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Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics*

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We empirically analyze firm-level uncertainty generated from extreme weather events, guided by a theoretical framework. Stock options of firms with establishments in a hurricane's (forecast) landfall region exhibit large implied volatility increases, reflecting significant uncertainty (before) after impact. Comparing implied volatility to subsequent realized volatility shows that investors underreact. This underreaction diminishes for hurricanes after Sandy, a salient event that struck the U.S. financial center. Despite constituting idiosyncratic shocks, hurricanes affect hit firms' expected stock returns. Textual analysis of calls between firm management, analysts, and investors reveals that discussions about hurricane impacts spike during the long-lasting high-uncertainty period after landfall.

JEL classification: G12, G14, Q54
Keywords: extreme weather, uncertainty, implied volatility, expected returns, climate risks

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From hurricanes and severe snowstorms to floods and droughts, extreme weather events have caused widespread devastation. For instance, in 2017, the estimated damages from extreme weather events in the United States reached a record total of over \$300 billion.[1] While the unpredictable impact of extreme weather on a firm's capital, continuity of operations, and business environment could create significant uncertainty, firms can potentially offset some of these effects through insurance or adaptation. Thus, it is not obvious a priori that extreme weather events generate substantial uncertainty for firms. Further, an emerging climate finance literature and concerns voiced by policymakers suggest that asset markets mispricing climatic events could lead to sudden price corrections and threaten financial stability. However, little is known about the uncertainty that is generated by extreme weather events for firms or how such uncertainty is priced.[2]

In this paper, we present a comprehensive analysis of firm-level extreme weather uncertainty. We first use financial markets to isolate and quantify the extent of extreme weather uncertainty and then analyze the pricing of this uncertainty.[3] The exogenous, identifiable nature of extreme weather events allows us to isolate the associated uncertainty cleanly because prevailing conditions of the firm do not affect the timing and likelihood of such events. Extreme weather events are also local and impact only a subset of firms in the U.S. economy, creating a unique experimental setting. This allows us to thoroughly investigate first-order questions in asset pricing, including on informational efficiency and whether idiosyncratic (i.e., unsystematic) shocks impact asset prices not only through the cash flow channel but also through the discount rate channel.[4]

To ground our empirical analyses, we develop a simple theoretical framework that models the "incidence uncertainty" for a firm regarding whether it will be hit by an extreme weather

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

[2] Government agencies responsible for the resilience of the financial system have begun examining the potential impact of climatic events. According to the Federal Reserve's Financial Stability Report, November 2020: "...uncertainty about the timing and intensity of severe weather events and disasters, as well as the poorly understood relationships between these events and economic outcomes, could lead to abrupt repricing of assets." (https://www.federalreserve.gov/publications/2020-november-financial-stability-report-near-term-risks.htm).

[3] As in this paper, Bloom (2009); Pástor and Veronesi (2012, 2013); Jurado, Ludvigson, and Ng (2015) and others define uncertainty as expected volatility, distinct from the literature on Knightian uncertainty.

[4] The local and idiosyncratic nature of extreme weather events differentiates them from the market-wide shocks generally considered in the disaster risk literature as in Barro (2006).

event and the "impact uncertainty" about the event's effect on the firm conditional on it being hit. Although this framework applies to extreme weather events broadly, we focus our main empirical analyses on U.S. hurricanes because of three key features that enable identification. First, hurricanes are economically destructive extreme weather events that impact a wide variety of major centers of economic activity, which include a large number of firms in a variety of industries.[5] Second, NOAA publishes a range of relevant data on hurricane forecasts and realizations. These data are accessible to investors in real time. Third, hurricanes develop from inception as storms over the ocean and resolve following landfall or dissipation over fairly short time frames, isolating effects in time. We assess the external validity of our baseline analysis for other extreme weather events.

We estimate the firm-level uncertainty generated by extreme weather events using changes to the implied volatility of stock options, a measure that captures investor expectations of volatility (Bloom, 2009). We collate single-stock options data starting in 1996 and spanning 24 years with data on hurricanes and data on the establishments of individual firms. We calculate a firm's exposure to each hurricane as the share of its establishments located in the landfall region. We then use this continuous treatment measure to conduct difference-in-differences analyses where hurricane inceptions demarcate the pre-period.

Indicative of substantial impact uncertainty, we find that the implied volatilities of firms with establishments in regions hit by hurricanes increase up to 18%.[6] Implied volatilities remain elevated for several months after hurricane landfall, suggesting that the resolution of impact uncertainty is slow. Mirroring this period of persistent volatility, a systematic textual analysis of the transcripts of calls between analysts, investors, and firm management reveals that the number of discussions of hurricane impacts jumps after landfall for "hit" firms and also remains elevated for several months. These results are consistent with the idea that discussions about a hurricane in analyst calls occur while its impact on a firm's performance is potentially material but still uncertain. While it has been long-documented that volatility can be persistent, little is known about the economic mechanisms underlying

[5] For instance, in 2017, \$265 billion of the aforementioned \$300 billion in damages from extreme weather events in the United States were due to hurricanes.

[6] Duffee (1995); Albuquerque (2012); Grullon, Lyandres, and Zhdanov (2012) show that, unlike at the aggregate market level, stock returns and volatility at the firm level generally exhibit positive contemporaneous correlation. As such, since our analysis is on firm-level volatility, the negative return-volatility relationship documented for market index volatility (e.g., French, Schwert, and Stambaugh (1987)) is not driving our results.

such persistence.[7] Our findings show that learning about how a firm is affected by a specific event takes time, which leads to volatility persistence.

Understanding how investors form expectations regarding the uncertainty generated by extreme weather events is important because volatility affects, for example, the risk associated with investment decisions, the cost of hedging physical climate risks, and option prices. We analyze how the volatility risk premia (VRP)—computed as the difference between option-implied volatility and the subsequent realized volatility of the underlying stock over the remaining life of the option—of hit firms change relative to those of control firms. We find that the VRP of firms with establishments in a hurricane landfall region are substantially lower for over a month after landfall. This result implies that investors underreact to the volatility that arises due to a hurricane and do not efficiently update their volatility expectations based on the information available in real time.

We further examine whether this bias in volatility expectations changes after a particularly salient event experienced by investors.[8] In our sample, the hurricane most likely to have had such an effect is Hurricane Sandy, which hit the New York tri-state area in 2012. Sandy was an unprecedented, highly damaging event that struck the financial center of the United States—an area home to a large share of mutual funds and hedge funds—which had previously been largely spared from head-on hits by hurricanes. We find that the underreaction to hurricanes diminishes after Hurricane Sandy, suggesting that the informational efficiency of markets improved.[9,10] A salient event inducing such a marked shift in the pricing of long-observed events like hurricanes calls into question whether financial markets efficiently

[7]See, for example, Mandelbrot (1963) and Fama (1965). Other papers examining the origins of volatility persistence focus on, for example, the volatility effects of macroeconomic announcements—which affect all firms—and find only short-lasting effects (Ederington and Lee, 1993; Andersen and Bollerslev, 1998). Andersen and Bollerslev (1998) write on page 223: “The origin of longer run volatility persistence remains an important topic for future research.”

[8]Personal experiences can make investors more attuned to risks. See, for example, Malmendier and Nagel (2016) on personal inflation experiences and expectations and Alekseev, Giglio, Maingi, Selgrad, and Stroebel (2022) on local temperature shocks and mutual fund manager portfolio choice.

[9]The saliency of Hurricane Sandy has been highlighted in other studies. For example, Kuchler, Li, Peng, Stroebel, and Zhou (2022) find that the liquidity provision of institutional investors decreased shortly after Sandy made landfall due to operational frictions, and Addoum, Eichholtz, Steiner, and Yönder (2023) show a shift in how flood risk is priced in commercial real estate.

[10]The most damaging and arguably most prominent hurricane before Sandy was Hurricane Katrina, which made landfall in Louisiana in 2005. Katrina is unlikely to have had the same impact on asset managers as Sandy and indeed, we do not find a shift in pricing efficiency after Katrina.

price novel risks stemming from climate change. These findings are in line with the beliefs of finance professionals and academics that financial markets underestimate climate risks (Stroebel and Wurgler, 2021).

To determine the economic channels that drive extreme weather uncertainty, we use a systematic textual analysis of the transcripts of calls between analysts, investors, and firm management. We identify five topics that come up frequently when discussing hurricane impacts: business interruption, physical damages, insurance, demand, and supply. The more uncertainty a given channel generates, the more discussion should be allocated to this channel during calls with firm management in the aftermath of a hurricane. Our analysis shows that discussions on analyst calls about hurricane impacts increase by up to 15 paragraphs over the first six months in response to a hurricane hit. The number of paragraphs in which a hurricane's impact on business interruption and physical damages is discussed increases by up to 3 and 5 paragraphs, respectively, relative to control firms. There are also significant, albeit smaller, increases with the insurance, supply, and demand channels. The finding that there is uncertainty regarding insurance in the aftermath of a hurricane hit suggests it is not immediately apparent whether firms have coverage or when and to what extent firms' claims will be paid. Our findings are directly relevant to the ongoing debate about mandating climate risk disclosures for firms.[11] Our results suggest that disclosures about firms' business continuity plans, resilience or vulnerability of physical structures, insurance coverage, and supply and demand exposures to extreme weather events could generate significant value by reducing uncertainty.

We next examine if investors require compensation in the form of higher expected stock returns for bearing extreme weather uncertainty. If so, the resulting increase in the firm's cost of capital would be a channel that amplifies the negative impacts of extreme weather by tightening financing constraints just when firms may need capital to rebuild or revamp their operations. Prior studies on uncertainty in other contexts have focused on systematic shocks, which have been shown to affect expected returns (e.g., Anderson, Ghysels, and Juergens

[11]See, for example, the SEC's March 2022 Proposed Rules to Enhance and Standardize Climate-Related Disclosure for Investors. The proposed rules "would require a registrant to disclose information about... governance of climate-related risks and relevant risk management processes" and "the impact of climate-related events (severe weather events and other natural conditions) ... on the line items of a registrant's consolidated financial statements." See "SEC Proposes Rules to Enhance and Standardize Climate-Related Disclosures for Investors" available at https://www.sec.gov/news/press-release/2022-46.

(2009); Pástor and Veronesi (2012, 2013); Brogaard, Dai, Ngo, and Zhang (2019) analyze general and political uncertainty). In contrast, extreme weather events constitute local, idiosyncratic shocks. In an extension to our theoretical framework, we model how extreme weather uncertainty can impact both cash flows and expected returns of a firm. Our model is based on Levy (1978) and Merton (1987), who show theoretically how idiosyncratic volatility can be "priced" and thus impact discount rates because, in practice, investors may not hold the market portfolio as predicted by the capital asset pricing model.[12] We test whether expected returns rise due to the increase in expected idiosyncratic volatility caused by a hurricane.[13] We find no evidence that hurricanes affect expected returns in the early sample, during the period when investors underestimate extreme weather uncertainty. However, after Hurricane Sandy, when volatility expectations are less biased, there is strong evidence that firms with higher idiosyncratic volatility due to a hurricane hit have significantly higher expected stock returns.

Thus far, we have discussed the uncertainty after landfall, which reflects impact uncertainty in our theoretical framework. We next analyze the uncertainty before landfall, which reflects both incidence uncertainty and expected impact uncertainty. Here, we use two types of forecasts: real-time hurricane-specific forecasts and seasonal outlooks. We show that exposure to the forecast path of an imminent hurricane increases firms' implied volatilities even at low forecast probabilities. We find that implied volatility responses tend to increase with the probability of an extreme weather event occurring, increasing as much as 22% when hurricane wind speed probabilities reach at least 50%, in line with the predictions of our theoretical framework. However, as in the post-landfall analysis, we find these implied volatility responses to be an underreaction until Hurricane Sandy. Further, we do not find evidence that investors react to seasonal outlooks, which are much less informative than the short-term forecasts for imminent hurricanes. Whether or not investors pay attention and price in climatic events before they occur is an important question in the climate finance literature. For example, Carney (2015) discusses how the sudden repricing of climate events

[12] Such investor underdiversification has been established empirically and can stem from, for example, investors only investing in securities that they are familiar with or restricted to (e.g., Erruna and Losq (1985); Coval and Moskowitz (1999); Polkovnichenko (2005); Goetzmann and Kumar (2008)).

[13] Each hurricane can be considered an exogenous, idiosyncratic shock in this context because it affects a subset of firms distributed across different industries and does not affect the general U.S. economy (Strobl, 2011). The vast majority of firms within the market will be unaffected by a specific hurricane. Also, the sets of affected firms will vary for each hurricane.

can be a threat to financial stability. Our analyses suggest that asset prices respond not only ex post to extreme weather events but also ex ante to extreme weather event forecasts that have a track record of being informative. However, these responses may be biased until investors experience a particularly salient event.

Finally, we conduct a series of robustness checks and additional extensions. Consistent with the general predictions of our model of extreme weather uncertainty, we find that firm-level uncertainty also increases in response to floods, severe snowstorms, and tornadoes. We show that our baseline findings hold across and within industries, are not driven by firm selection issues, and are robust to the exclusion of individual hurricanes, to using model-free instead of model-based implied volatility, to measuring firm exposure based on the location of sales instead of establishments, and to alternative definitions of hurricane landfall regions. Further, hurricanes increase the dispersion of hit firms' abnormal cumulative returns and—at the tails of the distribution—can lead them to underperform or outperform control firms, indicating that these events pose upside as well as downside risk. While financial firms are excluded from our baseline samples, we show in separate analyses that the single-stock options of property and casualty insurance firms also react to hurricane hits and reflect substantial extreme weather uncertainty.

Our paper contributes to the climate finance literature in several ways. Our focus on understanding how extreme weather shocks affect volatility expectations, whether the pricing of these expectations is efficient, and the associated economic channels of impact makes this paper distinct. Other papers looking at the pricing efficiency of extreme weather events examine stock markets and find evidence of both underreaction (see Hong, Li, and Xu (2019) on how drought indices predict food company stock returns) and overreaction (see Alok, Kumar, and Wermers (2020) on mutual fund performance following natural disasters). Climate finance research that examines volatility has focused on the transition to a low carbon economy, as opposed to physical climatic events. Ilhan, Sautner, and Vilkov (2021) analyze options markets and find that the protection against downside risk is costlier for carbon-intense firms due to climate policy uncertainty. Others, like Andersson, Bolton, and Samama (2016); Roth Tran (2019); Engle, Giglio, Kelly, Lee, and Stroebel (2020); Bolton and Kacperczyk (2021); Baker, Hollifield, and Osambela (2022); Sautner, van Lent, Vilkov, and Zhang (2022a,b), study stock markets and transition risks. The fact that this transition has not yet been completed makes it difficult to assess whether financial markets efficiently price such risks. Other work shows that natural disaster shocks can affect firms and propagate along supply chains (Barrot and Sauvagnat, 2016; Pankratz and Schiller, 2021). Further, Hassan, Hollander, Van Lent, and Tahoun (2019); Sautner, van Lent, Vilkov, and Zhang (2022a,b) use analyst call transcripts to determine which firms are exposed to political and climate risks that are otherwise difficult to observe. In contrast, we use our empirical strategy to identify firms exposed to hurricanes and use discussions in call transcripts to understand the economic channels generating extreme weather uncertainty.

The simple theoretical framework we develop formalizes our understanding of uncertainty before and after extreme weather events. The framework captures incidence and impact uncertainty and relates them to cash flow, return volatility, and expected returns. Because the events we study are identifiable, exogenous, and idiosyncratic, our analysis differs from, for example, studies of macroeconomic or political uncertainty, where periods of uncertainty are generally endogenous to prevailing conditions of the economy or firm.[14]

Further, we exploit the experimental setting of extreme weather shocks to examine three key questions in asset pricing. First, this paper advances our understanding of why volatility can be persistent. Volatility persistence is the basis for the vast literature on autoregressive conditional heteroskedasticity models starting with Engle (1982) and Bollerslev (1986). Our findings contribute to the understanding of the economic mechanisms underlying the persistence of volatility because our setting allows us to identify multiple exogenous, nonsystematic shocks to the volatility of some but not all firms. Second, the findings in this paper contribute to our understanding of how volatility expectations are formed and whether they are efficient. Other research in the volatility literature finds that investors fail to correctly update expectations based on the realized volatility over the preceding months (Cheng, 2019; Lochstoer and Muir, 2022). The investor underreaction we document is a distinct phenomenon from the extrapolation of preceding realized volatility because the inception of a hurricane is unrelated to preceding realized volatility. Our findings could be applicable to

[14]E.g., Bloom (2009); Jurado, Ludvigson, and Ng (2015); Baker, Bloom, and Davis (2016); Dew-Becker, Giglio, Le, and Rodriguez (2017); Hassan, Hollander, Van Lent, and Tahoun (2019). An exception is Baker, Bloom, and Terry (2023), who use disasters to instrument for country-level uncertainty shocks. Some studies on political uncertainty like Julio and Yook (2012); Kelly, Pástor, and Veronesi (2016); Jens (2017) focus on scheduled political events, which are interpreted as known, exogenous points in time *when* a policy (or regime) change might occur. However, the likelihood of *whether* a policy/regime change occurs on the prescheduled date can still be endogenous to prevailing economic conditions. As Pástor and Veronesi (2012) discuss, such a change is more likely during downturns.

other unexpected major events that lead to sudden spikes in volatility. Third, our analysis on whether the uncertainty associated with hurricanes impacts firms' cost of capital contributes to our understanding of whether idiosyncratic volatility is priced. Prior papers such as Ang, Hodrick, Xing, and Zhang (2006) and Fu (2009) have empirically tested the Merton (1987) prediction assuming a particular volatility model or factor structure for stock returns and arrived at mixed conclusions.[15] In contrast, by exploiting our empirical setting, we analyze exogenous increases to idiosyncratic volatility.

The remainder of this paper is structured as follows. We describe our data and research design in Sections I and II, respectively. Section III presents our main results, followed by extensions and robustness tests in Section IV. We conclude in Section V.

I. Data

Our analyses use data from a range of sources. We combine NOAA hurricane data with firm establishment data from the National Establishment Time-Series (NETS) database. We obtain stock and firm data from the CRSP/Compustat Merged database, and options data from OptionMetrics. We source transcripts of calls between analysts, investors, and firm management from Refinitiv. We describe each of these data sources in this section and give further details in Internet Appendix B.

A. Hurricane data

A hurricane is a tropical cyclone with high-speed surface wind that rotates around an "eye." While the air is calm inside the eye, the eyewall has intense winds that radiate outward in a spiral fashion. These winds can reach a diameter of up to several hundred miles. Hurricanes originate in the ocean as tropical depressions, strengthening into tropical storms and then hurricanes as they traverse across water and sometimes over land before dissipating. The point at which a hurricane eye crosses from the ocean to land is called landfall. Around landfall, hurricanes deliver not only intense winds that can exceed 100 miles per hour but

[15] Martin and Wagner (2019) derive excess return predictions from option prices. Their analysis focuses on the pricing of firm-specific sensitivity to aggregate volatility shocks like the global financial crisis, not shocks to purely idiosyncratic volatility. Here, we isolate and examine variation in firm-specific idiosyncratic volatility, independent of market-wide shocks.

also significant rainfall and storm surge, all of which can cause major damage. After landfall, hurricanes continue to move over land, bringing strong winds and rain with them. In the United States, hurricanes typically occur between June and November and are most common along the Gulf Coast and the southern portion of the Atlantic Coast.

We use NOAA hurricane track data to identify hurricane landfall regions for 37 Atlantic and Gulf Coast hurricanes from 1996 to 2019. These data show the actual location and intensity of each hurricane's eye at six-hour intervals. To account for the fact that a hurricane can impact counties not located in immediate proximity to its eye, we consider a county to be in the hurricane landfall region if the county's centroid lies within a specified radius of the hurricane eye within a 24-hour window before and after landfall.[16,17] This window ensures that we capture counties that lie more inland and, for hurricanes that move along the coast before turning inland, counties that were close to the eye before landfall. Figure 1 shows which counties fall within 50, 100, 150, and 200 miles of the eye of hurricanes Katrina (2005), Sandy (2012), Matthew (2016), and Harvey (2017). Table I Panel A lists the hurricanes in our landfall sample.

We use a 200-mile radius around the eye as hurricane landfall regions in our main analyses. We validate this choice using NOAA reanalysis data, which include hurricane-specific estimates of windspeed radii that are released anywhere from weeks to months after hurricanes have occurred and are available starting in 2004. These data show that the average outer border of a hurricane storm system—the area where wind speeds are at least 34KT—is 219 miles from the eye of the storm.[18] We also consider landfall regions based on smaller radii closer to the nucleus of the hurricane. In the Internet Appendix, we show robustness of our main analyses to using hurricane-specific radii based on the reanalysis data.

The NOAA landfall data we use in our analyses are published in real time, meaning that investors can know the landfall region of a hurricane as soon as it happens. Other papers

[16] We also consider other time windows, for example, within 12, 36, and 48 hours before and after landfall, and the results are qualitatively similar.

[17] Two hurricanes in the sample, Charley in 2004 and Katrina in 2005, made two landfalls in the United States. To avoid double-counting these hurricanes, the date when the hurricane made landfall at a higher wind speed—corresponding to a higher storm category on the Saffir-Simpson scale—is considered the landfall date in our analysis. Including both landfalls for each hurricane in the analysis leads to qualitatively similar results.

[18] Although the 200-mile radius is slightly lower than this empirical measure, in practice the two measures align well because we include a county in the landfall region if the region includes the county centroid but not necessarily the whole county.

that do not focus on market pricing use damaged counties to discern the firms affected by natural disasters (e.g., Barrot and Sauvagnat (2016); Dessaint and Matray (2017)). In our setting, where we isolate the uncertainty reflected in options markets, using damage data would introduce a forward-looking bias because financial market investors do not know at the time of a hurricane's landfall which counties will experience damage—this is part of the uncertainty. County-specific damage estimates generally become available with a lag of several months.

For our pre-landfall analyses, we draw on two types of NOAA forecast data. First, we use National Hurricane Center wind speed probability forecast advisories. These text-based advisories are released in real time, intra-daily, as storms evolve to communicate probabilities of hurricane-level wind speeds occurring in particular locations. These advisories capture the same underlying model outputs as commonly viewed forecast maps published by media outlets. We use the last forecast available before market close on each trading day, which reflects the latest information available to investors before end-of-day option prices are determined. This analysis includes more storms than our baseline post-landfall analyses because it includes storms that were forecast to possibly make landfall in U.S. mainland but that did not ultimately do so. The list of included storms is in Table I Panel B. Figure 3 illustrates how these forecast data capture the evolving forecast path for Hurricane Sandy in the days leading up to landfall. Second, to examine seasonal dynamics, we use NOAA's annual May outlook announcements of the probability of the upcoming hurricane season being above-normal in terms of the number of hurricanes.

B. Firm establishment data

We use NETS firm establishment location data to estimate a firm's exposure to each hurricane. These data, which have been used in several other studies, contain establishment location information and are updated annually each January.[19] Figure 2 shows the number of establishments per county sorted into deciles using NETS data for 2010, illustrating that economic activity as measured by the density of firm establishments is high in areas exposed to hurricanes along the Atlantic and Gulf Coasts.

[19] For example, Neumark, Wall, and Zhang (2011) investigate the job creation of small businesses based on NETS. Addoum, Ng, and Ortiz-Bobea (2020) use NETS to analyze the effect of temperature fluctuations on firm sales.

C. Financial data

We obtain daily data on single-name stock options from OptionMetrics. These are American-style options, for which OptionMetrics obtains implied volatilities using a binomial tree approach to account for early exercise premia. We use data on traded options with non-missing pricing information that are slightly out-of-the-money. Such options are generally more liquid than far out-of-the-money or in-the-money options and have relatively small price impacts from potential early-exercise premia (Carr and Wu, 2009; Kelly, Pástor, and Veronesi, 2016; Martin and Wagner, 2019). We apply standard filters to the options data consistent with the existing literature. In our sample, we include single-stock options that meet the following criteria: (i) standard settlement; (ii) a positive open interest; (iii) a positive bid price and bid-ask spread (valid prices); (iv) the implied volatility estimate is not missing; (v) greater than 7 days and at most 200 calendar days to expiry; and (vi) an option delta, δ, that satisfies $0.2 \leq |\delta| \leq 0.5$. The estimate for the average implied volatility of firm i at time t is

$$IV_{i,t} = IV_{i,t,M} = \frac{1}{Z}\sum_{z=1}^{Z} IV_{i,z,t,M}, \tag{1}$$

where M denotes the nearest-to-maturity expiration at time t of options on firm i stock that satisfy the above six criteria and Z denotes the number of valid options for firm i with that expiry. $IV_{i,t,M}$ proxies for the ex ante risk-neutral expected value of the future stock return volatility of firm i between time t and M and is similar to the measure used in Kelly, Pástor, and Veronesi (2016) for options on international stock indices. While we use a model-based measure of implied volatility for our analysis, we show in Internet Appendix Section C.6 that our results are robust to using model-free implied volatility.

To compute the VRP, we use the annualized standard deviation of the underlying stock's daily returns over the remaining life of the option, between t and M, as the measure of realized volatility, $RV_{i,t,M}$. $VRP_{i,t}$ is then defined as

$$VRP_{i,t} = VRP_{i,t,M} = IV_{i,t,M} - RV_{i,t,M}. \tag{2}$$

This definition of VRP captures the difference between ex ante market expectations of future volatility over a period and the ex post realized volatility over the same period, not a lagged or predicted measure of realized volatility. This is important because we use our VRP measure to analyze how efficiently investors price the uncertainty associated with extreme weather events. Our definition of VRP is similar to that used by Lochstoer and Muir (2022) when analyzing underreaction and overreaction in volatility expectations and by Kelly, Pástor, and Veronesi (2016) and others.[20]

The stock data and headquarter address information are from the CRSP/Compustat Merged dataset. Only stocks that are traded on Amex, NASDAQ, or NYSE are included in the sample. To ensure that stocks with stale prices are excluded from our analysis, we require share prices of at least \$5 (Amihud, 2002) and show robustness of our results to excluding stocks in the bottom 20% in terms of market capitalization of NYSE-listed stocks (Fama and French, 2008). We use transcripts of calls between analysts and firm managers obtained from Refinitiv to examine the economic channels through which firms are affected by hurricanes.

We use firm name and headquarter address to link the firms in NETS to those in the CRSP/Compustat dataset. We then link the matched sample to the OptionMetrics and Refinitiv data using common firm identifiers. Our linked sample starts in 1996, the first year of the OptionMetrics data, and ends in 2019. Because financial firms' geographic exposures to extreme weather events may not be reflected by their establishment locations and financial firms are generally excluded in asset pricing studies, we exclude all financial firms from our baseline analyses by dropping firms with SIC numbers from 6000 to 6799. We separately analyze insurance firms in Section IV.E.

D. *Summary statistics*

We report firm-level summary statistics in Table II. Panel A shows that there are 3,254 unique firms in our sample. For comparison, we show summary statistics for both the full sample and for the subsample of firms that have significant exposure to a hurricane at least once during our sample period. In this table, a firm is included in the subsample of "hit" firms if it had 25% or more of its establishments within a 200-mile radius around the eye

[20]For instance, Kelly, Pástor, and Veronesi (2016) define the variance risk premium as $E_t^{\mathbb{Q}}[RV_{i,t,M}^2] - E_t^{\mathbb{P}}[RV_{i,t,M}^2] = IV_{i,t,M}^2 - RV_{i,t,M}^2$ because the realized variance over the remaining life of the option, $RV_{i,t,M}^2$, is an unbiased estimate of the expected variance over the remaining life of the option. Instead of variance risk premia, we use volatility risk premia in our empirical analysis for its intuitive interpretation, as in Della Corte, Ramadorai, and Sarno (2016).

of at least one hurricane. This subsample includes 1,799 firms. On average, a firm has 123 establishments in a given year. The average number of establishments for the subsample of hit firms is similar at 124. The hit firms are also comparable to the non-hit firms in terms of market capitalization, with a $5.1 billion average market capitalization for hit firms and an average of $5.0 billion for all firms. The summary statistics of the option measures are also very similar between the total sample and the subsample of hit firms. The average (annualized) IV and VRP for all firms are 47.4% and 4.7%, respectively.

II. Research design

A. Theoretical framework

In this section, we summarize our theoretical framework for examining extreme weather uncertainty. More details of the framework and its extensions are in Internet Appendix A where, adapting Merton (1987), we relate extreme weather events to return volatility, cash flows, and expected returns.

When a firm is located in an area in which an extreme weather event occurs, the firm's operations can be affected through a range of channels. For example, the event could damage the firm's property or increase demand for its products as part of the rebuilding process. When the ultimate impact of an extreme weather event on a firm is not immediately discernible, we call this impact uncertainty.

We specify firm i's one-period return at time $t+1$, when the firm is hit by an extreme weather event, as

$$\tilde{R}_{i,t+1} = \bar{R}_i + b_i \tilde{Y}_{t+1} + \sigma_i \tilde{\epsilon}_{i,t+1} + \tilde{g}_{i,t+1}, \tag{3}$$

where $\tilde{g}_{i,t+1}$ is a random variable that captures the impact of the extreme weather event on firm i; $\tilde{g}_{i,t+1}$ is distributed with mean $\mu_{g,i}$ and variance $\sigma^2_{g,i}$, where $\sigma^2_{g,i}$ captures the impact uncertainty. This definition of uncertainty as the variance of an unpredictable disturbance is in line with, for example, Pástor and Veronesi (2012, 2013) and Jurado, Ludvigson, and Ng (2015). The other return components are independent of the extreme weather event. $\bar{R}_i$ is a drift term, $\tilde{Y}_{t+1}$ is the market factor to which firm i has a sensitivity of b_i, and $\sigma_i \tilde{\epsilon}_{i,t+1}$ is the product of a scalar σ_i and random variable $\tilde{\epsilon}_{i,t+1}$ that has a mean of zero and variance of 1.

The impact uncertainty described above is conditional on the firm being hit by an extreme weather event. However, ex ante, the occurrence of an extreme weather event is itself unpredictable, introducing uncertainty about whether an extreme weather event will hit a firm. Our framework captures this second component of extreme weather uncertainty, defined as incidence uncertainty—the uncertainty about whether an extreme weather event will occur where the firm is located. We expand the return specification in equation (3) to account for incidence uncertainty as follows

$$\tilde{R}_{i,t+1} = \bar{R}_i + b_i \tilde{Y}_{t+1} + \sigma_i \tilde{\epsilon}_{i,t+1} + \tilde{g}_{i,t+1}\tilde{\theta}_{i,t+1}, \tag{4}$$

where the random variable $\tilde{\theta}_{i,t+1}$ indicates whether firm i is hit by the extreme weather event. $\tilde{\theta}_{i,t+1}$ has a Bernoulli distribution (one draw of a binomial distribution), $\tilde{\theta}_{i,t+1} \sim B(1,\phi)$, where $Pr(\tilde{\theta}_{i,t+1} = 1) = 1 - Pr(\tilde{\theta}_{i,t+1} = 0) = \phi$ and $0 \leq \phi \leq 1$. Whether a firm will be hit by an extreme weather event is independent of the impact conditional on the hit, that is, $E(\tilde{g}_{i,t+1}\tilde{\theta}_{i,t+1}) = E(\tilde{g}_{i,t+1})E(\tilde{\theta}_{i,t+1})$.[21] The variance of the return is

$$Var_t(\tilde{R}_{i,t+1}) = b_i^2 + \sigma_i^2 + \sigma_{g,i}^2\phi + \mu_{g,i}^2\phi(1-\phi), \tag{5}$$

where $\sigma_{g,i}^2\phi$ is the *expected* impact uncertainty and $\mu_{g,i}^2\phi(1-\phi)$ is the incidence uncertainty.[22]

While the expected impact uncertainty monotonically increases with ϕ, the relationship between incidence uncertainty and ϕ is non-monotonic. Incidence uncertainty is highest when ϕ equals 0.5.

In our empirical analysis, we use implied volatility backed out from option prices to measure the expected volatility of a firm's stock returns, that is, uncertainty, similar to Bloom (2009); Kelly, Pástor, and Veronesi (2016); Dew-Becker, Giglio, and Kelly (2021) and others. Option-implied variance captures the risk-neutral expected variance. In our framework, equation (5) captures the true expected variance. Option-implied variance is a function of the true expected variance and VRP, where the VRP can capture variance risk premia or

[21]Intuitively, firm i's expected return conditional on being hit or not is, respectively, $E_t(\tilde{R}_{i,t+1}|\theta = 1) = \bar{R}_i + \mu_{g,i}$ and $E_t(\tilde{R}_{i,t+1}|\theta = 0) = \bar{R}_i$. The variance of the firm's returns conditional on being hit or not is, respectively, $Var_t(\tilde{R}_{i,t+1}|\theta = 1) = b_i^2 + \sigma_i^2 + \sigma_{g,i}^2$ and $Var_t(\tilde{R}_{i,t+1}|\theta = 0) = b_i^2 + \sigma_i^2$.

[22]This is obtained by $Var_t(\tilde{g}_{i,t+1}\tilde{\theta}_{i,t+1}) = E_t(\tilde{g}_{i,t+1}^2\tilde{\theta}_{i,t+1}^2) - (E_t(\tilde{g}_{i,t+1}\tilde{\theta}_{i,t+1}))^2 = E_t(\tilde{g}_{i,t+1}^2)E_t(\tilde{\theta}_{i,t+1}^2) - (E_t(\tilde{g}_{i,t+1}))^2(E_t(\tilde{\theta}_{i,t+1}))^2$, where $E_t(\tilde{g}_{i,t+1}^2)E_t(\tilde{\theta}_{i,t+1}^2) = [Var_t(\tilde{g}_{i,t+1}) + (E_t(\tilde{g}_{i,t+1}))^2][Var_t(\tilde{\theta}_{i,t+1}) + (E_t(\tilde{\theta}_{i,t+1}))^2] = \mu_{g,i}^2\phi + \sigma_{g,i}^2\phi$.

mispricing (e.g., Bollerslev, Tauchen, and Zhou (2009); Lochstoer and Muir (2022)). While we abstract from VRP in this simple framework, we investigate the empirical effects of extreme weather events on VRP in Section III.B. The predominant focus of our analyses is the extreme weather uncertainty after hurricane landfall (after the extreme weather event has occurred), which captures impact uncertainty. In Section III.E, we also analyze the uncertainty before hurricane landfall (before the extreme weather event occurs) by looking at forecasts for individual hurricanes and hurricane seasons. These forecasts give us probabilities of firm exposure to a hurricane, which proxy for ϕ.

A variety of factors can make it difficult to predict at the time of an extreme weather event how firms will be affected. For example, it can be challenging if not impossible to know ex ante which areas will flood in a particular storm, the extent and duration of power outages, whether a levy will break, or how long infrastructure repairs will take. Such factors could create significant extreme weather uncertainty for firms. At the same time, firms could insure against extreme weather events, relocate establishments away from vulnerable locations, or implement other adaptations to lower the extreme weather uncertainty they face. Thus, whether or not extreme weather uncertainty is substantial is ultimately an empirical question.

B. Measuring treatment

To empirically test hypotheses on firm-level extreme weather uncertainty, we identify firms treated by such events based on their geographic footprints. In the case of hurricane landfalls, we determine firm exposure in two steps. First, we determine which counties are in the landfall region of a hurricane. Second, we calculate the share of a firm's establishments located in these counties. This share is our continuous measure of treatment intensity for each firm and each hurricane. Figure 4 Panel A shows a stylized example of this approach to measuring a firm's exposure to a landfall region.[23]

In basing our firm exposure measure on the share of establishments in hurricane landfall regions, we place equal weight on different types of establishments that could potentially be important to firms. For example, while a store location that generates sales could be important for one firm, a manufacturing plant without any direct sales could be crucial to

[23] We employ similar methodologies to measure a firm's exposure to hurricane forecasts, hurricane season forecasts, and extreme weather events other than hurricanes. Sections III.E and IV.A provide more details.

another. In the Internet Appendix, we show robustness to using an alternative measure of landfall region exposure based on establishment-level sales data from NETS.

We define a county c to be in the set $L_{R,h}$ of counties in the landfall region if the county centroid lies inside a radius R of the eye of hurricane h. We then calculate the share of firm i's establishments in counties within the hurricane's landfall region. Firm i's exposure to the landfall region of hurricane h is

$$LandfallRegionExposure_{i,R,h} = \sum_{c}(FirmCountyExposure_{i,c} \times I_{c \in L_{R,h}}), \tag{6}$$

where $FirmCountyExposure_{i,c}$ is the share of firm i's establishments in county c in the year hurricane h hits, and $I_{c \in L_{R,h}}$ is an indicator equal to 1 if county c is in the landfall region for hurricane h. A firm's exposure to a hurricane landfall region is thus a continuous variable ranging from 0 to 1. With larger R, the average intensity of impact on hit firms decreases, but the number of firms with a meaningful share of establishments in the landfall region increases. For example, in Figure 4 Panel A, a larger R would translate to more counties in the shaded area and a larger share of a firm's establishments within the landfall region. Table II Panel B also illustrates this point, showing that the number of firms with high $LandfallRegionExposure_{i,R,h}$ increases with R. For landfall regions based on 200- and 50-mile radii around the eye of a hurricane, the average U.S. firm has 7% and 1% of its establishments in a given landfall region, respectively. These values are reasonable as each hurricane generally only affects a few states and our sample encompasses firms across the United States. Columns 5 to 8 show that our sample includes a large number of firms with a high share of their establishments within a hurricane landfall region. For example, for the 200- and 50-mile radii, we have 3,131 and 213 firm-hurricane observations, respectively, with 25% or more of their establishments in the corresponding landfall region.

C. Baseline estimation strategy

We test the predictions of the theoretical framework in Section II.A by employing a difference-in-differences strategy and jointly estimating the treatment effect across all hurricanes. In the case of hurricane landfalls, each landfall yields a separate treatment. Treatment intensity varies due to the continuous nature of the hurricane landfall exposure variable defined in equation (6). Firms with zero exposure to a particular hurricane serve as the controls for that event.[24] As illustrated in Figure 1, which depicts the landfall regions of four hurricanes in our sample, hurricanes can strike different regions of the United States. As such, the set of hit firms varies across hurricanes. We follow the recommendation of Bertrand, Duflo, and Mullainathan (2004) by collapsing the time series information into a pre- and post-treatment period for each difference in differences, that is, each hurricane. Figure 4 Panel B illustrates the hurricane timeline, with $T_0^h - 1$ marking the pre-treatment period as the last trading day before hurricane inception, which occurs up to two weeks before landfall.[25]

We estimate uncertainty at hurricane landfall using the following firm-hurricane panel regression model, where each hurricane enters as a separate time period:

$$log\left(\frac{IV_{i,T_L^h+\tau}}{IV_{i,T_0^h-1}}\right) = \lambda_{L,R,\tau} LandfallRegionExposure_{i,R,h} + \pi_h + \psi_{Ind} + \epsilon_{i,h,\tau}. \tag{7}$$

The dependent variable is the change in implied volatility from the day before hurricane inception ($T_0^h - 1$) to τ trading days after landfall ($T_L^h + \tau$). We include hurricane fixed effects (π_h), which is equivalent to including time fixed effects because each hurricane enters the regression as a separate time period. This fixed effect parametrically accounts for correlation of errors across firms within a time period (Petersen, 2009). We include industry fixed effects (ψ_{Ind}) based on SIC classifications either by themselves or interacted with the hurricane (time) fixed effects to absorb industry-wide shocks. Given that we measure the hurricane shock at the county level, firms with establishments predominantly in the same county likely experience correlated changes due to a hurricane. Therefore, we cluster standard errors by county, assigning each firm to the county where it has the most establishments.[26]

Shortly after landfall, investors know that the hurricane made landfall and where it landed. But they do not necessarily know what the eventual impact on exposed firms will be. While a hurricane can move inland, by five days after landfall, it has either dissipated

[24] We exclude firms that have been hit by a hurricane from the control set of other hurricanes that occur within 180 calendar days to avoid distortions due to overlapping. For this purpose, we deem a firm "hit" if the landfall region exposure is at least 0.25. Varying this threshold leads to qualitatively similar results.

[25] We specify the inception day as the first day that NOAA publicizes a wind speed probability forecast advisory that, with at least 1% probability, the hurricane will ultimately make landfall. For hurricanes before 2007, when these forecast advisories are unavailable, we specify the inception day as the first day that the hurricane appeared as a tropical depression.

[26] Our results are robust to alternate clustering choices including clustering by firm, county-hurricane (county-time), or by county after assigning each firm to the county of its headquarter location.

or is no longer a hurricane. Thus, incidence uncertainty has been largely resolved, and we interpret the estimate of $\lambda_{L,R,\tau}$ as of five or more trading days after landfall as reflecting impact uncertainty.

III. Results

A. Uncertainty after landfall

A.1. Magnitude of impact uncertainty

We begin by testing the hypothesis that hurricanes generate higher expected return volatility. We estimate the impact uncertainty priced in options of hit firms after hurricane landfall. In Table III, we present results from estimating equation (7) for 1 week (5 trading days) and 1 month (20 trading days) after landfall. We show results from regressions for which the landfall region is based on a 200-mile radius around the hurricane eye in Panel A. In Panels B and C, the radius is set to 100 and 50 miles, respectively. The number of observations decreases for radii below 200 miles in Panels B and C because the firms that have exposure to the 200-mile landfall region but not to the 100- and 50-mile landfall regions are dropped from the control set.

Table III Panel A shows that for the 200-mile radius the $\lambda_{L,R,\tau}$ estimates go up to close to 8% and are positive and significant across all specifications. In Panels B and C, exposure is based on smaller radii, which means that the treated establishments are on average hit more intensely. The estimates based on these radii are as high as 18%, suggesting that firms that have establishments closer to the epicenter of the hurricane face greater impact uncertainty. The results imply that a firm with 100% of its establishments within 50 miles of landfall will see its implied volatility increase by about 18%. These are substantial magnitudes for impact uncertainty. The coefficient estimates are higher one month after landfall than one week after landfall, which could stem from the slow diffusion of information or investor inattention.

To obtain intuition regarding the dollar value of the implied volatility increases, we perform a back-of-the-envelope calculation of the implied increased cost of purchasing sufficient options to insure the total equity market value of hit firms. We estimate that the total additional cost of the post-hurricane landfall impact uncertainty over our sample period would have been as high as \$94 billion in 2019 inflation-adjusted terms.[27] This magnitude is considerable and represents around 14% of the \$659 billion in total hurricane damages estimated by NOAA for the same time period (see Table I).

A.2. Persistence of uncertainty

A question that naturally follows is how long these large estimates of impact uncertainty last. In other words, for how long are investors uncertain about the hurricane's ultimate impact on the firm? In Figure 5 Panel A, each point shows the coefficient estimate from a separate regression estimating equation (7) for τ trading days after landfall. This figure shows how the effect of exposure to hurricane landfall on firms' implied volatilities evolves over the 120 trading days (about 6 months) after landfall. As in Table III, the coefficient estimates increase until about 1 month after landfall, at which point it is close to 8%. From around 30 trading days, the implied volatility effect gradually decreases but remains statistically significant for just over 3 months. These results show that impact uncertainty is persistent.

These estimates of long-lasting impact uncertainty are confirmed by our textual analysis of calls between analysts, investors, and managers of hit firms. The length of time over which we observe elevated uncertainty after landfall is similar to the length of time over which we observe elevated levels of discussions of hurricane impacts in the analyst calls of hit firms. Figure 5 Panel B shows that the frequency of analyst call discussions of hurricanes per call increases sharply after hurricane landfall for hit firms but not for control firms. Discussion levels then remain high for some time before dropping sharply around 3 months after landfall. This observation shows that over the period during which impact uncertainty as measured by options is high, investors are obtaining information from management on the hurricane's impact on a firm. These results indicate that learning about how a firm is affected by a specific hurricane takes time and is an important driver of uncertainty persistence.

[27] These values are based on coefficient estimates of implied volatility changes for the 200-mile radius around the eye of the hurricane, as shown in Table III, of 7.676 for 20 trading days after landfall. The implied volatility, landfall region exposure, vega, and number of shares outstanding of hit firms are used for the computation.

B. *Efficiency of volatility expectations*

We next test the hypothesis that the change in volatility expectations in response to a hurricane is efficient. To do so, we analyze the volatility risk premium (VRP), defined as the difference between the ex ante risk-neutral expectation and ex post realization of return volatility, as shown in equation (2). We test how this spread varies for firms exposed to a hurricane relative to control firms by estimating the regression:

$$\overline{VRP}_{i,T_L^h+\tau} = \lambda_{L,R,\tau}^{VRP} LandfallRegionExposure_{i,R,h} + \pi_h + \Psi_i + \epsilon_{i,h,\tau}. \tag{8}$$

The dependent variable is VRP averaged from landfall to τ trading days after landfall. Ψ_i is a firm fixed effect that absorbs the average differences in the VRP levels across firms.[28] A negative estimate of $\lambda_{L,R,\tau}^{VRP}$ is consistent with investor underreaction. This would represent a systematic bias in option prices for hurricane-hit firms compared to control firms.

Table IV reports the results of the regression model in equation (8). The coefficient captures the VRP (i.e., the spread between the ex ante market expectations of future volatility and ex post realized volatility) change due to a hurricane hit. The table shows the effects of hurricanes on average VRP over several time frames after landfall. In line with investors underreacting to hurricanes, the one week post-landfall coefficient estimates are consistently negative and significant. Panel B shows that the underreaction is particularly strong for firms with establishments within 50 miles of the hurricane's eye—a firm with all its establishments within that landfall region experiences up to a 21 percentage point lower VRP relative to control firms. In both Panels A and B, the investor underreaction becomes smaller as the post-landfall horizon extends but remains severe even a month after landfall. Thus, our results show that investors correctly anticipate that a hurricane will lead to higher realized volatility but underestimate by how much.

Internet Appendix Section C.3 presents the returns to a trading strategy that takes on the implied volatility exposure using delta-neutral straddles at landfall for firms hit by hurricanes against the returns to the same strategy for control firms that are not hit. The

[28] Unlike with the implied volatility regression in equation (7), it is not possible to subtract the pre-inception value of the dependent variable in these VRP regressions. This is because the realized volatility over the remaining life of an option calculated on the pre-inception date, $RV_{i,T_0^h-1,M}$, will include the hurricane's impact. Including a firm fixed effect instead effectively allows for the estimation of deviations from a firm's mean VRP.

results show that the trading strategy can profitably exploit the underreaction of option prices to hurricanes.

We next examine if this underreaction diminishes in response to a particularly salient hurricane. In our sample, the hurricane most likely to have had such an effect is Hurricane Sandy in 2012, which made landfall in the New York tri-state area. Not only was Sandy very damaging as reported in Table I, but it also hit an area that had previously been largely spared from head-on hits by hurricanes. The New York Stock Exchange closed for two days as a result. New York City and the surrounding states of Connecticut and New Jersey are home to a large share of mutual funds and hedge funds. Personal experiences can make investors more attuned to risks (Malmendier and Nagel, 2016; Alekseev, Giglio, Maingi, Selgrad, and Stroebel, 2022), and Hurricane Sandy was particularly salient for financial investors (Kuchler, Li, Peng, Stroebel, and Zhou, 2022; Addoum, Eichholtz, Steiner, and Yönder, 2023). As such, experiencing Hurricane Sandy may have made investors more aware of extreme weather risks and led to increased pricing efficiency through the capital they manage.

We test whether the negative VRP effect diminished after Hurricane Sandy by estimating the regression in equation (8) with an additional term that interacts the landfall exposure variable with a $PostSandy_h$ indicator that equals one for hurricanes from 2013 onward. Table V reports the results for 1 week, 1 month, and 2 months (5, 20, and 40 trading days) after landfall. The coefficient estimates on the interaction term are always positive and are significant for the majority of the specifications. The coefficients are also economically large, canceling out the negative coefficient estimate on the uninteracted $LandfallRegionExposure$ term in several specifications at longer time horizons.

In Figure 6, we show how long after hurricane landfall it takes for the negative VRP effect to revert back to zero, at which point investor underreaction has resolved. The figure depicts the estimates of $\lambda_{L,R,\tau}^{VRP}$ in equation (8) with VRP averaged over five-trading-day increments after landfall. In Panel A, we see that before Hurricane Sandy, investor underreaction persists for about one-and-a-half months (30 trading days). Panel B shows that, after Hurricane Sandy, the VRP effect was generally not distinguishable from zero. In fact, we estimate a significant positive effect around 20 to 30 trading days, indicating that options markets price in a premium.

The Internet Appendix contains additional analyses on the saliency of Hurricane Sandy.

First, we test that the saliency effect captured by the post-Sandy indicator variable is distinct from general concerns about climate change. We include two climate change concern indices interacted with landfall region exposure as control variables. The first index is from Ardia, Bluteau, Boudt, and Inghelbrecht (2022), who use textual analysis of news articles to create their measure. They build on the methodology of Engle, Giglio, Kelly, Lee, and Stroebel (2020) by expanding the set of included news outlets and covering a more recent time period. The second index is the Google Trends measure for searches on the topic of climate change in the United States. The results in Table C.13 show that the post-Sandy interaction term remains significant and positive after including these controls. Second, in Table C.14, we show results for a modified regression specification where we split the post-Sandy interaction term into year-specific interaction terms, some of which capture relatively few hit firms. The results reveal that the reversal is generally largest for the first year in the post-Sandy sample, in line with Hurricane Sandy representing a saliency shock for investors.

Overall, these results suggest that options markets have started to price the uncertainty associated with hurricanes more efficiently. However, it took a particularly salient event for efficiency to improve. This finding calls into question whether financial markets will be attentive and react quickly to efficiently price extreme weather events that are novel in terms of intensity or location due to climate change.

C. Economic channels of extreme weather uncertainty

We next investigate the economic channels driving the firm-level uncertainty generated by hurricanes. To identify the economic channels, we examine the transcripts of calls between analysts, investors, and firm management by applying natural language processing tools. To test the hypothesis that a particular channel drives the uncertainty, we leverage the idea that a discussion in an analyst call of a particular channel in relation to an extreme weather event generally occurs when the impact of that channel on the firm's performance is potentially material but not obvious. Consistent with this interpretation, discussions of hurricanes in these calls jump after landfall for hit firms and remain elevated while uncertainty is high (see Figure 5). For example, investors could be uncertain about how the hurricane affects the demand for a firm's product or to what extent a firm's property is insured. In such cases, discussions on these topics would occur in analyst calls to obtain information when available and potentially resolve uncertainty. The more uncertainty exists around a given channel, the more this channel will be discussed during calls in the aftermath of an extreme weather event.

We focus on "hurricane paragraphs"—analyst call paragraphs that contain some form of the terms "hurricane" or "tropical storm"—that follow a hurricane hit. By carefully examining a random sample constituting 5% of all hurricane paragraphs, we identify five distinct channels: business interruption, physical damages, insurance, supply, and demand. For each channel, we set a paragraph-level indicator equal to 1 if a hurricane paragraph contains a term assigned to the channel in our dictionary (see Internet Appendix Table C.1). We develop this dictionary by applying judgment to balance Type I and Type II errors. We validate this methodology by performing a latent Dirichlet allocation analysis of all hurricane paragraphs, which confirms that we are not missing any major channels through our manual inspection. More details on the data processing and methodology are in Section C.1 of the Internet Appendix.

To analyze the relevance of the economic channels through which hurricanes generate uncertainty, we estimate the regression:

$$HurricaneDiscussions_{i,T_L^h+120} = \lambda_{L,R}^{RC} LandfallRegionExposure_{i,R,h} + \pi_h + \psi_{Ind} + \epsilon_{i,h}. \quad (9)$$

The dependent variable is the number of paragraphs in analyst calls of a firm over the 120 trading days (6 months) after landfall that discuss hurricanes or alternatively hurricanes in combination with an economic channel (i.e., business interruption, physical damages, insurance, supply, or demand). We choose a six-month period to capture multiple analyst calls but avoid any overlap with the subsequent hurricane season. A positive $\lambda_{L,R}^{RC}$ estimate indicates that concern about the economic channel increases in response to hurricanes. For a given landfall region exposure, a higher $\lambda_{L,R}^{RC}$ means that more discussions occur regarding the channel, indicating its greater relevance for uncertainty.

Table VI presents results from the regression model given in equation (9). Column 1 shows that the number of hurricane paragraphs increases significantly with landfall exposure. In Panel A, the coefficient estimate implies that a firm having all its establishments in a 200-mile radius landfall region generates four paragraphs of discussion. Panel B shows that a firm with all its establishments within a 50-mile radius landfall region is predicted to discuss hurricanes even more frequently, across 15 paragraphs more than control firms.

In columns 2 to 6, we examine the economic channels generating the impact uncertainty. A firm's $LandfallRegionExposure$ increases discussion of the five channels to varying degrees.[29] Relative to control firms, a hurricane's impact on business interruption and physical damages is discussed in up to 3 and 5 paragraphs more, respectively. There are also significant, albeit smaller, increases with the insurance, supply, and demand channels.

Firm-level uncertainty can be generated through these channels due to several factors. In the absence of constraints, firms with vulnerable operations and infrastructure could relocate away from hurricane-prone coastal areas. In the United States, centers of economic activity are often located along the coast, as we show in Figure 2. Many firms locate near population centers due to customer demand and labor supply. In our data, 35% of all establishments are in counties located within 50 miles of the Atlantic or Gulf Coasts. Over 90% of these coastal establishments are concentrated in the top 10% most populous counties within that region. We also find that relocation is rare.[30] High costs, location of natural resources, inflexibility, myopia, and agency problems are other factors that could prevent firms from relocating.

In theory, firms can reduce uncertainty through insurance. However, the positive and strongly significant coefficient estimates for insurance in column 4 suggest that, in practice, there is uncertainty regarding the insurance coverage of firms.[31] Uncertainty regarding insurance could reflect concerns about delays or disputes regarding payment of claims or that firms are underinsured due to high costs, lack of availability, and limited types of losses covered.[32]

[29]The observation count changes in columns 2 to 6 because we restrict the sample to the firm-storm observations for which hurricanes are discussed at least once. This ensures that we are not simply measuring again the fact that hurricanes are being discussed. This also ensures that we only count the discussion of a specific channel if hurricane terms are also mentioned.

[30]An analysis of NETS data relocations reveals across-county relocations are fairly rare, with the 75th percentile showing zero county relocations and the 90th percentile showing just one (see Internet Appendix Table C.19).

[31]Insurance is only material when physical damages and business disruptions are not de minimis, which can explain why the coefficient on insurance discussions is small relative to the coefficients in columns 2 and 3.

[32]Insurance companies have been shown to move out of areas that they deem too risky and costly to insure given regulatory constraints and other frictions. The New York Times writes in July 2021: "And it adds to growing concern among economists about a new issue in the climate crisis: whether some parts of the United States are becoming too risky to insure, at least at a cost that most people can afford." This article can be found at https://www.nytimes.com/2021/07/17/us/miami-building-collapse-condo-surfside.html. While FEMA and other government programs could step in to assist, such aid for businesses is limited and uncertain in terms of timing and magnitude.

The significant increases in discussions around supply and demand in columns 5 and 6 indicate that firms are affected by hurricanes through market dynamics over which they have little control or means to adapt to or insure against. Also, unlike in the cases of physical damages, business interruption, and insurance, where uncertainty centers on the extent of losses, changes in demand can present opportunities for firms, for example, for those selling products like building materials, generators, and mosquito remediation.[33] Thus, demand is likely a key channel through which extreme weather uncertainty reflects both upside and downside risk.

The relatively small increase in discussions of supply can be partially driven by suppliers of hit firms being located outside the hurricane path. However, the small response is also in line with investors being inattentive to the supply channel. In Internet Appendix Section C.1, we regress VRP on the frequency of discussions of economic channels and find that the supply channel is associated with the strongest underreaction by investors, consistent with the prior literature showing investors are inattentive to shocks to a firm's suppliers (Menzly and Ozbas, 2010).

D. *Extreme weather uncertainty and expected returns*

We next analyze whether the uncertainty generated for firms by hurricanes is priced in the underlying stocks. Our analysis sheds light on how the idiosyncratic shocks associated with hurricanes impact firms through the cost of capital channel, yielding a more complete view of the real effects of extreme weather. If firms' cost of capital increases in the immediate aftermath of an extreme weather event due to the generated uncertainty, it would amplify impacts by tightening financing constraints just when firms may need capital to rebuild or revamp their operations.

Motivating our empirical analysis, in Internet Appendix A, we show theoretically with a simple extension of the Merton (1987) model how extreme weather uncertainty can affect expected returns even if the shock is purely idiosyncratic. Under the standard capital asset

[33] For example, in discussions with analysts, Procter & Gamble Co. states on November 4, 2003: "Another factor was the blackout and hurricane Isabel. Obviously, both were bad news for a lot of people but for Duracell, they created a surge in battery buying." American Vanguard Corp on November 2, 2017: "...we recorded strong sales of Dibrom, our mosquito adulticide, as domestic customers responded to FEMA's requirement for aerial spraying of about 6 million acres over coastal Texas and Florida in the aftermath of Hurricanes Harvey and Irma."

pricing model, such shocks would be diversifiable and would not affect the discount rate of the representative investor. However, shocks to expected idiosyncratic volatility due to an extreme weather event affect expected returns when investors are not perfectly diversified due to segmented markets or other frictions. In this section, we test this hypothesis.

We use our difference-in-differences setting to estimate the impact on expected returns from changes in idiosyncratic volatility due to exogenous extreme weather events.[34] We estimate a firm-hurricane panel regression model similar to our previous specifications. Here, the dependent variable is the cumulative abnormal return (CAR) relative to the Fama-French five-factor model (Fama and French, 2015), but results are qualitatively similar when using excess returns (see Internet Appendix Table C.17.) We first estimate the Fama-French five-factor model for each stock and hurricane based on 120 trading days (6 months) before the hurricane inception date. We next use the coefficient estimates from this first stage to compute for each firm and hurricane the CAR earned during a defined period that occurs after hurricane landfall. We use this CAR as our dependent variable in the following regression:

$$CAR_{i,h,T_L^h+\tau:T_L^h+\tau+ReturnHorizon} = \lambda^{Ret}_{L,R,\tau} LandfallRegionExposure_{i,R,h} + \pi_h + \psi_{Ind} + \epsilon_{i,h,\tau}, \tag{10}$$

where $LandfallRegionExposure_{i,R,h}$ serves as our proxy for firm uncertainty caused by hurricane landfall. We set $T_L^h + \tau$, the starting point of the CARs, to 30 trading days after landfall. This is around when implied volatility tends to peak after hurricane landfall. However, the results are qualitatively similar for smaller values of τ. We examine multiple return horizons, with $ReturnHorizon$ equal to 20, 30, and 40 trading days, in line with the average expiry of options in our sample, which exceeds a month (see Table II).

If the uncertainty caused by a hurricane leads to higher abnormal returns, we would expect the estimate of $\lambda^{Ret}_{L,R,\tau}$ in equation (10) to be positive. In the results shown in Table VII Panel A, the coefficient estimates are insignificant for all specifications. These results are inconsistent with investors demanding a premium for holding stocks of firms subject to higher uncertainty due to hurricanes.

A potential explanation for this finding is that investors fail to correctly price the uncertainty because they systematically underestimate the extent of uncertainty generated by

[34]In the Internet Appendix, we analyze the variance decomposition and show that hurricane shocks affect the stocks of hit firms via both the discount rate and the cash flow channels.

hurricanes. In this case, the underestimation of the volatility of affected firms could yield noisy and insignificant return estimates because prices do not adjust sufficiently. We discuss this case more formally in the context of our theoretical framework in Internet Appendix A. Other factors might contribute to the mispricing. For example, investors might have biased expectations of how the hurricane affects a firm's cash flow.

Given that we find less systematic bias in the uncertainty reflected in options markets after Hurricane Sandy, the price of this uncertainty may also be different in equity markets in the later period. We thus extend the regression model in equation (10) by adding a term that interacts our landfall region exposure variable with an indicator that equals one for the hurricanes in our sample after Sandy. We report the results in Table VII Panel B. While the coefficient estimates on $LandfallRegionExposure$ are always negative and insignificant, the coefficient estimates on $LandfallRegionExposure$ interacted with the post-Sandy indicator are always positive and significant. The estimates on the uninteracted variable predict an effect on returns of around -1%, while the prediction from the estimates on the interacted variable range from 2.9% to 7.0%. The sum of the two coefficient estimates is always positive, ranging from 1.9% to 6.0%, capturing that the net effect on abnormal returns is positive after Sandy. Correspondingly, the regressions on the subsample including only post-Sandy hurricanes show positive and significant effects on returns (see Internet Appendix Table C.16). Further, these results are qualitatively similar when using excess returns in place of abnormal returns, and when excluding firms below the 20$^{\text{th}}$ percentile of NYSE-listed equity (see Tables C.17 and C.18 in the Internet Appendix, respectively).

These results indicate that uncertainty associated with hurricanes is priced and affects firms' equity cost of capital in the post-Sandy sample.

E. Uncertainty before landfall

In this section, we examine how uncertainty reflected in options markets before landfall is related to the short-term, daily forecasts for a hurricane's path after its inception and the longer-term, annual hurricane season forecasts made by NOAA. In the context of the theoretical framework described in Section II.A, the uncertainty generated for a firm before an extreme weather event occurs includes both incidence uncertainty and expected impact uncertainty. After the event occurs (e.g., after a hurricane makes landfall), incidence uncertainty is resolved and only impact uncertainty remains.

E.1. Short-term forecasts of a hurricane path

We use NOAA hurricane wind speed forecast text advisories to develop daily firm-specific exposures to hurricanes before landfall. As with our approach in Section II.B, we first identify which counties are exposed to hurricane forecasts and then develop continuous firm forecast exposure measures based on each firm's share of establishments in counties in the forecast path of a hurricane.

To estimate how hurricane forecast exposure affects uncertainty, we compute the log change in the implied volatility from the last trading day before hurricane inception, $T_0^h - 1$, to Γ days before a storm makes landfall or dissipates, $T_L^h - \Gamma$ (see Figure 4 Panel B for an illustration of the timeline). Then, we regress this change in implied volatility on a firm's forecast exposure:

$$log\left(\frac{IV_{i,T_L^h-\Gamma}}{IV_{i,T_0^h-1}}\right) = \lambda_{F,P,\Gamma} ForecastExposure_{i,P,T_L^h-\Gamma} + \pi_h + \psi_{Ind} + \epsilon_{i,h,\Gamma}. \tag{11}$$

We estimate this regression model separately for Γ ranging from 1 to 5 days and probability thresholds P from 1% to 50%, where each regression includes at least 5 storms.

Table VIII presents the results. The results in each column are from a separate regression performed for the specified Γ and P. Location-specific NOAA wind speed probabilities generally remain low when a hurricane is far from landfall. As such, there are fewer probability thresholds with observations when days before landfall or dissipation increase. Also, the number of firms with a given exposure to the forecast path of a hurricane decreases as the probability threshold increases because the region facing a higher probability is smaller. The results show that substantial uncertainty arises for firms in a hurricane forecast path. The estimates of $\lambda_{F,P,\Gamma}$ are always positive and statistically significant, regardless of whether time and industry fixed effects are included separately (Panel A) or interacted (Panel B). For a given Γ, the magnitude of the coefficient estimate tends to increase with higher landfall probabilities, reaching up to 22% in column 5, consistent with the predictions of our theoretical framework. This indicates that having all its establishments in the likely path of a hurricane can increase a firm's implied volatility up to 22%.

The results show that investors pay attention and react to NOAA's hurricane forecasts, a finding that is not obvious given prior investigations showing mixed results on investor attention to other climatic events (e.g., Bernstein, Gustafson, and Lewis (2019); Hong, Li, and Xu (2019); Baldauf, Garlappi, and Yannelis (2020); Murfin and Spiegel (2020); Giglio, Maggiori, Rao, Stroebel, and Weber (2021); Bakkensen and Barrage (2022)). When analyzing VRP, and in line with the post-landfall analyses, we find that investors underreact to these forecasts until Hurricane Sandy (see Internet Appendix Table C.15).

E.2. Seasonal hurricane forecasts

We next examine whether investors also price in longer-term seasonal hurricane forecasts. Every May, NOAA releases a seasonal outlook for the June–November hurricane season reporting the probability that the season will be above-normal, near-normal, or below-normal.[35] We test whether the options of firms with establishments in higher risk counties exhibit higher implied volatilities when NOAA forecasts a hurricane season with above-normal activity. For this analysis, we use options with 120 to 210 calendar days to expiry to span the majority of hurricane season s. We measure a firm's exposure to s as either the share of its establishments in counties along the Atlantic and Gulf Coasts, $CoastalExposure_{i,s}$, or as the share of its establishments in counties with high historical probabilities of being hit (i.e., counties hit in at least 10% or 25% of the previous 30 years), $HistoricalHurricaneExposure_{i,s}$. Our regression specification is as follows:

$$\begin{aligned} log\left(\frac{IV_{i,T_0^s+5}}{IV_{i,T_0^s-1}}\right) =& \lambda_{S,1} CoastalExposure_{i,s} \times AboveNormalSeasonProb_s \\ &+ \lambda_{S,2} CoastalExposure_{i,s} + \pi_s + \psi_{Ind} + \epsilon_{i,s}, \end{aligned} \tag{12}$$

where $T_0^s - 1$ is the last trading day before NOAA's hurricane season outlook is announced in May, and $T_0^s + 5$ occurs 5 trading days after the announcement. The variable $AboveNormalSeasonProb_s$ denotes the probability of an above-normal hurricane season. A positive estimate of $\lambda_{S,1}$ would be consistent with investor attention to longer-term seasonal forecasts and imply that a high probability of an above-normal season raises uncertainty.

Table IX presents the estimates using firm exposure to coastal counties in Panel A and to counties with a high historical probability of being hit by a hurricane in Panel B. None of

[35] A plot in the Internet Appendix shows that these data, which start in 2001, display significant annual variation.

the estimates of $\lambda_{S,1}$ are statistically significant, and some point estimates are even negative. One potential explanation for this lack of investor response to seasonal hurricane forecasts is that the forecasts do not have sufficient predictive power for damaging hurricanes making landfall. We find only a weakly positive relationship between the seasonal outlooks and the number of hurricanes making landfall in a given year (see Internet Appendix Figure B.4). Another potential explanation is that investors do not pay attention to seasonal forecasts because these forecasts are longer term and lack the immediacy of specific hurricane path forecasts. While it is not feasible to distinguish between these two explanations with the available data, exploring investor reactions to short- and long-term forecasts of climatic risks is an interesting avenue for future research.

IV. Robustness and extensions

A. *Other types of extreme weather events*

While the main empirical analysis in this paper focuses on hurricanes, the theoretical framework and empirical approach can also be applied to other extreme weather events. We test for external validity by examining if options markets reflect higher uncertainty when firms are exposed to other types of extreme weather events, namely floods (unrelated to hurricanes), snowstorms, and tornadoes. This analysis captures both a wider range of extreme weather event types and a broader set of affected geographic regions.

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 firm i's establishments in the impacted region for a specific extreme weather event h. We estimate the regression model in equation (7), with $LandfallRegionExposure$ replaced with $ImpactRegionExposure$. Because there is no readily and consistently available forecast information for these types of extreme weather events, we use the date one week before the reported incident begin date for each event as the pre-period.

The results in Table X show that the implied volatilities of exposed firms rise in response to floods, snowstorms, and tornadoes. The coefficient estimates and statistical significance are mostly lower than for hurricanes, which is likely due to these extreme weather events being less destructive and affecting a smaller number of firms. Tornadoes exhibit the largest uncertainty response, with a magnitude comparable to the estimates for hurricanes. Interestingly, the uncertainty dynamics of these extreme weather events are similar to hurricanes. The implied volatility remains elevated for an extended period of time and peaks at least one month after the start date.

B. Industry effects

We analyze whether our baseline results are driven by a particular industry by adding an industry-specific interaction term to equation (7). We analyze the construction, manufacturing, mining, retail, services, transportation, and wholesale industries based on firm SIC numbers. We exclude the agriculture and non-classified categories due to the small number of firms.

Table XI presents the results. The uninteracted $LandfallRegionExposure$ coefficient estimates remain positive and significant in every industry specification, suggesting that our baseline results presented in Table III are not driven by just one sector. The coefficient estimates on the interaction terms are insignificant for most specifications, suggesting limited industry-specific heterogeneity. Construction is the only industry for which the coefficient estimate on the interaction term is strongly significant and negative. The negative sum of the interacted and uninteracted coefficient estimates for the construction industry suggests that investors perceive lower uncertainty for construction firms due to hurricanes, which could reflect an expected boost in demand from rebuilding activity. The negative coefficient estimate on the interaction term for manufacturing suggests that manufacturing firms could also benefit from increased demand from rebuilding activity. However, this coefficient is only weakly significant and not large enough to offset the positive coefficient on the uninteracted term.

For mining, the interacted coefficient estimate is strongly significant and positive, indicating that mining firms experience disproportionately large uncertainty after a hurricane hit. This is consistent with anecdotal evidence that Gulf Coast hurricanes can affect much of the oil and gas extraction sector. Further, mining firms are generally geographically bound to be close to natural resources, giving them less discretion over where to set up operations when trying to avoid hurricanes. Wholesale firms also have a significant and positive coefficient estimate. The relatively higher uncertainty for wholesale firms could be due to their operations being less diversified compared to, for example, a retail company. They have fewer but larger establishments and customer shipments.

C. *Firm selection*

Another potential question is whether our results are driven by small firm size. Our baseline analysis only includes firms with publicly traded options, which excludes very small firms. Further, as reported in Table II, relative to the total sample, the subsample of hit firms—those that had a significant exposure to a hurricane at least once—has a comparable, if slightly higher, average market capitalization.

Firms with coastal exposure can differ from other firms based on unobserved characteristics, but for a given hurricane event, we have coastal firms in both the treatment and control sets. A firm that is severely affected by one hurricane could have zero exposure to others. As such, selection on a specific set of coastal firms is unlikely to drive our results. Further, it is possible that firms that would be more vulnerable to hurricanes because of their particular line of business avoid being exposed to the Atlantic or Gulf Coasts. However, such sorting would bias us against finding evidence of large extreme weather uncertainty priced in options markets.

D. *Tail effects*

We explore whether the large estimates of extreme weather uncertainty are driven by downside risk alone or both upside and downside risk. Some firms might profit from opportunities presented by hurricanes while others suffer losses. For example, as discussed in Sections III.C and IV.B, some firms appear to experience increased demand for their products as a result of rebuilding.

In Internet Appendix Table C.6, we analyze the cross-sectional dispersion of cumulative abnormal returns and excess returns following hurricane inception of the stocks of hit firms and control firms.[36] We find that the dispersion of returns is larger for hit firms than for control firms, which is consistent with the higher stock return volatility of hit firms

[36] We analyze returns instead of option-based measures of tail risk like the implied volatility slope because a large share of the firms in our sample do not have a sufficient number of liquid options at different strike prices to reliably compute the implied volatility slope.

documented in Section III. Underperforming hit firms have lower cumulative returns than underperforming control firms. However, the dispersion is not only restricted to the left tail of the distribution. Outperforming hit firms also have higher cumulative returns than outperforming control firms.

E. Insurance firms

While we exclude financial firms from the main analyses, we separately conduct a similar analysis on the stock options of property and casualty insurance firms. We use statutory financial statements data from S&P Global Market Intelligence to obtain the share of total premiums written by U.S. property and casualty insurance firms in each state. We estimate the regression in equation (7) for these property and casualty insurance firms, measuring an insurance firm's exposure to a hurricane by the firm's share of total premiums written in states that are in the landfall region. We find even larger estimates of extreme weather uncertainty for insurance firms than in our baseline results. The implied volatility is estimated to increase by 70% for an insurance firm that has all its premiums in states hit by a hurricane. Internet Appendix Section C.5 provides more details.

V. Conclusion

This paper presents a comprehensive analysis of firm-level extreme weather uncertainty. Extreme weather events constitute exogenous shocks because prevailing conditions of the firm do not affect the timing and likelihood of such events. Their impact regions are local and thus affect only a subset of firms in the economy, creating a unique experimental setting to study the pricing of firm-level uncertainty. We present a simple model distinguishing between incidence uncertainty and impact uncertainty. We isolate and estimate extreme weather effects through a well-identified empirical framework focusing on hurricanes.

We find that the stock options of firms operating in regions affected by a hurricane have considerably higher implied volatility after the hurricane hits, implying substantial impact uncertainty. Implied volatility returns to pre-hurricane levels only several months after landfall, indicating that the impact uncertainty resolves slowly. Mirroring this finding of significant and prolonged increases to uncertainty, a systematic textual analysis of the transcripts of calls between analysts and firm management reveals that discussions of hurricanes jump after landfall for hit firms and remain elevated for a prolonged time. Our results show that learning about how a firm is affected by a specific event takes time, which can drive the observed volatility persistence.

Despite these large increases in the expectations of volatility implied by options markets, we find that investors underestimate a hurricane's impact on the eventual realized return volatility of hit firms until Hurricane Sandy in 2012. After Sandy hit the financial center of the United States in an unprecedented and highly damaging manner, the ex ante expectations of future volatility embedded in the option prices of hit firms are closer to the ex post realized volatility over the life of the option. This suggests that the informational efficiency of markets increased after many investors personally experienced a particularly salient event.

We find that the idiosyncratic extreme weather shocks impact firms' cost of capital. In the post-Sandy period, the increase in expected idiosyncratic volatility caused by a hurricane predicts higher returns.

A systematic analysis of discussions in transcripts of calls between analysts, investors, and firm management reveals that there are multiple economic channels through which hit firms are affected by hurricanes, namely, business interruption, physical damages, insurance, demand, and supply. Our results suggest that firms are likely not fully adapted to or insured against extreme weather risks. Even when a firm is insured or has adapted, the extent of such measures may not be immediately apparent to investors.

Overall, our results suggest that markets need time to learn how to price extreme weather events and are unlikely to efficiently price novel climatic risks stemming from climate change. Further, extreme weather events that are predicted to become more frequent and severe may not be diversified away by investors and could affect firms' cost of capital even if the events are local. One potential way to reduce the uncertainty associated with extreme weather events and increase pricing efficiency could be to require better firm disclosures related to the economic channels driving extreme weather uncertainty.

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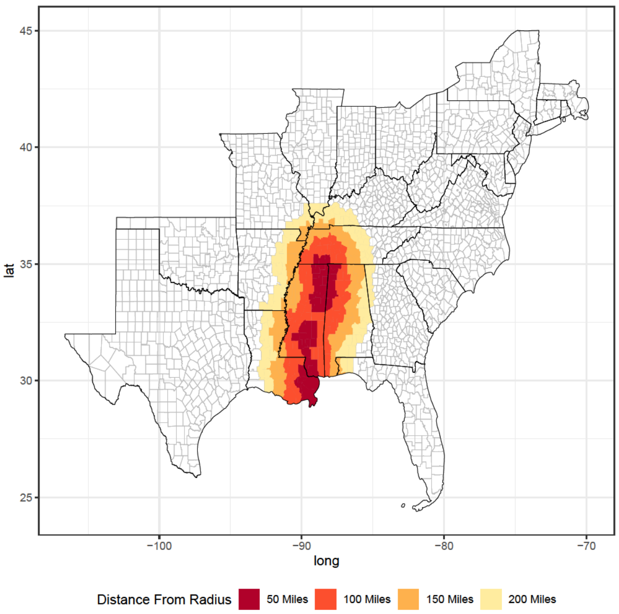
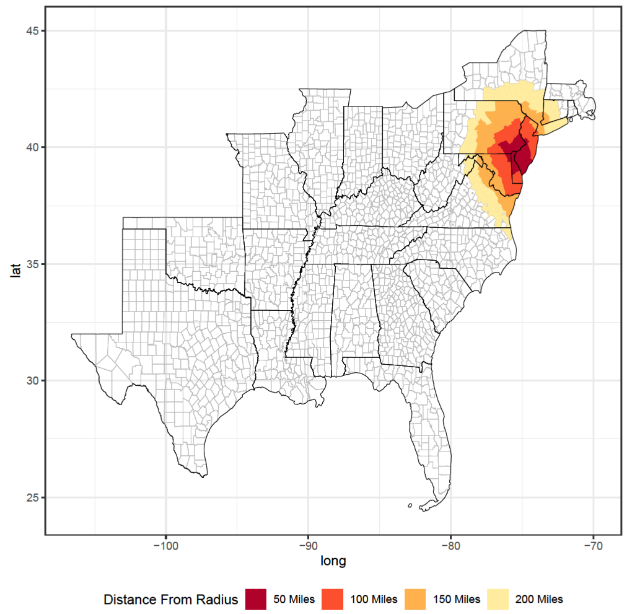
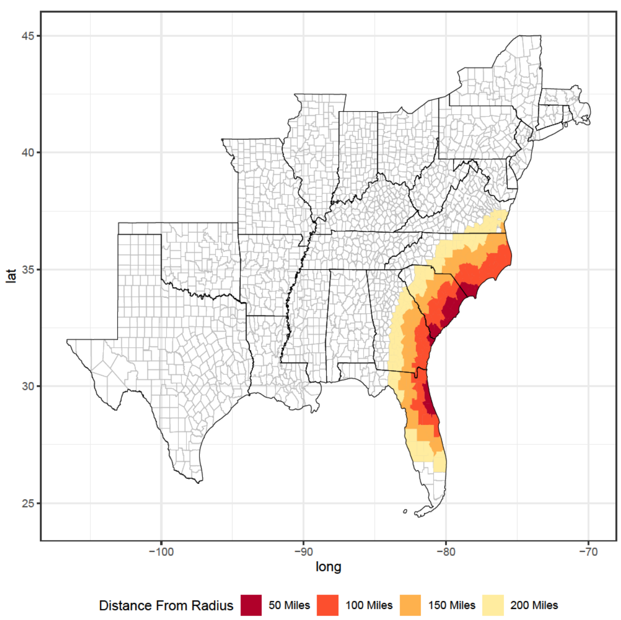


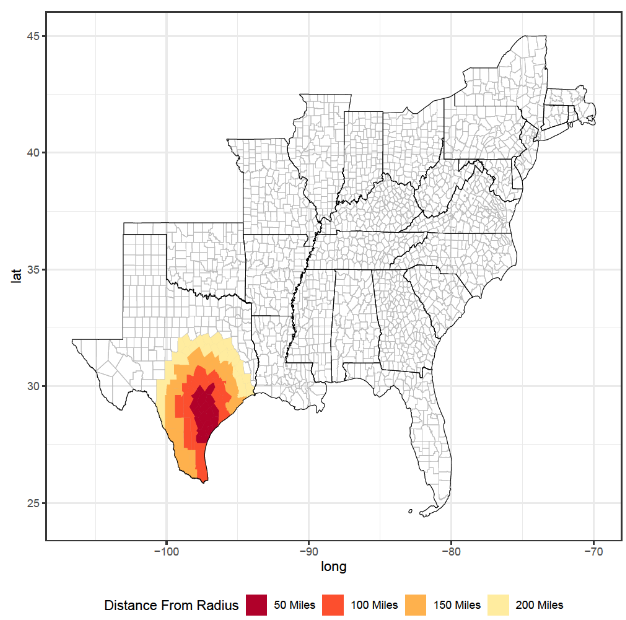
(a) 2005 Katrina



(b) 2012 Sandy



(c) 2016 Matthew



(d) 2017 Harvey

Figure 1: Counties in a hurricane landfall region

This figure shows the counties that are within 50, 100, 150, and 200 miles of the eye of the hurricane at landfall for four selected hurricanes from our sample of 37 hurricane landfalls.

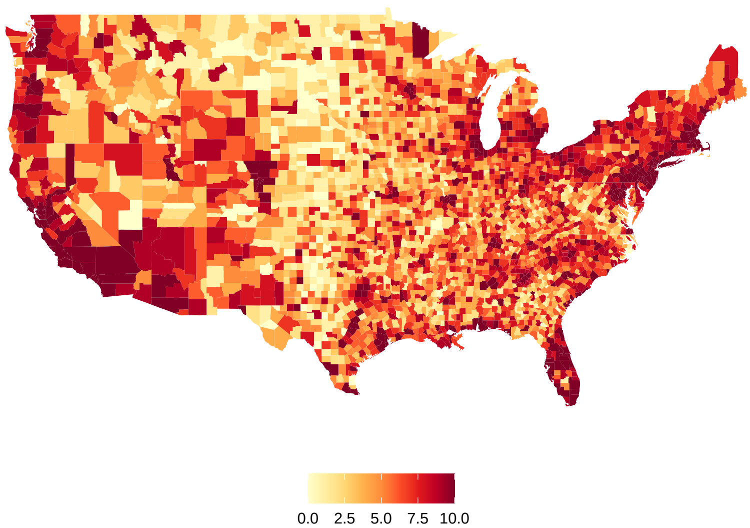


Figure 2: Firm establishments by county

This figure plots counties based on the number of establishments located in that county in 2010. The counties are sorted into deciles based on the number of establishments for the firms in our sample. The darker the shade the greater the number of establishments in a county. Data are from the National Establishment Time Series.

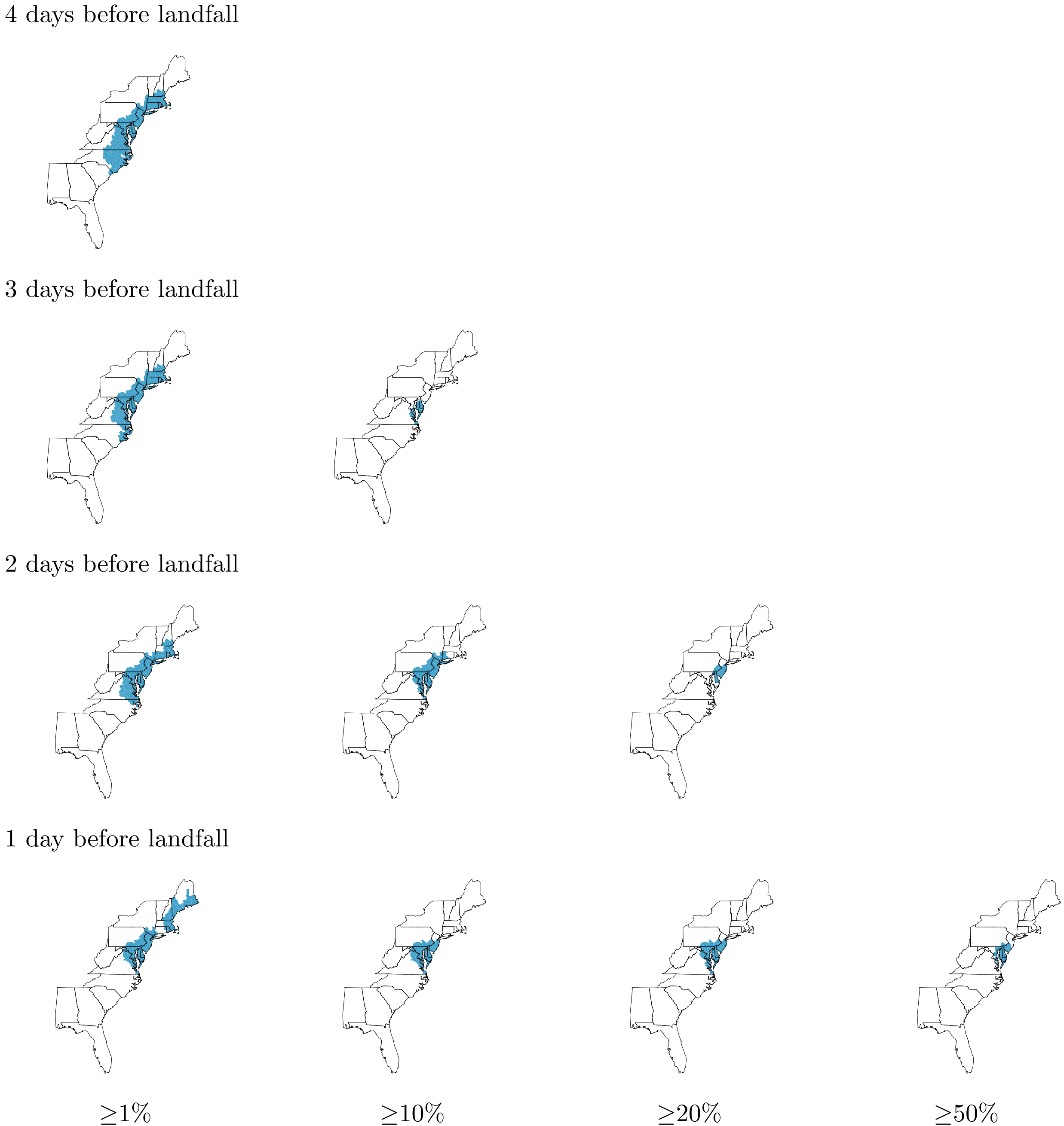
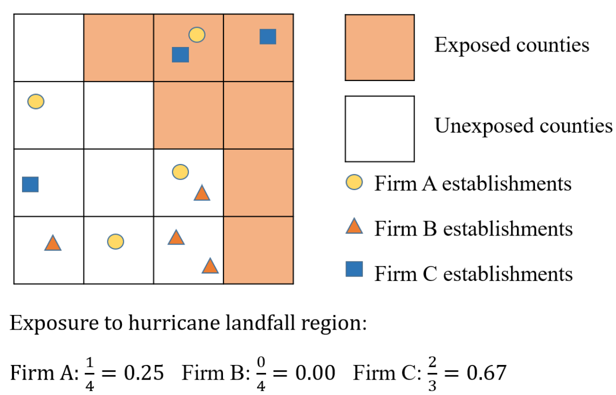
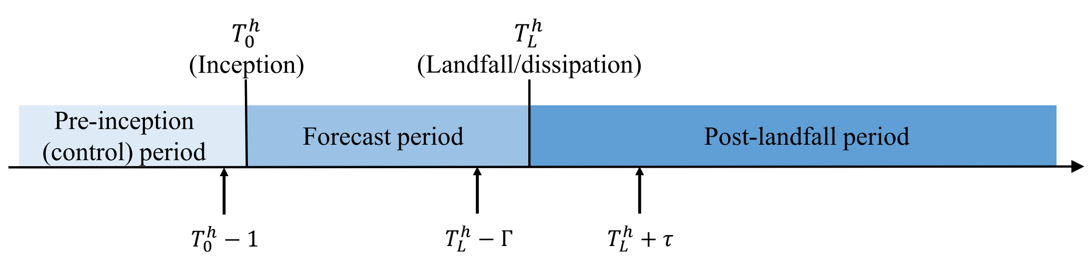


Figure 3: Hurricane forecasts by day and wind speed probability threshold
This figure presents an example of the processed wind speed forecast data. Each map shows the counties included in the forecast path for Hurricane Sandy given the number of days before landfall in each row (from 4 days to 1 day before landfall) and the wind speed probability threshold in each column (≥1% , ≥10%, ≥20%, and ≥50%).



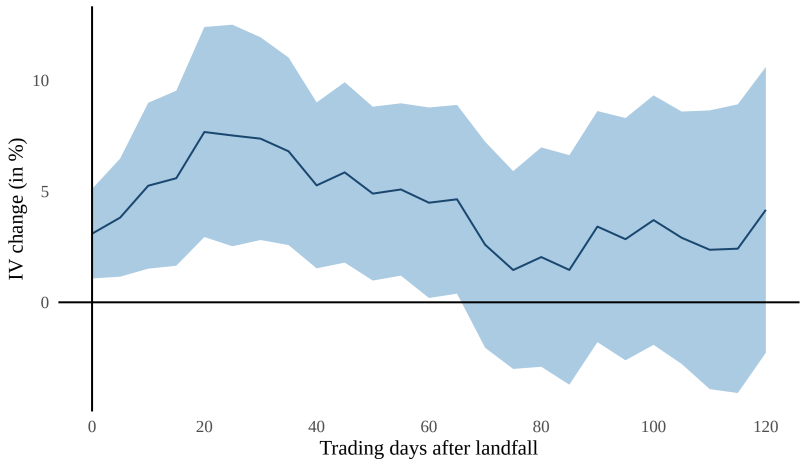
(a) Stylized example of firm exposure



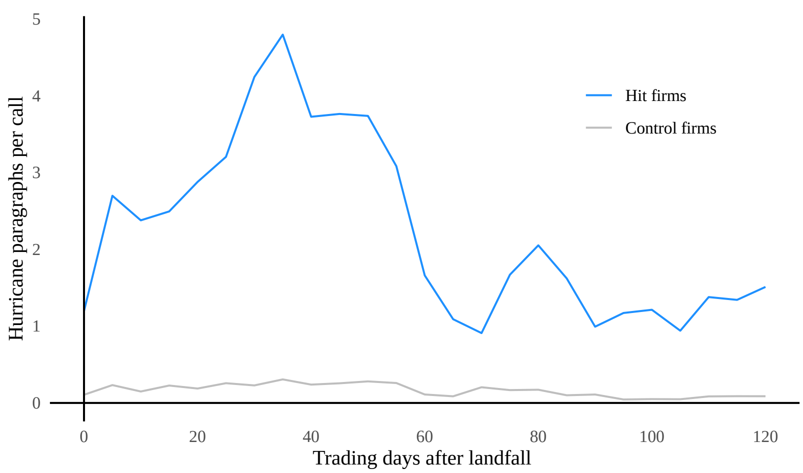
(b) Hurricane timeline

Figure 4: Identification strategy

Panel A shows a stylized example of firm exposure to a hurricane landfall region based on the share of establishments located in counties in the landfall region. These firm exposures illustrate the variable $LandfallRegionExposure$ in our analysis. Panel B illustrates the timeline of a hurricane.



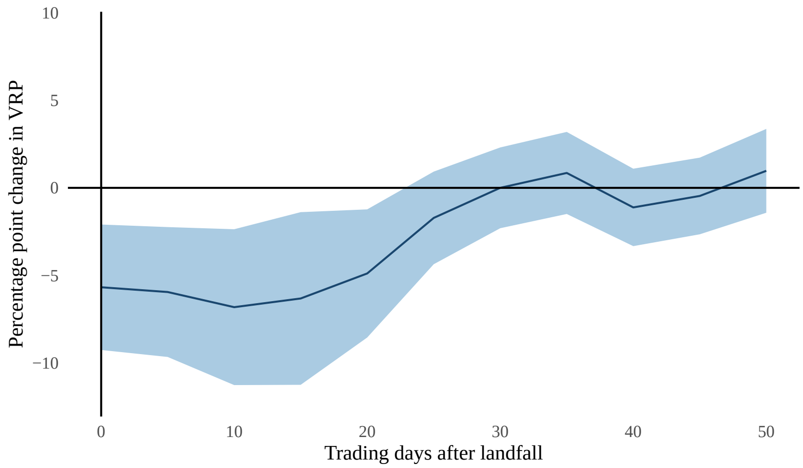
(a) Changes in implied volatilities



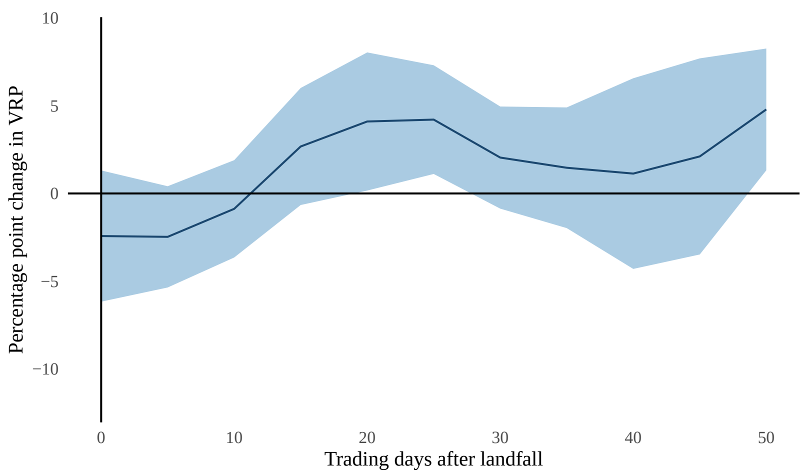
(b) Hurricane discussions in analyst calls

Figure 5: Uncertainty after hurricane landfall

Panel A plots coefficient estimates from running separate regressions estimating specification (7) when varying the number of trading days after landfall. Changes in implied volatilities from the day before hurricane inception to up to 120 trading days (6 months) post-hurricane landfall are regressed on the share of firm establishments in the landfall region. A coefficient estimate of, for example, 5 means that a firm with all its establishments in the landfall region is estimated to experience a 5% increase in implied volatility, relative to control firms with no establishments in the landfall region. The landfall region is based on a 200-mile radius around the hurricane eye. Confidence bands of 95% are shown. Panel B shows discussions of hurricanes in Refinitiv transcripts of calls between analysts, investors, and firm management. Each point reflects the average number of paragraphs per call discussing hurricanes over the given week. For firms with positive exposure to the landfall region (hit firms), the number of paragraphs are weighted by the firm's landfall exposure. A value of, for example, 3 means that a firm with all its establishments in the landfall region has 3 paragraphs per call discussing hurricanes.



(a) Pre-Sandy



(b) Post-Sandy

Figure 6: Changes in volatility risk premium after hurricane landfall

This figure plots coefficient estimates when regressing VRP averaged over increments of 5 trading days on the landfall region exposure of a firm, as shown in equation (8). VRP is the difference between ex ante implied and ex post realized volatility, as shown in equation (2). A coefficient estimate of, for example, -5 means that a firm with all its establishments in the landfall region is estimated to have a 5 percentage points lower VRP than control firms. Panel A shows estimates for the subsample of hurricanes from 1996 up to and including Hurricane Sandy in 2012. Panel B shows estimates for the subsample of post-Sandy hurricanes from 2013 to 2019. The landfall region is based on a 200-mile radius around the eye of the hurricane. Confidence bands of 95% are shown.

Table I: Hurricane sample

Panel A lists the hurricanes in our landfall analyses along with their landfall and inception dates. The damage estimates come from the National Hurricane Center's Tropical Cyclone Reports and have been inflated to 2019 values using the consumer price index from the U.S. Bureau of Labor Statistics. Panel B lists the storms in the forecast analysis. This sample includes storms that were at some point forecast to produce hurricane-force winds in U.S. mainland locations with a probability of at least 1%. Because the forecasts include storms that ultimately never made landfall in the United States (and dissipated out at sea), we indicate storms that made landfall with asterisks (*).

Panel A: Hurricanes in landfall analyses

Hurricane	Landfall	Inception	Damages 2019 \$mn	Hurricane	Landfall	Inception	Damages 2019 \$mn
Bertha	Jul. 12, 1996	Jul. 5, 1996	440	Humberto	Sep. 13, 2007	Sep. 13, 2007	62
Fran	Sep. 6, 1996	Aug. 23, 1996	5,214	Dolly	Jul. 23, 2008	Jul. 20, 2008	1,247
Danny	Jul. 18, 1997	Jul. 16, 1997	159	Gustav	Sep. 1, 2008	Aug. 25, 2008	5,484
Bonnie	Aug. 27, 1998	Aug. 19, 1998	1,129	Ike	Sep. 13, 2008	Sep. 2, 2008	35,053
Earl	Sep. 3, 1998	Aug. 31, 1998	124	Irene	Aug. 27, 2011	Aug. 21, 2011	17,958
Georges	Sep. 28, 1998	Sep. 15, 1998	9,983	Isaac	Aug. 29, 2012	Aug. 22, 2012	2,617
Bret	Aug. 23, 1999	Aug. 18, 1999	92	Sandy	Oct. 30, 2012	Oct. 24, 2012	55,676
Floyd	Sep. 16, 1999	Sep. 7, 1999	10,588	Arthur	Jul. 4, 2014	Jul. 1, 2014	2
Irene	Oct. 15, 1999	Oct. 13, 1999	1,228	Hermine	Sep. 2, 2016	Sep. 1, 2016	586
Lili	Oct. 3, 2002	Sep. 21, 2002	1,315	Matthew	Oct. 8, 2016	Sep. 29, 2016	10,652
Claudette	Jul. 15, 2003	Jul. 8, 2003	250	Harvey	Aug. 26, 2017	Aug. 23, 2017	130,373
Isabel	Sep. 18, 2003	Sep. 6, 2003	7,461	Irma	Sep. 10, 2017	Sep. 4, 2017	52,149
Charley	Aug. 13, 2004	Aug. 9, 2004	20,454	Nate	Oct. 8, 2017	Oct. 5, 2017	235
Frances	Sep. 5, 2004	Aug. 25, 2004	12,867	Florence	Sep. 14, 2018	Sep. 8, 2018	24,435
Ivan	Sep. 16, 2004	Sep. 2, 2004	25,471	Michael	Oct. 10, 2018	Oct. 8, 2018	25,453
Jeanne	Sep. 26, 2004	Sep. 13, 2004	10,367	Barry	Jul. 13, 2019	Jul. 11, 2019	600
Dennis	Jul. 10, 2005	Jul. 4, 2005	3,332	Dorian	Sep. 6, 2019	Aug. 27, 2019	1,600
Katrina	Aug. 29, 2005	Aug. 23, 2005	141,377				
Rita	Sep. 24, 2005	Sep. 18, 2005	15,757				
Wilma	Oct. 24, 2005	Oct. 15, 2005	27,499				

Panel B: Storms in forecast analyses

2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Dean	Dolly*	Ana	Alex	Don	Debby	Andrea	Arthur*	Ana	Colin	Cindy	Alberto	Barry*
Noel	Edouard	Bill	Bonnie	Emily	Ernesto	Karen		Bill	Herm.*	Harvey*	Chris	Dorian*
	Fay	Danny	Earl	Irene*	Isaac*			Erika	Matt.*	Irma*	Florence*	
	Gustav*	Ida	Paula	Katia	Leslie			Joaquin		Jose	Gordon	
	Hanna		Richard	Nate	Sandy*					Maria	Michael*	
	Ike*									Nate*		
	Kyle											
	Paloma											

Table II: Firm establishment and option summary statistics

This table reports summary statistics for firms in our sample, which spans from 1996 to 2019. Panel A reports statistics separately for all firms in the sample and for a set of hit firms—here defined as those that at least once had 25% or more of their establishments within a radius of 200 miles around the hurricane eye at landfall. Establishment data are observed at an annual frequency, market capitalization at a quarterly frequency, and options data at a daily frequency. Implied and realized volatility levels are annualized. Panel B reports summary statistics on firm establishment shares in hurricane landfall regions. The last four columns show the total number of firm observations with an establishment share above the listed threshold for landfall regions based on the specified radii around the hurricane eye.

Panel A: Firm characteristics

Number of unique firms	3,254						
Number of unique hit firms	1,799						
	Avg.	Std. dev.	10^{th} percentile	25^{th} percentile	50^{th} percentile	75^{th} percentile	90^{th} percentile
Establishments	123.241	488.924	1.000	3.000	13.000	57.000	237.000
Establishments hit firms	123.631	477.850	2.000	5.000	17.000	68.000	246.000
Market cap. (in billion $)	4.993	25.433	0.037	0.124	0.517	2.066	7.784
Market cap. hit firms (in billion $)	5.110	20.677	0.082	0.233	0.772	2.667	8.946
$IV_{i,t}$ (in %)	47.362	27.419	21.877	29.100	40.514	58.062	80.403
$IV_{i,t}$ hit firms (in %)	47.519	27.007	22.276	29.508	40.827	58.262	80.192
$VRP_{i,t}$ (in %)	4.709	21.184	-13.409	-2.383	5.182	13.020	23.496
$VRP_{i,t}$ hit firms (in %)	4.495	20.666	-13.781	-2.513	5.138	12.968	23.278
$log(IV_{i,t}/IV_{i,t-1})$ (in %)	0.162	12.063	-10.115	-4.046	0.080	4.404	10.815
$log(IV_{i,t}/IV_{i,t-1})$ hit firms (in %)	0.168	11.904	-10.010	-4.004	0.073	4.342	10.707
Days to expiry$_{i,t}$	35.918	32.780	10.000	16.000	26.000	38.000	81.000
Days to expiry$_{i,t}$ hit firms	36.377	32.892	10.000	17.000	26.000	38.000	84.000
Total open interest$_{i,t}$	1,894.256	7,536.257	12.000	49.000	225.000	1,072.000	3,993.000
Total open interest$_{i,t}$ hit firms	1,693.684	6,201.178	11.000	46.000	211.000	990.000	3,711.000

Panel B: Firm observation counts and establishment shares (0 to 1) in hurricane landfall regions

				Total firm observations with landfall region estab. share $\geq x$			
Radius around eye of the hurricane	Number of hurricanes	Avg. firm estab. share	Std. dev. firm estab. share	Estab. share ≥ 0.1	Estab. share ≥ 0.25	Estab. share ≥ 0.50	Estab. share $= 1$
200 miles	37	0.070	0.143	9,090	3,131	1,224	339
100 miles	37	0.026	0.082	2,797	909	340	105
50 miles	37	0.008	0.040	634	213	77	23

Table III: Hurricane effects on implied volatility

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

Panel A: 200-mile radius landfall region

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

	1 week post landfall			1 month post landfall		
$LandfallRegionExposure_{i,R,h}$	3.698***	3.818***	2.751**	7.661***	7.676***	6.148***
	(2.706)	(2.809)	(2.173)	(3.155)	(3.178)	(2.831)
Adjusted R^2 (%)	12.459	12.463	12.964	24.570	24.598	25.099
Observations	38,886	38,886	38,886	38,905	38,905	38,905
Hurricanes	37	37	37	37	37	37
Industry FE	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No
Industry × Time (Hurricane) FE	No	No	Yes	No	No	Yes

Panel B: 100-mile radius landfall region

$LandfallRegionExposure_{i,R,h}$	6.887***	7.021***	5.644***	9.466***	9.408***	7.061**
	(3.490)	(3.555)	(2.973)	(2.819)	(2.801)	(2.438)
Adjusted R^2 (%)	12.696	12.696	13.215	25.479	25.491	26.069
Observations	33,310	33,310	33,310	33,323	33,323	33,323
Hurricanes	37	37	37	37	37	37
Industry FE	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No
Industry × Time (Hurricane) FE	No	No	Yes	No	No	Yes

Panel C: 50-mile radius landfall region

$LandfallRegionExposure_{i,R,h}$	11.513**	11.589**	8.043*	17.925*	17.728*	10.509
	(2.434)	(2.451)	(1.911)	(1.925)	(1.883)	(1.378)
Adjusted R^2 (%)	12.198	12.203	12.762	25.155	25.169	25.790
Observations	28,041	28,041	28,041	28,042	28,042	28,042
Hurricanes	37	37	37	37	37	37
Industry FE	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No
Industry × Time (Hurricane) FE	No	No	Yes	No	No	Yes

Table IV: Hurricane effects on volatility risk premium

This table reports coefficients and test statistics from estimating the panel model in equation (8). The dependent variable is the VRP (in %) averaged over 1 week, 1 month, and 2 months (5, 20, and 40 trading days, respectively) after landfall. The VRP is computed as the difference between the ex ante implied and ex post realized volatility, as specified in equation (2). 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) and 50 miles (Panel B) around the hurricane eye at landfall. The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include firm, time, and industry-time fixed effects as indicated. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: 200-mile radius landfall region

Dependent variable: VRP (in %) avg. over τ trading days post landfall, $\overline{VRP}_{i,T_L^h+\tau}$	1 week post landfall			1 month post landfall			2 months post landfall		
$LandfallRegionExposure_{i,R,h}$	-6.035***	-4.655***	-2.918***	-5.315***	-3.727***	-1.753*	-3.566***	-1.467	0.165
	(-4.414)	(-3.607)	(-2.798)	(-3.043)	(-2.606)	(-1.937)	(-2.752)	(-1.492)	(0.241)
Adjusted R^2 (%)	17.206	26.914	28.221	22.454	34.212	35.491	22.653	38.599	40.001
Observations	36,539	36,539	36,539	36,675	36,675	36,675	36,674	36,674	36,674
Hurricanes	37	37	37	37	37	37	37	37	37
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry X Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel B: 50-mile radius landfall region

$LandfallRegionExposure_{i,R,h}$	-21.463***	-16.123**	-8.799**	-21.232***	-15.523*	-7.828*	-14.679***	-8.895	-2.268
	(-3.286)	(-2.139)	(-2.050)	(-3.012)	(-1.871)	(-1.695)	(-3.030)	(-1.612)	(-0.761)
Adjusted R^2 (%)	16.854	26.410	27.766	20.959	32.925	34.080	20.494	37.368	38.648
Observations	26,090	26,090	26,090	26,185	26,185	26,185	26,166	26,166	26,166
Hurricanes	37	37	37	37	37	37	37	37	37
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry X Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Table V: Hurricane effects on volatility risk premium after Sandy

This table reports the coefficients and test statistics when estimating the panel model in equation (8) with a post-Sandy (post-2012) interaction term added. The dependent variable is the VRP (in %) averaged over 1 week, 1 month, and 2 months (5, 20, and 40 trading days, respectively) after landfall. The VRP is computed as the difference between the ex ante implied and ex post realized volatility, as specified in equation (2). 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 an indicator variable that equals 1 for all hurricanes after Sandy (after 2012). The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include firm, time, and industry-time fixed effects as indicated. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: VRP (in %) avg. over τ trading days post landfall, $\overline{VRP}_{i,T_L^h+\tau}$									
	1 week post landfall			1 month post landfall			2 months post landfall		
$LandfallRegionExposure_{i,R,h}$	-7.579***	-5.807***	-3.317**	-7.843***	-5.835***	-3.167***	-4.838***	-2.788**	-0.755
	(-3.701)	(-3.302)	(-2.543)	(-3.271)	(-2.917)	(-2.661)	(-2.914)	(-2.289)	(-0.884)
$LandfallRegionExposure_{i,R,h}$ $\times PostSandy_h$	4.620*	3.677*	1.237	7.572***	6.718***	4.372***	3.891*	4.299***	2.905**
	(1.651)	(1.761)	(0.676)	(2.739)	(3.132)	(2.732)	(1.932)	(3.532)	(2.471)
Adjusted R^2 (%)	17.221	26.921	28.220	22.506	34.247	35.504	22.672	38.619	40.009
Observations	36,539	36,539	36,539	36,675	36,675	36,675	36,674	36,674	36,674
Hurricanes	37	37	37	37	37	37	37	37	37
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry X Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Table VI: Hurricane effects and economic channels

This table reports coefficients and test statistics when estimating the panel model in equation (9) using transcript data of calls between analysts, investors, and firm management. In column (1), the dependent variable is the count of call paragraphs discussing hurricanes after landfall. In columns (2) to (6), the dependent variables are the number of paragraphs discussing hurricanes with at least one term associated with the channel in question (see Internet Appendix Table C.1 for the dictionary of terms). The independent variable is the share (from 0 to 1) of a firm's establishments within a radius of 200 miles (Panel A) or 50 miles (Panel B) around the hurricane eye at landfall. The data span from 2002 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include industry and time fixed effects. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: 200-mile radius landfall region

		Discussion of hurricane and channel				
	Hurricane discussions	Business interruption	Physical damages	Insurance	Supply	Demand
$LandfallRegionExposure_{i,R,h}$	4.037***	1.157***	1.520***	0.369**	0.213**	0.574***
	(9.544)	(6.131)	(6.859)	(2.445)	(2.193)	(4.106)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2 (%)	16.240	11.141	11.947	5.890	7.232	2.862
Observations	18,733	4,966	4,966	4,966	4,966	4,966
Obs. Landfall Exposure > 0	11,550	3,876	3,876	3,876	3,876	3,876
Obs. Landfall Exposure ≥ 0.25	1,195	448	448	448	448	448
Hurricanes	28	28	28	28	28	28

Panel B: 50-mile radius landfall region

		Discussion of hurricane and channel				
	Hurricane discussions	Business interruption	Physical damages	Insurance	Supply	Demand
$LandfallRegionExposure_{i,R,h}$	15.012***	3.308***	5.191***	1.390**	0.330	1.312***
	(5.135)	(5.823)	(5.410)	(2.001)	(1.075)	(3.185)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2 (%)	16.958	8.970	9.632	4.314	5.120	2.976
Observations	12,571	3,491	3,491	3,491	3,491	3,491
Obs. Landfall Exposure > 0	5,388	2,401	2,401	2,401	2,401	2,401
Obs. Landfall Exposure ≥ 0.25	61	27	27	27	27	27
Hurricanes	28	28	28	28	28	28

Table VII: Idiosyncratic hurricane shocks and abnormal returns

This table reports coefficients and test statistics from estimating effects of hurricanes on abnormal returns relative to the Fama-French 5 factor model as per the panel model in equation (10). Panel A (B) shows results without (with) a post-Sandy (post-2012) interaction term. The dependent variable is the abnormal return (in %) aggregated over windows of 20, 30, and 40 trading days, respectively. In each case, the first day of the return windows is 30 trading days after landfall. The independent variable is the share (from 0 to 1) of a firm's establishments that are within a radius of 200 miles around the hurricane eye at landfall. In Panel B, the landfall region exposure variable is interacted with an indicator variable that equals 1 for all hurricanes post-Sandy. The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include industry, time, and industry-time fixed effects as indicated. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Without post-Sandy interaction

Dependent variable: Cumulative abnormal return (in %), $CAR_{i,h,T_L^h+30:T_L^h+30+ReturnHorizon}$

Return horizon (trading days)	20			30			40		
$LandfallRegionExposure_{i,R,h}$	-0.022	0.071	-0.327	0.007	0.127	-0.388	0.450	0.638	-0.010
	(-0.039)	(0.116)	(-0.565)	(0.010)	(0.188)	(-0.500)	(0.534)	(0.815)	(-0.012)
Adjusted R^2 (%)	0.693	0.840	2.919	0.597	0.906	3.511	0.466	0.859	3.139
Observations	43,419	43,419	43,419	43,340	43,340	43,340	43,254	43,254	43,254
Hurricanes	37	37	37	37	37	37	37	37	37
Industry FE	No	Yes	No	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry × Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel B: With post-Sandy interaction

$LandfallRegionExposure_{i,R,h}$	-0.963	-0.832	-0.916	-1.145	-0.957	-1.209	-0.976	-0.703	-0.941
	(-1.551)	(-1.350)	(-1.322)	(-1.337)	(-1.193)	(-1.300)	(-0.910)	(-0.718)	(-0.853)
$LandfallRegionExposure_{i,R,h}$	4.599***	4.412***	2.857**	5.640***	5.299***	3.989***	6.965***	6.545***	4.513***
$\times PostSandy_h$	(3.157)	(2.971)	(2.190)	(4.118)	(3.781)	(2.971)	(4.258)	(3.923)	(3.074)
Adjusted R^2 (%)	0.729	0.873	2.931	0.630	0.935	3.525	0.501	0.890	3.151
Observations	43,419	43,419	43,419	43,340	43,340	43,340	43,254	43,254	43,254
Hurricanes	37	37	37	37	37	37	37	37	37
Industry FE	No	Yes	No	No	Yes	No	No	Yes	No
Time (Hurricane) FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry × Time (Hurricane) FE	No	No	Yes	No	No	Yes	No	No	Yes

Table VIII: Effects of hurricane path forecasts on implied volatility

This table reports coefficients and test statistics from estimating the panel model in equation (11). The model is estimated for different probability thresholds and days before landfall or dissipation, Γ. The dependent variable is the change (in %) in implied volatility of firm i from the trading day before hurricane inception ($T_0^h - 1$), to Γ days before hurricane landfall or dissipation ($T_L^h - \Gamma$). The independent variable is the share (from 0 to 1) of a firm's establishments that are in counties located in the forecast path of a hurricane. The forecast paths are defined based on the specified probability thresholds, which reflect minimum probabilities of hurricane force winds. A 50% threshold indicates that counties in the forecast path are estimated to have at least a 50% probability of experiencing hurricane force winds as of the last forecast available before market close on day $T_L^h - \Gamma$. For each regression, the total number of firm observations with an establishment share in the forecast path of greater than 0 and at least 0.25 are reported. The data span from 2007 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. Industry and time fixed effects are included individually in Panel A and interacted in Panel B. The time fixed effect can be interpreted as a hurricane fixed effect because each hurricane enters the regression as one separate time period. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

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

Dependent variable: Change in IV from hurricane inception to Γ days before landfall/dissipation (in %), $log\left(IV_{i,T_L^h-\Gamma}/IV_{i,T_0^h-1}\right)$

Γ	1 Day					2 Days					3 Days			4 Days		5 Days
Prob. of hurricane hit $\geq$	1%	10%	20%	40%	50%	1%	10%	20%	40%	50%	1%	10%	20%	1%	10%	1%
$ForecExposure_{i,P,T_L^h-\Gamma}$	4.600***	12.847***	20.671***	20.145***	22.396***	2.260***	7.688***	8.961***	16.085***	15.566***	1.818**	10.587***	13.280***	2.053**	10.850***	2.337***
	(3.472)	(4.954)	(4.784)	(3.772)	(4.798)	(3.210)	(4.662)	(4.885)	(3.353)	(2.589)	(2.244)	(3.360)	(2.972)	(2.312)	(2.950)	(3.233)
Adjusted R^2 (%)	11.027	11.113	11.494	11.749	11.856	9.688	10.111	10.351	9.953	3.417	9.270	10.638	10.634	11.880	15.430	10.713
Observations	54,470	14,607	12,874	10,171	9,117	44,602	17,842	13,034	8,184	7,008	31,124	10,504	6,896	21,376	6,473	15,498
Obs. ForecExpo. > 0	15,895	4,576	3,710	2,801	2,585	19,400	6,562	4,672	3,013	2,362	15,861	4,459	2,869	10,718	3,257	8,752
Obs. ForecExpo. ≥ 0.25	897	173	101	73	72	2,482	299	204	106	48	2,576	189	104	2,259	156	1,538
Hurricanes	40	12	11	9	8	33	16	12	7	6	23	11	7	16	6	12
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: With industry $\times$ time (hurricane) fixed effects

$ForecExposure_{i,P,T_L^h-\Gamma}$	3.027**	9.834***	15.519***	12.799**	15.463***	1.845***	5.721***	6.324***	10.643***	16.026***	1.745**	7.058***	7.447**	1.455**	6.800***	2.328***
	(2.352)	(3.163)	(3.565)	(2.435)	(3.271)	(2.597)	(3.133)	(2.781)	(3.643)	(2.594)	(2.106)	(2.951)	(2.252)	(1.992)	(3.129)	(3.108)
Adjusted R^2 (in %)	11.466	11.524	11.880	12.197	12.281	10.183	10.532	10.837	10.564	3.808	9.816	11.235	11.273	12.763	16.320	11.333
Industry $\times$ Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IX: Effects of hurricane season outlooks on implied volatility

This table reports the coefficients and test statistics when estimating the panel model in equation (12). The dependent variable is the change (in %) in implied volatility of firm i from the last trading day before NOAA's outlook for the hurricane season is released ($T_0^s - 1$) to 5 trading days thereafter ($T_0^s + 5$). Longer-dated options that cover the majority of the hurricane season (120 to 210 days to expiry) are used. The independent variable $AboveNormalSeasonProbability_s$ is the probability NOAA assigns to an "above average" hurricane season in terms of number of storms. In Panel A, the independent variable $CoastalExposure_{i,s}$ is the share of a firm's establishments located in Atlantic and Gulf coastal counties. For columns (4) and (5), the counties on the Atlantic Coast north of Florida are excluded from this measure. In Panel B, the independent variable $HistoricalHurricaneExposure_{i,s}$ is the share of a firm's establishments (0 to 1) located in counties that had a historical probability of being hit by a hurricane in a given season of at least 0.10 and 0.25. The data span from 2001 to 2019. T-statistics are shown in parentheses. Standard errors are clustered by county based on a firm's largest establishment share. The specifications include industry, time, and industry-time fixed effects as indicated. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Panel A: Atlantic and Gulf coast counties

Dependent variable: Change in IV (in %), $log\left(\frac{IV_{i,T_0^s+5}}{IV_{i,T_0^s-1}}\right)$

	All coastal counties		Excl. counties north of FL	
$CoastalExposure_{i,s}$	0.356	0.356	1.229*	1.092
	(0.740)	(0.755)	(1.940)	(1.624)
$CoastalExposure_{i,s}$	0.187	0.193	-1.122	-0.732
$\times AboveNormalSeasonProb_s$	(0.179)	(0.974)	(-0.718)	(-0.590)
Adjusted R^2 (%)	5.157	5.696	5.161	5.700
Observations	21,117	21,117	21,117	21,117
Total firm obs. with exposure > 0	17,738	17,738	13,439	13,439
Total firm obs. with exposure ≥ 0.25	11,404	11,404	2,291	2,291
Industry FE	Yes	No	Yes	No
Time FE	Yes	No	Yes	No
Industry × Time FE	No	Yes	No	Yes

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

	Counties with prob. ≥ 0.10		Counties with prob. ≥ 0.25	
$HistoricalHurricaneExposure_{i,s}$	0.565	0.514	0.463	0.661
	(1.095)	(1.020)	(0.574)	(0.800)
$HistoricalHurricaneExposure_{i,s}$	-0.225	-0.188	0.184	-0.333
$\times AboveNormalSeasonProb_s$	(-0.192)	(-0.165)	(0.098)	(-0.179)
Adjusted R^2 (%)	5.162	5.697	5.149	5.687
Observations	21,117	21,117	21,117	21,117
Total firm obs. with exposure > 0	18,615	18,615	13,835	13,835
Total firm obs. with exposure ≥ 0.25	16,535	16,535	2,455	2,455
Industry FE	Yes	No	Yes	No
Time FE	Yes	No	Yes	No
Industry × Time FE	No	Yes	No	Yes

Table X: 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 (not hurricane-related), snowstorms, and tornadoes, where $ImpactRegionExposure_{i,h}$ is based on 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 before the FEMA incident begin date. The independent variable, $ImpactRegionExposure_{i,h}$, 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. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include industry and time fixed effects. 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

Dependent Variable: Change in IV (in %), $log(IV_{i,T_L^h+\tau}/IV_{i,T_0^h-1})$				
Time post landfall	1 week	1 month	2 months	3 months
$ImpactRegionExposure_{i,h}$	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: Snowstorms

Time post landfall	1 week	1 month	2 months	3 months
$ImpactRegionExposure_{i,h}$	0.586	4.932**	5.712*	6.153
	(0.376)	(2.210)	(1.827)	(1.446)
Adjusted R^2 (%)	8.245	9.371	6.380	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
Snowstorms	32	32	32	32

Panel C: Tornadoes

Time post landfall	1 week	1 month	2 months	3 months
$ImpactRegionExposure_{i,h}$	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

Table XI: Hurricane effects on implied volatility by industry

This table reports coefficients and test statistics from estimating the panel model in equation (7) with SIC industry indicator interaction terms added. The dependent variable is the change (in %) in implied volatility of firm i from the day before hurricane inception ($T_0^h - 1$), until 1 week (5 trading days) after landfall ($T_L^h + 5$). The independent variable is the share (from 0 to 1) of a firm's establishments that are within a 200-mile radius around the hurricane eye at landfall. The data span from 1996 to 2019. T-statistics are shown in parentheses. The standard errors are clustered by county based on a firm's largest establishment share. The specifications include industry and time fixed effects. The time fixed effect can be interpreted as a hurricane fixed effect, as we include a separate time period in the panel for each hurricane. The significance of each coefficient estimate is indicated by * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Dependent variable: Change in IV (in %), $log\left(IV_{i,T_L^h+5}/IV_{i,T_0^h-1}\right)$							
	Industry interacted with $LandfallRegionExposure_{i,R,h}$						
	Manufacturing	Wholesale	Services	Transport	Retail	Mining	Construction
$LandfallRegionExposure_{i,R,h}$	5.739***	3.381**	4.094***	3.282***	3.892***	2.985**	3.929***
	(3.379)	(2.459)	(2.659)	(2.608)	(2.845)	(2.271)	(2.870)
$LandfallRegionExposure_{i,R,h}$	-4.343*	10.311**	-1.685	3.771	-1.796	5.567**	-8.144**
$\times Industry_i$	(-1.947)	(2.213)	(-0.680)	(1.043)	(-0.436)	(2.055)	(-1.990)
Adjusted R^2 (%)	12.475	12.473	12.462	12.466	12.461	12.471	12.463
Observations	38,886	38,886	38,886	38,886	38,886	38,886	38,886
Observations in interacted industry	19,258	1,487	7,697	4,163	3,305	2,148	614
Hurricanes	37	37	37	37	37	37	37
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes