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

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A A theoretical framework on extreme weather uncertainty

In this section, we present a simple framework illustrating how extreme weather uncertainty affects return volatility, which is summarized in Section II.A of the paper. We then use this framework to extend the Merton (1987) model. This allows us to show that extreme weather uncertainty, despite being idiosyncratic, can affect expected returns if investors are not fully diversified.

A.1 Incidence and impact uncertainty

We specify firm i's end-of-period cash flow as

$$\tilde{CF}_i = I_i[\mu_i + a_i\tilde{Y} + s_i\tilde{\epsilon}_i + \tilde{\eta}_i\tilde{\theta}_i]. \tag{A.1}$$

As in Merton (1987), the notation $\sim$ over a variable denotes it is random and realized in $t+1$. The investors make their investment decisions at time t. In this section, we drop these time subscripts to keep the notation parsimonious. The random market factor $\tilde{Y}$ is distributed with $E(\tilde{Y}) = 0$ and $E(\tilde{Y}^2) = 1$, and the idiosyncratic random variable $\tilde{\epsilon}_i$ is

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independent of the market factor with $E(\tilde{\epsilon}_i) = 0$ and $E(\tilde{\epsilon}_i^2) = 1$. I_i denotes the investments in the firm. The variables μ_i, a_i, and s_i are firm-specific constants. The parameters are the same as in Merton (1987) with the exception of the term $\tilde{\eta}_i\tilde{\theta}_i$, which represents the impact of an extreme weather event like a hurricane on a firm's cash flows. The random variable $\tilde{\eta}_i \sim N(\mu_{\eta,i}, \sigma_{\eta,i}^2)$ captures the impact of the extreme weather event conditional on firm i being hit. The normal distribution accounts for our empirical finding that some firms are also positively affected by an extreme weather event (see Section IV.D). However, our derivation below does not rely on this assumption. The random variable $\tilde{\theta}_i$ indicates whether firm i is hit by the extreme weather event. $\tilde{\theta}_i$ has a Bernoulli distribution (one draw of a binomial distribution), $\tilde{\theta}_i \sim B(1, \phi)$, where $Pr(\tilde{\theta}_i = 1) = 1 - Pr(\tilde{\theta}_i = 0) = \phi$ and $0 \leq \phi \leq 1$. Whether a firm will be hit by an extreme event is independent of the impact conditional on being hit, i.e., $E(\tilde{\eta}_i\tilde{\theta}_i) = E(\tilde{\eta}_i)E(\tilde{\theta}_i)$.

The two random variables $\tilde{\eta}_i$ and $\tilde{\theta}_i$ are independent of the idiosyncratic random variable $\tilde{\epsilon}_i$ and the random market factor $\tilde{Y}$. This formulation is motivated by the exogenous nature of extreme weather events and the fact that local extreme weather events generally do not have aggregate, economy-wide impacts (e.g., Strobl (2011)).

The return on firm i is then given by

$$\tilde{R}_i = \frac{\tilde{CF}_i}{V_i} = \bar{R}_i + b_i\tilde{Y} + \sigma_i\tilde{\epsilon}_i + \tilde{g}_i\tilde{\theta}_i, \tag{A.2}$$

where V_i is the value of the firm at the beginning of the period and $\bar{R}_i \equiv I_i\mu_i/V_i$, $b_i \equiv I_ia_i/V_i$, $\sigma_i \equiv s_iI_i/V_i$, and $\tilde{g}_i \equiv \tilde{\eta}_iI_i/V_i$.

The variance of the return in equation (A.2) is

$$Var(\tilde{R}_i) = b_i^2 + \sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi), \tag{A.3}$$

where $\mu_{g,i} \equiv \mu_{\eta,i}I_i/V_i$ and $\sigma_{g,i} \equiv \sigma_{\eta,i}I_i/V_i$. The term $\sigma_{g,i}^2\phi$ is the expected impact uncertainty and $\mu_{g,i}^2\phi(1-\phi)$ is the incidence uncertainty generated for the firm due to the extreme weather event.[1] The impact uncertainty is the uncertainty about the ultimate impact on the firm conditional on the firm being hit by the extreme weather event. The incidence uncertainty

[1] The expected impact uncertainty and incidence uncertainty are obtained by $Var(\tilde{g}_i\tilde{\theta}_i) = (E(\tilde{g}_i^2)E(\tilde{\theta}_i^2) - E(\tilde{g}_i)^2E(\tilde{\theta}_i)^2)$, where $E(\tilde{g}_i^2)E(\tilde{\theta}_i^2) = (Var(\tilde{g}_i) + E(\tilde{g}_i)^2)(Var(\tilde{\theta}_i) + E(\tilde{\theta}_i)^2) = \mu_{g,i}^2\phi + \sigma_{g,i}^2\phi$.

captures the uncertainty about whether the firm will be hit.

When $\mu_{g,i} = 0$, meaning that an extreme weather event has no mean impact on firm returns, incidence uncertainty does not contribute to total variance. In this case, $Var(\tilde{R}_i)$ varies with ϕ purely through the expected impact uncertainty, $\phi\sigma^2_{g,i}$. For a given $\mu_{g,i} \neq 0$, incidence uncertainty is highest when the probability of incidence, ϕ, is 0.5. Therefore, ϕ monotonically increases impact uncertainty but not incidence uncertainty. The non-monotonicity of incidence uncertainty can be understood intuitively from there being no uncertainty about the occurrence of an extreme weather event if ϕ is either 0 or 1. Intermediate values of ϕ generate greater uncertainty. As ϕ increases, incidence uncertainty increases (decreases) when $\phi < 0.5$ ($\phi > 0.5$).

Figure A.1 presents a graphical illustration. The variance prior to an extreme weather event, $Var(\tilde{R}_i)$, varies with ϕ, the probability of incidence, using example parameters, baseline firm variance $b_i^2 + \sigma_i^2 = 0.16$, and variance of impact $\sigma^2_{g,i} = 0.0025$. The four dashed lines have absolute values for expected impact $\mu_{g,i}$ of 0.1, 0.07, 0.05, and 0. The horizontal solid line shows the level of variance conditional on the firm being hit by the extreme weather event, $Var(\tilde{R}_i|\theta = 1) = b_i^2 + \sigma_i^2 + \sigma^2_{g,i}$. The x-axis intersects the y-axis at the level of variance if the firm is not hit by the extreme weather event, $Var(\tilde{R}_i|\theta = 0) = b_i^2 + \sigma_i^2$. Prior to an event, as the probability of incidence, ϕ, varies from 0 to 1, the relative contribution to total variance from incidence uncertainty and expected impact uncertainty will vary depending on the parameter values of μ_g and σ_g^2. All else equal, as μ_g increases, the contribution of incidence uncertainty to total variance increases. Incidence uncertainty at a given ϕ is the vertical distance between a curve and the red dot-dash straight line depicting $Var(\tilde{R}_i)$ when $\mu_{g,i} = 0$.[2] This distance is largest for $\phi = 0.5$.

Our main empirical analysis focuses on the impact uncertainty, $\sigma^2_{g,i}$. We analyze the uncertainty reflected in option prices and show that the impact uncertainty remains elevated for several months after a hurricane makes landfall (see Section III.A). In Section III.E, we analyze the uncertainty prior to a potential extreme weather event at different probabilities of incidence, ϕ. The sum of incidence and expected impact uncertainty is estimated through option price reactions to forecasts for specific hurricanes and for the hurricane season. We

[2] $Var(\tilde{R}_i)$ will be greater than $Var(\tilde{R}_i|\theta = 1)$ when $|\mu_{g,i}| > \frac{1}{\sqrt{\phi}}\sigma_{g,i}$ and ϕ is not 0 or 1. 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 $\mu_{g,i}$ or $\sigma_{g,i}$ is non-zero, $Var(\tilde{R}_i)$ is always greater than $Var(\tilde{R}_i|\theta = 0)$.

find that uncertainty responds strongly to increases in landfall probabilities of individual hurricanes.

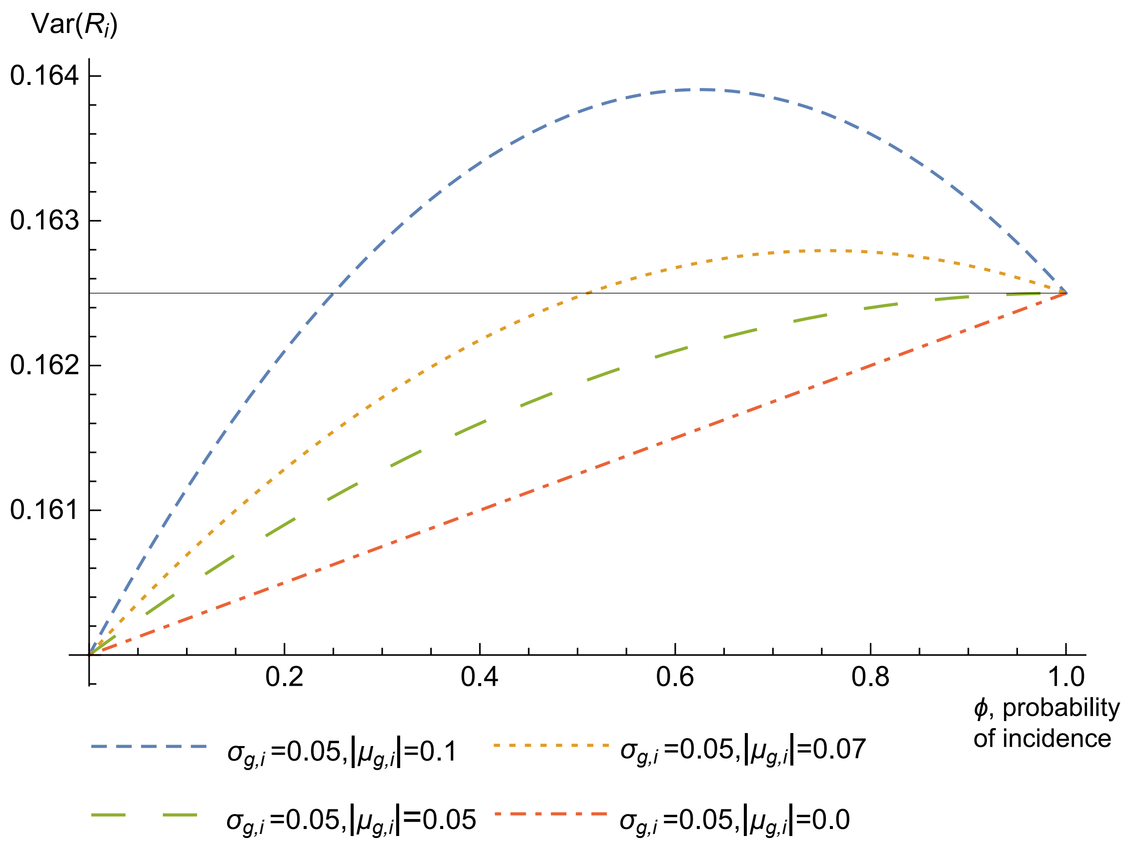

Figure A.1: Expected variance as a function of the probability of an event

This figure shows the return variance, $Var(\tilde{R}_i)$, prior to an extreme weather event, derived in equation (A.3), as the probability of the event occurring, ϕ, varies from 0 to 1. In this figure, $b_i^2+\sigma_i^2 = 0.16$ and $\sigma_{g,i}^2 = 0.0025$. The four dashed lines have absolute value for $\mu_{g,i}$ of 0.1, 0.07, 0.05, and 0, respectively. The horizontal solid line is the level of variance conditional on the firm experiencing an event, $Var(\tilde{R}_i|\theta = 1) = b_i^2 + \sigma_i^2 + \sigma_{g,i}^2$. The x-axis is plotted at the variance level of a firm that is unaffected by the event, $Var(\tilde{R}_i|\theta = 0) = b_i^2 + \sigma_i^2$.

A.2 Expected returns

In this section, we extend the Merton (1987) model to show how extreme weather uncertainty can affect expected returns. As in Merton (1987), two additional securities are assumed to be present in the economy. The first is a riskless security with return R^f. The second is a forward contract with cash settlement on the observed market factor Y. The return on the forward contract is

$$\tilde{R}_{K+1} = \bar{R}_{K+1} + \tilde{Y}, \tag{A.4}$$

where $E(\tilde{R}_{K+1}) = \bar{R}_{K+1}$.

There are K firms in the economy. The fraction of wealth invested in firm i by investor j is $w_{i,j}$. The fraction of investor j's wealth invested in the forward contract is $w_{K+1,j}$. The return on investor j's portfolio can then be written as

$$\tilde{R}_j = \bar{R}_j + b_j\tilde{Y} + \tilde{\epsilon}_j + \tilde{g}_j\tilde{\theta}_j, \tag{A.5}$$

where the exposure to the market factor is

$$b_j = (\sum_{i=1}^{K} w_{i,j}b_i + w_{K+1,j}), \tag{A.6}$$

and the exposure to the idiosyncratic factors unrelated and related to the extreme weather event, respectively, are

$$\tilde{\epsilon}_j = \sum_{i=1}^{K} w_{i,j}\sigma_i\tilde{\epsilon}_i \tag{A.7}$$

$$\tilde{g}_j\tilde{\theta}_j = \sum_{i=1}^{K} w_{i,j}\tilde{g}_i\tilde{\theta}_i. \tag{A.8}$$

$\bar{R}_j$ is the expected return without the extreme weather component as given in Merton (1987):

$$\bar{R}_j = R^f + b_j(\bar{R}_{K+1} - R^f) + \sum_{i=1}^{K} w_{i,j}\Delta_i. \tag{A.9}$$

To obtain equation (A.9), we use the fact that the portfolio share of the riskless security is

$w_{K+2,j} = 1 - \sum_{i=1}^{K+1} w_{i,j}$ and set $\Delta_i \equiv \bar{R}_i - R^f - b_i(\bar{R}_{K+1} - R^f)$.

The variance and expected return of investor j's portfolio can then be written as

$$Var(\tilde{R}_j) = b_j^2 + \sum_{i=1}^{K} w_{i,j}^2(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi)) \tag{A.10}$$

and

$$E(\tilde{R}_j) = \bar{R}_j + \sum_{i=1}^{K} w_{i,j}\mu_{g,i}\phi. \tag{A.11}$$

For an investor with mean-variance preferences, the maximization problem is

$$Max_{b_j,w_j}\left[E(\tilde{R}_j) - \frac{\delta_j}{2}Var(\tilde{R}_j) - \sum_{i=1}^{K}\lambda_{i,j}w_{i,j}\right], \tag{A.12}$$

where w_j is a vector with elements $w_{i,j}$. The key element, as in Merton (1987), is the last term. This term captures the constraint that investors cannot invest in securities that they do not know about. Each investor j has a set of securities that they know about, denoted S_j, and another set they do not know about, denoted S_j^c. The Kuhn-Tucker multiplier $\lambda_{i,j}$ equals zero if i is in S_j. If the investor does not know about security i, then $w_{i,j} = 0$. This constraint is motivated by empirical evidence that points to underdiversification of investors. Possible explanations for this underdiversification are wide ranging, including factors like home bias (see Coval and Moskowitz (1999)).

The first-order conditions with respect to b_j and w_j are

$$0 = \bar{R}_{K+1} - R^f - \delta_j b_j \tag{A.13}$$

$$0 = \Delta_i + \mu_{g,i}\phi - \delta_j w_{i,j}(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi)) - \lambda_{i,j}, \text{ for } i = 1, ..., K. \tag{A.14}$$

The solutions for the market factor exposure and the portfolio weights for each firm are given by

$$
\begin{aligned}
b_j =& [\bar{R}_{K+1} - R^f]/\delta_j && \text{(A.15)}\\
w_{i,j} =& (\Delta_i + \mu_{g,i}\phi)/(\delta_j(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi)), \text{ for } i \in S_j && \text{(A.16)}\\
w_{i,j} =& 0, \text{ for } i \in S_j^c && \text{(A.17)}\\
w_{K+1,j} =& b_j - \sum_{i=1}^{K} w_{i,j} b_i && \text{(A.18)}\\
w_{K+2,j} =& 1 - b_j + \sum_{i=1}^{K} w_{i,j}(b_i - 1). && \text{(A.19)}
\end{aligned}
$$

Based on the solutions for individual investor demand, we can aggregate across the N investors in the economy to obtain equilibrium asset prices and expected returns. Following Merton (1987), we assume that all the investors have the same risk aversion and initial wealth, that is, $\delta_j = \delta$ and $W_j = W$. Consequently, the exposure to the market factor given in equation (A.15) is the same for every investor:

$$b_j = b = \frac{\bar{R}_{K+1} - R^f}{\delta}. \tag{A.20}$$

Using equation (A.16), we can write the aggregate demand for security i as

$$D_i = N_i W \frac{\Delta_i + \mu_{g,i}\phi}{\delta(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi))}, \tag{A.21}$$

where N_i investors know about security i. When denoting the total number of investors as N, the equilibrium total wealth is $M \equiv NW$. The share of security i of the total market is

$$\frac{V_i}{M} = x_i = \frac{q_i(\Delta_i + \mu_{g,i}\phi)}{\delta(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi))}, \tag{A.22}$$

where q_i is the share of investors who know about the security, N_i/N, and $D_i = V_i$ in equilibrium.

Using the definition of Δ_i together with equations (A.20) and (A.22), the equilibrium expected return on security i is given by

$$E(\tilde{R}_i) = \bar{R}_i + \mu_{g,i}\phi = R^f + b_i b\delta + \Delta_i + \mu_{g,i}\phi$$
$$= R^f + b_i b\delta + \frac{\delta x_i(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi))}{q_i}. \tag{A.23}$$

In the case where a firm is hit by the extreme weather event (i.e., $\phi = 1$), the expected return is

$$E(\tilde{R}_i) = R^f + b_i b\delta + \frac{\delta x_i(\sigma_i^2 + \sigma_{g,i}^2)}{q_i}. \tag{A.24}$$

It follows from equations (A.23) and (A.24) that an increase in either the impact uncertainty $\sigma_{g,i}^2$ or the incidence uncertainty $\mu_{g,i}^2\phi(1-\phi)$ leads to a higher expected return. The derivative of equation (A.23) with respect to the extreme weather component $\sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi)$ is given by

$$\frac{\partial E(\tilde{R}_i)}{\partial(\sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi))} = \frac{\delta x_i}{q_i}. \tag{A.25}$$

The three parameters on the right-hand side of equation (A.25) are the share of investors who know about a firm (q_i), the risk aversion (δ), and the share of firm i of the total economy (x_i). All three parameters are non-negative.

We document in the paper that over the full sample, investors' return volatility expectations in response to hurricanes are too low compared to the subsequent realized volatility. Table IV shows that the VRP (computed as the difference (in %) between the ex ante implied and ex post realized volatility) is significantly lower after landfall for hit firms compared to control firms. In our theoretical framework, this would imply that the investors' expectations of $\sigma_{g,i}$ are too low. Therefore, the expected return is smaller than it would be under the correct expectation of $\sigma_{g,i}$ and noisier to estimate empirically. This is a likely reason for why we only find positive return effects for hurricanes post-Sandy, as shown in Table VII. After Hurricane Sandy, the underreaction to the uncertainty from a hurricane shock diminishes, and implied volatility is more in line with subsequent realized volatility for hit firms, as shown in Table V.[3]

[3]There are other potential factors for more efficient pricing after Hurricane Sandy. For example, the efficiency of investors' expectations of the mean impact on a firm's cash flow, $\mu_{\eta,i}$, could have improved after Hurricane Sandy. Such an efficiency improvement in cash flows expectations is more challenging to estimate empirically due to the limited and low frequency firm-level cash flows expectations data.

A.3 Firm value

We next investigate the impact of the extreme weather event on the value, that is, the price, of firm i's security. Using equation (A.23) and $E(\tilde{R}_i) = I_i\mu_i/V_i + I_i\mu_{\eta,i}\phi/V_i$, we obtain

$$V_i = \frac{I_i}{R^f}[\mu_i + \mu_{\eta,i}\phi - a_i b\delta - \frac{\delta I_i(s_i^2 + \sigma_{\eta,i}^2\phi + \mu_{\eta,i}^2\phi(1-\phi))}{q_i M}], \tag{A.26}$$

where the definitions for b_i, σ_i, $\sigma_{\mu,i}$, and $\sigma_{g,i}$ given in equations (A.2) and (A.3) and x_i from equation (A.22) are substituted in.

The value of the security is affected by the extreme weather event through two components. The value covaries positively with the first component $\mu_{\eta,i}\phi$, which captures the expected impact on the cash flow of the firm. The second component, $\sigma_{\eta,i}^2 I_i\phi + I_i\mu_{\eta,i}^2\phi(1-\phi)$, captures the impact of the extreme weather event on the cash flow variance of the firm. An increase in this second component lowers the security's value, because the cash flows are discounted more heavily.

B Data

B.1 Details on hurricane landfall region data

We use hurricane track data collated from the National Oceanographic and Atmospheric Administration (NOAA), which can be found in the National Hurricane Center's (NHC) hurricane archives (see https://www.nhc.noaa.gov/archive) to determine which counties are located in hurricane landfall regions. NOAA publishes forecast advisory text files from the inception of a storm until the storm dissolves. Every six hours a new file is published with the coordinates of the eye of a storm. The file also contains information on the storm category, indicating whether the storm was, for example, a tropical depression or a hurricane. For the landfall sample, we select all the storms for which the eye gets within 50 miles of at least one county while being of hurricane level strength. Many storms in NOAA's hurricane archive never get close to landfall.

To determine the landfall region of each hurricane, we first hand-collect the landfall times 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 of the storm's eye as the hurricane moves within a time window of 24 hours before and after the landfall time. Having this time window around the landfall time ensures that we capture counties that lie more inland and counties that are close to the eye before the actual landfall for hurricanes that move along the coast. Also, because we only require the storm to be hurricane-level strength at landfall, as described previously, this methodology captures counties that are affected by strong rainfall even when the storm's wind speeds fall below hurricane level after landfall. While 24 hours is our baseline time window, we also analyze additional time windows, namely 12, 36, and 48 hours, and the results are qualitatively similar.

The radius R that we use most for our main analyses is 200 miles. Based on reanalysis data for hurricanes, which are released by NOAA anywhere from weeks to months after hurricanes have occurred, we find that the average outer border of a hurricane storm system—the area where wind speeds are at least 34 knots (KT)—is 219 miles from the eye of the storm. Although the 200-mile radius is a bit lower than this empirical measure, in practice the two measures align well because we include a county in the landfall region if the landfall region includes the county centroid but not necessarily the whole county. We also perform analyses where landfall exposure is based on a radius of 50 miles. This reflects a more intense treatment level and aligns fairly well with the average observed 64 KT wind speed radius of 73 miles. Table B.1 shows that the average hurricane has 212 counties within the 200-mile radius landfall region, but only 27 counties for the 50-mile radius landfall region.

B.2 Details on hurricane forecast data

We use wind speed forecast advisories from NOAA, which can also be found in the NHC's hurricane archives. For each tropical storm, NOAA issues text files in real time that contain wind speed forecasts for up to five days out for selected locations largely along the coast. These forecasts are an output of the same models that NOAA uses to create graphical forecasts like that in Figure B.1. NOAA updates these forecasts every six hours and archives are available for storms starting in 2007. We obtain the forecasts just before market close for each trading day in our analysis and exclude forecasts made on the day of landfall to distinguish between price reactions to forecasts and landfall. Figure B.2 provides an example of a wind speed forecast advisory text file. The file lists the locations in the first column, and then provides for each location and up to three different wind speeds (34 KT, 50 KT, and 64 KT) the daily and cumulative probabilities (the latter in parentheses) of that location experiencing wind above the respective thresholds between 12 and 120 hours out.

We implement a two-stage process to translate these wind speed forecasts into a list of counties in the forecast path of a hurricane. 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% to determine which locations in the text files are in the forecast path. For example, when we apply a probability threshold of 1% for 64 KT wind, Surf City, North Carolina, is the only location on the list in Figure B.2 that is considered exposed on that day. (Note that although we focus on the 64 KT wind speed, our results are qualitatively similar when we use the 34 KT wind speed.) We then identify the counties for these exposed locations. Because the locations in the NOAA advisories are not exhaustive, leaving gaps between listed locations, in a second step, we add to our list of exposed counties the counties that are within a 75-mile radius of the counties from the counties identified in the first step.[4] The 75-mile radius balances Type I errors (which we

[4]We use Census county centroids for this purpose, which can be found at: https://www2.census.gov/geo/

can see when larger radii include locations typically included in the advisory files but not for the given forecast) and Type II errors (which we can see when smaller radii leave gaps in between reported locations.) However, our results are robust to using other reasonable radii.

Table B.2 reports summary statistics on the hurricane forecast data. Panel A shows that the number of storms for which we observe forecasts decreases as the probability threshold increases. Panel A also reports the mean, median, and standard deviation of the number of county-day observations for which we have hurricane forecasts for each storm at a given probability threshold. There are 52 storms with forecasts at or above a minimum probability threshold of 1%, with the average storm having 360 county-day observations at or above that threshold. There are only 12 storms with forecasts at or above a minimum probability threshold of 50%. Panel B presents the observation count by days to resolution at a given probability threshold.

In Figure B.3, we plot the counties used for the seasonal outlook analysis in Section III.E.2. NOAA releases seasonal outlooks every May for the hurricane season from June to November. Panel A of Figure B.4 shows there is significant variation in these outlooks. Dating back to 2001, each seasonal outlook reports the probability that the season will be above-normal, near-normal, or below-normal.[5] The scatter plot in Figure B.4 Panel B shows only a weakly positive relationship between the seasonal outlooks and the number of hurricanes making landfall in a given year.

tiger/TIGER2017/COUNTY/.

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

Table B.1: Summary statistics of counties in hurricane landfall regions

This table reports summary statistics on the number of counties in the hurricane landfall regions derived from NOAA data as described in Section B.1 of this Internet Appendix. The data span from 1996 to 2019. Column 1 specifies the radius around the eye of the hurricane used to calculate the landfall region.

	Across all hurricanes			By hurricane		
Radius	Hurricanes	Total counties	Unique counties	Average	Std. dev.	Median
200 miles	37	7,856	1,482	212.324	110.767	194
100 miles	37	2,920	1,047	78.919	49.252	69
50 miles	37	1,010	621	27.297	18.080	25

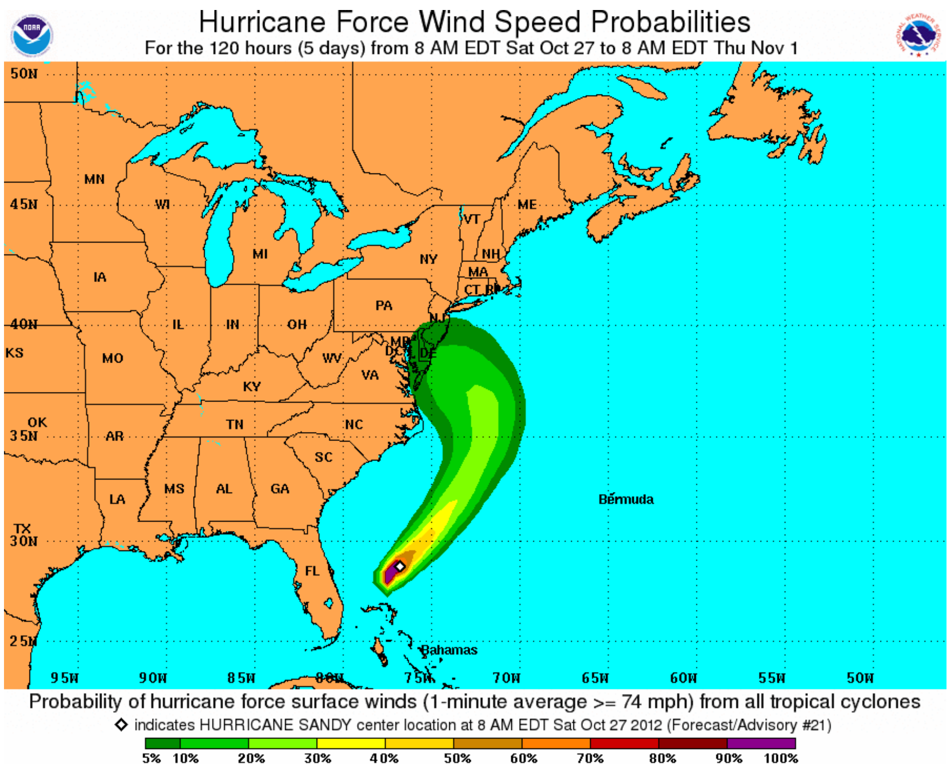

Figure B.1: Example of a hurricane forecast

This figure from NOAA illustrates the five-day forecast for Hurricane Sandy on October 27, 2012. We obtain and process text data derived from the same raw data underpinning such hurricane forecast visualizations.

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 - - - - 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 B.2: Partial sample raw text file for wind speed 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 1% 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 a 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% 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%.

Table B.2: Summary statistics of hurricane forecast data

This table reports summary statistics of NOAA wind speed forecasts from 2007 to 2019 for storms 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-day 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 sea) at a given probability threshold.

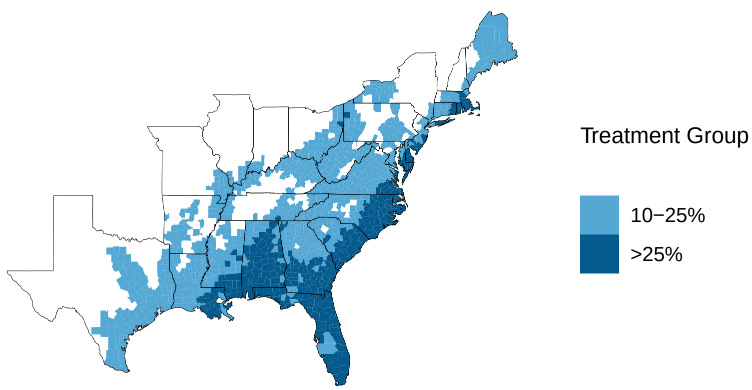
Panel A: Summary statistics of county-day forecast observations per storm

	Probability ≥				
	1	10	20	40	50
Storms	52	22	16	13	12
County-day observations	18,700	3,278	1,745	801	565
Mean	359.615	149.000	109.063	61.615	47.083
Median	147.500	101.000	72.000	50.000	37.500
Std. dev.	451.903	160.261	109.833	57.412	36.167

Panel B: Number of county-day forecast observations

Days to dissipation or landfall	Probability ≥				
	1	10	20	40	50
1	2661	774	601	392	318
2	4254	919	444	177	144
3	3736	604	228	85	28
4	3066	505	204	57	39
5	2246	221	143	45	15

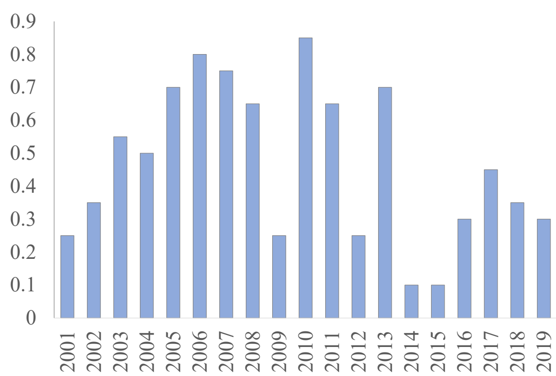
(a) Atlantic and Gulf counties



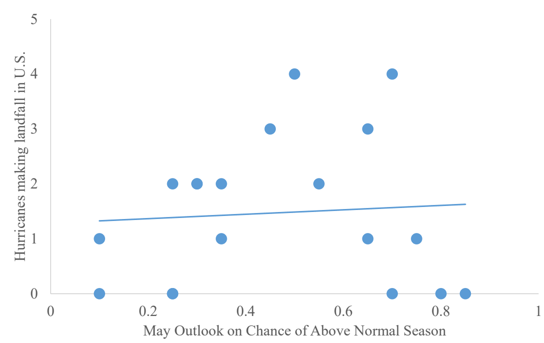
(b) Historical probability of hurricane landfall

Figure B.3: Coastal counties and hurricanes

This figure shows the coastal counties used for the analysis in Section III.E.2 of the paper. Panel A shows all the counties that are either directly bordering the Atlantic/Gulf coast or are within 50 miles of a county that does. Panel B depicts the historical probability of a county being in a hurricane landfall region at least once in a year. The plotted probabilities are as of 2019 and computed based on a historical window of 30 years. The landfall regions are based on a 50-mile radius around the eye of the hurricane.



(a) Probability of above average hurricane season



(b) Hurricane landfall count per year

Figure B.4: NOAA's Atlantic and Gulf Hurricane Season Outlook

Panel A shows the probability of an "above average" hurricane season announced in the May Outlook that NOAA issues each year in advance of the Atlantic and Gulf hurricane season. An above average designation is based on the number of hurricanes predicted to form in the Atlantic Ocean and the Gulf. Panel B depicts the relationship between NOAA's season outlook and the number of hurricanes that ultimately make landfall in a season.

B.3 Mapping NETS to financial data

We map firm-level establishment data from NETS to firm level options and stock data by matching on firm name and headquarter address in two steps.[6]

In the first step, we map NETS data to the CRSP/Compustat Merged data. We require that the firms have a name, ZIP Code, city, and street address. After cleaning the firm names by deleting words like INC and CORP, we require that a successful mapping between NETS and CRSP/Compustat data satisfies two conditions. The first condition is that there is match in the first two words of the company name (or first word for a one-word name like "Starbucks") and headquarter ZIP Code and city. However, this first condition will lead to some false matches because the first two words in some firm names are generic and based on their location (e.g., Santa Barbara Restaurant Group). In these cases, the ZIP Code and city do not necessarily result in a quality match. Therefore, we impose a second condition, which requires that for a given match at least $N - 1$ words of the name are the same, where N is the maximum number of words in the firm's NETS and CRSP/Compustat names. In addition, the street number or at least two words of the address have to be the same. Then, we manually confirm that the mapping is correct.

In a second step, we extend the mapping from CRSP/Compustat to OptionMetrics and Refinitiv based on the CUSIPs for the firms' stocks.

[6] We note that NETS, which has data on both public and private firms, includes over 50 million firms. Simply conducting a fuzzy string match and checking the matches manually is therefore not feasible.

C Additional methodology description and analysis

C.1 Textual analysis of calls between analysts, investors, and firm management

Table C.1 shows the dictionary of terms we use to identify the five channels discussed in calls between analysts, investors, and firm management, in the aftermath of a hurricane hit: business interruption, physical damages, insurance, supply, and demand. Paragraphs in the call transcripts can be lengthy and discuss a variety topics unrelated to hurricanes. Such paragraphs could lead to false positives in terms of identifying discussions of economic channels in relation to hurricanes. Therefore, our analysis focuses on paragraphs that are either 100 words or less or that are no longer than 300 words and mention hurricanes within the first 50 words or first fifth of the paragraph.

Tables C.2 and C.3 show results of an analysis in which we estimate how the VRP (i.e., the spread between the ex ante market expectations of future volatility and ex post realized volatility) responds to hurricane landfall exposure under different economic channels of impact. The dependent variable in each case is the VRP averaged over a month after landfall. The independent variable of interest is the frequency of discussions of a particular channel over the six months post landfall interacted with $LandfallRegionExposure$. This interaction variable measures the relevance of a particular economic channel for the uncertainty generated by a hurricane. These regressions estimate the relationship between VRP and discussions between analysts, investors, and firm management. The interpretation is not causal. Ideally, we would observe which channels generate uncertainty at the same frequency as the VRP, but analyst calls are generally pre-scheduled and occur mostly at quarterly or lower frequencies. If, when a firm is hit, investors underestimate the uncertainty generated for the firm through a particular channel, VRP will be negatively related to subsequent discussions of that channel in relation to the hurricane. In other words, the implied volatility reflected in option markets is particularly low compared to the subsequent realized volatility when that channel is generating uncertainty. If investors do not underestimate the uncertainty generated through a particular channel, VRP will be unrelated to subsequent discussions of that channel when discussing hurricane impacts.

The results in Table C.2 indicate that market underreactions increase with discussions of business interruption, physical damages, demand, and supply. The supply channel generates the strongest investor underreaction, which is in line with investors not accurately anticipating supply issues that are material to firm performance. This result is consistent with the prior literature showing investors are inattentive to shocks to suppliers (see, for example, Menzly and Ozbas (2010)). Another potential explanation is that investors do not have a good understanding of where firm suppliers are located and therefore fail to account for the exposure of suppliers to extreme weather events.

Interestingly, investors do not underreact to the uncertainty generated through the insurance channel, suggesting that they pay more attention and/or have a better understanding of the uncertainty that can be generated due to the lack of insurance coverage or the extent of possible delays and disputes before insurance claims are paid. Consistent with our findings in Section III.B, the analysis of VRP after Hurricane Sandy in Table C.3 shows that the underreactions in response to the channels shown in Table C.2 reversed after Hurricane Sandy.

Table C.1: Dictionary for economic channels related to hurricane impacts

This table shows the terms used to identify the discussion of an economic channel in relation to hurricanes in transcript data of calls between analysts, investors, and firm management. A particular channel is identified if one of the terms below occurs in a paragraph that also discusses some form of the terms "hurricane" or "tropical storm." An asterisk (∗) indicates a wildcard, meaning that the word can end with any combination of letters following the root shown. The channels and associated terms in this dictionary are based on careful examination of a random sample constituting 5% of all hurricane paragraphs in the transcript data.

Business Interruption	Physical Damages	Insurance	Supply	Demand
cancel* AND flight*	cleanup	claim* AND settle*	availability	admission*
curtail* AND production	clean* up	insur*	shortage*	buyer*
disrupt*	damage*	uninsur* AND	suppli*	cancel* AND
downtime OR down time	destr* AND	NOT(health*	supply	NOT flight*
evacuat*	NOT(demand destr*)	OR admission*	third party	demand
interrupt*	rebuil*	OR patient*	upstream	downstream
knock* out	remediat*	OR physician*)		order* AND
offline	repair*			NOT(in order to)
outage*	replac*			subscrib*
reopen*	wipe* AND out *[in*			
restart*	*same sentence]*			
restor* AND				
(service OR power)				
resume*				
schedul*				
shut in				
shutdown* OR shut down*				
suspend*				
without power				

Table C.2: Economic channels and investor underreaction

This table reports the coefficients and test statistics of panel regressions estimating how VRP respond to hurricane landfall exposure under different economic channels of impact. The dependent variable is the VRP (in %) averaged over the first month (20 trading days) after landfall. The VRP is computed as the difference between the ex ante implied and ex post realized volatility, as specified in equation (2) in the paper. The independent variable is the share (from 0 to 1) of a firm's establishments that are in a 200-mile radius of the hurricane eye at landfall interacted with the number of paragraphs discussing both the specified channel and hurricanes in post-landfall calls between analysts, investors, and firm management. The columns show results, respectively, for the business interruption, physical damages, insurance, supply, and demand channels. The data span from 2002 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest exposure. Controls include landfall exposure on its own and landfall exposure interacted with an indicator for hurricane discussion. Firm and time fixed effects are included. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: VRP (in %) avg. over 1 month post landfall, $\overline{VRP}_{i,T_L^h+20}$					
$LandfallRegionExposure_{i,R,h}$ ×					
Business interruption	-2.151				
	(-1.633)				
Physical damages		-1.790**			
		(-2.491)			
Insurance			-3.049		
			(-0.895)		
Supply				-5.955**	
				(-2.459)	
Demand					-1.931*
					(-1.791)
Firm FE	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2 (%)	39.051	39.053	39.042	39.083	39.037
Observations	17,824	17,824	17,824	17,824	17,824
Obs. Landfall Exposure > 0	11,235	11,235	11,235	11,235	11,235
Obs. Landfall Exposure ≥ 0.25	1,108	1,108	1,108	1,108	1,108
Hurricanes	28	28	28	28	28

Table C.3: Economic channels, investor underreaction, and Hurricane Sandy

This table reports the coefficients and test statistics of panel regressions estimating how VRP respond to hurricane landfall exposure under different economic channels of impact and allows for differential effects after Hurricane Sandy. The dependent variable is the VRP (in %) averaged over the first month after landfall. The VRP is computed as the difference between the ex ante implied and ex post realized volatility, as specified in equation (2) in the paper. The independent variable is the share (from 0 to 1) of a firm's establishments that are in a 200-mile radius of the hurricane eye at landfall interacted with the number of paragraphs discussing both the specified channel and hurricanes in post-landfall calls between analysts, investors, and firm management. This variable is then also interacted with with an indicator variable that takes a value of one when the hurricane occurred after Hurricane Sandy (post-Sandy). The columns show results, respectively, for the business interruption, physical damages, insurance, supply, and demand channels. The data span from 2002 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. Controls include pre- and post-Sandy landfall exposure on its own and interacted with an indicator for hurricane discussion. Firm and time fixed effects are included. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: VRP (in %) avg. over 1 month post landfall, $\overline{VRP}_{i,T_L^h+20}$					
$LandfallRegionExposure_{i,R,h}$ ×					
Business interruption	-3.873***				
	(-3.895)				
Business interruption × post-Sandy	5.781***				
	(4.227)				
Physical damages		-2.039***			
		(-2.723)			
Physical damages × post-Sandy		3.563***			
		(2.806)			
Insurance			-2.465		
			(-0.648)		
Insurance × post-Sandy			3.379		
			(0.566)		
Supply				-6.892**	
				(-2.352)	
Supply × post-Sandy				5.067	
				(0.959)	
Demand					-2.820**
					(-2.089)
Demand × post-Sandy					3.112
					(1.530)
Firm FE	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2 (%)	39.162	39.128	39.105	39.152	39.113
Observations	17,824	17,824	17,824	17,824	17,824

C.2 Cash flow and discount rate decomposition

In this section, we test whether price changes of stocks of firms hit by hurricanes are driven by discount rate or cash flow news. For this purpose, we adapt the framework of Chen, Da, and Zhao (2013), who use earnings forecasts and the corresponding implied cost of capital (ICC) to decompose price changes into discount rate and cash flow news. This methodology does not resort to stock return predictability as in, for example, Campbell and Shiller (1988) and Vuolteenaho (2002). Stock return predictability is generally found at longer horizons, but the methodology of Chen, Da, and Zhao (2013) can be used at horizons as short as a month. This allows us to better isolate in time the impact of a hurricane. However, while the main focus in our paper is on implied and realized daily return volatility, the methodology used in this section decomposes the variance of monthly capital gain returns.

The ICC is the value of q that solves the standard present value of future dividends formula:

$$P_{i,t} = \sum_{k=1}^{15} \frac{FE_{i,t+k}(1-b_{i,t+k})}{(1+q_{i,t})^k} + \frac{FE_{i,t+16}}{q_{i,t}(1+q_{i,t})^{15}} = f(c_{i,t}, q_{i,t}), \tag{C.1}$$

where $P_{i,t}$ is the stock price of firm i on day t, $FE_{i,t+k}$ is the k years ahead consensus earnings per share (EPS) forecast from the Institutional Brokers Estimate System, and $b_{i,t+k}$ is the plow back rate. We follow Pástor, Sinha, and Swaminathan (2008) and Chen, Da, and Zhao (2013) and consider forecasts up to a 16-year horizon and denote this series of earnings forecast as $c_{i,t}$.

As shown by Chen, Da, and Zhao (2013), the cash flow and discount rate components of the capital gain return, $Retx_{i,t+m} = (P_{i,t+m} - P_{i,t})/P_{i,t}$, are given by

$$CF_{i,t:t+m} = \left(\frac{f(c_{i,t+m}, q_{i,t+m}) - f(c_{i,t}, q_{i,t+m})}{P_{i,t}} + \frac{f(c_{i,t+m}, q_{i,t}) - f(c_{i,t}, q_{i,t})}{P_{i,t}} \right) /2 \tag{C.2}$$

$$DR_{i,t:t+m} = \left(\frac{f(c_{i,t}, q_{i,t+m}) - f(c_{i,t}, q_{i,t})}{P_{i,t}} + \frac{f(c_{i,t+m}, q_{i,t+m}) - f(c_{i,t+m}, q_{i,t})}{P_{i,t}} \right) /2, \tag{C.3}$$

where we set m to be one month. The discount rate and cash flow shares of the capital gain return variance are then obtained as

$$Var(Retx_{i,t:t+m}) = Cov(CF_{i,t:t+m}, Retx_{i,t:t+m}) + Cov(DR_{i,t:t+m}, Retx_{i,t:t+m}) \tag{C.4}$$

$$1 = \frac{Cov(CF_{i,t:t+m}, Retx_{i,t:t+m})}{Var(Retx_{i,t:t+m})} + \frac{Cov(DR_{i,t:t+m}, Retx_{i,t:t+m})}{Var(Retx_{i,t:t+m})}, \tag{C.5}$$

where the two terms in equation (C.5) are the slope coefficients of regressing the cash flow and discount rate components on the capital gain return. Importantly, the variance of the capital gain return differs from the implied volatility used in the analyses in the paper. While the implied volatility provides an expectation of daily return variation, the variance of the capital gain return is realized and monthly. The EPS forecasts used here are not updated daily, and this makes it impossible to decompose the returns at a daily frequency.

To estimate whether the share of variance driven by cash flow news (as opposed to discount rate news) differs significantly between firms that are hit by a hurricane and firms that are not, we split firm-month observations into two samples. The first sample ("hit") contains all firm-month observations in which firms have at least 10% (25%) of their establishments in the landfall region in a given month. The second sample ("control") contains the remaining control firm-month observations. We estimate a pooled regression for each of the two samples with $CF_{i,t:t+m}$ and $DR_{i,t:t+m}$ being the dependent variables, respectively, and $Retx_{i,t:t+m}$ being the independent variable.[7] By construction, the cash flow and discount rate news shares add up to one in this variance decomposition.

Table C.4 presents the results for the hit and control samples. The results confirm that the return variance and the variances of the cash flow and discount rate return components are higher for hit observations than for control observations. We also show the difference between hit and control return observations in cash flow news shares and discount rate news shares, respectively, as well as the lower and upper 95% confidence bands of these differences. Our estimates of the discount rate and cash flow shares for the control observations are generally comparable to the estimates in Chen, Da, and Zhao (2013), whose sample ends in 2010. Further, the Hit-Control columns reveal that the shares of discount rate and cash flow news in the variance decomposition for the hit firms are not significantly different from the control firms. Overall, these results suggest that the increase in variance after a firm is hit by a hurricane is driven not only by impacts on expected firm cash flows. The rate at which the expected cash flows are discounted also changes.

[7] Chen, Da, and Zhao (2013) estimate the regression for each individual firm and then average across firms. This approach does not work in our setting because the same firm is generally not hit in a sufficient number of time periods to allow for a time series regression on an individual firm.

Table C.4: Cash flow and discount rate decomposition

This table reports the decomposition of monthly capital gain return variation, $Var(Retx)$, into shares attributable to discount rate and cash flows news for firm-month observations of hit and control samples. A firm-month observation is assigned to the hit sample if the firm has at least 10% (25%) of its establishments in the hurricane landfall region in that month. The differences in variance shares attributable to discount rate and cash flow news between the hit and control samples are also shown. The discount rate and cash flow news shares are estimated with a pooled panel regression that regresses discount rate and cash flow return components given in equations (C.3) and (C.2), respectively, on capital gain returns. The variances of the capital gain return and these two components are reported in the last three rows. The landfall region is defined based on a 200-mile radius around the hurricane eye at landfall. The data span from 1996 to 2019. For each estimate, lower and upper bounds of 95% confidence bands are shown. The standard errors are clustered by firm and time.

	Hit firms have landfall region estab. share of					
	≥ 0.1			≥ 0.25		
	Hit	Control	Hit-Control	Hit	Control	Hit-Control
Cash Flow	0.268	0.193	0.075	0.379	0.193	0.186
2.5%	0.113	0.131	-0.092	0.038	0.136	-0.160
97.5%	0.423	0.256	0.242	0.720	0.250	0.531
Discount Rate	0.732	0.807	-0.075	0.621	0.807	-0.186
2.5%	0.577	0.744	-0.242	0.280	0.750	-0.531
97.5%	0.887	0.869	0.092	0.962	0.864	0.160
Observations	5,894	13,245		1,886	17,265	
$Var(Retx)$ (in %)	1.220	1.151		1.562	1.130	
$Var(CF)$ (in %)	6.351	4.744		8.272	4.908	
$Var(DR)$ (in %)	6.916	5.450		8.651	5.603	

C.3 The returns to trading options at landfall

Our results in Section III.B of the paper show that investors underreact to a hurricane making landfall, because the VRP—calculated as the difference between ex ante implied volatility and ex post realized volatility—is significantly lower for hit firms than for control firms. This result raises the question of whether this market inefficiency could be profitably exploited. In other words, if an investor trades a portfolio of options on hurricane-hit 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 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, our setting has several distinctive features and challenges we address through our empirical design. Unlike stocks or even index options, most single-stock options do not necessarily have daily quoted prices. 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 Goyal and Saretto (2009); Hu and Jacobs (2020)). 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 (e.g., 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 treatment set versus those that are in the control set, that is, 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 by filtering the option data in line with the existing literature as described in Section I.B of the paper.

We calculate the returns to trading portfolios of delta-neutral straddles in the nearest-to-maturity expiry for each firm. The calendar days to expiry when an option is traded is greater than 7 and at most 45.[8] A delta-neutral straddle is commonly used to obtain a long position on the implied volatility of the underlying stock, while minimizing directional exposure to underlying price movements.[9] 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 prices available from OptionMetrics at the first market close after hurricane landfall. Because the bid-ask spread can be significant for options, we analyze the returns to a long straddle position if one were to trade at the best ask (best offer). 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.[10]

We compute the returns to each straddle position as

$$StraddleReturn = (Payoff - BestOffer)/BestOffer. \tag{C.6}$$

We estimate the difference between hit and control portfolio returns by estimating the regression jointly over all hurricanes in the sample,

$$StraddleReturn_{i,h} = \kappa IsHit_{i,h} + \pi_h + \psi_{Ind} + \epsilon_{i,h}, \tag{C.7}$$

where $IsHit_{i,h}$ equals 1 if a firm has at least 10% or 25% of its establishments in the hurricane landfall region, and 0 otherwise. $IsHit_{i,h}$ is specified as an indicator variable in this regression rather than a continuous variable to simulate an investor deciding to buy the option straddle on a firm based on an exposure threshold.[11] A positive and significant κ would indicate that investors could profitably exploit the underreaction of option prices to a hurricane landfall that we document in Section III.B of the paper. As in the paper, π_h is a hurricane fixed effect that is equivalent to a time fixed effect as there is at most one buy-and-hold return observation per firm per hurricane, and ψ_{Ind} is an industry fixed effect.

[8] Alternative days-to-expiry limits lead to qualitatively similar results.

[9] See, for example, Coval and Shumway (2001); Goyal and Saretto (2009); Muravyev (2016); Hu and Jacobs (2020); Muravyev and Pearson (2020).

[10] As in Hu and Jacobs (2020), if the market is closed on the Friday of the expiration date, we use the closing price of the most recent prior trading date.

[11] In this analysis, we only include hurricanes for which there are at least three hit firms.

Table C.5 shows the κ estimate for regressions with different thresholds at which a firm is considered "hit" and different radii around the eye of the hurricane on which the landfall region is based. We find evidence that the trading strategy can profitably exploit the underreaction of option prices to hurricanes. The coefficient estimates are positive and significant in the majority of the cases.

The economic magnitude of the coefficient estimates is substantial. The returns generated with the option straddle are up to 31%. The statistical significance is weaker than when analyzing the underreaction through the forward VRP in Section III.B of the paper, because the number of observations drops due to firms not having a sufficient number of liquid options to trade the straddle.

Table C.5: Difference in option (straddle) returns between hit and control firms

This table reports the coefficients and test statistics when estimating the panel model in equation (C.7). The dependent variable is the return (in %) 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 given in equation (C.6). The independent variable is an indicator variable that equals 1 for hit firms and 0 for control firms. This variable is used to estimate the difference between holding a straddle on a hit firm versus a control firm. In the results shown, a firm is considered hit if it has at least 10% or 25% of its establishments in the landfall region of a hurricane. Control firms have no establishments in the counties in the landfall region. To identify counties in the landfall region, we apply a radius of 50 or 200 miles around the hurricane eye. The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. Industry and time fixed effects are included. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period and there is at most one buy-and-hold return observation per firm per hurricane in a particular regression. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: Option return (in %), $StraddleReturn_{i,h}$								
	Hit firms have landfall region estab. share of							
	≥ 0.1				≥ 0.25			
Radius of landfall region	50 miles		200 miles		50 miles		200 miles	
$IsHit_{i,h}$	31.153**	28.469**	9.946***	10.147***	26.014	21.307	15.041***	14.890**
	(2.181)	(2.012)	(3.046)	(2.895)	(1.213)	(0.989)	(2.649)	(2.499)
Adjusted R^2 (%)	12.975	13.011	9.717	9.730	16.870	17.325	8.110	8.058
Observations	2,929	2,929	9,383	9,383	1,340	1,340	6,335	6,335
Obs. hit	209	209	3,283	3,283	61	61	1,007	1,007
Obs. control	2,720	2,720	6,100	6,100	1,279	1,279	5,328	5,328
Hurricanes	17	17	37	37	9	9	32	32
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

C.4 Tail effects

The higher volatility following hurricane landfall is likely to lead to a large cross-sectional dispersion in cumulative abnormal stock returns of hit firms. However, it is unclear if hit firms will only be negatively affected by the hurricane, or if some firms can profit from the opportunity that a hurricane presents. Firms could, for example, benefit from rebuilding activity and an increase in demand for their products. As discussed in Section III.C of the paper, Refinitiv analyst call transcript data reveal multiple examples of discussions describing how hurricanes drive up demand.

In this section, we analyze the cross-sectional dispersion of the cumulative abnormal stock returns of hit firms compared to control firms. We estimate the Fama-French five-factor model (Fama and French, 2015) for each stock with 120 trading days (roughly half a calendar year) before the inception day of the hurricane. The hurricane season lasts half a calendar year (from June to November), and thus, we avoid overlaps with the previous year's hurricane season. The coefficient estimates from this first-stage regression are then used to compute abnormal returns for each firm and hurricane. We next aggregate the abnormal returns to a cumulative abnormal return (CAR) from inception to 120 trading days after landfall, $CAR_{i,T_0^h:T_L^h+\tau}$.

To account for cross-sectional shocks that coincide with but are independent of a given hurricane, we take the CAR for a given firm i and hurricane h and subtract the mean CAR across all stocks for the concurrent period of the hurricane. We split the firm-hurricane observations into two groups. One group contains the CARs 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 CARs of the control firms, that is, firms with less than 25% establishment exposure. Then, we compute the differences in percentiles between the CAR distributions of the hit and control firms across all the hurricanes.

In Table C.6, we show the results. There are significant return differences between hit and control firms. Hit firms have a substantially larger dispersion of abnormal returns. The second set of columns shows that results are even stronger when using excess returns instead of abnormal returns. This increased dispersion is driven by both the left tail and the right tail of the distribution. High performing hit firms have higher abnormal returns than high performing control firms. The differences between the hit and control firms' return distributions are -6.4 and -5.9 percentage points and strongly significant for the 5^{th} and

10^{th} percentile, respectively. However, the 90^{th} and 95^{th} percentiles also exhibit statistically significant differences of 4.4 and 8.1 percentage points, respectively.

Table C.6: Tail effects of cumulative abnormal and excess stock returns

This table reports differences in percentage points between percentiles of the hit and control firms' return distributions, as described in Section C.4. Cumulative abnormal stock returns (columns 2 and 3) and excess return (columns 4 and 5) are used. For a firm to be characterized as hit for a specific hurricane, at least 25% of its establishments have to be in the 200-mile radius hurricane landfall region. The cumulative returns cover the period from hurricane inception to 120 trading days (6 months) after hurricane landfall. The abnormal returns are estimated based on the Fama-French five-factor model. The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are bootstrapped and clustered by county based on a firm's largest establishment share. The significance of the difference in returns is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	Abnormal returns		Excess returns	
Percentiles	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat
5%	-6.443***	(-6.361)	-9.306***	(-6.658)
10%	-5.887***	(-5.915)	-6.832***	(-7.242)
20%	-4.866***	(-6.578)	-4.718***	(-7.076)
30%	-2.041***	(-3.083)	-2.403***	(-4.848)
40%	-1.531**	(-2.218)	-1.209***	(-2.767)
50%	-0.369	(-0.599)	-1.208***	(-2.642)
60%	-0.848	(-1.296)	-0.688	(-1.442)
70%	0.527	(0.732)	0.065	(0.113)
80%	1.419	(1.391)	0.021	(0.035)
90%	4.398**	(2.498)	2.581*	(1.688)
95%	8.109**	(2.138)	11.082***	(3.091)
Obs. hit firms (exposure $\geq$ 25%)		3,510		3,510
Obs. control firms (exposure < 25%)		39,693		39,693
Hurricanes		37		37

C.5 Insurance firms

In the paper, we focus on the universe of firms excluding financial firms, as is 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 extreme weather events. In this section, we investigate if extreme weather uncertainty is also reflected in the option prices of insurance firms.

We use statutory financial statements data 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 U.S. We estimate the regression in equation (7) in the paper for these property and casualty insurance firms, with $LandfallRegionExposure_{i,R,h}$ measured as the share of total premiums, lagged by one year, written in states that experienced landfall by a hurricane. The results are reported in Table C.7. A state is considered to have experienced a hurricane landfall if at least 25% of the state's counties were within a given radius of that hurricane's eye. For the 50-mile radius, fewer hurricanes are included in the sample, because certain hurricanes do not reach the required threshold of hit counties (25%) in any state. In contrast to our baseline analysis in the paper, the number of publicly traded insurance firms with liquid options is relatively limited and the data on the hurricane exposure of an insurance firm are available by state and not by county.[12]

The coefficient estimates are positive and statistically significant for all specifications, implying that there is impact uncertainty for property and casualty insurance firms in the aftermath of a hurricane. The magnitudes of the coefficient estimates are economically significant, with the implied volatility being up to 70% higher for insurance firms with a 100% exposure to the landfall region of the hurricane. The coefficient magnitudes are lower for the 200-mile radius around the eye of the hurricane than for the 50-mile radius but remain significant up to three months after landfall.

[12]For insurance firms, the establishment-level data from NETS is likely not a precise measure of exposure to a certain region because insurance firm establishments and the physical location of properties they cover need not be located close together. For example, an insurance firm that insures a homeowner in Harris County (Houston), Texas, does not need to have a physical branch in that (or nearby) county.

Table C.7: Hurricane effects on implied volatility of insurance firms

This table reports the coefficients and test statistics when estimating the panel model in equation (7) in the paper for insurance firms. The dependent variable is the change (in %) in implied volatility of firm i from the trading day before hurricane inception ($T_0^h - 1$) to 1 week (5 trading days), 1 month (20 trading days), and 3 months (60 trading days) after landfall ($T_L^h + 5$, $T_L^h + 20$, and $T_L^h + 60$, respectively). The independent variable measures the share of total premiums (from 0 to 1) written by an insurance firm in states that were hit by a hurricane. A state is considered to be hit by a hurricane if at least 25% of the state's counties lie within a radius of 50 miles (columns 1 to 3) or 200 miles (columns 4 to 6) around the hurricane eye at landfall. Hurricanes that do not reach this threshold for any state are excluded. The data span from 1996 to 2017. T-statistics are shown in parentheses. The standard errors are clustered by the state in which the insurance firm has the largest premium share. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. 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 (in %), $log(IV_{i,T_L^h+\tau}/IV_{i,T_0^h-1})$						
	50-mile radius landfall region			200-mile radius landfall region		
Time post landfall	1 week	1 month	3 months	1 week	1 month	3 months
$LandfallRegionExposure_{i,R,h}$	77.655***	51.534***	40.528***	19.363**	19.584**	17.318***
	(5.732)	(2.899)	(4.281)	(2.592)	(2.202)	(2.714)
Adjusted R^2 (%)	18.344	32.155	49.802	23.040	45.931	45.097
Observations	299	301	305	692	693.000	699
Obs. landfall exposure > 0	290	294	297	668	670	676
Obs. landfall exposure ≥ 0.25	6	7	7	73	76	72
Hurricanes	14	14	14	31	31	31
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

C.6 Additional tables and figure

Table C.8 reports results when using county-level sales instead of number of establishments to measure firms' exposures to hurricanes. Table C.9 shows the baseline estimates when excluding one hurricane at a time. In Table C.10, NOAA estimates of hurricane-specific radii based on reanalyses that are used for hurricanes starting in 2004. The reanalyses are generally released several months after hurricane landfall and are therefore not available in real time. Tables C.11 and C.12 show estimates using changes to model-free implied volatility rather than OptionMetrics implied volatility.[13]

Table C.13 shows results when using two climate change concern indices to examine the potential role of climate change salience in explaining the VRP reversal effects after Hurricane Sandy. We interact the landfall region exposure variable with the climate change concern index of Ardia, Bluteau, Boudt, and Inghelbrecht (2022) and the Google Trends index for searches on the topic of climate change in the U.S. The two climate change indices are both monthly and plotted in Figure C.1. Table C.14 presents the results when interacting the firm exposure to a hurricane landfall region with a set of year indicators for hurricanes after Hurricane Sandy (as opposed to one indicator for all hurricanes after Sandy). In Table C.15, we present estimates when examining VRP responses to hurricane forecasts rather than landfall.

Table C.16 examines abnormal and excess returns for the subsample of hurricanes that occurred after Hurricane Sandy. Table C.17 is equivalent to Table VII Panel B in the paper, but excess returns instead of abnormal returns act as the dependent variable. Table C.18 is another variation of Table VII Panel B in which the sample excludes the bottom 20% of NYSE stocks in terms of market capitalization.

Table C.19 reports statistics on firm establishment locations and relocations.

[13] The model-free implied volatility generation uses the "standardized" options surface data for single stocks from OptionMetrics at a 30-day time-to-expiry horizon and code generously provided by Greg Vilkov at https://doi.org/10.17605/OSF.IO/Z2486 (Vilkov, 2021). Given that the single-stock option surface data does not filter out prices from untraded options, to reduce the impact of stale prices in the earlier part of the sample, in Tables C.11 and C.12, we analyze the implied volatility surface data for the period from 2000 onwards. However, results using the implied volatility surface data from 1996 onwards are qualitatively similar. The lack of traded options at multiple strikes is particularly an issue for single-stock options of smaller firms and of those outside the S&P 500 index. Kadan and Tang (2020) find that the number of firms with multiple traded, liquid options is low before 2000 even within the S&P 500 Index.

Table C.8: Hurricane effects on implied volatility with geographic sales footprint

This table reports coefficients and test statistics from estimating the panel model in equation (7) in the paper. The dependent variable is the change (in %) in implied volatility of firm i from the trading day before hurricane inception ($T_0^h - 1$) to 1 week (5 trading days) and 1 month (20 trading days) after landfall ($T_L^h + 5$ and $T_L^h + 20$, respectively). The independent variable is the share (from 0 to 1) of a firm's sales that are within a radius of 200 miles (Panel A), 100 miles (Panel B), or 50 miles (Panel C) around the hurricane eye at landfall. The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include industry, time, and industry-time fixed effects as indicated. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: 200-mile radius landfall region

Dependent variable: Change in IV (in %), $log\left(IV_{i,T_L^h+\tau}/IV_{i,T_0^h-1}\right)$						
	1 week post landfall			1 month post landfall		
$LandfallRegionExposure_{i,R,h}$	2.853***	2.935***	2.075**	6.224***	6.201***	4.943***
	(2.884)	(2.959)	(2.301)	(3.645)	(3.667)	(3.360)
Adjusted R^2 (%)	12.472	12.476	12.979	24.525	24.549	25.058
Observations	39,038	39,038	39,038	39,061	39,061	39,061
Hurricanes	37	37	37	37	37	37
Industry FE	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No
Industry × Time (Hurricane) FE	No	No	Yes	No	No	Yes

Panel B: 100-mile radius landfall region

$LandfallRegionExposure_{i,R,h}$	5.565***	5.655***	4.666***	9.018***	8.983***	7.269***
	(3.827)	(3.898)	(3.235)	(3.943)	(3.955)	(3.673)
Adjusted R^2 (%)	12.681	12.680	13.201	25.410	25.423	25.994
Observations	33,189	33,189	33,189	33,199	33,199	33,199
Hurricanes	37	37	37	37	37	37
Industry FE	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No
Industry × Time (Hurricane) FE	No	No	Yes	No	No	Yes

Panel C: 50-mile radius landfall region

$LandfallRegionExposure_{i,R,h}$	9.573***	9.669***	6.893***	16.435**	16.346**	10.097*
	(3.707)	(3.756)	(2.766)	(2.324)	(2.303)	(1.847)
Adjusted R^2 (%)	12.145	12.148	12.711	25.106	25.117	25.744
Observations	27,912	27,912	27,912	27,909	27,909	27,909
Hurricanes	37	37	37	37	37	37
Industry FE	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No
Industry × Time (Hurricane) FE	No	No	Yes	No	No	Yes

Table C.9: Hurricane effects on implied volatility (excl. hurricanes)

This table reports the coefficients and t-statistics from repeatedly estimating the panel model in equation (7) in the paper while excluding individual hurricanes from the regression. The dependent variable is the change (in %) in the implied volatility of firm i from the trading day before hurricane inception ($T_0^h - 1$), until 1 week (5 trading days) after landfall ($T_L^h + 5$). The independent variable is the share (from 0 to 1) of a firm's establishments that are within a 200-mile radius around the hurricane eye at landfall. The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. Industry and time fixed effects are included. 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. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: Change in IV (in %), $log\left(IV_{i,T_L^h+5}/IV_{i,T_0^h-1}\right)$						
Excl. hurricane	Year	Coeff. estimate	T-stat	Adjusted R^2 (%)	Observations	Hurricanes
Bertha	1996	3.999***	2.883	12.401	38,366	36
Fran	1996	3.950***	2.866	12.570	38,365	36
Danny	1997	3.766***	2.741	12.445	38,211	36
Bonnie	1998	3.861***	2.818	11.576	38,097	36
Earl	1998	4.088***	3.036	12.325	38,087	36
Georges	1998	3.848***	2.841	12.536	38,087	36
Bret	1999	3.789***	2.780	12.401	38,172	36
Floyd	1999	4.358***	3.021	12.639	38,022	36
Irene	1999	3.855***	2.816	12.450	38,171	36
Lili	2002	3.867***	2.715	12.415	38,028	36
Claudette	2003	4.015***	2.864	12.622	38,069	36
Isabel	2003	3.988***	2.963	12.627	38,042	36
Charley	2004	3.902***	2.830	12.556	37,954	36
Frances	2004	3.901***	2.900	12.268	37,955	36
Ivan	2004	3.824***	2.804	12.356	37,952	36
Jeanne	2004	3.843***	2.859	12.505	37,953	36
Dennis	2005	3.654***	2.646	12.705	37,911	36
Katrina	2005	3.776***	2.711	12.686	37,920	36
Rita	2005	3.761***	2.850	12.597	37,920	36
Wilma	2005	3.848***	2.814	12.694	37,926	36
Humberto	2007	4.193***	2.760	12.184	37,744	36
Dolly	2008	3.893***	2.867	12.434	37,779	36
Gustav	2008	3.132***	2.631	12.210	37,769	36
Ike	2008	2.635**	2.174	9.756	37,747	36
Irene	2011	3.702***	2.588	12.669	37,728	36
Isaac	2012	3.895***	2.864	12.637	37,780	36
Sandy	2012	3.648**	2.483	12.685	37,748	36
Arthur	2014	4.052***	2.848	12.833	37,623	36
Hermine	2016	4.149***	3.082	12.927	37,425	36
Matthew	2016	3.569***	2.582	13.054	37,418	36
Harvey	2017	3.707***	2.813	12.857	37,458	36
Irma	2017	3.449**	2.419	12.830	37,482	36
Nate	2017	3.939***	2.766	12.771	37,458	36
Florence	2018	3.736***	2.808	13.008	37,363	36
Michael	2018	3.914***	2.960	11.436	37,359	36
Barry	2019	3.673***	2.697	12.941	37,379	36
Dorian	2019	4.009***	3.035	12.003	37,428	36

Table C.10: Hurricane effects on implied volatility using alternative radii

This table reports coefficients and test statistics from estimating the panel model in equation (7) in the paper. The dependent variable is the change (in %) in implied volatility of firm i from the trading day before hurricane inception ($T_0^h - 1$) to 1 week (5 trading days), 1 month (20 trading days), and 3 month (60 trading days) after landfall ($T_L^h + 5$, $T_L^h + 20$, and $T_L^h + 60$, respectively). The independent variable is the share (from 0 to 1) of a firm's establishments that are within the hurricane-specific estimated 34 KT (Panel A) or 64 KT (Panel B) wind speed radius of the hurricane eye at landfall, based on reanalysis data made available via NOAA after hurricane landfall starting in 2004. The data span from 2004 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include industry, time, and industry-time fixed effects as indicated. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Radius based on 34 KT wind speed

Dependent Variable: Change in IV (in %), $log(IV_{i,T_L^h+\tau}/IV_{i,T_0^h-1})$						
Time post landfall	1 week		1 month		3 months	
$LandfallRegionExposure_{i,h}$	7.173***	5.889***	12.162***	9.958***	10.304***	8.043**
	(3.943)	(3.630)	(3.711)	(3.403)	(3.460)	(2.534)
Industry FE	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No
Industry × Time (Hurricane) FE	No	Yes	No	Yes	No	Yes
Adjusted R^2 (%)	11.842	12.353	27.220	27.760	32.882	33.340
Observations	29,584	29,584	29,563	29,563	29,551	29,551
Obs. LandfallExposure > 0	15,444	15,444	15,440	15,440	15,405	15,405
Obs. LandfallExposure ≥ 0.25	2,304	2,304	2,309	2,309	2,322	2,322
Hurricanes	25	25	25	25	25	25

Panel B: Radius based on 64 KT wind speed

Dependent Variable: Change in IV (in %), $log(IV_{i,T_L^h+\tau}/IV_{i,T_0^h-1})$						
Time post landfall	1 week		1 month		3 months	
$LandfallRegionExposure_{i,h}$	14.139***	13.046***	22.988***	19.510***	16.558***	11.516**
	(4.189)	(4.116)	(4.121)	(3.815)	(2.712)	(1.985)
Industry FE	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No
Industry × Time (Hurricane) FE	No	Yes	No	Yes	No	Yes
Adjusted R^2 (%)	12.092	12.680	28.852	29.466	33.442	34.012
Observations	23,166	23,166	23,146	23,146	23,158	23,158
Obs. LandfallExposure > 0	8,819	8,819	8,813	8,813	8,801	8,801
Obs. LandfallExposure ≥ 0.25	450	450	448	448	453	453
Hurricanes	25	25	25	25	25	25

Table C.11: Hurricane effects on model-free implied volatility

This table reports coefficients and test statistics from estimating the panel model in equation (7) in the paper. The dependent variable is the change (in %) in the model-free at-the-money implied volatility of firm i from the trading day before hurricane inception ($T_0^h - 1$) until 1 week (5 trading days), 1 month (20 trading days), and 3 months (60 trading days) after landfall ($T_L^h + 5$, $T_L^h + 20$, and $T_L^h + 60$, respectively). The independent variable is the share (from 0 to 1) of a firm's establishments that are within a radius of 200 miles (Panel A) or 50 miles (Panel B) around the hurricane eye at landfall. The data span from 2000 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include industry, time, and industry-time fixed effects as indicated. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: 200-mile radius landfall region

Dependent variable: Change in model-free volatility (in %), $log\left(MFV_{i,T_L^h+\tau}/MFV_{i,T_0^h-1}\right)$

	1 week post landfall			1 month post landfall			3 months post landfall		
$LandfallRegionExposure_{i,R,h}$	4.760**	4.692**	2.841	11.628***	11.412***	9.894***	6.877***	6.131***	6.293**
	(2.195)	(2.057)	(1.500)	(4.374)	(4.177)	(4.202)	(3.085)	(2.595)	(2.547)
Adjusted R^2 (%)	19.435	19.440	20.055	31.439	31.451	32.235	44.768	44.832	45.296
Observations	29,698	29,698	29,698	29,673	29,673	29,673	29,612	29,612	29,612
Hurricanes	28	28	28	28	28	28	28	28	28
Industry FE	No	Yes	No	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry X Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel B: 50-mile radius landfall region

	1 week post landfall			1 month post landfall			3 months post landfall		
$LandfallRegionExposure_{i,R,h}$	13.497***	13.849**	8.510	35.848***	35.115***	25.177***	23.976***	21.176***	14.868**
	(2.659)	(2.545)	(1.602)	(3.874)	(3.628)	(3.750)	(3.300)	(2.946)	(2.300)
Adjusted R^2 (%)	19.427	19.429	20.073	32.442	32.432	33.283	44.227	44.300	45.805
Observations	20,874	20,874	20,874	20,846	20,846	20,846	20,785	20,785	20,785
Hurricanes	28	28	28	28	28	28	28	28	28
Industry FE	No	Yes	No	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry X Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Table C.12: Hurricane effects on model-free volatility risk premium post Hurricane Sandy

This table reports the coefficients and test statistics when estimating the panel model in equation (8) in the paper with a post-Sandy (post-2012) interaction term added. The dependent variable is the model-free VRP (in %) averaged over 1 week, 1 month, and 2 months (5, 20, and 40 trading days, respectively) after landfall. The model-free VRP is computed as the difference between the ex ante model-free implied and ex post realized volatility, as specified in equation (2) in the paper. The independent variable is the share (from 0 to 1) of a firm's establishments that are within a radius of 200 miles around the hurricane eye at landfall. In addition, this landfall region exposure variable is interacted with an indicator variable that equals 1 for all hurricanes after Sandy (after 2012). The data span from 2000 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include firm, time, and industry-time fixed effects as indicated. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: Model-free VRP (in %) avg. over τ trading days post landfall, $\overline{VRP}_{i,T_L^h+\tau}$

	1 week post landfall			1 month post landfall			2 months post landfall		
$LandfallRegionExposure_{i,R,h}$	-12.263***	-8.584***	-5.712***	-8.713***	-4.385*	-2.648	-4.954***	-0.632	-0.611
	(-4.295)	(-3.232)	(-3.443)	(-3.270)	(-1.781)	(-1.591)	(-3.238)	(-0.454)	(-0.441)
$LandfallRegionExposure_{i,R,h}$ $\times PostSandy_h$	10.984**	12.414***	9.123***	9.449**	11.078***	8.902***	2.656	6.107**	5.574**
	(2.171)	(3.199)	(3.522)	(1.997)	(3.448)	(3.653)	(0.590)	(2.475)	(2.424)
Adjusted R^2 (%)	11.958	35.769	36.241	14.615	42.271	42.774	11.884	47.595	47.924
Observations	29,538	29,538	29,538	29,637	29,637	29,637	29,580	29,580	29,580
Hurricanes	28	28	28	28	28	28	28	28	28
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry $\times$ Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

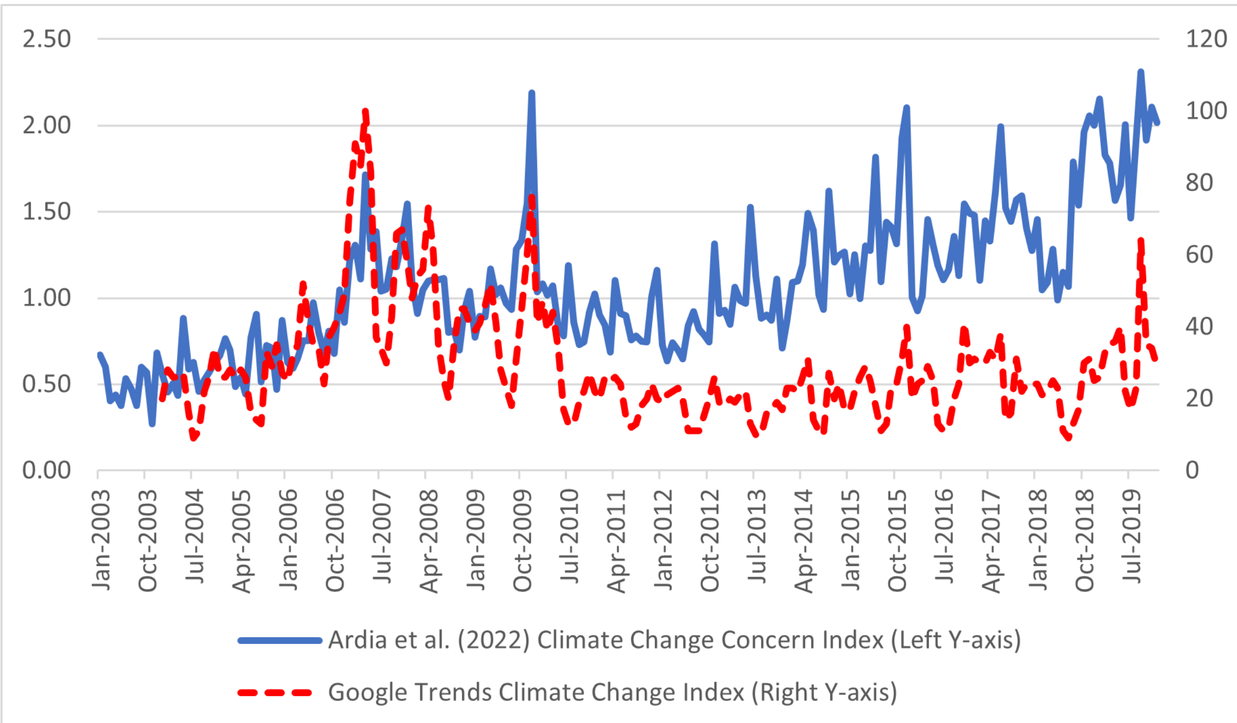


Figure C.1: Climate change indices

This figure shows the two climate change indices used for the analyses in Table C.13. The two indices are the climate change concerns index from Ardia, Bluteau, Boudt, and Inghelbrecht (2022) and the Google Trends index for searches on the topic of climate change in the U.S. The data are monthly and span from 2003 (2004 for the Google Trends index) to 2019.

Table C.13: Hurricane effects on volatility risk premium post Hurricane Sandy with climate change indices

This table reports the coefficients and test statistics when estimating the panel model in equation (8) in the paper with a post-Sandy (post-2012) and climate change index interaction terms added. The dependent variable is the VRP (in %) averaged over 1 week, 1 month, and 2 months (5, 20, and 40 trading days, respectively) after landfall. The VRP is computed as the difference between the ex ante implied and ex post realized volatility, as specified in equation (2) in the paper. The independent variable is the share (from 0 to 1) of a firm's establishments that are within a radius of 200 miles around the hurricane eye at landfall. The landfall region exposure variable is interacted with an indicator variable that equals 1 for all hurricanes after Sandy (after 2012) as well as with the climate change concerns index from Ardia, Bluteau, Boudt, and Inghelbrecht (2022) and a Google Trends index for searches on the topic of climate change in the U.S. The data span from 2003 (2004 for the Google Trends index) to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. Firm and time fixed effects are included. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: VRP (in %) avg. over τ trading days post landfall, $\overline{VRP}_{i,T_L^h+\tau}$

	1 week post landfall			1 month post landfall			2 months post landfall		
$LandfallRegionExposure_{i,R,h}$	-8.721***	-10.468**	-3.072	-7.968***	-5.235	1.360	-4.008***	-2.146	0.928
	(-4.127)	(-2.161)	(-0.919)	(-3.137)	(-1.144)	(0.468)	(-2.579)	(-0.655)	(0.338)
$LandfallRegionExposure_{i,R,h}$ $\times PostSandy_h$	6.815***	5.399**	6.291***	9.008***	11.390***	7.874***	5.776***	7.255***	5.418***
	(2.983)	(2.088)	(2.779)	(3.542)	(4.235)	(3.702)	(4.069)	(3.608)	(3.522)
$LandfallRegionExposure_{i,R,h}$ $\times CCIndex_m$		2.265			-3.654			-2.395	
		(0.488)			(-0.896)			(-0.750)	
$LandfallRegionExposure_{i,R,h}$ $\times GoogleTrends_m$			-0.266***			-0.422***			-0.236***
			(-2.789)			(-5.226)			(-3.039)
Adjusted R^2 (%)	33.823	33.800	34.700	41.529	41.500	42.400	45.993	46.000	47.000
Observations	29,494	29,560	27,936	29,533	29,599	27,980	29,490	29,557	27,932
Hurricanes	27	27	25	27	27	25	27	27	25
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table C.14: Hurricane effects on volatility risk premium by year post Hurricane Sandy

This table reports the coefficients and test statistics when estimating the panel model in equation (8) in the paper with a set of year-specific post-Sandy (post-2012) interactions term added. The dependent variable is the VRP (in %) averaged over 1 week, 1 month, and 2 months (5, 20, and 40 trading days, respectively) after landfall. The VRP is computed as the difference between the ex ante implied and ex post realized volatility, as specified in equation (2) in the paper. The independent variable is the share (from 0 to 1) of a firm's establishments that are within a radius of 200 miles around the hurricane eye at landfall. In addition, the landfall region exposure variable is interacted with a set of indicator variables that equal 1 for hurricanes in a designated year after 2012. There are no indicators for years in which no hurricanes made landfall. The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include firm and time fixed effects as indicated. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: Model-free VRP (in %) avg. over τ trading days post landfall, $\overline{VRP}_{i,T_L^h+\tau}$

	1 week post landfall		1 month post landfall		2 months post landfall	
$LandfallRegionExposure_{i,R,h}$	-7.579***	-5.801***	-7.843***	-5.833***	-4.838***	-2.785**
	(-3.701)	(-3.301)	(-3.271)	(-2.914)	(-2.914)	(-2.287)
$LandfallRegionExposure_{i,R,h} \times I_{y=2014}$	12.115***	4.010	16.838***	8.484**	13.559***	6.737***
	(3.532)	(1.177)	(4.329)	(2.568)	(4.604)	(3.135)
$LandfallRegionExposure_{i,R,h} \times I_{y=2016}$	-3.775	-2.596	4.669	5.198	1.122	2.758
	(-0.931)	(-0.804)	(0.895)	(1.281)	(0.256)	(0.899)
$LandfallRegionExposure_{i,R,h} \times I_{y=2017}$	3.942	5.526**	3.819	5.293**	1.607	3.563**
	(1.128)	(2.122)	(1.083)	(2.274)	(0.558)	(2.153)
$LandfallRegionExposure_{i,R,h} \times I_{y=2018}$	1.270	3.379	3.714	6.079	-0.733	3.240
	(0.242)	(0.613)	(0.621)	(1.113)	(-0.151)	(0.773)
$LandfallRegionExposure_{i,R,h} \times I_{y=2019}$	6.410**	6.185**	6.100*	8.148***	0.246	3.985**
	(2.174)	(2.244)	(1.778)	(2.827)	(0.078)	(1.963)
Adjusted R^2 (%)	17.200	26.900	22.500	34.200	22.700	38.600
Observations	36,539	36,539	36,675	36,675	36,674	36,674
Hurricanes	37	37	37	37	37	37
Firm FE	No	Yes	No	Yes	No	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes

Table C.15: Effects of hurricane path forecasts on volatility risk premium post Sandy

This table reports the coefficients and test statistics when estimating the panel model in equation (11) in the paper with a post-Sandy (post-2012) interaction term added and VRP (in %) as the dependent variable. The VRP is computed as the difference between the ex ante implied and ex post realized volatility, as specified in equation (2) in the paper. The VRP of a firm is measured at Γ days before hurricane landfall or dissipation ($T_L^h - \Gamma$). The model is estimated for the set of probability thresholds and days before landfall or dissipation for which we have at least 5 hurricanes in the pre- and post-Sandy periods. The independent variable is the share (from 0 to 1) of a firm's establishments that are in counties located in the forecast path of a hurricane. The forecast paths are defined based on the specified probability thresholds, which reflect minimum probabilities of hurricane force winds. A 20% threshold indicates that counties in the forecast path are estimated to have at least a 20% probability of experiencing hurricane force winds as of the last forecast available before market close on day $T_L^h - \Gamma$. For each regression, the numbers of firm observations with establishment shares in the forecast path greater than 0 and at least 0.25 are reported. The data span from 2007 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. Firm and time fixed effects are included. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Without Post-Sandy interaction

Dependent variable: VRP at Γ days before landfall/dissipation (in %), $VRP_{i,T_L^h-\Gamma}$									
Γ	1 Day			2 Days			3 Days		4 Days
Prob. of hurricane hit $\geq$	1%	10%	20%	1%	10%	20%	1%	10%	1%
$ForecExposure_{i,P,T_L^h-\Gamma}$	-2.797	-8.857***	-20.187***	0.468	-6.767**	-9.370***	1.001	-13.706***	-5.050**
	(-1.489)	(-2.644)	(-3.214)	(0.352)	(-2.040)	(-3.536)	(0.837)	(-3.314)	(-2.102)
Adjusted R^2 (%)	32.260	34.845	33.882	30.803	29.418	33.957	45.245	43.806	40.688
Observations	47,300	12,531	11,015	38,734	15,296	11,084	27,255	8,982	18,734
Obs. ForecExpo. > 0	14,312	4,080	3,304	17,405	5,878	4,166	14,269	3,993	9,647
Obs. ForecExpo. ≥ 0.25	766	142	85	2,134	248	167	2,225	164	1,997
Hurricanes	40	12	11	33	16	12	23	11	16
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: With Post-Sandy interaction

$ForecExposure_{i,P,T_L^h-\Gamma}$	-5.919**	-23.135***	-28.820***	-1.352	-19.640***	-30.387***	-1.069	-20.861***	-5.944**
	(-1.987)	(-3.714)	(-5.340)	(-0.612)	(-3.403)	(-5.323)	(-0.545)	(-4.091)	(-2.083)
$ForecExposure_{i,P,T_L^h-\Gamma}$ $\times PostSandy_h$	6.433**	24.915***	26.597**	3.615	18.948***	29.840***	4.803*	17.261**	2.698
	(2.075)	(3.631)	(2.157)	(1.268)	(3.055)	(3.807)	(1.682)	(2.094)	(0.926)
Adjusted R^2 (%)	32.268	34.943	33.938	30.809	29.497	34.131	45.260	43.845	40.690
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table C.16: Idiosyncratic hurricane shocks and returns in the post-Sandy sample

This table reports the coefficients and test statistics from estimating the effects of hurricanes on abnormal and excess returns from the panel model in equation (10) in the paper for the post-Sandy subsample from 2013 to 2019. The abnormal returns are relative to the Fama-French 5 factor model. The dependent variable is the cumulative abnormal (excess) return (in %) aggregated over windows of 20, 30, and 40 trading days, respectively. The first day of the return windows is 30 trading days post landfall. The independent variable is the share (from 0 to 1) of a firm's establishments that are within a radius of 200 miles around the hurricane eye at landfall. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. Industry, time, and industry interacted with time fixed effects are included as specified. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Cumulative abnormal return (in %) as dependent variable, $CAR_{i,h,T_h+30:T_h+30+ReturnHorizon}$

Return horizon (trading days)	20			30			40		
$LandfallRegionExposure_{i,R,h}$	2.989***	3.535**	1.935*	2.832**	4.255***	2.771**	3.861***	5.723***	3.571***
	(3.315)	(2.496)	(1.789)	(2.357)	(3.689)	(2.564)	(2.914)	(4.437)	(3.245)
Adjusted R^2 (%)	16.438	0.778	4.609	10.894	0.896	4.923	22.000	0.959	5.480
Observations	10,289	10,289	10,289	10,273	10,273	10,273	10,258	10,258	10,258
Hurricanes	10	10	10	10	10	10	10	10	10
Industry FE	No	Yes	No	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry X Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel B: Cumulative excess return (in %) as dependent variable, $CumulativeExcessReturn_{i,h,T_h+30:T_h+30+ReturnHorizon}$

$LandfallRegionExposure_{i,R,h}$	2.989***	2.918***	1.902**	2.832**	2.651**	2.345**	3.861***	3.644***	3.187***
	(3.315)	(3.145)	(2.191)	(2.357)	(2.335)	(2.195)	(2.914)	(2.995)	(2.925)
Adjusted R^2 (%)	16.438	16.648	18.646	10.894	11.204	13.263	22.000	22.313	24.433
Observations	10,289	10,289	10,289	10,273	10,273	10,273	10,258	10,258	10,258
Hurricanes	10	10	10	10	10	10	10	10	10
Industry FE	No	Yes	No	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry X Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Table C.17: Idiosyncratic hurricane shocks and excess returns

This table reports the coefficients and test statistics from estimating the effects of hurricanes on excess returns from the panel model in equation (10) in the paper with a post-Sandy (post-2012) interaction term. The dependent variable is the cumulative excess return (in %) aggregated over windows of 20, 30, and 40 trading days, respectively. The first day of the return windows is 30 trading days post landfall. The independent variable is the share (from 0 to 1) of a firm's establishments that are within a radius of 200 miles around the hurricane eye at landfall. $PostSandy_h$ is an indicator variable that equals 1 for all hurricanes post Sandy. The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include industry, time, and industry-time fixed effects as indicated. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: Cumulative excess return (in %), $CumulativeExcessReturn_{i,h,T_h+30:T_h+30+ReturnHorizon}$									
Return horizon (trading days)	20			30			40		
$LandfallRegionExposure_{i,R,h}$	-0.370	-0.266	-0.648	-0.124	0.268	-0.274	0.222	0.445	0.029
	(-0.530)	(-0.374)	(-0.989)	(0.146)	(0.320)	(-0.301)	(0.210)	(0.456)	(0.027)
$LandfallRegionExposure_{i,R,h}$	3.360***	3.239***	2.566**	2.717**	2.469*	2.659**	3.632**	3.325**	3.189**
$\times PostSandy_h$	(2.991)	(2.834)	(2.267)	(1.972)	(1.797)	(2.062)	(2.456)	(2.257)	(2.276)
Adjusted R^2 (%)	24.542	24.766	27.259	23.583	23.895	26.833	20.455	20.844	23.696
Observations	43,419	43,419	43,419	43,340	43,340	43,340	43,254	43,254	43,254
Hurricanes	37	37	37	37	37	37	37	37	37
Industry FE	No	Yes	No	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry X Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Table C.18: Idiosyncratic hurricane shocks and abnormal returns with market capitalization filter

This table reports coefficients and test statistics from estimating effects of hurricanes on abnormal returns relative to the Fama-French 5 factor model as per the panel model in equation (10) in the paper with a post-Sandy (post-2012) interaction term. The sample excludes stocks below the 20^{th} percentile of the market capitalization of stocks listed on the NYSE. The dependent variable is the cumulative abnormal return (in %) aggregated over windows of 20, 30, and 40 trading days, respectively. The first day of the return windows is 30 trading days post landfall. The independent variable is the share (from 0 to 1) of a firm's establishments that are within a radius of 200 miles around the hurricane eye at landfall. $PostSandy_h$ is an indicator variable that equals 1 for all hurricanes post-Sandy. The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include industry, time, and industry-time fixed effects as indicated. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: Cumulative abnormal return (in %), $CAR_{i,h,T_h+30:T_h+30+ReturnHorizon}$									
Return horizon (trading days)	20			30			40		
$LandfallRegionExposure_{i,R,h}$	-0.560	-0.338	-0.747	-1.292	-0.973	-1.748	-1.553	-1.110	-1.941
	(-0.799)	(-0.487)	(-0.911)	(-1.374)	(-1.144)	(-1.574)	(-1.243)	(-1.026)	(-1.451)
$LandfallRegionExposure_{i,R,h}$	4.642**	4.280**	2.525	5.878***	5.254***	3.945**	7.555***	6.750***	4.567**
$\times PostSandy_h$	(2.534)	(2.342)	(1.512)	(3.217)	(2.878)	(2.193)	(3.415)	(3.085)	(2.264)
Adjusted R^2 (%)	0.902	1.103	4.037	0.821	1.250	4.930	0.801	1.318	4.669
Observations	32,395	32,395	32,395	32,372	32,372	32,372	32,331	32,331	32,331
Hurricanes	37	37	37	37	37	37	37	37	37
Industry FE	No	Yes	No	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry × Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Table C.19: Summary statistics of firm locations and relocations

This table reports summary statistics on firm locations and relocations. Statistics on firm establishments located in Atlantic/Gulf coast counties and the population centers of these counties (measured as the top decile of counties based on population) are shown. Relocations are measured as the lesser of the number of counties which a firm entered in a given year and the number of counties the firm exited. In the last set of rows, this measure is shown normalized by the total number of counties in which the firm had establishments in the previous year. The data span from 1996 to 2019.

	Avg.	Std. dev.	10^{th} perc.	25^{th} perc.	50^{th} perc.	75^{th} perc.	90^{th} perc.
Firm establishment share in							
Atlantic/Gulf coast counties (in %)	35.260	37.693	0.000	0.000	24.175	62.500	100.000
Atlantic/Gulf coast population centers (in %)	32.374	36.847	0.000	0.000	19.680	51.010	100.000
Firm relocations (# counties)							
All firms	0.564	2.220	0.000	0.000	0.000	0.000	1.000
Atlantic/Gulf coast firms	0.728	2.566	0.000	0.000	0.000	0.000	2.000
Atlantic/Gulf coast pop. center firms	0.595	2.131	0.000	0.000	0.000	0.000	2.000
Firm relocations (% of firm's total counties)							
All firms	1.864	8.647	0.000	0.000	0.000	0.000	3.876
Atlantic/Gulf coast firms	2.156	8.842	0.000	0.000	0.000	0.000	5.000
Atlantic/Gulf coast pop. center firms	2.158	9.064	0.000	0.000	0.000	0.000	5.000

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