What Drives Beliefs about Climate Risks? Evidence from Financial Analysts

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Abstract

This study examines how experiences of weather events influence financial forecasts. Using a unique dataset spanning natural disasters and equity analysts' forecasts across 24 US states from 1999 to 2020, I investigate shifts in first-time-treated analysts' forecasts after unexpected weather shocks. The findings reveal that analysts have lower forecast bias and error after experiencing these events. When comparing analysts with different performances and firms' climate exposures, I observe that high-performance analysts adjust forecasts exclusively for firms with high climate risks, while low-performance analysts become more pessimistic across all firms, regardless of their exposure.

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

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1 Introduction

Modeling beliefs about risk is a challenging task, and the complexity of climate risks adds an additional layer of intricacy. The intricate nature of climate risks arises from the close interplay between physical risks, such as natural disasters, and transition risks, such as carbon reduction policies. Lenient carbon regulations today affect the number and severity of future extreme weather events. Consequently, the incentive to implement mitigation policies in the present is contingent on the projected economic severity of future physical events. However, given the limited understanding of worst-case scenarios caused by climate change, this relationship is inherently uncertain (Kemp et al., 2022).[1] As such, comprehending how individuals and organizations perceive future physical risks is crucial in the battle against climate change.

In this paper, I try to shed light on how agents form beliefs about climate physical risks (henceforth climate beliefs) and how experiences of weather events affect these beliefs. To study how climate beliefs are included in expectations and how this inclusion affects financial markets, I exploit earnings forecasts issued by equity analysts. Analysts constitute an ideal setting because they are important information producers (Mikhail et al., 2007). Additionally, by exploiting timely forecasts before and after an exogenous weather shock, my study claims that earnings forecasts can be a useful tool to pin down variations in climate beliefs. Showing how experiences of weather shocks affect beliefs and consequently earnings forecasts.

This study will complement recent but fast-growing literature that investigates the effect of experiencing climate events on market participants' behavior. For example,

[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).

Choi et al. (2020) document that retail investors sell stocks of firms with high carbon footprints during months with atypically high temperatures. Anderson and Robinson (2019) note that Swedish households are more likely to invest in green funds after experiencing a heatwave. Alekseev et al. (2021) show that mutual funds managers change their portfolio allocation across industries after experiencing idiosyncratic climate belief shocks such as extreme heat events.[2] Despite the considerable attention given to the impact of climate-related events on behavior, the current body of literature has yet to fully explore the mechanisms through which beliefs about climate risks are initially formed and the factors that influence the development of such beliefs.

My conceptual framework, building upon the influential work of Malmendier and Nagel (2011), provides an initial yet straightforward definition of beliefs about climate risk and the components that shape them. Note that my study focuses solely on physical risks, hence climate beliefs as the anticipated future economic damages resulting from climate change in the United States. Similar to Malmendier and Nagel (2011), I define beliefs as a weighted sum of an endowed fixed prior climate belief and past experiences of weather shocks. However, my framework diverges in that it considers only firsthand experiences of weather shocks that significantly impact an individual's climate beliefs, emphasizing the selection of highly salient weather events.[3]

The empirical strategy to uncover analysts' climate beliefs relies upon using variations in their earnings forecasts following weather shocks as a proxy. Earnings forecasts capture analysts' perceptions of firms' future financial performance based on all available information, including their beliefs about climate risks. Assuming that weather shocks do not directly or indirectly impact firms' earnings, any changes in earnings forecasts must be due to a change in analysts' beliefs. Hence, by holding the information set constant, I can provide evidence of how weather shocks shape climate beliefs, thus

[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.

[3] Andersen et al. (2019) present empirical evidence that only direct experiences of shocks have a significant impact on an individual's level of risk aversion. In my empirical strategy, I additionally use first-time experiences such as to alleviate the issue of how memory influences the formation of expectations.

affecting the financial market.

So, why should analysts change their forecast if firms are not affected by the event? There are three potential arguments. First, a change in analysts' forecast may result from the acquisition of new insights into the future economic costs of climate change, which are obtained from exposure to salient weather events (*information hypothesis*). This would be extremely valuable for the analysts, allowing them to be able to better forecast firms with large climate risks. Second, analysts' risk-taking behavior may be influenced by the emotional impact of traumatic weather events, leading to a temporary alteration in their perceptions of climate risks (*heuristic hypothesis*). In this vein, experienced shocks have only a short-term on analysts' risk assessment and we expect to revert back after a couple of months. Third, analysts have limited attention and the experience of an extreme event will make them focus on a subset of firms (*distraction hypothesis*). This paper investigates these three hypotheses and presents evidence that, while operating in conjunction, analysts could gain insights from experiencing a climate event.

To do so, I start by building a comprehensive dataset with analysts' and weather shocks' characteristics. Salient weather shocks are defined as natural hazards that have at least 100 injured, 10 fatalities, or 1 billion in economic damages. Following Alekseev et al. (2021), I provide evidence that my selected weather events affect beliefs by showing that, after an extreme weather event, there is a relative increase in interest in climate change (proxied by Google search trends).[4] The final dataset includes 49 different natural hazards across the US matched with the IBES earnings forecasts of 2,816 equity analysts in 29 different US states. Equity analysts in my sample issue 2,196,138 earnings forecasts for 6,846 firms from 1999 to 2020.

Using a quasi-staggered differences-in-difference regression approach, I exploit weather events occurring near equity analysts to study variations in forecast bias and error. Forecast bias is computed as the difference between firms' actual and forecasted earnings

[4] No statistically significant increase in climate news indexed is found during months with extreme weather events. Indicating that my selected shocks influence beliefs in the area where the event happens but not overall climate news.

divided by the stock price in the previous period, while forecast error differs from forecast bias only by having the numerator in absolute terms (as in Hong and Kacperczyk, 2010). While bias serves as an indicator of analysts' optimism or pessimism, error provides insights into analysts' accuracy. Analysts were divided into treatment and control groups, with the former consisting of first-time treated analysts located within 100 miles of weather shocks, while the latter included never-treated analysts.[5]

As mentioned above, to infer climate beliefs from variations in earnings forecasts, it is crucial to ensure that selected weather shocks do not have any direct or indirect impact on firms' earnings.[6] This guarantees that any observed changes in earnings forecasts are purely driven by a change in analysts' beliefs, rather than a change in the firms' fundamentals. I control for this by only considering forecasts of firms located at least 100 miles from the event and by showing that firms' fundamentals are constant in the period surrounding the event. The final sample used for the analysis comprises 1,389 analysts across 24 states providing forecasts for untreated 2,746 firms. Among these, 835 analysts are treated for the first time in their role as analysts.

The baseline results provide compelling evidence that analysts' forecasts are affected by weather shocks. In line with previous studies, I document that analysts' accuracy and pessimism increase after a weather event (Han et al., 2020; Tran et al., 2020; and Reggiani, 2022). I find that first-time treated analysts, after experiencing a weather shock, have a lower forecast bias of 0.14 p.p. and a lower forecast error of 0.23 p.p. compared to the control group. These correspond to a 14% decrease in bias and 11% in forecast error when compared to the average forecast bias and error.

I also show some interesting facts relating to the effect of weather shocks. First, by replicating the baseline analysis across several subgroups of analysts' characteristics (gender, experience, ex-ante sentiments, performance, political factors, and residence),

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

[6]Direct effect such as firms suffering revenue losses from the weather shock, while indirect is if suppliers or competitors are affected by the event.

I find a consistent, homogeneous effect of weather shocks on forecast bias and error. Second, analysts exhibit increased pessimism and accuracy in sectors linked to higher climate risks (e.g., agriculture, construction, manufacturing, mining, retail, and transportation). Third, it's worth noting that certain climate events, like hail, debris flow, and tropical storms, lead to analysts displaying a more optimistic bias in their forecasts, indicating nuanced reactions to distinct weather-related occurrences.

I then investigate the potential roles of *heuristic* and *information channels* by leveraging on firms' climate risk profiles and analysts' performance subgroups. The focus is on analysts' performance subgroups because I hypothesize that low-performance analysts are more vulnerable to heuristic channels, whereas high-performance analysts may leverage their expertise to extract new information from the event. Indeed, high-performance (defined following Hong et al., 2000) analysts possess more experience and knowledge across multiple industries and demonstrate lower forecast errors than low-experience analysts.

The findings reveal that high-performance analysts exhibit a pessimistic shift of 0.14 p.p. exclusively for firms operating in climate-sensitive sectors. In contrast, low-performance analysts become more pessimistic across all firms. Both high and low-performance analysts demonstrate increased forecast accuracy following the weather event. When examining the specific physical risks associated with firms, both high and low-performance analysts display pessimism for high-risk firms. However, the magnitude of pessimism is twice as large for low-performance analysts. Given that the downward adjustment of forecasts for climate-sensitive firms could be attributed to either the *representativeness heuristic* or the acquisition of new climate risk-related *information*.

To assess whether analysts can extract information about future economic damages of climate change from weather events, the study decomposes the firms' physical risk score into distinct types of weather event risks. If analysts extract climate risk information from the event, they should learn more about the particular type of event they experienced. For example, after experiencing a hurricane, they will have more knowledge about hurricane risks compared to wildfire risks. Results indicate that high-performance analysts become more pessimistic only for firms with high risks of the weather event experienced by the analyst, while low-performance analysts revise their forecasts for all firms.

Similarly, if analysts are learning the future economic costs of climate change from experiencing a salient weather event, the amount of information extraction should be larger for shocks with economic-related damages compared to health-related damages. I test this by exploiting weather shocks' damage types, classified in terms of salient health-related and economic-related damages. In line with the previous findings, high-performance analysts are largely affected by economic damages, while low-performance analysts are more influenced by health-related damages.

Notice, that my baseline results are in contrast with the distraction hypothesis since it 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. If analysts are distracted by extreme weather events, I expect that their attention will be disproportionately channeled toward pivotal companies for their professional careers. In this line, the results show that analysts become increasingly more pessimistic and accurate for firms with high institutional ownership and relative importance. However, both analysts in large and small brokerage firms become more accurate after the event, and only analysts in large brokerage firms become more pessimistic. Lastly, no statistically significant effects are found in the number of forecasts issued, indicating a constant level of attention. Collectively, although the findings might suggest a reorientation of alert towards more pivotal firms, they do not definitively negate the observation that analysts also revise their forecasts for less significant entities, all the while maintaining their volume of forecasts unchanged.

An essential element in distinguishing between heuristic and information channels is the persistence of the effect. In the absence of weather events providing any shock to analysts' heuristics, forecasts should eventually return to their fundamental values, given that firms are not directly impacted by the shock. However, this poses a challenge for empirical investigation as it assumes that no additional information about climate risks is realized in the aftermath of the event, and the longer the horizon of the study, the less likely this assumption is to hold. With these caveats in mind, I find that analysts continue to maintain a pessimistic outlook for up to six months following the weather event, with no statistically significant effect observed thereafter. Nevertheless, when examining forecasts separately (and independently of the time component), there is no evidence that treated analysts revert their forecasts to the pre-event levels for up to 5 forecasts after the shock. In sum, the results are mixed, and no clear conclusion can be drawn.

Ascertaining beliefs regarding climate risks is a multifaceted task, given the intricate interplay between physical risks and transition risks. Analysts who have been exposed to extreme weather events may alter their beliefs regarding both physical and transition risks, leading them to anticipate stricter regulations. To test for this mechanism, I repeat the analysis by dividing firms into high and low terciles of transition risks, proxied by firms' absolute emissions estimated in Trucost. The findings suggest that the results are driven by firms with both high transition and physical risks.[7]

Transition risks seem to play a significant role when looking at questions asked by analysts during earnings calls following extreme weather events. These analysts are less likely to ask questions concerning regulatory risks and more likely to ask questions related to climate transition opportunities during earnings calls. However, further research is necessary to fully comprehend this phenomenon.

Climate physical risks are usually regarded as long-term risks. However, since physical risks can affect short-term as well as long-term expectations, I then examine whether analysts believe that climate risks threaten long-term firms' earnings. I apply the baseline methodology on analysts' bias and forecast error from one-year to five-year horizons separately, as well as long-term growth rates. The results show that analysts' forecast

[7] However, it is important to notice that when replicating the analysis with carbon earnings at risks, which is more of a forward-looking measure of transition risks, the findings indicate that transition risks do not appear to be the primary driver of the observed results.

error and bias decrease after the event only for short-term horizons (1 to 2 years ahead and 1 to 3 years ahead). However, I find that analysts' forecast error increases for 5-year-ahead forecasts, highlighting the fact that climate physical risks are a long-term risk that leads to greater uncertainty for long-term earnings forecasts. Additionally, long-term growth rates are revised downwards after the weather shock, suggesting that analysts believe in lower future growth rates.

Moving forward, I explore the effect of experiencing a second weather shock on analysts' forecast bias and error. The results indicate that, on average, analysts tend to become more pessimistic and accurate after experiencing a second shock. Interestingly, high-performance analysts exhibit improved accuracy without alterations in bias. Conversely, low-performance analysts exhibit heightened pessimism. This once again aligns with the hypothesis that low-performance analysts are influenced by the heuristic shift, while high-performance analysts lean towards the information channel.

If analysts learn from climate-related shocks, then ex-post-treated analysts should be better at forecasting companies impacted by weather shocks. To investigate this, I divide analysts into those with prior shock experience and those without, forecasting firms directly influenced by weather events, but both analysts without direct exposure to the event itself. Using a panel regression within 3-month post-treatment windows, I find no significant difference, on average, in error and bias when predicting for treated firms. However, A notable observation emerges with a lower forecast error linked to triple interaction terms involving analysts in climate-sensitive regions or forecasting firms with high climate risks. No discernible impact is found for high-performance analysts or shocks with high economic consequences. Additionally, by comparing analysts with zero shock experience, the results reveal that analysts with shock experience exhibit reduced forecast error, particularly up to 5 prior shocks, without a bias effect.

Several robustness checks are conducted to test the validity of my results. First, the results are robust by excluding New York City, where the majority of sell-side analysts are located, and by controlling for correlation across brokerage houses. Second, by excluding firms with a business presence in the state where the event occurred (using

Garcia and Norli (2012) index), the findings remained consistent. In addition, the outcomes remain robust even when excluding firms with known establishment locations near the event (using the NETS establishment database). Third, proximity to the event emerged as a crucial factor, as analysts located within a 50-mile radius exhibited more pronounced forecast revisions. Lastly, by conducting a placebo analysis, I show that analysts' changes in their forecast errors and bias are similar in magnitude to experiencing a traumatic event such as a terrorist attack while not replicating the same pattern for high climate exposure firms. Corroborating the hypothesis that only experiences of climate-related events affect climate beliefs.

Finally, my setting allows me to study whether beliefs diffuse across analysts. Previous studies document that analysts tend to herd All-Star analysts.[8] Unfortunately, I do not have data on the latter, hence I use high-performance analysts as proxies for All-Star analysts. In this setting, my treated group is composed of firms where a high-performance analyst experiences a climate event. The variables of interest are firms' averaged forecast bias and error over low-performance analysts for treated and control firms. The estimated results suggest that low-performance analysts do not change their forecasts when high-performance analysts update their forecasts after experiencing a weather shock. However, since we lack data on All-Star analysts, a possible concern is that high-performance analysts are not influential enough to affect other analysts' beliefs, leading to statistically insignificant results.

To summarize, this study provides evidence that both *information* and *heuristic* hypotheses affect analysts' forecasts. The former affects low-performance analysts, which are more naive and inexperienced, while the latter impacts high-performance analysts. However, since these beliefs do not seem to diffuse among analysts, the study underscores the need for policymakers to enforce climate risk disclosures to increase climate awareness, benefiting low-performance analysts in particular.

[8] All-star analysts are the first-ranked analysts based on a questionnaire that evaluates analysts on six dimensions (accessibility and responsiveness, earnings estimates, useful and timely calls, stock selection, industry knowledge, and written reports) and weighted by the size of the respondent's firm. Unfortunately, my analysts' performance score captures only one of these dimensions.

My work differs from past studies on how climate shocks affect analysts' forecasts three-fold. First, I investigate how beliefs about climate risks are formed and how changes in beliefs affect forecasts. Conversely, previous studies analyze whether extreme natural events affect analysts' biases (Bourveau and Law, 2020; Tran et al., 2020; Kong et al., 2021; Han et al., 2020), processing of earnings news (Dehaan et al., 2017), and if analysts extract climate risks information from experienced abnormal temperatures (Pankratz et al., 2019; Addoum et al., 2019; and Cuculiza et al., 2021). My work, by explicitly defining how climate beliefs are formed and enter into earnings forecasts, provides evidence of what underlying channels (information and/or heuristics) affect ex-post forecasts. Second, these studies have a sample of extreme weather events that mostly comprehend extreme temperature (Pankratz et al., 2019; Addoum et al., 2019; Cuculiza et al., 2021; Zhang, 2021) or one billion disastrous natural hazards (Bourveau and Law, 2020; Han et al., 2020; Tran et al., 2020). This paper, using a more flexible definition of weather shocks, aims at understanding how different weather events and related damages, defined in terms of both health and economic damages, shape climate beliefs. Third, while these studies mostly focus on short-term forecasts, besides Tran et al. (2020), I provide a complete analysis of the effect of climate shocks on the temporal dimension of analysts' earnings forecasts (from one quarter to five years ahead).[9]

In a concomitant work, Reggiani (2022) also investigates how shifts in climate change perception affect analysts' forecasts. The main distinction between the two works is that this study aims to develop a novel approach to defining and understanding climate beliefs and what channels affect them, thus exploiting analysts' characteristics, while Reggiani (2022) primarily looks at changes in earning forecasts for firms in different industries after an increase in temperature or extreme weather events.[10] Nonetheless,

[9] Alike studies that explore the effect of transition risks on credit risks, which provide evidence that the transformation to a low carbon economy would have a differential impact on different horizons of firms' creditworthiness (Blasberg et al., 2021; Kolbel et al., 2020; Barth et al., 2020).

[10] Notice that Reggiani (2022) uses a pooled regressions on forecasted firms using analysts located near the event as treated. The author uses raw EPS forecast as the dependent variable and does not exploit any analysts' characteristics to study the channel of his results. Contrarily, I use only first-time and first-hand treated analysts who forecast firms that are not affected by the event to pin down what shifts climate beliefs.

The two studies exhibit mutual support and corroboration of each other's findings. Both work documents that analysts who experience weather events become more pessimistic in the aftermath of the event for both firms with high transitional and physical risks. Consistently to my estimated term structure of climate beliefs, Reggiani (2022) shows that the effect is concentrated between 8 to 10 quarters ahead.

At last, this paper contributes to other strands of literature. First, by showing how experiences of weather shocks affect individuals' perception of climate physical risks, it complements the experience-based learning literature by constructing a model of belief formation about climate risks (see Malmendier and Wachter, 2021 for a summary of this literature). Second, it documents what underlying channels affect analysts' forecasts, hence complementing the literature on the reaction of market participants to climate events (Alekseev et al., 2021; Hong et al., 2020; Bernile et al., 2017; Dessaint and Matray, 2017; Alok et al., 2020; Choi et al., 2020; Anderson and Robinson, 2019). At last, by providing evidence about the characteristics of a natural event that makes a weather shock salient, the study also supplements the literature on salient shocks (see Bordalo, Gennaioli and Shleifer, 2021 for a summary of the role of salience).

The rest of the paper is organized as follows. Section 2 presents a literature review. Section 3 develops the conceptual framework. Section 4 describes the hypotheses and section 5 the methodology used. Section 6 describes the data and section 7 reports the descriptive statistics. Section 8 presents the results. Section 9 concludes.

2 Literature Review

This section provides an overview of the literature on belief formation and the effect of climate events on analysts' forecasts. The conceptual framework of this study is based on the experience-based learning (EBL) model presented by Malmendier and Nagel (2011). The authors find that an agent's risk aversion and behavior are strongly influenced by lifetime events. The EBL model is not limited to investment decisions but also explains how past inflation rates affect individuals' perception of future inflation rates (Malmendier and Nagel, 2016). It also provides a link between past experiences and current behaviors, such as how past inflation experiences affect homeownership choices (Malmendier and Wellsjo, 2020) or how consumption choices are explained by past unemployment experiences (Malmendier and Shen, 2018). Moreover, the model is robust to expert knowledge, as shown by Malmendier et al. (2021), who demonstrate that even members of the Federal Reserve Bank's Federal Open Market Committee have their forecasts affected by past experiences.[11]

The second stream of relevant literature is related to how climate shocks affect financial analysts. At present, the studies present contrasting evidence. Pankratz et al. (2019) find that analysts, who experienced a climate shock (defined as abnormal temperatures), do not incorporate such shock in their earnings forecasts. Addoum et al. (2019) show that forecast consensus emerges following a climate shock in certain industries only. While Addoum et al. (2019) use daily-temperature variation to explain earnings variation, Zhang (2021) use cumulative temperature and precipitation exposure at the firm's headquarters to quantify earnings seasonality. The latter shows that firms with higher operating weather exposure are more affected by unexpected weather events and less by regular seasonal factors. Thus larger uncertainty translates into higher forecast dispersion and lower accuracy. Cuculiza et al. (2021) provides evidence that analysts, who are located in more climate-sensitive areas, deliver less optimistic and more accurate forecasts for climate-sensitive firms during and after a month of extremely high temperature. Conversely to Addoum et al. (2019), Cuculiza et al. (2021) find significant differences within analysts located in areas with different political affiliations. While these studies use historical fluctuations in temperature and precipitation

[11] While the EBL model explains how beliefs are formed, another parallel body of literature, built on the concept of representative heuristics, studies the dynamics of beliefs. According to Kahneman and Tversky (1972)'s notion of representative heuristics, an agent tends to overestimate the probability of the representative types after the news. Under the diagnostic expectation literature, Bordalo et al. (2019) document that analysts, after a positive earnings surprise, tend to overestimate firms' fundamentals. Similarly, Bordalo et al. (2020) observe that macroeconomic forecasters tend to overreact to positive macroeconomic news. At last, this literature shows that diagnostic expectations give rise to credit cycles (Bordalo et al., 2018) and asset price bubbles (Bordalo, Gennaioli, Kwon and Shleifer, 2021).

as indicators of climate risks, Kim et al. (2021), show that firms located in countries with higher drought risks have higher forecasted errors and dispersion, particularly for inexperienced analysts, driven by an increase in uncertainty by consumer pressure.

Other studies, instead of focusing on the incorporation of climate-related risks, document how extremely negative events affect analysts' heuristics.[12] For example, Bourveau and Law (2020) investigate whether experiencing a disastrous hurricane affects analysts' risk-aversion, as measured by analyst relative optimism. They find that analysts who experience a hurricane have less optimistic one-quarter-ahead forecasts for the following two years.[13] Similarly, Kong et al. (2021) tries to pin down what are the channels that drive analysts' short-term post-shock pessimism. They show that analysts' pessimism (after experiencing an earthquake) is amplified for low-sophisticated analysts and when there is high media attention coverage.

Within this literature, multiple studies rely on the definition of Barrot and Sauvagnat (2016) for the selection of extreme natural hazards, which is: "major disasters with total estimated damage above $1 billion 2013 constant dollars that lasted less than 30 days". Using their definition of salient climate events, Han et al. (2020) provide evidence that treated analysts have larger forecast errors in the 3 months after the event but only for firms with low market capitalization, low institutional ownership, and that are less salient (i.e. extremely high or low stock returns). They suggest that this effect is driven by a "distraction hypothesis", which posits that experiencing a traumatic event makes a person more stressed and distracted, causing analysts to focus only on more important firms, thus providing worse forecasts to other companies. Additionally, Tran et al. (2020) present evidence that natural events make ex-ante pessimistic ana-

[12] Notice, that there is a large stream of accounting and financial literature that studies the number of biases that influence analysts' forecasts. For example, young analysts may tend to avoid bold forecasts (distant from consensus forecasts) because they may damage their careers (Hong et al., 2000). They may prefer to issue optimistic forecasts for long-term gains (management relation) by giving up short-term gains (greater accuracy). Moreover, firms followed by more analysts have better forecasts due to less competition bias (Hong and Kacperczyk, 2010).

[13] Cuculiza et al. (2020) show that analysts located near a terrorist attack issue more pessimistic forecasts (lower than consensus forecasts) and they are more accurate. The latter is driven by the fact that treated analysts have bold downward revisions driven by a non-economic event, which outweighs their over-optimism bias.

lysts become even more pessimistic after a shock (and less accurate), while optimistic analysts become more optimistic.

Finally, a recent work examines the impact of risk disclosure on analysts' forecasts. Wang et al. (2017) find that forecast accuracy increases when annual reports have higher risk disclosure, as larger risk disclosure decreases market information asymmetry. Similarly, Krueger et al. (2021) show that mandatory environmental, social, and governance (ESG) disclosures improve the information quality of firms' risks, resulting in more accurate and less dispersed forecasts. Derrien et al. (2021) exploit ESG incidents to investigate how they affect equity forecasts and therefore firms' value, while Chan (2022) show that the consensus incorporates information from climate disclosure (using the Carbon Disclosure Project, CDP) only for industries most exposed to climate change.

3 Conceptual Framework

In this section, I present the conceptual framework that establishes the process through which climate beliefs are developed. Specifically, I demonstrate how the experience-based learning (EBL) model can be adapted for application in the climate context in a general sense. Furthermore, I tailor the EBL model to suit the analyst's forecast setting and delineate the methodology for extracting climate beliefs from analysts' earnings forecasts.

Formation of Climate Beliefs

This study relies on the EBL model as presented in Malmendier and Wachter (2021), where beliefs are a weighted sum of a prior belief and past experiences under an overlapping-generation model with finitely lived agents.[14] In the climate context, I assume that agents are endowed with a prior belief ($\bar{\theta}$) about climate change. The prior $\bar{\theta}$ can be thought of as the mean of a distribution of possible future economic damages

[14]See Appendix B for a more detailed explanation and derivation.

caused by climate change in a geographical area.[15] In addition to the prior, agents have weather shock experiences during their lifetimes, which is equivalent to the conceptual framework in Malmendier and Nagel (2011).

My setting differs from Malmendier and Wachter (2021) in three main points: (i) only direct experiences of weather shocks enter into posterior climate beliefs, (ii) shocks experienced before working as an analyst do not matter for climate beliefs, (iii) weather shocks are perceived as a realization of climate change.

First, Malmendier and Nagel (2011) use publicly available US stock and bond market returns to show that only experienced returns (i.e. returns during an individual lifetime) matter for posterior beliefs. Similarly, Malmendier and Nagel (2016) show that only observed US inflation rates affect expectations of future inflation rates. In this study, only first-hand experienced weather shocks (shocks that occurred geographically near the analysts) are assumed to impact analysts' beliefs. Conjecturing that weather shocks geographically distant are not salient enough to impact analysts' beliefs.[16]

Second, since I do not have data on analysts before they start working, in my setting the weighting function depends on when agents start their jobs as financial analysts. This implies that only weather shocks directly experienced during their work have an impact on analysts' posterior beliefs.[17]

Third, the study relies on the assumption that weather shocks are a realization of climate change. However, sociological studies such as McCright et al. (2014) indicate that the individual's perception of weather shocks as climate change realization depends on individual characteristics. For this reason, I modify the EBL setting such that

[15] For example, some individuals are ex-antes very pessimistic, they grew up in a very climate-sensitive area and/or in a location with a strong climate change ideology. Therefore, they tend to have a very high perception of future climate scenarios whose corresponds to a very high prior ($\bar{\theta}$).

[16] Andersen et al. (2019) points out that investors' risk-taking is affected only when investors directly experience losing investments after banks' defaults. They found no supporting evidence for the second of the third-hand effect of knowing a relative affected by the banks' default or living near the defaulted bank.

[17] Malmendier and Nagel (2011) points out that using a shorter time period for lifetimes' experiences leads to a lower λ since the model does not need to down-weight shocks experienced early in life. Moreover, since the sample of data shrunk (after dropping early in life observation), they find a lower estimated $\hat{\beta}$ for the effect of past experiences on financial behavior.

whether analysts perceive a weather event as a climate realization depends also on analysts' prior beliefs about climate change. Therefore, the prior belief is included in the weighting function of weather shock experiences.[18]

Analysts do not change the number of forecasts issued after the event.

Taking this together, the posterior beliefs θ_t at time t for an agent is:

$$\theta_t = (1 - w_{\mathrm{z}}) * \bar{\theta} + w_{\mathrm{z}} * \sum_{k=0}^{\mathrm{Z}} w(k, \lambda, \bar{\theta}, \mathrm{z}) * \text{ Weather Shocks }_{t-k} \tag{1}$$

Where z is the number of years as an analyst at time t, *Weather Shocks* are salient natural hazards (i.e. wildfires, hurricanes, etc.), k is the time period when the shock occurred and λ is a weight assigned to recent versus former shocks. The weight assigned to the prior and past experiences is $w_z = \frac{z+1}{\tau+z+1}$ and the weighting function of past experiences is $w(k, \lambda, \bar{\theta}, \mathrm{z}) = \frac{(\mathrm{z}+1-k)^{\lambda}}{\sum_{k'=0}^{z}(z+1-k\prime)^{\lambda}}$. Notice that when $\lambda > 0$, recent weather shocks receive more weight compared to early-in-life weather shocks. In Malmendier and Nagel (2011), the authors find $\lambda = 1$, i.e. the agents assign approximate linearly decreasing weights to past experiences.

This model provides four main features.[19] First, past experiences of weather shocks are a strong determinant of individuals' behaviors in the long run (long-lasting effect). Second, recent weather shocks have a stronger effect on young individuals (recency bias). Third, whether shocks' experiences affect how individuals assess the distribution of future realization only in climate-related domains (context dependence). Fourth, these findings also apply to expert forecasters such as analysts (robustness to expert knowledge).

Variation in Analysts Forecasts

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'

[18]Please be aware that this section is currently under development and necessitates further refinement.
[19]For a more detailed explanation of the EBL key features see Malmendier and Wachter (2021).

earnings forecasts can be defined as a function of analyst's beliefs, including climate beliefs, and all the available information in the market.[20] 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.[21] Second, selected shocks are salient natural hazards and they are perceived as climate change realization for analysts with a non-zero prior. 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.

With the previously discussed conceptual framework in mind, I can now extrapolate some testable assumptions from the EBL model on climate beliefs.

4 Hypotheses Development

Why should analysts change their forecasts if firms are not affected by the event? I propose here three potential explanations: i) the information hypothesis (analysts are able to extrapolate information about the cost of future climate-related hazards); ii) the heuristics hypothesis (analysts overestimate the probability of these events happening); iii) the distraction hypothesis (analysts, distracted by the event, focus their attention

[20] Formally, analysts' forecasts can be represented as $(belief) * (information)$, where analysts' *beliefs* encompass climate beliefs as well as beliefs pertaining to firms' fundamentals or the wider economy.

[21] 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.

to certain firms). It's worth noting that these explanations are not mutually exclusive, but they may actually work in tandem.

The first 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 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, we 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).[22]

[22] 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

Lastly, several studies suggest that experience of extreme events could make analysts distracted and potentially influence earnings forecasts (Han et al. (2020); Liu et al., 2022). This gives rise to three potential outcomes. Firstly, analysts might exhibit lower forecasting accuracy given their limited attention. Second, analysts would focus on firms more pivotal for their careers, usually proxy by high institutional ownership and market capitalization. Third, if the distraction is driven by limited attention, I expect that analysts in smaller brokerages, potentially less equipped to handle weather shocks, might face greater challenges, and thus are the ones mostly affected by the event.

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

Hyp. 1 *If weather shocks provide new information to analysts, new climate beliefs should be long-lasting (in the absence of any other shock) but it may take time to be incorporated into forecasts.*

Hyp. 2 *If weather shocks affect analysts' heuristics, new climate beliefs rapidly affect analysts' forecasts but they will dissipate after 3 months (in the absence of any other shock). Under the availability heuristic, recent weather events should affect the beliefs of all firms. While under the representativeness heuristic, firms or areas associated with higher climate risks should present a larger change in beliefs.*

Hyp. 3 *With respect to the timing and damages of the event, following the heuristic hypothesis, firms' forecasts should be largely affected by weather shocks that cause health-related damages. Under the information hypothesis, if extreme events occurred more or less recently should not matter and firms' forecasts should be largely affected by weather shocks with large economic-related damages.*

Hyp. 4 *If weather shocks make analysts distracted, forecast accuracy and the number of forecasts should decrease after the event. Analysts will focus on firms with high*

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.

institutional ownership and high market capitalization since they are the most important for the analysts' careers. Lastly, analysts in small brokerage firms should present the largest impact on forecast error and bias.

5 Empirical Strategy

To investigate my testable questions, I exploit extreme natural hazards as randomly distributed weather shocks. In this section, I explain how I define salient weather shocks, the methodology use, 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.[23] 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 which 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.

Baseline Regression. 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. 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 that issue forecasts

[23] 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 is the standard definition by Barrot and Sauvagnat (2016).

for firms in the same sectors as the "treated firms" (i.e. followed by treated analysts). To ensure that a change in forecasts is driven by changes in beliefs (i.e. keeping the information set constant), I exclude all firms located 100 miles from the event, using the firm's headquarters location as a proxy for the firm's location.[24] As shown in figure 1, I only look at treated and control analysts that forecast untreated firms (colored in green).

The following analysis is conducted at the monthly level: keeping only one forecast per month issued by an analyst for each firm. For example, for an analyst who supplies multiple forecasts in a given month (for the same firm), I only keep 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:

$$\text{Y}_{\ i,f,h,t} = \beta treat * post_{i,f,h,t} + \theta X_i + \gamma_{i*h} + \delta_{y*h} + \eta_{f*h} + \varepsilon_{i,f,h,t} \tag{2}$$

for an analyst i, firm f, for a forecast horizon h and at month-year t. Where $treat * post_{c,t}$ is the interaction term between the indicator for treated analysts and post-treatment periods, and θX_i are controls for pre-trend differences. Fixed effects (FE) included are: γ_{i*h} analyst, δ_{y*h} forecasted year, and η_{f*h} firm.[25] Each fixed effect interacts with the forecast horizon fixed effect (h), because the results are reported at the aggregate level for all forecast horizons (1 to 5 years ahead).[26] Additionally, I include brokerage and firm-year fixed effects. Since climate shocks occur within a 100-mile radius of the analyst's office location, standard errors are clustered by analyst's office location.

[24] I demonstrate that the findings remain robust even when excluding firms with business locations in the same state as the weather shock, as indicated by the geographic index proposed by Garcia and Norli (2012) or NETS establishments location.

[25] The baseline results remain consistent when using the forecast announcement year.

[26] It's important to highlight that I do not include month-year fixed effects, which would control for time trend characteristics but they would also absorb all fluctuations in analysts' forecasts. To address this concern, in the *Robustness* section, I replicate the analysis using a single observation per quarter as a standard stacked DID. By introducing the variable denoted as *Post*, I control for time trend attributes.

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 analysts' 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_{it} included are common controls 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 issued for a firm j and the analyzed forecasts. I also include firm leverage, size and operating income.

Concern & Limitation. 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. To mitigate this problem, my control group is 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. To corroborate the results, in the last column of my baseline specification, I interact with each fixed effect with a unique identifier for each weather shock (i.e. group ID). This corresponds to running separate standard differences in difference (with only one treatment period) for each weather shock individually.

Empirical Strategy: Climate Beliefs. After showing if a weather shock affects analysts' beliefs, I can dig deeper into how different priors affect the perception of climate change realization. To do so, I exploit analysts', firms', and shocks' characteristics.

I start by repeating my baseline regression for different sub-samples of analysts' characteristics. For example, I can divide equity analysts based on: work experience, ex-ante optimism, past performance, state's climate sensitivity, county's political ideology, and state's climate beliefs. If one of these characteristics implies that analysts have a higher prior about climate risks, then I would expect to observe smaller forecast revisions after a weather shock. Thus allowing me to shed light on what characteristics affect analysts' perception of future climate realization.

Similarly, to study whether climate beliefs' revision is context-specific (i.e. the beliefs update is larger for firms with higher climate risks), I divide my sample into forecasts for firms with high and low exposure to climate risks. Firms' climate exposure is defined as the firms' climate sectors sensitivity (as in Addoum et al., 2019) or firms' specific physical risks estimated by Trucost.[27]

Lastly, while my main analysis focuses on yearly forecasts aggregated for 1 to 5-year horizons, I exploit forecasts' temporal dimension to analyze if climate beliefs have a heterogeneous effect on different forecast horizons. The granularity of analysts' forecasts allows me to study whether analysts revise forecasts for short-term (quarterly to 2-year forecasts) or long-term horizons (3 to 5 years and long-term growth forecasts).

[27]See table 23 and 24 for a detailed description of each subgroup.

6 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.

6.1 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.

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 happened (FIPS code translation is obtained from the Storm Prediction Center WCM Page, NOAA, 2016) and build coordinates for the centroid of the county location.[28] Finding the geographical location for 92% of the events in the dataset while discarding the remaining 8%.

6.2 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

[28] I use the FIPS code from Wikipedia's "Table of United States counties" (Wikipedia, 2020). The FIPS code is a unique number assigned to each county by the National Institute for Standards and Technology, NIST. Using the FIPS code, I precisely pinpoint the centroid of the county where the event took place.

industry classification (SIC code), I merge the IBES dataset with Compustat Quarterly by IBES TICKER. Since I do not have access to the exact plant's location, I follow previous literature (for example, Alok et al., 2020, and Barrot and Sauvagnat, 2016) that use the headquarter's address as the firm's location. 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, n.d.). 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.

To proxy for firms' transition risks, I use the absolute emission from Trucost. For firms' physical risks, I use firms' forecasted physical risk and climate-sensitive sectors. The latter follows Addoum et al. (2019) by diving firms into high climate-sensitive sectors (i.e. consumer discretionary, industrial, utilities, and health care) and not climate-sensitive sectors (i.e. all other sectors), while the former is a composite physical risk score (ranging from 1-low risk to 100-high risk) from Trucost's Climate Change Physical Risk Forecast. Trucost reports the composite score of a company's physical risk exposure as a weighted average across 8 different physical risks (wildfire, coldwave, heatwave, hurricane, sea level rise, flood, and water stress) for three forecast horizons (the year 2020, 2030 and 2050) and scenarios (high, medium and low). For my analysis, I use the composite physical risks 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 individual physical risk averages from 3 points for flood and sea level rise to 57 points for water stress.

6.3 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 download 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 (NPAs) 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 located in the same state as analysts previously found in Refinitiv, are located in the same city. To avoid mismatch I manually check analysts, which moved at least once in my sample, using BrokerCheck.[29]

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 horizon.

This leads to a final dataset of 2,816 equity analysts in 29 different US states covering 2,196,138 earnings forecasts for 6,846 firms from 1999 to 2020. Analysts' characteristics

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

are explained in detail in the Appendix C.

7 Descriptive Statistics

In this section, I present descriptive statistics of analysts and weather shocks in my sample. Following the empirical strategy described in section 5, my final sample includes salient weather shocks that occurred 100 miles from analysts that issue earnings forecasts for firms not directly impacted by the shocks (i.e. 100 miles distant from the event). Moreover, the control group contains only analysts who issue forecasts for firms in the same sector as the firms forecasted by the treated analysts and never experienced a salient weather shock. After applying these filters, the sample under study shrinks to 1,389 equity analysts in 24 different US states covering 2,746 firms from 1999 to 2020.

Analysts Characteristics. Figure A1 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 1 reports the summary statics for my entire sample of analysts and forecasted firms used in the analysis from 1999 to 2020. The average bias for analysts is 0.94% while the average forecast error is 2.1% (respectively with a standard deviation of 3.9 and 3.7). An analyst in my sample follows on average 15 firms, with an average of 2 years of forecasting a single firm and approximately 4 years overall of work experience. Moreover, the average analyst follows 1 to 2 sectors and works in a brokerage firm with other 69 analysts.[30]

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,

[30]Note that because of the filtering for the staggered DID (selecting never treated analysts for the control group and only treated once for the treatment group), the analysts' years of firm and general experiences are quite low compared to previous studies. However, before our filtering, analysts in my sample had a mean of 3 and 6 years of firm and general experience, which is in line with previous studies. See table A3 in the Appendix for the unfiltered summary statistic.

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 heat have the highest number of deaths, while winter storms have the highest number of injuries. In our sample, weather events with the most occurrence are tornadoes and heat.[31]

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. 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 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 all not statistically significant, except for column 9 which indicates that in months with extreme events there is less news about climate change.

[31] Since tornadoes are not yet fully attributed to climate change, I conduct a robustness test by excluding them from the analysis. See this article about tornadoes and climate change: https://www.npr.org/2021/12/13/1063676832/the-exact-link-between-tornadoes-and-climate-change-is-hard-to-draw-heres-why?t=1652888106301

These findings highlight that selected extreme events affect climate change beliefs, but not climate news.

8 Empirical Results

The following results are conducted for analysts' yearly forecasts. Since analysts issue forecasts for different horizons (1 to 5 years ahead), I report here the results aggregated by all horizons.

Baseline Results. Table 4 reports the baseline regression for both analysts' forecast bias and error. Each column includes a different combination of fixed effects and covariates. Column 1 includes analysts, firms, and year-fixed effects (all interacted by horizon fixed-effect). Column 2 adds additional covariates: forecast days gap, broker size, companies followed, firms experience, industries followed, forecasted firm size, forecasted firm leverage, and forecasted operating income. Column 3 includes brokerage fixed effects and column 4 firm-time fixed effects. Lastly, column 5 interacts with each fixed effect to a unique identifier for each weather shock (i.e. shock ID). The latter controls for possible problems of the staggered DID setting, such as the comparison of already treated to the late treated group (see Baker et al., 2022).

The baseline results are in line with previous studies that document a significant effect on analysts' accuracy and pessimism after a climate event (Cuculiza et al., 2021; Tran et al., 2020; Han et al., 2020).

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. The difference between the treated and control group is 0.14 p.p. and 0.23 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 14% decrease in forecast bias and 11% in forecast error. All the other columns, except column 4, confirms the robustness of the results with different specification.

Moreover, figure 3 presents the baseline regression for each sector individually. Notably, I observe analysts become more pessimistic about sectors that are highly associated with climate risks. This includes sectors such as agriculture, mining, construction, manufacturing, retail, and transportation. Figure 4 shows that certain climate events, like hail, debris flow, and tropical storms, lead to analysts displaying a more optimistic bias in their forecasts, indicating nuanced reactions to distinct weather-related occurrences.

To ensure that variations in analysts' forecast bias and error stem from shifts in their climate beliefs, I check that forecasted firm fundamentals within a three-month window around the weather event remain constant. Figure 5 demonstrates that, with the exception of a statistically significant increase in Capex and firm size, there is no substantial statistical variation in firm fundamentals surrounding the event.

Analysts Characteristics. To investigate if analysts with dissimilar priors are differently affected by experienced weather shocks, I repeat the baseline regression by sorting analysts into subgroups with specific characteristics. Figure 6 reports the estimated coefficients of interest for analysts' forecast bias and error respectively for low (blue) and high values (red) of the following subgroups: analysts' political donation (i.e. democratic vs republican), county's political ideology (i.e. democratic vs republican), and states' climate beliefs (i.e. the share of state population believing that climate change is happening), states' climate risk (i.e. number of climate shocks in a state), sex (male or female), mindset (ex-ante optimism or pessimism), ex-ante performance and experience. See table 23 and 24 as well as Appendix C for a detailed description of each subgroup.

The results reveal a consistent effect on analysts' forecast bias and error. Analyst characteristics associated with a higher sensitivity to climate factors, such as being democratic, residing in weather-prone regions, holding strong beliefs in climate change, being female, and exhibiting high performance and experience, have a smaller impact on forecast bias and accuracy. This may suggest that these analysts had already integrated climate risk into their assessments. In the appendix, table A1 presents z-tests to compare the estimated coefficients between subgroups. The most significant disparity, observed in both forecast error and bias, is related to analysts' sex. Other factors, such as residing in climate-affected regions, experience, and performance, also show notable differences, but their effect on forecast bias is not statistically significant.[32]

Distraction Hypothesis. 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. 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 expect that their attention would be disproportionately channeled toward companies deemed pivotal for their professional careers. These firms would be characterized by a preponderance of institutional ownership and have the highest market capitalization within analysts' portfolios. Table 5 shows that analysts become increasingly more pessimistic and accurate for firms with high institutional ownership and relative importance. Second, analysts in smaller brokerage firms may have fewer resources and may be worse at coping with extreme weather events. The results indicate that analysts in large brokerage firms become more pessimistic compared to analysts in small brokerage firms, while forecast accuracy de-

[32] A major concern arises from the decline in the optimism of ex-ante optimistic analysts, which could be driven by analysts' "walk-down" behavior, i.e. initial optimism followed by downward adjustments in forecasts to attain easily beatable estimates (Matsumoto, 2002). To address this concern, the regression models control for the remaining days until the end of the period. Additionally, note that only 8% of the forecasts fall within three months before earnings announcements, and when replicating the analysis by excluding forecasts within three months from the announcement yields consistent and stable results.

creases in both. Lastly, distracted analysts might present a sudden drop in the number of forecasts compared to the control group. However, no statistically significant effects are associated with this phenomenon.

Collectively, although the findings might suggest a reorientation of attention towards more pivotal firms, they do not definitively negate the observation that analysts also revise their forecasts for less significant entities, all the while maintaining their volume of forecasts unchanged.

Analysts' Performance & Firms' Climate Risks. To understand what is turning beliefs, I look at how analysts with different ex-ante performance forecast firms with different salience of climate risks. Firms' climate risks are proxied by using firms' composite physical risk score calculated by Trucost as well as the climate-sensitivity of their sector (following Addoum et al., 2019).

Table 6 and 7 present the estimated coefficients for high and low-performance analyst subgroups separately, focusing on forecasts for firms with varying levels of climate risks.

Table 6 indicates that high-performance analysts exhibit an increase in pessimism by 0.13 p.p. for firms operating in climate-sensitive sectors, making them more accurate. Although not statistically significant, the magnitude of this estimated effect holds economic significance. No effect is found for non-climate-sensitive sectors. On the other hand, low-performance analysts exhibit an increase in both pessimism and accuracy for all firms, irrespective of their climate sensitivity.

Turning to table 7, which utilizes Trucost's composite physical risk assessment for each firm, it is found that high-performance analysts display improved accuracy for firms with high physical risks, although the statistical and economic significance is not significant. This finding suggests that high-performance analysts had already factored in climate risks into their assessments. Conversely, low-performance analysts demonstrate an increase in pessimism only for firms with substantial physical risks, while no significant changes are observed for firms with low physical risks.

Analysts' Performance & Shocks' Characteristics. The previous findings indicate divergent effects among high and low-performance analysts. High-performance analysts exhibit increased pessimism solely for stocks associated with high climate risks, including both sector climate risks and firm-specific physical risks. In contrast, low-performance analysts do not differentiate between high and low climate-sensitive sectors but display heightened pessimism for firms characterized by high levels of physical risk.

Two different channels could explain this result: after a shock. analysts may overestimate the risks of firms with high climate risks (representative heuristics) or they extract some information from the event. Exploiting shocks' characteristics I try to disentangle these two effects. First, I look at analysts who experience, for example, a hurricane and investigate if they become more pessimistic for firms with high hurricane risks or high composite physical risks (independently of which type of physical risk). Second, I investigate what type of shock damages affect analysts' forecasts.

Table 8 presents the findings for firms categorized into high and low physical risks, based on the shocks experienced by the analysts. The results demonstrate that high-performance analysts exhibit increased pessimism specifically for firms characterized by high physical risks following the experienced shock. In contrast, these analysts display a more optimistic outlook when dealing with firms that possess lower physical risks. These results align with the earlier findings.

Conversely, low-performance analysts exhibit a consistent effect on firms regardless of the risk type, although the magnitude of the effect for low-risk firms is half that of high-risk firms. These findings support the notion that analysts may learn from the event, where high-performance analysts are capable of extracting precise information about the shock, while low performers are influenced by available heuristics

A concern is high-performance analysts are overestimating the risks of firms with high physical risk as the shock experienced. By looking at the effect of weather shocks that either caused remarkable economic damages (more than 1 billion dollars) or health-related damages (more than 10 deaths or 100 injuries), I strive to pin down what mechanism drives the results. Since climate beliefs depend on the future economic costs of climate change, if analysts are learning from the event, I assume that shocks with larger economic damages would lead to greater information about these economic costs. Contrarily, health-related damages are usually more traumatic experience events that affect agents' risk-taking (Bernile et al., 2017), but they provide less information on the economic costs of global warming.

Table 9 reports the baseline results by dividing the sample by the characteristics of weather shock-related damages (economic or health-related damages). The results show that high-performance analysts, after a shock that caused only health-related damages, decrease their forecast bias by 0.03 percentage points. While after experiencing a shock with economic damages, they have a 0.15 p.p. reduction in bias, which make them significantly more accurate. Contrarily, low-performance analysts decrease their forecast bias for both shocks with health-related damages and economic damages. The results are in line with the previously delineated hypothesis.

Reversal. If weather events carry no information on climate risks, then equity analysts' forecasts should eventually revert to their fundamental values, given that firms are not directly or indirectly affected by the shock. However, this hypothesis is challenging to test empirically because it requires assuming that no additional information about climate risks is released after the event. Despite these limitations, I investigate whether analysts revise their forecasts to previous forecasts after the weather event.

Table 10 reports the results, showing that analysts remain pessimistic up to 5 forecasts after the event. However, this analysis disregards the time component, as analysts can issue forecasts whenever they want, and the fifth forecast after the event can be within only one month of the shock. Therefore, I also examine the change in forecast bias after 6, 12, and 18 months following the event compared to the last forecast issued before the event for treated analysts, as presented in Table 11. The results indicate that analysts remain pessimistic up to 6 months after the event. Furthermore, when considering different analysts' performances and firms' climate risks, this effect is statistically significant only for low-performance analysts forecasting firms with high climate risks.

8.1 Term Structure of Climate-Risks and Multiple Shocks

The previous analysis reported the results aggregated for all analysts' forecast horizons (from 1 year to 5 years ahead). Since climate risks affect both short and long-term expectations, I investigate whether analysts believe that climate risks threaten short as well as long-term firms' earnings.[33]

Breakdown by Forecast Horizons. Table 12 reports the estimated coefficients separately for each year's forecast horizons. The decrease in forecast error after a weather shock seems to be driven by short-term forecasts (1 to 3 years ahead). Similarly, analysts present a smaller forecast bias for 1 to 4 years-ahead forecasts, even if not statistically significant after 2 years-ahead. Interestingly, analysts become more optimistic and less accurate for 5 years horizon forecasts. The last column reports the baseline regression for the long-term growth rate (LTG). The estimated coefficients show a decrease in the LTG forecast after the event. Thus confirming the previously documented negative effect on analysts' forecasts.

Multiple Shocks. So far, the analysis focused on analysts that were treated for the first time (since they entered the dataset), I now investigate the effect of experiencing a second weather shock.[34] Table 13 reports the analysis for analysts that experience a second weather shock, where the control group is composed of analysts with one shock experience. Experiencing a second shock decreases analysts' bias and error of respectively 0.27 and 0.45 p.p. Columns 3 and 4 (5 and 6) report the estimated effect for the subgroup of high-performance analysts (low-performance analysts). While both subgroups become more accurate and pessimistic, the estimated effect is not statistically significant for the forecast bias of high-performance analysts.

[33]Note that what I define as 5-year ahead forecasts are all forecasts with 5 or more years horizons.

[34]For lack of data to construct an appropriate control group, I only perform the analysis on the effect of a second shock.

Forecasting Treated Firms. Based on the hypothesis of learning from climate-related events, I anticipate that analysts who have personally experienced a weather shock will demonstrate enhanced forecasting skills in assessing the impact of weather events on affected firms. To explore this, I replicate the analysis, focusing on firms directly influenced by weather events. I categorize analysts into two distinct groups: those with prior exposure to significant weather shocks and those without such experience. Importantly, neither group has been directly exposed to the event itself.

Given the constraints of my dataset, I employ a simplified panel regression approach. This entails evaluating bias and error metrics during post-treatment periods spanning 1 to 3 months after the event. The key independent variable is "treated analysts," which takes a value of 1 for analysts who have previously encountered a weather shock. I also incorporate a control for the number of previous shocks experienced.

The findings of the analysis are presented in Table 14. Columns 1 and 2 reveal that, on average, there seems to be no substantial discrepancy in error and bias among analysts with prior shock experience when forecasting treated firms. To delve deeper, I introduce interaction terms between the independent variable and various analyst and firm characteristics. Columns 3 and 4 demonstrate no discernible distinction between high and low-performance analysts. Columns 5 and 6 replicate the conclusions drawn from Cuculiza et al. (2021), highlighting that analysts located in climate-sensitive regions tend to exhibit greater forecasting accuracy. Consistent with this, columns 7 to 10 suggest that analysts treated ex-ante perform better in predicting impacts on firms facing elevated climate risks. Lastly, columns 11 and 12 illustrate that analysts, in general, do not possess a particular proficiency in predicting shocks associated with high economic damages.

Figure 7 shows the change in forecast bias and error based on the number of previously experienced shocks, using zero shocks as the reference point. The outcomes indicate a positive correlation between the number of shocks experienced and an enhanced ability to predict the impacts on treated firms, but no difference is found after experiencing 5 shocks and bias does not seem to be significantly influenced.

8.2 Post-Event Analyst Responses

This section investigates the interaction between transition and physical risks as well as whether analysts, following extreme events ask fewer or more climate-related questions during earnings calls.

Physical & Transition Risks. Understanding beliefs about climate risks is complex because of the close interconnection between the physical (natural disasters) and the transition (carbon reduction policies) risks: lenient carbon regulations today translate into an increased number of future extreme weather events. Hence, analysts, who experience extreme weather events, may not only change their beliefs about physical risks but also about transition risks: believing that stricter regulation policies will be implemented. If this hypothesis is true, I expect treated analysts to become more pessimistic about firms with higher transition risks than firms with lower transition risks.

To explore this mechanism, I repeat the analysis by categorizing firms into the upper and lower terciles of transition risks, proxied by absolute emissions from Trucost. Table 15 reports the estimated results divided by high and low transition risks alongside low and high physical risks. The findings suggest that the most substantial revisions in bias and error occur among firms with high physical and transition risks, although these effects are not statistically significant. Notably, there is an increase in accuracy for firms with high transition risks and low physical risks, as well as the converse, but no statistically significant effect on bias is identified. For firms with low transition and physical risks, although forecast error exhibits a large and positive magnitude, no statistically significant effect is found.

Earnings Calls' Questions. Li et al. (2022) provide empirical evidence that female analysts are more prone to asking questions on environmental and social issues during earnings calls. In this study, I examine whether analysts who experience extreme weather events are more inclined to ask climate-related questions during such calls.

To this end, I obtained earnings transcripts from 2000 to 2019 from WRDS and matched them with my sample of analysts by their names, which enabled me to identify 962 analysts who asked at least one question during earnings calls. I use the unigrams and bigrams developed by Sautner et al. (2020) to identify climate-related questions.[35] My dependent variable is "climate-related questions" which represents the proportion of questions in which analysts mention any of the unigrams or bigrams out of the total number of questions asked in a year, expressed as a percentage. I also construct the proportion of questions relating to physical, regulatory, and opportunity risks. Table 16 reports the results of the estimated linear probability model, where the dependent variable of interest is the share of climate-related questions during earnings calls in a given year. The table suggests that treated analysts are less likely to ask questions concerning regulatory risks and more likely to ask questions related to climate opportunity. The estimated coefficients are of similar magnitude, which explains why, on average, I do not find any significant effect on the overall proportion of climate-related questions.

Belief Diffusion Results. The baseline results highlight that high-performance analysts become more pessimistic after a weather shock because they extract information about future climate risks from the event. I then inspect whether this new information diffused among other low-performance analysts who had not experienced the shocks but forecasted the same firm as the treated high-performance analysts. If non-treated analysts also revise their forecasts, this may be driven by beliefs' diffusion. Non-treated analysts learn about firms' physical risk from observing a change in forecasts of treated analysts. Conversely, non-treated analysts may update their forecasts by pure herding behaviors.

I start by dividing my sample into treated and control firms. For both groups, I only include forecasted firms that have at least three analysts following the firm,

[35] It should be noted that the full list of bigrams is not publicly available, so I rely on the bigrams reported in "OA Table 9: Top-100 Regulatory Climate Change Bigrams", "OA Table 8: Top-100 Opportunity Climate Change Bigrams" and "OA Table 10: Top-50 Physical Climate Change Bigrams" in Sautner et al. (2020). I remove, what I define, as deceptive bigrams and complete these lists with additional bigrams and unigrams. See the full list in table A6.

where one analyst is a high-performance analyst. Treated firms are firms where a high-performance analyst experiences a weather shock, while for control firms all analysts have never experienced a salient weather event. My dependent variables are firms' average bias and error averaged over low-performance analysts. Figure 8 plots the estimated coefficients (blue dot) of pre and post-period interactions between treatment and time variables with a 99% confidence interval (blue line). The figure indicates that no statistically significant difference is found for the average forecast error and bias of low-performance analysts between treated and control firms.

Notice that All-star analysts are the first-ranked analysts based on a questionnaire that evaluates analysts on six dimensions (accessibility and responsiveness, earnings estimates, useful and timely calls, stock selection, industry knowledge, and written reports) and weighted each composite score by the size of the respondent's firm. Unfortunately, analysts' performance score constructed using Hong et al. (2000) captures only one of these dimensions. A possible concern is that selected high-performance score analysts do not coincide with All-Star analysts, and hence they are not influential enough to affect other analysts' beliefs.

8.3 Robustness Tests

This section reports the robustness test for the baseline results as well as a placebo analysis using terrorist attacks.

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 17 shows that the findings are robust by selecting only analysts working far away from New York, even if bias becomes not significant when introducing firm*time and group interacted fixed effects. Second, I examine the robustness of the results to different analyst distances from the event. Table 18 shows that analysts within a 50-mile radius of the event exhibit a substantial impact on bias and error. In the 100-200 mile range, the effect on bias is half of that observed in the baseline (100 miles), and beyond 200 miles only forecast error decreases.

Firm's Location

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.[36]

To address this concern, I use the firm's geographical dispersion measure developed by Garcia and Norli (2012) using data from 10-K filings.[37] This measure not only indicates the share of US states in which a firm has its business operation but also reports which states are mentioned in the 10-K fillings. This will be used to control for firms with extensive geographic dispersion, which may present challenges for analysts in accurately estimating climate risks. Additionally, it enables me to exclude firms that have business locations in the treated states, thus allowing for more precise analysis.

Table 19 presents the results for firms divided into two categories. Columns 1-2 include firms that have at least one business location mentioned in their 10-K filings that is in the same state as the weather shock onset, while columns 3-4 consist of firms with business locations in other states. The results indicate no significant differences between these two groups. Additionally, firms are further divided into highly geographically dispersed firms, defined as those with more than the above-average number of states in their 10-K filings (i.e., more than 10 states). However, this subdivision also does not show significant differences, except for a smaller forecast error observed for highly dispersed firms.

In addition, I use the National Establishment Time-Series (NETS) Database to add information about establishments of US firms along with their corresponding coordinates. Among the 2736 firms in our baseline analysis, I successfully link 899 firms with their respective establishment locations. Among these, only 200 firms have establish-

[36] However, this concern is partly addressed by ensuring that the fundamentals of the firms remain unchanged during the events.

[37] I thank Mandeep Sigh for sharing the updated version of the geographical dispersion measured up to 2018.

ments located within 100 miles from the weather shock. In columns 1 and 2 of table 20, I observe that when firms are 100 miles distant from the event, analysts' accuracy tends to improve, although pessimism appears to decrease insignificantly. 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 pessimistic outlook with a larger, but not significant, forecast error. Lastly, in columns 5 and 6 I use all firms in my sample and I exclude firms that in the NETS database are confirmed to be in close proximity to the event's location. This reiteration of my primary findings reaffirms that the coefficients remain significant and negative.

Quarterly Analysis

As a robustness check, I alter the data frequency from monthly to quarterly, keeping one observation per quarter. Around each event, I retain the last observation for the quarter before the shock and the first observation for the quarter after it. The months in which the events occur are considered as treated. I also employ the classical Difference-in-Differences (DID) specification:

$$Y_{i,f,t} = \alpha + \beta_1 \cdot \text{Post} + \beta_2 \cdot \text{Treat} + \beta_3 \cdot (\text{Post} \cdot \text{Treat}) + \beta X_{i,t} + \gamma_{w \cdot h} + \text{error}_{i,t}$$

Where Y represents either the forecast bias, error, or the actual forecast value for analyst i predicting firm f (located more than 100 miles from the event) in quarter t. The variable *Post* takes the value 1 in the quarter following the shock, and *Treat* is 1 for analysts within 100 miles from the shock. The control variables include broker size, companies followed, firm experience, industries followed, forecasted firm size, forecasted firm leverage, and forecasted operating income. Fixed effects are incorporated using the shock ID interacted with the forecast horizon, considering that the data is organized as a stacked DID for each distinct shock and forecast horizon.

Table 21 shows results obtained by considering all first-time treated analysts and control analysts who have forecasted a firm at least twice.[38] This involves a total of 991 analysts (460 treated and 711 controls) who predicted 1314 firms following 42 shocks. The table demonstrates a reduction in both forecast bias and error after the event. Further, I narrow my focus to a pair of analysts, one treated and one control, predicting the same firm, as shown in the "same firm" column. Within this subset, there are 577 analysts (291 controls and 350 treated) forecasting 578 firms after 35 shocks. The findings indicate a decrease in forecast bias, error, and value post-event, with only forecast error showing statistical significance in this context.

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.[39] Table 22 reports the results of this placebo analysis. Columns 1 and 2 show that the forecast bias and error of analysts that 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 subsequent to 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 risks sensitive sectors, while the same applies to low-performance analysts

[38] It's important to note that this doesn't necessitate forecasts from both a treated and control analyst for the same firm.

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

for both high and low physical risks. Considering the limited number of observations, this placebo analysis appears to confirm previous findings.

9 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 and pessimism. These effects can be attributed to two distinct mechanisms: a heuristic channel and an information channel.

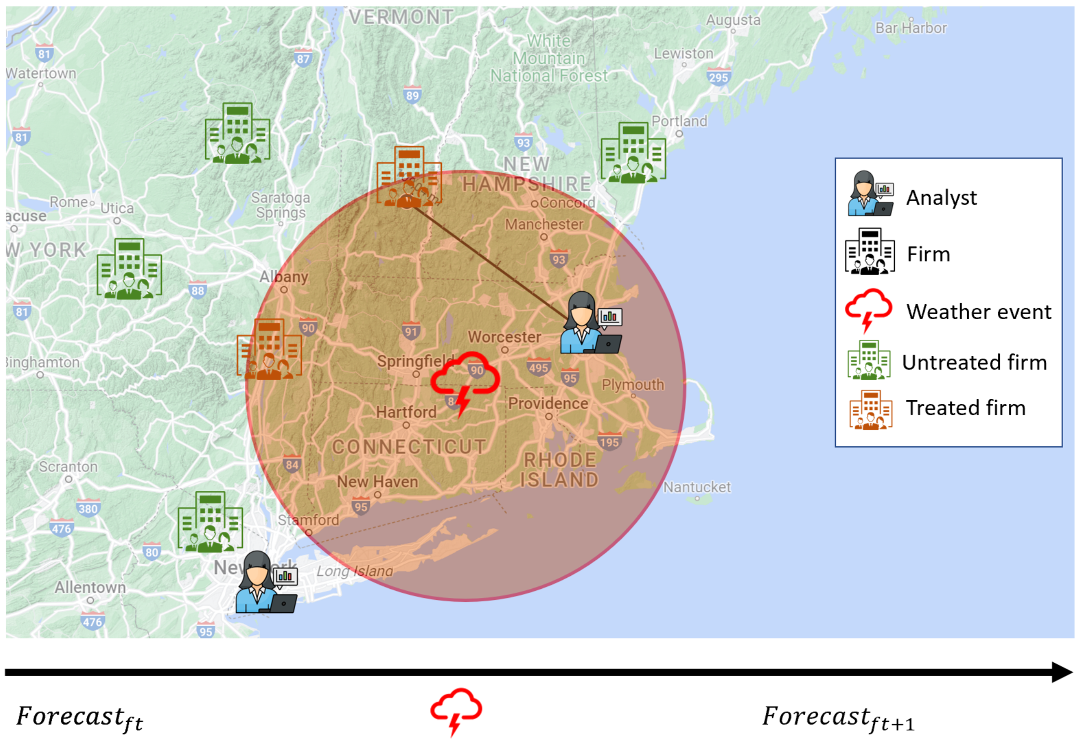
The findings reveal that both channels operate in tandem. Specifically, the study provides evidence that high-performance analysts acquire new information following a salient weather event, leading them to update their forecasts for firms in high-climate-risk sectors. As predicted by the information 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, regardless of the level or type of climate risks involved. While I find that the analysts revise their forecast toward more important firms, I do not find that they focus less on less important firms, hindering the possible channel that analysts get distracted by the event.

The study also indicates that transition risks play a pivotal role in analysts' responses, as they adjust firm question patterns during earnings calls. However, further exploration is needed to comprehend this phenomenon fully.

Lastly, the study finds no evidence that the new information acquired by treated high-performance analysts diffuses from treated to non-treated analysts. Underscoring the need for policy interventions to enhance climate risk disclosures, especially among low-performance analysts. I hope that forthcoming studies will yield further insights into the intricate dynamics governing the relationship between climate events, belief systems, and financial forecasts.

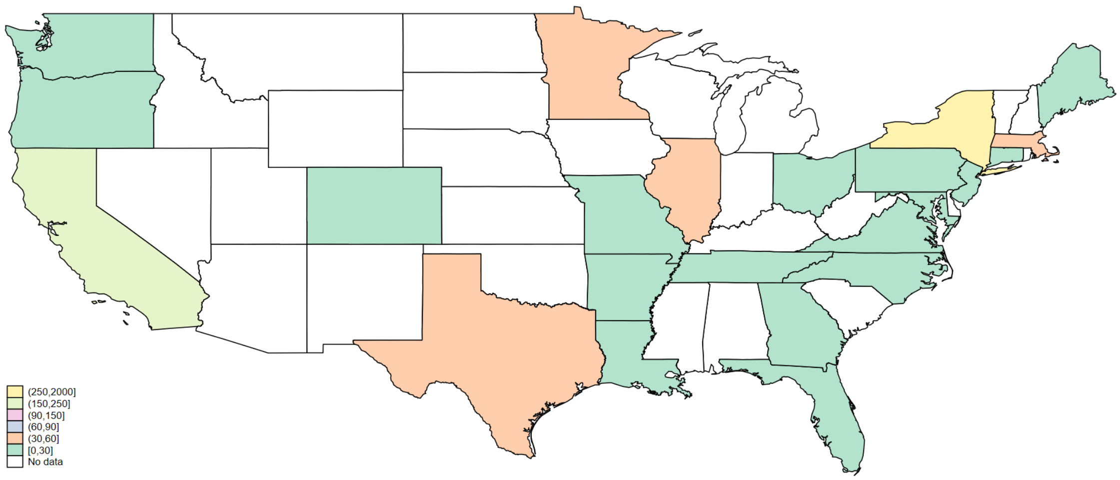
Figures

Figure 1: Representation of the empirical setting



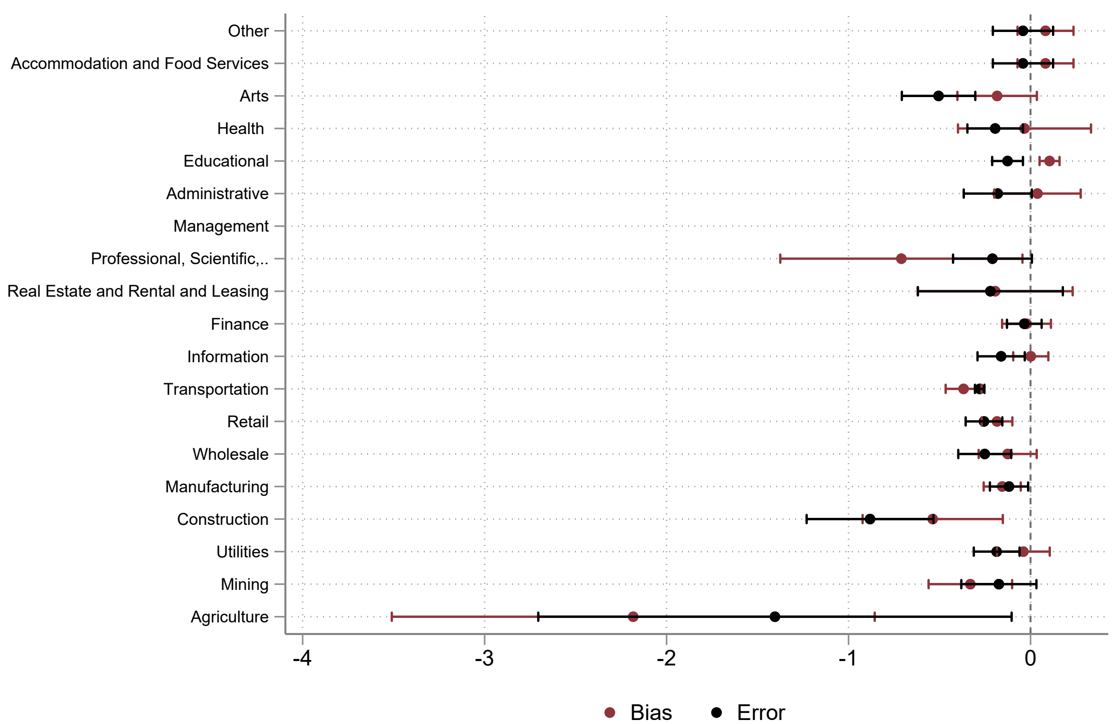
Note: The figure represents the empirical setting exploited in the analysis. Analysts located within a 100-mile radius of a weather shock are considered treated analysts (within the red circle) and I only exploit firms that are more than 100 miles radius from the event (green untreated firms) for my analysis.

Figure 2: Analysts' location from 1999 to 2020 by state



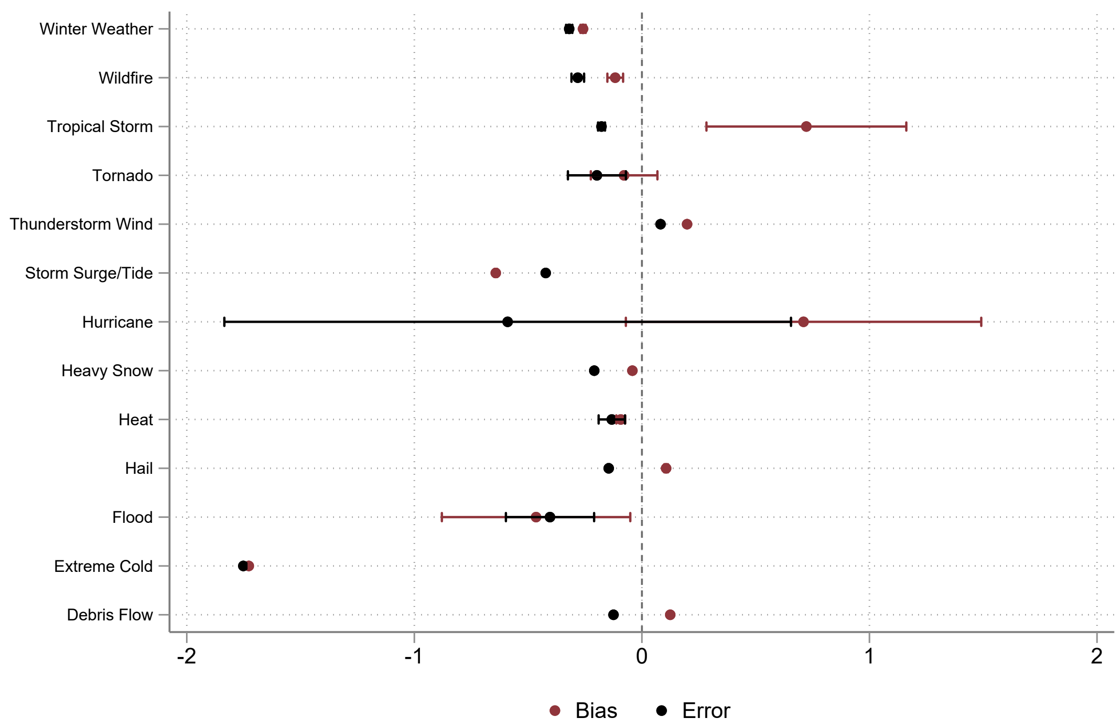
Note: The graph maps the sample of matched IBES analysts' locations to weather shock from 1999 to 2020 by US state. The state of New York has the highest number of analysts with 831 individuals, followed by 157 in California, 60 in Illinois, and 56 in Massachusetts.

Figure 3: Effect on analysts forecasts by firms sector



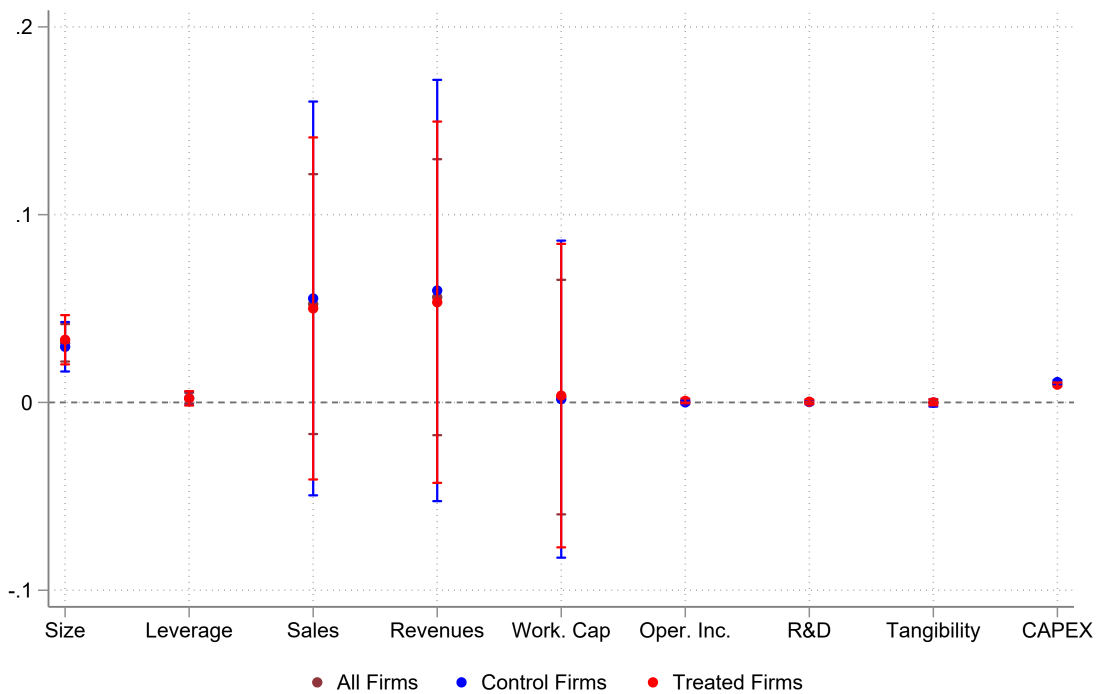
Note: The graph plots the estimated coefficients for both analysts' forecast bias and error. The regressions are run separately for each firm's sector.

Figure 4: Effect on analysts forecasts by type of event



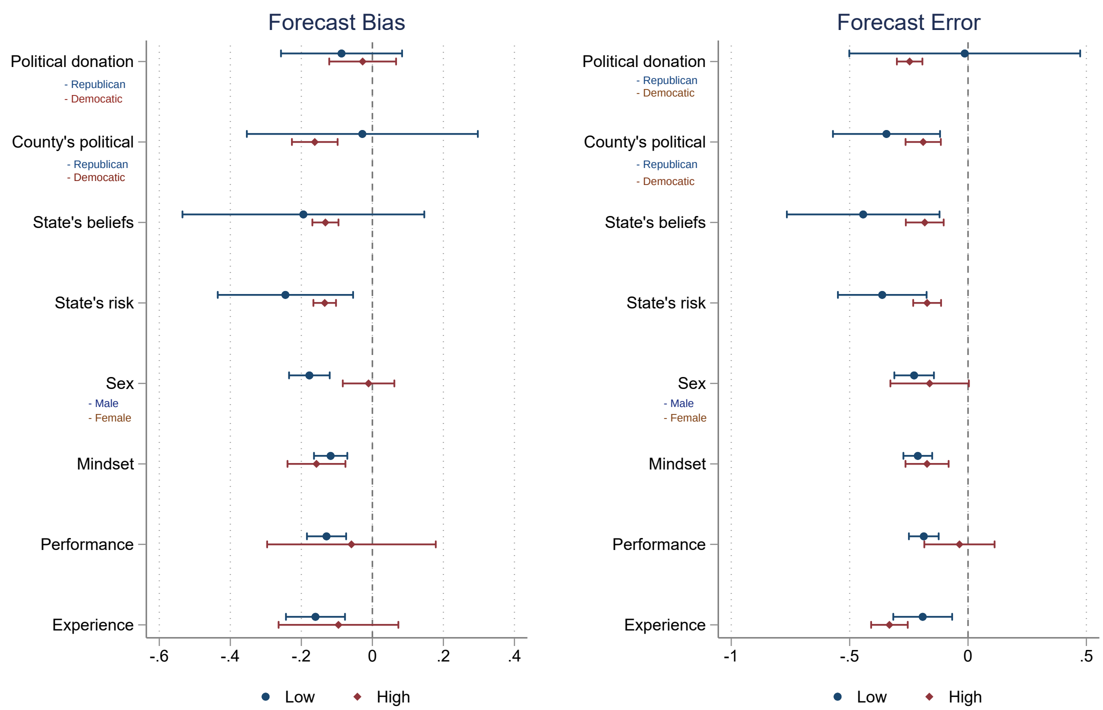
Note: The graph plots the estimated coefficients for both analysts' forecast bias and error. The regressions are run separately for each event's type.

Figure 5: Changes in firms' fundamentals around the weather shock



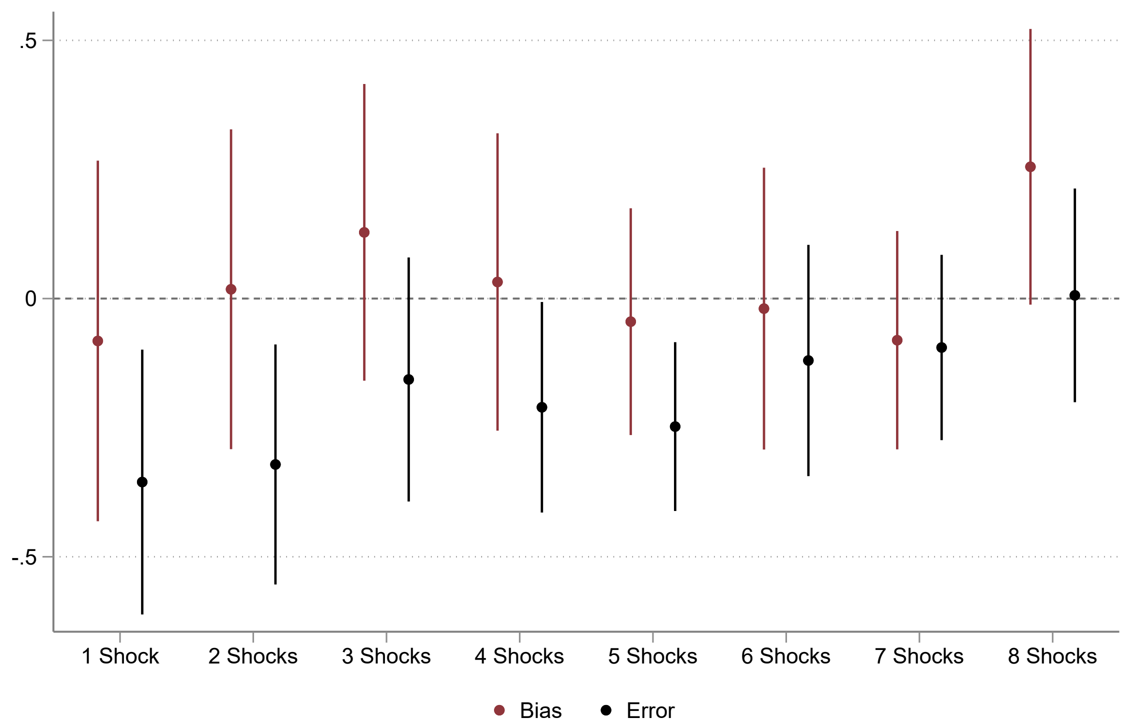
Note: the graph plots the differences in firms' fundamentals before and after the weather event experienced by the analysts. The independent variable is an indicator that takes values one after the weather event and zeroes before. We select the first data available for the forecasted firm before and after the weather shock (discarding fundamentals outside the 3 months window). The table includes firm and weather event fixed effects. A robustness test is conducted using only fundamentals announced at least 1 month after the weather shock to ensure that the effect of the shock, if any, is incorporated. The results are similar to the table presented.

Figure 6: Analysts' Characteristics



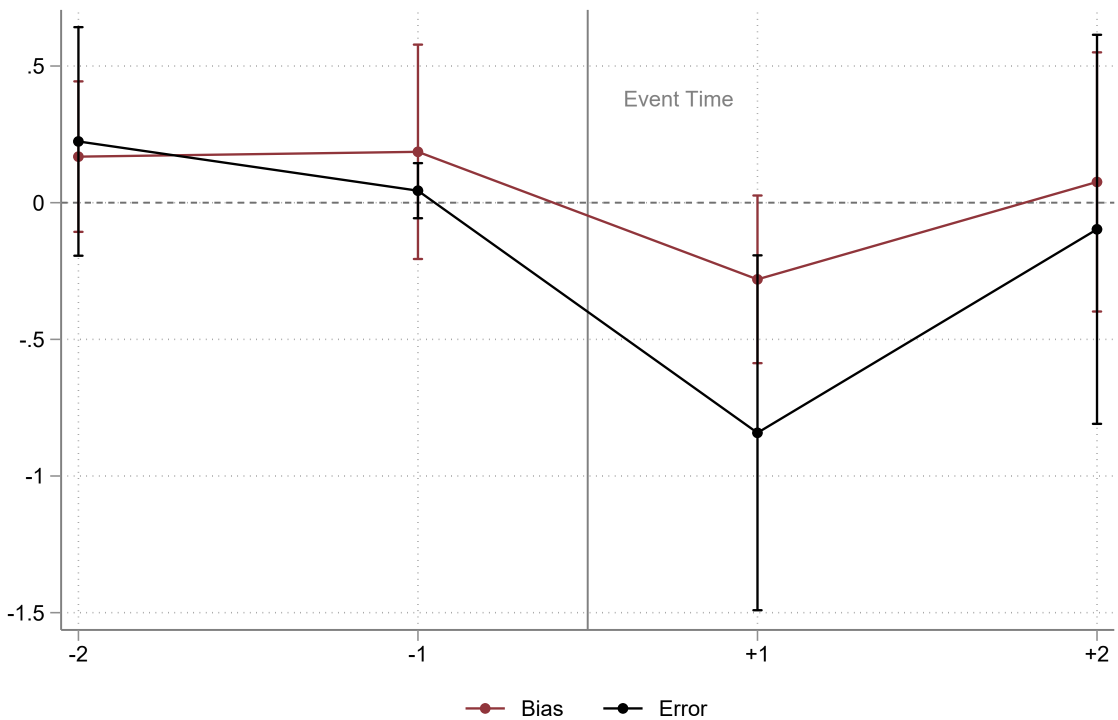
Note: figures plot the estimated coefficients from the baseline regression in bar plots with 90% confidence intervals for error (left graph) and bias (right graph). The specification includes all covariates plus analyst, year, and firm fixed effects (interacted with horizon fixed effects). The event window is 4 months around the event time. The standard errors are clustered at the analyst's office location.

Figure 7: Difference between never-treated analysts and already treated analysts on forecasting treated firms



Note: figures plot the estimated coefficients for the difference between never-treated analysts, which is the baseline omitted variable, and the number of shocks experienced by analysts in bar plots with 90% confidence intervals for error (black) and bias (maroon). The specification includes all covariates plus analyst and month*horizon*firm FE. The event window is 3 months after the firm is treated by an extreme time. The standard errors are clustered at the firm's office location.

Figure 8: Belief diffusion: effect on firms with one treated high-performance analyst



Note: the figure plots the estimated coefficients of pre and post-period interactions between treatment and time variables with a 99% confidence interval. The omitted year is the year of the treatment (vertical gray line). The specification includes all covariates. The fixed effects (analyst, year, and firm) interact with forecast horizon fixed effects. The event window includes the 2 months before (-2 and -1), the time of the event, and the 2 months after the event (1 and 2). The standard errors are clustered at the analysts' office location.

Tables

Table 1: Summary statistics.

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

Note: The table reports the summary statistics of the yearly forecasts dataset used in the analysis for all analysts and time periods. 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 23 and 24 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
Excessive Heat	0	13	88	3
Extreme Cold/Wind Chill	0	10	0	1
Thunderstorm Wind	0	1	100	1
Winter Weather	0	1	200	1
Heavy Snow	1	0	100	1
Tornado	77	7	120	10
Heat	92	13	56	16
Tropical Storm	109	11	77	2
Debris Flow	289	18	89	2
Storm Surge/Tide	1082	0	0	1
Flood	1155	0	0	2
Wildfire	1358	9	45	2
Hurricane (Typhoon)	1850	1	10	3
Hail	2186	0	0	1
Flash Flood	2928	4	0	3
Coastal Flood	5073	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

Dependent Variable:	Forecast Bias				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.136***	-0.149***	-0.149***	-0.107***	-0.118***
	(0.0324)	(0.0298)	(0.0299)	(0.0346)	(0.0367)
R^2	0.752	0.753	0.759	0.913	0.923
N	52992	48736	48736	48726	48697
Dependent Variable:	Forecast Error				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.229***	-0.215***	-0.211***	-0.179***	-0.175***
	(0.0409)	(0.0482)	(0.0467)	(0.0333)	(0.0345)
Control	No	Yes	Yes	Yes	Yes
Analyst, firm, year FE	Yes	Yes	Yes	Yes	Yes
Brokerage FE	No	No	Yes	Yes	Yes
Firm-year FE	No	No	No	Yes	No
Shock FE	No	No	No	No	Yes
R^2	0.754	0.755	0.760	0.910	0.920
N	52992	48736	48736	48726	48697

Note: the table shows the baseline regression for yearly forecasts. Since the results are aggregate for all horizons (1 to 5 years ahead forecasts), each fixed effect interacts with the horizon fixed effect. Column 1 includes analysts, firms, and year-fixed effects. Column 2 adds additional covariates: forecast days gap, broker size, companies followed, firms experience, industries followed, forecasted firm size, forecasted firm leverage, and forecasted operating income. Column 3 includes brokerage fixed effects and column 4 firm*time fixed effects. At last, column 5 interacts each fixed effect with the group of each singular shock. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Table 5: 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	-0.218*	-0.330***	-0.0972***	-0.144***	-0.187*	-0.288***	-0.0834***	-0.120*	-0.0756	-0.159**	-0.130***	-0.177***	-0.0445
	(0.121)	(0.0828)	(0.0306)	(0.0519)	(0.106)	(0.0351)	(0.0273)	(0.0601)	(0.129)	(0.0772)	(0.0244)	(0.0431)	(0.0292)
Group	High	High	Low	Low	High	High	Low	Low	Small	Small	Large	Large	-
FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.924	0.943	0.925	0.917	0.903	0.899	0.932	0.927	0.940	0.940	0.920	0.914	0.746
N	7449	7449	41113	41113	19214	19214	29313	29313	11808	11808	36829	36829	48718

Note: This table presents the baseline regression 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, 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.

Table 6: Analysts' performance and climate-sensitive sector

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

Note: the table shows the baseline regression for subgroups of high and low-performance analysts forecasting firms in the high and low climate-sensitive sectors. Analysts' performance score is created following Hong et al. (2000). High-performance analysts are analysts that have an average performance score in the 3 previous years in the top tercile, otherwise, they are low-performance analysts. Firms' climate-sensitive sectors follow Addoum et al. (2019) by dividing firms into high climate-sensitive sectors (i.e. consumer discretionary, industrial, utilities, and health care) and not climate-sensitive sectors (i.e. all other sectors). 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 analysts' office location.

Table 7: Analysts' performance and firms' physical risk

	High performance analyst				Low performance analyst			
	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error	(7) Bias	(8) Error
treat*post	-0.0774	-0.0547	0.0548	0.0289	-0.146***	-0.179***	-0.0198	-0.207***
	(0.118)	(0.0969)	(0.193)	(0.105)	(0.0366)	(0.0361)	(0.0396)	(0.0455)
Firm Physical Risk	High	High	Low	Low	High	High	Low	Low
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Analyst*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
Year*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.845	0.824	0.940	0.919	0.770	0.778	0.860	0.862
N	7418	7418	1822	1822	31603	31603	7829	7829

Note: the table shows the baseline regression for subgroups of high and low-performance analysts forecasting firms with high and low physical risks. Analysts' performance score is created following Hong et al. (2000). High-performance analysts are analysts that have an average performance score in the 3 previous years in the top tercile, otherwise, they are low-performance analysts. 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. 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.

Table 8: Analysts' performance and shock information

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

Note: the table shows the baseline regression for subgroups of high and low-performance analysts forecasting 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. 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.

Table 9: Analysts' performance and shock characteristics

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

Note: the table shows the baseline regression for subgroups of high and low-performance analysts forecasting firms with high and low physical risks. 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 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.

Table 10: Persistence of analysts' pessimism after the event

	Forecast Bias		
	(1)	(2)	(3)
Sample	All	High-Perfomance	Low-Perfomance
1. forecast t+1	-0.0606***	-0.0190	-0.0848***
	(0.0200)	(0.0346)	(0.0222)
1. forecast t+2	-0.0882***	-0.0907**	-0.111***
	(0.0266)	(0.0423)	(0.0292)
1. forecast t+3	-0.145***	-0.143***	-0.165***
	(0.0321)	(0.0465)	(0.0396)
1. forecast t+4	-0.254***	-0.179***	-0.311***
	(0.0557)	(0.0642)	(0.0671)
1. forecast t+5	-0.201**	-0.264*	-0.224**
	(0.0833)	(0.135)	(0.0998)
(Analysts, Year & Firm)*Horizon FE	Yes	Yes	Yes
N	54125	12559	41294

Note: the table shows the change in forecasts' bias for treated analysts' forecasts after the events, disregarding the time component, hence looking at subsequent forecasts. 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.

Table 11: Persistence of analysts' pessimism after the event - semiannual analysis

	Forecast Bias						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. (6 months)	-0.357*	0.265	-0.271	0.0154	-0.426	-0.370**	0.236
	(0.214)	(0.360)	(0.291)	(0.508)	(0.723)	(0.166)	(0.299)
1. (1 year)	-0.105	0.123	-0.0311	-0.331	-0.237	0.0163	0.337
	(0.126)	(0.179)	(0.175)	(0.918)	(0.271)	(0.105)	(0.349)
1. (1.5 year)	-0.256	-0.234	-0.163	0.416	-0.604	-0.0676	0.0386
	(0.194)	(0.270)	(0.300)	(0.749)	(0.366)	(0.172)	(0.441)
Analysts' Performance	All	High	Low	High	High	Low	Low
Firm's Climate Risks	All	All	All	High	Low	High	Low
(Analysts, Year & Firm)*Horizon FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15047	2123	10563	522	1156	18106	718

Note: the table shows the change in forecasts' bias for 6 months, 1 year, and 1.5 years with respect to the last forecast before the event for treated analysts. 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.

Table 12: Forecast horizons decomposition

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

Note: the table shows the baseline regression for yearly forecasts dis-aggregated at different forecast horizons: 1 to 5 years and long-term growth rate. Each specification includes 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 standard errors are clustered at the analyst's office location.

Table 13: Experiencing a second shock

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

Note: the table shows the baseline regression for analysts that have experienced more than one weather shock. Column 1 and 2 looks at all analysts in the sample, column 3 and 4 at high-performance analysts, and column 5 and 6 at low performance. All columns have analysts, firms, and year-fixed effects interacted by forecast horizon. The covariates included are broker size, companies followed, firm 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.

Table 14: Forecasting firms' affected by weather shocks

	(1) Bias	(2) Error	(3) Bias	(4) Error	(5) Bias	(6) Error	(7) Bias	(8) Error	(9) Bias	(10) Error	(11) Bias	(12) Error
Treated analyst	-0.0214	0.0466										
	(0.0727)	(0.0642)										
Treated analyst*1(performance)			-0.00943	0.110								
			(0.0894)	(0.0693)								
Treated analyst*1(High Risk State)					-0.184	-0.197*						
					(0.132)	(0.101)						
Treated analyst*1(High Physical Risk)							0.00219	-0.130				
							(0.0890)	(0.0840)				
Treated analyst*1(High Climate Sector)									-0.125	-0.143*		
									(0.0916)	(0.0776)		
Treated analyst*1(High Economic Damage)											0.0422	0.0970
											(0.0957)	(0.0747)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	17609	17609	17609	17609	17609	17609	13634	13634	17609	17609	17609	17609

Note: the table shows the panel regression with firms located 100 miles near the event and their respective analyst' forecasts 3 months after the event. The FE included are firm ID*Horizon*month and analyst FE. The controls included are the number of shocks experienced by the analysts, 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 firm level.

Table 15: Forecasting firms with different physical and transition risk

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

Note: the table shows the regression with firms in the top and bottom tercile of both physical and transition risk. The controls included are the number of shocks experienced by the analysts, 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 firm level.

Table 16: Earnings Call Questions

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

Note: the table shows the regression for treated analysts that ask questions about climate-related risks during earnings calls.

Table 17: Robustness baseline - excluding NY

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

Note: the table show the baseline regression for yearly forecasts excluding analysts located in NY. Since the results are aggregate for all horizons (1 to 5 years ahead forecasts), each fixed effect is interacted with the horizon fixed effect. Column 1 includes analysts, firms, and year-fixed effects. Column 2 adds additional covariates: forecast days gap, broker size, companies followed, firms experience, industries followed, forecasted firm size, forecasted firm leverage, and forecasted operating income. Column 3 includes brokerage fixed effects and column 4 firm*time fixed effects. At last, column 5 interacts with each fixed effect with the group of each singular shock. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the analyst's office level.

Table 18: Robustness: analyst' distance from the weather shock

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

Note: This table presents the baseline regression 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 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, firm size, 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.

Table 19: Robustness: firms' business location

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

Note: This table presents the baseline regression estimates for yearly forecasts. The data is divided using the firm's business location index developed by Garcia and Norli (2012). Garcia and Norli (2012) counts the number of times a firm mentions having at least one business location in a particular state within a year in their 10-k filing. Columns 1-2 focus on firms that mention the same state as the weather shocks at least once a year, while columns 3-4 examine firms that do not mention the state as the weather shock. Columns 5-8 consider firms with above or below-average (i.e. 10 states) mentions in the dataset. 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, firm size, 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.

Table 20: 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	-0.0701	-0.288***	-0.170**	0.141	-0.111**	-0.224***
	(0.114)	(0.0442)	(0.0722)	(0.147)	(0.0470)	(0.0207)
Controls	Y	Y	Y	Y	Y	Y
FE	Y	Y	Y	Y	Y	Y
R^2	0.913	0.912	0.911	0.886	0.925	0.924
N	9954	9954	4850	4850	43868	43868

Note: This table presents the baseline regression estimates for yearly forecasts. The data is divided using the firm's NETS establishment location. Columns 1-2 focus on firms that are recorded in NETS with no establishment within 100 miles from the event, columns 3-4 examine firms that have an establishment within 100 miles from the event, and Column 5-6 keep all firms in the dataset but drop firms that have establishments near the event. Each specification includes forecast horizon and shock ID interacted with analysts, year, and firm fixed-effects. The control variables are forecast days gap, broker size, companies followed, firms experience, industries followed, firm size, 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.

Table 21: Robustness - quarterly analysis

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

Note: the table shows the regression for the baseline DID. The control variables are broker size, companies followed, firm experience, industries followed, forecasted firm size, forecasted firm leverage, and forecasted operating income. When the sample indicates "All" it implies that all analysts forecasting at least 2 firms surrounding the event are included, while the "Same Firms" implies that the treated and control analysts to respectively forecast the same firm. The dependent variables are multiplied by 100 for interpretability purposes and winsorized at the bottom and top 5th percentile. The standard errors are clustered at the analyst's office location.

Table 22: 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 regression 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.

Table 23: 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
Shock Experienced	How many climates shocks the analyst encountered
Experienced analysts	analysts with more than the average years of experience in the sample (13 years)
State political ideology	The party with the highest number of votes in the previous election in a state: 1(Democrat) (from Data and Lab (2018))
County political ideology	the party (Democratic or Republican) with the majority of votes in the previous election (from Data and Lab, 2017)
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
Top 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 (the data is 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, as quantified by the number of employees

Table 24: Variables description - firm level

Variable Name	Description
Firm-level variable	
Firm Size	Logarithm of book assets
Leverage	Total debt (short term debt+ long term debt) divided by book assets
Operating Income	Operating income before depreciation divided by book assets
Market Leverage	Market value of firm equity from CRSP divided by book assets
ROA	Income before extraordinary items divided by book assets
Stock Price	Stock price at $t-1$
Climate Sensitive Sector	follows the definition of Addoum et al. (2019) to define firms in high climate-sensitive sectors (i.e. consumer discretionary, industrial, utilities, and health care) and not climate-sensitive sectors (i.e. all other sectors)
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
High Transition Risk	takes the value 1 if the firm's transition risks are in the top tercile and zero otherwise. Transition risks are proxied by Unpriced Carbon Cost adjusted EBITDA of the year 2020 (Carbon Earnings at Risks) forecasted for the year 2020 averaged across all future scenarios (high, medium, and low)
Geographic Dispersion Score	the share of the state in the US whether a firm as a business location declared in the 10-k filling (Garcia and Norli, 2012)
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* .

Bordalo, P., Gennaioli, N., Kwon, S. Y. and Shleifer, A. (2021), 'Diagnostic bubbles', *Journal of Financial Economics* **141**(3), 1060–1077.

Bordalo, P., Gennaioli, N., Ma, Y. and Shleifer, A. (2020), 'Overreaction in macroeconomic expectations', *American Economic Review* **110**(9), 2748–82.

Bordalo, P., Gennaioli, N., Porta, R. L. and Shleifer, A. (2019), 'Diagnostic expectations and stock returns', *The Journal of Finance* **74**(6), 2839–2874.

Bordalo, P., Gennaioli, N. and Shleifer, A. (2018), 'Diagnostic expectations and credit cycles', *The Journal of Finance* **73**(1), 199–227.

Bordalo, P., Gennaioli, N. and Shleifer, A. (2021), Salience, Technical report, National Bureau of Economic Research.

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*

Dehaan, E., Madsen, J. and Piotroski, J. D. (2017), 'Do weather-induced moods affect the processing of earnings news?', *Journal of Accounting Research* **55**(3), 509–550.

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.

Dessaint, O. and Matray, A. (2017), 'Do managers overreact to salient risks? evidence from hurricane strikes', *Journal of Financial Economics* **126**(1), 97–121.

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.

Garcia, D. and Norli, Ø. (2012), 'Geographic dispersion and stock returns', *Journal of Financial Economics* **106**(3), 547–565.

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.

Hong, H., Wang, N. and Yang, J. (2020), *Mitigating disaster risks to sustain growth*, National Bureau of Economic Research.

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.

Kemp, L., Xu, C., Depledge, J., Ebi, K. L., Gibbins, G., Kohler, T. A., Rockström, J., Scheffer, M., Schellnhuber, H. J., Steffen, W. et al. (2022), 'Climate endgame: Exploring catastrophic climate change scenarios', *Proceedings of the National Academy of Sciences* **119**(34), e2108146119.

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* .

Li, K., Mai, F., Wong, G., Yang, C. and Zhang, T. (2022), 'Female equity analysts and corporate environmental and social performance', *Available at SSRN* .

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.

Malmendier, U. and Nagel, S. (2011), 'Depression babies: Do macroeconomic experiences affect risk taking?', *The quarterly journal of economics* **126**(1), 373–416.

Malmendier, U. and Nagel, S. (2016), 'Learning from inflation experiences', *The Quarterly Journal of Economics* **131**(1), 53–87.

Malmendier, U., Nagel, S. and Yan, Z. (2021), 'The making of hawks and doves', *Journal of Monetary Economics* **117**, 19–42.

Malmendier, U., Pouzo, D. and Vanasco, V. (2020), 'Investor experiences and financial market dynamics', *Journal of Financial Economics* **136**(3), 597–622.

Malmendier, U. and Shen, L. S. (2018), Scarred consumption, Technical report, National Bureau of Economic Research.

Malmendier, U. and Wachter, J. A. (2021), 'Memory of past experiences and economic decisions', *Available at SSRN 4013583* .

Malmendier, U. and Wellsjo, A. (2020), 'Rent or buy? the role of lifetime experiences on homeownership within and across countries'.

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

McCright, A. M., Dunlap, R. E. and Xiao, C. (2014), 'The impacts of temperature anomalies and political orientation on perceived winter warming', *Nature Climate Change* **4**(12), 1077–1081.

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'.

Sautner, Z., van Lent, L., Vilkov, G. and Zhang, R. (2020), 'Firm-level climate change exposure', *European Corporate Governance Institute–Finance Working Paper* (686).

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.

Tran, A., Truong, C. and Zhao, Q. (2020), 'Disastrous weather events and analysts' earnings forecasts'.

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.

Wikipedia (2020), 'Table of united states counties', Website.
URL: *https://en.wikipedia.org/wiki/User:Michael$_J$/County$_t$able*

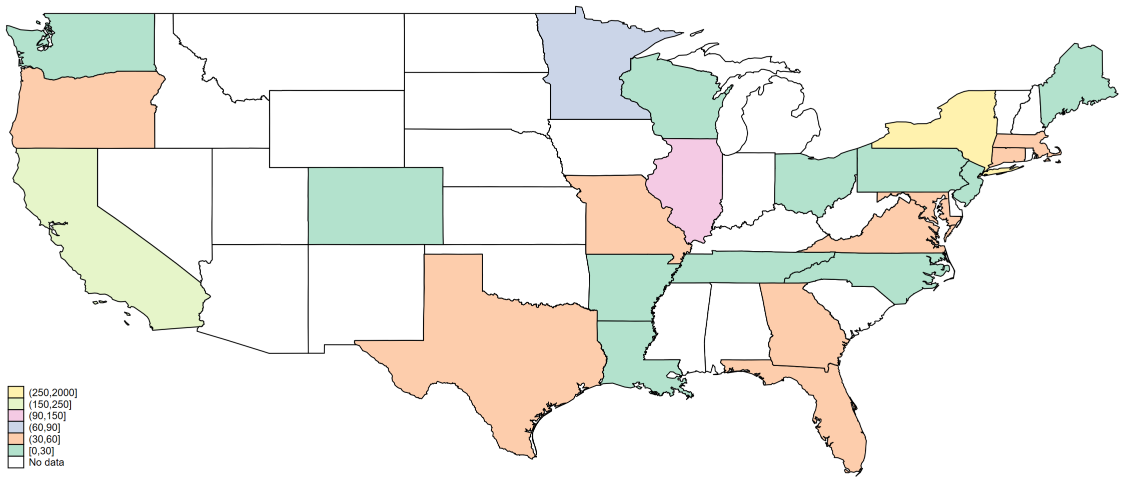
Wirtz, A., Kron, W., Löw, P. and Steuer, M. (2014), 'The need for data: natural disasters and the challenges of database management', *Natural Hazards* **70**(1), 135–157.

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

Appendix

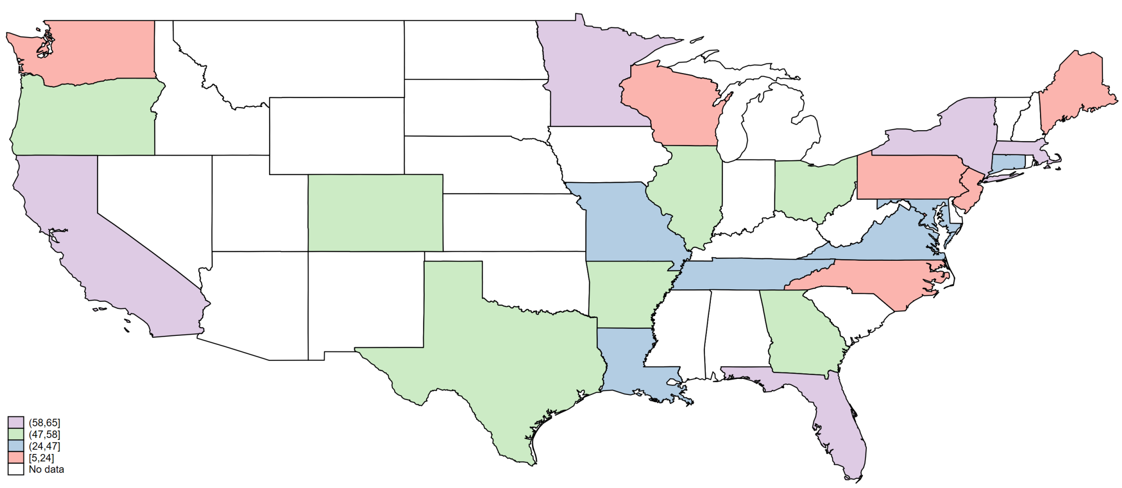
A All Sample Figures

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



Note: The graph maps the IBES analysts' locations from 1999 to 2020 by US state obtained from Refinitiv and Capital IQ-Professional. The state of New York has the highest number of analysts with 1,784 individuals, followed by California with 207 analysts, 99 analysts in Illinois, and 58 in Massachusetts.

Figure A2: Salient storm events from 1999 to 2020 by state



Note: The graph maps the Selected Storm Events from 1999 to 2020 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, Missouri, Massachusetts, Minnesota, and Florida. While Delaware with only one weather shock is the State with the least events.

B In-depth Conceptual Framework

B.1 Experience of weather shocks

This study relies on the EBL model as presented in Malmendier and Wachter (2021). The authors define the formation of beliefs using an overlapping-generation model with finitely lived agents, where beliefs are a weighted sum of a prior belief and past experiences.[40]

In the climate context, I assume that agents are endowed with a prior belief (CC) about climate change. The prior CC can be thought as the mean of a distribution of possible future economic damages caused by climate change in the US.[41] In addition to the prior, agents have weather shock experiences during their lifetimes, which is equivalent to the conceptual framework in Malmendier and Nagel (2011). The posterior beliefs θ_t^n at time t for an agent born at time n is:

$$\theta_t^n = (1 - w_{\text{age}}) * CC + w_{\text{age}} * \sum_{k=0}^{\text{age}} w(k, \lambda, \text{ age }) * \text{ Weather Shocks }_{t-k} \tag{3}$$

Where *age* is the age of the agent at time t, *Weather Shocks* are salient natural hazards (i.e. wildfires, hurricanes, etc.), k is the time period when the shock occurred and λ is a weight assigned to recent versus former shocks. The weight assigned to the prior and past experiences is $w_{age} = \frac{age+1}{\tau+age+1}$ and the weighting function of past experiences is $w(k, \lambda, \text{age}) = \frac{(\text{age}+1-k)^\lambda}{\sum_{k'=0}^{age}(age+1-k\prime)^\lambda}$. Notice that when $\lambda > 0$, recent weather shocks receive more weight compared to early-in-life weather shocks. In Malmendier and Nagel (2011), the authors find $\lambda = 1$, i.e. the agents assign approximate linearly decreasing weights to past experiences.

[40] Notice that with finitely lived agents and no rationality assumption, posterior beliefs never converge to the truth (Malmendier et al., 2020).

[41] For example, some individuals are ex-ante very pessimistic, they grew up in a very climate-sensitive area and/or in a location with a strong climate change ideology. Therefore, they tend to have a very high perception of future climate scenarios. Hence, in this setting, they have a very high prior (CC).

This model provides four main features.[42] First, past experiences of weather shocks are a strong determinant of individuals' behaviors in the long run (long-lasting effect). Second, recent weather shocks have a stronger effect on young individuals (recency bias). Third, whether shocks' experiences affect how individuals assess the distribution of future realization only in climate-related domains (context dependence). Forth, these findings also apply to expert forecasters such as analysts (robustness to expert knowledge).

However, my setting differs from Malmendier and Wachter (2021) in three main points: (i) only direct experiences of weather shocks enter into posterior climate beliefs, (ii) shocks experienced before working as an analyst do not matter for climate beliefs, (iii) weather shocks are perceived as a realization of climate change.

First, Malmendier and Nagel (2011) use publicly available US stock and bond market returns to show that only experienced returns (i.e. returns during an individual lifetime) matter for posterior beliefs. Similarly, Malmendier and Nagel (2016) show that only observed US inflation rates affect expectations of future inflation rates. In contrast to previous studies, only first-hand experienced weather shocks (shocks that occurred geographically near the analysts) are assumed to impact analysts' beliefs. Conjecturing that weather shocks geographically distant are not salient enough to impact analysts' beliefs.[43]

Second, since I do not have data on analysts before they start working, in my setting the weighting function depends on when an agent starts her job as a financial analyst. This implies that only weather shocks directly experienced during their work have an impact on analysts' posterior beliefs.[44] Hence, I can rewrite equation 3 as the posterior

[42] For a more detailed explanation of the EBL key features sees Malmendier and Wachter (2021).

[43] Andersen et al. (2019) points out that investors' risk-taking is affected only when investors directly experience losing investments after banks' defaults. They found no supporting evidence for the second of the third-hand effect of knowing a relative affected by the banks' default or living near the defaulted bank.

[44] Malmendier and Nagel (2011) points out that using a shorter time period for lifetimes' experiences leads to a lower λ since the model does not need to down-weight shocks experienced early in life. Moreover, since the sample of data shrunk (after dropping early in life observation), they find a lower estimated $\hat{\beta}$ for the effect of past experiences on financial behavior.

at time t for an analyst such as:

$$\theta_t = (1 - w_{\mathbf{work}}) * CC + w_{\mathbf{work}} * \sum_{k=0}^{\mathbf{work}} w(k, \lambda, \mathbf{work}) * \text{ Weather Shocks }_{t-k} \quad (4)$$

Third, the study relies on the assumption that weather shocks are a realization of climate change. However, sociological studies such as McCright et al. (2014) indicate that the individual's perception of weather shocks as climate change realization depends on individuals characteristics. For this reason, I modify the EBL setting such that whether analysts perceive a weather event as a climate realization depends on analysts' prior beliefs about climate change. Therefore, I include the prior belief on the weighting function of weather shock experiences, such as:

$$\theta_t = (1 - w_{\text{work}}) * CC + w_{\text{work}} * \sum_{k=0}^{\text{work}} w(k, \lambda, \mathbf{CC}, \text{work}) * \text{ Weather Shocks }_{t-k} \quad (5)$$

To further clarify, let's assume that the prior can take any value between 0 and 1.[45] Two analysts with the same works years and past weather shock experiences would react differently to a new weather shock (i.e. have a different posterior climate belief) based on the values of their prior. Thus, the analyst with the highest prior (CC closer to 1) would be more affected by a new weather shock (*heuristic hypothesis*). In other words, the analyst with higher ex-ante climate beliefs is more likely to recognize the weather event as a climate change realization, thus overestimating the likelihood of future realization of natural disasters driven by climate change. Another possible interpretation is that analysts with ex-ante low prior beliefs would be more affected by the shock because they would learn more from the experienced weather event (*information hypothesis*). Thus, the lower ex-ante value of CC (with $CC \neq 0$) implies a larger effect on posterior

[45] Where an analyst with zero beliefs in climate change ($CC = 0$) is not affected by any experiences of weather shocks, thus $\theta_t^n = 0$.

beliefs after a shock.

C 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.[46] 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 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. The majority of the analysts live in

[46] 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?

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 locations (State). Moreover, I manually checked that companies (if reported) match the brokerage firm with which the analyst is working. Using the data from 2000 to 2018, I am able to find 203 analysts of which 51% conducted democratic donations. [47]

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.

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.

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

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.

Table A1: Baseline Results by Analysts' Characteristics - BIAS & ERROR

Variable		Forecast Bias					Forecast Error				
		DID	(s.e.)	R^2	N	Difference	DID	(s.e.)	R^2	N	Difference
Experience	Low	-0.160***	(0.0424)	0.792	35456		-0.191***	(0.0635)	0.793	35456	
	High	-0.096	(0.0860)	0.750	13269	-0.06	-0.332***	(0.0394)	0.753	13269	0.14*
Performance	Low	-0.129***	(0.0281)	0.772	39437		-0.187***	(0.0321)	0.781	39437	
	High	-0.059	(0.121)	0.856	9241	-0.07	-0.036	(0.0757)	0.834	9241	-0.15*
Mindset	Pessimism	-0.118***	(0.0239)	0.821	29987		-0.212***	(0.0310)	0.809	29987	
	Optimisms	-0.157***	(0.0416)	0.803	18745	0.04	-0.173***	(0.0465)	0.800	18745	-0.04
State's climate risk	Low	-0.245**	(0.0972)	0.790	17256		-0.362***	(0.0956)	0.740	17256	
	High	-0.134***	(0.0162)	0.773	31475	-0.11	-0.173***	(0.0300)	0.802	31475	-0.19*
State's climate beliefs	Low	-0.194	(0.174)	0.857	4454		-0.443**	(0.164)	0.880	4454	
	High	-0.132***	(0.0187)	0.779	29069	-0.06	-0.183***	(0.0408)	0.802	29069	-0.26
Gender	Male	-0.177***	(0.0292)	0.772	41686		-0.228***	(0.0427)	0.766	41686	
	Female	-0.011	(0.0370)	0.834	4554	-0.17***	-0.162*	(0.0846)	0.845	4554	-0.07
Political countie's affiliation	Republican	-0.028	(0.166)	0.817	6916		-0.344***	(0.115)	0.808	6916	
	Democratic	-0.162***	(0.0328)	0.754	40121	0.13	-0.189***	(0.0380)	0.764	40121	-0.16
Analysts' political donation	Republican	-0.087	(0.0870)	0.863	2180		-0.014	(0.249)	0.830	2180	
	Democratic	-0.027	(0.0480)	0.832	3737	-0.06	-0.247***	(0.0275)	0.866	3737	0.23

Note: the table shows the baseline regression for yearly forecasts. The specification includes all covariates plus analyst, year, and firm fixed effects (interacted with horizon fixed effects). Since the results are aggregate for all horizons (1 to 5 years ahead forecasts), each fixed effect is interacted with the horizon fixed effect. The event window is 4 months around the event time. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

Notes on analysts' characteristics.

D Variables Correlation.

As a preliminary analysis, I regress analysts' and firms' characteristics on analysts' bias and error. Forecast bias is computed as the difference between firms' actual and forecasted earnings divided by the stock price in the previous period, while forecast error differs from forecast bias only by having the numerator in absolute terms (as in Hong and Kacperczyk, 2010). For this exercise, I only keep the first forecast issued after earnings announcements such as to mitigate possible noise coming from multiple forecasts over time. In line with the literature, I find that firms' characteristics such as stock price and operating income lead to more accurate and optimistic forecasts (i.e. lower forecast errors and larger bias). Similarly, an increase in analysts' experience, as the number of years forecasting firms or the number of industries forecasted, decreases (increases) forecast error (bias). While an increase in the days' gap between when the forecast is issued and the earnings announcement leads to more inaccurate (higher forecast error) and more pessimistic forecasts (lower forecast bias).

I then include a series of climate variables both at the firm, analyst, and state levels. I define firms' climate exposure as the sectors' climate sensitivity and firms' specific physical risks. The former follows the study of Addoum et al. (2019) by defining climate-sensitive sectors as sectors that are impacted by weather events, while the latter is a composite physical risk score obtained from a novel S&P-Trucost data. The findings indicate that forecasted firms in climate-sensitive sectors as well as with high physical risks have more pessimistic and inaccurate forecasts compared to firms with low climate exposure. All the other climate variables (such as analysts' or a state's cumulative number of experienced weather shocks) are neither statistically nor economically significant.

I compute a simple OLS regression to investigate the relation between my dependent and independent variables. For this analysis, I only take the first forecast issued by each analyst after the firms' earnings announcements. Keeping only the first forecast allows me to mitigate possible noise arising from changes in forecasts over time.

Table A2 reports the estimated coefficients of interest. Columns 1 and 5 regress analysts' and firms' characteristics on respectively forecast error and bias. The results indicate that analysts' years of experience are negatively correlated with forecast error. Indeed, analysts with several years of experience in forecasting a specific firm or industry are associated with more accurate forecasts (i.e. lower forecast error). Under Hong and Kacperczyk (2010), competition among analysts leads to more accurate forecasts. Accordingly, I find that the number of analysts following a firm is negatively correlated with analysts' forecast errors. In addition, analysts tend to be more inaccurate and pessimistic when firms' earnings announcements are distant in time. Concerning firms' characteristics, the results suggest that higher stock price, large operating income, and larger leverage lead to lower forecasts error and larger bias. This is not surprising since larger firms are usually easier to forecast (i.e.lower forecasts error) and analysts tend to be more optimistic (i.e. larger bias).

Columns 2 and 6 include the number of cumulative shocks experienced by each analyst as well as a binary variable that takes the value of one if firms are in a climate sector. The analysts' forecast bias is on average lower of 0.18 p.p. for forecasts of firms in climate-sensitive sectors, while no statistically significant effect is found by regressing the number of shocks experienced by a forecaster. Columns 3 and 7 indicate that state-level regressors, such as the cumulative number of weather shocks in a state and the cumulative economic damages caused by natural hazards, are statistically significant, but not economically significant.

At last, columns 4 and 8 include the physical risks score of each firm. The estimated coefficients indicate that an increase in firm physical risks leads to a 0.02 p.p. increase in forecast error. Moreover, analysts forecast error is on average 0.2 p.p. larger for forecasts of firms in climate-sensitive sectors when controlling for firms' physical risks. In the next section, I use exogenous weather events to disentangle what drives different forecast biases and errors for firms with distinct climate exposure.

Table A2: OLS results: climate variables on forecasts error and bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	error	error	error	error	bias	bias	bias	bias
Brokerage size	0.000193	0.000205	0.000204	0.000573	-0.000621*	-0.000591*	-0.000618*	-0.000558*
	(0.000503)	(0.000499)	(0.000501)	(0.000551)	(0.000335)	(0.000336)	(0.000321)	(0.000333)
Companies followed	0.00415	0.00446	0.00470	0.00349	-0.00173	-0.00251	-0.00178	-0.00254
	(0.00388)	(0.00387)	(0.00394)	(0.00443)	(0.00243)	(0.00249)	(0.00247)	(0.00253)
Firm experience	-0.0281***	-0.0269***	-0.0255***	-0.0240***	0.00226	0.00179	0.00276	0.00186
	(0.00678)	(0.00650)	(0.00645)	(0.00657)	(0.00393)	(0.00415)	(0.00415)	(0.00429)
Industries followed	-0.0648***	-0.0622***	-0.0652***	-0.0459**	0.0531***	0.0441***	0.0416***	0.0362***
	(0.0209)	(0.0210)	(0.0207)	(0.0214)	(0.0118)	(0.0118)	(0.0116)	(0.0120)
Date to period end	0.00290***	0.00290***	0.00290***	0.00280***	-0.000307***	-0.000294***	-0.000277***	-0.000160
	(0.000140)	(0.000140)	(0.000143)	(0.000162)	(0.000100)	(0.0000998)	(0.000102)	(0.000120)
Stock price	-0.00781***	-0.00784***	-0.00770***	-0.00641***	0.000872***	0.000973***	0.000961***	0.000378***
	(0.000707)	(0.000712)	(0.000703)	(0.000608)	(0.000144)	(0.000147)	(0.000147)	(0.000136)
Analyst following	-0.0323***	-0.0324***	-0.0334***	-0.0295***	-0.00340	-0.00373	-0.00340	-0.00380
	(0.00681)	(0.00677)	(0.00676)	(0.00701)	(0.00437)	(0.00434)	(0.00437)	(0.00444)
Firm size	-0.178***	-0.176***	-0.175***	-0.141***	-0.00348	-0.0133	-0.0160	-0.00470
	(0.0180)	(0.0188)	(0.0190)	(0.0204)	(0.0104)	(0.0102)	(0.0103)	(0.0116)
Leverage	1.775***	1.767***	1.721***	1.368***	-0.0897	-0.0512	-0.0312	-0.0142
	(0.118)	(0.118)	(0.117)	(0.120)	(0.0690)	(0.0702)	(0.0707)	(0.0851)
Oper inc	-14.93***	-14.93***	-14.88***	-16.28***	1.603**	1.597**	1.544**	1.516*
	(1.068)	(1.068)	(1.078)	(0.951)	(0.642)	(0.641)	(0.645)	(0.888)
Firm's climate sector		0.0441	0.0472	0.200***		-0.184***	-0.192***	-0.140***
		(0.0549)	(0.0552)	(0.0580)		(0.0320)	(0.0317)	(0.0328)
Analysts experienced shocks		-0.00697	-0.00887	-0.0107		0.0116	0.00952	0.00911
		(0.0167)	(0.0166)	(0.0168)		(0.00830)	(0.00828)	(0.00891)
State shocks			0.000235***	0.000230***			0.000103***	0.000123***
			(0.0000622)	(0.0000686)			(0.0000376)	(0.0000439)
Shock total damages			0.0000160***	0.0000159***			-0.00000242	0.000000682
			(0.00000516)	(0.00000582)			(0.00000410)	(0.00000403)
Firm's Physical Risk				0.0200***				0.000741
				(0.00401)				(0.00246)
Error					0.541***	0.541***	0.539***	0.479***
					(0.0133)	(0.0133)	(0.0134)	(0.0157)
cons	2.857***	2.822***	2.558***	0.904***	-0.337***	-0.179*	-0.284**	-0.423*
	(0.139)	(0.154)	(0.173)	(0.345)	(0.106)	(0.105)	(0.111)	(0.227)
Year*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.157	0.157	0.159	0.165	0.289	0.290	0.289	0.243
N	325840	325840	319053	240312	325840	325840	319053	240312

Note: The table reports the estimated coefficients of an OLS regression with forecast error (columns 1-4) and forecasts bias (columns 5-8) as dependent variables. For this analysis, I only take the first forecast issued by each analyst after firms' earnings announcements to mitigate for possible noise arising from changes in forecasts over time. Columns 1 and 5 regress respectively forecast error and bias on analysts' and firms' characteristics. In columns 2 and 6, I include the number of cumulative shocks experienced by each analyst as well as a binary variable that takes one of the firms to be in a climate sector (defined following Addoum et al. (2019)). Column 3 and 7 add state-level control for the cumulative number of the state's previous weather events as well as cumulative economic damages caused by natural hazards. At last, columns 4 and 8 include the physical risks score of each firm from Trucost. Each regression includes year times forecast horizon fix-effects. Standard errors are clustered at the analysts level.

E Robustness

Table A3: Summary Statistics before Filtering

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

Note: The table reports the summary statistics of the yearly forecasts dataset used in the analysis for all analysts and time periods. The dataset includes all merged analysts to the selected Weather shocks (with no firms located near the shocks) and the corresponding matched analysts in the control group (following a firm in the same sector as the treated analysts).

Table A4: Differences between high and low performance analysts

Variables	Difference between High and Low Performance Analysts	(s.e.)
Av. Forecast Bias	-0.0359	(0.0557)
Av. Forecast Error	-0.103**	(0.0512)
Size Brokerage Firm	1.340*	(0.753)
Number of Companies Followed	1.463***	(0.0921)
Years forecasting a firm	0.330***	(0.0340)
Number of Industries Followed	0.204***	(0.0162)
Av. Forecasted Firm Size	-0.0675***	(0.0259)
Av. Forecasted Firm Leverage	-0.00228	(0.00321)
Av. Forecasted Firm Operating Income	0.000359	(0.000764)
Ex-Ante Pessimism	0.00389	(0.00673)
Years of analysts experience	0.0643***	(0.00641)
Climate-Sensitivity of Sector forecasted	0.0498***	(0.00604)
Physical Risks of Firms	0.00294	(0.00792)
State's Climate Beliefs	-0.0304***	(0.00514)
County's Political Ideology	-0.0236***	(0.00440)

Note: the table shows the difference in high and low-performance analysts on a series of characteristics, both the forecasted firms and analysts level.

Table A5: Baseline Results (1 period before and after)

Dependent Variable:	Forecast Bias				
	(1)	(2)	(3)	(4)	(5)
Treat*time	-0.177***	-0.188***	-0.186***	-0.114**	-0.133**
	(0.0635)	(0.0500)	(0.0469)	(0.0456)	(0.0514)
R^2	0.752	0.752	0.759	0.921	0.933
N	32760	30059	30055	28165	25914
Dependent Variable:	**Forecast Error**				
	(1)	(2)	(3)	(4)	(5)
Treat*time	-0.215***	-0.200**	-0.195**	-0.162***	-0.158**
	(0.0685)	(0.0799)	(0.0754)	(0.0599)	(0.0651)
Control	No	Yes	Yes	Yes	Yes
Analyst, firm, year FE	Yes	Yes	Yes	Yes	Yes
Brokerage FE	No	No	Yes	Yes	Yes
Firm-year FE	No	No	No	Yes	No
Shock FE	No	No	No	No	Yes
R^2	0.760	0.761	0.767	0.919	0.931
N	32760	30059	30055	28165	25914

Note: the table shows the baseline regression for yearly forecasts. Since the results are aggregate for all horizons (1 to 5 years ahead forecasts), each fixed effect interacts with the horizon fixed effect. Column 1 includes analysts, firms, and year-fixed effects. Column 2 adds additional covariates: forecast days gap, broker size, companies followed, firms experience, industries followed, forecasted firm size, forecasted firm leverage, and forecasted operating income. Column 3 includes brokerage fixed effects and column 4 firm*time fixed effects. At last, column 5 interacts with each fixed effect with the group of each singular shock. The dependent variables are multiplied by 100 for interpretability purposes. The standard errors are clustered at the office location.

F Earnings Calls.

I report here the lists of unigrams and bigrams used to identify climate-related questions.

Table A6: Earnings Calls Bigrams

List Name	**Unigrams/Bigrams**
Unigram Physical Risk	hurricane, heat, storm, flood, wildfire, heatwave, tornado, hail, tide
Bigram Physical Risk	global warm, global warming, climate change, natural hazard, warm climate, coastal area, snow ice, sea level, storm water, heavy snow, water scarcity, thunderstorm wind, winter weather, extreme cold, excessive heat, wind chill, winter storm, debris flow, storm surge, flash flood, tropical storm
Bigram Physical Risk (Sautner et al., 2020)	coastal area, global warm, snow ice, friendly product, forest land, area florida, sea level, provide water, nickel metal, storm water, heavy snow, air water, natural hazard, sea water, warm climate, water discharge, ice product, security energy, water act, management district, weather snow, service reliable, management water, ability party, hurricane, flood, wildfire, heatwave, ice control, inland area, non coastal, storm january, sale forest, value forest, land forest, particularly coastal, golf ground, especially coastal, sewer overflow, combine sewer, area coastal, large desalination, plant algeria, warm product, solution act, fluorine product, area inland, fight global, sell forest, exposure coastal, city coastal, marina east, day desalination, snow storm, typhoon, heat

Bigram Opportunity Risk (Sautner et al., 2020)	renewable energy, electric vehicle, clean energy, new energy, wind power, wind energy, solar energy, plug hybrid, heat power, renewable resource, solar farm, battery electric, electric hybrid, reinvestment act, issue rfp, construction megawatt, rooftop solar, grid power, recovery reinvestment, solar generation, energy standard, sustainable energy, vehicle charge, guangdong province, hybrid car, charge infrastructure, micro grid, grid connect, clean efficient, carbon free, hybrid technology, generation renewable, energy wind, battery charge, gas clean, vehicle lot, vehicle place, meet energy, vehicle type, vehicle future, energy commitment, electronic consumer, expand energy, gigawatt install, bus truck, ton waste, energy research, focus renewable, pure electric, ev charge, grid technology, geothermal power, type energy, solar program, vehicle development, energy important, install solar, vehicle battery, energy vehicle, energy bring, vehicle space, opportunity clean, demand wind, vehicle good, medical electronic, incremental content, supply industrial, energy target, term electric, power world, vehicle small, renewable electricity, wave power, carbon neutral, auction new, cost renewable, vehicle talk, vehicle offer, customer clean, power solar, vehicle opportunity, community solar, energy goal, vehicle hybrid, invest renewable, incorporate advance, talk solar, ton carbon, small hydro, base solar, target gigawatt, charge network, capacity generation, vehicle add, vehicle infrastructure, solar array, energy auction, product hybrid, product solar, exist wind

Bigram Regulatory Risk (Sautner et al., 2020)	greenhouse gas, reduce emission, carbon emission, carbon dioxide, gas emission, air pollution, reduce carbon, energy regulatory, carbon tax, carbon price, environmental standard, nox emission, emission trade, dioxide emission, epa regulation, energy independence, carbon reduction, know clean, standard requirement, development renewable, carbon market, trade scheme, deliver clean, mercury emission, reduce air, save technology, talk clean, energy alternative, place energy, reduce nox, air resource, target energy, change climate, impact climate, issue air, promote energy, emission free, implement energy, recovery pollution, control regulation, florida department, commission license, gas regulation, appeal district, source electricity, effective energy, nitrous oxide, impact clean, think carbon, global climate, produce carbon, clean job, efficient natural, emission monitor, emission issue, quality permit, product carbon, china air, reduce sulfur, available control, emission rate, regulation low, capture sequestration, nation energy, emission year, efficient combine, carbon economy, comply environmental, glacier hill, hill wind, nox sox, tax australia, way comply, emission intensity, oxide emission, emission improve, emission increase, install low, commission public, castle peak, capture carbon, wait commission, emission compare, clean electricity, high hydrocarbon, emission come, weight fuel, stability reserve, quality regulation, request public, additive process, gas carbon, epa requirement, liter diesel, meet reduction, talk climate, expect carbon, emission ton, ambient air, know carbon