What Drives Beliefs about Climate Risks? Evidence from Financial Analysts

Matilde Faralli *(Imperial College London)*
Contact me: m.faralli20@imperial.ac.uk
@MatildeFaralli matildefaralli.github.io

Imperial College Business School

1 Motivation & Research Questions

In the US, **the total costs of natural disasters** are approximately 2.2 trillion US dollars from 1980 to 2022. Given the current trajectory of global warming, these costs are expected to rise. Recent studies document market participants' reactions after experiencing **climate-related events**. For example, Choi, Gao and Jiang (2020) document that investors sell stocks of firms with high carbon footprints during months with **atypically high temperatures**. However, we lack an understanding of **how beliefs about climate physical risks** (risks of **weather events**) are formed.

This paper investigates the following questions:

1. How are **beliefs about climate physical risks** formed?
2. How do **experiences of weather shocks** affect **climate beliefs**?
3. What are the network effects of these **beliefs**?

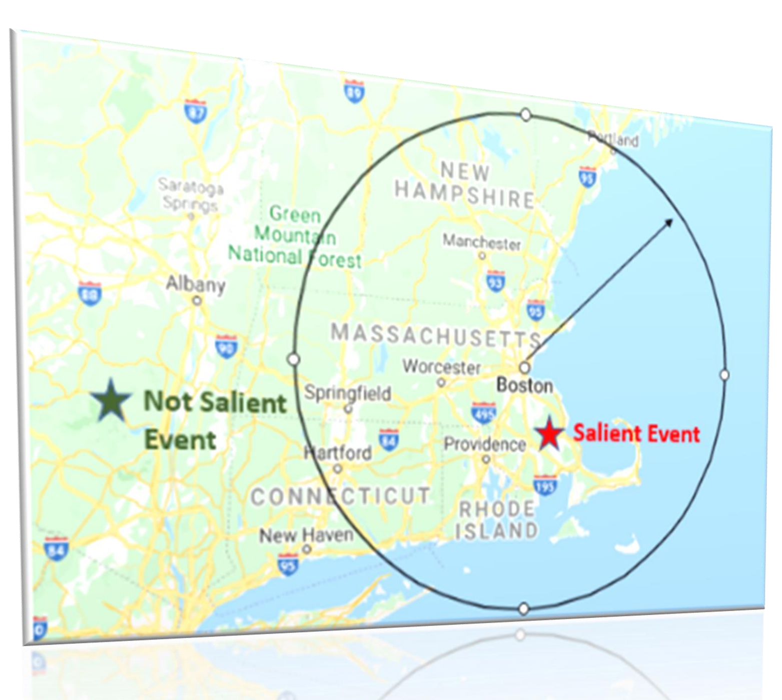
2 Contribution

1. Use the **Experience-Based Learning model** in the context of **climate beliefs** (Malmendier and Nagel, 2011).
2. Shed light on how **experiences of weather events** affect **analysts' climate beliefs** and thus **earnings forecasts.**
3. Construct a **novel dataset** with localized analysts and natural disasters.
4. Provide evidence of the **potential mechanisms** that drive market participants' **reactions** after experiencing **climate-related events.**

3 Data & Empirical Strategy

The **dataset** is constructed using: (i) **Weather shocks** are natural disasters that caused either more than 10 fatalities, more than 100 injuries, or more than 1 billion dollars in total economic damages [NOAA] (ii) Analysts' forecasts and analysts' office location [IBES and Refinitiv], (iii) firms' fundamentals and headquarters' location [Compustat], (iv) firms' climate risks [Trucost].

I **cannot directly observe climate beliefs**, but I use variation of analysts' earnings forecasts after **a weather shock** to **extract beliefs**. Analysts' forecasts can be defined as the interaction of analysts' beliefs and the information set (i.e., all available data). If the information set does not change, then a change in forecasts can only be driven by a change in beliefs.



Dependent Variables: Forecast Error & Bias

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

Where i is analyst, t is period, f is firm, F is the forecasted EPS for a firm, Y is the actual EPS, and P is the stock price.

Staggered difference-in-differences:

$$Y_{ifct} = \beta DD_{ct} + FE + \theta X_{it} + \epsilon_{icft}$$

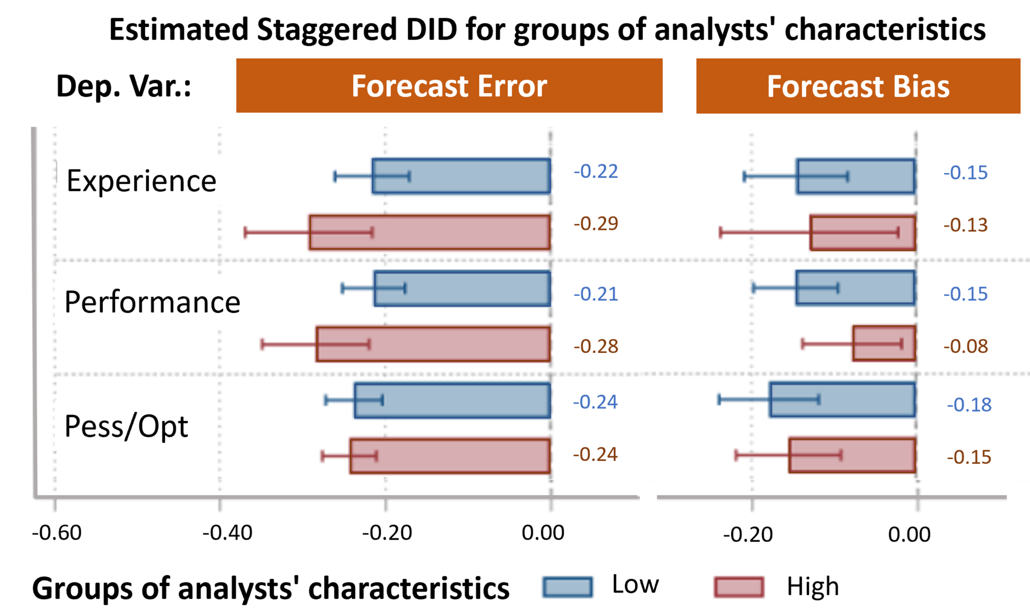
Fixed effects (FE) included are analyst, year, firm and forecast horizon.

When multiple forecasts are issued, I only take one forecasts per month. The event window is 2 months before and after the event.

The treated group is composed of analysts that are within 100 miles from the shock and forecasted firms are more than 100 miles distant from the event.

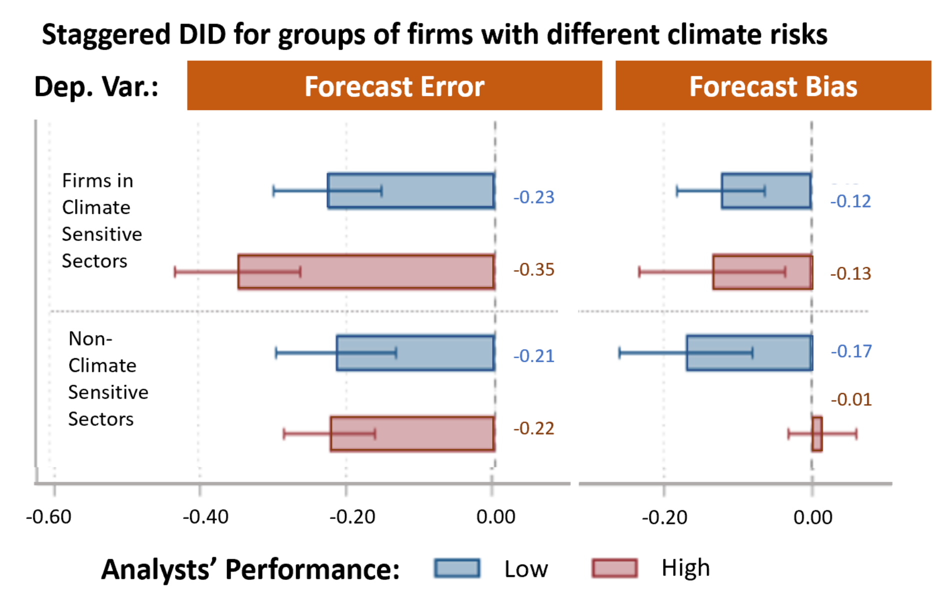
The control group is composed of never-treated analysts that issued a forecast for firms in the same sector as the firm forecasted by treated analysts.

4 Empirical Results



- After a **weather shock**, treated analysts present a lower forecast bias (more pessimistic) of 0.16 p.p. and a lower forecast error (more accurate) of 0.24 p.p. compared to the control group.
- Looking at groups of **analysts with different characteristics** (such as experience, performance, etc.), I observe an **overall homogeneous effect on analysts' forecast bias and error** after experiencing a **weather shock**.
- High and low-performance analysts present the largest difference between subgroups, even if not statistically significant.

4.a *Are analysts becoming pessimistic about all firms or firms with high physical risk?*



- Henceforth, I focus on high and low-performance analysts.
- Low-performance analysts become **pessimistic for all firms**, irrespective of their climate risks.
- High-performance analysts become **pessimistic only for stocks with high climate risks**.

4.b *What are the mechanisms?*

	Dep. Var.: Forecast Bias							
Analysts Group:	High Performance		Low Performance		High Performance		Low Performance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimated DID	-0.0472**	-0.346***	-0.125***	-0.276	-0.108**	0.0327	-0.190***	-0.116*
	(0.0191)	(0.125)	(0.0169)	(0.197)	(0.0427)	(0.140)	(0.0539)	(0.0658)
Weather Shock damages:	Heath	Econ	Heath	Econ	-	-	-	-
Weather Shock and firm risk:	-	-	-	-	Same	Different	Same	Different

Two possible mechanisms can drive the results:

- **Heuristic:** they overestimate the overall risk of weather events (*availability*), or they overestimate the risk of firms with high climate risks (*representativeness*);
- **Information:** they extract information from the event;

Weather shock's characteristics can help to disentangle these two channels.

- ***Weather shock damages:*** are analysts more pessimistic after experiencing a shock that caused remarkable economic damages (more than 1 billion dollars) or health-related damages (more than 10 fatalities or 100 injuries)?
- ***Weather shock as firms' physical risks:*** are analysts who experience, for example, a hurricane more pessimistic for firms with high hurricane risks or firms with high composite physical risks?

The results suggest a *heuristic channel* for low-performance analysts and an *information channel* for high-performance analysts.

- High-performance (low-performance) analysts are largely affected by economic damages (health damages) and they become pessimistic for firms with the same risks as the weather shock experienced (all firms).

5 Additional Results

1. **Network effects:** using high-performance analysts as a proxy of All-Star analysts, I investigate if **climate beliefs** diffuse (i.e., if analysts that did not **experience any weather events** herd from treated analysts). No statistically significant effect is found.
2. **Forecast Horizons:** the decrease in forecast error and bias, **after a weather shock**, is found for short-term forecasts (1 to 3 years ahead) as well as the Long-Term Growth rate.
3. **Transition Risks:** analysts, after a **weather event**, may believe that stricter regulation policies will be implemented. The results indicate that high-performance (low-performance) analysts decrease their forecast bias only for firms with low (high) transition risks.
4. **Firms' Coverage and Earnings Calls' Questions:** analysts, after **experiencing a weather shock**, cover fewer firms with high transition risks and ask fewer questions about climate transition risks.