What Drives Beliefs about Climate Risks? Evidence from Financial Analysts

Matilde Faralli*

January 19, 2024

Abstract

This paper studies how exposure to extreme weather events affects financial forecasts. Using a unique dataset that matches natural disasters with the location of equity analysts across 24 US states over 2000-2020, I apply a staggered differences-in-differences methodology to examine shifts in the earnings forecasts of analysts exposed to weather shocks. I find that analysts become more accurate after experiencing an extreme weather event. I also document that the post-exposure effect on forecasting accuracy is more pronounced for experienced analysts and for firms with high physical climate risk which are exposed to events similar to those experienced by the analysts.

Keywords: Belief Formation, Climate Risks, Physical Risks, Analysts Forecasts.

JEL Codes: G1, G2, G3, Q5, Q54

*Ph.D. candidate at Imperial College Business School. I thank my supervisor Marcin Kacperczyk for invaluable feedback and guidance. I also thank Ulrike Malmendier, Ugo Panizza, Claudia Custodio, Luigi Falasconi, and seminar participants at Imperial College Business School, the NSEF Workshop, the Centre for Climate Finance & Investment (CFFI), Berkeley Haas, the European Sustainable Finance PhD Workshop 2023, Summer School in Finance and Product Markets (USI Lugano), EEA 2023, UN PRI and at the Norges Bank Research Workshop for their comments. All errors are mine.

1 Introduction

Modeling beliefs about climate risk is a challenging task that involves assessing the interplay between physical risks, such as natural disasters, and transition risks associated with carbon reduction policies. This paper focuses on how agents form beliefs about climate physical risks (henceforth climate beliefs) by studying how exposure to extreme weather events affects earnings forecasts issued by equity analysts.[1] This is an ideal setting for studying the formation of beliefs about climate risk because analysts are important information producers (Mikhail et al., 2007) who are required to issue frequent earnings forecasts on the stocks they follow.

I find that exposure to extreme weather events leads to more accurate earnings forecasts and that this effect is more pronounced for experienced analysts and firms with high physical climate risk.

To study the formation of climate beliefs, I match data on the location of equity analysts spanning 24 US states with information on extreme weather events over 20 years. I then split the sample of analysts into two groups: treated analysts (this group consists of analysts who are located within 100 miles from the weather event) and control analysts (this group consists of analysts located farther than 100 miles from the weather event), both forecasting firms that more are 100 miles distant from the weather event. Using a staggered differences-in-differences estimation, I assess how exposure to an extreme weather event affects earnings forecasts. The underlying assumption is that—besides capturing perceptions of firms' fu-

[1] In the US the total costs of natural disasters from 1980 to 2022 are approximately 2.2 trillion US dollars (NOAA, 2022). This number is however a lower bound because it does not take into account real economic losses. For example, Park et al. (2021) show that higher temperature increases the likelihood of workplace injuries. Hugon and Law (2019) document that unexpected high temperatures decrease firms' sales and increase operating experiences. If supplies are hit by weather shocks, companies experience a decrease in operating performance (Pankratz and Schiller, 2021) and loose sales (Barrot and Sauvagnat, 2016 and Custodio et al., 2021). Additionally, Huang et al. (2018) indicate that firms located in countries with higher risks of weather events suffer from more volatile earnings and cash flows. Nonetheless, sophisticated academics and practitioners perceive physical risks as the most important source of long-term climate risks (Stroebel and Wurgler, 2021).

ture financial performance based on all available public information—earning forecasts also incorporate analysts' non-observable beliefs, including beliefs about climate risks. As I only consider weather shocks that do not have a direct effect on firms' earnings, it is plausible that if a weather shock affects an analyst's forecasts, the change in forecast is driven by a change in the analyst's beliefs.

Note that there are two possible reasons why exposure to an extreme weather event might affect earnings forecasts for firms that are *not* affected by this event. One possible explanation is that the post-exposure change in forecast is due to the acquisition of new insights about the future economic costs of climate change. According to this *information hypothesis*, exposure to extreme weather events has a positive effect on an analyst's ability to forecast firms' climate risks. The alternative explanation is that exposure to an extreme weather event has an emotional impact that affects analysts' risk-taking behavior. According to this *heuristic hypothesis*, exposure to weather events can lead to an overestimation of climate risks without any clear and long-term effect on the performance of earning forecasts.

My finding that exposure to extreme weather events leads to more accurate earnings forecasts is in line with the information hypothesis and the fact that this effect is stronger for firms with high physical climate risk is consistent with the idea that exposure does lead to a reassessment of climate beliefs.

My results are related to the recent but fast-growing literature on the effects of climate events on investors' behavior. Key results include the findings that retail investors sell stocks of firms with high carbon footprints or are more likely to invest in green funds during months with atypically high temperatures or after experiencing a heatwave (Choi et al., 2020 and Anderson and Robinson, 2019). There is also evidence that mutual funds managers change their portfolio allocation across industries after experiencing extreme heat events (Alekseev et al., 2021).[2] I contribute to this literature by providing evidence on the formation of beliefs

[2]Consistently, Huynh and Xia (2021) show that investor overreacts when firms are exposed to natural hazards by depressing the bond and stock prices of the impacted firms.

among information providers.

To study the effect of exposure to weather events I build a comprehensive dataset that matches detailed information about weather events with analysts' characteristics (including their location) and Institutional Brokers Estimate System (IBES) earnings forecasts. I focus on the period 2000-2020 and define salient weather shocks as natural hazards that have at least 100 injured people, 10 fatalities, or $1 billion in economic damages. The resulting dataset includes 1,588,202 earnings forecasts issued by 2,894 equity analysts covering 5,109 firms and 49 extreme weather events located near the analysis included in my sample. The analysts are located in 29 different US states and the firms are distributed across the United States.

I start by documenting that the weather events included in my sample lead to an increase in Google searches about climate change (see Alekseev et al., 2021, for a similar approach).[3] Next, I use a staggered differences-in-difference regression approach to study how weather events occurring near equity analysts affect changes in earnings forecast bias and error. As in Hong and Kacperczyk (2010), I define the forecast bias as the difference between actual and forecasted earnings per share divided by the stock price in the previous period and the forecast error as the absolute value of the forecast bias. While the forecast bias is a measure of analysts' optimism or pessimism, the forecast error captures the accuracy of the forecast.

I classify analysts into two groups: (i) first-time treated and (ii) control group. The group of first-time treated analysis includes all analysts located within 100 miles of an area affected by a salient weather shock. The control group includes both analysts who have never been exposed to climate events (never treated) and analysts who in a given period have not yet been exposed to a weather shock but who will be exposed in the future (yet-to-be-treated).[4]

[3] I also verify that during extreme weather events, there is no statistically significant increase in climate-change related news. This confirms that beliefs are influenced by weather events and not by climate news in general.

[4] My setting implies that never-treated analysts have never experienced a weather shock since they start working as analysts. Unfortunately, I do not have information on the analysts' locations before they enter the sample.

To infer climate beliefs from variations in earnings forecasts, I need to ensure that the selected weather shocks do not have any direct or indirect impact on firms' fundamentals.[5] With this objective in mind, I exclude from my sample earnings forecasts for firms located within 100 miles from the weather event shock and I show that there are no changes in firms' fundamentals during the period surrounding the event. After making these adjustments, I am left with a sample that includes 67,000 earnings forecasts issued by 1,293 analysts located in 24 states and covering 2,923 firms. About 40% of the analysts included in the sample (511) have been exposed to an extreme weather event and are classified as treated for the first-time treated.

My baseline results provide compelling evidence that exposure to weather shocks improves analysts' forecasts in terms of both forecast bias and error. The point estimates indicate a statistically significant reduction in forecast error of 0.07 percentage points (3.2% of the average forecast error) and 0.05 percentage point reduction in the forecast bias (6.2% of the average forecast bias; note, however, that the reduction in forecast bias is not statistically significant at conventional confidence levels).

As mentioned, there are two possible channels—heuristics and information—through which exposure to weather events might affect climate beliefs. To discriminate between these two channels, I match detailed information about firms' climate risk profiles sourced from Trucost with analysts' exposure to specific climate events. Consistent with the information hypothesis, I find that exposure to a specific event increases accuracy for firms that are subject to that specific risk.[6] These findings are consistent with the idea that exposure to the shocks does have an effect on climate beliefs.

To probe further, I explore whether there is heterogeneity across analysis with different levels of experience and I find that my results are driven by experience analysis. Given that

[5] Direct effects include revenue losses from the weather shock and indirect effects are related to the impact of the weather shock on suppliers or competitors.

[6] For instance, I show that analysts who experienced a hurricane are more accurate in predicting the earnings of companies that are subject to hurricane risk vis-à-vis companies subject to wildfire risks.

inexperienced analysts are more likely to be subject to the heuristic channels and experienced analysts may be better able to extract useful information from extreme weather events, this result is also in line with the information channel.

As a final step in discriminating between the heuristic and the information channels, I study the persistence of the exposure effect documented above. The underlying assumption of this test is that the effect of exposure on analysts' heuristics should be short-lived whereas a shock that affects an analyst's ability to process information related to climate risk should have a long-lasting effect. The fact that I find that exposure leads to more accurate forecasts for a period of up to two years provides further support for the information channel.[7]

I conduct a battery of robustness checks and show that my results hold when I exclude analysts based in New York and California and when I exclude firms with establishments near the event. The results are also robust—in fact, they become stronger—to only consider analysts located within a 50-mile radius of extreme weather events.

Summing up, I find that extreme weather events have long-lasting effects on the accuracy of earning forecasts by exposed analysts and that this exposure effect is stronger for more experienced analysts when they forecast earnings for companies that are subject to the type of physical climate risk the analyst has been exposed to. Taken together, these results support the information hypothesis as they show that exposure has an important and lasting effect in improving forecast accuracy for those analysts who, a priori, should be better able to extract complex information about climate risk.

The rest of the paper is organized as follows. Section 2 provides a review of the literature. Sections 3 develop the conceptual framework and present the methodology. Section 4 presents the data. Section 5 discusses the results, and Section 6 concludes.

[7]Note that the results of persistence estimations should be taken with caution because they implicitly assume that no additional information about climate risks is realized in the aftermath of the event. This assumption is less likely to hold when I extend the horizon of my analysis.

2 Related Literature.

There is a fast-growing literature that analyzes how weather events affect financial markets. In this section, I review a subset of studies that focus on analysts' behavior and are thus closely related to my paper.

There is conflicting evidence on how climate shocks affect analysts' forecasts. On the one hand, some studies show that forecast errors tend to be larger and more variable for firms with low market capitalization, low institutional ownership, and less salience (Han et al., 2020), firms with earnings that are sensitive to weather seasonality (Zhang, 2021), and firms located in countries with greater climate risk (Kim et al., 2021). On the other hand, there are studies that find that extreme temperature events do not have any effect on earnings forecasts (Pankratz et al., 2019) or that they only affect forecasts for specific industries (Addoum et al., 2019). One key difference between these studies and my own work is that, while this literature focuses on firm-specific events, I concentrate on analyst-specific exposure.[8]

A paper which is closely related to my work is Cuculiza et al. (2021). These authors find that analysts based in US states with many firms exposed to abnormal temperature risk become more pessimistic and accurate in the aftermath of heatwaves. One key difference between my work and Cuculiza et al. (2021) is that I focus on a wider range of climate events, I also study the role of analysts' experience, and I match the type of climate event with firm-specific physical climate risk. Using a more flexible definition of weather shocks, including events with extreme economic and health-related damages, allows me to match exposure to firm-level information and study whether analysts become more accurate or pessimistic

[8]Papers that study the effect of exposure to climate events also include Bourveau and Law (2020) and Alok et al. (2020). However, Bourveau and Law (2020) only use one-billion-dollar natural hazards (Han et al., 2020 use the same definition) and concentrates on bias by showing that exposure leads to more pessimistic forecast (These studies rely on the definition of Barrot and Sauvagnat (2016) and define extreme natural hazards as "major disasters with total estimated damage above $1 billion 2013 constant dollars that lasted less than 30 days."). Alok et al. (2020), instead, study the behavior of mutual fund managers and not that of analysts.

for all firms (a finding consistent with the *heuristic hypothesis*) or firms with event-specific physical climate risks (a finding that is in line the *information hypothesis*). My results in support of the information hypothesis corroborate previous studies which found that there is increased analyst accuracy for firms with higher climate risk disclosure in their annual report (Wang et al., 2017), for firms with mandatory ESG disclosure (Krueger et al., 2021), after ESG incidents (Derrien et al., 2021), and firms that participate in the Carbon Disclosure Project (Chan, 2022).

My findings show that exposure to extreme climate events increases forecast accuracy for experienced analysts and leads to more pessimistic forecasts for inexperienced analysts, consistent with Kong et al. (2021)'s results that earthquakes lead to a short-term increase in pessimism which is more pronounced among less sophisticated analysts.

A final difference between my paper and existing work on the effect of exposure to climate events is that, while the literature has concentrated on the short-term effects of exposure (for example, Bourveau and Law, 2020), I also study the impact of exposure to climate shocks on the temporal dimension of analysts' earnings forecasts (from one to five years ahead, as well as long-term growth rates).[9][10]

3 Hypotheses Development and Empirical Strategy

I do not observe variations in analysts' climate beliefs, but I can exploit variations in earnings forecasts following a weather shock to proxy for climate beliefs. Analysts' earnings forecasts can be defined as a function of analyst's beliefs, including climate beliefs, and all the available

[9]Similar to studies exploring the effect of transition risks on credit risks, providing evidence that the transformation to a low-carbon economy would differentially impact firms' creditworthiness across various horizons (Blasberg et al., 2021; Kolbel et al., 2020; and Barth et al., 2020).

[10]In parallel work, Reggiani (2022) uses pooled regression to examine post-weather-event pessimism among analysts, concentrating on EPS changes across industries. Despite methodological distinctions, both studies mutually support findings of increased pessimism among analysts for firms with high climate risks. However, my study also contributes by demonstrating an increase in accuracy and identifying the driving factors behind these results.

information in the market.[11] Therefore, if the information set remains constant and firms are not directly or indirectly impacted by the weather shock, any changes in analysts' forecasts can only be attributed to shifts in their beliefs.

To determine how weather shocks impact climate beliefs, I make two primary assumptions. First, weather shocks do not have a direct or indirect impact on the firms. Thus, forecasted firms in the sample must be at a significant distance from the weather event and their fundamentals remain constant around the event period.[12] Second, selected shocks are salient natural hazards and they are perceived as climate change realization by analysts. However, other possible sources of climate change information such as climate news or climate risk maps can shape individuals' climate beliefs. For example, analysts who experience a large number of climate-related news during their lifetime may have a higher posterior belief about climate risks. For the moment, I rely on Andersen et al. (2019) that provides evidence that only first-hand experiences matter for changing beliefs.

Why should analysts change their forecasts if firms are not affected by the event? I propose here two potential explanations: i) the information hypothesis (analysts can extrapolate information about the cost of future climate-related hazards); and ii) the heuristics hypothesis (analysts overestimate the probability of these events happening). It's worth noting that these explanations are not mutually exclusive, but they may work in tandem.

The two hypotheses imply that changes in forecasts are driven by new information about climate risks acquired by experiencing the shock or because a traumatic event could lead to an effect on risk-taking (Bourveau and Law, 2020; Cuculiza et al., 2020), called *information* and *heuristic hypothesis* respectively. While the former may take time to be incorporated and have a permanent effect (under the assumption of no fading memory), the latter rapidly

[11] Formally, analysts' forecasts can be represented as $(belief) * (information)$, where analysts' *beliefs* include climate beliefs as well as beliefs about firms' fundamentals and the economy.

[12] Firms can however be impacted indirectly by their suppliers or competitors. This is a second-order effect. In a perfectly competitive market, a climate shock to a supplier or competitor would be insignificant. In an imperfect market, controlling for industry-fixed effects or concentration indexes should mitigate the issue.

affects analysts' forecasts but may dissipate soon.

To disentangle whether the estimated effect is driven by the *information* or the *heuristic hypothesis*, I exploit firms' climate exposure and shocks' characteristics. Firms' climate exposure allows me to understand if analysts, after a weather shock, are becoming more pessimistic for all firms (*availability heuristic*) or firms with higher levels of climate risks. The latter could be either driven by *representative heuristics* or an *information channel*. The *representative heuristic* implies that an agent, after the news, tends to overestimate the probability of the representative types (Kahneman and Tversky, 1972). Therefore, after a weather shock, I expect treated analysts to abnormally overestimate firms with high climate exposure. Contrarily, if analysts are extracting some information from the experienced weather event, I expect a larger forecast revision for firms that are exposed to physical risks such as the weather events experienced by the analysts.

To further investigate the channels driving the results, I examine the timing and damages of weather shocks. If the effect is long-lasting and driven by new information, the timing of the shock should not matter. Conversely, if the effect is driven by heuristics, it will fade after a few months. Additionally, larger economic damages should lead to a greater change in beliefs if analysts are learning the future economic costs of climate change from the event, while health-related damages may primarily affect risk-taking (Bernile et al., 2017).[13] [14]

In summary, the testable hypotheses on the effect of weather shocks on analysts' forecasts are:

[13] Deryugina (2013) uses the timing of the event to understand whether the beliefs update is driven by a Bayesian update process or a heuristic effect. Another key hypothesis in Deryugina (2013) is the length and the magnitude (in terms of damages). The former implies that the magnitude of the damages and the length of the event matter. However, since my selected shocks are already tail events, using the length and the magnitude of the event would not help me disentangle the two effects.

[14] In the robustness section, I investigate the potential impact of weather shocks on analysts' distraction, drawing from studies (Han et al. (2020); Liu et al., 2022). This analysis explores three potential outcomes: a potential decrease in forecasting accuracy due to limited attention, a focus on more pivotal firms for analysts' careers (indicated by high institutional ownership and market capitalization), and a potential disproportionate impact on analysts in smaller brokerages, less equipped to handle weather shocks.

Hyp. 1 **Information**: *analysts will become more accurate after the weather shocks and their change in accuracy would be long-lasting with no importance on the timing of the shock.*

Hyp. 2 **Heuristic**: *new climate beliefs rapidly affect analysts' forecasts but they will dissipate after 3 months. Moreover, recent weather events should affect the beliefs of all firms, with a larger effect on health-related damages.*

3.1 Empirical Strategy

In this section, I explain how I define salient weather shocks, the methodology used, the main assumption for the validity of my methodology, and how to test the previously discussed hypotheses.

Salient Weather Shock. Taylor and Thompson (1982) characterize a salient event as "a phenomenon that when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighing in subsequent judgments". My definition of natural disaster includes shocks that have at least one of the following three criteria: (1) more than 10 fatalities; (2) more than 100 injured people; (3) more than 1 billion dollars total economic damages.[15] By selecting only the largest disasters in terms of economic and health-related damages in any state, I hope to discard seasonal and common climate events that may not be attributed to climate change realization. A weak definition of salient event risks would include natural disasters that are not informative for equity analysts, hence biasing the estimators downwards.

Difference-in-differences. To study the effect of salient climate shocks on analysts' forecasts, I start by dividing my sample of analysts into my treatment and control groups.

[15] Criteria 1 and 2 are commonly employed as standard criteria to classify weather events as natural disasters (Wirtz et al., 2014), while the 3rd criteria are the standard definition by Barrot and Sauvagnat (2016).

Similar to Alok et al. (2020), I use analysts within a 100-mile radius of a salient shock as a treated group. The control group is represented by analysts who issue forecasts for firms in the same sectors as the firms followed by treated analysts.

To ensure that a change in forecasts is driven by changes in beliefs, I exclude all analysts forecasting at least a firm located 100 miles from the event, using the firm's headquarters location as a proxy for the firm's location.[16] The analysis is conducted at the monthly level: keeping the last forecasts in the pre-treatment months and the first forecast in the post-treated months. By exploiting the staggered arrival of the extreme natural events at the analysts' location, I use the following regression:

$$\mathrm{Y}_{\ i,f,h,t} = \beta post_{i,f,h,t} + \beta treat_{i,f,h} + \beta treat * post_{i,f,h,t} + \theta X_{i,f,t} + \gamma_{h*s} + \varepsilon_{i,f,h,t} \tag{1}$$

for an analyst i, firm f, for a forecast horizon h and at month-year t. Where $treat*post_{i,t}$ is the interaction term between the indicator for treated analysts and the post-treatment period, and $\theta X_{i,t}$ are controls for pre-trend differences. Fixed effects (FE) included are γ_{h*s} which is an interaction between the shock indicator and the forecast horizon. Since climate shocks occur within a 100-mile radius of the analyst's office location, standard errors are clustered by the analyst's office location.[17]

Two types of dependent variables are then used to study whether analysts change their forecasts after a weather shock. Specifically, I follow Hong and Kacperczyk (2010) and use an-

[16] I demonstrate that the findings remain robust even when excluding firms with an establishment location near the event.

[17] Fast-growing literature highlights the problem arising by implementing a staggered differences-in-differences methodology (see Baker et al., 2022). When using multiple treatments over time, the estimated staggered DID coefficient can be seen as a weighted average across shocks. The problem arises when analysts experiencing a weather shock are compared to analysts that already received treatment in the recent past. Notice that this concern is addressed by using a control group composed of analysts that are never been treated or are yet to be treated. Thus, analysts are removed from the control group after experiencing a weather shock. Furthermore, I control this problem by implementing a standard differences-in-differences analysis across shock and forecast horizons, which is captured by the γ_{h*s}.

alysts' forecast bias and forecast error. Forecast bias is defined as $BIAS_{ift} = (F_{ift} - Y_{ft}) / P_{f,t-1}$, where F_{ift} is the earnings forecast of an equity analyst i for a firm f in the month t, and Y_{ft} is the earnings for a firm f at time t divided by $P_{f,t-1}$, the stock price for firm f in the previous fiscal year $t-1$. Since the bias could be positive as well as negative, I use forecast error to explore whether the analyst becomes more accurate (lower forecast errors). Forecast error is defined as $FERROR_{ift} = |F_{ift} - Y_{ft}| / P_{f,t-1}$, which differs from BIAS only by having the numerator in absolute terms.

The set of additional covariates $X_{i,t}$ included are common control variables used in previous studies (Addoum et al., 2019, Cuculiza et al., 2020, Cuculiza et al., 2021, Hong and Kacperczyk, 2010, etc.) such as (i) days to end, the difference in days between the forecast and earnings announcement date; (ii) broker size, how many analysts are issuing forecasts for a brokerage firm in a year; (iii) companies followed, how many firms are forecasted by an analyst in a year; (iv) industries followed, how many industries are forecasted by an analyst in a year; (v) general experience, the difference in years between the first forecast issued on IBES and the analyzed forecasts; and (vi) firm experience, the difference in years between the first forecast analysts issued for a firm j and the analyzed forecasts. In addition, I include firm size (proxy by total assets) and firm leverage.

Parallel Trend Assumption. To ensure the internal validity of my econometric methodology, I check whether the parallel assumption holds. A common test is to run a regression with pre-treatment interaction dummies between periods and treated groups, such as:

$$\begin{aligned} \mathrm{Y}_{i,f,h,t} = &\sum_{j \neq 0} \beta_j \text{Relative Month}_{i,f,h,t+j} + \beta \text{treat}_i \\ &+ \sum_{j \neq 0} \beta_j \text{treat} \times \text{Relative Month}_{i,f,h,t+j} + \Gamma_{s*h} + \varepsilon_{i,f,h,t} \end{aligned} \tag{2}$$

Where *Relative Months* is a binary variable that indicates the month when the forecasts were issued (from -3 months to + 3 months), relative to the baseline month ($t = -1$), and *treat* takes value one for a treated analyst. The regression also includes shock indicators interacted by forecasts' horizon (Γ_{s*h}). The parallel assumption is satisfied if the difference between the control and treated group needs is either not significantly different or statistically different but constant throughout the pre-treatment months.

4 Data

The dataset used in the paper is based on five main databases: (i) Climate events are obtained from the Storm Events Database (NOAA); (ii) Analyst forecasts are retrieved from IBES; (iii) analysts' office location is found on Refinitiv and Capital-IQ; (iv) Stock price are from CRSP; (v) firms headquarter location is from Compustat and FactSet Reserve.

Natural Events. The Storm Events Database, obtained from the official National Oceanic and Atmospheric Administration (NOAA) website, provides a total of 298,423 climate shocks from 1999 to 2020 for 49 different event types reported by several sources (such as meteorological stations, Media, Call Centers, etc.). When available, the data includes information on direct as well as indirect deaths and injuries, geographical coordinates, the timing of the event, and the property and crop damages derived from climate events. In my study, I define total economic damages are the sum of property and crop damages converted in real terms using 2013 as a base year.

For 74% of the events, the data reports precise geographical coordinates. For events with missing coordinates, I use the reported FIPS code of the county where the event occurred (FIPS code translation is obtained from the Storm Prediction Center WCM Page, NOAA, 2016) and build coordinates for the centroid of the county location.[18] Finding the

[18]The FIPS code is a unique number assigned to each county by the National Institute for Standards and Technology, NIST. They are obtained from Wikipedia's "Table of United States counties" (`https://en.wikipedia.org/wiki/User:MichaelJ/Countytable`).

geographical location for 92% of the events in the dataset while discarding the remaining 8%.

Equity Information. Stock-price data are from CRSP and they are matched with the IBES dataset of earnings forecasts by both TICKER and Cusip identifiers. To retrieve firms' location and industry classification (SIC code), I merge the IBES dataset with Compustat Quarterly by IBES TICKER. To proxy for the firm's location, I follow previous literature that uses the headquarters address (for example, Alok et al., 2020, and Barrot and Sauvagnat, 2016). Headquarter information (City, State, and ZIP code) are from Compustat Quarterly and they are linked by firms' ZIP code to the respective latitude and longitude coordinates using a large public dataset from CivicSpace Labs (opendatasoft). Out of the 9,182 firms in my dataset, about 50% can be linked by IBES TICKER using Compustat Quarterly. Following Pankratz et al. (2019), I match the remaining 50% firms by using FactSet Reserve by both TICKER and Cusip identifiers.

As a proxy for firms' climate risks, I use firms' specific forecasted physical risks from Trucost. Trucost reports the composite score of a company's physical risk exposure (ranging from 1-low risk to 100-high risk) as a weighted average across 8 different physical risks (wildfire, coldwave, heatwave, hurricane, sea level rise, flood, and water stress) for three forecasts horizons (the year 2020, 2030 and 2050) and scenarios (high, medium and low). For my analysis, I use the composite physical risk forecasts of the year 2020 averaged across all future scenarios (high, medium, and low). In my sample, the average firm composite physical risk score is 60 points. Each physical risk averages from 3 points for flood and sea level rise to 57 points for water stress.[19]

[19] As physical risks remain relatively consistent across time and geography, my choice of using the year 2020 should not significantly impact the results. In the Appendix, I corroborate the robustness of the results by categorizing firms into high climate-sensitive sectors (including consumer discretionary, industrial, utilities, and health care) and non-climate-sensitive sectors (comprising all other sectors), as defined by Addoum et al. (2019).

Analysts Forecasts. I use the Details of Institutional Brokers' Estimate System (I/B/E/S) to collect short-term as well as long-term earnings forecasts (EPS) by analysts located in the US from 1999 to 2020. The data are then merged with the IBES Recommendation file to obtain the analyst's last name, initial of the first name, and brokerage house abbreviation. To de-anonymize the broker ID, I use the IBES Translation file.

To obtain information on analysts' locations, I manually downloaded analysts for a sample of firms in Refinitiv, obtaining full names, email, brokerage names, and phone numbers. However, Refinitiv only provides information on active analysts that are currently producing forecasts and it does not provide any information on analysts' office locations. Luckily, the US uses a numbering plan area (NPA) that allows me to find the location of the analyst by exploiting analysts' first 3-digits of their phone number.

To expand the sample, I use Capital IQ - Professional to search for professionals located in the US and for which the profession title includes the term "Analyst" (for example, "Equity Analyst", "Research Analyst", "Former Analyst", etc.). Since the available version of Capital IQ - Professional provides only the US state location of the analysts, to find the city of the analyst's office location, I assume that analysts working for the brokerage firms in a given state are located in the same city as analysts previously found in Refinitiv. To avoid mismatch I manually check analysts, which moved at least once in my sample, using BrokerCheck.[20]

Lastly, the dataset is further cleaned by: (i) only including forecasts made in US dollars; (ii) excluding all forecasts with an absolute forecast error (difference between the forecast and the actual earning) greater than \$10 (Hong and Kacperczyk, 2010); (iii) excluding all firms that have an average share price lower than \$5 (Hong and Kacperczyk, 2010); (iv) excluding all firms that are followed by less than five analysts to avoid competition bias (Hong and Kacperczyk, 2010); (v) winsorizing the data at 0.5% for each tail and forecast

[20] BrokerCheck is an open-source database provided by the Financial Industry Regulatory Authority (FINRA). See https://brokercheck.finra.org/

horizon; (vi) excluding forecast less than a 30 days from the forecast announcement.

This leads to a final dataset of 2,894 equity analysts in 29 different US states covering 1,588,202 earnings forecasts for 5,109 firms from 2000 to 2020. For my sample of analysts, I also collect a large set of individual characteristics that are explained in detail in the Appendix B.

5 Empirical Findings and Descriptive Statistics.

5.1 Descriptive Statistics

In this section, I present the descriptive statistics of analysts and weather shocks in my sample. Using the empirical strategy outlined in section 3.1, my final sample includes weather shocks located 100 miles from analysts who provide earnings forecasts for firms (unaffected by the weather event) and a control group of analysts forecasting firms in the same sector. After applying these filters, the sample under study shrinks to 1,293 equity analysts in 24 different US states covering 2,923 firms from 2000 to 2020.

Analysts Characteristics. Figure 1 maps the location of my sample of analysts throughout the US (filtered by control and treated). Not surprisingly, 58% of equity analysts are located in the state of New York, followed by 7% in California and 4% in Illinois. Table A1 reports the summary statics for my sample of analysts and firms. The average bias for analysts is 0.81% while the average forecast error is 2.2% (respectively with a standard deviation of 4.3 and 4.1). An analyst in my sample follows on average 17 firms, with an average of 3 years of forecasting a single firm and approximately 7 years overall of work experience. Moreover, the average analyst follows two sectors and works in a brokerage firm alongside 85 other analysts.

Weather Shocks Characteristics. Table 2 reports the characteristics of the salient events within a 100-mile radius of an analyst's location. For each type of weather event, the table indicates the average total number of damages (in millions $), the total number of deaths and injuries, and the number of events. The table shows that coastal floods are the most disastrous type of weather shock in terms of economic damages. In terms of health-related damages, debris flows and tropical storms have the highest number of deaths, while winter storms have the highest number of injuries. In my sample, weather events with the most occurrence are tornadoes and heat.[21]

Climate Beliefs and News after a Weather Shock. To validate that my selected weather events affect beliefs, I follow Alekseev et al. (2021) and download Google trends about climate change in the state where analysts are situated. By regressing state-monthly Google trends on the constructed indicator for extreme events with state and year-fixed effects, I investigate if states with salient weather events present more Google searchers about climate change than states with no events.[22] Columns 1-3 of table 3 report the coefficients of interest for the different types of damages caused by the salient events. All indicators are positive, while only fatalities and economic damages are statistically significant. Similar to Alekseev et al. (2021), experiencing any fatalities or economic damages caused by extreme events increases relative interest in climate change by respectively 9.5% and 8.6%.

Then, I explore whether the news about climate change increases after an extreme event. This is important because changes in analysts' beliefs should be driven by first-hand experience shocks and not other types of occurring events, such as climate news. Two climate news indexes are used as dependent variables: columns 4-6 use the Sentometric index on news about global warming constructed by Ardia et al. (2020), while columns 7-9 use the Wall Street Journal (WSJ) climate news indices created by Engle et al. (2020). The results are not statistically significant. These findings highlight that selected extreme events affect

[21] In the appendix, figure A3 maps the selected salient weather shocks that occurred near an analyst's office location while figure A2 plots all the salient shocks in NOAA from 2000 to 2020 by US states.

[22] Note that the entire sample of selected climate events was used, not just those near the analyst's location, such to prevent the misclassification of month-states as non-treated, which could result in underestimated findings.

climate change beliefs, but not climate news.

5.2 Empirical Results

The following results are conducted for analysts' yearly forecasts. Since analysts issue forecasts for different horizons, I report here the results aggregated by all horizons.

Baseline results. Table 4 reports the baseline differences-in-differences (DID) for both analysts' forecast bias and error using only one month before and after the weather event. The estimated coefficients indicate that, after a weather shock, first-time treated analysts become more accurate (i.e. smaller forecast error) and less optimistic (i.e. smaller bias) compared to never-treated analysts, while the latter is not statistically different than zero given conventional confidence interval levels. The difference between the treated and control groups is 0.05 p.p. and 0.07 p.p., for bias and error respectively. Comparing the estimated results to the average bias and error in the sample, the effects correspond to a 6% decrease in forecast bias and 3.2% in forecast error.

Moreover, figure A5 plots the estimated DID for each sector. It suggests an increase in pessimism among analysts in the accommodation and food service, scientific, and mining sectors, while analysts have enhanced accuracy in sectors such as scientific, retail, and wholesale. Turning to figure A6, specific climate events, including wildfires, surge tides, and tropical storm-related floods, contribute to a more pessimistic outlook. On the other hand, analysts appear to be more (less) accurate following thunderstorms, storm surges, heatwaves, hail, and debris flow (extreme cold and heavy snow). This highlights how analysts react differently to various sectors and weather-related incidents.

Parallel trend. I test the validity of my DID by assessing whether the parallel trend assumption holds. Figure A4 plots the estimated coefficients of pre and post-period interaction terms between treatment and time dummies for both forecast error and forecast bias, using the month before the event ($t = -1$) as the reference month. The figures corroborate the findings that the forecast bias and error of control and treated groups are not statistically different in pre-treatment periods, thus suggesting that the empirical strategy is robust.[23]

Change in firms' fundamentals. To confirm that changes in analysts' forecast bias and error are attributed to changes in their climate beliefs, I verify that forecasted firm fundamentals remain stable between one quarter before and immediately after the event.[24] Figure 3 illustrates that, aside from a small statistically significant increase in Capex, there is no significant statistical variation in firm fundamentals surrounding the event.

Analysts characteristics. To investigate whether analysts react differently to experiencing a weather shock, I repeat the baseline DID analysis by categorizing analysts into subgroups based on specific characteristics. Certain characteristics in the literature are associated with ex-ante prior beliefs about climate change, which are then categorized in Figure 4 as low (blue) and high (red) values of ex-ante climate beliefs.

These characteristics include analysts' political donations (Republican - blue, or Democratic - red), county's political ideology (Republican or Democratic), states' climate beliefs (the share of the state population believing that climate change is happening), states' climate risk (number of climate shocks in a state), sex (male or female), mindset (ex-ante optimism or pessimism), ex-ante performance, and experience. In this setting, Republican affiliation, states with a low number of climate events or average climate beliefs, male analysts, and low experience are associated with low ex-ante climate beliefs (blue). [25]

The findings show an overall homogeneous impact on analysts' forecast bias and error across various characteristics. In general, most analysts tend to become both more pes-

[23] Note that the figure includes analysts who provide forecasts for all three months in the pre-treatment period. In the appendix, figure A4 displays analysts' forecasts for all analysts in my sample; if an analyst does not issue a forecast at times -3 or -2, I fill backward. The parallel trend remains robust.

[24] The results remain consistent also when compared to one quarter after the event.

[25] Refer to Table 15 and 16, as well as Appendix B, for a detailed description of each subgroup.

simistic and more accurate after experiencing a weather shock. Specifically, analysts residing in states with higher climate risk beliefs, facing a greater number of shocks, those who were initially overoptimistic, and those located in democratic counties appear to adopt a more pessimistic outlook post-event.[26][27]

When examining forecast error, analysts donating to democratic parties, residing in republican counties, and states with fewer climate risks, male analysts, with lower performance, and more experience, tend to become more accurate after the event. This suggests their ability to extrapolate valuable information from the weather shock. Furthermore, analysts who were initially overoptimistic benefit from their decrease in optimism by becoming more accurate (similar to Cuculiza et al., 2020).[28]

Firms' climate risks. To comprehend the factors influencing belief shifts, I examine how analysts forecast firms with different levels of climate risks. In table 5, the estimated coefficients are presented for firms with high and low climate risks, using Trucost physical risks score and climate risk sectors (as per Choi et al., 2020). The results indicate that, on average, analysts are becoming more accurate and pessimistic for both high and low-physical-risk firms. However, when considering climate sectors, the most substantial improvement appears to stem from firms in sectors categorized as low climate risks. One possible explanation is that analysts might have already incorporated adjustments into their forecasts for sectors

---

[26] However, it's crucial to exercise caution when interpreting these results at the state or county level, as they may not precisely reflect individual analysts' beliefs.

[27] A notable concern arises from the decline in optimism among initially optimistic analysts, potentially driven by analysts' "walk-down" behavior, characterized by initial optimism followed by downward adjustments in forecasts to achieve easily beatable estimates (Matsumoto, 2002). To address this concern, the regression controls for the remaining days until the end of the period. Additionally, it's noteworthy that only 8% of the forecasts fall within three months before earnings announcements, and replicating the analysis by excluding forecasts within three months from the announcement yields consistent and stable results.

[28] The most significant disparity observed in both forecast error and bias is related to analysts' performance. Here we notice that high-performance analysts become more optimistic but not more accurate after the event. In contrast, low-performance analysts become more pessimistic and accurate after the shock, suggesting that high-performance analysts may already incorporated climate risks after the event, leading to no change in their accuracy.

with high climate risks.

Shocks' characteristics. Exploiting shocks' characteristics I try to disentangle if analysts are affected by the *heuristic* or *information* hypothesis. First, I look at analysts who experienced, for example, a hurricane and investigate if they become more pessimistic about firms with high hurricane risks. Second, I investigate what type of shock damages, economic or health-related damages, shift analysts' beliefs.

Table 6 presents the findings for firms categorized into high and low physical risks, based on the shocks experienced by the analysts, and by the characteristics of weather shock-related damages. The results demonstrate that analysts exhibit increased pessimism and accuracy specifically for firms characterized by high physical risks following the experienced shock, while no effect is found for firms with different risks than the shock experienced. Additionally analysts, after a shock that caused only health-related damages, decreased their forecast bias by 0.06 percentage points and became more accurate of 0.12 percentage points. After a shock with economic damages, they have a 0.14 percentage points reduction in bias, which makes them more accurate at 0.07 percentage points, even if both are not statistically significant.

Analysts' experience. The previous findings indicate that analysts become more accurate for all firms, irrespective of the physical risks. However, they do become more accurate after weather shocks with the same risk as the shock experienced and for shocks with large health-related damages. But is this happening for all analysts?

Table 7 presents the findings for firms categorized into high and low physical risks (Panel A) and climate sector (Panel B) for highly experienced and less experienced analysts separately. The results indicate that highly experienced analysts exhibit increased accuracy specifically for firms characterized by high physical risks following the experienced shock. On the other hand, for less experienced analysts, the effect is significant only for firms with low physical risks. Notably, when dividing firms by low and high climate sectors, both highly and less experienced analysts exhibit pessimism for firms in the low climate risks sector.

Table 8 presents the findings for firms categorized into high and low physical risks based on the shocks experienced by the analysts. The results show that highly experienced analysts exhibit increased accuracy specifically for firms characterized by high physical risks following the experienced shock. In contrast, no significant result is found for less experienced analysts, supporting the hypothesis that only highly experienced analysts effectively incorporate experienced climate events into their forecasts.

Lastly, table 9 presents the baseline results, dividing the sample based on the characteristics of weather shock-related damages: economic or health-related damages. The findings indicate that highly experienced analysts, following a shock causing only health-related damages, reduced their forecast bias by 0.04 percentage points and increased accuracy by 0.13 percentage points. In the case of a shock with economic damages, they exhibited a 0.20 p.p. reduction in bias and a 0.23 p.p. increase in forecast error, although the latter is not statistically significant.

Taken together, the results indicate that only highly experienced analysts appear to possess the sophistication needed to extract information about the future costs of climate change from experiencing a weather shock. [29] This implication is supported by a more substantial increase in accuracy for firms with high physical risks, along with the same risks as the experienced shock, as well as improved forecasts for both shocks entailing significant health and economic damages.

5.3 Term Structure of Climate-Risks and Multiple Shocks

The previous analysis reported the results aggregated for all analysts' forecast horizons (from 1 year to 4 years ahead). Since climate risks affect both short and long-term expectations,

[29] The findings align with Kim et al. (2021), which highlight that less experienced analysts tend to exhibit elevated forecasted errors and dispersion for firms in countries characterized by heightened climate risks.

I investigate whether analysts believe that climate risks threaten short as well as long-term firms' earnings.[30]

Breakdown by Forecast Horizons. Table 10 presents the estimated coefficients separately for each year's forecast horizons. The reduction in forecast error following a weather shock seems to be primarily driven by short-term forecasts, specifically 1 year ahead. However, analysts display a smaller forecast bias for 1 to 3 years ahead, although this is not statistically significant. Looking at a longer horizon, the 4-year horizon shows an increase in optimism, making analysts less accurate, while the long-term growth (LTG) seems to decrease after the event, providing contrasting results.

Reversal. If weather events convey no information on climate risks, equity analysts' forecasts should eventually revert to their fundamental values, assuming firms are not directly or indirectly impacted by the shock. However, empirically testing this hypothesis is challenging as it requires assuming no additional information about climate risks is released after the event. Despite these limitations, I explore whether analysts adjust their forecasts back to previous levels following the weather event.

I examine the change in forecast bias and error after 3, 6, 12, and 18 months following the event relative to the last forecast issued before the event for treated analysts. Figure 5 indicates that analysts maintain a pessimistic and accurate stance up to 18 months after the event, even though statistical significance is not observed after 3 months. This persistence in the shift of beliefs suggests that it is driven by the *information hypothesis*.

5.4 Robustness Tests

A series of robustness checks are conducted to test the validity of the results. First, since 68% of analysts in the sample are working in New York, table 11 shows that the findings are

[30] Although my sample includes 5 years ahead forecasts, the limited amount of information prevents me from estimating a separate regression.

robust by excluding analysts in New York and California. Second, I examine the robustness of the results by controlling for different analyst distances from the event. Table 12 shows that analysts within a 50-mile radius of the event exhibit a larger impact on bias and error, with a decrease of 13 and 23 percentage points, respectively. In the 100-200 mile range, the effect on bias is even larger in magnitude but not statistically significant, and beyond 200 miles, there is no effect.

One major limitation of this study is the reliance on firms' headquarters as the firms' location. This is problematic since firms often have multiple locations, thus there is a risk of incorrectly assuming that a firm was not affected when it was. However, this concern is partly addressed by ensuring that the fundamentals of the firms remain unchanged during the events.

To address this concern, I use the National Establishment Time-Series (NETS) Database to add information about establishments of US firms along with their corresponding coordinates. Among the firms in my baseline analysis, I successfully link 899 firms with their respective establishment locations. In columns 1 and 2 of table 13, I observe that when firms are 100 miles distant from the event, analysts' accuracy and pessimism tend to increase.

On the other hand, columns 3 and 4 show that firms with establishments within 100 miles from the event's location cause analysts to adopt a notably optimistic outlook with a larger, but not significant, forecast error increase. Lastly, in columns 5 and 6 I replicate the baseline analysts by excluding firms that in the NETS database are near the event's location. This reiteration of my primary findings corroborates the baseline results.

Lastly, several studies have investigated the potential impact of weather shocks on analysts, proposing that such events could result in distraction, thus potentially influencing earnings forecasts (see for example, Han et al. (2020), and Liu et al., 2022). However, it is worth noting that while the distraction hypothesis would imply an increase in forecast errors following the event, my observed trend is the opposite. An alternative perspective could be that analysts are directing their attention toward non-affected firms, thereby enhancing the accuracy of assessments for this particular subgroup.[31]

To assess the potential influence of the distraction hypothesis on my findings, I adopt a conventional testing approach employed in the existing literature. First, if analysts are distracted by extreme weather events, I anticipate that their attention would be disproportionately directed toward companies considered crucial for their professional careers. These firms would typically exhibit high institutional ownership and hold the highest market capitalization within analysts' portfolios. Table 14 illustrates that analysts become increasingly more pessimistic and accurate for both firms with high and low institutional ownership, with statistical significance only for the latter. This trend persists also for firms with low relative importance.

Second, analysts in smaller brokerage firms may have fewer resources and may struggle to cope with extreme weather events. The results indicate that analysts in large brokerage firms become more pessimistic and accurate, whereas no significant effect is observed in small brokerage firms. Lastly, distracted analysts might exhibit a sudden drop in the number of forecasts compared to the control group. The final columns confirm that treated analysts issue fewer forecasts compared to control analysts.

In summary, although treated analysts issue fewer forecasts, there is no indication of a reorientation of attention toward more pivotal firms, thus failing to provide evidence for the distraction hypothesis.

6 Conclusion

This study contributes to our understanding of how experiences with weather shocks influence beliefs about physical risks. Consistent with previous research, the findings indicate that analysts adjust their forecasts following significant weather events, leading to increased accuracy. These effects can be attributed to two distinct mechanisms: a heuristic channel

[31] However, this is unlikely since I only consider analysts who forecast all untreated firms.

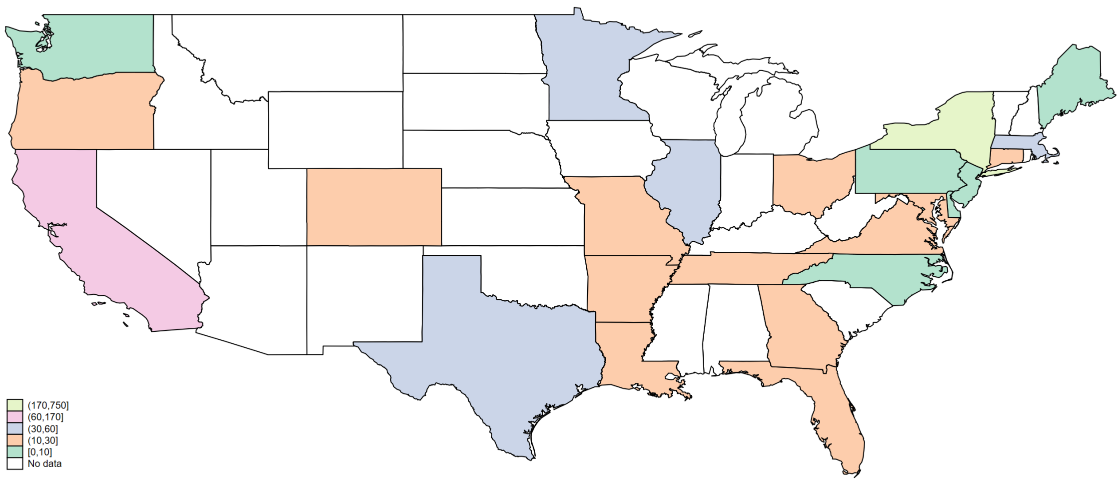
and an information channel.

The findings reveal that both channels operate in tandem. Specifically, the study provides evidence that highly experienced analysts acquire new information following a salient weather event, leading them to update their forecasts for firms with high climate risk. As predicted by the information hypothesis, these analysts become more pessimistic after experiencing shocks with significant economic damages and for firms with elevated physical risks such as the ones experienced by the analysts. In contrast, low-performance analysts exhibit a heuristic bias, becoming more pessimistic across all firms and showing an increase in accuracy only for firms with low climate risk.

Understanding how individuals and organizations perceive future climate-related physical risks is key for assessing the effects of climate change and implementing mitigation and adaptation policies. The need for enhanced climate risk disclosure requires urging policymakers to mandate comprehensive reporting on both physical and transition risks. The results of my research suggest that better disclosure should be accompanied by policy efforts aimed at incentivizing training and education programs to ensure analysts correctly incorporate climate-related risks into their forecasts. In conclusion, proactive measures in these areas can significantly boost climate risk awareness and responsiveness within the financial industry.

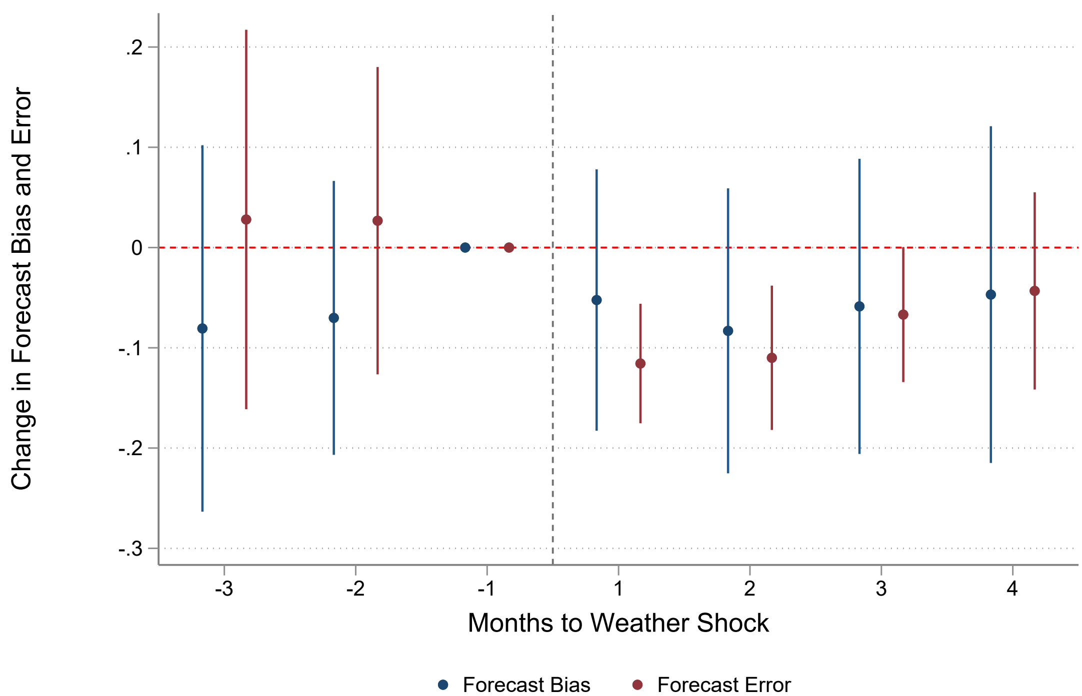
Figures

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



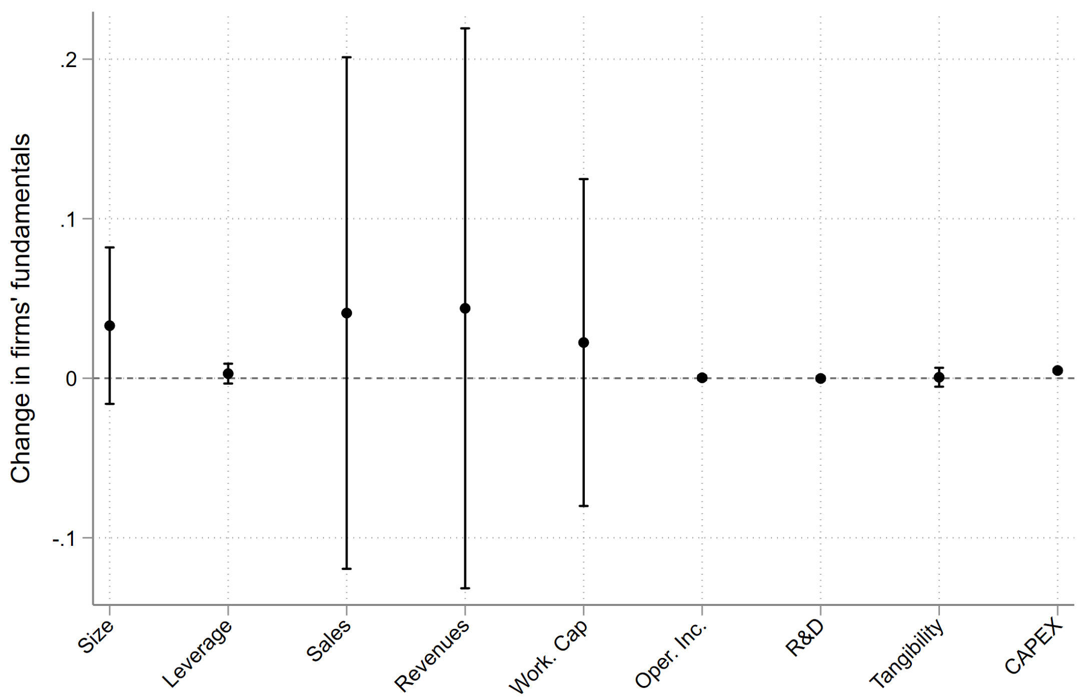
Note: The graph maps the sample of matched IBES analysts' locations to weather shock from 1999 to 2020 by US state. The state of New York has the highest number of analysts with 734 individuals, followed by 162 in California, 54 in Minnesota, and 53 in Illinois.

Figure 2: Parallel trend



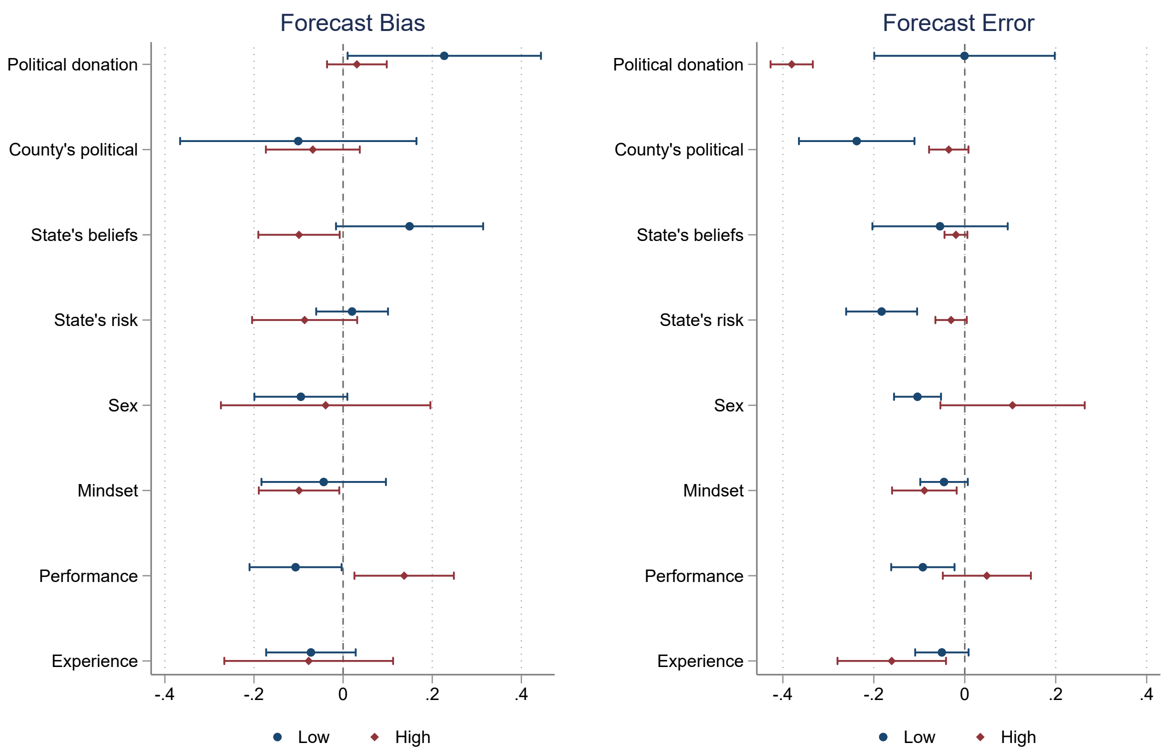
Note: figures plot the estimated coefficients of pre and post-period interactions between treatment and time variable with 90% confidence interval. The omitted month is the month before the weather event. The analysis includes all analysts that issue a forecast for each month before the event. The specification includes all covariates and shock interacted with horizon fixed effects. The event window includes 3 months before and 3 months after the event. The standard errors are clustered at the analysts' office location.

Figure 3: Changes in firms' fundamentals around the weather shock



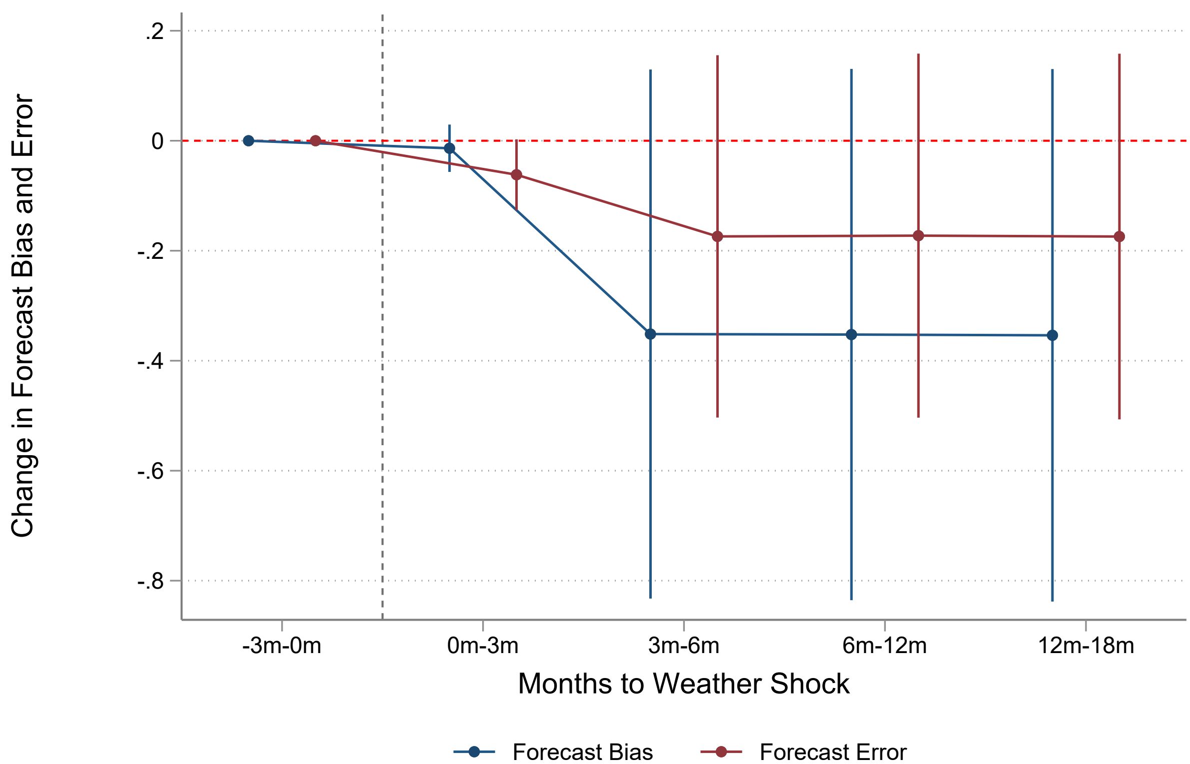
Note: the graph illustrates differences in firms' fundamentals for firms forecasted by the analysts before and after a weather event. The independent variable is an indicator that takes the value of one after the weather event and zero before. We selected the first available data for the forecasted firm one quarter before and during the quarter of the weather shock. The table includes fixed effects for the weather event. To ensure that any effect of the shock is incorporated, a robustness test is conducted using only fundamentals announced one quarter after the weather shock quarter. The results align with the presented graph.

Figure 4: Analysts' characteristics



Note: figures plot the estimated coefficients from the staggered difference in difference in bar plots with 90% confidence intervals for error (left graph) and bias (right graph). The plots categorize analysts' characteristics into low (blue) and high (red) ex-ante climate belief priors. Low climate belief priors include analysts who donated to Republican parties, reside in Republican counties, live in states with low climate beliefs and fewer weather events (lower state's risks), and are male. Additionally, this category includes analysts who are ex-antes overly pessimistic, have low performance, and possess low experience. Conversely, the high climate belief group consists of the opposite characteristics. The specification includes all covariates and forecasted horizon*weather shock fixed effect. The analysis keeps only one forecast before and after the event. The standard errors are clustered at the analyst's office location.

Figure 5: Persistence of the effect after the event



Note: figures plot the estimated coefficients from the staggered difference in difference in bar plots with 90% confidence intervals for error (left graph) and bias (right graph). The specification includes all covariates and forecasted horizon*weather shock fixed effect. The analysis keeps only one forecast before and after the event. The standard errors are clustered at the analyst's office location.

Tables

Table 1: Summary statistics for the staggered DID

	Mean	p50	SD	Min	Max
forecast bias (%)	0.81	0.04	4.31	-33.08	66.38
forecast error (%)	2.19	0.78	4.14	0.00	83.20
companies followed	17.47	17.00	7.83	1.00	80.00
firm experience	3.47	2.00	3.60	0.00	21.00
general experience	7.45	7.00	5.12	0.00	21.00
Industries followed	2.12	2.00	1.37	1.00	11.00
brokerage size	85.78	70.00	56.00	1.00	284.00
firm size	8.46	8.41	1.93	-0.86	14.83
leverage	0.25	0.22	0.23	0.00	5.10
market value	1.76	1.08	25.26	0.01	12253.26
stock price	50.79	35.94	67.24	0.32	3808.41
ROA	0.01	0.01	0.19	-166.00	10.69
N	1588202				

Note: The table reports the summary statistics used in the analysis. Forecast bias is defined as the difference between the earnings forecast of an equity analyst i for a firm f in the month t minus the actual earnings divided by the stock price for a firm f in the previous fiscal year $t-1$, while forecast error differs from forecast bias only by having the numerator in absolute terms. Both are expressed in percentages. See tables 15 and 16 for a description of the variables used.

Table 2: Description merged salient storm event

Event Type	Av. Total Damage (Mil. $)	Av. Total Deaths	Av. Total injuries	Number of Events
Extreme Cold/Wind Chill	0	10	0	1
Thunderstorm Wind	0	1	100	1
Winter Weather	0	1	200	1
Heavy Snow	0.80	0	100	1
Heat	36.75	10	54	10
Tornado	77.45	7	120	9
Tropical Storm	109.20	11	77	2
Debris Flow	289.37	18	89	2
Storm Surge/Tide	1082.22	0	0	1
Flood	1155.12	0	0	2
Wildfire	1358.24	9	45	2
Hurricane (Typhoon)	1850.46	1	10	3
Hail	2185.69	0	0	1
Flash Flood	2927.75	4	0	3
Coastal Flood	5073.30	1	0	1

Note: The table reports the selected salient weather events that are 100 miles from an analyst location. The table shows the average economic damages caused by each type of shock (converted in 2013 USD), the average number of related deaths and injuries, and the respective number of shocks across the dataset. Given our empirical strategy filters (i.e. only forecasts for firms 100 miles distant from the event, the control group composed of never-treated analysts, and the treated group composed of analysts treated only once), only a small number of shocks are selected.

Table 3: Climate beliefs and news after a weather shock

	Google Search			Sentometrics			WSJ		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fatalities	0.0955*			0.0334			-0.0185		
	(0.0496)			(0.0401)			(0.0421)		
Injuries		0.00942			-0.00776			-0.00518	
		(0.0868)			(0.0408)			(0.0414)	
1 bil. $ damages			0.0860**			0.0220			-0.0348
			(0.0327)			(0.0541)			(0.0556)
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	0.382	0.382	0.382	0.309	0.308	0.309
N	5028	5028	5028	4563	4563	4563	4239	4239	4239

Note: column 1-3 use the Alekseev et al. (2021) methodology to estimate the log scaled google search interest of the topic “climate change” in the states where analysts are located. The standard errors are clustered at the month and state level, and observations are weighted by each state’s population size. Column 4-6 and 7-9 report the regression on the Sentometric index on news about global warming (Ardia et al., 2020) and the Wall Street Journal (WSJ) climate news indices created by Engle et al. (2020).

Table 4: Baseline result

	(1) Bias	(2) Error	(3) Bias	(4) Error
post	0.00446	-0.0268*	0.00443	-0.0268*
	(0.0280)	(0.0153)	(0.0280)	(0.0153)
treat	-0.132	-0.0988	-0.117	-0.0362
	(0.153)	(0.0821)	(0.148)	(0.0827)
treat*post	-0.0531	-0.0772***	-0.0531	-0.0772***
	(0.0598)	(0.0259)	(0.0598)	(0.0260)
Controls	No	No	Yes	Yes
Shock*horizon FE	Yes	Yes	Yes	Yes
R^2	0.249	0.111	0.250	0.123
N	64604	64604	64594	64594

Note: the table shows the baseline staggered differences-in-differences (DID) for 1 to 5 years EPS forecasts of an analyst i forecasting a firm f. The weather shock indicator and the horizon fixed effect are incorporated to account for shock and horizon-specific characteristics. The controls used are forecast days gap, broker size, companies followed, firms experience, industries followed, and firm size. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Table 5: Firms' climate risk

Firm risk:	Physical Risk				Climate Sector Risk			
	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error	(7) Bias	(8) Error
treat*post	-0.0514	-0.0616*	-0.143	-0.0724**	-0.0897	-0.0355	-0.0353	-0.117***
	(0.0503)	(0.0360)	(0.122)	(0.0318)	(0.0773)	(0.0312)	(0.0429)	(0.0384)
Firm risk	High	High	Low	Low	High	High	Low	Low
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shock*horizon FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.267	0.145	0.220	0.133	0.190	0.151	0.524	0.146
N	52040	52040	11938	11938	43576	43576	20402	20402

Note: the table shows the baseline differences-in-differences for firms with high and low climate risks. The firm's physical risk is a composite score of all the company's physical risk exposure, i.e. wildfire, coldwave, heatwave, hurricane, sea level rise, flood, and water stress (from Trucost Climate Change Physical Risk Data). The score takes values from 1 (lowest risk) to 100 (highest risk). Firms with more (less) than the average physical risk composite score in the sample (i.e. more than 60 points) are defined as high (low) risk. Climate sector risks are delineated following the specifications provided by Choi et al. (2020), which identifies as risky sectors those defined by the IPCC. The weather shock indicator and the horizon fixed effect are incorporated to account for shock and horizon-specific characteristics. The controls used are forecast days gap, broker size, companies followed, firms experience, industries followed, and firm size. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Table 6: Shock information

	Firm Risk				Shock Damage			
	= shock experienced		≠ shock experienced		Health-related		Economic-damage	
	(1) Bias	(2) Error	(3) Bias	(4) Error	(1) Bias	(2) Error	(3) Bias	(4) Error
treat*post	-0.0774	-0.0985**	-0.0278	0.0531	-0.057	-0.12***	-0.14	-0.071
	(0.0730)	(0.0392)	(0.0499)	(0.0399)	(0.063)	(0.027)	(0.16)	(0.081)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shock*horizon FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.276	0.141	0.178	0.123	0.37	0.13	0.097	0.15
N	49226	49226	14752	14752	44796	44796	18830	18830

Note: the table shows the baseline differences-in-differences for firms with high and low physical risks such as the weather event experienced by the analysts. Firms with high physical risk as the analysts experienced shock are firms that have more than the average risks of a weather shock happening compared to the other firms in the sample. Shock damages are defined as health-related if the event caused more than 100 injured people or more than 10 fatalities. Shock damages are defined as economic-related if they cause more than 1 billion in economic damages. Each specification includes weather shock times horizon fixed effect to account for shock and horizon-specific characteristics. The controls used are forecast days gap, broker size, companies followed, firms experience, industries followed, and firm size. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Table 7: Analysts' experienced and firms' climate risk

	High experienced analyst				Low experienced analyst			
	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error	(7) Bias	(8) Error
Panel A								
treat*post	-0.0313	-0.179**	-0.317	-0.0661	-0.0613	-0.0394	-0.139	-0.0935***
	(0.0922)	(0.0804)	(0.235)	(0.0763)	(0.0506)	(0.0452)	(0.109)	(0.0336)
Firms' physical risk	High	High	Low	Low	High	High	Low	Low
Shock*horizon FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.338	0.158	0.313	0.236	0.255	0.150	0.198	0.118
N	14601	14601	3761	3761	37439	37439	8177	8177
Panel B								
treat*post	-0.126	-0.147	0.0299	-0.203**	-0.0699	-0.0239	-0.0691*	-0.113*
	(0.133)	(0.103)	(0.106)	(0.0746)	(0.0797)	(0.0341)	(0.0379)	(0.0662)
Climate Sector	High	High	Low	Low	High	High	Low	Low
Shock*horizon FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.256	0.159	0.612	0.207	0.188	0.147	0.494	0.165
N	12557	12557	5804	5804	33765	33765	11851	11851

Note: the table shows the baseline differences-in-differences for subgroups of high and low-experienced analysts after a weather event for firms with different climate risk. The firm's physical risk is a composite score of all the company's physical risk exposure, i.e. wildfire, coldwave, heatwave, hurricane, sea level rise, flood, and water stress (from Trucost Climate Change Physical Risk Data). The score takes values from 1 (lowest risk) to 100 (highest risk). Firms with more (less) than the average physical risk composite score in the sample (i.e. more than 60 points) are defined as high (low) risk. Climate sector risks are delineated following the specifications provided by Choi et al. (2020), which identifies as risky sectors those defined by the IPCC. Each specification includes weather shock times horizon fixed effect to account for shock and horizon-specific characteristics. The controls used are forecast days gap, broker size, companies followed, firms experience, industries followed, and firm size. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Table 8: Analysts' experienced and shock information

Analyst:	High experienced				Low experienced			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bias	Error	Bias	Error	Bias	Error	Bias	Error
treat*post	-0.0692	-0.209**	-0.105	-0.0145	-0.0843	-0.0834	-0.0216	0.0807
	(0.115)	(0.0932)	(0.117)	(0.0601)	(0.0771)	(0.0505)	(0.0431)	(0.0499)
Firm physical risks as the experienced shock	High	High	Low	Low	High	High	Low	Low
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shock*horizon FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	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

Note: the table shows the baseline differences-in-differences for subgroups of high and low-experienced analysts forecasting firms with high and low physical risks such as the weather events experienced by the analysts. Firms with high physical risk as the analysts experienced shock are firms that have more than the average risks of a weather shock happening compared to the other firms in the sample. Each specification includes weather shock times horizon fixed effect to account for shock and horizon-specific characteristics. The controls used are forecast days gap, broker size, companies followed, firms experience, industries followed, and firm size. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Table 9: Analysts' experienced and shock characteristics

Analyst:	High experienced				Low experienced			
	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error	(7) Bias	(8) Error
treat*post	-0.042	-0.13*	-0.20	-0.23	-0.078	-0.14***	-0.12	-0.0062
	(0.068)	(0.067)	(0.36)	(0.17)	(0.075)	(0.042)	(0.11)	(0.091)
Shock damage	Health	Health	Economic	Economic	Health	Health	Economic	Economic
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shock*horizon FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.41	0.16	0.16	0.14	0.35	0.13	0.082	0.16
N	13416	13416	5072	5072	31732	31732	14110	14110

Note: the table shows the baseline differences-in-differences for subgroups of high and low-experienced analysts after a weather shock with different damages. Shock damages are defined as health-related if the event caused more than 100 injured people or more than 10 fatalities. Shock damages are defined as economic-related if they cause more than 1 billion in economic damages. Each specification includes weather shock times horizon fixed effect to account for shock and horizon-specific characteristics. The controls used are forecast days gap, broker size, companies followed, firms experience, industries followed, and firm size. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Table 10: Forecast horizons decomposition

	Forecast Bias				Forecast Error				LTG
	(1) 1-Year	(2) 2-Year	(3) 3-Year	(4) 4-Year	(1) 1-Year	(2) 2-Year	(3) 3-Year	(4) 4-Year	(1) LTG
treat*post	-0.0560	-0.130	-0.115	0.468	-0.158***	-0.0280	-0.0186	1.534**	-0.877***
	(0.0605)	(0.0987)	(0.121)	(0.449)	(0.0323)	(0.0255)	(0.0943)	(0.591)	(0.290)
Shock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.270	0.223	0.228	0.389	0.0559	0.0680	0.127	0.263	0.873
N	34192	27300	2028	350	34192	27300	2028	350	2173

Note: the table shows the baseline staggered differences-in-differences for yearly forecasts dis-aggregated at different forecast horizons: 1 to 4 years and long-term growth rate. The control variables are forecast days gap, broker size, companies followed, firms experience, industries followed, forecasted firm size and forecasted firm leverage. The standard errors are clustered at the analyst's office location.

Table 11: Robustness: excluding New York or California

Excluding:	New York		California	
	(1) Bias	(2) Error	(3) Bias	(4) Error
treat*post	0.0676	-0.135***	-0.0985	-0.0742**
	(0.0535)	(0.0413)	(0.0616)	(0.0312)
Controls	Yes	Yes	Yes	Yes
Shock*horizon FE	Yes	Yes	Yes	
R^2	0.270	0.139	0.301	0.141
N	47727	47727	46012	46012

Note: the table shows the baseline staggered differences-in-differences for 1 to 5 years EPS forecasts of an analyst i forecasting a firm f. The weather shock indicator and the horizon fixed effect are incorporated to account for shock and horizon-specific characteristics. The controls used are forecast days gap, broker size, companies followed, firms experience, industries followed, and firm size. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Table 12: Robustness: analyst' distance from the weather shock

	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error
treat*post	-0.135	-0.230***	-0.839	-0.273	-0.0331	0.0250
	(0.144)	(0.0683)	(0.675)	(0.219)	(0.151)	(0.171)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Shock*horizon FE	Yes	Yes	Yes	Yes	Yes	Yes
Distance event	$\leq$ 50	$\leq$ 50	100-200	100-200	200-300	200-300
R^2	0.238	0.135	0.553	0.168	0.235	0.122
N	59508	59508	8426	8426	26808	26808

Note: This table presents the baseline staggered differences-in-differences estimates for analysts at different distances from the weather events. Columns 1-2 replicate the analysis for analysts within 50 miles from the event, columns 3-4 for analysts within 100 and 200 miles, and columns 3-4 for 200 to 300 miles. Each specification includes weather shock times horizon fixed effect to account for shock and horizon-specific characteristics. The controls used are forecast days gap, broker size, companies followed, firms experience, industries followed, and firm size. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Table 13: Robustness: firms' NETS establishment

Establishment	NETS > 100 miles		NETS < 100 miles		drop if NETS < 100 miles	
	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error
treat*post	-0.170	-0.176**	0.102	0.117	-0.0915	-0.0904***
	(0.147)	(0.0836)	(0.0843)	(0.0930)	(0.0705)	(0.0239)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Shock*horizon FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.262	0.177	0.228	0.170	0.264	0.140
N	13114	13114	4676	4676	59302	59302

Note: This table presents the baseline differences-in-differences estimates using the firm's NETS establishment location. Each specification includes forecast horizon and shock ID interacted. The controls used are forecast days gap, broker size, companies followed, firms experience, industries followed, and firm size. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Table 14: Robustness: distraction hypothesis

	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	-0.0510	-0.0742	-0.0394	-0.0565*	0.0136	0.0417	-0.0842*	-0.0606	0.0528	0.0171	-0.0984*	-0.0865**	-0.104***
	(0.106)	(0.0830)	(0.0600)	(0.0328)	(0.0492)	(0.0368)	(0.0464)	(0.0449)	(0.0923)	(0.0625)	(0.0564)	(0.0420)	(0.0220)
Group	High	High	Low	Low	High	High	Low	Low	Small	Small	Large	Large	-
Shock*horizon FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.295	0.185	0.263	0.140	0.262	0.183	0.285	0.146	0.373	0.169	0.207	0.129	0.382
N	7397	7397	54767	54767	10229	10229	34416	34416	16661	16661	47317	47317	63978

Note: This table presents the baseline staggered differences-in-differences estimates for yearly forecasts. High Institutional Owners take the value 1 if firms are ranked in the top 25th percentile in the number of institutional owners among all covered firms in an analyst's portfolio and 0 otherwise (from Thomson-Reuters 13F Database). Relative Importance takes value 1 if a firm is ranked among the top 25th percentile of market cap in an analyst's portfolio. Small Brokerage takes the value 1 an analyst is employed within a brokerage firm among the lowest tercile with regards to its size, as quantified by the number of employees (29 employees). Forecast frequency is the logarithm value of the number of forecasts issued by an analyst in a month. The control variables are forecast days gap, broker size, companies followed, firms experience, industries followed, firm size and firm leverage. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the analyst's office location.

Table 15: Variables description - analyst level

Variable Name	**Description**
Analyst-level variable	
Forecast Day Gap	The difference in days between the forecast and earnings announcement date
Brokerage Size	How many analysts are issuing forecasts for a brokerage firm in a year
Companies Followed	How many firms are forecasted by an analyst in a year
Industry Followed	How many industries are forecasted by an analyst in a year
Firm Experience	The difference in years between the first forecast issued for a firm j and the analyzed forecasts
Analyst Experience	The difference in years between the first forecast issued on IBES and the analyzed forecasts
Experienced analysts	analysts with more than the average years of experience in the sample (13 years)
County political ideology	the party with the majority of votes in the previous election (from Data and Lab, 2017), where 1 is democratic and 0 is republican
Climate-sensitive states	the state has more than the median climate shocks (4 weather shocks)
Ex-ante optimistic (pessimistic)	in the previous quarter the analyst was in the top tercile as an optimistic (pessimistic) analyst, i.e. the average of their forecasts was above (below) consensus
High Performance	I create analysts' score following Hong et al. (2000) and I select the top tercile performer based on the average performance score in the previous 3 years
Analysts' political donation	takes the value 1 if the analysts donate to a democratic party (from FEC)
State Climate Beliefs	states with high (low) climate beliefs are 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)
Sex	takes the value 1 if the analyst is female (estimated from the analyst's first name)
Forecast frequency	the logarithm value of the number of forecasts issued by an analyst in a month
Small Brokerage	takes value 1 if analysts are employed within a brokerage firm among the lowest tercile with regards to its size (proxied by the number of employees)

Table 16: Variables description - firm level

Variable Name	Description
Firm-level variable	
Firm Size	Logarithm of total assets
Leverage	Total debt (short term debt+long term debt) divided by book assets
Stock Price	Stock price at $t-1$
Climate Sensitive Sector	follow Choi et al. (2020) that categorized as high climate risk according to the IPCC, which includes agriculture, mining, utilities, construction, manufacturing, transportation, and warehousing, while classifying all other sectors as low climate risk.
Physical Risk	Composite score of the company's physical risk exposure, i.e. wildfire, coldwave, heatwave, hurricane, sea level rise, flood, and water stress (from Trucost Climate Change Physical Risk Data). Physical risk scores are represented as values from 1 (lowest risk) to 100 (highest risk) and forecasted for the year 2020 averaged across all future scenarios (high, medium, and low)
High Physical Risk firm	takes the value 1 if the firm's physical risk score is greater than the average physical risk composite score in the sample (i.e. more than 60 points)
Risk as the experienced shock	takes the value 1 if the firm individual score for a particular type of physical risk (the same as the one experienced by the forecasted analysts) is greater than the average physical risk in the sample
Establishment Location	geographical coordinates of establishment location from NETS Database
High Institutional Owners	takes the value 1 if firms that are ranked in the top 25th percentile in the number of institutional owners among all covered firms in an analyst's portfolio and 0 otherwise (from Thomson-Reuters 13F Database)
Relative Importance	takes value 1 if a firm is ranked among the top 25th percentile of market cap in an analyst's portfolio

References

Addoum, J. M., Ng, D. T. and Ortiz-Bobea, A. (2019), 'Temperature shocks and earning news', *Review of Financial Studies* .

Alekseev, G., Giglio, S., Maingi, Q., Selgrad, J. and Stroebel, J. (2021), 'A quantity-based approach to constructing climate risk hedge portfolios', *nBER Working Paper* .

Alok, S., Kumar, N. and Wermers, R. (2020), 'Do fund managers misestimate climatic disaster risk', *The Review of Financial Studies* **33**(3), 1146–1183.

Andersen, S., Hanspal, T. and Nielsen, K. M. (2019), 'Once bitten, twice shy: The power of personal experiences in risk taking', *Journal of Financial Economics* **132**(3), 97–117.

Anderson, A. and Robinson, D. T. (2019), 'Talking about the weather: Availability, affect and the demand for green investments', *Swedish House of Finance Research Paper* (19-14).

Ardia, D., Bluteau, K., Boudt, K. and Inghelbrecht, K. (2020), 'Climate change concerns and the performance of green versus brown stocks', *National Bank of Belgium, Working Paper Research* (395).

Baker, A. C., Larcker, D. F. and Wang, C. C. (2022), 'How much should we trust staggered difference-in-differences estimates?', *Journal of Financial Economics* **144**(2), 370–395.

Barrot, J.-N. and Sauvagnat, J. (2016), 'Input specificity and the propagation of idiosyncratic shocks in production networks', *The Quarterly Journal of Economics* **131**(3), 1543–1592.

Barth, F., Hübel, B. and Scholz, H. (2020), 'Esg and corporate credit spreads', *Available at SSRN 3179468* .

Bernile, G., Bhagwat, V. and Rau, P. R. (2017), 'What doesn't kill you will only make you more risk-loving: Early-life disasters and ceo behavior', *The Journal of Finance* **72**(1), 167–206.

Blasberg, A., Kiesel, R. and Taschini, L. (2021), 'Climate default swap–disentangling the exposure to transition risk through cds', *Available at SSRN 3856993* .

Bourveau, T. and Law, K. (2020), 'Do disruptive life events affect how analysts assess risk? evidence from deadly hurricanes', *Evidence from Deadly Hurricanes (May 20, 2020). Forthcoming at The Accounting Review* .

Chan, J. Y.-F. (2022), 'Climate change information and analyst expectations'.

Choi, D., Gao, Z. and Jiang, W. (2020), 'Attention to global warming', *The Review of Financial Studies* **33**(3), 1112–1145.

Cuculiza, C., Antoniou, C., Kumar, A. and Maligkris, A. (2020), 'Terrorist attacks, analyst sentiment, and earnings forecasts', *Management Science* .

Cuculiza, C., Kumar, A., Xin, W. and Zhang, C. (2021), 'Climate change, analyst forecasts, and market behavior', *Analyst Forecasts, and Market Behavior (February 18, 2021)* .

Custodio, C., Ferreira, M. A., Garcia-Appendini, E. and Lam, A. (2021), 'Economic impact of climate change', *Working Paper* .
URL: *https://ssrn.com/abstract=3724940 or http://dx.doi.org/10.2139/ssrn.3724940*

Data, M. E. and Lab, S. (2017), 'U.S. President 1976–2020'.
URL: *https://doi.org/10.7910/DVN/42MVDX*

Data, M. E. and Lab, S. (2018), 'County Presidential Election Returns 2000-2020'.
URL: *https://doi.org/10.7910/DVN/VOQCHQ*

Derrien, F., Krüger, P., Landier, A. and Yao, T. (2021), 'Esg news, future cash flows, and firm value'.

Deryugina, T. (2013), 'How do people update? the effects of local weather fluctuations on beliefs about global warming', *Climatic change* **118**(2), 397–416.

Engle, R. F., Giglio, S., Kelly, B., Lee, H. and Stroebel, J. (2020), 'Hedging climate change news', *The Review of Financial Studies* **33**(3), 1184–1216.

Han, Y., Mao, C. X., Tan, H. and Zhang, C. (2020), 'Distracted analysts: Evidence from climatic disasters', *Available at SSRN 3625803* .

Hong, H. and Kacperczyk, M. (2010), 'Competition and bias', *The Quarterly Journal of Economics* **125**(4), 1683–1725.

Hong, H., Kubik, J. D. and Solomon, A. (2000), 'Security analysts' career concerns and herding of earnings forecasts', *The Rand journal of economics* pp. 121–144.

Huang, H. H., Kerstein, J. and Wang, C. (2018), 'The impact of climate risk on firm performance and financing choices: An international comparison', *Journal of International Business Studies* **49**(5), 633–656.

Hugon, A. and Law, K. (2019), 'Impact of climate change on firm earnings: evidence from temperature anomalies', *Available at SSRN 3271386* .

Huynh, T. D. and Xia, Y. (2021), 'Panic selling when disaster strikes: Evidence in the bond and stock markets', *Management Science* .

Jiang, D., Kumar, A. and Law, K. K. (2016), 'Political contributions and analyst behavior', *Review of Accounting Studies* **21**, 37–88.

Kahneman, D. and Tversky, A. (1972), 'Subjective probability: A judgment of representativeness', *Cognitive psychology* **3**(3), 430–454.

Kim, I., Lee, S. and Ryou, J. W. (2021), 'Does climate risk influence analyst forecast accuracy?'.

Kolbel, J. F., Leippold, M., Rillaerts, J. and Wang, Q. (2020), 'Ask bert: How regulatory disclosure of transition and physical climate risks affects the cds term structure', *Available at SSRN 3616324* .

Kong, D., Lin, Z., Wang, Y. and Xiang, J. (2021), 'Natural disasters and analysts' earnings forecasts', *Journal of Corporate Finance* **66**, 101860.

Krueger, P., Sautner, Z., Tang, D. Y. and Zhong, R. (2021), 'The effects of mandatory esg disclosure around the world', *Available at SSRN 3832745* .

Liu, N., Chen, W., Wang, J. and Shi, H. (2022), 'Typhoon strikes, distracted analyst and forecast accuracy: Evidence from china', *Finance Research Letters* p. 103359.

Matsumoto, D. A. (2002), 'Management's incentives to avoid negative earnings surprises', *The accounting review* **77**(3), 483–514.

Mikhail, M. B., Walther, B. R. and Willis, R. H. (2007), 'When security analysts talk, who listens?', *The Accounting Review* **82**(5), 1227–1253.

NOAA (2016), 'Storm prediction center wcm page', Website.
URL: *https://www.spc.noaa.gov/wcm/data*

NOAA (2022), 'U.s. billion-dollar weather and climate disasters', Website.
URL: *https://www.ncei.noaa.gov/access/monitoring/billions/*

opendatasoft (n.d.), 'Us zip code latitude and longitude', Website.
URL: *https://public.opendatasoft.com/explore/dataset/us-zip-code-latitude-and-longitude/information/*

Pankratz, N., Bauer, R. and Derwall, J. (2019), 'Climate change, firm performance, and investor surprises', *Firm Performance, and Investor Surprises (May 21, 2019)* .

Pankratz, N. and Schiller, C. (2021), Climate change and adaptation in global supply-chain networks, *in* 'Proceedings of Paris December 2019 Finance Meeting EUROFIDAI-ESSEC, European Corporate Governance Institute–Finance Working Paper', number 775.

Park, R. J., Pankratz, N. and Behrer, A. P. (2021), 'Temperature, workplace safety, and labor market inequality'.

Reggiani, P. (2022), 'Climate change expectations: Evidence from earnings forecasts'.

Stroebel, J. and Wurgler, J. (2021), 'What do you think about climate finance?'.

Taylor, S. E. and Thompson, S. C. (1982), 'Stalking the elusive "vividness" effect.', *Psychological review* **89**(2), 155.

Wang, X., Li, Y. and Xiao, M. (2017), 'Do risk disclosures in annual reports improve analyst forecast accuracy?', *China Journal of Accounting Studies* **5**(4), 527–546.

Wirtz, A., Kron, W., Löw, P. and Steuer, M. (2014), 'The need for data: natural disasters and the challenges of database management', *Natural Hazards* **70**(1), 135–157.

Zhang, L. (2021), 'Operating exposure to weather, earnings predictability, and analyst forecast', *Earnings Predictability, and Analyst Forecast (June 11, 2021)* .

Appendix

A Descriptive Statistics.

Figure A1 maps the location of my total sample of analysts throughout the US (not filtered by control and treated). Not surprisingly, 68% of equity analysts are located in the state of New York, followed by 7% in California and 4% in Illinois.

Figure A3 maps the selected salient weather shocks that occur near an analyst's office location from 1999 to 2020 by the US state. The states with the highest number of shocks are California and Oregon with 46 and 47 shocks. The state with the lowest number of weather events is Washington with three weather shocks.

B Analysts' Characteristics

For studying individuals' beliefs, I construct a series of analysts' characteristics commented below.

Climate variables. *Climate-sensitive states* are constructed using the entire natural hazard dataset and looking at the median number of shocks per state and by setting high climate-sensitive states as states with more than 4 natural events. These states are Texas, Tennessee, Connecticut, Florida, Ohio, California, Pennsylvania, Maryland, and New York and 87% of analysts are located there.

State's climate beliefs are constructed using the 2021 wave of Yale Climate Opinion Maps which asks if individuals believe that global warming is happening.[32] States with high (low) climate beliefs are states in the top decile (bottom 5 deciles) as the percentage of the population believing that climate change is happening in 2021. States in the top decile have

[32] The question asks: "Recently, you may have noticed that global warming has been getting some attention in the news. Global warming refers to the idea that the world's average temperature has been increasing over the past 150 years, may be increasing more in the future, and that the world's climate may change as a result. What do you think: Do you think that global warming is happening?

between 77% and 83% of the population believing that climate change is happening, while the bottom 5 have between 56% and 70% and they are 26 states. These high climate beliefs states are California, DC, Massachusetts, Maryland and New York and they contain 92% of all analysts.

Political variables. *State and county political ideology* is constructed using data from MIT Election Data and Science Lab of Presidential election, respectively Data and Lab (2017) and Data and Lab (2018). The data at the state (county) level is computed using the majority of votes for the US presidential election, setting the value equal to 1 if the state (county) had the majority of votes for the democratic party and 0 for a Republican.

Since analysts may live in a State or county that does not reflect its *political beliefs*, I try to proxy for political affiliation using Political Donation Data from the FEC dataset, which reports any individual donation above 200 dollars for a party. The merge is conducted by analysts' names and states. Moreover, I manually checked that the reported companies match the brokerage firm with which the analyst is working. Using the data from 2000 to 2018, I find 203 analysts of which 51% conducted democratic donations. [33]

Performance and Expertise. The performance measurement methodology, as described in Hong et al. (2000), follows a systematic process. Firstly, the forecast error is computed for each analyst by taking the absolute difference between their forecasted values and the actual values. Subsequently, analysts are ranked within their respective firms based on the forecast error, and this ranking is adjusted according to the number of analysts associated with each firm. The resulting rankings yield individual performance scores for analysts within a given year. To determine the overall performance score for an analyst, the average score across the previous 3 previous years is used. Analysts in the top tercile of performance scores from the previous year are identified as the *top-performing analysts*.

[33] Note that in Jiang et al. (2016) they are able to find a sample of 673 donor analysts, during the 1993 to 2008 period.

As for *analysts' experience*, it is quantified by the number of years an analyst has been included in the IBES dataset. On average, analysts in the dataset possess approximately 13 years of experience. Analysts with over 13 years of experience are considered to be experienced analysts.

Sex. The determination of the sex of equity analysts is accomplished using Chat GPT, which categorizes analysts' names as female, male, or uncertain. This categorization results in 14% of the total analyst sample being identified as female, while 5% remain uncertain.

Mindset. The value of optimism is assigned as value 1 if an analyst's forecast exceeds the consensus forecast (calculated as the average forecast for a specific firm over a month for a specific forecast horizon) and 0 otherwise. Subsequently, I compute the average optimism score for each analyst within a fiscal year. Based on these scores, analysts are categorized into terciles within a fiscal year. *Ex-ante optimistic analysts* are the ones in the top tercile of optimism scores in the previous year. Conversely, the opposite holds true for pessimism.

A Robustness

Placebo Test

To rule out alternative explanations, I employ a placebo exercise by examining the impact of terrorist attacks in the US that occurred within a 100-mile radius of analysts' locations. This exercise allows me to test whether the observed relationship between weather events and climate beliefs is driven by factors specific to weather events or is a more general phenomenon that can be triggered by any kind of exogenous shock.

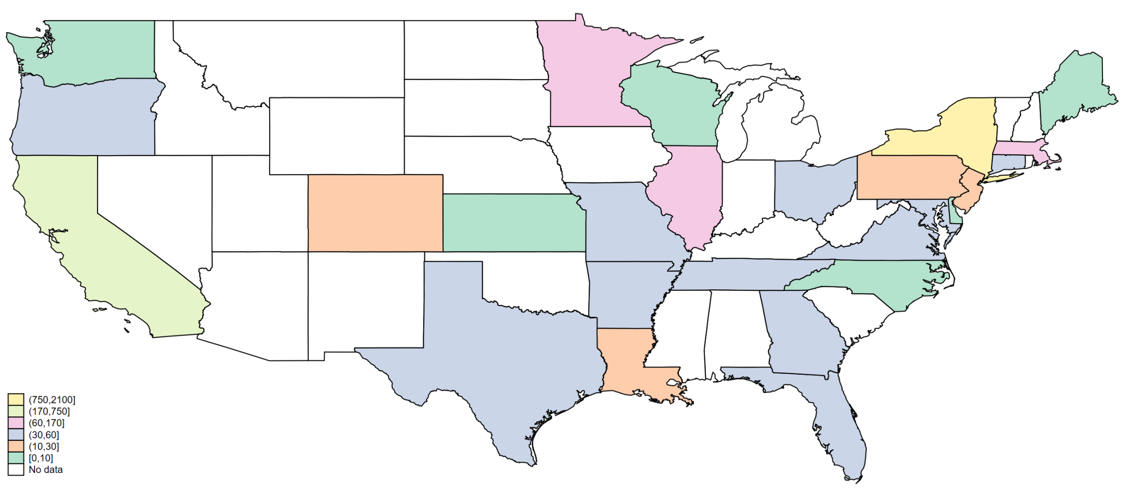
Similar to the weather shocks used in the analysis, I select salient terrorist attacks if they cause more than 10 fatalities or injure more than 100 people.[34] Table A2 reports the

[34] Note that there is no information on the economic-related damages of a terrorist attack.

results of this placebo analysis. Columns 1 and 2 show that the forecast bias and error of analysts who live 100 miles near a terrorist attack decreased by 0.23 p.p. and 0.3 p.p. after the event. Columns 3 to 14 repeat the analysts for subgroups of high and low-performance analysts forecasting firms with high and low physical risks. Due to the limited number of observations, I prioritize the magnitude of the coefficients rather than their significance. Examining columns 3-4 and 9-10, it becomes apparent that both high and low-performance analysts exhibit increased pessimism and accuracy after a terrorist attack. When dividing firms based on their climate sensitivity by sector, it appears that high-performance analysts reduce their bias and error only for firms in low-climate risk sectors. At the same time, the same applies to low-performance analysts for both high and low physical risks. Considering the limited number of observations, this placebo analysis confirms previous findings.

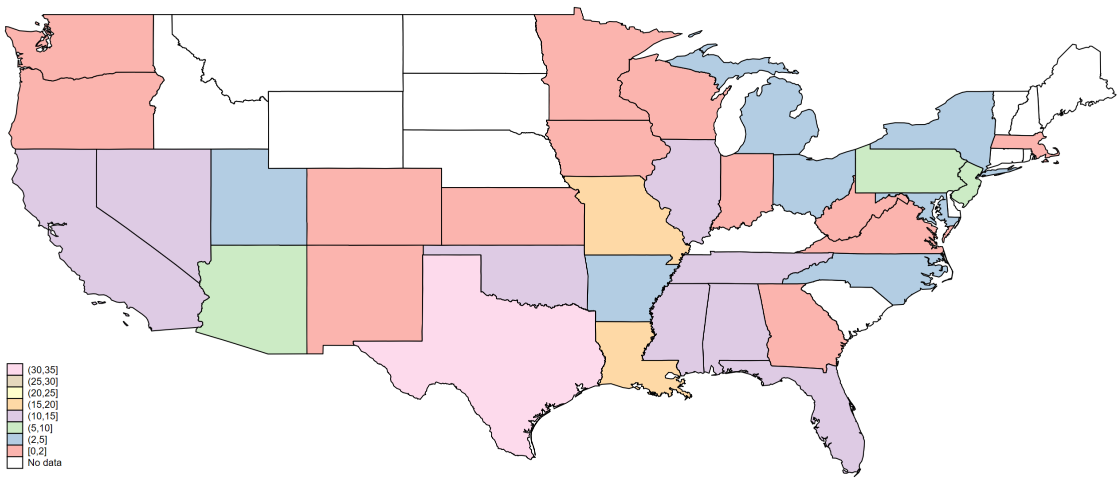
B Appendix Figures

Figure A1: Analysts' location from 1999 to 2020 by state - Full Sample



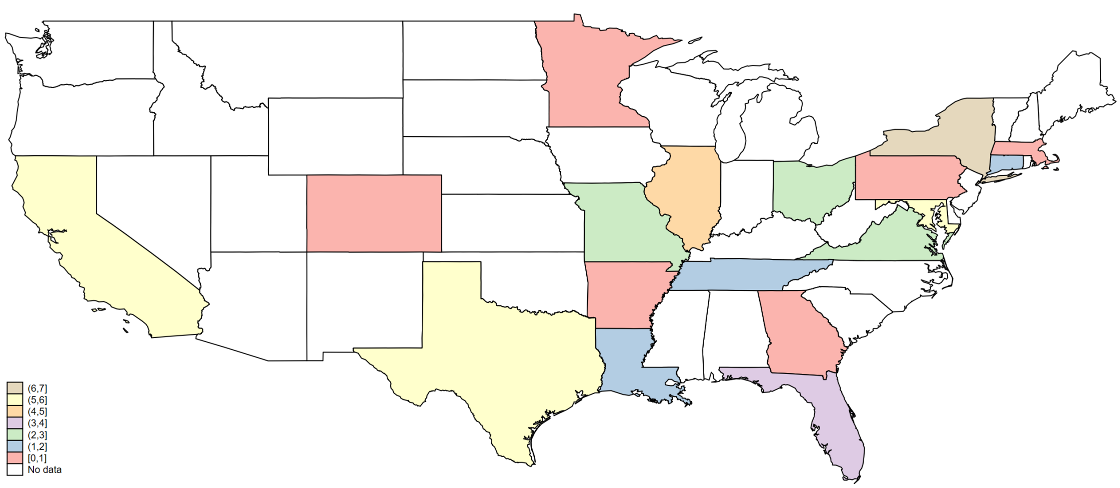
Note: The graph maps the IBES analysts' locations from 1999 to 2020 by US state obtained from Refinitiv and Capital IQ-Professional. Among 2894 analysts, the state of New York has the highest number of analysts with 2017 individuals, followed by California with 235 analysts, 105 analysts in Illinois, and 85 in Massachusetts.

Figure A2: All salient storm events from 1999 to 2020 by state



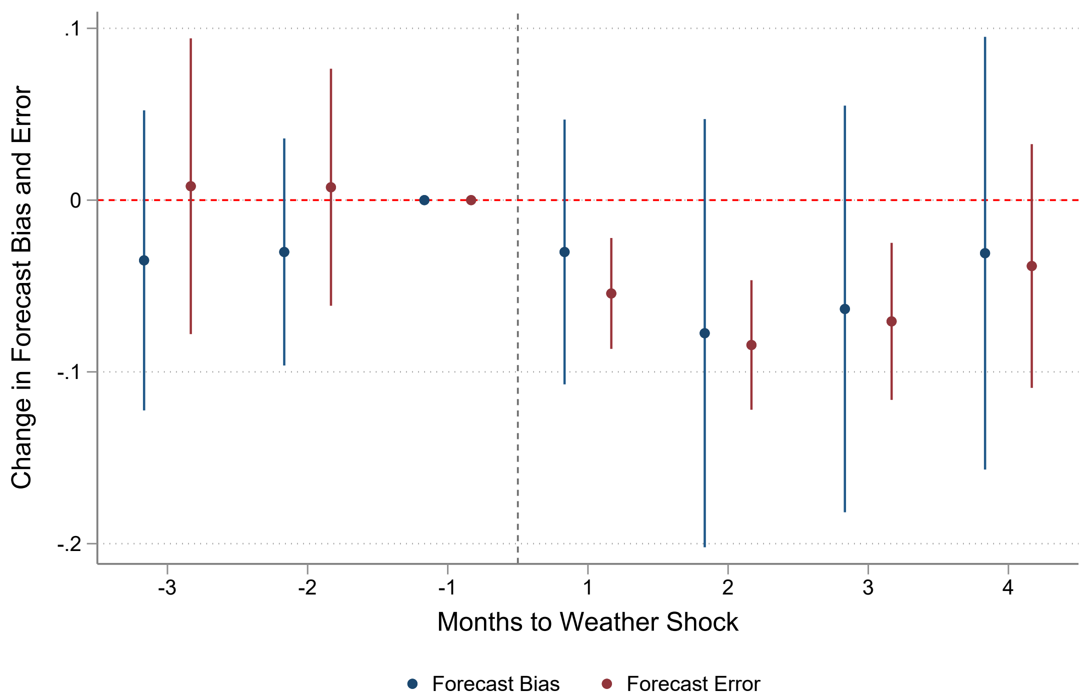
Note: The graph maps the Selected Storm Events from 1999 to 2020 by US state. The state with the highest number of shocks is Texas.

Figure A3: Salient storm events from 1999 to 2020 by state near treated analysts



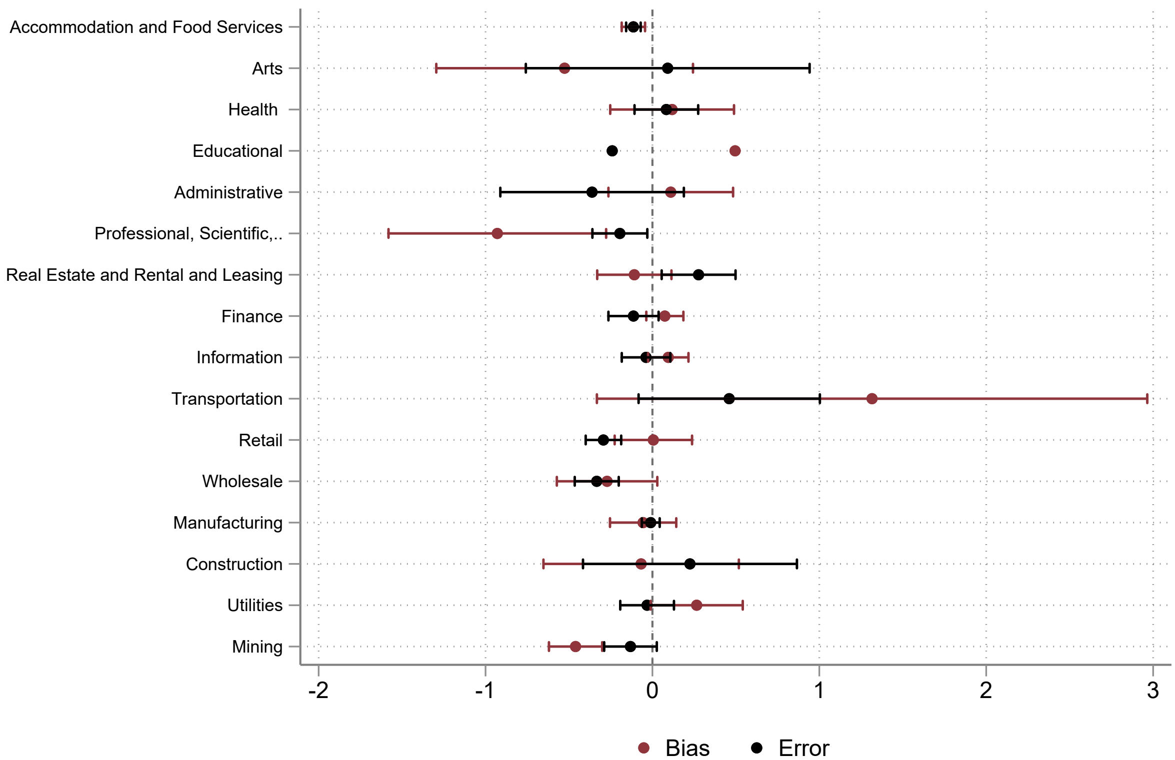
Note: The graph maps the Selected Storm Events from 1999 to 2020 merged to analysts location by US state. Notice that only weather shocks that occur near analysts are reported in the graph. The states with the highest number of shocks are New York, California, and Texas.

Figure A4: Parallel trend



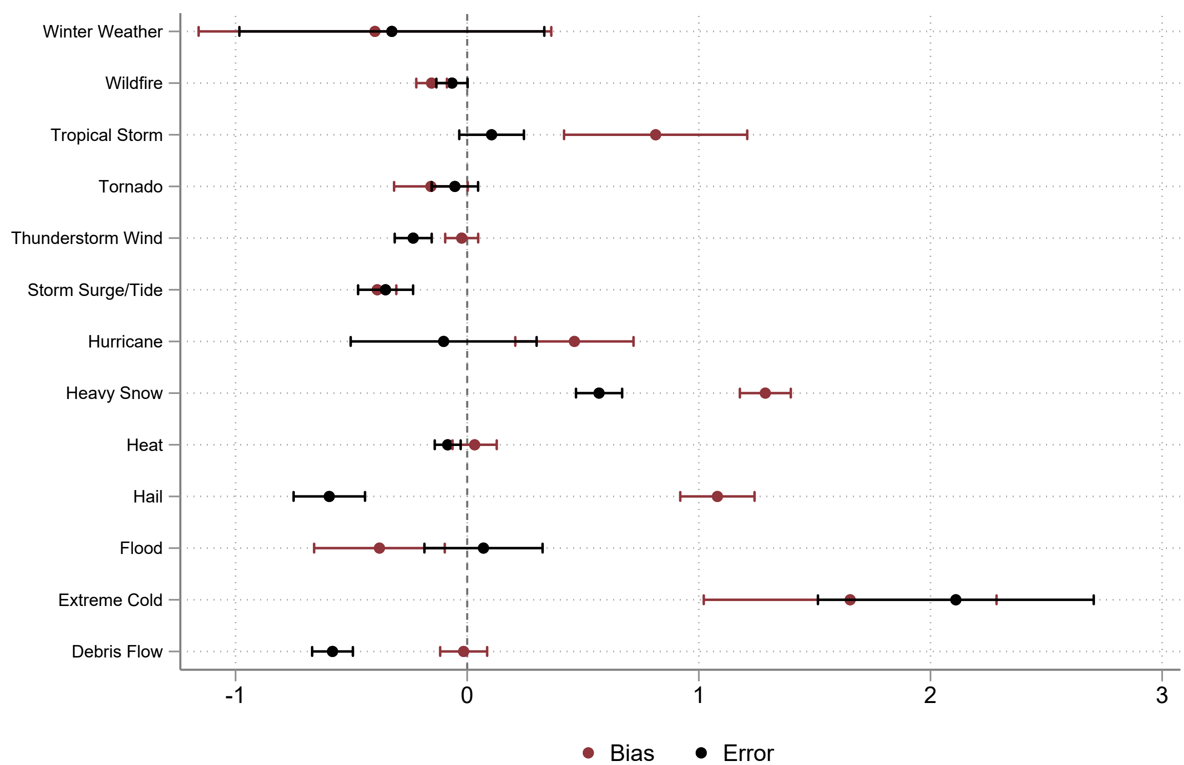
Note: figures plot the estimated coefficients of pre and post-period interactions between treatment and time variable with 90% confidence interval. The analysts included submitting at least one forecast per month in each of the three months of the pre-treatment period. The omitted month is the month before the weather event. The specification includes all covariates and shock interacted with horizon fixed effects. The event window includes 3 months before and 3 months after the event. The standard errors are clustered at the analysts' office location.

Figure A5: Effect on analysts forecasts by firms sector



Note: The graph plots the estimated coefficients from the difference in difference in bar plots with 90% confidence intervals for error (black) and bias (maroon). The DIDs are run separately for each event's type. The specification includes all covariates and forecasted horizon*weather shock fixed effect. The analysis keeps only one forecast before and after the event. The standard errors are clustered at the analyst's office location.

Figure A6: Effect on analysts forecasts by type of event



Note: The graph plots the estimated coefficients from the difference in difference in bar plots with 90% confidence intervals for error (black) and bias (maroon). The DIDs are run separately for each event's type. The specification includes all covariates and forecasted horizon*weather shock fixed effect. The analysis keeps only one forecast before and after the event. The standard errors are clustered at the analyst's office location.

C Appendix Tables

Table A1: Summary statistics for the entire dataset

	Mean	p50	SD	Min	Max
forecast bias (%)	0.69	0.03	3.48	-34.54	60.38
forecast error (%)	1.81	0.66	3.29	0.00	67.04
companies followed	14.59	14.00	6.45	1.00	47.00
firm experience	2.02	1.00	2.32	0.00	19.00
general experience	4.37	3.00	3.99	0.00	19.00
industries followed	1.79	1.00	1.10	1.00	11.00
brokerage size	67.32	52.00	52.65	1.00	284.00
firm size	7.66	7.63	1.81	1.43	14.76
leverage	0.20	0.16	0.21	0.00	3.95
market value	2.02	1.44	2.10	0.02	45.48
stock price	41.14	29.12	49.38	0.63	2027.09
ROA	0.00	0.01	0.08	-3.98	0.67
N	67026				

Note: The table reports the summary statistics for the whole sample of analysts (before matching with weather shocks). Forecast bias is defined as the difference between the earnings forecast of an equity analyst i for a firm f in the month t minus the actual earnings divided by the stock price for a firm f in the previous fiscal year $t-1$, while forecast error differs from forecast bias only by having the numerator in absolute terms. Both are expressed in percentages. See tables 15 and 16 for a description of the variables used.

Table A2: Placebo test - terrorist attacks

Analysts:	All Sample		High Performance Analysts						Low Performance Analysts					
	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error	(7) Bias	(8) Error	(9) Bias	(10) Error	(11) Bias	(12) Error	(13) Bias	(14) 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

Note: the table shows the baseline staggered differences-in-differences for yearly forecasts using the terrorist attack as a placebo shock. Terrorist attacks are salient events with at least 10 fatalities or 100 injured people. Columns 1 and 2 report the results for all analysts. while columns 3 to 14 report the results for subgroups of high and low-performance analysts forecasting firms with high and low physical risks. Each specification includes forecast horizon interacted with analysts, year, and firm fixed-effects. The control variables are forecast days gap, broker size, companies followed, firms experience, industries followed, forecasted firm size, forecasted firm leverage, and forecasted operating income. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the analyst's office location.