What Drives Beliefs about Climate Risks?

Evidence from Financial Analysts

Matilde Faralli*

EEA 2023

*PhD in Finance at Imperial College London

Motivation

- In the US the total costs of natural disasters from 1980 to 2022 are approximately 2.2 trillion US dollars (NOAA 2022).

Motivation

- In the US the total costs of natural disasters from 1980 to 2022 are approximately 2.2 trillion US dollars (NOAA 2022).

- Recent studies document market participants' reactions to climate-related events.

Motivation

- In the US the total costs of natural disasters from 1980 to 2022 are approximately 2.2 trillion US dollars (NOAA 2022).

- Recent studies document market participants' reactions to climate-related events.
  - Investors sell high carbon footprints stocks during months with atypically high temperatures (Choi et al. 2020);

Motivation

- In the US the total costs of natural disasters from 1980 to 2022 are approximately 2.2 trillion US dollars (NOAA 2022).

- Recent studies document market participants' reactions to climate-related events.
  - Investors sell high carbon footprints stocks during months with atypically high temperatures (Choi et al. 2020);
  - After experiencing a heatwave, households are more likely to change their pension choices towards green funds (Anderson & Robinson 2020);

Motivation

- In the US the total costs of natural disasters from 1980 to 2022 are approximately 2.2 trillion US dollars (NOAA 2022).

- Recent studies document market participants' reactions to climate-related events.
    - Investors sell high carbon footprints stocks during months with atypically high temperatures (Choi et al. 2020);
    - After experiencing a heatwave, households are more likely to change their pension choices towards green funds (Anderson & Robinson 2020);
    - Mutual funds' managers change their portfolio allocation across industries after experiencing extreme heat events (Alekseev et al. 2021).

Research Questions

- How are beliefs about climate risks formed?

Research Questions

- How are beliefs about climate risks formed?
    1. Develop a model to define what are climate beliefs and how experiences of weather shocks affect them, following the **EBL model** of Malmendier & Nagel (2011).

Research Questions

- How are beliefs about climate risks formed?
- How do experiences of weather shocks affect climate beliefs?

Research Questions

- How are beliefs about climate risks formed?

- How do experiences of weather shocks affect climate beliefs?
    1. Construct a **novel dataset** with localized analysts and natural disasters in the US from 1999 to 2020

Research Questions

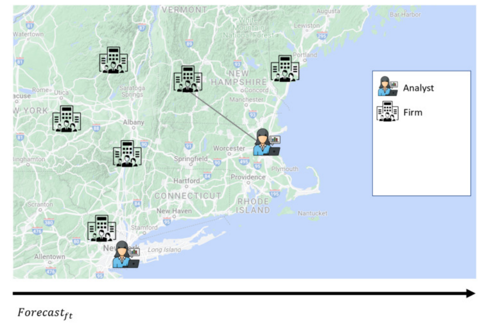
- How are beliefs about climate risks formed?

- How do experiences of weather shocks affect climate beliefs?
    1. Construct a **novel dataset** with localized analysts and natural disasters in the US from 1999 to 2020
    2. Shed light on **how experiences affects** analysts' climate beliefs and thus earnings forecasts

Research Questions

- How are beliefs about climate risks formed?

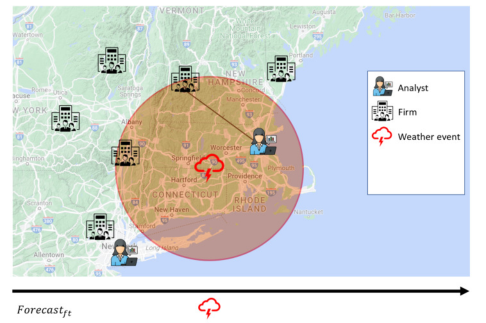
- How do experiences of weather shocks affect climate beliefs?
  1. Construct a **novel dataset** with localized analysts and natural disasters in the US from 1999 to 2020
  2. Shed light on **how experiences affects** analysts' climate beliefs and thus earnings forecasts



Research Questions

- How are beliefs about climate risks formed?

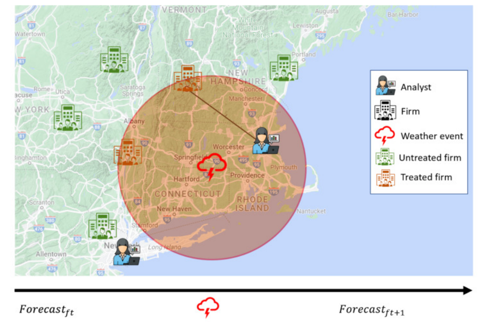
- How do experiences of weather shocks affect climate beliefs?
  1. Construct a **novel dataset** with localized analysts and natural disasters in the US from 1999 to 2020
  2. Shed light on **how experiences affects** analysts' climate beliefs and thus earnings forecasts



Research Questions

- How are beliefs about climate risks formed?

- How do experiences of weather shocks affect climate beliefs?
  1. Construct a **novel dataset** with localized analysts and natural disasters in the US from 1999 to 2020
  2. Shed light on **how experiences affects** analysts' climate beliefs and thus earnings forecasts



Research Questions

- How are beliefs about climate risks formed?

- How do experiences of weather shocks affect climate beliefs?
  1. Construct a **novel dataset** with localized analysts and natural disasters in the US from 1999 to 2020
  2. Shed light on **how experiences affects** analysts' climate beliefs and thus earnings forecasts
  3. Provide evidence of the **underlying channels** that drive market participants' reaction to climate-related events: information, heuristic and/or distraction channel

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.
    - This translates to a 14% reduction in bias and an 11% decrease in forecast error, compared to the average forecast bias and error.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.
    - This translates to a 14% reduction in bias and an 11% decrease in forecast error, compared to the average forecast bias and error.
    - These results hold consistently across analysts with different characteristics.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.

2. For **sectors with high climate risks** (e.g., agriculture, construction, manufacturing, mining, retail, transportation), analysts on average become more pessimistic and accurate.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.

2. For **sectors with high climate risks** (e.g., agriculture, construction, manufacturing, mining, retail, transportation), analysts on average become more pessimistic and accurate.
    - High-performance analysts exhibit increased pessimism and accuracy only for firms with high physical climate risks, while other analysts become more pessimistic for all firms.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.

2. For **sectors with high climate risks** (e.g., agriculture, construction, manufacturing, mining, retail, transportation), analysts on average become more pessimistic and accurate.
    - High-performance analysts exhibit increased pessimism and accuracy only for firms with high physical climate risks, while other analysts become more pessimistic for all firms.
    - High-performance analysts become more pessimistic for shocks with high economic damages and for firms with risks similar to those they experienced, while other analysts become more pessimistic for all firms.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.

2. For **sectors with high climate risks** (e.g., agriculture, construction, manufacturing, mining, retail, transportation), analysts on average become more pessimistic and accurate.
    - High-performance analysts exhibit increased pessimism and accuracy only for firms with high physical climate risks, while other analysts become more pessimistic for all firms.
    - High-performance analysts become more pessimistic for shocks with high economic damages and for firms with risks similar to those they experienced, while other analysts become more pessimistic for all firms.
    - Analysts become more pessimistic and accurate about firms with high institutional ownership and market capitalization.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.
2. For **sectors with high climate risks** (e.g., agriculture, construction, manufacturing, mining, retail, transportation), analysts on average become more pessimistic and accurate.
3. The results seem to be driven by firms with **both high transition and physical risks**.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.
2. For **sectors with high climate risks** (e.g., agriculture, construction, manufacturing, mining, retail, transportation), analysts on average become more pessimistic and accurate.
3. The results seem to be driven by firms with **both high transition and physical risks**.
    - Treated analysts tend to follow fewer firms with high transition risks and focus more on climate transition opportunities, with fewer questions about transition risks.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.
2. For **sectors with high climate risks** (e.g., agriculture, construction, manufacturing, mining, retail, transportation), analysts on average become more pessimistic and accurate.
3. The results seem to be driven by firms with **both high transition and physical risks**.
4. When breaking down forecasts by their respective horizons (ranging from 1 to 5 years ahead), analysts' increase in accuracy and pessimism is statistically significant **up to 3 years ahead horizons**.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.
2. For **sectors with high climate risks** (e.g., agriculture, construction, manufacturing, mining, retail, transportation), analysts on average become more pessimistic and accurate.
3. The results seem to be driven by firms with **both high transition and physical risks**.
4. When breaking down forecasts by their respective horizons (ranging from 1 to 5 years ahead), analysts' increase in accuracy and pessimism is statistically significant **up to 3 years ahead horizons**.
   - The change in pessimism and accuracy is persistent up to 6 months after the event.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.
2. For **sectors with high climate risks** (e.g., agriculture, construction, manufacturing, mining, retail, transportation), analysts on average become more pessimistic and accurate.
3. The results seem to be driven by firms with **both high transition and physical risks**.
4. When breaking down forecasts by their respective horizons (ranging from 1 to 5 years ahead), analysts' increase in accuracy and pessimism is statistically significant **up to 3 years ahead horizons**.
   - The change in pessimism and accuracy is persistent up to 6 months after the event.
   - The effect is amplified following a second shock.

Preview Results

1. After experiencing a weather shock, first-time treated analysts become **more pessimistic and accurate** in their forecasts for firms distant from the event, compared to analysts who haven't been treated yet.
2. For **sectors with high climate risks** (e.g., agriculture, construction, manufacturing, mining, retail, transportation), analysts on average become more pessimistic and accurate.
3. The results seem to be driven by firms with **both high transition and physical risks**.
4. When breaking down forecasts by their respective horizons (ranging from 1 to 5 years ahead), analysts' increase in accuracy and pessimism is statistically significant **up to 3 years ahead horizons**.
5. Analysts with **prior exposure to shocks** tend to be **more accurate in forecasting firms with high physical risks**.

Related Literature

Belief formation

- **The role of Salience** (Bordalo, Gennaioli, Shleifer, 2022)
- **Climate beliefs**: the impact of political beliefs (McCright et al. 2014), sophisticated agents (Stroebel and Wurgler , 2021)
- **Past experiences**: great depressions (Malmendier and Nagel, 2011), inflation experiences (Malmendier and Nagel, 2016; Malmendier and Steiny, 2017; Malmendier et al., 2021), cultural enviroment (Guiso, Sapienza, and Zingales 2004 and 2008; Osili and Patheulson 2008; Alesina and Fuchs-Schündeln 2007)
- **Diagnostic expectation** and stock return (Bordalo et al., 2018); credit cycles (Bordalo et al., 2017); bubbles (Bordalo et al., 2018); overreaction to macro-expectation (Bordalo et al., 2020)

Analysts and Climate

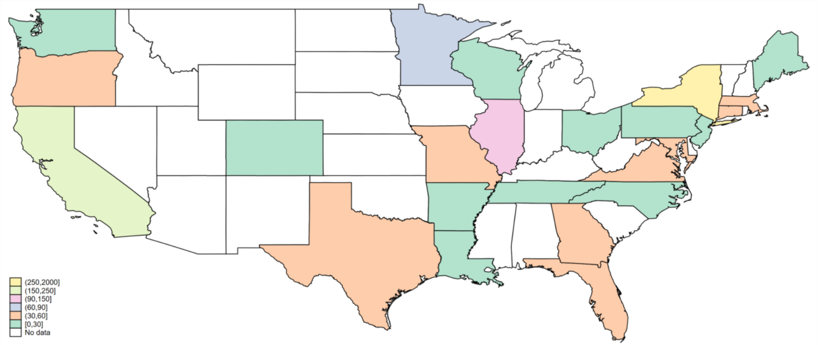
- **Firms' Geographic Risks**: drought risks (Kim,Lee and Ryou, 2021), general climate risks (Liu, 2021)
- **Risk Disclosure**: annual risk disclosures (Wang et al., 2017), ESG mandatory disclosure (Krueger at al., 2021), ESG incidents and firms value (Krueger at al., 2021).
- **Natural Hazards and heuristic behaviors**: hurricanes (Bourveau and Law ,2020), extreme natural hazards (Han et al., 2020 & Tran et al., 2020), earthquakes (Kong et al., 2021)
- **Abnormal temperature-precipitations effect on short-term forecasts**: no effect (Pankratz et al., 2019), consensus forecasts emerge in some industries (Addoum et al., 2020), analysts are less optimistic if they live in a climate-sensitive area (Cuculiza et al., 2021), lower short-term accuracy and higher dispersion of analysts forecasts for firms with lower earnings seasonality (Zhang, 2021).
- Parallel work of Reggiani (2022).

Data

- **IBES forecasts**
  → Annual, Long Term EPS
- **Analysts' location**
  → Use the phone number to retrieve analysts' location and manually checked using BrokerCheck (FINRA)
  → I only have information since they started working as analysts
- **Climate events**
  → Storm Event Database, National Oceanic and Atmospheric Administration (NOAA)
- **Firms Information**
  → CRSP/Compustat WRDS merge
  → Location is at the headquarters level
  → Robustness test with NETS establishment and business location from Garcia & Norli (2012)
  → Trucost Climate Change Physical Risk Dataset
  → Trucost emission level

Descriptive Statistics: Analysts Location

Figure 1: Analysts' location from 1999 to 2020 by State



Note: The graph maps the IBES analysts' locations from 1999 to 2020 by US state obtained from Refinitiv and Capital IQ-Professional.

→ Approximately 70 % of analysts are in NY

Descriptive Statistics: Natural Disasters

Extreme natural hazards: (1) ten or more people reported killed; (2) 100 or more people reported affected (EM-Dat); (3) equal or more than 1 billion dollars total economic damages (Barrot & Sauvagnat 2016).

Table 1: Extreme Weather Events near Analysts'location

Event Type	Av. Total Damage	Av. Total Deaths	Av. Total injuries	Number of Events
Thunderstorm Wind	0	1	100	1
Winter Weather	0	1	200	1
Heat	0	9	132	2
Extreme Cold/Wind Chill	0	10	0	1
Excessive Heat	0.1	11	154	7
Heavy Snow	0.8	0	100	1
Winter Storm	10.0	2	250	1
Tornado	254.7	10	178	15
Debris Flow	572.4	21	168	1
Storm Surge/Tide	1082.2	0	0	1
Flood	1225.5	3	0	3
Wildfire	1324.9	14	90	1
Hail	1752.9	0	0	2
Flash Flood	2321.0	4	25	4
Hurricane (Typhoon)	2369.1	160	8	4
Tropical Storm	3363.8	11	77	2
Total				47

Location all weather events

Conceptual Framework (2)

We cannot directly observe climate beliefs, but we can use a variation of analysts' earning forecasts after a weather shock to extract beliefs.

Conceptual Framework (2)

We cannot directly observe climate beliefs, but we can use a variation of analysts' earning forecasts after a weather shock to extract beliefs.

Forecasts can be seen as

$$\text{Analyst's Forecast} = (\textit{beliefs}) * (\text{information set})$$

If the information set does not change, then a change in forecasts can only be driven by a change in beliefs.

Conceptual Framework (2)

We cannot directly observe climate beliefs, but we can use a variation of analysts' earning forecasts after a weather shock to extract beliefs.

Forecasts can be seen as

$$\text{Analyst's Forecast} = (\textit{beliefs}) * (\text{information set})$$

If the information set does not change, then a change in forecasts can only be driven by a change in beliefs.

Main assumptions:

1. Weather shocks **do not impact** forecasted firms either **directly** (firms are near the event) or **indirectly** (suppliers or competitors are affected).
   → I only use firms 100 miles distant from the event and I show that there is no change in fundamentals around the weather shock.

Conceptual Framework (2)

We cannot directly observe climate beliefs, but we can use a variation of analysts' earning forecasts after a weather shock to extract beliefs.

Forecasts can be seen as

$$\text{Analyst's Forecast} = (\textit{beliefs}) * (\text{information set})$$

If the information set does not change, then a change in forecasts can only be driven by a change in beliefs.

Main assumptions:

1. Weather shocks **do not impact** forecasted firms either **directly** (firms are near the event) or **indirectly** (suppliers or competitors are affected).
   → I only use firms 100 miles distant from the event and I show that there is no change in fundamentals around the weather shock.
2. Weather shocks are salient events that effect climate beliefs.
   → I show that Google searches for the term "climate change" increase during months with salient weather shocks, but there is no significant effect on news concerning climate risks.

Empirical Strategy

- **First-time treated analysts** are located 100 miles from the shock (Alok et al. 2020) and forecasted firms are more than 100 miles distant from the event
- **Control group** is defined as a never-treated *analyst i* that issued a forecast for a *firm f* in the same *sector s* and for the same *forecast period fpe*
- **Event window**: [-3,3] months around the extreme weather shock
- When multiple forecasts are issued, I only keep one forecast per month

Methodology

Dependent variables:

$$BIAS_{ift} = \frac{(F_{ift} - Y_{ft})}{P_{f,t-1}} \qquad FERROR_{ift} = \frac{|F_{ift} - Y_{ft}|}{P_{f,t-1}}$$

Staggered Differences-in-Difference:

$$\text{Y}_{\ i,f,c,t} = \beta DD_{c,t} + \theta X_{it} + FE + \varepsilon_{i,f,c,t}$$

To validate the parallel trend assumption:

$$\text{Y}_{\ i,f,c,t} = \sum_{j \neq 0} \beta_j Treat * \text{Relative Month}_{c,t+j} + \theta X_{it} + \Gamma_{i*h} + \Gamma_{f*h} + \Gamma_{t*h} + \varepsilon_{i,f,c,t}$$

- → **FE:** i analyst, t year, f firms, h forecast horizon
- → **Controls:** period end, brokerage size, companies followed, firm experience, Industries followed, firm size, leverage, operating income
- → **The standard errors** clustered analysts' location (city)

Outline: Results

1. Descriptive statistics
2. Baseline results
3. By analysts' characteristics
4. By firms climate risks and analysts' performance
5. By types and damages of weather shocks
6. Transition risk
7. Distraction Hypothesis
8. By analysts' coverage and earnings calls questions
9. Term structure and additional experiences of weather events
10. Persistence & Diffusion
11. Robustness

Summary Statistics Overall

	Mean	p50	SD	Min	Max
forecast bias (%)	0.94	0.11	3.95	-23.64	64.10
forecast error (%)	2.12	0.77	3.77	0	66.03
companies followed	15.22	15	6.90	1	47
firm experience	1.95	1	2.24	0	19
general experience	4.33	3	3.98	0	19
industries followed	1.81	1	1.13	1	11
brokerage size	68.88	56	51.51	1	284
firm size	7.82	7.77	1.86	1.81	14.72
leverage	0.21	0.18	0.22	0	3.87
operating income	0.02	0.03	0.05	-0.84	0.29
market value	1.87	1.30	1.95	0.02	45.48
stock price/earnings	42.19	29.21	65.99	0.63	2027.09
ROA	0.00	0.01	0.09	-3.98	0.26
N	53004				

Total number of analysts: 1389; treated: 835; control: 841

Baseline Results: Yearly - Aggregate

Parallel Trend | By Sector

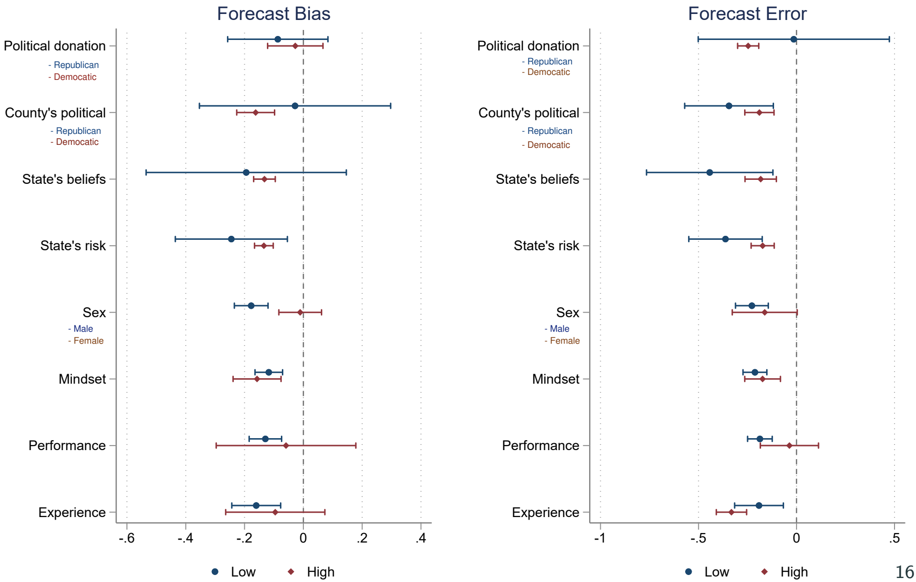
Dependent Variable:	Forecast Bias				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.136***	-0.149***	-0.149***	-0.107***	-0.118***
	(0.0324)	(0.0298)	(0.0299)	(0.0346)	(0.0367)
R^2	0.752	0.753	0.759	0.913	0.923
N	52992	48736	48736	48726	48697

Dependent Variable:	Forecast Error				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.229***	-0.215***	-0.211***	-0.179***	-0.175***
	(0.0409)	(0.0482)	(0.0467)	(0.0333)	(0.0345)
Control	No	Yes	Yes	Yes	Yes
Analyst, firm, year FE	Yes	Yes	Yes	Yes	Yes
Brokerage FE	No	No	Yes	Yes	Yes
Firm-year FE	No	No	No	Yes	No
Shock FE	No	No	No	No	Yes
R^2	0.754	0.755	0.760	0.910	0.920
N	52992	48736	48736	48726	48697

Results (1): Analysts' Characteristics

1. Analyst's political donation: takes the value 1 if the analysts donate to a democratic party.
2. County's political ideology: takes the value 1 if the democratic party had the majority of votes in the previous election
3. States' climate beliefs: states in the top percentile (bottom 5 percentiles) as the percentage of the population believing that climate change is happening in 2021 (from Yale Climate Opinion Maps for 2021)
4. Live in climate-sensitive states: the state has more than the median climate shocks (4 weather shocks)
5. Gender: estimated from the analyst's first name
6. Mindset: ex-ante optimistic (pessimistic) if the average of their forecasts was above (below) consensus in the previous quarter
7. Performance: top tercile performer based on the average performance score in the previous 3 years (following Hong et al. 2000)
8. Experience: analysts with more than the average years of experience (13 years)

Results (1): Analysts' Characteristics



Interpretation

- The results highlight an overall **homogeneous effect** on analysts' forecast bias and error.
- However, there are noteworthy differences within groups. Analysts with characteristics correlated with higher prior beliefs of climate risks seem to revise less their forecast after an extreme weather event.

Exploit Firms' Physical Climate Risks & Analysts' Perfomance

- Next, I investigate the potential roles of heuristic and information channels by leveraging on **firms' climate risk** and analysts' performance subgroups.

- To proxy for firms' climate risks, I use

  - Trucost forecasted physical risk (index ranging from 1 to 100)

  - climate-sensitive sectors (following Addoum et al. 2019)

Results: Firms' Climate risks

Analysts' Performance and Firm' Risk Information

	High performance analyst				Low performance analyst			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bias	Error	Bias	Error	Bias	Error	Bias	Error
treat*post	-0.138	0.0610	-0.00797	-0.142	-0.129***	-0.155***	-0.163***	-0.222***
	(0.185)	(0.121)	(0.171)	(0.0909)	(0.0267)	(0.0447)	(0.0593)	(0.0283)
Climate Sensitive Sector	High	High	Low	Low	High	High	Low	Low
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Analyst*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
Year*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.841	0.830	0.891	0.850	0.743	0.781	0.846	0.809
N	5114	5114	4126	4126	22005	22005	17430	17430

What are the Channels?

- **Low-performance** analysts have a homogeneous effect for both firms with high and low climate risks (*availability heuristics*).

- **High-performance** analysts become pessimistic only for stocks with **high climate risks**. This could be driven by two different channels:
  - *representative heuristics*: they overestimate the risks of firms with high climate risks
  - *Information channel*: they extract information from the event and then they revise their forecast downwards

What are the Channels?

I use **shocks' characteristics** to disentangle these two effects.

- **Type of weather shock:** are analysts that experience, for example, a hurricane becoming more pessimistic for firms with high hurricane risks or all firms with high physical risks?
- **Type of shock's damage:** are analysts becoming more pessimistic after a weather shock that caused remarkable economic damages (more than 1 billion dollars) or health-related damages (more than 10 deaths or 100 injuries)?

Results: Type of weather shock

	High performance analyst				Low performance analyst			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bias	Error	Bias	Error	Bias	Error	Bias	Error
treat*post	-0.202*	-0.0685	0.345**	0.00963	-0.161***	-0.211***	-0.0900***	-0.134***
	(0.113)	(0.0842)	(0.165)	(0.160)	(0.0564)	(0.0430)	(0.0331)	(0.0285)
Firm physical risks as the experienced shock	High	High	Low	Low	High	High	Low	Low
Analyst*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
Year*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
r2	0.879	0.844	0.911	0.912	0.801	0.799	0.844	0.869
N	7043	7043	2188	2188	29550	29550	9876	9876

High-performance analysts become pessimistic (optimistic) for firms with high (low) risk as the weather event experienced, while low-performance analysts become pessimistic for all firms (*availability heuristics*).

Results: Type of shock's damage

	High performance analyst				Low performance analyst			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bias	Error	Bias	Error	Bias	Error	Bias	Error
treat*post	0.032	0.019	-0.14	-0.24*	-0.14***	-0.15***	-0.17	-0.45***
	(0.079)	(0.077)	(0.21)	(0.12)	(0.014)	(0.037)	(0.22)	(0.092)
Shock Damage	Health	Health	Economic	Economic	Health	Health	Economic	Economic
Analyst*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
Year*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.87	0.82	0.91	0.91	0.80	0.80	0.87	0.87
N	5151	5151	2265	2265	23807	23807	7834	7834

High-performance analysts become pessimistic after experiencing events with high economic damages (*Information channel*), while low-performance analysts become pessimistic after all events (*availability heuristics*).

Other Explanations: Transition Risks

- Does experience of a weather shock affect beliefs about physical risks or/and transition risks?
    - Analysts, that experience extreme weather events, may believe that stricter regulation policies will be implemented.
    - If this hypothesis is true, I expect firms with higher transition risks to be penalized more than those with lower transition risks by treated analysts.
    - To proxy for transition risks, I use absolute carbon emission from Trucost in a given year. I then divide firms into high emissions (the top tercile of emissions) and low emissions (the bottom tercile).

Results: Transition Risks

	High Transition Risk				Low Transition Risk			
	High Physical		Low Physical		High Physical		Low Physical	
	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error	(7) Bias	(8) Error
treat*post	-0.386	-0.471	-0.0201	-0.201***	-0.0491	-0.387*	-0.0765	0.499
	(0.297)	(0.230)	(0.165)	(0.0349)	(0.0534)	(0.166)	(0.497)	(0.397)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.916	0.908	0.975	0.973	0.930	0.922	0.952	0.936
N	2196	2196	1431	1431	1384	1384	383	383

$\rightarrow$ The results seem to be driven by firms with both high physical and transition risks, even if not statistically significant.

Other Explanations: Distraction Hypothesis Table

Does experience of a weather shock make analysts more distracted?

- If this is true, I expect that their attention would be disproportionately channeled toward companies deemed pivotal for their professional careers.
  - → Analysts become more pessimistic and accurate for firms with high institutional ownership and relative importance
- Analysts in smaller brokerage firms may have fewer resources and may be worse at coping with extreme weather events.
  - → Analysts in large brokerage firms become more pessimistic compared to analysts in small brokerage firms, while forecast accuracy decreases in both.
- Distracted analysts might present a sudden drop in the number of forecasts compared to the control group.
  - → No statistically significant effect is found.

Other Effects

- **Analysts' Coverage:** Do treated analysts shift their firms' coverage to specific firms or industries? Do treated analysts follow more/fewer firms with large climate exposure?

  → Low-performance analysts seem to follow fewer firms with high transition risks in the 2 years after the extreme event compared to the control group. Table

- **Earnings Calls:** Do treated analysts ask more questions about climate risks?

  - Look at the share of climate-related questions following Sautner et al. (2020) methodology.

  → Treated analysts ask fewer questions about regulatory risks and more questions about climate transition opportunities after experiencing a weather shock. Table

Term Structure of Climate Risks and Memory Effect

The previous analysis reported the results aggregated for all analysts' forecast horizons (from 1 year to 5 years ahead). Since climate risks affect both short and long-term expectations, I investigate whether analysts believe that climate risks threaten short as well as long-term firms' earnings.

- Decompose for forecast horizons
  - → The results are driven by forecast horizons up to 3 years ahead. Table
- Multiple Shocks
  - → A second shock enhances average results. High-performance analysts become more accurate without increased pessimism, while low-performance analysts improve accuracy and become more pessimistic. Table

Persistence & Beliefs Diffusion

If weather events carry no information on climate risks, then equity analysts' forecasts should eventually revert to their initial forecasts, given that firms are not affected by the shock.

→ Treated analysts remain pessimistic up to 5 forecasts after the event.

→ Analysts remain pessimistic up to 6 months following the event compared to the last forecast issued before the event.

Additionally, I investigated whether untreated analysts modify their forecasts after the shocks by analyzing changes in forecasts made by treated analysts for the same firm. My findings indicate that there is no observable impact on untreated analysts after the event.

→ No evidence is found of belief diffusion. Table

Robustness

- Remove analysts working in New York. Result 1
- Cluster standard errors at different levels Result 2: brokerage cluster
- Placebo exercise by exploiting terrorist attacks in the US that occurred 100 miles near analysts' locations Result 3
- Analysts with different distances from the event Result 4
- Remove firms with a business location in the event' state Result 5 and establishment Result 6
- Replication using one observation per quarter and standard DID methodology Result 7

Conclusion

- This study sheds light on how experiences of weather shocks affect beliefs about physical risks.
- In line with previous studies, I find that analysts become more pessimistic and accurate after experiencing a salient weather shock.
- My findings suggest that both information and heuristic channel coexist
  - High-performance analysts change their forecasts only for firms with high climate risks (*information hyp.*)
  - Low-performance analysts become more pessimistic for all types of firms (*heuristic hyp.*)
- Although the findings might suggest a reorientation of attention towards more pivotal firms, they do not definitively negate the observation that analysts also revise their forecasts for less significant entities, all the while maintaining their volume of forecasts unchanged.

Thank you!

Conceptual Framework (1) Details

Experience-Based Learning (EBL) model (Malmendier & Nagel 2011; Malmendier & Wachter 2021)

θ_t Posterior beliefs about climate physical risks: beliefs about the distribution of future total damages caused by natural hazards in the US.

The posterior climate beliefs θ_t at time t:

$$\boxed{\theta_t} = \underbrace{(1 - w_{\text{work}}) * CC}_{\text{prior belief about climate risk}} + \overbrace{w_{\text{work}} * \sum_{k=0}^{\text{work}} w(k, \lambda, \text{CC}, \text{work}) * \text{ Weather Shocks }_{t-k}}^{\text{experienced weather shocks}}$$

My setting differs from Malmendier & Wachter (2021) in three main points:

1. Only direct experiences of weather shocks enter into posterior climate beliefs.
2. Shocks experienced before working as an analyst do not matter for climate beliefs.
3. Weather shocks are perceived as a realization of climate change.

Location of all weather events defined as extreme natural hazards Back

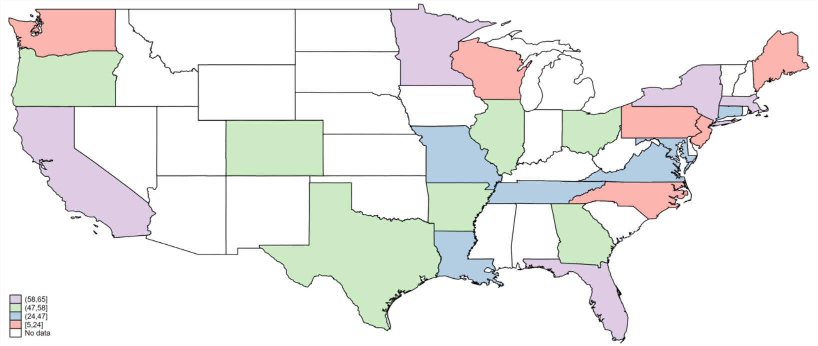


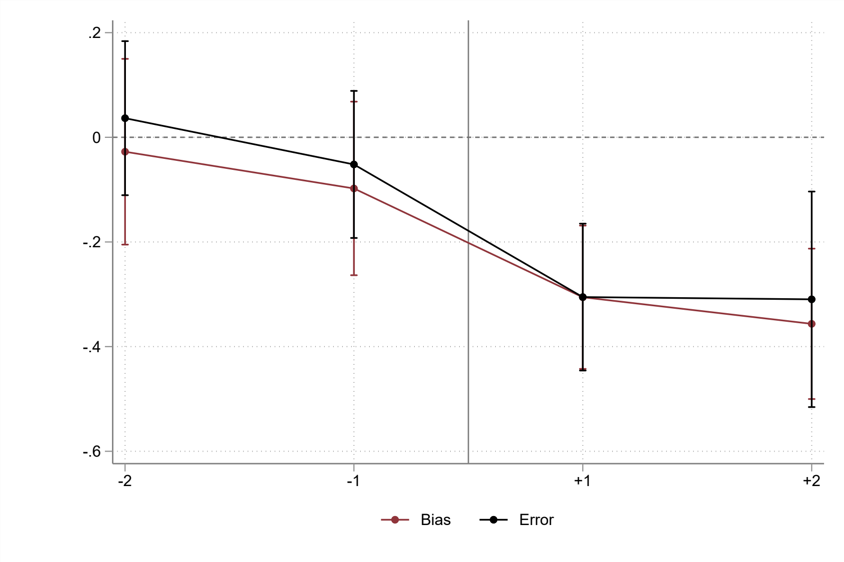
Figure 2: All Extreme Weather Events

Summary Statistics before Filtering

Back

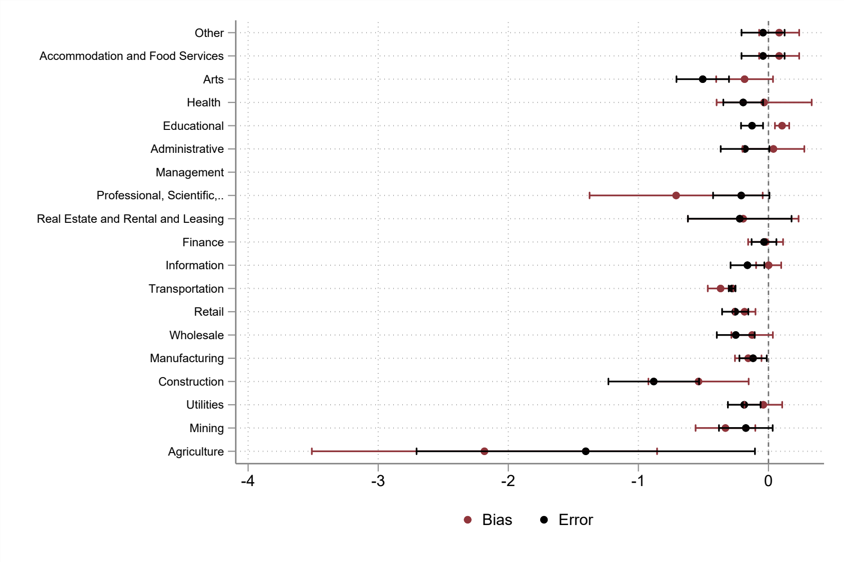
	Mean	p50	SD	Min	Max
forecast bias (%)	0.76	0.04	3.92	-33.60	80.67
forecast error (%)	2.01	0.70	3.72	0.00	80.67
companies followed	17.17	16.00	7.53	1.00	80.00
firm experience	3.33	2.00	3.40	0.00	20.00
general experience	7.09	6.00	4.96	0.00	21.00
Industries Followed	2.10	2.00	1.33	1.00	11.00
brokerage size	87.32	71.00	58.11	1.00	284.00
firm size	8.26	8.20	1.90	-0.22	14.83
leverage	0.24	0.22	0.22	0.00	3.95
operating inc	0.03	0.03	0.05	-1.79	0.61
market value	1.84	1.23	6.62	0.02	1933.73
stock price	48.55	35.12	59.13	0.53	2970.35
ROA	0.01	0.01	0.06	-3.98	0.68
N	493815				

Yearly - Parallel Trend Back



Yearly by Sector

Back

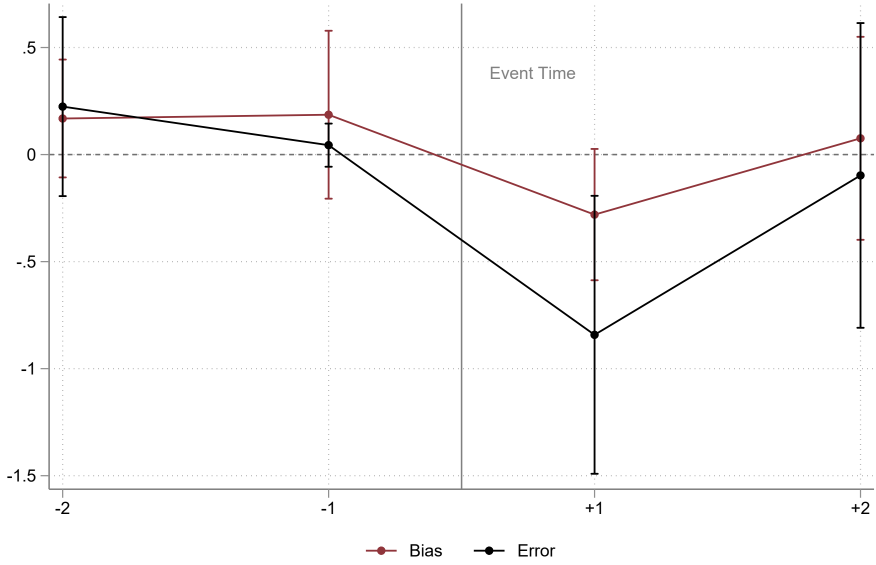


Belief Diffusion Back

- We saw high-performance analysts becoming more pessimistic after a weather shock.
- Does this effect diffuse?
- I define treated firms as firms where a high-performance analyst experiences a weather shock, while in the control firms all analysts have never experienced a salient weather event.
- My dependent variables are firms' average bias and error averaged over low-performance analysts.
- No statistically significant difference is found for the average forecast error and bias of low-performance analysts between treated and control firms.

Results: Belief Diffusion

Back



Results Distraction Hypothesis Back

	Institutional Owner				Relative Importance				Brokerage Firms				Forecast Frequencies
	(1) Bias	(2) Error	(3) Bias	(4) Error	(1) Bias	(2) Error	(3) Bias	(4) Error	(1) Bias	(2) Error	(3) Bias	(4) Error	(1) log(n forecast)
treat*post	-0.218*	-0.330***	-0.0972***	-0.144***	-0.187*	-0.288***	-0.0834***	-0.120*	-0.0756	-0.159**	-0.130***	-0.177***	-0.0445
	(0.121)	(0.0828)	(0.0306)	(0.0519)	(0.106)	(0.0351)	(0.0273)	(0.0601)	(0.129)	(0.0772)	(0.0244)	(0.0431)	(0.0292)
Group	High	High	Low	Low	High	High	Low	Low	Small	Small	Large	Large	-
FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.924	0.943	0.925	0.917	0.903	0.899	0.932	0.927	0.940	0.940	0.920	0.914	0.746
N	7449	7449	41113	41113	19214	19214	29313	29313	11808	11808	36829	36829	48718

Analysts' Coverage

Back

Panel A	All Analysts			
	(1)	(2)	(3)	(4)
	N. of Firms Forecasted	Av. ESG Score	Av. Transition Risk	Av. Physical Risk
treat*post	-0.321	-0.105	-653.0*	-0.189
	(0.363)	(0.389)	(339.2)	(0.217)
R^2	0.705	0.778	0.734	0.663
N	25690	13165	24554	24670

Panel B	Low Performance Analysts			
	(1)	(2)	(3)	(4)
	N. of Firms Forecasted	Av. ESG Score	Av. Transition Risk	Av. Physical Risk
treat*post	-0.483	0.0588	-835.4**	-0.0760
	(0.467)	(0.362)	(339.3)	(0.231)
R^2	0.714	0.783	0.735	0.656
N	19685	9797	18674	18780

Panel C	High Performance Analysts			
	(1)	(2)	(3)	(4)
	N. of Firms Forecasted	Av. ESG Score	Av. Transition Risk	Av. Physical Risk
treat*post	-0.148	-0.474	-349.1	-0.437
	(0.500)	(0.709)	(678.1)	(0.497)
R^2	0.808	0.888	0.823	0.831
N	5853	3225	5721	5730

Analysts' Questions during Earnings Calls Back

	(1) Climate-Related Questions	(2) Physical Risks	(3) Regulatory Risks	(4) Climate Transition Opportunity
Treat	0.0488	0.0492	-0.0222*	0.0228*
	(0.0656)	(0.0650)	(0.0131)	(0.0128)
Analyst	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Earnings Call	Yes	Yes	Yes	Yes
R^2	0.772	0.768	0.760	0.790
N	1176103	1176103	1176103	1176103

Results: Decompose for forecast horizons Back

Forecast Horizons Decomposition

	Forecast Bias					Forecast Error					LTG
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)
	1-Year	2-Year	3-Year	4-Year	5-Year	1-Year	2-Year	3-Year	4-Year	5-Year	LTG
treat*post	-0.0775**	-0.251***	-0.196	-0.164	0.414	-0.276***	-0.241***	-0.180**	0.188	1.269*	-0.877***
	(0.0320)	(0.0410)	(0.124)	(0.106)	(0.486)	(0.0244)	(0.0571)	(0.0740)	(0.137)	(0.582)	(0.290)
Analyst	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.681	0.721	0.863	0.924	0.904	0.673	0.726	0.836	0.932	0.846	0.873
N	24401	20176	3242	657	260	24401	20176	3242	657	260	2173

Results: Multiple Shocks

Back

Multiple Shocks - Experiencing a 2nd Shock

	All Analysts		High Performance		Low Performance	
	(1)	(2)	(3)	(4)	(5)	(6)
	Bias	Error	Bias	Error	Bias	Error
treat*post	-0.155***	-0.235***	-0.0277	-0.143***	-0.214***	-0.255***
	(0.0340)	(0.0575)	(0.0428)	(0.0283)	(0.0339)	(0.0654)
Analyst*Horizon FE	Y	Y	Y	Y	Y	Y
Year*Horizon FE	Y	Y	Y	Y	Y	Y
Firm*Horizon FE	Y	Y	Y	Y	Y	Y
R^2	0.707	0.721	0.805	0.796	0.726	0.752
N	69457	69457	15546	15546	53800	53800

Results Robustness: excluding NY

Back

Dependent Variable:	Forecast Bias				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.199***	-0.213***	-0.209***	-0.0551	-0.0550
	(0.0579)	(0.0627)	(0.0633)	(0.0669)	(0.0709)
R^2	0.723	0.729	0.734	0.914	0.925
N	37319	34596	34596	34593	34569
Dependent Variable:	**Forecast Error**				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.290***	-0.303***	-0.304***	-0.266***	-0.253***
	(0.0503)	(0.0547)	(0.0573)	(0.0325)	(0.0390)
Controls	No	Yes	Yes	Yes	Yes
Analyst, Year and Firm FE	Yes	Yes	Yes	Yes	Yes
Brokerage FE	No	No	Yes	Yes	Yes
Firm*Time FE	No	No	No	Yes	Yes
Group interacted FE	No	No	No	No	Yes
R^2	0.726	0.731	0.737	0.909	0.921
N	37319	34596	34596	34593	34569

Results Robustness: cluster SE at brokerage level Back

Dependent Variable:	Forecast Bias				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.136***	-0.149***	-0.149***	-0.107***	-0.118***
	(0.0355)	(0.0363)	(0.0359)	(0.0362)	(0.0397)
R^2	0.752	0.753	0.759	0.913	0.923
N	52992	48736	48736	48726	48697
Dependent Variable:	Forecast Error				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.229***	-0.215***	-0.211***	-0.179***	-0.175***
	(0.0317)	(0.0317)	(0.0317)	(0.0309)	(0.0337)
Controls	No	Yes	Yes	Yes	Yes
Analyst, Year and Firm FE	Yes	Yes	Yes	Yes	Yes
Brokerage FE	No	No	Yes	Yes	Yes
Firm*Time FE	No	No	No	Yes	Yes
Group interacted FE	No	No	No	No	Yes
R^2	0.754	0.755	0.760	0.910	0.920
Firm*Time FE	52992	48736	48736	48726	48697

Results Robustness: Placebo terrorist Back

Analysts:	All Sample		High Performance Analysts						Low Performance Analysts					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Bias	Error	Bias	Error	Bias	Error	Bias	Error	Bias	Error	Bias	Error	Bias	Error
treat*post	-0.228*	-0.300***	-0.263*	-0.494	-0.00454	-0.0190	-0.356	-0.665*	-0.193	-0.176**	-0.263**	-0.143	-0.127	-0.205***
	(0.117)	(0.0919)	(0.114)	(0.280)	(0.121)	(0.0228)	(0.229)	(0.296)	(0.155)	(0.0720)	(0.118)	(0.121)	(0.180)	(0.0608)
Climate Sensitive Sector	All	All	All	All	High	High	Low	Low	All	All	High	High	Low	Low
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.948	0.958	0.959	0.962	0.882	0.917	0.959	0.961	0.941	0.954	0.951	0.959	0.889	0.897
N	1244	1244	314	314	78	78	236	236	770	770	382	382	388	388

Results Robustness: Analysts' distance to the event Back

	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error
treat*post	-0.408***	-0.335***	-0.0794**	-0.210***	-0.0418	-0.159***
	(0.0702)	(0.0785)	(0.0321)	(0.0219)	(0.0485)	(0.0383)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes
Distance event	$\leq$ 50	$\leq$ 50	100-200	100-200	200-300	200-300
R^2	0.741	0.745	0.626	0.647	0.592	0.644
N	39375	39375	156944	156944	209421	209421

Results Robustness: Garcia and Norli Index Back

Firm business location	= shock's state		≠ shock's state		high disperse		low disperse	
	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error	(7) Bias	(8) Error
treat*post	-0.140***	-0.164***	-0.130***	-0.251***	-0.107**	-0.245***	-0.147***	-0.199***
	(0.0303)	(0.0483)	(0.0214)	(0.0708)	(0.0502)	(0.0299)	(0.0375)	(0.0460)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst, Year and Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.837	0.827	0.762	0.771	0.792	0.817	0.758	0.763
N	21219	21219	27472	27472	16602	16602	27510	27510

Results Robustness: NETS Establishments Back

Establishment	NETS > 100 miles		NETS < 100 miles		drop if NETS < 100 miles	
	(1)	(2)	(3)	(4)	(5)	(6)
	Bias	Error	Bias	Error	Bias	Error
treat*post	-0.0701	-0.288***	-0.170**	0.141	-0.111**	-0.224***
	(0.114)	(0.0442)	(0.0722)	(0.147)	(0.0470)	(0.0207)
Controls	Y	Y	Y	Y	Y	Y
FE	Y	Y	Y	Y	Y	Y
R^2	0.913	0.912	0.911	0.886	0.925	0.924
N	9954	9954	4850	4850	43868	43868

Results Robustness: Quarterly Back

	(1) EPS forecast	(2) EPS forecast	(3) Bias	(4) Bias	(5) Error	(6) Error
treat	-0.114	-0.0397	-0.0403	-0.0129	-0.0777	-0.00764
	(0.124)	(0.119)	(0.0852)	(0.123)	(0.0804)	(0.116)
post	0.0823***	-0.0317	0.0394	-0.0702	0.0149	-0.0637*
	(0.0217)	(0.0321)	(0.0396)	(0.0487)	(0.0383)	(0.0350)
treat*post	-0.0891***	-0.00737	-0.151**	-0.0606	-0.149**	-0.104*
	(0.0320)	(0.0457)	(0.0669)	(0.113)	(0.0710)	(0.0601)
Controls	Y	Y	Y	Y	Y	Y
Shock ID*Horizon FE	Y	Y	Y	Y	Y	Y
Sample	All	Same Firm	All	Same Firm	All	Same Firm
R^2	0.270	0.212	0.328	0.387	0.260	0.350
N	31636	8796	31636	8796	31636	8796