A theoretical framework on extreme weather uncertainty

In this section, we present a simple framework illustrating how extreme weather uncertainty affects return volatility. 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

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

As in Merton (1987), the $\sim$ superscript denotes that a variable is random and realized in $t+1$. The investors make their investment decisions in $t$. In this appendix, 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 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 $\mu_i$, $a_i$, and $s_i$ are firm-specific constants. The parameters are the same as in Merton (1987) with the exception of the last 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 as discussed in Section 5.4 of the paper. However, the 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. $\tilde{\theta}_i \sim B(1, \phi)$, 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 assumption is motivated by the exogenous nature of extreme weather events and the fact that local extreme weather events are generally not found to have aggregate, economy-wide impacts (see, for example, Strobl (2011)).

The return on firm $i$ is then given by

$$\tilde{R}_i = \frac{\tilde{C}F_i}{V_i} = \tilde{R}_i + b_i\tilde{Y} + \sigma_i\tilde{\epsilon}_i + \tilde{g}_i\tilde{\theta}_i, \quad (A.2)$$

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

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

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

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 captures the uncertainty about whether the extreme weather event will hit the firm.

\(^1\)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 $E(\tilde{g}_i^2)E(\tilde{\theta}_i^2) = (Var(\tilde{g}_i) + E(\tilde{g}_i)^2)(Var(\tilde{\theta}_i) + E(\tilde{\theta}_i)^2) = \mu_{g,i}^2 + \sigma_{g,i}^2\phi$.  

2
When $\mu_{g,i} = 0$, meaning that an extreme weather event has no mean impact on firm returns, there is no contribution from incidence uncertainty to total variance. In this case, $\text{Var}(\tilde{R}_i)$ varies with $\phi$ purely through the expected impact uncertainty, $\phi \sigma_{g,i}^2$. For a given $\mu_{g,i} \neq 0$, incidence uncertainty is highest when the probability of incidence, $\phi$, is 0.5. Therefore, $\phi$ 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 $\phi$ is either 0 or 1. Intermediate values of $\phi$ generate greater uncertainty. A higher probability of incidence can reduce incidence uncertainty for $\phi > 0.5$ but increase incidence uncertainty for $\phi < 0.5$.

Figure A.1 provides a graphical illustration. The variance prior to an extreme weather event, $\text{Var}(\tilde{R}_i)$, varies with $\phi$, the probability of incidence, using example parameters, baseline firm variance, $b_i^2 + \sigma_i^2 = 0.16$ and variance of impact $\sigma_{g,i}^2 = 0.0025$. 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, $\text{Var}(\tilde{R}_i|\theta = 1) = b_i^2 + \sigma_i^2 + \sigma_{g,i}^2$. The x-axis intersects the y-axis at the level of variance if the firm is not hit by the extreme weather event, $\text{Var}(\tilde{R}_i|\theta = 0) = b_i^2 + \sigma_i^2$. Prior to an event, as the probability of incidence, $\phi$, 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 $\mu_g$ and $\sigma_g^2$. All else equal, as $\mu_g$ increases, the contribution of incidence uncertainty to total variance increases. Incidence uncertainty at a given $\phi$ is the vertical distance between a curve and the red dot-dash straight line depicting $\text{Var}(\tilde{R}_i)$ when $\mu_{g,i} = 0$.\footnote{\text{Var}(\tilde{R}_i) will be greater than $\text{Var}(\tilde{R}_i|\theta = 1)$ when $|\mu_{g,i}| > \frac{1}{\sqrt{\phi}} \sigma_{g,i}$ and $\phi$ 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, $\text{Var}(\tilde{R}_i)$ is always greater than $\text{Var}(\tilde{R}_i|\theta = 0)$.}

Our main empirical analysis focuses on the impact uncertainty, $\sigma_{g,i}^2$. We analyze the uncertainty reflected in option prices and show that the impact uncertainty remains elevated for several months after a hurricane has made landfall, as discussed in Section 4.1. In the analysis presented in Section 4.5, we analyze the uncertainty prior to a potential extreme weather event at different probabilities of incidence, $\phi$. 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 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](image)

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, $\phi$, 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 level of variance if the firm is not exposed to the event, $Var(\tilde{R}_i|\theta = 0) = b_i^2 + \sigma_i^2$. 
A.2 Expected returns

In this section, we extend the model in Merton (1987) 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

$$
\tilde{R}_{K+1} = \hat{R}_{K+1} + \tilde{Y}, \quad (A.4)
$$

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

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

$$
\hat{R}_j = \tilde{R}_j + b_j \tilde{Y} + \tilde{\epsilon}_j + \tilde{g}_j \tilde{\theta}_j, \quad (A.5)
$$

where the exposure to the market factor is

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

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

$$
\tilde{\epsilon}_j = \sum_{i=1}^{K} w_{i,j}\sigma_i \tilde{\epsilon}_i \quad (A.7)
$$
$$
\tilde{g}_j \tilde{\theta}_j = \sum_{i=1}^{K} w_{i,j} \tilde{g}_i \tilde{\theta}_i. \quad (A.8)
$$

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

$$
\hat{R}_j = R^f + b_j(\tilde{R}_{K+1} - R^f) + \sum_{i=1}^{K} w_{i,j} \Delta_i. \quad (A.9)
$$
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 \( \Delta_i \equiv \tilde{R}_i - R^f - b_i(\tilde{R}_{K+1} - R^f) \).

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

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

and

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

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

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

where \( w_j \) is a vector with elements \( w_{i,j} \). The key element of the Merton (1987) model 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 do not know about, denoted \( S^c_j \). 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 phenomena like home bias (see Coval and Moskowitz (1999)).

The first order conditions with respect to \( b_j \) and \( w_j \) are

\[ 0 = \tilde{R}_{K+1} - R^f - \delta_j b_j \] (A.13)

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

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

\[ b_j = \left( \bar{R}_{K+1} - R_f \right) / \delta_j \] (A.15)

\[ w_{i,j} = \frac{(\Delta_i + \mu_{g,i}\phi)}{(\delta_j (\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2(1 - \phi)))}, \text{ for } i \in S_j \] (A.16)

\[ w_{i,j} = 0, \text{ for } i \in S^c_j \] (A.17)

\[ w_{K+1,j} = b_j - \sum_{i=1}^{K} w_{i,j}b_i \] (A.18)

\[ w_{K+2,j} = 1 - b_j + \sum_{i=1}^{K} w_{i,j}(b_i - 1) \] (A.19)

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), it is assumed 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:

\[ b_j = b = \frac{\bar{R}_{K+1} - R_f}{\delta}. \] (A.20)

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

\[ D_i = N_i W \frac{\Delta_i + \mu_{g,i}\phi}{\delta(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2(1 - \phi))}, \] (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

\[ \frac{V_i}{M} = x_i = \frac{q_i(\Delta_i + \mu_{g,i}\phi)}{\delta(\sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2(1 - \phi))}, \] (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 \( \Delta_i \) together with equations (A.20) and (A.22), the equilibrium
expected return on security $i$ is given by

$$E(\tilde{R}_i) = \tilde{R}_i + \mu_{g,i}\phi = R^f + \delta + \mu_{g,i}\phi$$

$$= R^f + \delta + \frac{\delta x_i (\sigma_i^2 + \sigma_{g,i}^2 \phi + \mu_{g,i}^2 \phi (1 - \phi))}{q_i}. \quad (A.23)$$

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

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

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

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

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 ($\delta$), 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 4 shows that the VRP (computed as the difference (in %) between the ex ante implied and ex post realized volatility) is significantly lower post landfall for hit firms compared to control firms. In our framework presented here, 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 9, when the investor underreaction to the uncertainty associated with the hurricane shock diminishes, and implied volatility is more inline with subsequent realized volatility for hit firms, as shown in Table 5.
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. By using equation (A.23) and \( E(\tilde{R}_i) = \frac{I_i \mu_i}{V_i} + I_i \mu_{\eta,i} \phi / V_i \), we obtain

\[
V_i = \frac{I_i}{R_f} \left[ \mu_i + \mu_{\eta,i} \phi - a_i b \delta - \frac{\delta I_i (s_i^2 + \sigma_{\eta,i}^2 \phi + \mu_{\eta,i}^2 \phi (1 - \phi))}{q_i \tilde{M}} \right],
\]

(A.26)

where the definitions for \( b_i, \sigma_i, \sigma_{\mu,i}, \) and \( \sigma_{\eta,i} \) 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 first component is \( \mu_{\eta,i} \phi \), 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 firm value, because the cash flows are discounted more heavily. In our empirical analysis in Section 4.4, we use earnings forecasts as a measure of cash flow expectation and decompose price movements of firms hit by extreme weather events into cash flow and discount rate news. These empirical results are in line with an extreme weather event not only leading to cash flow but also discount rate news.
B Data

B.1 Details on hurricane landfall region data

We use hurricane track data collated from the NOAA hurricane archives to determine which counties were located in hurricane landfall regions. For each hurricane, NOAA publishes forecast advisory text files from the inception of the storm until the storm dissolves. Every six hours a new file is published with information on the current location, that is, the coordinates, of the eye of a storm. The file also contains information on the storm category, for example, whether the storm was a tropical depression or a hurricane at a given point in time. Many storms in NOAA’s hurricane archive never get close to landfall. 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.

To determine the landfall region of each of the selected hurricanes, 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 $R$ of the storm 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 of the hurricane before the actual landfall for hurricanes that move along the coast. Also, because we only require the storm to be of hurricane level strength at landfall, as described previously, this methodology captures counties that are affected by strong rainfall even when the storm 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 all of the county. We also perform analyses where landfall exposure is based on a radius $R$ 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

In the paper, we use wind speed forecast advisories from NOAA which can be found in the National Hurricane Center’s hurricane archives (see https://www.nhc.noaa.gov/archive). 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 translate these wind speed forecasts into counties that are located in the forecast path of a hurricane in two steps. First, we apply a series of probability thresholds—a minimum reported cumulative probability 5 days (120 hours) out for a 64 KT wind speed—ranging from 1% to 50% to select locations in the text files. For example, when we apply a probability threshold of 1% for 64 KT wind, Surf City, NC, is the only location on the list in Figure B.2 that is selected. (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 map these selected locations to specific counties. Because the locations in the NOAA advisories are not exhaustive, leaving gaps between listed locations, in a second step, we add counties that are within a 75-mile radius of the counties from the first step.\(^3\) The 75-mile radius balances Type I errors (which we can see because larger radii include locations typically included in the advisory files but not for the given forecast) and Type II errors (which we can see because

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\(^3\)We use Census county centroids for this purpose, which can be found here https://www2.census.gov/geo/tiger/TIGER2017/COUNTY/.
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%, with the average storm having just 47 county-day observations at or above that threshold. Panel B presents the observation count by days to resolution at a given probability threshold.

Figure B.3 plots the counties used for the seasonal outlook analysis in Section 4.5.2 of the paper. 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. 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.

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4See National Weather Service “NOAA 2012 Atlantic Hurricane Season Outlook” https://www.cpc.ncep.noaa.gov/products/outlooks/hurricane2012/May/hurricane.shtml for an example.
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 1996 to 2019. Column 1 specifies the radius around the eye of the hurricane used to calculate the landfall region.

| Radius | Across all hurricanes | By hurricane |
|--------|-----------------------|--------------|
|        | 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.
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%.

| LOCATION      | TIME PERIOD | FORECAST HOURS | 34KT | 50KT | 64KT | CUMULATIVE PROBABILITY |
|---------------|-------------|----------------|------|------|------|------------------------|
| DANVILLE VA   | Fri 12Z     | 1 (1)          | 2 (3)| 2 (5)| 1 (6)| X (6)                  |
| NORFOLK NAS  | Fri 06Z     | X (X)          | X (2)| X (4)| 3 (6)| X (4)                  |
| NORFOLK VA    | Fri 12Z     | X (X)          | X (3)| X (6)| 1 (9)| X (4)                  |
| OCEANA NAS VA | Fri 06Z     | X (X)          | X (1)| X (4)| 3 (4)| X (5)                  |
| ELIZABETH CTY | Fri 12Z     | X (X)          | X (2)| X (4)| 4 (6)| X (8)                  |
| GREENSBORO NC | Fri 12Z     | X (X)          | 1 (1)| 3 (4)| 4 (8)| X (8)                  |
| RALEIGH NC    | Fri 12Z     | X (X)          | 1 (1)| 4 (5)| 5 (10)| X (12) | X (10) |
| ROCKY MT NC   | Fri 12Z     | X (X)          | 1 (1)| 4 (5)| 5 (10)| X (10) | X (11) |
| CAPE HATTERAS | Fri 12Z     | X (X)          | 4 (4)| X (8)| 8 (12)| X (14) |
| FAYETTEVILLE | Fri 12Z     | X (X)          | 5 (5)| 9 (14)| 7 (21)| 1 (22) | X (22) |
| CHARLOTTE NC  | Fri 12Z     | X (X)          | 5 (5)| 9 (14)| 3 (12)| 1 (13) | X (13) |

Figure B.2: Partial sample raw text file for windspeed forecast data
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 that are forecast to make landfall within five days with wind speeds of at least 64KT with a given minimum probability. Panel A reports the mean, median, and standard deviation of the number of county-days 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-days forecast observations per storm

| Probability ≥ |
|--------------|
| 1 | 10 | 20 | 40 | 50 |

| Storms | 52 | 22 | 16 | 13 | 12 |
| County-days 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-days 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 |
This figure plots the coastal counties used for the analysis in Section 4.5.2 of the paper. Panel A shows all the counties that are either directly bordering the Atlantic/Gulf coast or are within a 50-mile distance 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.
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 have firm level establishment data from NETS, which we map to firm level options and stock data by matching on firm name and headquarter address in two steps.\textsuperscript{5}

In the first step, we map NETS to CRSP-Compustat. 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 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, as in the case of 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, Refinitiv, and IBES based on the CUSIPs for the firms’ stocks.

\textsuperscript{5}We note 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 and firm management

To examine the real channels through which firms are affected by hurricanes and which can explain investor expectations of the associated uncertainty, we develop paragraph-level indicators showing whether paragraphs discussing hurricanes also discuss particular channels. The discussions fit into five channels: business interruption, physical damages, insurance, supply, and demand. Table C.1 shows the dictionary of terms used to identify each of these channels. We developed this dictionary by examining a 5 percent random sample of paragraphs discussing hurricanes and balancing Type I and Type II errors in the classification. We validated this methodology by performing a Latent Dirichlet Allocation analysis of all hurricane paragraphs, which confirmed that we are not missing any major channels through our manual inspection. Consistent with the baseline post-Sandy VRP results shown in Table 5 and discussed in section 4.2 of the paper, Table C.2 shows that the underreactions in response to particular mechanisms shown in Table 7 reversed after Hurricane Sandy.
**Table C.1: Dictionary for real channels related to hurricane impacts**

This table shows the terms used to identify the discussion of a real channel in relation to hurricanes in transcript data of calls between analysts and firm management. A channel is designated if one of the terms below occurs in a paragraph that also mentions a variation of “hurricane.” The * symbol 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 the examination of a 5 percent random subsample of hurricane discussions 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*          | unsur* AND | suppli* | cancel* AND |
| downtime OR down time | NOT(demand dest*) NOT(health*) | OR admission* | supply | NOT flight* |
| evacuat*              | NOT(demand dest*) NOT(health*) | OR admission* | third party | demand |
| interrupt*            | rebuild*         | OR patient* | upstream | downstream |
| knock* out            | remediat*         | OR physician* | order* AND | NOT(in order to) |
| offline               | replac*          |           |        | subscrib* |
| outage*               | wipe* AND out [in same sentence] |           |        |        |
| reopen*               |                 |           |        |        |
| restart*              |                 |           |        |        |
| restor* AND           |                 |           |        |        |
| (service OR power)    |                 |           |        |        |
| resume*               |                 |           |        |        |
| schedul*              |                 |           |        |        |
| shut in               |                 |           |        |        |
| shutdown* OR shut down* |               |           |        |        |
| suspend*              |                 |           |        |        |
| without power         |                 |           |        |        |
Table C.2: Real channels and volatility risk premium post Sandy

This table reports the coefficients and test statistics of panel regressions estimating how volatility risk premia respond to hurricane landfall exposure under different real channels of impact, along with interactions with an indicator for whether the hurricane occurred after Hurricane Sandy in 2012 (post-Sandy). The dependent variable is the VRP (in %) averaged over the first week (5 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 (7). The independent variable is the share (from 0 to 1) of a firm’s establishments that are in the 200-mile radius landfall region of a hurricane interacted with the number of paragraphs mentioning both the specified channel and hurricanes in transcripts of post-landfall calls between analysts and firm management. The columns show results, respectively, for the business interruption, physical damages, insurance, supply, and demand channels. Internet Appendix Table C.1 presents the dictionary of discussion terms identifying each channel. The data span 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 mention. 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 \( p < 0.01 \).

| LandfallRegionExposure_{i,R,T_{L}} \times | Business interruption | -3.443*** (3.430) |
|------------------------------------------|-----------------------|---------------------|
| Business interruption \times post-Sandy | 6.298*** (3.414)      |
| Physical damages                        | -2.555*** (-2.784)    |
| Physical damages \times post-Sandy      | 4.378* (1.880)        |
| Insurance                               | -1.632 (-0.693)       |
| Insurance \times post-Sandy             | 0.733 (0.087)         |
| Supply                                  | -6.649*** (-3.573)    |
| Supply \times post-Sandy                | 8.487*** (2.756)      |
| Demand                                  | -3.788*** (-4.078)    |
| Demand \times post-Sandy                | 6.269*** (4.731)      |

| LandfallRegionExposure_{i,R,T_{L}} \times | Yes | Yes | Yes | Yes | Yes |
|------------------------------------------|-----|-----|-----|-----|-----|
| LandfallRegionExposure_{i,R,T_{L}} \times hurricane mentioned | Yes | Yes | Yes | Yes | Yes |
| LandfallRegionExposure_{i,R,T_{L}} \times post-Sandy | Yes | Yes | Yes | Yes | Yes |
| LandfallRegionExposure_{i,R,T_{L}} \times hurricane mentioned \times post-Sandy | Yes | Yes | Yes | Yes | Yes |
| Firm FE                                  | Yes | Yes | Yes | Yes | Yes |
| Time (Hurricane) FE                      | Yes | Yes | Yes | Yes | Yes |

| Observations | 11,096 | 11,096 | 11,096 | 11,096 | 11,096 |
|---------------|--------|--------|--------|--------|--------|
| Adjusted R² (%)| 39.761 | 39.719 | 39.666 | 39.761 | 39.727 |
C.2 Other types of extreme weather events

While the empirical analyses in the paper use data on hurricanes, the empirical and theoretical framework for examining extreme weather uncertainty is general and can be applied to other types of extreme weather events. In this section, we analyze whether investors price in higher uncertainty when firms are exposed to other types of extreme weather events, namely floods, snow storms, and tornadoes. This analysis provides external validity for our baseline analysis not only due to the different types of events but also because the geographic regions where these events occur can differ from regions prone to hurricanes.

We use FEMA disaster declarations to determine which counties have been hit and when each event began. $ImpactRegionExposure_{i,h}$ measures the share (from 0 to 1) of a firm’s establishments that are in the impacted region for a specific event. Because we do not have readily available forecast information for these extreme weather events, we use the day one week before the reported incident begin date for each event as a pre-period for our difference-in-differences analysis.

We show results in Table C.3. We find that the option-implied volatilities of exposed firms rise in response to floods, extreme snow, and tornadoes. Interestingly, the uncertainty remains elevated for an extended period of time as for hurricanes. For all three extreme weather events, the largest effects are found at least one month after the event occurred. The coefficient estimates and statistical significance are mostly lower than for hurricanes. This result is likely due to these extreme weather events being generally less destructive and affecting a smaller number of firms. For tornadoes, the uncertainty response is the largest and comparable to the estimates for hurricanes.
### Table C.3: Implied volatility responses to other extreme weather events

This table reports the coefficients and test statistics of panel regressions estimating how implied volatility responds to floods, snow events, and tornadoes, where $\text{ImpactRegionExposure}_{i,h}$ is based on Federal Emergency Management Agency (FEMA) disaster declarations. The “landfall” date ($T_{L}^h$) is defined as the reported FEMA incident begin date and the inception date ($T_{0}^h$) is 7 days prior to the FEMA incident begin date. The independent variable, $\text{ImpactRegionExposure}_{i,h}$, measures the share (from 0 to 1) of a firm’s establishments that are in the impacted region for the specific event. The number of firm observations with an impact region exposure of greater than 0 and at least 0.25 are shown. The standard errors are clustered by county based on a firm’s largest establishment share. The time fixed effect can be interpreted as an event fixed effect because each extreme weather event 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 $p < 0.01$.

#### Panel A: Floods

| ImpactRegionExposure$_{i,h}$ | 1 week  | 1 month | 2 months | 3 months |
|------------------------------|---------|---------|----------|----------|
| Time post landfall | 1.591$^*$ | 3.325$^{***}$ | 2.871$^*$ | 4.710$^{**}$ |
| (1.904) | (3.185) | (1.735) | (2.119) |
| Industry FE | Yes | Yes | Yes | Yes |
| Time (Event) FE | Yes | Yes | Yes | Yes |
| Adjusted R$^2$ | 10.449 | 14.766 | 15.443 | 17.479 |
| Observations | 371,348 | 372,479 | 372,956 | 373,470 |
| Observations Expos. > 0 | 77,437 | 77,566 | 77,580 | 77,578 |
| Observations Expos. ≥ 0.25 | 2,684 | 2,698 | 2,706 | 2,713 |
| Floods | 340 | 340 | 340 | 340 |

#### Panel B: Snow

| ImpactRegionExposure$_{i,h}$ | 1 week | 1 month | 2 months | 3 months |
|------------------------------|--------|---------|----------|----------|
| Time post landfall | 0.586 | 4.932$^{**}$ | 5.712$^*$ | 6.153 |
| (0.376) | (2.210) | (1.827) | (1.446) |
| Adjusted R$^2$ | 8.245 | 9.371 | 6.38 | 5.226 |
| Observations | 36,260 | 36,338 | 36,433 | 36,488 |
| Observations Expos. > 0 | 9,003 | 9,012 | 9,003 | 9,022 |
| Observations Expos. ≥ 0.25 | 575 | 579 | 573 | 576 |
| Snow events | 32 | 32 | 32 | 32 |

#### Panel C: Tornadoes

| ImpactRegionExposure$_{i,h}$ | 1 week | 1 month | 2 months | 3 months |
|------------------------------|--------|---------|----------|----------|
| Time post landfall | 5.166 | 17.220$^{**}$ | 21.834$^{**}$ | 14.908 |
| (0.936) | (2.284) | (1.982) | (1.241) |
| Adjusted R$^2$ | 8.711 | 6.514 | 7.821 | 11.508 |
| Observations | 13,775 | 13,847 | 13,880 | 13,906 |
| Observations Expos. > 0 | 2,464 | 2,473 | 2,478 | 2,482 |
| Observations Expos. ≥ 0.25 | 27 | 26 | 27 | 27 |
| Tornadoes | 13 | 13 | 13 | 13 |
C.3 The returns to trading options at landfall

Our results in Section 4.2 of the paper show that investors underreact to the 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, the current 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 Hu and Jacobs (2020); Goyal and Saretto (2009)). This buy-and-hold strategy ensures that if, after trading, an option becomes deeper in-the-money or out-of-the-money due to price changes in the underlying stock, we are still able to measure the returns to such options in our portfolios without having to drop such observations due to a lack of quoted prices. We address the concern that option moneyness and time to maturity affect options returns (see, for example, Coval and Shumway (2001)) by comparing option returns within the same moneyness and time-to-maturity ranges in our difference-in-differences analysis. We address concerns regarding similar sources of potential noise or bias in option price and return data by estimating the difference between the returns of a treated and a control set of options. As long as a particular feature of option returns does not differentially affect options in the treated set versus those that are in the control set, 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 existing literature as described in Section 2.2 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. 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. 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 \( \frac{\delta_{\text{call}}}{\text{abs}(\delta_{\text{put}})} \). 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 (\( \text{Payoff} \)) 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.

We compute the returns to each straddle position as

\[
\text{StraddleReturn} = \frac{(\text{Payoff} - \text{BestOffer})}{\text{BestOffer}}
\]  

(C.1)

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

\[
\text{StraddleReturn}_{i,h} = \kappa I_{\text{Hit}}_{i,h} + \pi_h + \psi_{\text{Ind}} + \epsilon_{i,h},
\]  

(C.2)

where \( I_{\text{Hit}}_{i,h} \) equals 1 if a firm has at least 10% or 25% of its establishments in the hurricane landfall region, and 0 otherwise. \( I_{\text{Hit}}_{i,h} \) is specified as a dummy 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. A positive and significant \( \kappa \) would indicate that investors could profitably exploit the underreaction of option prices to a hurricane landfall that we document in Section 4.2 of the paper. As in the paper, \( \pi_h \) is a hurricane fixed effect which is equivalent to a time fixed effect as there is at most one buy-and-hold return observation per firm per hurricane, and \( \psi_{\text{Ind}} \) is an industry fixed effect.

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6 Alternative days-to-expiry limits lead to qualitatively similar results.
7 See, for example, Coval and Shumway (2001); Goyal and Saretto (2009); Muravyev (2016); Hu and Jacobs (2020); Muravyev and Pearson (2020).
8 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.
9 We only include in this analysis hurricanes for which there are at least three hit firms.
Table C.4 shows the $\kappa$ 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 under-reaction 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 4.2 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.4: 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.2). 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.1). The independent variable is a dummy variable that equals 1 for hit firms and 0 for control firms, and 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 located 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 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 $p < 0.01$.

| Hit threshold | 10% | 25% |
|---------------|-----|-----|
| Radius        |     |     |
| 50 miles      |     |     |
| IsHit$_{i,h}$ | 31.153** | 26.014 |
|               | (2.181) | (1.213) |
| 200 miles     | 28.469** | 21.307 |
|               | (2.012) | (0.989) |
|               | 9.946*** | 15.041*** |
|               | (3.046) | (2.649) |
|               | 10.147*** | 14.890** |
|               | (2.895) | (2.499) |
| Adjusted R$^2$ (%) | 12.975 | 16.870 |
| Total obs.    | 2.929 | 2.929 |
| Obs. hit      | 209 | 209 |
| Obs. control  | 2,720 | 2,720 |
| Hurricanes    | 17 | 17 |
| Industry FE   | No | No |
| Time (Hurricane) FE | Yes | Yes |

*Dependent variable: Option return (in %), $StraddleReturn_{i,h}$*
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 4.3 of the paper, Refinitiv analyst call transcript data reveal multiple examples of firm discussions describing how hurricanes have driven 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 (see Fama and French (2015)) for each stock with 120 trading days (roughly half a calendar year) before the inception day of the hurricane. The coefficient estimates from this first stage regression are then used to compute abnormal returns for each firm and hurricane as follows:

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

We next aggregate the abnormal returns to a cumulative abnormal return from inception to \( \tau \) trading days after landfall, \( CAR_{i,T^h_{L+\tau}} \).

To account for cross-sectional shocks that coincide with but are independent of a given hurricane, we take the cumulative abnormal return for a given firm \( i \) and hurricane \( h \) and subtract the mean cumulative abnormal return across all stocks for the concurrent period of the hurricane. We split the firm-hurricane observations into two groups. One group contains the cumulative abnormal returns of the hit firms, that is, the firms with at least 25 percent of their establishments in the hurricane landfall region. The other group contains the cumulative abnormal returns of the control firms, that is, firms with less than 25 percent establishment exposure. Then, we compute the differences in percentiles between the cumulative abnormal return distributions of the hit and control firms across all the hurricanes. We show results for the 120 trading day (6 month) horizon, which corresponds to half a calendar year. The hurricane season lasts half a calendar year (from June to November), and thus, we avoid overlaps with the subsequent year’s hurricane season.

Table C.5 shows that significant return differences between hit and control firms are evi-
dent even six months after hurricane landfall. Hit firms have a substantially larger dispersion of abnormal returns. The second set of columns shows results are even stronger when using excess returns instead of abnormal returns. This increased dispersion is not only driven by the left tail of the distribution, but also the right tail. High performing hit firms have higher abnormal returns than high performing control firms. By 120 trading days post-landfall, the differences between the hit and control firms’ return distributions are -7.9 and -7.5 percentage points and strongly significant for the 5\textsuperscript{th} and 10\textsuperscript{th} percentile, respectively. However, the 90\textsuperscript{th} and 95\textsuperscript{th} percentiles also exhibit statistically significant differences, of 4.6 and 5.9 percentage points, respectively.
Table C.5: Tail effects of cumulative abnormal and excess stock return differences

This table reports differences in percentage points between percentiles of the hit and control firms’ return distributions post landfall, as described in Section C.4. Cumulative abnormal stock returns (columns 2 and 3) and excess return (columns 4 and 5) are used, respectively. For a firm to be characterized as hit, at least 25% of its establishments have to be in the 200-mile radius hurricane landfall region. The cumulative returns are from hurricane inception to 120 trading days (6 months) post hurricane landfall. The abnormal returns are estimated based on the Fama-French five factor model. The data span 1996 to 2019. 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 \( p < 0.01 \).

| Percentiles | Abnormal returns | Excess returns |
|-------------|------------------|----------------|
|             | Cumulative r diff. | T-stat | Cumulative r diff. | T-stat |
| 5%          | -7.868***       | (-7.123) | -9.880***       | (-7.532) |
| 10%         | -7.493***       | (-7.741) | -7.104***       | (-6.170) |
| 20%         | -5.375***       | (-7.319) | -5.034***       | (-7.424) |
| 30%         | -2.917***       | (-4.445) | -2.614***       | (-6.018) |
| 40%         | -1.740***       | (-2.821) | -1.475***       | (-2.753) |
| 50%         | -0.665          | (-1.157) | -0.765*         | (-1.817) |
| 60%         | -0.673          | (-1.074) | 0.309           | (0.594)  |
| 70%         | 0.524           | (0.663)  | 0.340           | (0.526)  |
| 80%         | 1.781*          | (1.951)  | 0.340           | (0.526)  |
| 90%         | 4.564**         | (2.405)  | 3.382**         | (2.300)  |
| 95%         | 5.915*          | (1.793)  | 12.571***       | (2.778)  |
| Obs. hit firms (exposure ≥ 25%) | 3,466 | 3,466 |
| Obs. control firms (exposure < 25%) | 38,518 | 38,518 |
| Hurricanes  | 37              |            | 37              |            |
C.5 Insurance firms

The analysis and discussion in the paper 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 data on insurance statutory financials from S&P Global Market Intelligence, which provides us with the share of total premiums in each state written by property and casualty insurance firms in the US. We estimate the regression in equation (6) of the paper for these property and casualty insurance firms, with $\text{LandfallRegionExposure}_{i,R,h}$ replaced by a variable that measures the share of total premiums, lagged by one year, written in states that experienced landfall by hurricane $h$. The results are reported in Table C.6. A state is considered to have experienced a hurricane landfall, if at least 10% or 25% of the counties of that state 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 (10% or 25%) in any state. The empirical challenges include the fact that the number of publicly traded insurance firms with liquid options is relatively limited, and that the data on the exposure of an insurance firm are available by state and not by county.10

The coefficient estimates are positive for all specifications implying that the impact uncertainty for property and casualty insurance firms is substantial in the aftermath of a hurricane. The magnitudes of the coefficient estimates are economically significant, with the implied volatility being up to 70 percent higher for insurance firms with a 100 percent exposure to the landfall region of the hurricane. The magnitude of the coefficient tends to decrease for larger radii around the eye of the hurricane. The statistical significance is weaker than for the non-financial firms in Table 3 of the paper likely because the number of insurance firms in our sample is relatively small and the economic exposure of insurance firms is observed at a state-level granularity as opposed to county-level.

10For insurance firms, the establishment-level data from NETS is likely not a precise measure of exposure to a certain region because an insurance firm that, for example, insures a homeowner in Louisiana does not need an establishment close by.
Table C.6: Hurricane effects on implied volatility of insurance firms

This table reports the coefficients and test statistics when estimating the panel model in equation (6) of the paper for insurance firms. The dependent variable is the change (in %) in the implied volatility of insurance firm $i$ from the day before the inception day of the hurricane ($T_0^{h} - 1$) until 5 trading days (1 week) after landfall ($T_0^{h} + 5$). The independent variable measures the share of total premiums (from 0 to 1) written by an insurance firm in states that were in the landfall region of a hurricane. In columns 1 and 2 (3 and 4), if at least 10% (25%) of a state’s counties lie in the hurricane landfall region, the state is considered to be hit by the hurricane. Counties are in the landfall region of a hurricane if located within a radius of 50 miles (columns 1 and 3) or 200 miles (columns 2 and 4) around the hurricane eye at landfall. The data span 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, as shown in equation (6). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

| Landfall region radius | Minimum share of counties in landfall region for state to be considered hit | 10% | 25% |
|------------------------|---------------------------------------------------------------------------|-----|-----|
|                        |                                                                           | 50 miles | 200 miles | 50 miles | 200 miles |
| $LandfallRegionExposure_{i,R,h}$ |                                                                     | (6.882) | (1.060) | (4.332) | (2.266) |
| Adjusted R² (%)         |                                                                           | 22.625  | 18.525  | 8.407   | 18.699  |
| Observations            |                                                                           | 557     | 731     | 301     | 693     |
| Hurricanes              |                                                                           | 25      | 33      | 13      | 31      |
| Time (Hurricane) FE     |                                                                           | Yes     | Yes     | Yes     | Yes     |

Dependent variable: Change in IV (in %), $\log\left(\frac{IV_{i,T_0^{h}+5}}{IV_{i,T_0^{h}-1}}\right)$
C.6 Additional tables

This section provides additional figures and tables. Table C.7 presents the results of our baseline regression, Table 3 in the main paper, estimating the uncertainty after hurricane landfall when measuring the firms’ geographic footprint with county level sales instead of establishments. Table C.8 reports the baseline estimates when excluding one hurricane at a time to ensure our results are not driven by one outlier event. Table C.9 reports the baseline estimates when using NOAA estimates of actual hurricane radii based on reanalyses. The data, which are available for hurricanes starting in 2004, are generally released after several months after hurricane landfall and are therefore not available in real time as hurricanes make landfall. Tables C.10 and C.11 show estimates using changes to model-free implied volatility rather than OptionMetrics implied volatility.\textsuperscript{11} Table C.12 is equivalent to Table 9 Panel B but uses excess returns instead of abnormal returns.

\textsuperscript{11}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.10 and C.11, 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.7: Hurricane effects on implied volatility with geographic sales footprint

This table reports coefficients and test statistics from estimating the panel model in equation (6) of the paper. The dependent variable is the change (in %) in implied volatility of firm \( i \) from the trading day before hurricane inception \( (T_h^0 - 1) \) to 1 week (5 trading days) and 1 month (20 trading days) after landfall \( (T_h^L + 5 \text{ and } T_h^L + 20, \text{ respectively}) \). 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 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, 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, as shown in equation (6). 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

| LandfallRegionExposure_{i,R,h} | 1 week post landfall | 1 month post landfall |
|---------------------------------|---------------------|----------------------|
|                                 | \( 2.756^{***} \) | \( 2.830^{***} \) |
| Adjusted R² (%)                 | (2.778)             | (2.856)              |
| Observations                    | 12.413              | 12.417               |
| Hurricanes                       | 39,033              | 39,033               |
| Hurricanes                       | 37                  | 37                   |
| Industry FE                     | No                  | Yes                  |
| Time (Hurricane) FE             | Yes                 | No                   |
| Industry × Time (Hurricane) FE  | No                  | No                   |

### Panel B: 100-mile radius landfall region

| LandfallRegionExposure_{i,R,h} | 5.478^{***} | 5.555^{***} | 4.583^{***} | 8.927^{***} | 8.880^{***} | 7.183^{***} |
|---------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Adjusted R² (%)                 | (3.758)     | (3.823)     | (3.177)     | (3.887)     | (3.901)     | (3.623)     |
| Observations                    | 12.616      | 12.616      | 13.102      | 25.350      | 25.363      | 25.911      |
| Hurricanes                       | 33.185      | 33.185      | 33.185      | 33.202      | 33.202      | 33.202      |
| 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} | 9.466^{***} | 9.553^{***} | 6.779^{***} | 16.333^{**} | 16.234^{**} | 9.990^{*} |
|---------------------------------|-------------|-------------|-------------|-------------|-------------|-----------|
| Adjusted R² (%)                 | (3.647)     | (3.700)     | (2.712)     | (2.304)     | (2.283)     | (1.825)   |
| Observations                    | 12.131      | 12.135      | 12.669      | 25.082      | 25.093      | 25.700    |
| Hurricanes                       | 27.908      | 27.908      | 27.908      | 27.912      | 27.912      | 27.912    |
| 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.8: Hurricane effects on implied volatility (excl. hurricanes)

This table reports the coefficients and t-statistics from estimating the panel model in equation (6) 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 ($T_{h0} - 1$), until 1 week (5 trading days) after landfall ($T_{hL} + 5$). 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 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 as shown in equation (6). The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

| Excl. hurricane | Year | Coeff. estimate | T-stat | Adjusted $R^2$ (%) | Observations | Hurricanes |
|-----------------|------|-----------------|--------|-------------------|--------------|------------|
| Bertha          | 1996 | 3.909***        | 2.817  | 12.334            | 38,361       | 36         |
| Fran            | 1996 | 3.862***        | 2.803  | 12.511            | 38,360       | 36         |
| Danny           | 1997 | 3.681***        | 2.678  | 12.389            | 38,206       | 36         |
| Bonnie          | 1998 | 3.775***        | 2.753  | 11.492            | 38,092       | 36         |
| Earl            | 1998 | 4.002***        | 2.971  | 12.252            | 38,082       | 36         |
| Georges         | 1998 | 3.763***        | 2.777  | 12.469            | 38,082       | 36         |
| Bret            | 1999 | 3.704***        | 2.717  | 12.346            | 38,017       | 36         |
| Floyd           | 1999 | 4.265***        | 2.958  | 12.578            | 38,023       | 36         |
| Irene           | 1999 | 3.768***        | 2.753  | 12.394            | 38,166       | 36         |
| Lili            | 2002 | 3.782***        | 2.654  | 12.343            | 38,023       | 36         |
| Claudette       | 2003 | 3.929***        | 2.802  | 12.565            | 38,064       | 36         |
| Isabel          | 2003 | 3.899***        | 2.896  | 12.566            | 38,037       | 36         |
| Charley         | 2004 | 3.814***        | 2.763  | 12.500            | 37,949       | 36         |
| Frances         | 2004 | 3.814***        | 2.835  | 12.216            | 37,950       | 36         |
| Ivan            | 2004 | 3.737***        | 2.740  | 12.304            | 37,947       | 36         |
| Jeanne          | 2004 | 3.757***        | 2.794  | 12.450            | 37,948       | 36         |
| Dennis          | 2005 | 3.568***        | 2.582  | 12.647            | 37,906       | 36         |
| Katrina         | 2005 | 3.691***        | 2.649  | 12.630            | 37,915       | 36         |
| Rita            | 2005 | 3.675***        | 2.785  | 12.539            | 37,915       | 36         |
| Wilma           | 2005 | 3.762***        | 2.749  | 12.637            | 37,921       | 36         |
| Humberto        | 2007 | 4.107***        | 2.703  | 12.134            | 37,739       | 36         |
| Dolly           | 2008 | 3.807***        | 2.802  | 12.382            | 37,774       | 36         |
| Gustav          | 2008 | 3.046***        | 2.561  | 12.133            | 37,764       | 36         |
| Ike             | 2008 | 2.548**         | 2.108  | 9.638             | 37,742       | 36         |
| Irene           | 2011 | 3.608***        | 2.523  | 12.615            | 37,723       | 36         |
| Isaac           | 2012 | 3.809***        | 2.800  | 12.581            | 37,775       | 36         |
| Sandy           | 2012 | 3.556***        | 2.416  | 12.632            | 37,743       | 36         |
| Arthur          | 2014 | 3.956***        | 2.771  | 12.768            | 37,618       | 36         |
| Hermine         | 2016 | 4.060***        | 3.015  | 12.865            | 37,420       | 36         |
| Matthew         | 2016 | 3.569***        | 2.582  | 13.054            | 37,418       | 36         |
| Harvey          | 2017 | 3.620***        | 2.747  | 12.800            | 37,453       | 36         |
| Irma            | 2017 | 3.361**         | 2.356  | 12.775            | 37,477       | 36         |
| Nate            | 2017 | 3.851***        | 2.703  | 12.715            | 37,453       | 36         |
| Florence        | 2018 | 3.648***        | 2.743  | 12.955            | 37,358       | 36         |
| Michael         | 2018 | 3.823***        | 2.890  | 11.336            | 37,354       | 36         |
| Barry           | 2019 | 3.585***        | 2.635  | 12.883            | 37,374       | 36         |
| Dorian          | 2019 | 3.922***        | 2.968  | 11.960            | 37,423       | 36         |
Table C.9: Hurricane effects on implied volatility using alternative radii

This table reports coefficients and test statistics from estimating the panel model in equation (6) in the paper. The dependent variable is the change (in %) in implied volatility of firm $i$ from the trading day before hurricane inception ($T^h_0 - 1$) to 1 week (5 trading days) and 1 month (20 trading days) after landfall ($T^h_L + 5$ and $T^h_L + 20$, respectively). The independent variable is the share (from 0 to 1) of a firm’s establishments that are within the estimated 34 KT (Panel A) or 64 KT (Panel B) windspeed radius of the hurricane eye at landfall, based on reanalysis data made available via NOAA after hurricane landfall starting in 2004. The data span 2004 to 2019. 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, as shown in equation (6). 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 %), $\log(IV_{i,T^h_L+\tau}/IV_{i,T^h_0-1})$

| Time post landfall | 1 week | 1 month | 3 months |
|--------------------|--------|---------|----------|
| **LandfallRegionExposure_{i,h}** | 6.862*** (3.681) | 5.787*** (3.564) | 11.978*** (3.594) | 9.846*** (3.356) | 10.136*** (3.396) | 7.909** (2.487) |
| 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 R² (%) | 11.691 | 12.199 | 27.129 | 27.687 | 32.959 | 33.407 |
| Observations | 29,579 | 29,579 | 29,568 | 29,568 | 29,551 | 29,551 |
| Obs. LandfallExposure > 0 | 15,441 | 15,441 | 15,442 | 15,442 | 15,405 | 15,405 |
| Obs. LandfallExposure ≥ 0.25 | 2,303 | 2,303 | 2,310 | 2,310 | 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 %), $\log(IV_{i,T^h_L+\tau}/IV_{i,T^h_0-1})$

| Time post landfall | 1 week | 1 month | 3 months |
|--------------------|--------|---------|----------|
| **LandfallRegionExposure_{i,h}** | 13.879*** (4.108) | 12.994*** (4.095) | 22.832*** (4.105) | 19.454*** (3.802) | 16.485*** (2.699) | 11.464** (1.975) |
| 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 R² (%) | 11.987 | 12.559 | 27.129 | 27.687 | 32.959 | 33.407 |
| Observations | 23,162 | 23,162 | 23,149 | 23,149 | 23,158 | 23,158 |
| Obs. LandfallExposure > 0 | 8,817 | 8,817 | 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.10: Hurricane effects on model-free implied volatility

This table reports coefficients and test statistics from estimating the panel model in equation (6) 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 ($T_i^{h_0} - 1$) until 1 week (5 trading days), 1 month (20 trading days), and 3 months (60 trading days) after landfall, $T_i^{h_L}$, 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 2000 to 2019. 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, as shown in equation (6). 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

| Landfall Region | Exposure $i_{R,h}$ | 1 week post landfall | 1 month post landfall | 3 months post landfall |
|-----------------|---------------------|----------------------|-----------------------|------------------------|
|                 |                     | 4.242*               | 4.025*                | 2.284                  |
|                 |                     | (1.855)              | (1.701)               | (1.161)                |
|                 | Adjusted $R^2$ (%)  | 19.233               | 19.237                | 19.848                 |
| Observations    |                     | 29,728               | 29,728                | 29,728                 |
| Hurricanes      |                     | 28                   | 28                    | 28                     |
| Industry FE     | No                  | Yes                  | No                    | Yes                    |
| Time (Hurricane) FE | Yes                | Yes                  | Yes                   | Yes                    |
| Industry X Time (Hurricane) FE | No            | No                   | Yes                   | No                     |

### Panel B: 50-mile radius landfall region

| Landfall Region | Exposure $i_{R,h}$ | 12.446**             | 12.440**              | 7.473                  |
|-----------------|---------------------|----------------------|-----------------------|------------------------|
|                 |                     | (2.436)              | (2.272)               | (1.449)                |
| Adjusted $R^2$ (%)  |                     | 19.372               | 19.370                | 20.038                 |
| Observations    |                     | 20,894               | 20,894                | 20,894                 |
| Hurricanes      |                     | 28                   | 28                    | 28                     |
| Industry FE     | No                  | Yes                  | No                    | Yes                    |
| Time (Hurricane) FE | Yes                | Yes                  | Yes                   | Yes                    |
| Industry X Time (Hurricane) FE | No          | No                   | Yes                   | No                     |
Table C.11: Hurricane effects on model-free volatility risk premium post 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 (7). 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 dummy variable that equals 1 for all hurricanes post Sandy (after 2012). The data span 2000 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm’s largest establishment share. Firm, time, and time interacted with industry 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, as per equation (8). 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 \( \tau \) trading days post landfall, \( VRP_{i,T}^{hL+\tau} \) | 1 week post landfall | 1 month post landfall | 2 months post landfall |
|---|---|---|---|
| \( LandfallRegionExposure_{i,R,h} \) | -12.263*** | -8.584*** | -5.712*** |
| | (-4.295) | (-3.232) | (-3.443) |
| \( LandfallRegionExposure_{i,R,h} \times PostSandy_h \) | 10.984** | 12.414*** | 9.123*** |
| | (2.171) | (3.199) | (3.522) |
| Adjusted R\(^2\) (%) | 11.958 | 35.769 | 36.241 |
| Observations | 29,538 | 29,538 | 29,538 |
| Hurricanes | 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 |
Table C.12: Excess returns post hurricane landfall

This table reports the coefficients and test statistics from estimating the effects of hurricanes on excess returns from the panel model given in equation (14) 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 ($\tau = 30$). 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 a dummy variable that equals 1 for all hurricanes post-Sandy. The data span 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, 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 $p < 0.01$.

| Return horizon (trading days) | 20      | 30      | 40      |
|-------------------------------|---------|---------|---------|
| $LandfallRegionExposure_{i,R,Th}$ |         |         |         |
| -0.914                        | -1.058  | -0.823  | -0.914  |
| (-1.429)                      | (-1.261)| (-0.790)| (-1.429)|
| $LandfallRegionExposure_{i,R,Th} \times PostSandy_h$ |         |         |         |
| 2.432**                      | 2.802** | 3.830***| 2.432** |
| (2.230)                      | (2.440) | (2.847) | (2.230) |
| Adjusted R² (%)              | 28.438  | 27.777  | 25.541  |
| Observations                 | 42,207  | 42,152  | 42,092  |
| Hurricanes                   | 37      | 37      | 37      |

Industry FE                   | No      | Yes     | No      | No      | Yes     | No      | No      | Yes     |
Time (Hurricane) FE           | Yes     | Yes     | No      | Yes     | Yes     | No      | Yes     | Yes     |
Industry X Time (Hurricane) FE | No      | No      | Yes     | No      | No      | Yes     | No      | No      | Yes
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