct. 24, 05	Oct. 15, 05	26,433				

Table 2: Firm establishment and option summary statistics

This table reports the summary statistics for the firms included in our sample 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 (using 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^{th} percentile	25^{th} percentile	50^{th} percentile	75^{th} percentile	90^{th} percentile
Establishments per firm	All firms	106.847	411.645	1.000	2.000	9.000	49.000	199.000
	Hit firms	115.958	419.809	1.000	3.000	11.000	55.000	216.000
County presence per firm	All firms	47.973	131.356	1.000	1.000	6.000	32.000	117.000
	Hit firms	49.977	134.683	1.000	2.000	8.000	34.000	123.000
Market cap. (billion $)	All firms	4.524	19.588	0.076	0.217	0.684	2.244	7.617
	Hit firms	5.341	22.741	0.092	0.265	0.839	2.673	9.065
$IV_{i,t}$	All firms	0.485	0.276	0.223	0.300	0.417	0.595	0.827
	Hit firms	0.477	0.268	0.222	0.298	0.412	0.585	0.808
$log(IV_{i,t}/IV_{i,t-1})$ (daily in %)	All firms	0.136	11.511	-9.862	-3.953	0.038	4.201	10.424
	Hit firms	0.129	11.198	-9.667	-3.905	0.024	4.116	10.222
Days to expiry$_{i,t}$	All firms	36.598	32.665	11.000	17.000	28.000	39.000	82.000
	Hit firms	35.374	31.217	10.000	17.000	26.000	38.000	75.000
Total open interest$_{i,t}$	All firms	1,920.052	6,869.582	13.000	50.000	233.000	1,134.000	4,270.000
	Hit firms	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 firm-hurricane 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. Hurricanes for which Γ days before landfall or dissipation falls on a non-trading day are excluded. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, in terms of fraction of establishments, is in counties located in the forecast path of a hurricane. The forecast path of the hurricane is from NOAA and gives a minimum 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 $\times$ 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 $\times$ 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, in terms of fraction of 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 $\geq 20\%$	157	157	633	633	1,302	1,302	2,133	2,133
Total firm obs. with exposure $\geq 50\%$	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 $\geq 20\%$	158	158	640	640	1,309	1,309	2,141	2,141
Total firm obs. with exposure $\geq 50\%$	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 dummy 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, in terms of fraction of 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, $log\left(IV_{i,T_h+5}/IV_{i,T_h^*}\right)$

	Industry interacted with $LandfallRegionExposure_{i,R,T_h}$													
	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 $\geq$ 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 $\geq$ 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 based on NOAA estimates. 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, in terms of fraction of 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 $\geq 20\%$	129	129	538	538	1,053	1,053	1,841	1,841
Firm obs. with exposure $\geq 50\%$	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 $\geq 20\%$	130	130	542	542	1,056	1,056	1,847	1,847
Firm obs. with exposure $\geq 50\%$	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: Option return difference between hit and control firms

This table reports the coefficients and test statistics when estimating the panel model in equation (12). The dependent variable is the return (in percent) on a delta-neutral straddle formed the day of the landfall and computed for each firm in the sample as described in Section 6.2. The independent variable is a dummy variable that takes a value of 1 for hit firms and a value of 0 for control firms, which estimates the difference between holding a straddle on a hit firm versus a control firm. In Panel A, a hit firm has at least 10% of its establishments in counties located in the landfall region of a hurricane, and in Panel B the threshold is 25%. Control firms have no establishments in the counties located in the landfall region. 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 and the number of hit and control firms are reported. The data are from 1996 to 2017. Hurricanes with no firms in the landfall region for a given radius, that is, hurricanes without hit firms, are excluded from the analysis. 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 included. The time fixed effect is equivalent to a hurricane fixed effect as there is at most one buy-and-hold return observation per firm per hurricane in a particular regression. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Firm considered hit if establishment share in landfall region $\geq$ 10%

Dependent variable: Option return (in %)

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$IsHit_{i,h}$	36.848**	36.046*	11.447	11.691*	6.261	6.037	5.370	4.912
	(2.016)	(1.949)	(1.596)	(1.678)	(1.303)	(1.267)	(1.225)	(1.113)
Adjusted R^2 (%)	15.830	16.333	15.120	15.080	13.368	13.288	11.838	11.792
Total firm obs.	1,451	1,451	2,494	2,494	3,751	3,751	4,554	4,554
Firm obs. hit	130	130	508	508	1,042	1,042	1,669	1,669
Firm obs. control	1,321	1,321	1,986	1,986	2,709	2,709	2,885	2,885
Hurricanes	14	14	22	22	30	30	32	32
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Firm considered hit if establishment share in landfall region $\geq$ 25%

Dependent variable: Option return (in %)

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$IsHit_{i,h}$	32.413	21.067	13.241	10.747	14.644	14.656	8.845	8.012
	(1.006)	(0.670)	(0.863)	(0.732)	(1.510)	(1.535)	(1.342)	(1.227)
Adjusted R^2 (%)	13.690	15.833	13.371	13.529	12.738	12.721	12.938	12.981
Total firm obs.	366	366	1,792	1,792	2,673	2,673	2,962	2,962
Firm obs. hit	31	31	178	178	374	374	598	598
Firm obs. control	335	335	1,614	1,614	2,299	2,299	2,364	2,364
Hurricanes	4	4	17	17	24	24	25	25
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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 insurance 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. Hurricanes that do not reach this threshold for any state are excluded. 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 at least 10% of its counties were in landfall region

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 $\geq$ 20%	17	50	107	149
Firm obs. with exposure $\geq$ 50%	7	12	24	34
Hurricanes	25	31	33	33
Time (Hurricane) FE	Yes	Yes	Yes	Yes

Panel B: State considered hit if at least 25% of its counties were in landfall region

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 $\geq$ 20%	6	22	55	93
Firm obs. with exposure $\geq$ 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 (13). The dependent variable is the change (in percent) in the implied volatility of firm i from the last trading day before NOAA's 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 $AboveNormalSeasonProbability_{T_s}$ is the probability which NOAA assigns to an above average hurricane season in terms of number of storms. In Panel A, the independent variable $CoastalExposure_{i,T_s}$ 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 $HistoricalHurricaneExposure_{i,T_s}$ measures the share of a firm's establishments (0 to 1) 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 historical 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	
$CoastalExposure_{i,T_s}$	1.315*	1.364*	0.998	0.956
	(1.850)	(1.857)	(1.309)	(1.194)
$CoastalExposure_{i,T_s}$ $\times AboveNormalSeasonProb_{T_s}$	-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. $\geq$ 0.05		Counties with prob. $\geq$ 0.1	
$HistoricalHurricaneExposure_{i,T_s}$	1.533**	1.457**	1.138	1.097
	(2.105)	(2.021)	(1.436)	(1.294)
$HistoricalHurricaneExposure_{i,T_s}$ $\times AboveNormalSeasonProb_{T_s}$	-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

Table 10: Long-run cumulative abnormal stock return differences

This table reports differences in cumulative abnormal stock returns post landfall for the mean and nine percentiles between hit firms and control firms as described in Section 6.5. 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. Hurricanes with no firms in the landfall region for a given radius, that is, hurricanes without hit firms, are excluded from the analysis. The standard errors are bootstrapped (for the percentiles only) 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

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

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1 Hurricane data

Our 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 the 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 ≥				
	1	10	20	40	50
Storms	49	17	14	9	9
County-days observations	14,988	2,093	913	414	335
Mean	305.878	123.118	65.214	46.000	37.222
Std. Dev.	402.974	121.418	61.541	25.822	25.932
Median	124.000	91.000	56.000	41.000	34.000

Panel B: Number of county-days forecast observations

Days to dissipation or landfall	Probability ≥				
	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

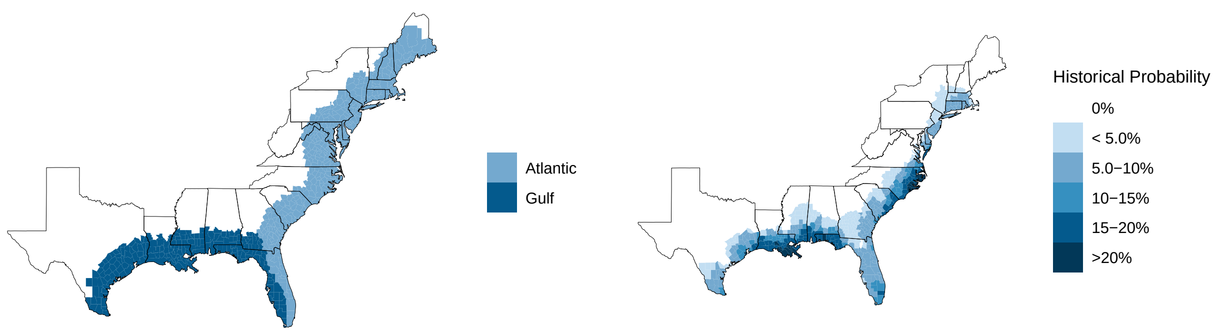
Table A2: Summary statistics of hurricane landfall region data

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. Tables A5 and A6 report the option return analysis described in Section 6.2 of the paper, but accounting for the bid-ask spread when computing option returns and using a short delta-neutral straddle. Table A7 reports the baseline estimates when excluding one hurricane at a time. Tables A8 and A9 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 10 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 of the paper. 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 firm-hurricane panel model in equation (9) of the paper. 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. Hurricanes for which Γ days before landfall or dissipation falls on a non-trading day are excluded. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, that is sales, are in counties located in the forecast path of a hurricane. The forecast path of the hurricane is from NOAA and gives a minimum 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) of the paper. 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, are 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 ≥ 20%	168	168	635	635	1,247	1,247	1,960	1,960
Total firm obs. with exposure ≥ 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 × 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 ≥ 20%	169	169	640	640	1,252	1,252	1,967	1,967
Total firm obs. with exposure ≥ 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 × Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A5: Option return difference between hit and control firms - going long at the ask price

This table reports the coefficients and test statistics when estimating the panel model in equation (12) of the paper. The dependent variable is the return (in percent) on a long delta-neutral straddle traded at the best ask price, formed the day of the landfall and computed for each firm in the sample as described in Section 6.2. The independent variable is a dummy variable that takes a value of 1 for hit firms and a value of 0 for control firms, which estimates the difference between holding a straddle on a hit firm versus a control firm. In Panel A, a hit firm has at least 10% of its establishments in counties located in the landfall region of a hurricane, and in Panel B the threshold is 25%. Control firms have no establishments in the counties located in the landfall region. 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 and the number of hit and control firms are reported. The data are from 1996 to 2017. Hurricanes with no firms in the landfall region for a given radius, that is hurricanes without hit firms, are excluded from the analysis. 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 included. The time fixed effect is equivalent to a hurricane fixed effect as there is at most one buy-and-hold return observation per firm per hurricane in a particular regression. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Firm considered hit if establishment share in landfall region $\geq$ 10%

Dependent variable: Option return (in %)

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$IsHit_{i,h}$	34.354**	33.327**	12.110*	12.208**	6.670	6.337	5.906	5.436
	(2.090)	(2.020)	(1.904)	(2.006)	(1.596)	(1.531)	(1.540)	(1.424)
Adjusted R^2 (%)	16.166	16.579	15.724	15.712	13.804	13.764	12.081	12.037
Total firm obs.	1,451	1,451	2,494	2,494	3,751	3,751	4,554	4,554
Firm obs. hit	130	130	508	508	1,042	1,042	1,669	1,669
Firm obs. control	1,321	1,321	1,986	1,986	2,709	2,709	2,885	2,885
Hurricanes	14	14	22	22	30	30	32	32
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Firm considered hit if establishment share in landfall region $\geq$ 25%

Dependent variable: Option return (in %)

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$IsHit_{i,h}$	34.225	23.636	14.661	11.948	14.931*	14.709*	8.997	8.083
	(1.104)	(0.794)	(0.994)	(0.866)	(1.662)	(1.680)	(1.535)	(1.405)
Adjusted R^2 (%)	13.034	15.187	13.848	14.050	13.411	13.456	13.429	13.515
Total firm obs.	366	366	1,792	1,792	2,673	2,673	2,962	2,962
Firm obs. hit	31	31	178	178	374	374	598	598
Firm obs. control	335	335	1,614	1,614	2,299	2,299	2,364	2,364
Hurricanes	4	4	17	17	24	24	25	25
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A6: Option return difference between hit and control firms - going short at the bid price

This table reports the coefficients and test statistics when estimating the panel model in equation (12) of the paper. The dependent variable is the return (in percent) on a short delta-neutral straddle traded at the best bid price, formed the day of the landfall and computed for each firm in the sample as described in Section 6.2. The independent variable is a dummy variable that takes a value of 1 for hit firms and a value of 0 for control firms, which estimates the difference between holding a straddle on a hit firm versus a control firm. In Panel A, a hit firm has at least 10% of its establishments in counties located in the landfall region of a hurricane, and in Panel B the threshold is 25%. Control firms have no establishments in the counties located in the landfall region. 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 and the number of hit and control firms are reported. The data are from 1996 to 2017. Hurricanes with no firms in the landfall region for a given radius, that is hurricanes without hit firms, are excluded from the analysis. 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 included. The time fixed effect is equivalent to a hurricane fixed effect as there is at most one buy-and-hold return observation per firm per hurricane in a particular regression. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Firm considered hit if establishment share in landfall region $\geq$ 10%

Dependent variable: Option return (in %)								
	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$IsHit_{i,h}$	-41.833*	-42.106*	-9.025	-9.326	-7.959	-8.580	-3.727	-3.951
	(-1.850)	(-1.834)	(-1.004)	(-1.039)	(-1.142)	(-1.223)	(-0.639)	(-0.667)
Adjusted R^2 (%)	13.804	15.008	12.946	12.983	10.324	10.225	9.488	9.450
Total firm obs.	1,451	1,451	2,494	2,494	3,751	3,751	4,554	4,554
Firm obs. hit	130	130	508	508	1,042	1,042	1,669	1,669
Firm obs. control	1,321	1,321	1,986	1,986	2,709	2,709	2,885	2,885
Hurricanes	14	14	22	22	30	30	32	32
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Firm considered hit if establishment share in landfall region $\geq$ 25%

Dependent variable: Option return (in %)								
	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$IsHit_{i,h}$	-23.670	-13.105	-7.700	-6.362	-20.750	-21.902	-11.774	-11.661
	(-0.661)	(-0.363)	(-0.478)	(-0.397)	(-1.547)	(-1.628)	(-1.320)	(-1.315)
Adjusted R^2 (%)	13.025	14.900	11.628	12.043	9.042	9.039	9.506	9.535
Total firm obs.	366	366	1792	1792	2673	2673	2962	2962
Firm obs. hit	31	31	178	178	374	374	598	598
Firm obs. control	335	335	1,614	1,614	2,299	2,299	2,364	2,364
Hurricanes	4	4	17	17	24	24	25	25
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A7: Hurricane effects on implied volatility post landfall (excluding individual hurricanes)

This table reports the coefficients and test statistics when estimating the panel model in equation (10) of the paper while excluding individual hurricanes from the regression. 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) 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, are 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% and at least 20% are reported. The data are from 1996 to 2017. 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 $p < 0.01$.

Excl. hurricane	Year	Coeff. estimate	T-stat	Adjusted R^2 (%)	Total firm obs.	Firm obs. with expo. > 0%	Firm obs. with expo. ≥ 20%	Hurricanes
Bertha	1996	5.522***	5.372	12.164	19,903	10,141	2,128	32
Fran	1996	5.486***	5.324	12.328	19,888	10,071	2,080	32
Danny	1997	5.433***	5.221	12.194	19,789	10,129	2,126	32
Bonnie	1998	5.480***	5.311	11.121	19,716	10,058	2,123	32
Earl	1998	5.429***	5.320	12.104	19,714	10,003	2,100	32
Georges	1998	5.426***	5.138	12.362	19,713	10,107	2,123	32
Bret	1999	5.400***	5.196	12.206	19,744	10,086	2,124	32
Floyd	1999	6.285***	6.095	12.463	19,679	9,867	1,867	32
Irene	1999	5.549***	5.379	12.260	19,735	10,040	2,108	32
Lili	2002	5.691***	5.103	12.086	19,668	9,972	2,080	32
Claudette	2003	5.602***	5.354	12.380	19,693	9,976	2,091	32
Isabel	2003	5.618***	5.335	12.434	19,677	9,899	2,010	32
Charley	2004	5.536***	5.247	12.365	19,624	9,941	2,093	32
Frances	2004	5.539***	5.440	11.937	19,623	9,968	2,108	32
Ivan	2004	5.508***	5.362	12.096	19,616	9,910	2,099	32
Jeanne	2004	5.475***	5.310	12.243	19,621	9,964	2,105	32
Dennis	2005	5.203***	4.983	12.595	19,581	9,947	2,107	32
Katrina	2005	5.481***	5.301	12.504	19,582	9,952	2,097	32
Rita	2005	5.177***	4.837	12.392	19,584	9,868	2,048	32
Wilma	2005	5.559***	5.358	12.501	19,584	9,972	2,112	32
Humberto	2007	6.134***	5.006	11.913	19,446	9,873	2,047	32
Dolly	2008	5.443***	5.236	12.199	19,465	10,019	2,130	32
Gustav	2008	4.626***	4.776	11.872	19,454	9,876	2,054	32
Ike	2008	3.762***	4.054	8.080	19,437	9,793	1,996	32
Irene	2011	5.157***	4.753	12.545	19,420	9,771	1,952	32
Isaac	2012	5.511***	5.141	12.464	19,447	9,998	2,112	32
Sandy	2012	5.453***	4.967	12.543	19,429	9,781	1,968	32
Arthur	2014	5.619***	4.921	12.771	19,321	9,717	1,938	32
Hermine	2016	5.394***	5.050	12.902	19,307	9,823	2,040	32
Matthew	2016	5.167***	4.791	13.054	19,320	9,854	2,074	32
Harvey	2017	5.617***	4.851	12.722	19,348	9,836	2,042	32
Irma	2017	5.379***	5.106	12.678	19,394	9,904	2,095	32
Nate	2017	5.873***	5.407	12.670	19,366	9,852	2,079	32

Table A8: Cumulative abnormal stock 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 as described in Section 6.5 of the paper. 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 (for the percentiles only) 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 A9: Long-run cumulative abnormal stock 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 as described in Section 6.5 of the paper. 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 (for the percentiles only) 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