What Drives Beliefs about Climate Risks?
Evidence from Financial Analysts

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Outline

- Objective of the Paper
- Related literature
- Model of Climate Beliefs
- Data & Descriptive Statistics
- Methodology
- Results
- Robustness
- Conclusions

Motivation

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

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However, we lack an understanding of belief formation about climate risks.

Research Questions

- How are beliefs about climate risks formed?
- How do experiences of weather shocks affect climate beliefs?
- What are the network effects of these beliefs?

Contribution

1. Use the **Experience-Based Learning (EBL)** model in the context of climate beliefs (Malmendier & Nagel 2011)
2. Construct a **novel dataset** with localized analysts and natural disasters
   2,816 equity analysts in 29 different US states covering 2,196,138 earnings forecasts for 6,846 firms over 1999-2020
3. Shed light on **how experiences affects** analysts' climate beliefs and thus earnings forecasts
   Analysts are information producers for investors (Mikhail et al. 2007)
4. Provide evidence of the **underlying channels** that drive market participants' reaction to climate-related events
   Two possible channels: **information** or **heuristics**

Preliminary Findings

1. Using the **EBL model**, I show that experiences of weather shocks are an important determinant of climate beliefs.

2. I document how experiences of weather shocks lead to different climate beliefs and hence different earnings forecasts.
    - The treated analysts become more pessimistic of 0.16 p.p. and with a lower forecast error of 0.24 p.p. compared to the control group.
    - Analysts with ex-ante high performance become pessimistic only for firms with high physical risks, while other analysts become pessimistic for all firms.
    - High (low) performance analysts are affected by events with high economic (health-related) damages.
    - The findings for high (low) performance analysts reconcile by the information channel (heuristic channel).

3. Do not find any evidence of belief diffusion across analysts.

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)
- **Analysts**: 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)
- **Climate events (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).

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:

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

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

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3. Only weather events experienced since they started working as analysts are important for climate beliefs.

Hypotheses on belief formation

Other Studies

Weather shocks can

1. provide **new information** to analysts
   - → may **take time** to be incorporated into forecasts, but it is **long-lasting**
   - → weather events with large economic damages should provide more information about the future economic costs of climate change.

2. affect analysts' **heuristics**
   - → may **rapidly** affect analysts' forecasts, but it **dissipates** after a couple of months
   - → **Representativeness Heuristic**: firms/areas with higher climate risks should present larger changes in beliefs.
   - → **Availability heuristic**: overestimation of firms' climate risk, regardless of their climate exposure.

Hypotheses on belief diffusion

This study allows us to investigate if climate beliefs diffuse among individuals.

- → All-Star Analyst (ASA) update their forecasts after experiencing a weather shock.
- → After an ASA updates her beliefs and forecasts, other analysts will herd and consequently update their forecasts for treated firms (i.e. firms for which the treated ASA issues forecasts).
- → Forecasts revisions are driven by pure herding if analysts update their forecasts only for treated firms. In contrast, belief diffusion implies that analysts update forecasts for untreated firms with similar climate risks as the treated firm.

Data

- **IBES forecasts**
  - → Annual, Quarterly, Long Term EPS
- **Analysts' location**
  - → Use the phone number to retrieve analysts' location and manually checked using BrokerCheck (FINRA)
- **Climate events**
  - → Storm Event Database, National Oceanic and Atmospheric Administration (NOAA)
  - → *Climate Beliefs:* Google Trends for "Climate Change" from 2004 to 2020
  - → *Climate News:* Sentometrics (on global warmings) from Ardia et al. (2020) The Wall Street Journal (WSJ) climate news indices created by Engle et al. (2020)
- **Firms Information**
  - → CRSP/Compustat WRDS merge
  - → Trucost Climate Change Physical Risk Dataset

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).

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

Table 1: Merged Extreme Weather Events

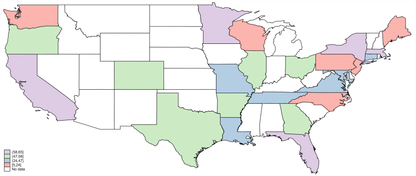


Figure 1: All Extreme Weather Events

Descriptive Statistics: Natural Disasters & Beliefs

- **Google Trends**

→ Follow Stroebel et al. (2022) to see whether my weather shock measures affect local climate change attention or beliefs, as measured by Google searches for the term "climate change"

- **Climate News Indexes**

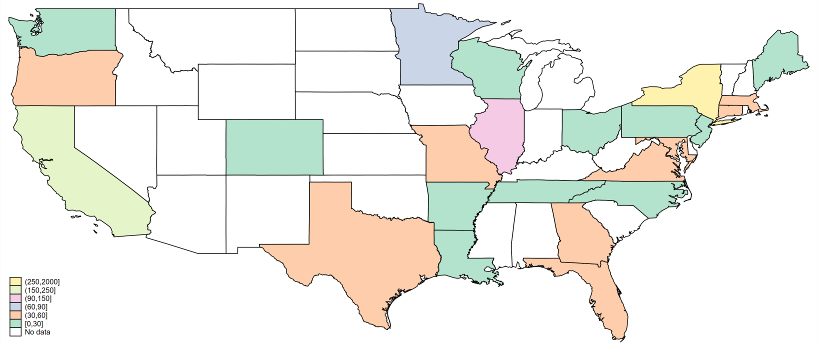
→ Sentometrics (on global warmings) from Ardia et al. (2020)

→ The Wall Street Journal (WSJ) climate news indices created by Engle et al. (2020)

	(1) Google Search	(2) Google Search	(3) Google Search	(4) Sentometrics	(5) Sentometrics	(6) Sentometrics	(7) WSJ	(8) WSJ	(9) WSJ
Fatalities	0.0955*			0.0150			-0.00475		
	(0.0496)			(0.0510)			(0.0517)		
Injuries		0.00942			-0.0182			-0.0225	
		(0.0868)			(0.0518)			(0.0508)	
1 bil. $ damages			0.0860**			-0.0727			-0.119*
			(0.0327)			(0.0687)			(0.0683)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	NO	NO	NO	NO	NO	NO
R^2	0.825	0.825	0.825	0.0000188	0.0000268	0.000244	0.0402	0.0402	0.0409
N	5028	5028	5028	4580	4580	4580	4484	4484	4484

Descriptive Statistics: Analysts Location

Figure 2: 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. The state of New York has the highest number of analysts with 2,212 individuals, followed by California with 245 analysts, 112 analysts in Illinois, and 89 in Massachusetts.

Empirical Strategy

- **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 an *analyst i* that issued a forecast for a *firm f* in the same *sector s* and for the same *forecast period fpe*
- **Event window**: [-2,2] 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* time period, *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)

Summary Statistics Overall

	Mean	p50	SD	Min	Max
forecast bias (%)	0.82	0.05	4.11	-26.15	60.75
forecast error (%)	2.13	0.74	3.88	0.00	60.75
companies followed	8.91	8.00	4.96	1.00	33.00
firm experience	1.24	0.00	2.13	0.00	20.00
general experience	3.27	2.00	3.93	0.00	20.00
industries followed	1.57	1.00	0.88	1.00	6.00
brokerage size	74.57	60.00	54.91	1.00	284.00
firm size	7.91	7.85	1.90	1.43	14.78
leverage	0.23	0.19	0.22	0.00	3.95
operating inc	0.02	0.03	0.05	-1.79	0.61
market value	1.97	1.29	2.25	0.02	76.38
stock price	43.38	31.81	50.36	0.63	2027.09
ROA	0.00	0.01	0.08	-3.98	0.68
N	118997				

Yearly - Aggregate Results

Parallel Trend

Dependent Variable:	Forecast Error				
	(1)	(2)	(3)	(4)	(5)
Treat*time	-0.237***	-0.234***	-0.239***	-0.0122	-0.241***
	(0.0202)	(0.0192)	(0.0204)	(0.0472)	(0.0242)
Controls	No	Yes	Yes	Yes	Yes
Analyst, Year, Horizon and Firm FE	Yes	Yes	Yes	Yes	Yes
Brokerage FE	No	No	Yes	Yes	Yes
Firm-Time FE	No	No	No	Yes	No
Group interacted FE	No	No	No	No	Yes
R^2	0.703	0.708	0.712	0.752	0.889
N	99781	92191	92188	72234	79263

Dependent Variable:	Forecast Bias				
	(1)	(2)	(3)	(4)	(5)
Treat*time	-0.157***	-0.134***	-0.131***	-0.0333	-0.158***
	(0.0318)	(0.0261)	(0.0260)	(0.0491)	(0.0233)
Controls	No	Yes	Yes	Yes	Yes
Analyst, Year, Horizon and Firm FE	Yes	Yes	Yes	Yes	Yes
Brokerage FE	No	No	Yes	Yes	Yes
Firm-Time FE	No	No	No	Yes	No
Group interacted FE	No	No	No	No	Yes
R^2	0.678	0.687	0.693	0.724	0.893
N	99781	92191	92188	72234	79263

Results (1): Analysts' Characteristics

1. Experience
2. Ex-ante performance
3. Ex-ante optimism/pessimism
4. Live in climate-sensitive states
5. County's political ideology
6. State's climate beliefs

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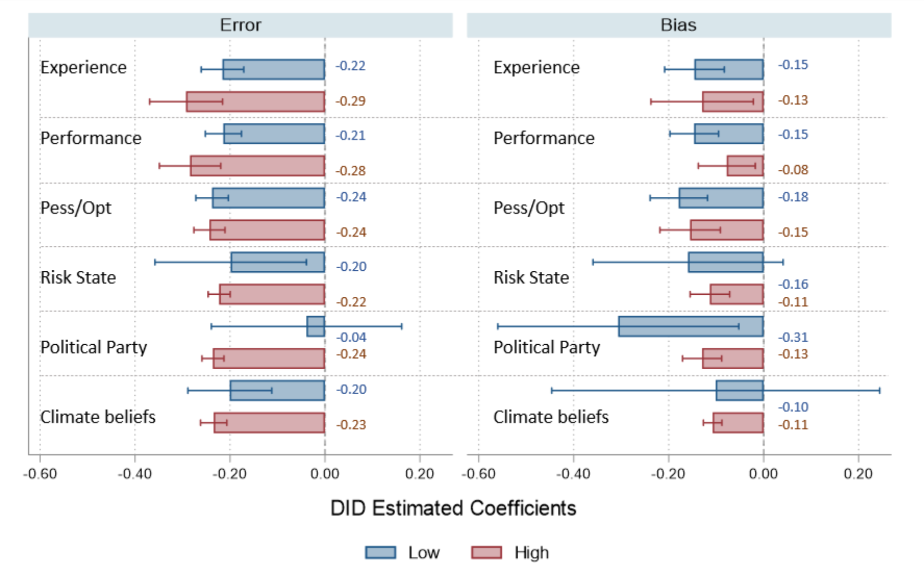


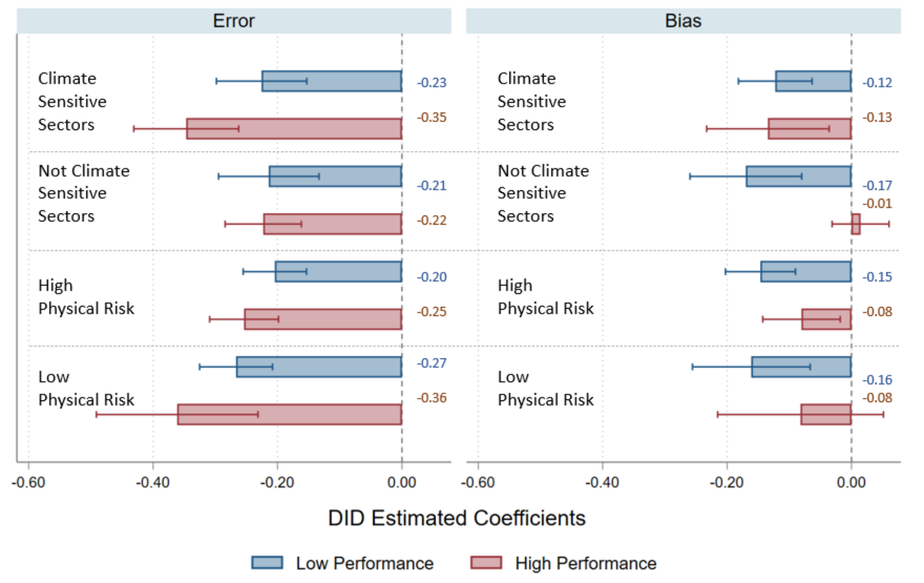
Interpretation

- The results highlight an overall **homogeneous effect** on analysts' forecast bias and error.
- The largest difference between subgroups is the one between analysts living in Democratic and Republican counties as well as high and low-performance analysts, even if both are not statistically significant.
- I focus on ex-ante high-performance analysts.

Exploit Firms' Physical Climate Risks

- Repeat the analysis for high and low-performance analysts forecasting firms with different climate exposures.
- To proxy for firms' climate risks, I use firms' Trucost forecasted physical risk (index ranging from 1 to 100) and climate-sensitive sectors (following Addoum et al., 2019).

Results: Firms' Climate risks



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 exploit the **shock 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

Analysts' Performance and Shock Information

	High performance analyst				Low performance analyst			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bias	Bias	Error	Error	Bias	Bias	Error	Error
Treat*Time	-0.108**	0.0327	-0.231***	-0.211***	-0.190***	-0.116*	-0.249***	-0.0796*
	(0.0427)	(0.140)	(0.0268)	(0.0659)	(0.0539)	(0.0658)	(0.0353)	(0.0426)
Firm physical risks as the experienced shock	High	Low	High	Low	High	Low	High	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	0.831	0.849	0.831	0.884	0.753	0.782	0.758	0.789
N	12425	3954	12425	3954	42065	11536	42065	11536

Results: Type of shock's damage

Analysts' Performance and Shock Characteristics

	High performance analyst				Low performance analyst			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bias	Bias	Error	Error	Bias	Bias	Error	Error
Treat*time	-0.0472**	-0.346***	-0.258***	-0.750	-0.125***	-0.276	-0.229***	-0.128
	(0.0191)	(0.125)	(0.0217)	(0.550)	(0.0169)	(0.197)	(0.0217)	(0.153)
Shock Damage	Health	Economic	Health	Economic	Health	Economic	Health	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	0.834	0.846	0.845	0.849	0.763	0.764	0.756	0.795
N	12244	4028	12244	4028	40380	13474	40380	13474

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 not only change their beliefs about physical risks but also about transition risks: believing that stricter regulation policies will be implemented.

  - If this hypothesis is true, then I expect firms with higher transition risks to be more penalized than firms with lower transition risks by treated analysts.

Results: physical risks or/and transition risks

	High performance analyst				Low performance analyst			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bias	Error	Bias	Error	Bias	Error	Bias	Error
Treat*Time	-0.0204	-0.251***	-0.243***	-0.461***	-0.163***	-0.212***	-0.0317	-0.221***
	(0.0402)	(0.0408)	(0.0751)	(0.0687)	(0.0307)	(0.0262)	(0.0415)	(0.0429)
Transition Risk	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
R^2	0.798	0.819	0.869	0.860	0.718	0.738	0.778	0.765
N	18245	18245	3541	3541	59417	59417	10171	10171

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?
    1. Look if analysts change their overall coverage based on the Physical, Transition, and ESG scores in the 2 years after the extreme event compared to the control group.
- **Earnings Calls:** Do treated analysts ask more questions about climate risks?
- **Consensus forecasts, Earnings Surprise and Stock Prices**

Analysts' Coverage

Panel A	All Analysts			
	(1)	(2)	(3)	(4)
	N. of Firms Forecasted	Av. ESG Score	Av. Transition Risk	Av. Physical Risk
treat*time	-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**			
	(5)	(6)	(7)	(8)
	N. of Firms Forecasted	Av. ESG Score	Av. Transition Risk	Av. Physical Risk
treat*time	-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**			
	(9)	(10)	(11)	(12)
	N. of Firms Forecasted	Av. ESG Score	Av. Transition Risk	Av. Physical Risk
treat*time	-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

	(1) Climate-Related Questions	(2) Physical Risks	(3) Regulatory Risks	(4) Climate 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

Temporal Dimension

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
- Multiple Shocks

Results: Decompose for forecast horizons

Forecast Horizons Decomposition

	Forecast Error					Forecast Bias					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	-0.338***	-0.199***	-0.181***	0.0530	0.441**	-0.0639**	-0.254***	-0.0535	-0.178	-0.0175	-0.877***
	(0.0353)	(0.0424)	(0.0571)	(0.0963)	(0.179)	(0.0243)	(0.0518)	(0.0650)	(0.115)	(0.202)	(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	0.547	0.628	0.774	0.908	0.898	0.518	0.594	0.804	0.935	0.931	0.873
N	41699	37713	9896	1920	963	41699	37713	9896	1920	963	2173

Results: Multiple Shocks

Multiple Shocks - Experiencing a 2nd Shock

	All Analysts		High Performance		Low Performance	
	(1)	(2)	(3)	(4)	(5)	(6)
	Error	Bias	Error	Bias	Error	Bias
Treat*Time	-0.454***	-0.265**	-0.701***	-0.273	-0.395***	-0.269***
	(0.0621)	(0.103)	(0.215)	(0.279)	(0.0912)	(0.0905)
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	0.879	0.931	0.907	0.926	0.886	0.944
N	3068	3068	604	604	2229	2229

Belief Diffusion

- We saw that high-performance analysts become 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

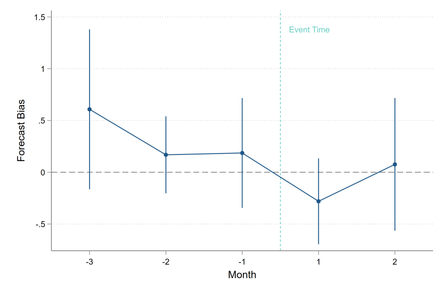


Figure 3: BIAS

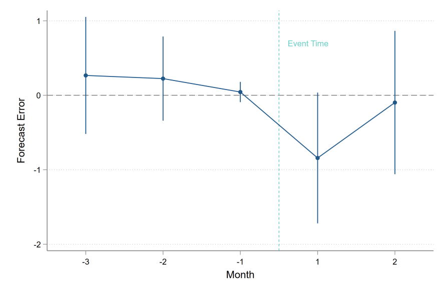


Figure 4: ERROR

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.*)
- No evidence is found of belief diffusion.

Conclusion

Thank you!