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

Mathias S. Kruttli, Brigitte Roth Tran, and Sumudu W. Watugala*

March 2021

1 Hurricane data

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

1.1 Details on hurricane forecast data

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

We translate these wind speed forecasts into counties that are located in the forecast path of a hurricane in two steps. First, we apply a series of probability thresholds — a

*Kruttli: The Board of Governors of the Federal Reserve System. Email: mathias.s.kruttli@frb.gov. Roth Tran: Federal Reserve Bank of San Francisco. Email: brigitte.rothtran@sf.frb.org. Watugala: Cornell University. Email: sumudu@cornell.edu.

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 A1 that is selected. We then map these selected locations to specific counties. In a second step, we add counties that are within a 75 mile radius of the counties from the first step.[1] We only focus on the 64 KT wind speed, because this is the minimum hurricane level wind speed.

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

1.2 Details on hurricane landfall region data

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

To determine the landfall region of each of the selected hurricanes, we first hand collect the landfall time of the hurricanes from NOAA's tropical cyclone reports, which can also be found in the hurricane archives. Then we include all counties in the landfall region that were at one point within a radius R of the storm eye 24 hours before or after the landfall

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

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

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

This figure shows a portion of a NOAA wind speed forecast text file for Hurricane Matthew on October 6, 2016. The left column shows selected locations with wind speed probabilities of at least 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 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 A1: Summary statistics of hurricane forecast data

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

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

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

Panel B: Number of county-days forecast observations

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

Table A2: Summary statistics of hurricane landfall region data

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

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

2 Mapping of NETS to financial data

We have firm level establishment data from NETS and map it to firm level options and stock data by matching based on a firm's name and headquarter address.[2]

In a 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 as, for example, INC and CORP, we require that a successful mapping between NETS and CRSP-Compustat satisfies two conditions. The first condition is that the first two words of the company name (or first word for a one word name as, for example, Starbucks), ZIP code, and city match. However, the first condition will lead to some false matches, because some firms have names with generic first two words based on their location as, for example, Santa Barbara Restaurant Group. In these cases, the ZIP code and city cannot necessarily help to conclusively determine the quality of the match. Therefore, a second condition is needed. The second condition requires that for a given match at least $N - 1$ words of the name have to be the same, where N is the maximum number of words of 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 check manually that the mapping is correct.

In a second step, we extend the mapping from CRSP-Compustat to OptionMetrics, which is straight forward as both databases have CUSIPs for the firms' stocks.

[2] We note here that the number of firms in NETS is large with over 50 million firms, because private firms are included. Simply conducting a fuzzy string match and checking the matches manually is therefore not feasible.

3 The returns to trading options at landfall

Our results in Section 4.3 of the paper show that investors underreact to the hurricane making landfall, because the VRP—calculated as the difference between ex ante expected volatility and ex post realized volatility—is significantly lower for hit firms than for control firms. This result raises the question if 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 3.3 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.[3] 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.[4] 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. 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.[5]

We compute the returns to each straddle position as

$$StraddleReturn = (Payoff - BestOffer)/BestOffer \tag{A1}$$

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

$$StraddleReturn_{i,h} = \kappa IsHit_{i,h} + \pi_h + \psi_{Ind} + \epsilon_{i,h}, \tag{A2}$$

where $IsHit_{i,h}$ is 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 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.[6] 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 4.3 of the paper. As in the paper, π_h is a hurricane fixed effect which is equivalent to a time fixed effect as there is at most one buy-and-hold return

[3] Alternative horizons lead to qualitatively similar results.

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

[5] 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.

[6] We only include hurricanes for which there are at least three hit firms.

observation per firm per hurricane, and ψ_{Ind} is an industry fixed effect.

Table A3 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 size of the coefficient estimates generally increase as the conditions for inclusion in the hit set tighten: as the radius around hurricane landfall decreases and as the firms' exposed establishment share threshold increases.

The economic magnitude of the coefficient estimates is substantial. The returns generated with the option straddle are up to 35%. The statistical significance is weaker than when analyzing the underreaction through the forward VRP in Section 4.3 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 A3: Option return difference between hit and control firms

This table reports the coefficients and test statistics when estimating the panel model in equation (A2). 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 (A1). The independent variable is a dummy variable that takes a value of 1 for hit firms and a value of 0 for control firms, which estimates the difference between holding a straddle on a hit firm versus a control firm. In Panel A, a hit firm has at least 10% of its establishments in counties located in the landfall region of a hurricane, and in Panel B the threshold is 25%. Control firms have no establishments in the counties located in the landfall region. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 50, 100, 150, and 200 miles surrounding the eye. For each regression, the total number of firm observations and the number of hit and control firms are reported. The data are from 1996 to 2017. Hurricanes with less than three firms in the landfall region for a given radius, that is hurricanes with less than three hit firms, are excluded from the analysis. The values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are included. The time fixed effect is equivalent to a hurricane fixed effect as there is at most one buy-and-hold return observation per firm per hurricane in a particular regression. The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

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

Dependent variable: Option return (in %)

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$IsHit_{i,h}$	35.223**	35.203**	14.795***	16.201***	5.672	6.341*	5.907*	6.060*
	(2.421)	(2.364)	(2.722)	(2.908)	(1.529)	(1.658)	(1.936)	(1.890)
Adjusted R^2 (%)	14.621	14.526	12.309	12.223	11.855	11.806	11.099	11.063
Observations	2,091	2,091	4,191	4,191	5,882	5,882	6,955	6,955
Obs. hit	173	173	768	768	1,613	1,613	2,646	2,646
Obs. control	1,918	1,918	3,423	3,423	4,269	4,269	4,309	4,309
Hurricanes	14	14	26	26	32	32	33	33
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

$IsHit_{i,h}$	27.967	29.002	25.112**	25.347**	17.507**	17.628**	12.810**	12.773**
	(0.995)	(1.023)	(2.053)	(2.078)	(2.096)	(2.106)	(2.161)	(2.101)
Adjusted R^2 (%)	14.578	15.392	11.065	10.914	10.870	10.720	10.030	9.931
Observations	708	708	2,957	2,957	4,009	4,009	4,468	4,468
Obs. hit	49	49	272	272	553	553	878	878
Obs. control	659	659	2,685	2,685	3,456	3,456	3,590	3,590
Hurricanes	6	6	21	21	26	26	27	27
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

4 Insurance firms

The analysis and discussion in the paper focus on the universe of firms excluding financial firms, as common in the asset pricing literature. One contribution of this paper is to show that the uncertainty around extreme weather events affects a wide range of firms and not only insurance firms which are often thought of in the context of natural disasters. In this section, we also investigate if extreme weather uncertainty is reflected in the option prices of insurance firms. The challenge that we face is that the number of publicly traded insurance firms with liquid options is relatively limited, and we only have data on the exposure of an insurance firm by state and not by county.[7]

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. Having a measure of the insurance firms' geographic exposure together with our real-time measure of the hurricane landfall region is an important difference to Ammar (2020), who also looks at option price reactions of insurance firms after natural disasters. We estimate the regression in equation (10) of the paper for these property and casualty insurance firms, with $LandfallRegionExposure_{i,R,T_h}$ replaced by a variable that measures the share of total premiums, lagged by one year, written in states that experienced landfall by hurricane h. The results are reported in Table A4. A state is considered to have experienced a hurricane landfall in Panel A (B), if at least 10% (25%) of the counties of that state were within a given radius of that hurricane's eye. For smaller radii, fewer hurricanes are included in the sample, because certain hurricanes do not reach the required threshold of hit counties (10% or 25%) in any state.

The coefficient estimates are positive for all specifications implying that the impact uncertainty for property and casualty insurance firms is substantial in the aftermath of a hurricane. The magnitude of the coefficient estimates are economically significant, with the implied volatility being up to 70 percent higher for insurance firms with a 100 percent exposure to the landfall region of the hurricane. The magnitude of the coefficient tends to decrease for larger radii around the eye of the hurricane. The statistical significance is weaker than for the non-financial firms in Table 4 of the paper as the number of insurance firms in

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

our sample is relatively small and the economic exposure of insurance firms is observed at a state-level granularity as opposed to county-level.

Table A4: Hurricane effects on implied volatility of insurance firms post landfall

This table reports the coefficients and test statistics when estimating the panel model in equation (10) 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_h^*, until 5 trading days (1 week) after landfall, T_h. 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. For Panel A, if at least 10% of a state's counties lie in the hurricane landfall region, the state is considered to be hit by the hurricane. For Panel B, the threshold is 25% of the counties. Hurricanes that do not reach this threshold for any state are excluded. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 50, 100, 150, and 200 miles surrounding the eye. The data are from 1996 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by the state to which the insurance firm has the largest exposure. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (10). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: State considered hit if at least 10% of counties were in landfall region

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

	Radius around eye of the hurricane			
	50 miles	100 miles	150 miles	200 miles
$LandfallRegionExposure_{i,R,T_h}$	38.615***	20.978*	18.232	6.779
	(6.882)	(1.902)	(1.571)	(1.060)
Adjusted R^2 (%)	22.625	18.391	18.958	18.525
Observations	557	693	731	731
Hurricanes	25	31	33	33
Time (Hurricane) FE	Yes	Yes	Yes	Yes

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

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

	Radius around eye of the hurricane			
	50 miles	100 miles	150 miles	200 miles
$LandfallRegionExposure_{i,R,T_h}$	70.207***	41.892***	19.887*	23.934**
	(4.332)	(6.850)	(1.757)	(2.266)
Adjusted R^2 (%)	8.407	19.700	18.341	18.699
Observations	301	601	693	693
Hurricanes	13	27	31	31
Time (Hurricane) FE	Yes	Yes	Yes	Yes

5 Trading volume and open interest

Extreme weather uncertainty could also affect option trading volume and open interest in addition to asset prices. Existing research has identified two particularly relevant effects. First, periods of high uncertainty can lead to lower trading volume because investors faced with high uncertainty find it difficult to rank-order alternative portfolios (see Easley and O'Hara (2010) and Rehse, Riordan, Rottke, and Zietz (2019)). Second, an increase in hedging activity drives up open interest in derivatives (see, for example, Hong and Yogo (2012)).

To test the impact of hurricanes on the daily trading volume and open interest of options before landfall or dissipation of a hurricane, we estimate the regression specification

$$log\left(\frac{\overline{Volume}_{i,T_h-\Gamma}}{\overline{Volume}_{i,T_h^*-1}}\right) = \lambda_{F,P,\Gamma} ForecastExposure_{i,P,T_h-\Gamma} + \pi_h + \psi_{Ind} + \epsilon_{i,h,\Gamma}, \tag{A3}$$

where the dependent variable is the log difference between the average daily volume from hurricane inception, T_h^*, to Γ days before landfall or dissipation, T_h, and the average daily volume over five trading days prior to hurricane inception. We use the daily volume for the nearest expiry with options that meet the validity criteria described in section 3.3—the same expiry used to measure $IV_{i,t}$—and average the volume across options for firms with multiple outstanding options. We apply the same specification to estimate hurricane effects on open interest by simply replacing $Volume$ with $OpenInterest$.

Correspondingly, for the post landfall analysis, the regression specification takes the form

$$log\left(\frac{\overline{Volume}_{i,T_h+\tau}}{\overline{Volume}_{i,T_h^*-1}}\right) = \lambda_{L,R,\tau} LandfallRegionExposure_{i,R,T_h} + \pi_h + \psi_{Ind} + \epsilon_{i,h,\tau}, \tag{A4}$$

where the dependent variable is the log difference between the average daily volume from hurricane landfall, T_h, to τ trading days after landfall and the average volume over five trading days prior to hurricane inception.

We show the results in Table A5. Panel A reports the results of the analysis one day before landfall or dissipation of the hurricane. As described in Section 2.1, uncertainty just before landfall or dissipation is particularly high because incidence and impact uncertainty are both unresolved, and thus a reduction in trading volume due to uncertainty as described in Easley and O'Hara (2010) would be most pronounced. Our estimates confirm a large decrease in trading volume. This drop in trading volume tends to be larger for firms with establishments in regions that have a higher probability of being hit. Not shown in Table A5, we find smaller but still significant decreases in volume when using hurricane forecasts more than one day before landfall or dissipation. During this forecast period just prior to landfall, open interest remains flat.

Panel B provides insights into the post landfall effect on volume and open interest. We compute the average volume and open interest in 5 trading day increments post landfall up to 30 trading days.[8] For the volume, the coefficient estimate is not statistically different from zero, implying that after the sharp drop in volume right before landfall, the trading volume reverts back to its level before hurricane inception. However, open interest increases considerably and stays elevated up to 30 trading days post landfall. This increase in open interest is in line with an increase in hedging demand.

[8] We consider the baseline landfall region of 200 miles around the eye of the hurricane, which provides the largest number of firms with considerable exposure to the landfall region. For smaller radii the coefficient estimates have a similar magnitude but lower statistical significance because of the smaller number of hit firms.

Table A5: Hurricane effects on option volume and open interest

This table reports the coefficients and test statistics when estimating the effects of hurricanes on trading volume and open interest of options through the panel models given in equations (A3) and (A4). In Panel A, the dependent variable is the log difference (in %) between: (1) the average volume (open interest) of firm i's options from hurricane inception, T_h^*, to 1 day before landfall or dissipation, T_h; and (2) the average volume (open interest) over five trading days before the hurricane's inception. The regression is estimated for different landfall probabilities. Hurricanes for which 1 day before landfall or dissipation falls on a non-trading day are excluded. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, in terms of fraction of establishments, is in counties located in the forecast path of a hurricane. The forecast path of the hurricane is from NOAA and gives a minimum probability of being hit by a specific hurricane for each county. In Panel B, the dependent variable is the log difference (in %) between: (1) the average volume (open interest) of firm i's options over five trading day increments post landfall; and (2) the average volume (open interest) over five trading days before the hurricane's inception. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, in terms of fraction of establishments, is in counties located in the landfall region of a hurricane. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 200 miles surrounding the eye. The data are from 1996 to 2017. In both panels, the values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry interacted with time fixed effects are used. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equations (A3) and (A4). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Forecast hurricane path

Dependent variable: Log change in avg. volume/OI (in %), $log\left(\frac{\overline{Volume}_{i,T_h-1}}{\overline{Volume}_{i,T_h^*-1}}\right)$

	Volume						Open interest					
Prob. of hurricane hit ≥	1	10	20	30	40	50	1	10	20	30	40	50
$ForecastExposure_{i,P,T_h-1}$	-18.821	-69.856***	-113.334***	-116.324***	-103.945***	-104.617***	6.882	16.868	10.820	10.914	-4.446	-3.803
	(-1.345)	(-3.000)	(-3.358)	(-3.504)	(-3.867)	(-3.889)	(1.136)	(1.470)	(0.927)	(1.075)	(-0.446)	(-0.408)
Adjusted R^2 (%)	1.993	3.093	3.470	3.390	2.843	3.707	2.041	1.193	1.208	0.987	0.964	0.887
Observations	22,375	7,660	6,788	5,150	4,344	3,470	36,692	11,060	9,891	7,529	6,348	5,027
Hurricanes	30	9	8	6	5	4	30	9	8	6	5	4
Industry X Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

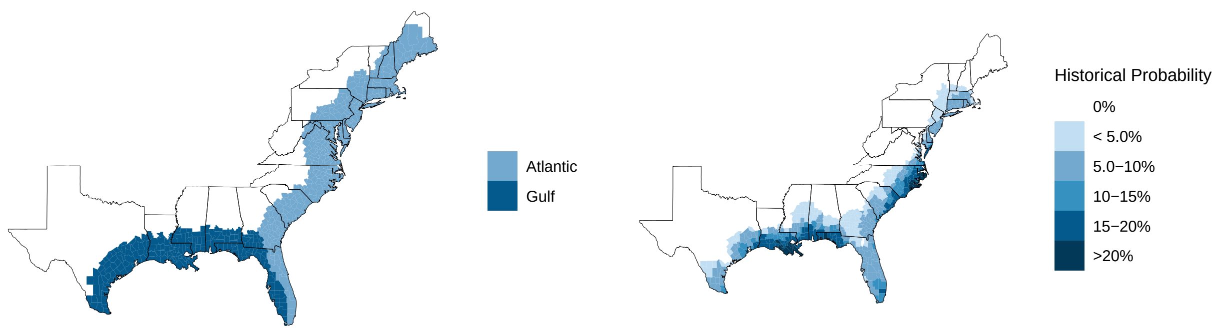
Panel B: Post landfall

Dependent variable: Log change in avg. volume/OI (in %), $log\left(\frac{\overline{Volume}_{i,T_h+\tau}}{\overline{Volume}_{i,T_h^*-1}}\right)$

	Volume						Open interest					
Volume/OI averaged over days post landfall	1 to 5	6 to 10	11 to 15	16 to 20	21 to 25	26 to 30	1 to 5	6 to 10	11 to 15	16 to 20	21 to 25	26 to 30
$LandfallRegionExposure_{i,R,T_h}$	-2.291	9.939	2.294	3.029	-0.546	1.882	8.643*	11.450**	8.762	12.372**	11.841**	10.720**
	(-0.288)	(1.238)	(0.260)	(0.333)	(-0.058)	(0.199)	(1.811)	(2.297)	(1.643)	(2.407)	(2.203)	(2.020)
Adjusted R^2 (%)	2.521	2.583	1.969	2.491	3.081	3.186	2.831	1.703	1.460	2.586	3.784	3.879
Observations	21,950	21,887	21,977	21,811	21,754	21,717	32,197	32,122	31,981	31,859	31,822	31,715
Hurricanes	33	33	33	33	33	33	33	33	33	33	33	33
Industry X Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

6 Additional figures and tables

This section provides additional figures and tables. Figure A2 plots the counties used for the seasonal outlook analysis in Section 5.3 of the paper. Tables A6 and A7 present the results of our baseline regressions that estimate the uncertainty before and after hurricane landfall when measuring the firms' geographic footprint with county level sales instead of establishments. Table A8 reports the baseline estimates when excluding one hurricane at a time. Table A9 shows additional results for the analysis in Section 5.2 of the paper.



(a) Atlantic and Gulf counties (b) Historical probability of hurricane landfall

Figure A2: Coastal counties and hurricanes

This figure plots the coastal counties used for the analysis in Section 5.3 of the paper. Panel A shows all the counties that are either directly bordering the Atlantic/Gulf coast or are within a 100 mile distance of a county that does. Panel B shows the counties' historical probabilities of being in the landfall region of a hurricane at least once in a given year. The plotted probabilities are as of 2001 and computed based on a window of 30 years. The landfall regions are based on a 100 mile radius around the eye of the hurricane.

Table A6: Forecasted hurricane path and implied volatility (firms' geographic footprints based on sales)

This table reports the coefficients and test statistics when estimating the firm-hurricane panel model in equation (9) of the paper. The model is estimated for different probabilities of landfall and days before landfall or dissipation, Γ. The dependent variable is the change (in %) in the implied volatility of firm i from the trading day before hurricane inception, T_h^*, to Γ days before landfall or dissipation, T_h, of the hurricane. Hurricanes for which Γ days before landfall or dissipation falls on a non-trading day are excluded. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, in terms of fraction of sales, is in counties located in the forecast path of a hurricane. The forecast path of the hurricane is from NOAA and gives a minimum probability of being hit by a specific hurricane for each county. For each regression, the total number of firm observations with a sales share in the forecast path of greater than 0 and at least 0.2 are reported. The data are from 2007 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are used separately in Panel A and are interacted in Panel B. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (9). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

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

Dependent variable: Change in IV from hurricane inception to Γ days before landfall/dissipation (in %), $log\left(IV_{i,T_h-\Gamma}/IV_{i,T_h^*-1}\right)$

Γ	1 Day					2 Days					3 Days			4 Days		5 Days
Prob. of hurricane hit ≥	1%	10%	20%	40%	50%	1%	10%	20%	40%	50%	1%	10%	20%	1%	10%	1%
$ForecExpo_{i,P,T_h-\Gamma}$	3.282***	8.640***	15.203***	17.216***	16.867***	1.512**	5.798***	9.268***	15.730***	12.138**	1.258**	8.217**	15.379***	1.260**	8.012**	0.855
	(3.704)	(4.948)	(7.177)	(6.461)	(6.524)	(2.296)	(3.107)	(5.434)	(7.480)	(2.495)	(2.266)	(2.414)	(8.801)	(2.006)	(2.155)	(1.470)
Adjusted R^2	12.851	16.499	15.876	16.288	21.587	10.882	12.128	13.629	16.561	4.756	11.666	16.210	14.409	14.904	20.116	10.890
Observations	36,732	11,027	9,860	6,300	4,994	27,296	13,621	9,993	5,041	3,843	20,745	9,851	4,908	15,778	6,176	15,667
Obs. ForecExpo. > 0	11,423	2,776	2,200	1,303	1,075	12,101	4,018	2,923	1,631	1,028	10,243	2,965	1,681	8,706	2,216	7,468
Obs. ForecExpo. ≥ 0.2	1,134	173	103	74	73	2,301	318	230	125	37	2,237	217	117	2,475	185	1,445
Hurricanes	30	9	8	5	4	22	11	8	4	3	17	8	4	13	5	13

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

Γ	1 Day					2 Days					3 Days			4 Days		5 Days
Prob. of hurricane hit ≥	1%	10%	20%	40%	50%	1%	10%	20%	40%	50%	1%	10%	20%	1%	10%	1%
$ForecExpo_{i,P,T_h-\Gamma}$	2.288***	5.487***	10.347***	10.718***	10.988***	1.310*	3.540*	6.637***	11.157***	12.675***	0.886*	4.869*	10.854***	0.835	4.187	0.840
	(2.708)	(2.593)	(4.103)	(3.439)	(3.438)	(1.914)	(1.871)	(3.051)	(4.798)	(2.600)	(1.722)	(1.707)	(5.218)	(1.534)	(1.513)	(1.392)
Adjusted R^2	13.258	16.868	16.203	16.684	22.238	11.339	12.596	14.083	17.203	4.745	12.220	16.817	15.001	15.813	21.114	11.450
Industry × Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A7: Hurricane effects on implied volatility post landfall (firms' geographic footprints based on sales)

This table reports the coefficients and test statistics when estimating the panel model in equation (10) of the paper. The dependent variable is the change (in %) in the implied volatility of firm i from the trading day before hurricane inception, T_h^*, until 5 trading days (1 week) and 30 trading days (1.5 months) after landfall, T_h, in Panel A and B, respectively. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, in terms of fraction of sales, is in counties located in the landfall region of a hurricane. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 50, 100, 150, and 200 miles surrounding the eye. The data are from 1996 to 2017. The values in parentheses are the t-stats. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are used. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (10). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

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

Dependent variable: Change in IV (in %), $log\left(IV_{i,T_h+5}/IV_{i,T_h^*-1}\right)$

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,R,T_h}$	9.583***	5.984**	5.300***	4.099***	2.473**	1.791*	2.885***	1.936**
	(3.250)	(2.348)	(3.492)	(2.892)	(2.274)	(1.748)	(3.226)	(2.468)
Adjusted R^2 (%)	12.208	12.708	12.337	12.908	12.328	12.895	12.371	12.916
Observations	33,316	33,316	33,044	33,044	32,898	32,898	32,960	32,960
Hurricanes	33	33	33	33	33	33	33	33
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry × Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

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

Dependent variable: Change in IV (in %), $log\left(IV_{i,T_h+30}/IV_{i,T_h^*-1}\right)$

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,R,T_h}$	19.583***	12.111***	5.621**	3.152	4.704**	3.412**	5.829***	4.464***
	(3.023)	(2.631)	(2.090)	(1.455)	(2.557)	(2.071)	(2.949)	(2.725)
Adjusted R^2 (%)	35.139	35.443	35.613	35.960	35.592	35.911	35.628	35.919
Observations	33,390	33,390	33,116	33,116	32,972	32,972	33,039	33,039
Hurricanes	33	33	33	33	33	33	33	33
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry × Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Table A8: Hurricane effects on implied volatility post landfall (excl. hurricanes)

This table reports the coefficients and test statistics when estimating the panel model in equation (10) of the paper while excluding individual hurricanes from the regression. The dependent variable is the change (in %) in the implied volatility of firm i from the day before the inception day of the hurricane, T_h^*, until 5 trading days (1 week) after landfall, T_h. The independent variable measures how much (from 0 to 1) of the geographic footprint of a firm, that is establishments, are in counties located in the landfall region of a hurricane. To identify counties that lie in the landfall region of a hurricane we rely on the location of the eye of the hurricane and a radius of 200 miles surrounding the eye. The data are from 1996 to 2017. The standard errors are clustered by county based on a firm's largest exposure. Industry and time fixed effects are used. The time fixed effect can be interpreted as a hurricane fixed effect as we include a separate time period in the panel for each hurricane as shown in equation (10). The significance of the coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: Change in IV (in %), $log\left(IV_{i,T_h+5}/IV_{i,T_h^*-1}\right)$						
Excl. hurricane	Year	Coeff. estimate	T-stat	Adjusted R^2 (%)	Observations	Hurricanes
Bertha	1996	3.796***	4.006	12.265	32,261	32
Fran	1996	3.947***	4.072	12.474	32,235	32
Danny	1997	3.694***	3.816	12.296	32,091	32
Bonnie	1998	3.805***	3.965	11.146	31,969	32
Earl	1998	3.833***	4.096	12.145	31,959	32
Georges	1998	3.778***	3.921	12.428	31,959	32
Bret	1999	3.700***	3.885	12.271	32,103	32
Floyd	1999	4.290***	4.278	12.562	31,902	32
Irene	1999	3.773***	3.933	12.309	32,093	32
Lili	2002	3.843***	3.693	12.266	31,906	32
Claudette	2003	3.988***	4.051	12.540	31,949	32
Isabel	2003	4.015***	4.341	12.555	31,921	32
Charley	2004	3.842***	3.947	12.442	31,832	32
Frances	2004	3.829***	4.084	12.049	31,833	32
Ivan	2004	3.781***	4.003	12.191	31,828	32
Jeanne	2004	3.791***	4.030	12.387	31,829	32
Dennis	2005	3.622***	3.760	12.660	31,779	32
Katrina	2005	3.686***	3.821	12.617	31,783	32
Rita	2005	3.654***	3.860	12.514	31,787	32
Wilma	2005	3.793***	3.951	12.628	31,794	32
Humberto	2007	4.286***	3.761	11.959	31,600	32
Dolly	2008	3.767***	3.938	12.278	31,634	32
Gustav	2008	2.969***	3.553	11.976	31,619	32
Ike	2008	2.294***	2.982	8.432	31,594	32
Irene	2011	3.561***	3.641	12.604	31,570	32
Isaac	2012	3.845***	3.963	12.566	31,627	32
Sandy	2012	3.603***	3.548	12.638	31,594	32
Arthur	2014	3.863***	3.588	12.827	31,453	32
Hermine	2016	3.996***	4.269	12.858	31,468	32
Matthew	2016	3.498***	3.519	13.100	31,481	32
Harvey	2017	3.863***	3.646	12.776	31,543	32
Irma	2017	3.599***	3.678	12.734	31,575	32
Nate	2017	3.998***	4.008	12.728	31,549	32

Table A9: Long-run cumulative abnormal stock return differences

This table reports differences between percentiles of the hit and control firms' long run cumulative abnormal stock return (in %) distributions post landfall, as described in Section 5.2. For a firm to be characterized as hit at least 25% of its establishments have to be in the hurricane landfall region. The hurricane landfall region is defined as a 50, 100, 150, or 200 mile radius around the eye of the hurricane at landfall. The cumulative returns are from hurricane inception to 120 trading days (6 months) post hurricane landfall. The abnormal returns are estimated based on the Fama-French five factor model. The data are from 1996 to 2017. Hurricanes with no firms in the landfall region for a given radius, that is, hurricanes without hit firms, are excluded from the analysis. The standard errors are bootstrapped and clustered by county based on a firm's largest exposure. The significance of the difference in abnormal returns is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
Percentiles	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat	Cumulative r diff.	T-stat
5%	-18.953***	(-4.073)	-12.802***	(-4.473)	-10.947***	(-6.016)	-8.883***	(-6.324)
10%	-15.650**	(-2.467)	-10.083***	(-4.605)	-8.594***	(-6.185)	-7.390***	(-7.879)
20%	-12.207***	(-3.889)	-6.631***	(-3.705)	-6.874***	(-8.411)	-6.002***	(-7.389)
30%	-9.919***	(-3.083)	-5.182***	(-3.446)	-4.700***	(-3.967)	-3.781***	(-5.044)
40%	-7.802***	(-4.060)	-3.523***	(-2.740)	-3.406***	(-4.231)	-3.392***	(-5.373)
50%	-8.036***	(-2.841)	-1.363	(-0.836)	-1.599*	(-1.658)	-1.486**	(-2.012)
60%	-4.946	(-1.569)	-1.095	(-0.720)	-0.724	(-0.732)	-0.555	(-0.778)
70%	-.447	(-.142)	1.543	(1.412)	1.363	(1.498)	0.808	(1.077)
80%	-2.501	(-0.473)	1.626	(0.749)	2.191*	(1.657)	1.073	(1.104)
90%	9.482	(.874)	7.823*	(1.756)	7.897***	(3.555)	5.451***	(3.314)
95%	34.932	(1.419)	30.113**	(2.223)	19.762***	(2.678)	12.317***	(2.964)
Obs. hit firms (exposure $\geq$ 25%)		184		750		1,595		2,563
Obs. control firms (exposure < 25%)		26,668		31,283		32,206		31,222
Hurricanes		26		31		33		33

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