Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics

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Motivation: Extreme Weather Finance

- Extreme weather events (hurricanes, snowstorms, floods) cause significant devastation.
- E.g., U.S. extreme weather damages exceeded $300B in 2017.
- These events could create firm-level uncertainty (capital, operations, business environment), but firms may offset.
- Research gap: How is extreme weather uncertainty generated and priced at the firm level?

Research Questions / Goals

- How to quantify firm-level extreme weather uncertainty? [using changes to the implied volatility of stock options]
- How is this uncertainty priced by investors?
- Questions about informational efficiency and whether idiosyncratic shocks impact asset prices through not only the cash flow channel but also the discount rate channel
- Understanding how investors form expectations regarding the uncertainty generated by extreme weather events + e.g., why volatility can be persistent
- economic channels that drive extreme weather uncertainty
- increase in the firm's cost of capital as compensation for bearing extreme weather uncertainty? (i.e, increase in expected idiosyncratic volatility)

Modeling Extreme Weather Uncertainty

The paper models two components of firm-level extreme weather uncertainty:

- **Incidence Uncertainty (ϕ):** Probability of being hit.
- **Impact Uncertainty ($\sigma^2_{g,i}$):** Impact if hit.

Firm's one-period return at $t+1$ when hit:

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

where $\tilde{g}_{i,t+1}$ is impact $\sim (\mu_{g,i}, \sigma^2_{g,i})$, $\tilde{\theta}_{i,t+1}$ is hit indicator ($\tilde{\theta}_{i,t+1} \sim B(1,\phi)$), meaning $Pr(\tilde{\theta}_{i,t+1} = 1) = \phi$.
(Other components are independent of the extreme weather event, $\tilde{Y}_{t+1}$=market factor that has a mean of zero and a variance of one)

Variance of Return

Whether a firm will be hit by an extreme weather event is independent of the impact conditional on the hit:

Total uncertainty (variance of return):

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

- $\sigma_{g,i}^2 \phi$: Expected impact uncertainty.
- $\mu_{g,i}^2 \phi(1-\phi)$: Incidence uncertainty (highest at $\phi = 0.5$).
- Option-implied volatility (IV) measures expected volatility.

This equation 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 mispricing. $\rightarrow$ also investigate the empirical effects of extreme weather events on VRP

Data Sources

- **NOAA:** Hurricane tracks, forecasts, seasonal outlooks (1996-2019).
- **NETS:** Firm establishment locations (exposure to each hurricane).
- **OptionMetrics:** Daily single-name stock options (1996-2019), Implied Volatilities of traded options that are slightly out-of-the-money
- **CRSP/Compustat:** Stock and firm data.
- **Refinitiv:** Analyst call transcripts.
- **FEMA:** Disaster declarations (floods, snowstorms, tornadoes).

Compute VRP

- estimate for the average implied volatility of firm i at time t is

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

  where M = the nearest-to-maturity expiration at time t of options on firm i stock,
  Z denotes the number of valid options for firm i with that expiry
  $IV_{i,t,M}$ = a proxy for the ex ante risk-neutral expected value of the future stock return volatility of firm i between time t and M

- 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, $RV_{i,t,M}$,

$$VRP_{i,t,M} = IV_{i,t,M} - RV_{i,t,M}$$

  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. [pricing efficiency of uncertainty]

Firm Summary Statistics

Sample: 3,254 unique firms (1996-2019). "Hit" firm: $\geq$ 25% establishments within 200-mile radius of at least one hurricane $\rightarrow$1,799 firms.

Panel A: Firm Characteristics

Firm Characteristics	**Avg.**	**Std. Dev.**	**50th pctl.**
Establishments	123.24	488.92	13.00
Establishments hit firms	123.63	477.85	17.00
Mkt. cap. ($bn)	4.99	25.43	0.52
$IV_{i,t}$ (%)	47.36	27.42	40.51
$VRP_{i,t}$ (%)	4.71	21.18	5.18

Panel B: Firm Observations by Hurricane Landfall Region Exposure

Radius	**Num. Hurricanes**	**Avg. Estab. Share**	**Obs. Share** ≥ 0.1	**Obs. Share** ≥ 0.25
200 miles	37	0.070	9,090	3,131
100 miles	37	0.026	2,797	909
50 miles	37	0.008	634	213

Simplified from Table II in the paper. IV: Implied Volatility, VRP: Volatility Risk Premium.

Measuring Treatment: Firm Exposure

Firm exposure: Share of establishments in hurricane's landfall region.

- County c in $L_{R,h}$ if centroid within radius R of hurricane h's eye.
- 24-hour window (before/after landfall).
- Main analysis: 200-mile radius (validated by NOAA reanalysis).

$$\text{LandfallRegionExposure}_{i,R,h} = \sum_{c} (\text{FirmCountyExposure}_{i,c} \times I_{c \in LR_h}) \tag{2}$$

where $\text{FirmCountyExposure}_{i,c}$ is firm i's establishment share in county c, $I_{c \in LR_h}$ is landfall region indicator.
(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.)

Identification Strategy: Hurricane Timeline

Difference-in-differences approach; each hurricane landfall is a separate event. Firms with zero exposure serve as controls.

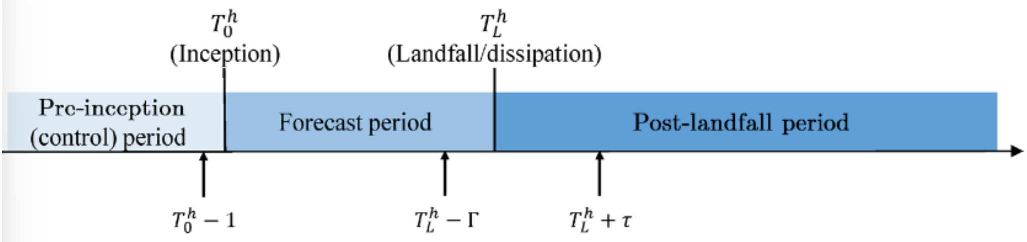


Figure: Stylized Hurricane Timeline (Adapted from Figure 4, Panel B). T_0^h: Inception, T_L^h: Landfall/Dissipation.

Pre-treatment period ($T_0^h - 1$): Last trading day before hurricane inception.

Baseline Estimation: Implied Volatility

Firm-hurricane panel regression to estimate uncertainty at hurricane landfall:

$$\log\left(\frac{\mathrm{IV}_{i,T_h^L+\tau}}{\mathrm{IV}_{i,T_h^0-1}}\right) = \lambda_{L,R,\tau}\mathrm{LandfallRegionExposure}_{i,R,h} + \pi_h + \psi_{\mathrm{Ind}} + \epsilon_{i,h,\tau} \tag{3}$$

- Dep. Var.: Change in IV (inception to τ days post-landfall).
- $\mathrm{LandfallRegionExposure}_{i,R,h}$: Continuous treatment.
- π_h: Hurricane fixed effects.
- ψ_{Ind}: Industry fixed effects.
- Standard errors clustered by county (assign a firm to the county with the most establishments)
- $\lambda_{L,R,\tau}$ (for $\tau \geq 5$ days): Reflects impact uncertainty.

Magnitude of Impact Uncertainty

Implied volatilities of hurricane-hit firms increase substantially.

Panel A: 200-Mile Radius	**1 Week Post-Landfall**		**1 Month Post-Landfall**	
Dep. Var.: ΔIV (in %)	**(1)**	**(2)**	**(3)**	**(4)**
LandfallRegionExposure	3.698***	2.751**	7.661***	6.148***
	(2.706)	(2.173)	(3.155)	(2.831)
Adjusted R^2 (%)	12.46	12.96	24.57	25.10
Observations	38,886	38,886	38,905	38,905

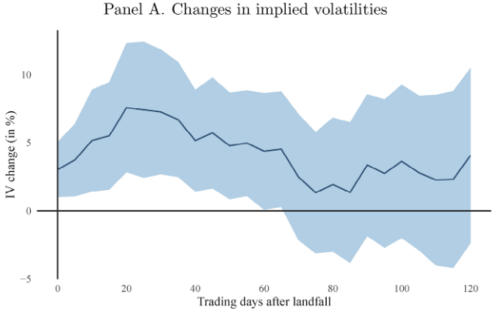
Key Findings:

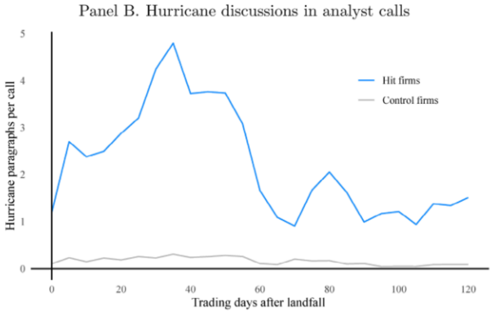
- $\lambda_{L,R,\tau}$ positive and significant (e.g., $\sim 8\%$ for 200-mile radius, 1 month post-landfall).
- Smaller radii show higher estimates (up to $\sim 18\%$ for 50-mile radius).
- Total market-implied cost of uncertainty: up to \$94B (2019 adjusted), $\sim 14\%$ of total hurricane damages.

Simplified from Table III. t-Stats in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Persistence of Uncertainty

Impact uncertainty persists for several months.





Key Findings:

- **IV (Panel A):** Peaks $\sim$ 1 month post-landfall ($\sim$ 8%), significant for $>$ 3 months.
- **Analyst Calls (Panel B):** Discussions spike post-landfall, remain high for $\sim$ 3 months.
- Learning about firm impact takes time, driving volatility persistence.

Volatility Risk Premium (VRP) - Efficiency of Volatility Expectations

VRP: Difference between option-implied volatility and subsequent realized volatility.

$$\text{VRP}_{i,t} = \text{IV}_{i,t,M} - \text{RV}_{i,t,M} \tag{4}$$

Regression model: how this spread varies for firms exposed to a hurricane relative to control firms

$$\text{VRP}_{i,T_h^L+\tau} = \lambda_{L,R,\tau}^{\text{VRP}} \text{LandfallRegionExposure}_{i,R,h} + \pi_h + \alpha_i + \epsilon_{i,h,\tau} \tag{5}$$

- Dep. Var.: VRP (landfall to τ days post-landfall).
- α_i: Firm fixed effect.
- Negative $\lambda_{L,R,\tau}^{\text{VRP}}$: Investor underreaction.

VRP Results: Investor Underreaction

Panel A: 200-Mile Radius	**1 Week Post-Landfall**		**1 Month Post-Landfall**	
Dep. Var.: VRP (in %)	**(1)**	**(2)**	**(3)**	**(4)**
LandfallRegionExposure	-6.035***	-2.918***	-5.315***	-1.753*
	(-4.414)	(-2.798)	(-3.043)	(-1.937)
Adjusted R^2 (%)	17.21	28.22	22.45	35.49
Observations	36,539	36,539	36,675	36,675

Key Findings:

- Consistently negative and significant coefficients: Investor underreaction.
- E.g., 100% exposure (50-mile radius) $\rightarrow$ up to 21 ppt lower VRP.
- Underreaction persists for at least a month.
- Investors underestimate realized volatility.
- Trading strategy exploiting underreaction is profitable.

Simplified from Table IV. t-Stats in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Impact of Hurricane Sandy

Underreaction diminished after Hurricane Sandy (2012), a salient event for the U.S. financial center.

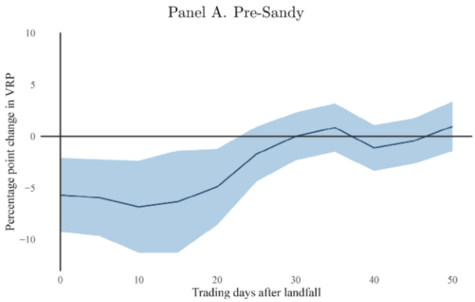
Dep. Var.: VRP (in %)	**1 Week Post-Landfall**		**1 Month Post-Landfall**	
Interaction: $\times$**PostSandy**$_h$	**(1)**	**(2)**	**(3)**	**(4)**
LandfallRegionExposure	-7.579***	-3.317**	-7.843***	-3.167***
	(-3.701)	(-2.543)	(-3.271)	(-2.661)
LandfallRegionExposure $\times$PostSandy$_h$	4.620*	1.237	7.572***	4.372***
	(1.651)	(0.676)	(2.739)	(2.732)
Adjusted R^2 (%)	17.22	28.22	22.51	35.50
Observations	36,539	36,539	36,675	36,675

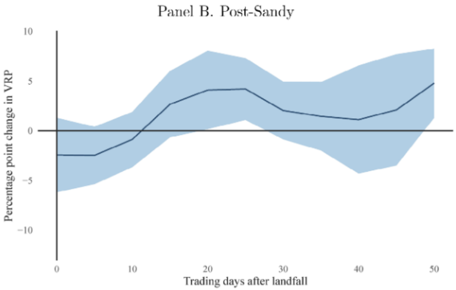
Key Findings:

- Positive and significant interaction terms: Underreaction diminished.
- For longer horizons, interaction offsets negative base effect.
- Implies improved informational efficiency post-Sandy due to salient experience.

Simplified from Table V. t-Stats in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

VRP Changes After Landfall





Key Findings:

- **Pre-Sandy (Panel A):** Underreaction persists $\sim$ 1.5 months.
- **Post-Sandy (Panel B):** VRP generally indistinguishable from zero, sometimes positive premium.
- Markets price uncertainty more efficiently post-salient event.

Identifying Economic Channels

Systematic textual analysis of analyst call transcripts identifies economic channels.

- "Hurricane paragraphs" analyzed —analyst call paragraphs that contain some form of the terms "hurricane" or "tropical storm"
- Five channels: business interruption, physical damages, insurance, supply, demand. set a paragraph-level indicator equal to one if a hurricane paragraph contains a term assigned to the channel in their dictionary
- Discussion frequency reflects channel's relevance for uncertainty.

Regression model for hurricane discussions:

$$\text{HurricaneDiscussions}_{i,T_h^L+120} = \lambda_{L,R}^{\text{EC}}\text{LandfallRegionExposure}_{i,R,h} + \pi_h + \psi_{\text{Ind}} + \epsilon_{i,h} \tag{6}$$

Dep. Var.: number of paragraphs discussing hurricanes/channels over 120 days post-landfall.

Economic Channels Results

Panel A: 200-Mile Radius **Dep. Var.: Discussion**	**Hurricane Discussions**	**Business Interruption**	**Physical Damages**	**Insurance**	**Supply**	**Demand**
LandfallRegionExposure	4.037***	1.157***	1.520***	0.369**	0.213**	0.574***
	(9.544)	(6.131)	(6.859)	(2.445)	(2.193)	(4.106)
Adjusted R^2 (%)	16.24	11.14	11.95	5.89	7.23	2.86
Observations	18,733	4,966	4,966	4,966	4,966	4,966

Key Findings:

- Total hurricane discussions increase significantly with exposure.
- Largest increases: business interruption, physical damages.
- Significant increases: insurance, supply, demand.
- Insurance uncertainty: Coverage, claim payments, timing are unclear.
- Demand changes: Can present both opportunities and risks.

Simplified from Table VI. t-Stats in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Idiosyncratic Shocks & Abnormal Returns

Investigates if hurricane uncertainty is priced in stocks, affecting cost of capital.

- CAPM: Idiosyncratic shocks are diversifiable.
- Merton (1987): If investors are not perfectly diversified, idiosyncratic volatility can affect expected returns.

Regression for Cumulative Abnormal Returns (CARs):

$$\text{CAR}_{i,h,T_h^L+\tau:T_h^L+\tau+\text{ReturnHorizon}} = \lambda_{L,R,\tau}^{\text{Ret}} \text{LandfallRegionExposure}_{i,R,h} + \pi_h + \psi_{\text{Ind}} + \epsilon_{i,h,\tau} \quad (7)$$

- Dep. Var.: CAR (Fama-French five-factor model).
- CARs start 30 days post-landfall (around when implied volatility tends to peak after hurricane landfall)
- Horizons: 20, 30, 40 trading days.

Expected Returns Results: Post-Sandy

Panel B: With Post-Sandy Interaction	**Return Horizon: 20 Days**		**Return Horizon: 40 Days**	
Dep. Var.: CAR (in %)	**(1)**	**(2)**	**(3)**	**(4)**
LandfallRegionExposure	-0.963	-0.916	-0.976	-0.941
	(-1.551)	(-1.322)	(-0.910)	(-0.853)
LandfallRegionExposure $\times$PostSandy$_h$	4.599***	2.857**	6.965***	4.513***
	(3.157)	(2.190)	(4.258)	(3.074)
Adjusted R^2 (%)	0.73	2.93	0.50	3.15
Observations	43,419	43,419	43,254	43,254

Key Findings:

- Early sample: Insignificant $\lambda^{\text{Ret}}_{L,R,\tau}$ (no premium).
- Post-Sandy: Positive and significant interaction term.
- Net effect on CARs positive post-Sandy (e.g., $4.599 - 0.963 = 3.636\%$ for 20-day horizon).
- Hurricane uncertainty affects equity cost of capital when volatility expectations are less biased.

Simplified from Table VII. t-Stats in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Short-Term Forecasts of Hurricane Path

Uncertainty reflected in options markets before landfall, using NOAA wind speed probability forecasts.

$$\log\left(\frac{\mathrm{IV}_{i,T_h^L-\delta}}{\mathrm{IV}_{i,T_h^0-1}}\right) = \lambda_{F,P,\delta}\text{ForecastExposure}_{i,P,T_h^L-\delta} + \pi_h + \psi_{\text{Ind}} + \epsilon_{i,h,\delta} \tag{8}$$

- ForecastExposure: Share of establishments in counties with $\geq P\%$ hurricane-force winds δ days before landfall.
- $\lambda_{F,P,\delta}$ positive and significant.
- Magnitude increases with higher probabilities (up to 22% for 50% probability).
- Investors react to NOAA forecasts, but underreact until Sandy.

Seasonal Hurricane Forecasts

Investigates pricing of longer-term seasonal hurricane forecasts (NOAA's annual May outlooks).
(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)

$$\log\left(\frac{\mathrm{IV}_{i,T_0^S+5}}{\mathrm{IV}_{i,T_0^S-1}}\right) = \lambda_{S,1}\mathrm{CoastalExposure}_{i,s} \times \mathrm{AboveNormalSeasonProbs} + \lambda_{S,2}\mathrm{CoastalExposure}_{i,s} + \pi_s + \psi_{\mathrm{Ind}} + \epsilon_{i,s} \tag{9}$$

- CoastalExposure: Share of establishments in Atlantic/Gulf Coastal counties. (alternative: HistoricalHurricaneExposure)
- AboveNormalSeasonProbs: Probability of above-normal season.
- **Key Finding:** $\lambda_{S,1}$ not statistically significant.
- Possible reasons: Insufficient predictive power or lack of investor attention to long-term forecasts.

Robustness and Extensions

- **Other Extreme Weather:** IVs rise for floods, snowstorms, tornadoes (tornadoes comparable to hurricanes).
- **Industry Effects:** Baseline results robust across industries. Construction: lower perceived uncertainty. Mining/Wholesale: higher uncertainty.
- **Firm Selection:** Results not driven by small firm size or coastal exposure bias.
- **Tail Effects:** CAR dispersion larger for hit firms (both upside and downside risk).
- **Insurance Firms:** Even larger uncertainty estimates for property/casualty insurers (up to 78% IV increase for fully exposed firms).

Key Contributions

- **Quantifying Uncertainty:** Comprehensive analysis of firm-level extreme weather uncertainty.
- **Persistence:** Impact uncertainty is substantial and resolves slowly due to learning.
- **Efficiency:** Investor underreaction to volatility diminishes after salient events (e.g., Sandy).
- **Pricing Idiosyncratic Shocks:** Extreme weather shocks impact cost of capital, predicting higher returns post-Sandy.
- **Economic Channels:** Identified business interruption, physical damages, insurance, demand, supply as key drivers.

Implications

- Markets learn slowly to price extreme weather; may not efficiently price novel climatic risks.
- Local extreme weather events can affect cost of capital and may not be diversified.
- **Policy Suggestion:** Better firm disclosures (business continuity, physical resilience, insurance, supply/demand exposures) could reduce uncertainty and increase pricing efficiency.

Discussion and Questions

Thank you for your attention! Questions?