CLIMATE ADAPTATION
RESEARCH SYMPOSIUM

MEASURING & REDUCING SOCIETAL IMPACTS

Before the Storm: Responses to Forecasts

Thanks for joining us!
The session will begin shortly.

UCLA Luskin Center for Innovation

Thank you to our event collaborators

CLIMATE ADAPTATION
RESEARCH SYMPOSIUM

MEASURING & REDUCING SOCIETAL IMPACTS

SPONSOR

EDISON INTERNATIONAL®

PARTNERS

Atlantic Council
Adrienne Arsht-Rockefeller Foundation Resilience Center

American Society of Adaptation Professionals

Climate Resolve

EcoAdapt™

The Greenlining Institute

Island Press

LARC

Lincoln Institute of Land Policy

UC Davis Climate Adaptation Research Center

UCLA Center for Healthy Climate Solutions

Union of Concerned Scientists

Widgets are resizable and movable

You can drag the presenter's video around your screen.

Have a question for presenters? Click the ? icon.

Mathias Kruttli
Federal Reserve Board

Jeffrey Shrader
Columbia University

Ai He
University of South Carolina

CLIMATE ADAPTATION
RESEARCH SYMPOSIUM
MEASURING & REDUCING SOCIETAL IMPACTS

UCLA Luskin Center for Innovation

Mathias Kruttli

Senior Economist, Federal Reserve Board

Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics

Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics

Mathias S. Kruttli[†, *], Brigitte Roth Tran[†], and Sumudu W. Watugala[‡, *]

[†] The Federal Reserve Board of Governors
[*] Oxford-Man Institute of Quantitative Finance
[‡] Cornell University

September 8, 2021

Outline

Background

- Intensification of hurricanes, droughts, wildfires, and flooding in recent years.
- Little is known about uncertainty generated for firms by extreme weather events.
  - Uncertainty in other contexts has wide ranging effects.
  - Uncertainty is defined as expectation of future volatility.
- Not obvious that extreme weather events generate significant uncertainty.
  - Possible unpredictable impacts on PPE, local labor, demand, supply chain, etc. $\rightarrow$ increases uncertainty
  - Vulnerable firms could insure, adapt, or relocate away from risky areas. $\rightarrow$ reduces uncertainty
- Efficient pricing of climatic risks is important for financial stability.
  - Mispricing could lead to sudden, large, destabilizing price corrections (Carney, 2015).

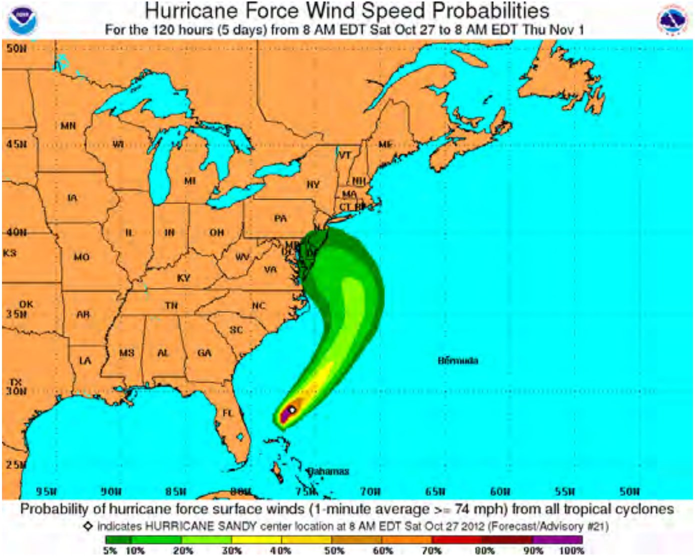
Questions

- Does extreme weather cause uncertainty for firms?
- Do investors price extreme weather uncertainty efficiently?

Our paper

- Analyze extreme weather uncertainty at the firm level using financial markets.
- **Framework**: Formalize ideas on the sources of extreme weather uncertainty.
  - *Incidence uncertainty:* Uncertainty about whether, when, where event will occur.
  - *Impact uncertainty:* Uncertainty about how event will impact firms.
- **Empirical setting**: Single-stock option price reactions around US hurricanes.
  - Changes to implied volatility (IV), a commonly used measure of uncertainty.
- **Identification**: Use a difference-in-differences setting.
  - Firms located in the forecasted or realized path of a hurricane vs unexposed firms.
  - Firm *establishment locations* determine treatment.
  - Multiple hurricane events with different landfall regions.

Example of Hurricane Sandy



What do we find?

- *Before landfall*: Investors pay attention to short-term forecasts and price in substantial uncertainty.
  - Reflects both incidence uncertainty and expected impact uncertainty.

- *After landfall*: Options of firms in the landfall region reflect large impact uncertainty.
  - Implied volatility is over 20% higher.
  - Result holds across industries.
  - Impact uncertainty resolution is slow and lasts up to 3 months.

- *Before and after landfall*: Evidence of significant underreaction.
  - Ex post realized volatility is larger than ex ante expected volatility.

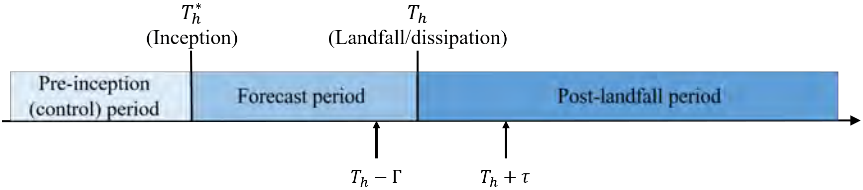
- *After Hurricane Sandy*:
  - Pricing inefficiency diminishes.
  - Expected stock returns compensate for idiosyncratic uncertainty.

Outline

Data

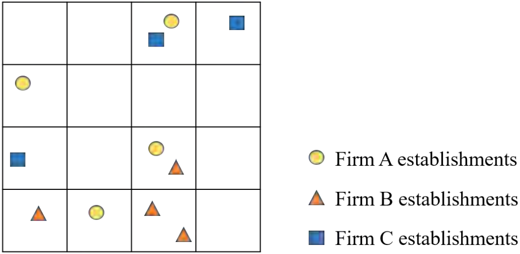
- Prior to landfall: county-level probabilities of hurricane-level wind speeds from NOAA forecasts.
  - 5-day forecast data available from 2007, covering 41 storms.
  - Includes storms that dissipate without making landfall as hurricanes.
- After landfall: location and distance from the eye of a hurricane.
  - 33 hurricane landfalls since 1996.
- Identify firms exposed or unexposed to a hurricane using establishments.
  - Data from National Establishment Time-Series (NETS).
- Measure change in IV relative to just before hurricane inception.
  - All single-stock options data from OptionMetrics from 1996.
  - Obtain daily average implied volatility measure for each firm, $IV_{i,t}$.

Identification strategy: Pre/post timeline



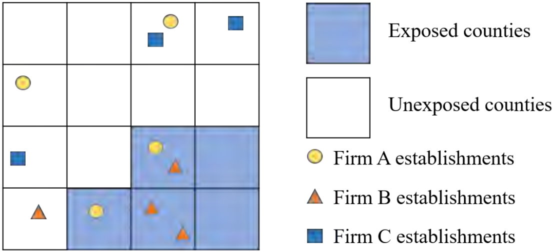
- Pre: The day prior to hurricane *inception*.
- Post (forecast analysis): Γ days prior to hurricane *landfall/dissipation*.
- Post (landfall analysis): τ days after hurricane *landfall*.

Identification strategy: Illustration of spatial variation



- Three illustrative firms.
- Firm establishments spatially distributed across different counties.

Identification strategy: A firm's **forecast** exposure

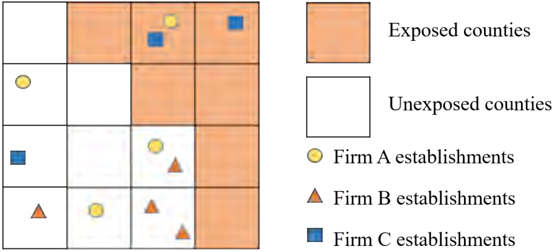


Exposure to hurricane forecast path:

Firm A: $\frac{2}{4} = 0.50$ Firm B: $\frac{3}{4} = 0.75$ Firm C: $\frac{0}{3} = 0.00$

$\rightarrow$ $ForecastExposure_{i,T_h-\Gamma}$: a continuous variable ranging from 0 to 1, reflecting treatment intensity.

Identification strategy: A firm's **landfall** exposure



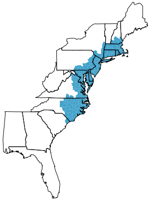
Exposure to hurricane landfall region:

Firm A: $\frac{1}{4} = 0.25$ Firm B: $\frac{0}{4} = 0.00$ Firm C: $\frac{2}{3} = 0.67$

$\rightarrow$ $LandfallRegionExposure_{i,T_h}$: a continuous variable ranging from 0 to 1, reflecting treatment intensity.

Forecast: Hurricane Sandy 4 days before landfall

October 26, 2012



≥1 percent

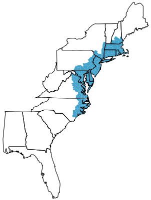
≥10 percent

≥20 percent

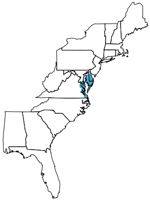
≥50 percent

Forecast: Hurricane Sandy 3 days before landfall

October 27, 2012



≥1 percent



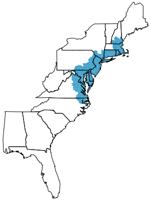
≥10 percent

≥20 percent

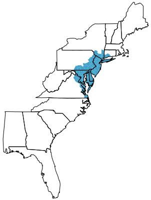
≥50 percent

Forecast: Hurricane Sandy 2 days before landfall

October 28, 2012



≥1 percent



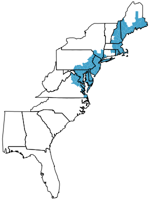
≥10 percent

≥20 percent

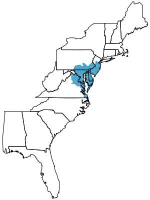
≥50 percent

Forecast: Hurricane Sandy 1 day before landfall

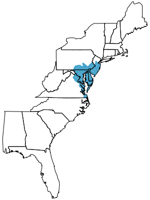
October 29, 2012



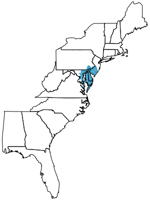
$\geq$1 percent



$\geq$10 percent

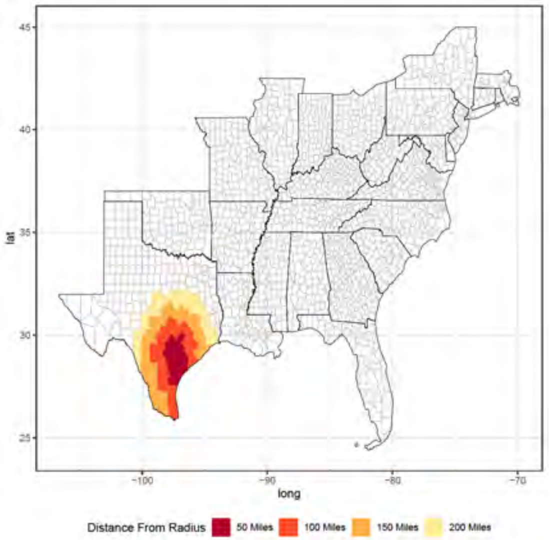


$\geq$20 percent



$\geq$50 percent

Landfall: 2017 Hurricane Harvey



Outline

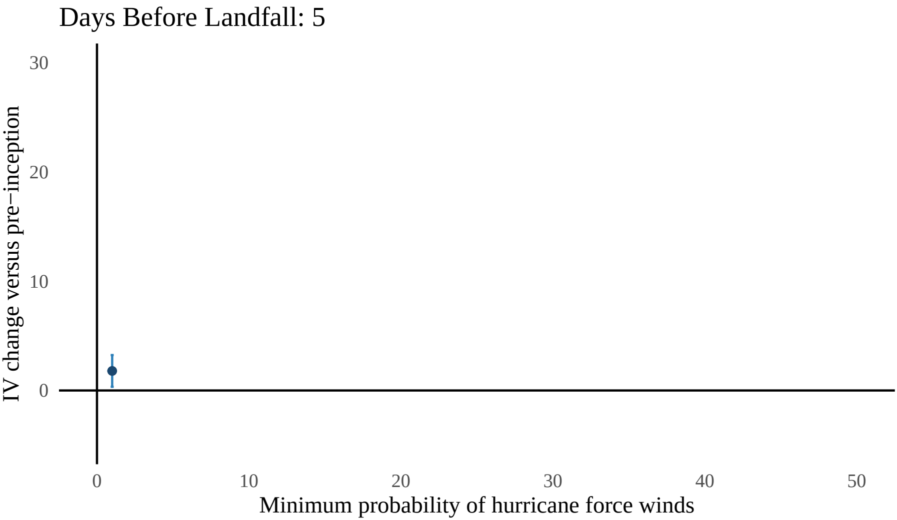
Uncertainty **before** landfall/dissipation

- Measure incidence and expected impact uncertainty.
- Estimate the panel regression, Γ days before landfall/dissipation:

$$log\left(\frac{IV_{i,T_h-\Gamma}}{IV_{i,T_h^*}}\right) = \lambda ForecastExposure_{i,T_h-\Gamma} + \pi_h + \psi_{Ind} + \epsilon_{i,h,\Gamma}.$$

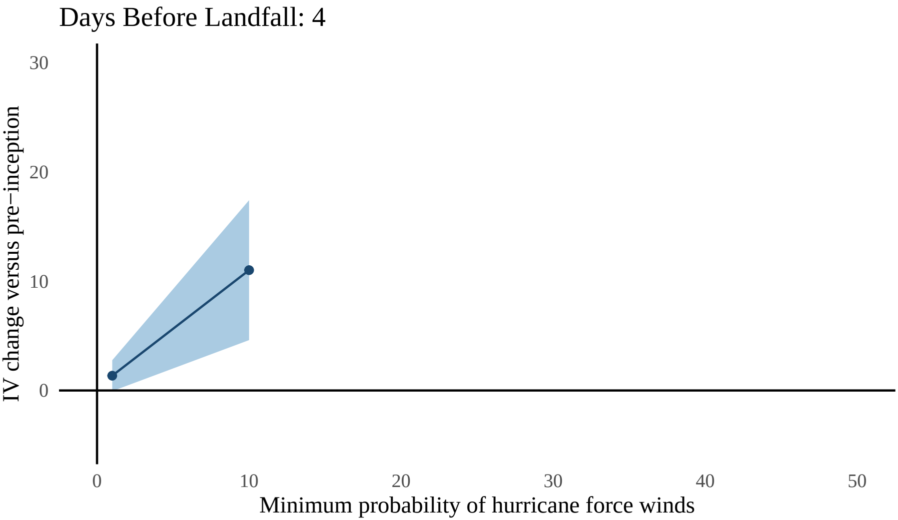
- Dependent variable is the change in IV since just before hurricane inception.
- λ captures the uncertainty increase due to exposure to hurricane forecasts.
  - λ is positive if uncertainty increases with forecast exposure.

Uncertainty before landfall/dissipation



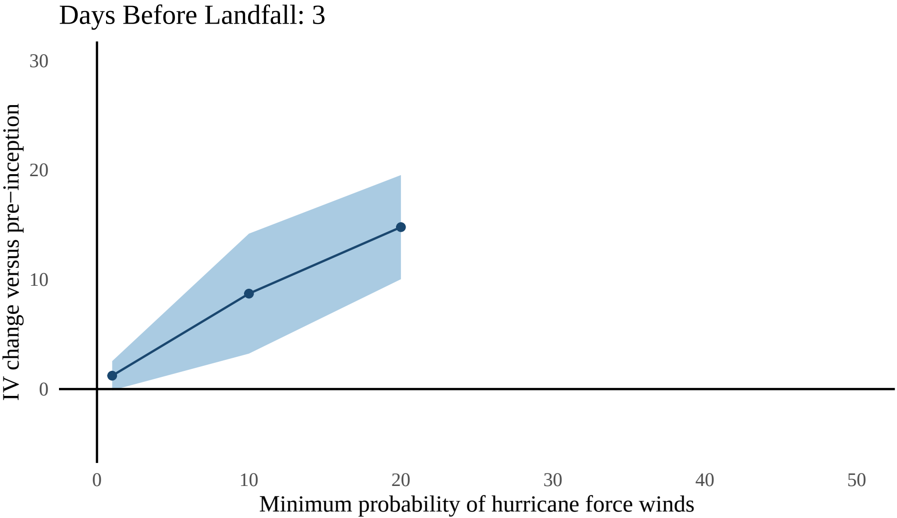
- Implied volatility is elevated as much as 5 days before landfall

Uncertainty before landfall/dissipation

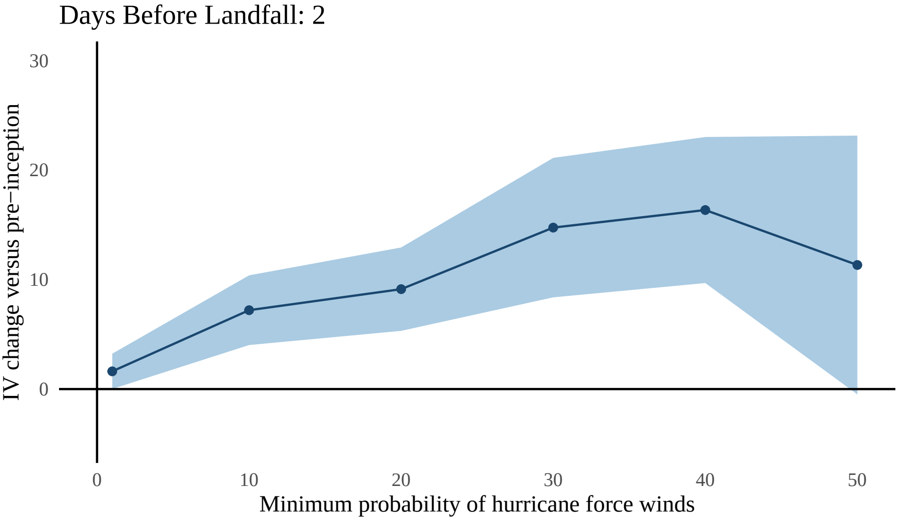


- Implied volatility increases with minimum probability of hurricane force winds

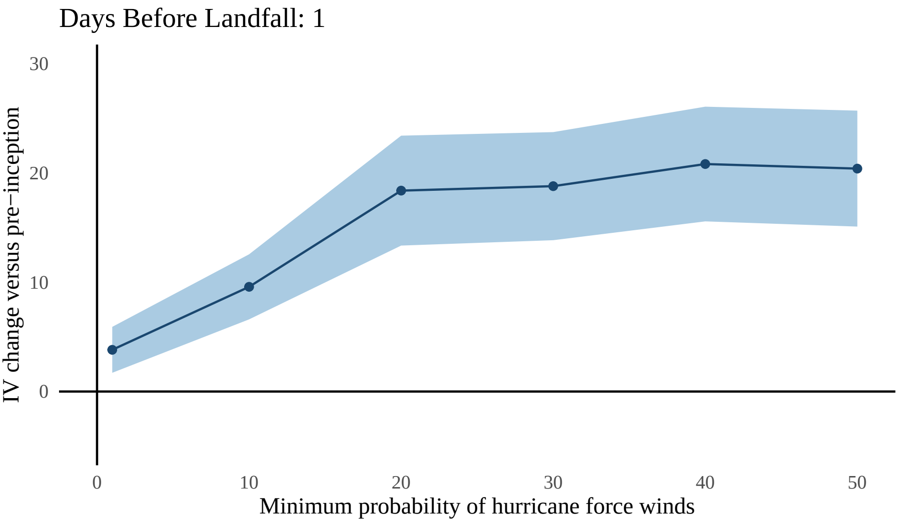
Uncertainty before landfall/dissipation



Uncertainty before landfall/dissipation



Uncertainty before landfall/dissipation



- Up to a 21% increase in IV for a firm with 100% exposure

Uncertainty **after** landfall

- After landfall, incidence uncertainty is resolved. Only impact uncertainty remains.
- Estimate the panel regression, τ days after landfall:

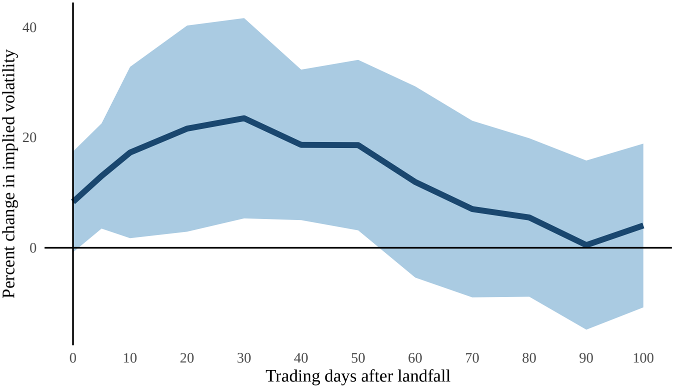
$$log\left(\frac{IV_{i,T_h+\tau}}{IV_{i,T_h^*}}\right) = \lambda LandfallRegionExposure_{i,T_h} + \pi_h + \psi_{Ind} + \epsilon_{i,h,\tau}.$$

- Dependent variable is the change in IV since just before hurricane inception.
- λ captures the uncertainty increase due to exposure to hurricane landfall.
  - λ is positive if uncertainty increases with landfall exposure.

Impact uncertainty a week after landfall

	Radius around eye of the hurricane							
	50 miles		100 miles		150 miles		200 miles	
$LandfallRegionExposure_{i,R,T_h}$	13.009***	8.337*	6.193***	4.474**	3.898***	3.014**	3.748***	2.511***
	(2.675)	(1.872)	(3.363)	(2.572)	(3.250)	(2.560)	(3.939)	(2.772)
Adjusted R^2 (%)	12.229	12.748	12.276	12.821	12.286	12.828	12.330	12.882
Observations	33,408	33,408	33,131	33,131	32,863	32,863	32,785	32,785
Hurricanes	33	33	33	33	33	33	33	33
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Time (Hurricane) FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry × Time (Hurricane) FE	No	Yes	No	Yes	No	Yes	No	Yes

Resolution of impact uncertainty: 50 mile radius



- Coefficient peaks at over 20% and reverses to pre-hurricane level after 3 months.

Are these expectations of future volatility efficient?

- Inefficient pricing of climate risks could pose financial stability risks.
- Define the difference between option-implied volatility and subsequent realized volatility over the remaining life of the option as the volatility risk premium.

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

- Analyze differences in VRP between firms exposed to hurricane forecasts/landfalls versus control firms.

$$\overline{VRP}_{i,T_h+\tau} = \lambda LandfallRegionExposure_{i,R,T_h} + \pi_h + \Psi_i + \epsilon_{i,h,\tau},$$

- Negative $\lambda \rightarrow$ ex ante expected volatility is systematically lower than ex post realized volatility for exposed firms compared to control firms $\rightarrow$ underreaction.

VRP difference prior to landfall

Prob. of hurricane hit $\geq$	1%	10%	20%	40%	50%
$ForecastExposure_{i,P,T_h-1}$	-2.777	-18.829***	-28.531***	-35.975***	-36.886***
	(-1.520)	(-5.320)	(-6.012)	(-3.801)	(-3.613)
Adjusted R^2 (%)	34.479	35.254	36.143	44.010	44.348
Observations	33,910	10,176	9,094	5,813	4,590
Hurricanes	30	9	8	5	4
Firm FE	Yes	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes	Yes

VRP is systematically lower for exposed firms compared to control firms → underreaction

VRP difference after landfall

	50 miles	100 miles	150 miles	200 miles
$LandfallRegionExposure_{i,R,T_h}$	-19.297***	-7.331***	-4.830***	-5.246***
	(-2.873)	(-3.693)	(-3.324)	(-4.020)
Adjusted R^2 (%)	28.275	28.408	28.628	28.711
Observations	31,400	31,121	30,883	30,793
Hurricanes	33	33	33	33
Firm FE	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes

VRP is again systematically lower for hit firms compared to control firms → underreaction

Do investors learn over time?

- A particularly damaging hurricane could increase the saliency of hurricane strikes.
- This could lead to investors pricing hurricanes more efficiently in option markets.
- We test if the underreaction result changes after Hurricane Sandy.
  - Hurricane Sandy in 2012 was a particularly destructive hurricane.
  - A large share of US institutional investors reside in the landfall region.

VRP difference after landfall: Post Hurricane Sandy

	50 miles	100 miles	150 miles	200 miles
$LandfallRegionExposure_{i,R,T_h}$	-21.027***	-7.936***	-5.571***	-6.368***
	(-3.179)	(-3.905)	(-3.344)	(-3.894)
$LandfallRegionExposure_{i,R,T_h}$	14.406	3.719	4.950**	4.899**
$\times PostSandy_h$	(1.645)	(1.032)	(2.126)	(2.344)
Adjusted R^2 (%)	29.295	29.399	29.610	29.705
Observations	31,530	31,251	31,012	30,926
Hurricanes	33	33	33	33
Hurricanes post Sandy	6	6	6	6
Firm FE	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes

- The inefficiency in pricing extreme weather uncertainty diminishes post Hurricane Sandy.

Expected returns

- Does heightened extreme weather uncertainty lead to higher cost of capital of exposed firms?

- Imperfect diversification/market segmentation lead to idiosyncratic volatility being positively related to expected stock returns.
  - Theory: Levy (1978) and Merton (1987)
  - Empirical evidence mixed: Ang, Hodrick, Xing, Zhang (2006, 2009), Fu (2009)
  - We exploit unique empirical setting to test theory using identified, exogenous shocks to volatility.

- Diff-in-diff specification similar to previous regressions with dependent variable being the difference of excess returns pre-inception and post-landfall.

$$
\begin{aligned}
ExcessReturn_{i,h,PostLandfall} - ExcessReturn_{i,h,PreInception} = \\
\lambda LandfallRegionExposure_{i,R,T_h} + \pi_h + \psi_{Ind} + \epsilon_{i,h}.
\end{aligned}
$$

Excess returns after landfall post-Sandy

	50 miles	100 miles	150 miles	200 miles
$LandfallRegionExposure_{i,R,T_h}$	-1.281	-5.106***	-3.106***	-2.873***
	(-0.625)	(-4.127)	(-3.598)	(-3.580)
$LandfallRegionExposure_{i,R,T_h}$	9.958	11.932***	10.449***	6.264**
$\times PostSandy_h$	(1.107)	(2.777)	(3.227)	(2.316)
Adjusted R^2 (%)	31.886	32.348	32.602	32.612
Observations	38,958	38,593	38,275	38,242
Hurricanes	33	33	33	33
Hurricanes post Sandy	6	6	6	6
Industry FE	Yes	Yes	Yes	Yes
Time (Hurricane) FE	Yes	Yes	Yes	Yes

- The relationship between excess returns and uncertainty as predicted by Levy (1978) and Merton (1987) holds, *after* Hurricane Sandy.
- Greater exposure to extreme weather uncertainty $\rightarrow$ higher cost of capital

Outline

Conclusion

- We show that extreme weather events cause substantial uncertainty for firms across industries.
  - Suggests potential real effects to extreme weather uncertainty.
- Before landfall, options react to hurricane forecasts reflecting both incidence uncertainty and expected impact uncertainty.
- After landfall, implied volatility increases over 20%, reflecting impact uncertainty, and remains elevated for up to 3 months.
- However, evidence of significant pricing inefficiencies.
  - Markets underreacted to repeated events like hurricanes.
  - Raises concerns for efficient pricing of novel risks caused by climate change.
- Inefficient pricing disappears after hurricane Sandy, and extreme weather uncertainty increases exposed firms' cost of capital.
  - Consistent with Merton (1987).

Jeffrey Shrader

Assistant Professor, Columbia University

The Value of Weather Forecasts

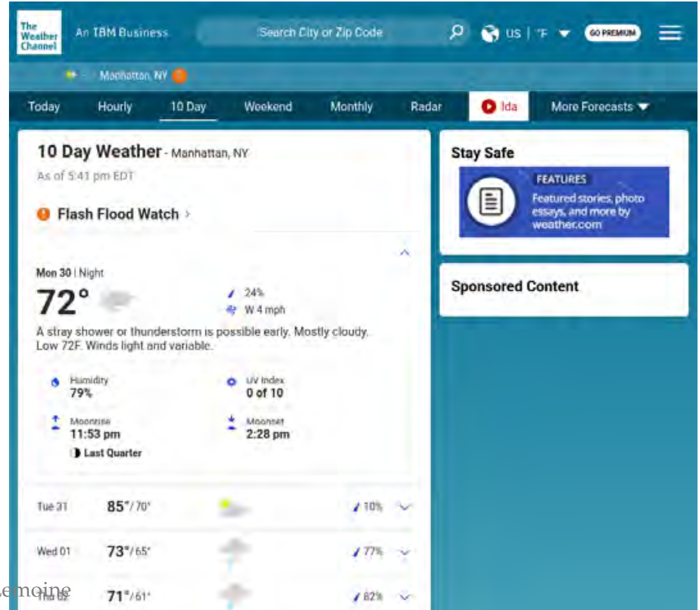
Value of Weather Forecasts

Jeffrey Shrader[1], Laura Bakkensen[2], Derek Lemoine[3]

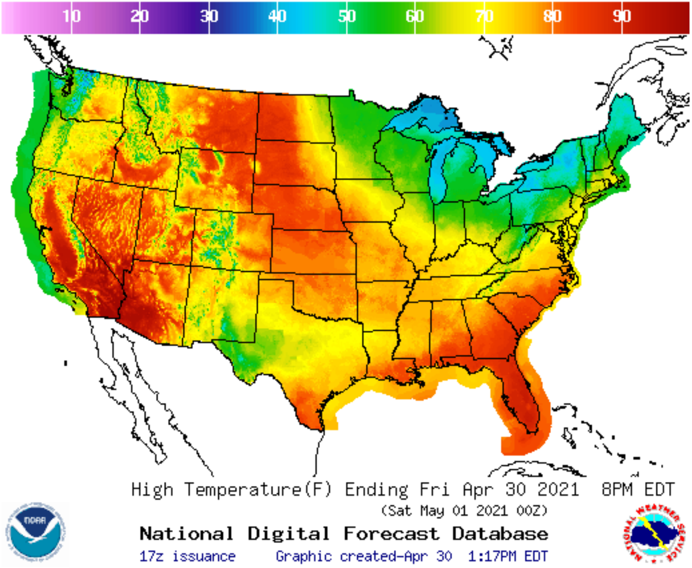
September 8, 2021

[1]School of International and Public Affairs, Columbia University
[2]School of Government and Public Policy, University of Arizona
[3]Eller College of Management, University of Arizona

DID YOU CHECK THE WEATHER TODAY?



DID YOU CHECK THE WEATHER TODAY?



What we know about forecast value

Costs

- National Oceanic and Atmospheric budget for weather forecasts: $2.7 billion
- Additional public expenditures for R&D: $0.9 billion
- Private sector expenditures: >$1 billion

Benefits

- Lazo et al. (2009) stated preference survey: Median household in 2006 willing to pay $260 per year
- No existing *revealed preference* estimates

Estimating benefits using real-world behavior

- We focus on mortality and temperature forecasts
  - Temperature is single deadliest form of extreme weather (Pielke and Carbon 2002)
  - Direct heat-related mortality is a large source of projected climate change damages (Carleton et al. 2020)
  - National Weather Service goals include mortality reduction
  - Avoidance behavior important
- Basic idea: look at how many deaths are avoided when forecasts are accurate

DATA

Mortality

- All mortality events in US from 2005–2017
- Daily, county-level

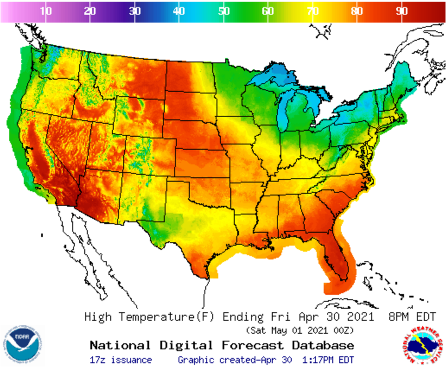
Temperature forecasts

- Universe of hourly forecasts from NDFD
- Aggregate to daily, county-level

Actual temperature

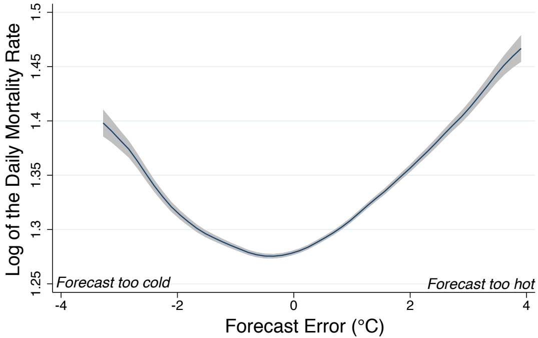
- From PRISM

Other variables: population, demographics, rainfall, local air pollution

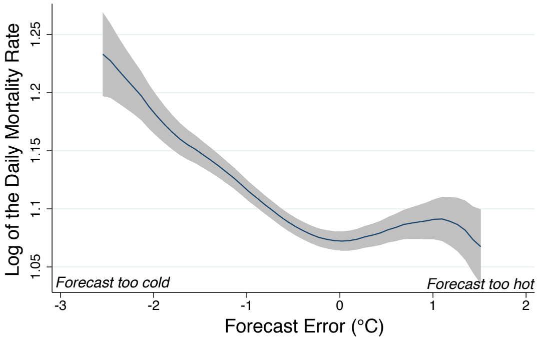


Initial evidence from raw data

Cold temperatures (< 5°C)



Hot temperatures (> 30°C)

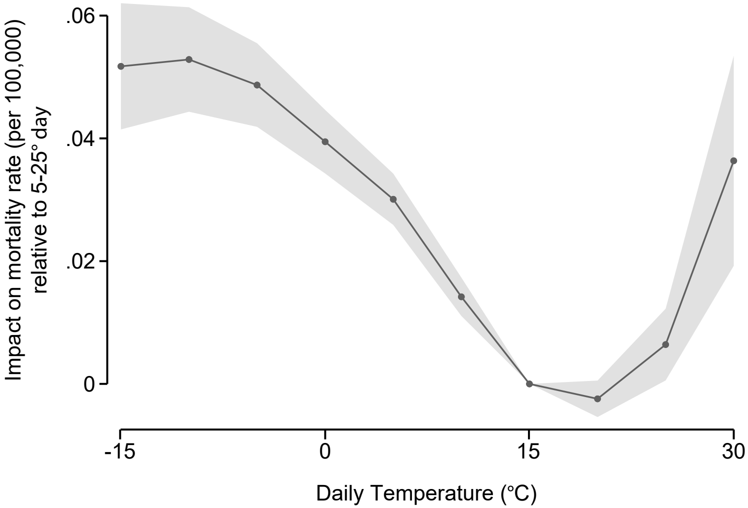


Estimating equation

$$y_{ct} = \sum_{\ell=0}^{L} \sum_{j=1}^{J} \left[\beta_{1,j,\ell} \mathbf{1}\{T_{c,t-\ell} \in B_j\} + \beta_{2,j,\ell} \mathbf{1}\{T_{c,t-\ell} \in B_j\} f(e_{c,t-\ell}) \right] + X_{ct}\gamma + \alpha_{cm} + \rho_t + \varepsilon_{ct}$$

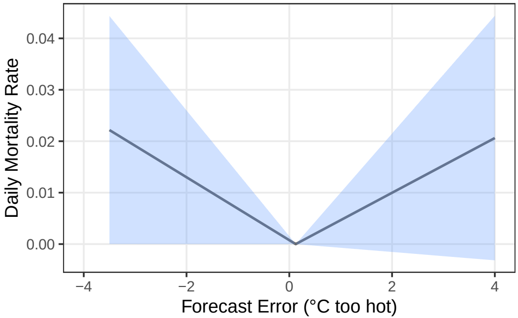
- Outcome variable: mortality rate per 100,000 people
- Flexible functions for realized temperature and forecast error
- Controls for location, time, season fixed effects + demographics and other weather
- Estimate 1-week cumulative effects

Updating mortality-temperature relationship

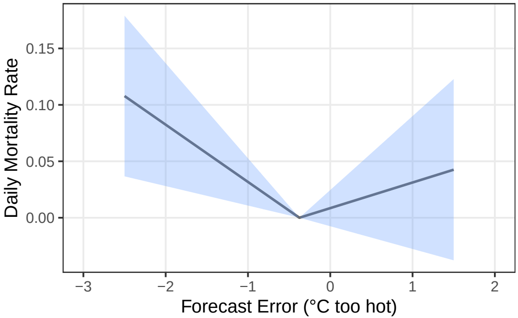


Effect of forecast accuracy

Cold temperatures ($< 5°C$)

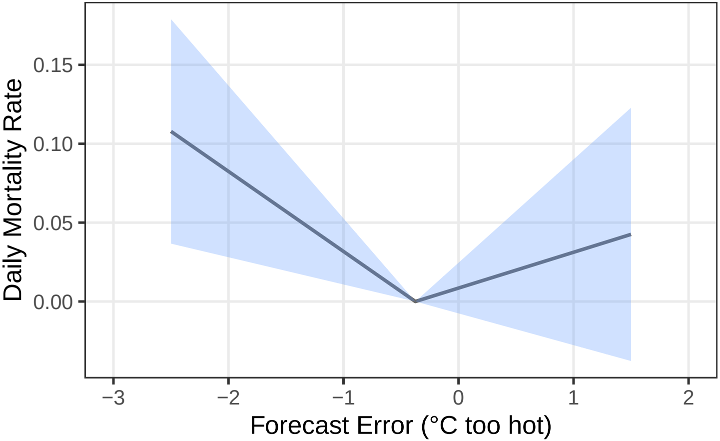


Hot temperatures ($> 30°C$)



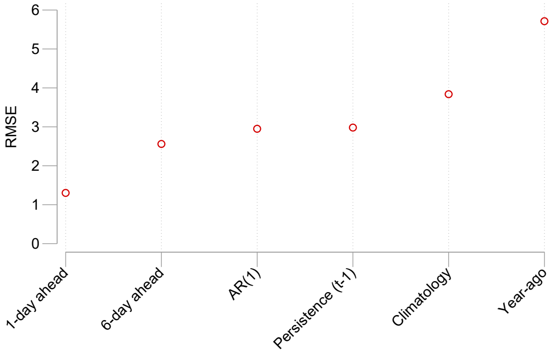
Effect of forecast accuracy

Hot temperatures (> 30°C)



Value of forecast improvements

- Reducing error by 1°C on a hot day saves 123 lives, on average
- On a cold day, 41 lives are saved
- Cold days are currently much more frequent than extremely hot days
- Monetized using EPA VSL ($9.76M): 1° error reduction is worth $22 billion per year



Forecasts and climate change

- Forecasts are useful for avoiding mortality from extreme temperatures
- Value of improved weather forecasts *currently* comes mainly from cold days
- But errors on hot days are more deadly
- More hot days as climate changes means more need for good forecasts

Jeff Shrader: jgs2103@columbia.edu

Art by Julia Blume

Ai He

Assistant Professor of Finance, University of South Carolina

The Rising Tide Lifts Some Interest Rates: Climate Change, Natural Disasters, and Loan Pricing

The rising tide lifts some interest rates: climate change, natural disasters, and loan pricing

Ricardo Correa
Federal Reserve Board, Division of International Finance

Ai He
University of South Carolina, Darla Moore School of Business

Christoph Herpfer
Emory University, Goizueta Business School

Ugur Lel
University of Georgia, Terry College of Business

September 6, 2021

Climate change is a key challenge for economies

Climate change: key challenge globally for economies

- Estimated damage up to 10% of U.S. GDP by the end of the century (Hong, Karolyi, and Scheinkman, 2020).
- Intergovernmental Panel on Climate Change (IPCC) projects that damages increase in warming and over time

Climate change is a key challenge for economies

Climate change: key challenge globally for economies

- Estimated damage up to 10% of U.S. GDP by the end of the century (Hong, Karolyi, and Scheinkman, 2020).
- Intergovernmental Panel on Climate Change (IPCC) projects that damages increase in warming and over time
- In November 2020, the Federal Reserve for the first time highlighted climate change as a potential threat to the stability of the financial system. Federal Reserve Governor Lael Brainard:

  "Climate poses risks to the stability of the broader financial system."
- In July 2021:
  ECB Governing Council is strongly committed to further incorporating climate change considerations into its monetary policy framework

Climate change and the financial system

- Potential devastating effects in the long term; but loans are short term
- Attempt to add an important piece to the literature
  - Existing papers focus on *long run discount rates* in *infinitely lived assets* (equity, real estate) (e.g., Giglio, Maggiori, and Stroebel, 2015; Giglio et al, 2018).
  - The debt market?
    - Mismatch between maturity of financial instruments and the long horizon of climate change
    - Municipal bond (avg maturity 10+ years) investors have only very recently started to price projected long-term sea level rises (Goldsmith-Pinkham et al, 2019; Painter 2020).

Linking climate change and finance through severe weather

Extreme weather events:
A potential channel through which climate change impacts banks today

- This paper: is there an **immediate, physical** effect of climate change on corporate funding costs even for short-lived loans?
  - Climate change leads to more severe and frequent disasters
  - Disasters impact the performance and creditworthiness of borrowers
  - **Banks update their priors about future severity by observing disasters**
  - Loan spreads rise to compensate

- Climate science studies: **severity** and **frequency** of specific disasters already directly linked to climate change: hurricanes, floods, wild fires (e.g., Stern, 2007; Mendelsohn and Saher, 2011; Risser and Wehner, 2017; Van Der Wiel et al., 2017)

Anecdotal evidence

Major banks mention climate change related natural disasters

2019 10-K filing:

Bank	Climate disasters	Worsening trend	Specific disasters
JPMorgan Chase	Yes	Yes	Flooding, wildfire, heat, storm
Bank of America	Yes	Yes	Fire, hurricanes
Citi	Yes	Yes	None
Wells Fargo	Yes	No	Hurricanes
Goldman Sachs	Yes	Yes	None
Morgan Stanley	Yes	No	None
U.S. Bankcorp	Yes	Yes	None
Truist	Yes	Yes	Hurricanes, storms
PNC	Yes	Yes	None
TD Bank	Yes	Yes	None

PNC: "Climate change may be **increasing the frequency or severity of adverse weather conditions**, making the impact from these types of natural disasters on us or our customers worse. [...] we could face reductions **in creditworthiness on the part of some customers or in the value of assets securing loans**."

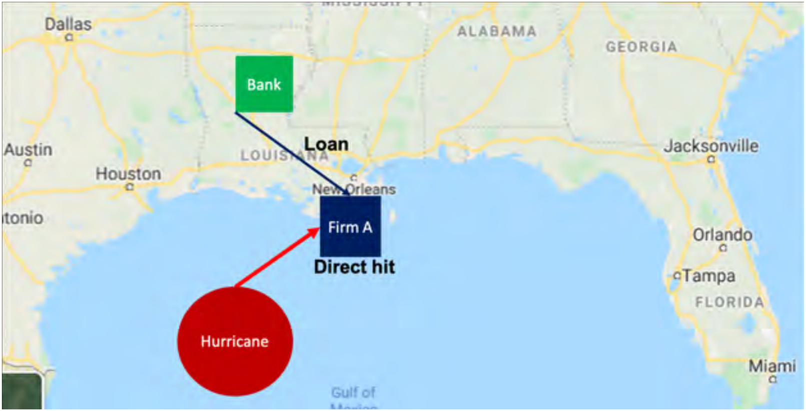
Anecdotal evidence II

Banks have been aware of this link for a while - 10-K 2010:

Bank	Climate disasters	Worsening trend	Specific disasters
JPMorgan Chase	No	No	None
Bank of America	No	No	None
Citi	No	No	None
Wells Fargo	Yes	No	None
Goldman Sachs	Yes	No	None
Morgan Stanley	Yes	No	None
U.S. Bankcorp	Yes	Yes	None
Truist (Suntrust)	Yes	Yes	Hurricanes
PNC	Yes	Yes	None
TD Bank	Yes	Yes	None

Empirical framework

Naïve approach: focus on **Firm A**, **direct** disaster hit on loan spreads

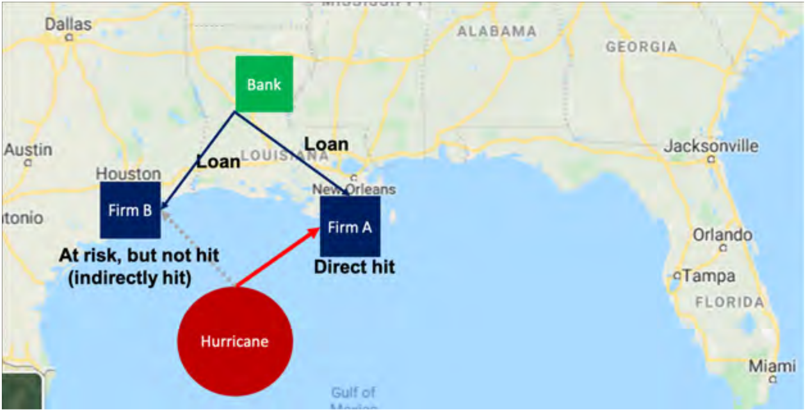


Confounding effects: the **direct effect** of the disaster on the borrower vs. **lender's expectation** about future disasters (Nordhaus, 2010)

▸ Direct effects

Empirical framework

Solution:
Do not use Firm A, focus on **indirect effects** for at risk, unaffected firms



Empirical framework

Important: shut down internal **bank-funding transmission channel**

Empirical framework

Our approach:

- Focusing on indirectly affected firms: **Firm B** and **Firm C**
- Drop directly affected firms (A)
- Intuitively, compare loans at the same time, to completely unaffected firms (**C**) and *at-risk but not directly hit* ("indirectly hit", **B**) firms while controlling for lenders' shock.

Data and final sample

Challenge: firms not located in a single spot!

- Detailed geographic footprints from National Establishment Time-Series (NETS) for the entire US
  - Firm-level disaster exposure: county-operations-weighted
  - *At-risk-firms* in the top 20% of firm-level disaster exposure:*Indirect disaster*
  - Conducted separately for each disaster type
- Disaster data from SHELDUS
  - Governor declared a “state of emergency” with a formal request for FEMA
  - Disaster prone counties as those in top decile of distribution of a type of disasters, rolling 10-year window
- DealScan for loan (size, maturity, covenants, type) and COMPUSTAT for firm controls (size, profitability, leverage)
- Final sample consists of 21262 loan facilities from 1996 to 2019

Natural disasters

We investigate each of these five types.

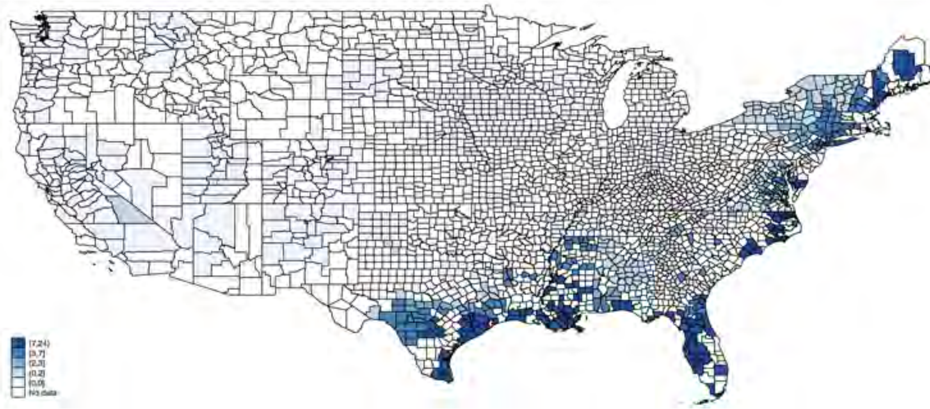
Disaster type	Number of affected counties	Total property damage across all affected counties ($B)	County property damage distribution ($M)			
			p25	p50	p75	p95
Hurricane	1912	296.19	0.17	1.45	15.94	398.07
Earthquake	16	4.34	18.77	20.17	594.41	975.55
Wildfire	556	39.13	0.05	0.77	4.51	108.33
Flooding	9247	371.12	0.05	0.36	2.00	32.50
Winter Weather	2693	14.17	0.03	0.31	2.19	24.50

Disaster characteristics

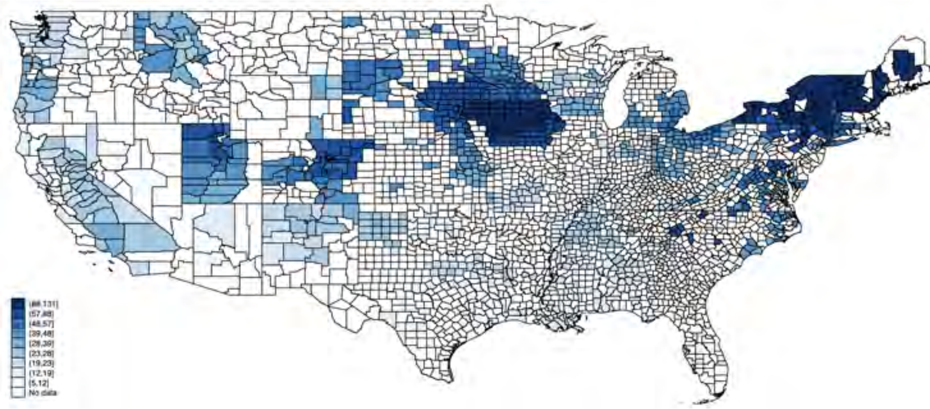
Following IPCC in defining Non-climate change disasters and Climate change disasters

Projection winter storm

Geographic distribution of hurricanes at mid-sample (2006)



Geographic distribution of winter at mid-sample (2006)



Empirical test: hurricane as an example

loan to firm i in month t (year y) from lender j

$$Spread_{i,j,t} = \boldsymbol{\beta_1} Indirect\ hurricane_{i,t} \times Recent\ hurricane_t + \beta_2 Indirect\ hurricane_{i,t} + \beta_3 Recent\ hurricane_t + \gamma X_{i,j,t} + \alpha_i + \phi_{j,y} + \epsilon_{i,j,t}$$

- Where:
  - $Recent\ hurricane_t$: an indicator of a hurricane occurance in prior 3 months
  - Only firms with zero exposure to $Recent\ hurricane_t$ are included (drop **A**)
  - $Spread_{i,j,t}$ is the interest rate paid in a loan contract originated at time t between firm i and lender j
  - $Indirect\ hurricane_{i,t}$: an indicator for firms at risk of hurricanes (Firm **B**)

Empirical test: hurricane as an example

loan to firm i in month t (year y) from lender j

$$
\begin{aligned}
Spread_{i,j,t} = \boldsymbol{\beta_1} Indirect\ hurricane_{i,t} \times Recent\ hurricane_t + \beta_2 Indirect\ hurricane_{i,t} \\
+ \beta_3 Recent\ hurricane_t + \gamma X_{i,j,t} + \alpha_i + \phi_{j,y} + \epsilon_{i,j,t}
\end{aligned}
$$

- Where:
  - $Recent\ hurricane_t$: an indicator of a hurricane occurance in prior 3 months
  - Only firms with zero exposure to $Recent\ hurricane_t$ are included (drop **A**)
  - $Spread_{i,j,t}$ is the interest rate paid in a loan contract originated at time t between firm i and lender j
  - $Indirect\ hurricane_{i,t}$: an indicator for firms at risk of hurricanes (Firm **B**)
  - α_i: borrower FE
  - $\phi_{j,y}$: bank-year FE to compare among loans from the same bank to different borrowers in the same year
  - $X_{i,j,t}$: loan and firm controls(loan type, maturity, covenant, firm size, profitability, debt ratio)
- $\boldsymbol{\beta_1} > 0$ implies lenders charge risk premium for borrowers with increased exposure to climate change disasters

Empirical results

Main result

Banks charge risk premium to at-risk borrowers after observing a disaster strike

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *Recent hurricane*	17.274**	18.751**	19.158**	18.778**
	(7.717)	(8.371)	(8.621)	(8.488)
Indirect hurricane	3.016	3.118	3.538	3.467
	(5.041)	(4.399)	(4.026)	(3.973)
Recent hurricane	3.419	0.501	0.857	1.178
	(3.790)	(3.712)	(3.551)	(3.556)
N	21262	21262	21262	21262
R^2	0.696	0.730	0.741	0.742
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Parentheses contain standard errors double clustered by firm and year.

- **Economic magnitude** about 10% of unconditional mean, similar to a downgrade by one notch from A to A-

Main test placebos

Disasters that are not affected by climate change do not exhibit the same behavior

These results are not driven by general rare-event effects. In additional tests, we show no effect for various non-climate change disasters:

- Earthquakes (domestic) Earthquake
- Earthquakes (foreign) Earthquake foreign
- Winter weather Winter

In contrast, we find similar pricing effects for other climate change related disasters:

- Fire fire
- Flood flood

Economic channel: attention?

Risk premia spike in times of high attention to climate change

	Spread		
	(1)	(2)	(3)
Indirect hurricane × *recent hurricane*	16.603*	-13.047	-44.620***
	(8.360)	(13.647)	(14.984)
Indirect hurricane × *recent hurricane* × *WSJ index*	41.659**		
	(17.006)		
Indirect hurricane × *recent hurricane* × *above median attention*		47.982**	
		(17.392)	
Indirect hurricane × *recent hurricane* × *medium tercile attention*			66.370***
			(18.420)
Indirect hurricane × *recent hurricane* × *top tercile attention*			83.067***
			(25.388)
N	19375	19375	19375
R^2	0.754	0.754	0.754
Bank× Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Wall Street Journal index : a time varying attention measure of climate change vocabulary appears on the WSJ. (Engle et al., 2021)

Climate change risk in the secondary market

- Secondary market loan prices from Refinitiv's Loan Pricing Corporation
- Quote price for outstanding loans
- Event study of loan pricing in 12 weeks before and after natural disasters
- **Economic magnitude** more than twice as large as primary market

Climate change risk in the secondary market

- Secondary market loan prices from Refinitiv's Loan Pricing Corporation
- Quote price for outstanding loans
- Event study of loan pricing in 12 weeks before and after natural disasters
- **Economic magnitude** more than twice as large as primary market

	Log Average Quote			
	(1)	(2)	(3)	(4)
Indirect hurricane $\times$ *Recent hurricane*	-0.032*	-0.024***	-0.033**	-0.021***
	(0.017)	(0.008)	(0.016)	(0.008)
Indirect hurricane	-0.015	-0.040**	-0.024	-0.055***
	(0.020)	(0.016)	(0.020)	(0.017)
Recent hurricane	-0.000	0.007**	0.008**	0.010***
	(0.004)	(0.003)	(0.004)	(0.003)
N	62085	62085	62085	62085
R^2	0.003	0.850	0.043	0.858
Loan FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
Std Errors	Loan	Loan	Loan	Loan

Climate change risk bank internal

- Bank internal risk assesment of borrowers (not loan level)
- Data from Y-14 reports (Stress tests)
- Event study of loan pricing in 12 weeks before and after natural disasters
- **Economic magnitude** more than twice as large as primary market

Climate change risk bank internal

- Bank internal risk assesment of borrowers (not loan level)
- Data from Y-14 reports (Stress tests)
- Event study of loan pricing in 12 weeks before and after natural disasters
- **Economic magnitude** more than twice as large as primary market

	(1)	(2)	(3)
Indirect hurricane × Recent hurricane_This quarter	0.013**	0.010*	0.010
	(0.006)	(0.005)	(0.006)
Indirect hurricane × Recent hurricane_1 quarter prior			0.003
			(0.005)
Indirect hurricane × Recent hurricane_2 quarters prior			0.001
			(0.004)
N	43008	43008	39458
R^2	0.355	0.375	0.374
Bank × Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Firm controls	No	Yes	Yes
Sum of coefficients			0.014*

Cross section: borrowers with more exposure

Climate change is priced more severely for borrowers under financial stress or those with assets at-risk

	Spread		
	(1)	(2)	(3)
Indirect hurricane $\times$ *recent hurricane*	17.538*	15.877*	7.114
	(8.888)	(8.003)	(9.292)
Indirect hurricane $\times$ *recent hurricane* $\times$ *market leverage*	25.262*		
	(14.684)		
Indirect hurricane $\times$ *recent hurricane* $\times$ *tangibility*		14.477*	
		(8.028)	
Indirect hurricane $\times$ *recent hurricane* $\times$ *non* $-$ *investment grade*			45.984*
			(23.960)
N	20269	20616	19658
R^2	0.746	0.741	0.753
Bank $\times$ Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Other interactions	Yes	Yes	Yes

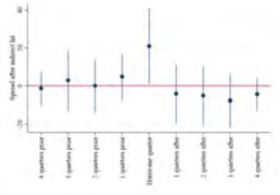
Cross section: more severe disasters

More severe disasters are associated with stronger pricing effects

	Spread		
	(1)	(2)	(3)
Indirect hurricane $\times$ *Recent hurricane$_{other}$*	16.136**		16.671**
	(7.692)		(7.707)
Indirect hurricane $\times$ *Recent hurricane$_{>\$100bn}$*		31.022*	34.059**
		(15.993)	(15.817)
Indirect hurricane	3.859*	4.292*	3.514
	(2.334)	(2.288)	(2.323)
Recent hurricane$_{other}$	1.355		1.094
	(2.274)		(2.285)
Recent hurricane$_{>\$100bn}$		-0.390	-1.151
		(4.453)	(4.483)
N	21262	21262	21262
R^2	0.742	0.742	0.741
Bank$\times$ Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes

Are the pricing effects permanent?

1. No anticipation (rise in yield prior to disaster)
2. Pronounced spike on event
3. No evidence of sustained elevated rates
4. Drop of liquidity in secondary loan markets around the event
5. Importantly, transitory effect in both primary **and** secondary loan market



Who is making a mistake here?

- Are investors overreacting to salient news similar to CEOs (Dessaint and Matray, 2017)
- Or are lenders making the correct decision initially, but have short memory?

Salience or short memory?

Test salience vs short memory: If “near misses”...

- ... **are** followed by an increase in actual hits, likely initial reaction correct
- ... **are not** followed by more severe hits, likely overreaction to salience

Salience or short memory?

Test salience vs short memory: If "near misses"...

- ... **are** followed by an increase in actual hits, likely initial reaction correct
- ... **are not** followed by more severe hits, likely overreaction to salience

	Direct hit	Direct hit large	Direct hit cont.
	(1)	(2)	(3)
Previous indirect hit	0.023***	0.024***	0.094***
	(0.004)	(0.004)	(0.018)
Indirect hurricane	0.026***	0.032***	0.109***
	(0.005)	(0.006)	(0.021)
N	557437	557437	557437
R^2	0.361	0.210	0.333
Firm FE	Yes	Yes	Yes
Year month FE	Yes	Yes	Yes

Other robustness tests

- Alternative climate disaster: Fire ▸ Fire
- Alternative climate disaster: Flood ▸ Flood
- Alternative placebo disaster: winter weather ▸ Winter
- Alternative: all climate change disasters combined ▸ Jointly

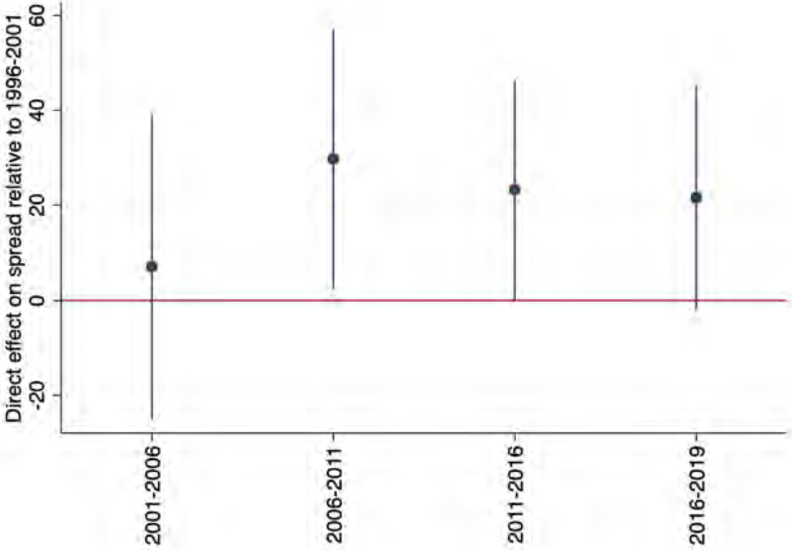
- Exposure weighted by employment ▸ Employment weighted
- Alternative definitions of treatment ▸ Robustness cutoffs

- Exclude financial crisis ▸ noFC
- Exclude hurricane season ▸ noHS
- Attention measured by IPCC reports ▸ IPCC
- Alternative channel: bank funding ▸ Bank funding
- Alternative channel: customer supplier links ▸ Customer supplier links
- Real effects ▸ Real effects

Conclusion

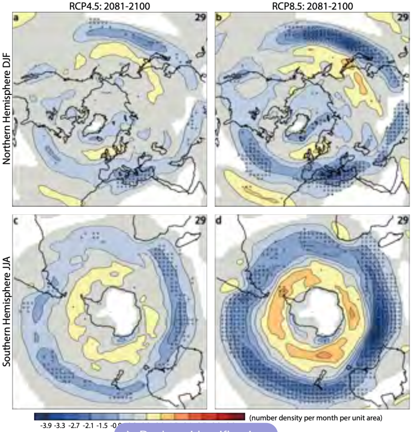
- Climate change already shapes economic risks today.
- Banks claim to be aware of the link between cliamte change, natural disasters, and loan risk
- Sharp, short lived spike in loan prices in primary and secondary market after climate change disasters, not after other disasters
- Learning effect seems short-lived
- We provide the first study to directly link climate change to present-day corporate loan costs.

Direct effects of hurricanes



Back to identification

Winterstorm projection



Back to identification

Individual disaster: fire

	Spread			
	(1)	(2)	(3)	(4)
Indirect fire × *Recent fire*	9.701**	9.668**	7.635*	7.632*
	(4.081)	(4.006)	(4.019)	(3.961)
Indirect fire	-3.789	-3.900	-1.489	-1.572
	(2.689)	(2.654)	(2.568)	(2.560)
Recent fire	-7.003*	-6.908	-5.254	-5.200
	(4.038)	(4.042)	(4.081)	(4.092)
N	21127	21127	21127	21127
R^2	0.762	0.762	0.774	0.774
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

▸ Back to main part

Individual disaster: flooding

	Spread			
	(1)	(2)	(3)	(4)
Indirect flooding × *Recent flooding*	9.820*	9.649*	8.984*	8.848*
	(4.820)	(4.741)	(4.437)	(4.358)
Indirect flooding	-2.562	-2.490	-1.973	-1.927
	(4.043)	(3.995)	(3.702)	(3.676)
Recent flooding	-6.794**	-6.895**	-5.929**	-5.994**
	(2.634)	(2.640)	(2.633)	(2.655)
N	21127	21127	21127	21127
R^2	0.762	0.762	0.774	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Back to main part

Individual disaster: winter

Indirect winter weather × *Recent winter weather*	-5.295	-5.346	-2.941	-2.977
	(9.342)	(9.331)	(8.322)	(8.305)
Indirect winter weather	9.573***	9.611***	9.188***	9.195***
	(3.083)	(3.039)	(2.757)	(2.761)
Recent winter weather	9.840*	9.804*	8.264	8.248
	(5.747)	(5.677)	(5.655)	(5.609)
N	21127	21127	21127	21127
R^2	0.762	0.762	0.775	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Back to main part

Main test placebo: Earthquakes I

Disasters that are not affected by climate change do not exhibit the same behavior

	Spread			
	(1)	(2)	(3)	(4)
Indirect earthquake × *Recent earthquake*	-4.202	-3.498	-1.889	-1.391
	(7.216)	(7.258)	(6.513)	(6.581)
Indirect earthquake	-3.358	-3.440	-0.260	-0.336
	(4.675)	(4.615)	(4.415)	(4.389)
Recent earthquake	11.868**	11.541**	11.593**	11.373**
	(5.526)	(5.522)	(4.832)	(4.877)
N	21127	21127	21127	21127
R^2	0.762	0.762	0.774	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Back to main part

Main test placebo: Earthquakes II

Use 13 large earthquakes abroad rather than domestic earthquakes

	Spread			
	(1)	(2)	(3)	(4)
Indirect earthquake × *Recent earthquake abroad*	3.951	3.674	2.464	2.338
	(6.059)	(6.021)	(5.976)	(5.933)
Indirect earthquake	-4.562	-4.540	-0.950	-0.972
	(5.691)	(5.626)	(5.274)	(5.228)
Recent earthquake abroad	9.989	9.988	7.983	7.988
	(7.063)	(6.974)	(6.997)	(6.953)
N	21127	21127	21127	21127
R^2	0.762	0.762	0.774	0.775
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Back to main part

Individual disaster: jointly

	Spread			
	(1)	(2)	(3)	(4)
Indirect disasters $\times$ *Recent disasters*	8.109***	6.460**	7.308**	6.045**
	(2.664)	(2.493)	(2.689)	(2.557)
Indirect disasters	-4.756*	-2.906	-4.282*	-2.683
	(2.643)	(2.374)	(2.448)	(2.224)
Recent disasters	-0.164	-0.666	-0.980	-1.439
	(3.402)	(3.357)	(3.267)	(3.237)
N	21127	21127	21127	21127
R^2	0.735	0.762	0.753	0.775
Direct Disaster Exposure	Yes	Yes	Yes	Yes
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Back to main part

Exclude financial crisis

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *recent hurricane*	17.623**	19.503**	18.340**	19.917**
	(7.485)	(7.912)	(8.042)	(8.112)
Indirect hurricane	1.611	1.913	1.998	2.199
	(5.132)	(4.493)	(4.450)	(4.036)
recent hurricane	1.171	-1.787	2.407	-0.756
	(3.483)	(3.382)	(3.328)	(3.372)
N	20372	20372	20372	20372
R^2	0.697	0.731	0.714	0.743
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Back to main part

Exclude hurricane season (June-November)

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *recent hurricane*	78.400***	69.840**	71.938**	64.442**
	(25.960)	(27.541)	(27.401)	(28.387)
Indirect hurricane	4.447	3.087	3.942	2.916
	(7.763)	(7.514)	(6.754)	(6.710)
Recent hurricane	-7.945	-9.299	-5.351	-7.162
	(9.202)	(8.622)	(8.891)	(8.299)
N	10307	10307	10307	10307
R^2	0.745	0.771	0.760	0.782
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Back to main part

IPCC reports

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × *recent hurricane*	11.846	11.029	11.727	11.230
	(9.212)	(9.420)	(9.590)	(9.723)
Indirect hurricane × *recent hurricane* × *IPCC*	94.216***	95.875***	88.214***	87.018***
	(30.131)	(30.426)	(26.075)	(26.672)
N	20071	20071	20071	20071
R^2	0.704	0.738	0.749	0.750
Bank× *Year FE*	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Back to main part

Weight operations by employment

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane (employment) $\times$ *recent hurricane*	14.298*	12.534	14.714*	12.918*
	(7.257)	(7.631)	(7.393)	(7.432)
Indirect hurricane (employment)	0.162	0.350	0.884	0.791
	(5.056)	(4.829)	(5.006)	(4.763)
N	21262	21262	21262	21262
R^2	0.696	0.730	0.713	0.742
Bank $\times$ Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes

Back to main part

Cutoffs

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane general × *recent hurricane*	18.772*			
	(9.550)			
Indirect hurricane general continuous × *recent hurricane*		4.536**		
		(2.020)		
Indirect hurricane continuous × *recent hurricane*			4.751**	
			(2.066)	
Any indirect hurricane × *recent hurricane*				17.142**
				(7.152)
N	21262	21262	21262	21262
R^2	0.743	0.742	0.742	0.742
Bank × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	Yes	Yes

Back to main part

Alternative explanation: bank funding channel

Banks move capital toward directly affected disaster firms (Cortes et al, 2017; He, 2020)

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × recent hurricane	17.481**	14.344*	17.546**	14.373*
	(7.941)	(7.855)	(7.945)	(7.852)
Indirect hurricane	0.428	1.264	0.454	1.276
	(3.233)	(2.693)	(3.237)	(2.694)
Recent hurricane	1.237	-1.375	1.040	-1.459
	(2.905)	(2.859)	(2.926)	(2.911)
Bank disaster exposure (loan incidence)	3.294**	1.532		
	(1.632)	(1.508)		
Bank disaster exposure (loan amount)			2.833**	1.310
			(1.259)	(1.261)
N	16723	16723	16723	16723
R^2	0.731	0.775	0.731	0.775
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	Yes	No	Yes

Back to main part

Alternative explanation: customer supplier linkage

Natural disasters ripple through the economy via input links (Barrot & Sauvagnat et al, 2016)

	Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
Indirect hurricane × Recent hurricane	17.086**	14.222*	17.134**	14.294*	17.271**	14.422*
	(7.835)	(7.843)	(7.755)	(7.800)	(7.763)	(7.818)
Indirect hurricane	0.513	1.320	0.593	1.407	0.624	1.437
	(3.230)	(2.695)	(3.206)	(2.679)	(3.218)	(2.686)
Recent hurricane	3.145	-0.596	3.505	-0.249	3.282	-0.458
	(2.928)	(2.911)	(2.903)	(2.875)	(2.935)	(2.901)
Customer disaster exposure	16.056	15.164			15.723	14.766
	(13.105)	(12.620)			(13.141)	(12.647)
Supplier disaster exposure			-31.775**	-33.739**	-31.697**	-33.657**
			(15.641)	(14.756)	(15.664)	(14.772)
N	16723	16723	16723	16723	16723	16723
R^2	0.731	0.775	0.731	0.775	0.731	0.775
Bank× Year Hurricane FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes

Back to main part

Real effects

The most at-risk firms reduce investment and increase cash holdings, consistent with precautionary motives

	CapEx/Lagged Asset (%)			Cash / Liabilities (%)		
	(1)	(2)	(3)	(4)	(5)	(6)
Indirect hurricane $\times$ *Recent hurricane*	0.012	0.042	0.025	-4.559***	-3.754*	-3.007*
	(0.125)	(0.091)	(0.082)	(1.686)	(1.936)	(1.731)
Indirect hurricane $\times$ *recent hurricane* $\times$ *non* $-$ *investment grade*	-0.399**	-0.398**	-0.277	4.036**	4.226**	4.075*
	(0.174)	(0.170)	(0.208)	(1.809)	(1.854)	(2.069)
N	100556	100556	88253	91255	91255	89103
R^2	0.435	0.470	0.532	0.591	0.593	0.649
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Quater FE	No	Yes	Yes	No	Yes	Yes
Firm controls	No	No	Yes	No	No	Yes
Other interactions	Yes	Yes	Yes	Yes	Yes	Yes

Back to main part

Are the pricing effects permanent?

	Spread			
	(1)	(2)	(3)	(4)
Indirect hurricane × Future hurricane_4 quarters future	0.207	1.147	-2.305	-1.301
	(5.317)	(5.726)	(4.590)	(5.073)
Indirect hurricane × Future hurricane_3 quarters future	2.619	3.400	2.175	2.891
	(9.561)	(9.731)	(8.934)	(9.214)
Indirect hurricane × Future hurricane_2 quarters future	-0.631	0.077	-0.776	0.030
	(9.593)	(8.621)	(8.822)	(8.175)
Indirect hurricane × Future hurricane_1 quarters future	6.739	5.489	5.965	4.832
	(7.456)	(7.147)	(7.442)	(7.061)
Indirect hurricane × Recent hurricane_This quarter	18.722*	18.995	20.774*	20.932*
	(10.220)	(11.866)	(10.381)	(11.769)
Indirect hurricane × Recent hurricane_1 quarter prior	-4.692	-2.476	-6.379	-4.123
	(9.731)	(10.000)	(8.688)	(9.100)
Indirect hurricane × Recent hurricane_2 quarter prior	-8.125	-6.651	-6.360	-5.144
	(8.551)	(9.247)	(8.294)	(8.994)
Indirect hurricane × Recent hurricane_3 quarters prior	-12.821	-8.529	-11.354	-7.616
	(7.566)	(8.142)	(7.970)	(8.370)
Indirect hurricane × Recent hurricane_4 quarters prior	-3.752	-3.394	-4.559	-4.423
	(4.301)	(4.549)	(4.948)	(4.887)
N	21262	21262	21262	21262
R^2	0.696	0.730	0.713	0.742
Bank× Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Firm controls	No	No	Yes	Yes

Back to main part

KEYNOTE ROUNDTABLE | 12:30-1:30PM PT

Setting the Research Agenda: Upcoming Priorities for Adaptation Researchers

Eleni Myrivili
Chief Heat Officer
City of Athens, Greece

Jonathan Parfrey
Executive Director,
Climate Resolve

Lauren Sanchez
Senior Climate Advisor, Office
of CA Governor Newsom

CLIMATE ADAPTATION
RESEARCH SYMPOSIUM
MEASURING & REDUCING SOCIETAL IMPACTS

UCLA Luskin Center for Innovation

CLIMATE ADAPTATION
RESEARCH SYMPOSIUM

MEASURING & REDUCING SOCIETAL IMPACTS

Thanks for tuning in!

UCLA Luskin Center for Innovation