What Drives Beliefs about Climate Risks? Evidence from Financial Analysts

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Abstract

This paper aims to understand how beliefs about climate physical risks (risks of weather events) are formed and how these beliefs affect financial forecasts. I start by developing the first conceptual framework of belief formation about climate risks along the lines of the Experience-Based Learning model of Malmendier and Nagel (2011). Then, to micro-fund the drivers of climate beliefs, I construct a novel dataset with geolocalized salient natural disasters and equity analysts in 29 different US states covering 6,846 firms from 1999 to 2020. Using a staggered differences-in-difference methodology, I study variations in analysts' earnings forecasts after experiencing an exogenous weather shock. In line with previous studies, my finding suggests that analysts, after experiencing a salient weather shock, have lower forecast bias and error. I find that analysts with high ex-ante performance update their forecasts only for firms with high climate physical risks. Contrarily, low-performance analysts become more pessimistic about all firms, disregarding firms' climate exposure. The results indicate that high-performance analysts acquire new information from experiencing salient weather events, while low-performance analysts are affected by availability heuristics.

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

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1 Introduction

Modeling beliefs about risk is challenging, but climate risks add an extra layer of complexity. The main difficulty stems from 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. Consequently, the incentive to implement mitigation policies nowadays depends on the expected economic severity of future physical events. This is as well brittle since researchers do not fully comprehend what are the bad-to-worst case scenario caused by climate change (Kemp et al., 2022).[1] Thus, understanding how agents perceive future physical risks is a fundamental matter in the fight against climate change.

In this paper, I try to shed light on how agents form beliefs about climate physical risks (henceforth climate beliefs), how experiences of weather events affect these beliefs, and what is the network effects of 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, Choi et al. (2020) document that retail investors sell stocks of firms with high carbon footprints during months with atypically high temperatures. 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. Similarly, Anderson and Robinson (2019) note that Swedish households are more likely to invest in green funds after experiencing a heatwave. These studies claim that experiencing a weather event raises climate awareness, and thus affects behaviors, however, the literature lacks an understanding of how beliefs about climate risks are formed in the first place and what channels influence these beliefs.

Following the seminal paper of Malmendier and Nagel (2011), my conceptual framework defines what are beliefs about climate risk and how they are formed. Note that this study only focuses on physical risks, hence climate beliefs are defined as the expectation of future economic damages caused by climate change in the US. Similar to Malmendier and Nagel (2011), I define these beliefs as a weighted sum of an endowed fixed prior climate belief and experiences of past weather shocks. The main difference is that I consider only first-hand experiences of weather shocks that affect climate beliefs (i.e. if the agent is 100 miles near the

[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).

event), while they use cohort events.[2] In addition, I assume that each experience of weather shocks is perceived as a realization of climate change, but the intensity for which these shocks affect analysts' climate (posterior) beliefs depends on analysts' prior. For example, an analyst with low ex-ante climate beliefs, after experiencing a weather shock, has a larger revision of her climate beliefs compared to an analyst with high ex-ante climate beliefs.[3] This feature of the model allows us to exploit differences in prior climate beliefs to study the effect of weather shock experiences.

Since I do not directly observe analysts' climate beliefs, I can extract beliefs using variations of analysts' earnings forecasts after weather shocks. Analysts' forecasts can be seen as an interaction of analysts' beliefs (which includes climate beliefs) and all the information set (i.e. all available data).[4] If the information set does not change, then a change in forecasts can only be driven by a change in beliefs. Hence, by holding the information set constant, we can provide evidence of how weather shocks shape climate beliefs, thus affecting the financial market.

To pin-down climate beliefs from variations in analysts' forecasts, two main assumptions are needed. First, weather shocks do not impact forecasted firms either directly (firms are hit by the weather shock) or indirectly (suppliers or competitors are affected). This assumption implies that the information set remains constant, thus allowing me to claim that any change in earnings forecasts, after a weather shock, is driven by a change in analysts' beliefs. Second, only salient natural hazards affect analysts' posterior climate beliefs. For now, we disregard other possible sources of climate change realization, such as news or maps about climate change, that could potentially lead to a change in posterior climate beliefs.[5]

If firms are not directly or indirectly impacted, any changes in firms' earning beliefs happen only through a change in climate beliefs. This could be either because the analysts learn from experiencing salient weather shocks (*information hypothesis*) or because traumatic weather shocks affect their risk-taking (*heuristic hypothesis*). The former implies that the release of new information about climate change affects our perception of future climate risks, thus motivating policymakers to enforce climate risk disclosures. While the latter indicates that weather shocks have only a temporary effect on analysts' perception of climate risks, which usually fade away after a couple of months.

To test my hypotheses, I start by building a comprehensive dataset with both analysts' and weather shocks' characteristics. 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.

Salient weather shocks are defined as natural hazards that had 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

[2] In line with the hypothesis of using only first-hand experiences of weather shocks, Andersen et al. (2019) provide evidence that only directly experienced shocks affect individuals' risk aversion.

[3] Notice that I could potentially find the opposite effect. Analysts with low ex-ante climate beliefs may not perceive weather shock as a climate change realization. Thus they are less affected compared to analysts with high climate beliefs.

[4] Analysts' beliefs include, besides climate beliefs, also beliefs about the economy and beliefs about the forecasted firms' fundamentals.

[5] Even if they are not included as sources of climate risk variation, my empirical strategy will control for them.

search trends). 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.

To investigate what drives different forecast bias and error for firms with distinct climate exposures, I start by studying the effect of experiencing a weather shock on analysts' forecasts. 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).

Salient weather shocks are exogenous events that allow me to use a staggered differences-in-difference methodology to compare forecasts of analysts that experience a weather shock for the first time to analysts with no experience. Analysts are divided into treatment and control groups: the former includes analysts located 100 miles from weather shocks, while the latter includes never treated analysts.[6] To ensure that any change in analysts' bias and error is driven by a change in beliefs (and not the information set), I discard forecasted firms that are within 100 miles from the event.

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 (Tran et al., 2020; Han et al., 2020). I find that the treated groups, after experiencing a weather shock, have a lower forecast bias of 0.16 p.p. and a lower forecast error of 0.24 p.p. compared to the control group. These correspond to a 20% decrease in bias and 11% in forecast error when compared to the average forecast bias and error.

Since climate priors are an important determinant of posteriors, analysts' characteristics may play an important role in how weather shock enters into analysts' posterior climate beliefs. I replicate the baseline staggered DID for distinct subgroups of analysts' characteristics: years of analysts' experience, ex-ante optimism/pessimism, ex-ante performance, county's political ideology, living in a climate-sensitive state, or living in states with high climate beliefs. The findings indicate an overall homogeneous effect of experiencing a weather shock on analysts' forecast bias and error across all subgroups. Only analysts living in states with low climate risks (with less than 4 extreme weather shocks) as well as states with low climate beliefs (more than 60 % of the states' population not believing in climate change) seem to not be affected by experiencing extreme weather events. State-level information, however, may be too broad and not able to pin down the exact climate beliefs and climate risks of the location where the analysts are situated.

After highlighting a homogeneous effect of weather shocks on different subgroups of analysts' characteristics, I exploit firms' climate risks to disentangle if the decrease in optimism and forecast error is driven by a *heuristic* or *information channel*. If forecasts are affected by the former, analysts, after a shock, will overestimate the likelihood of natural disasters for all firms. Contrarily, analysts may become more pessimistic only for firms with high climate risks. This could be driven either because they abnormally overestimate the risks for firms with high climate exposure (*representative heuristics*) or because they learn that they were ex-ante underestimating the risks of climate-sensitive firms and hence updating their forecast downwards after the event (*information hypothesis*).

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

To understand what is turning beliefs, I exploit analysts' changes in forecast error and bias for firms with distinct climate exposure. For this analysis, I only focus on the analysts' performance subgroups. High-performance analysts are usually more experienced, they follow more industries and they present a lower bias and error compared to low-experienced analysts. Therefore, I hypothesize that while low-performance analysts are more likely to be subject to the heuristic channels, high-performance analysts, given their higher level of expertise, may be able to extract some new information from the event.

Interestingly, I find that high-performance analysts become 0.13 p.p. more pessimistic only for climate-sensitive firms, while low-performance analysts become more pessimistic for all firms. Both analysts' subgroups become more accurate after the weather event. The results are robust to both definitions of climate risks: sectors' climate risks and firms' physical risks. The findings for low-performance analysts corroborate the hypothesis that forecasts revision seems to be driven by an increase in risk aversion after experiencing a traumatic event (*heuristic hypothesis*).

If high-performance analysts can extract information about future economic damages of climate change from experiencing weather events, this information extraction should be larger for 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. My data allows me to decompose the physical risk score in each type of weather event risk. The results highlight that while low-performance analysts revise their forecasts for all firms with high physical risks score, irrespective of their climate exposure, high-performance analysts become more pessimistic only for firms with high risks of weather events such as the one experienced by the analyst.

To further corroborate the results, I exploit weather shocks' damage types, which are defined both in terms of salient health-related and economic-related damages. The idea is that if analysts are learning the future economic costs of climate change from a weather event, the amount of information extraction should be larger for shocks with economic-related damages compared to health-related damages. In line with the hypothesis, I find that top-performer analysts are largely affected by economic damages, while non-top performers by health-related damages.

So far, the analysis focused only on first-time treated analysts, but what is the effect of experiencing multiple weather shocks? Using shock information, I can investigate if high and low-performance analysts have different forecast bias and error after experiencing a second shock. Again, the shock characteristics would allow me to disentangle what channels drive the results. For example, if analysts first experienced a shock with health-related damages and then the second weather event has high economic damages. If the information channel is driving the results, only shocks with different characteristics would affect analysts. Because analysts would be able to extra new information from shocks with different characteristics. Contrarily, the heuristic channels indicate that multiple experiences will largely bias climate beliefs, independently of the similarity with the previous weather event in terms of damages or event type.

Keeping the control group as never treated analysts, I then construct a treated group with analysts that experienced a second weather shock. The estimated coefficients suggest that analysts become more pessimistic and more accurate after a second shock. When looking at events with different and similar characteristics compared to the previously experienced event, the results indicate that only similar events affect analysts' forecasts, thus suggesting a heuristic channel. However, given the small sample of analysts that experience dissimilar shocks, I believe that further research is needed.

Climate physical risks are usually categorized as long-term risks. However, since physical risks can affect short-term as well as long-term expectations, I consider whether analysts believe that climate risks threaten long-term firms' earnings. To analyze earnings forecasts for different time lengths, I apply the baseline staggered differences-in-difference methodology on analysts' bias and forecasts error from one-year to five-year horizons separately as well as long-term growth rate. The estimated results show that analysts' forecast error and bias decrease after the event only for short-term horizons (respectively, 1 to 2 years ahead and 1 to 3 years ahead). When looking at long-term forecasts, I find that analysts' forecast error increases for 5 years-ahead forecasts. Highlighting that climate physical risks are a long-term risk that leads to greater uncertainty for long-term earnings forecasts. While long-term growth rates are revised downwards after the weather shock, suggesting that analysts believe in lower future growth.

A series of robustness checks are conducted to test the validity of my results. 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. Additionally, by conducting a placebo analysis I show that analysts' changes in their forecasts error and bias for firms with high climate exposure are not affected by terrorist attacks. Corroborating the hypothesis that only experiences of climate-related events affect climate beliefs.

At last, my setting allows me to study whether beliefs diffuse across analysts. Previous studies document that analysts tend to herd All-Star analysts.[7] Unfortunately, I do not have data on the latter, hence I assume that high-performance analysts are All-Star analysts. In this setting, my treated group is averaged forecast bias and error over low-performance analysts for firms where a high-performance analyst experiences a climate event. 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. Since I do not observe who are All-start analysts, a possible concern is that high-performance score analysts are not influential enough to affect other analysts' beliefs, hence leading to not statistically significant results.

Overall, my 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 urges policymakers to fasten new regulations for climate risk disclosure such as to increase climate awareness. This would benefit in particular non-performer analysts.

My work differs from past studies on how climate shocks affect analysts' forecasts threefold. 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), or if analysts extract climate risks information from experienced abnormal temperatures (Pankratz et al., 2019; Addoum

[7] 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.

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, these studies mostly focus on short-term forecasts, besides Tran et al. (2020). Instead, my work will 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).[8]

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 (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. Section 7 presents the results. Section 8 concludes.

2 Literature Review

This section provides a brief discussion of the literature on belief formation and the effect of climate events on analysts' forecasts.

This study founds its conceptual framework in the experience-based learning (EBL) model presented in the seminal paper of Malmendier and Nagel (2011). In their study, the authors provide evidence that agents' risk-aversion, and therefore behavior, is strongly influenced by lifetime experienced events. They note that agents tend to invest less in the stock market when experiencing lower stock returns during their lifetime.[9] This is in contrast to standard economic models which assume that agents use all possible data available to make their best guess about future events.

The EBL model has some useful features. First, it is not limited to investment decisions, but it also explains how past observed inflation rates affect individuals' perception of future inflation rates (Malmendier and Nagel, 2016). Second, it provides a link between past experiences and agents' current behaviors. For example, how past inflation experiences affect

[8] 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).

[9] Before Malmendier and Nagel (2011), earlier works noted that experiences affect financial behaviors (Guiso et al., 2008; Guiso et al., 2004; Osili and Paulson, 2008)

homeownership choices (Malmendier and Wellsjo, 2020) or how consumption choices are explained by past unemployment experiences (Malmendier and Shen, 2018). Third, the model is robust to expert knowledge. Malmendier et al. (2021) show that also the members of the Federal Reserve Bank's Federal Open Market Committee (FOMC) have their forecasts affected by past experiences. This is particularly relevant for my study since it indicates that the EBL model could also be applied in the equity analysts' context.

While the EBL model set the basis for how beliefs are formed (Malmendier and Wachter, 2021), another relevant stream of literature studies the dynamics of beliefs. This work is built on the concept of representative heuristics. This notion, firstly proposed in Kahneman and Tversky (1972), highlight that an agent, after the news, tend to overestimate the probability of the representative types. In this setting beliefs are called diagnostic expectations: when an attribute is common to a population group (i.e. diagnostic for the population), an individual tends to exaggerate the likelihood of the attribute being in that particular group. 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).

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 headquarter 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 lowers 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 previous studies have focused on historical variation in temperatures and precipitation as a measure of climate risks, a recent study by Kim et al. (2021) exploit forward-looking drought risks.[10] The author finds that firms located in countries with higher drought risks present higher forecasted errors and dispersion. This effect is amplified for inexperienced analysts, consumer-driven sectors, and developed countries. They hypothesized that consumers in wealthier countries impose higher pressures on companies, which makes earnings more volatile and therefore increases uncertainty in earnings forecasts.

Other studies, instead of focusing on the incorporation of climate-related risks, document how extreme negative events affect analysts' heuristics.[11] For example, Bourveau and Law

[10] The idea is similar to Hong et al. (2019) that study whether the stock market price drought risks.

[11] 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

(2020) research whether experiencing a disastrous hurricane impacts analysts' risk-aversion (proxy by analyst relative optimism, i.e. the difference between analyst's forecasts and consensus forecasts). Using one-quarter ahead forecasts they find that analysts that experience a hurricane have less optimistic forecasts for the following two years.[12] Moreover, 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, another stream of studies relies 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 forecasts 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": experiencing a traumatic event makes a person more stressed and distracted. For this reason, analysts will only focus 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 analysts become even more pessimistic after a shock (and less accurate), while optimistic analysts become more optimistic.

Ultimately, a novel literature studies the effect of risk disclosure on analysts' forecasts. Wang et al. (2017) show that forecast accuracy increases when the annual reports have higher risk disclosure because larger risk disclosure decreases market information asymmetry. Similarly, Krueger et al. (2021) show that mandatory ESG disclosures improve the information quality of firms' risks, and therefore analysts' forecasts become more accurate and less dispersed. While Derrien et al. (2021) exploit ESG incidents to investigate how they affect equity forecasts and therefore firms' value. Chan (2022) show the consensus incorporates information from climate disclosure (using the Carbon Disclosure Project, CDP) only for industries most exposed to climate change.

3 Conceptual Framework

This section lays out the conceptual framework used in my study. First, I describe how climate beliefs are formed, showing how the experience-based learning (EBL) model can be applied in the climate context in general. Then, I tailor the EBL model to the analyst's forecast setting. At last, I delineate how to extract climate beliefs from analysts' earnings forecasts.

3.1 Formation of Climate Beliefs

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

accuracy). Moreover, firms followed by more analysts have better forecasts due to less competition bias (Hong and Kacperczyk, 2010).

[12] 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 out-weight their over-optimism bias.

lived agents, where beliefs are a weighted sum of a prior belief and past experiences.[13]

In the climate context, we 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.[14] 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:

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

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 $w(k, \lambda, \text{age}) = \frac{(\text{age }+1-k)^{\lambda}}{\sum_{k\prime=0}^{age}(age+1-k\prime)^{\lambda}}$. 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.

This model provides four main features.[15] 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.[16]

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

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

[14] 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).

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

[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.

analysts' posterior beliefs.[17] Hence, I can rewrite equation 1 as the posterior at time t for an analyst such as:

$$\theta_t = (1 - w_{\textbf{work}}) * CC + w_{\textbf{work}} * \sum_{k=0}^{\textbf{work}} w(k, \lambda, \textbf{work}) * \text{ Weather Shocks }_{t-k} \tag{2}$$

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:

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

To further clarify, let's assume that the prior can take any value between 0 and 1.[18] 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 beliefs after a shock.

For the rest of the study, I will rely on equation 3 as the main specification for my conceptual framework.

3.2 Variation in Analysts Forecasts

I cannot directly observe climate beliefs, but I can use variations in analysts' earning forecasts after a weather shock to extract beliefs. Analysts' earnings forecasts can be seen as an interaction between analysts' beliefs (which also includes climate beliefs) and the information set (i.e. all data available in the market).[19] If the information set remains constant and firms are not directly (or indirectly) affected by the weather shock, any change in analysts' forecasts can be only driven by a change in analysts' beliefs.

[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.

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

[19] Formally, let's think about analyst's forecasts as $(belief) * (information)$. Analysts' *beliefs* include climate beliefs as well as beliefs about firms' fundamentals or the surrounding economy.

To extract how weather shocks affect climate beliefs, my main assumptions are two-fold. First, weather shocks do not impact forecasted firms either directly or indirectly. This implies that forecasted firms in my samples are distant from the event. Additionally, I want to control that the firms' fundamentals are not indirectly impacted by the event, i.e. if weather shocks hit a firm's suppliers or competitors. I note, however, that this is a second-order effect. In a fully competitive market, a climate shock to a supplier or a competitor would not be relevant. While in an imperfect market, if competitors are affected, I could mitigate this problem by controlling for industry-fixed effects or some concentration indexes.

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 that 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 analysts' beliefs.

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

4 Hypotheses Development

In this section, I delineate a series of testable hypotheses for how climate beliefs are affected by salient weather shocks.

4.1 Testable Hypotheses on climate belief formation

What are the underlying channels that lead to a change in posterior climate beliefs after experiencing a weather shock? If firms are not directly or indirectly impacted, any changes in firms' earning beliefs happen only through a change in climate beliefs. This could be either because of 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). 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 shortly. Therefore, my first two hypotheses are:

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

Hyp. 2 *If weather shocks affect analysts' heuristics, we expect the new climate beliefs to rapidly affect analysts' forecasts but to dissipate after 3 months (in absence of any other shock).*

Hypothesis 1 and 2 are key in understating how climate beliefs are formed. Nonetheless, they also provide evidence on how we should move forward to mitigate climate change. If weather shock provides new information to analysts, we might urge policymakers to fasten new regulations for climate risk disclosure such as to increase climate awareness. In particular, in states that are less impacted by climate shocks. On the contrary, if climate risk awareness rapidly dissipates after a shock, we might need to develop new tools to constantly raise awareness.

To disentangle whether the estimated effect is driven by the information or the heuristic hypothesis, I exploit the richness of my data. 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 high 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.

In addition, shocks timing and damages are key to providing further evidence on which channels drive the results. If the effect of experiencing an event is long-lasting, whether analysts experienced an event more or less recently should not matter. While if the effect is driven by the heuristic hypothesis, it will fade away after a couple of months. In terms of shock-related damages, since analysts are trying to forecast the future economic costs of climate change, if the analysts are learning from the event, I assume that shocks with larger economic damages would lead to a larger change in beliefs. Contrarily, health-related damages are usually more traumatic experience events that affect mainly agents' risk-taking Bernile et al. (2017).[20]

Therefore, additional testable hypotheses on the effect of weather shocks on analysts' forecasts are:

Hyp. 3 *Under a heuristic effect, firms' forecasts should be largely affected by weather shocks that caused health-related damages.*

Hyp. 4 *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. 5 *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 many economic-related damages.*

4.2 Testable Hypothesis on Belief Diffusion

If treated analysts are learning from the event, is this new information spreading across untreated analysts? It may be possible that analysts, that do not directly experience the event but observe changes in treated analysts' forecasts, are consequently updating their forecasts. A large literature documents that analysts have herding behaviors either for reputation reasons, new private information, or "higher-order expectations" as in Keynes' classical beauty contest

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

framework (see for example Hong et al., 2000, and Rangvid et al., 2013). This setting allows me to investigate how beliefs diffuse across analysts and what are the channels of analysts' herding behaviors.

To do so, I exploit All-Star analysts that are important price-settler and I investigate whether they affect other analysts' beliefs. First, I document whether All-Star analysts are affected by directly experiencing weather shocks. As discussed in the previous section, the EBL model is robust to expert knowledge. Hence if All-Star analysts have a non-zero prior about climate risks I expect them to be affected by weather shocks. Second, I exploit changes in forecasts of All-Star analysts to investigate if they affect the beliefs of other analysts that did not directly experience weather shocks. Third, to disentangle whether changes in analysts' forecasts are driven by new information about climate risks or pure herding (reputation reasons or beauty contests), I exploit the fact that analysts provide forecasts for multiple firms at the same time. Therefore, I can observe if they only change their forecasts for firms forecasted by treated All-Star analysts (pure herding) or also for other firms, forecasted by all control analysts, with similar risks as the firms forecasted by treated All-Star analysts (belief diffusion).

My testable hypotheses are then:

Hyp. 5 *All-Star analysts update their forecasts after experiencing a weather shock.*

Hyp. 6 *After treated All-Star analysts update their forecasts, other analysts will herd and consequently update their forecasts.*

Hyp. 7 *Forecasts revisions are driven by pure herding if analysts update only the firm forecasted by the treated All-Start analysts. Whereas belief diffusion implies that analysts update their forecasts also for firms forecasted by control analysts but with similar risks as the firm forecasted by the treated All-Start analysts.*

5 Empirical Strategy

To investigate my testable questions, I employ a staggered Differences-In-Difference (DID) using extreme natural hazards as randomly distributed weather shocks. In this section, I explain how I define salient weather shocks, the staggered DID used, the main assumption for the validity of my methodology, and how I modify the general empirical strategy 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 (Wirtz et al., 2014); (3) more than 1 billion dollars total economic damages (Barrot and Sauvagnat, 2016). 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.

Staggered DID. 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 100 miles radius of a salient shock as a treated group. While the control group is represented by analysts that issue forecasts 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.

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 that 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 on analysts' location, I use the following difference-in-difference:

$$\mathrm{Y}\ _{i,f,c,t} = \beta_1 TREAT * POST_{c,t} + \theta X_{it} + FE + \varepsilon_{i,f,c,t} \tag{4}$$

for an analyst i, firm f, in a city c and at time t. $TREAT * POST_{c,t}$ is the interaction term between the indicator for treated analysts and post-treatment periods, and θX_{it} are controls for pre-trend differences. Fixed effects (FE) included are: γ_i analyst, δ_t year, and η_f firm FE. Additionally, I include brokerage and firm-time fixed effects. When results are reported at the aggregate level for all forecast horizons (1 to 5 years ahead), each fixed effect is interacted with the horizon fixed effect. Since climate shocks occur within 100 miles radius of the analyst's office location, standard errors are clustered by analysts' office location.[21]

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 underlying assumption is that if an analyst is negatively affected by a salient weather shock, I expect to observe a decrease in the analyst's bias after the natural hazard.

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

[21] Note that I also repeat the analysis with standard errors clustered at the analyst level, at the office location-analyst level, at the office location-time level, and office location-analyst-time level. Overall, different clustering does not impact the significance of the estimated coefficients in my model. The results can be reported upon request.

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.

Concern & Limitation of Staggered DID. 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, an analyst is removed from the control group after she/he experiences 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.

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

$$\text{Y}_{\ i,f,c,t} = \sum_{j \neq 0} \beta_j Treat * \text{Relative Month}_{c,t+j} + \theta X_{it} + \Gamma_{i*h} + \Gamma_{f*h} + \Gamma_{t*h} + \varepsilon_{i,f,c,t} \tag{5}$$

Where *Relative Months* is a binary variable that indicates the month when the forecasts were issued, *Treat* takes value one for a treated analyst, and $Treat * Relative\ Month_{c,t+j}$ is the interaction terms for the treated group j months before and after the climate shock. The regression includes also analyst, firm, and time-fixed effects interacted by forecasts' horizon $(\Gamma_{i*h}, \Gamma_{f*h}, \Gamma_{t*h})$ as well as additional covariates (θX_{it}).

To show that the parallel assumption holds, the difference between my control and treated group need to be either not significantly different or statistically different but constant throughout the pre-treatment months. The underlying idea is that the control group is the counterfactual of the treated group, hence in absence of any shock, the treated group would have acted as the control group. This holds if the two groups are non-different in any observable and unobservable characteristics. Notice that these two groups may be statistically different but their differences should be constant through time. This would not violate my empirical strategy because the regression's fixed effects would be able to capture any non-varying differences across the two groups.

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 staggered DID 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 larger 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.[22]

At last, while my main analysis focus 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).

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.[23] 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 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

[22]See table 19 and 20 for a detailed description of each subgroup.

[23]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.

(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' 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 report 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 forecasts 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.

To proxy for firms' transition risks, I use the Unpriced Carbon Cost adjusted EBITDA which is the share of EBITDA at risk from the unpriced expected future carbon price. Similar to the physical risks, the Unpriced Carbon Cost adjusted EBITDA is averaged across all scenarios (high to low) using the forecasted year 2020. High (low) risk firms are firms in the highest terciles (middle and bottom terciles) of unpriced carbon costs.

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 same brokerage firms located in the same state (as an analyst found on Refinitiv) are located in the same brokerage's city as analysts previously identified through Refinitiv. To avoid mismatch I manually check analysts, which moved at least once in my sample, using BrokerCheck.[24]

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.

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 that 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 2,479 equity analysts in 25 different US states covering 3,876 firms from 1999 to 2020.

Analysts Characteristics. Figure 1 maps the location of my sample of 2,546 analysts throughout the US. Not surprisingly, 68% 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 0.82% while the average forecast error is 2% (respectively with a standard deviation of 4.1 and 3.9). An analyst in my sample follows on average 9 firms, with on average 1 year of forecasting a single firm and approximately 3 years overall of work experience. Moreover, the average analysts follow 1 to 2 sectors and work in a brokerage firm with other 75 analysts.[25]

Weather Shocks Characteristics. Figure 2 maps the selected salient weather shocks that occur near an analyst's office location from 1999 to 2020 by US state. The states with the highest number of shocks are New York, California, Missouri, Massachusetts, Minnesota, and Florida, with an average of 70 shocks. While the state with the lowest number of weather events is Delaware with only one weather shock.

Table 2 reports for each type of weather event 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

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

[25] 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 have a mean of 3 and 6 years of respectively firm and general experience, which is in line with previous studies. See table A2 in the Appendix for the unfiltered summary statistic.

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.[26]

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

8 Empirical Results

8.1 Aggregate 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.

DID Baseline Results. Table 4 report the baseline staggered differences-in-differences for both analysts' forecast bias (panel A) and error (panel B). Each column includes a different combination of fixed effects and covariates. As the standard staggered DID, 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. At last, column 5 interacts with each fixed effect to a unique identifier for each weather shock (i.e. group 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).

[26]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

The baseline results are in line with previous studies that document a significant effect on analysts' accuracy and optimism 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 0.13 p.p. and 0.24 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 16% decrease in forecast bias and 10% in forecast error. All the other columns, except column 4, confirms the robustness of the results with different specification.

Parallel Trend Assumption. I test the validity of my staggered DID by assessing whether the parallel trend assumption holds. Figure 3 plots the estimated coefficients of pre and post periods interaction terms between treatment and time dummies for both forecast error (panel a) and forecast bias (panel b). The figures corroborate the findings that the forecast bias of control and treated groups are not statistically different in pre-treatment periods, while they are statistically different but parallel for the forecast error. Thus suggesting that the empirical strategy is robust.

Analysts Characteristics. To investigate if analysts with dissimilar priors are differently affected by experienced weather shocks, I repeat the baseline staggered DID by sorting analysts into subgroups with specific characteristics. Figure 4 reports the DID coefficients of interest for analysts' forecast bias and error respectively for low (blue histogram) and high values (red histogram) of the following subgroups: experience, ex-ante performance, ex-ante optimism-pessimism, climate-sensitive states (i.e. number of climate shocks in a state), 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). See table 19 and 20 for a detailed description of each subgroup.

The results highlight an overall homogeneous effect on analysts' forecast bias and error. Only analysts living in states with low climate risks (with less than 4 extreme weather shocks) as well as states with low climate beliefs seem to be unaffected by experiencing extreme weather events. State-level information, however, may be too broad and not able to pin down the exact climate beliefs and climate risks of the location where the analysts are situated. Interestingly, no significant effect is found on analysts' forecast errors when analysts are located in Republican counties. I speculate that this may be because republican analysts have a low prior belief of climate change, thus experiencing a weather shock does not have any effect on analysts' posterior.

Table 5 computes z-tests to check whether the estimated coefficient of the low-value subgroup (β_l) is statistically different from the high-value subgroup (β_h). The table reveals that the largest difference between subgroups, for both forecast error and bias, is the one between analysts living in Democratic and Republican counties as well as analysts with high and low ex-ante performance. Even if the z-score does not reject the null hypothesis at a 10% statistical level, I further investigate these two subgroups.

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. 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 obtained from Trucost (ranging from 1 to 100, with 100 being the highest risk).

Table 6 and 7 report the estimated coefficients of our baseline differences-in-difference for subgroups of high and low-performance analysts for forecasts of firms with different climate risks. The estimate coefficients indicate that top performers become more pessimistic of 0.13 p.p. for firms in climate-sensitive sectors, but they do not change their bias for firms in non-climate-sensitive sectors. While forecast errors diminish for firms in both climate and not-climate-sensitive sectors, respectively by 0.35 and 0.22 percentage points. Contrarily, low-performance analysts become more pessimistic and more accurate for all firms, indistinctly of their climate-sensitive sectors.

The results are robust by using the composite score of physical risks estimated for each firm by Trucost. High-performance analysts become more accurate for firms with both high and low physical risks, but they become more pessimistic only for firms with high physical risks. Whereas low performer analysts have a homogeneous effect on firms with high and low climate risks.

Analysts' Performance & Shocks' Characteristics. Previous results highlight that high-performance analysts become pessimistic only for stocks with high climate risks (both in terms of sector climate risks and firm-specific physical risk). Two different channels could explain this result: top performers, after a shock, 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 reports the results of the staggered DID for firms divided into high and low physical risks conditional to the shock experienced by the analysts. The result indicates that high-performance analysts become more pessimistic only for firms with high physical risks as the shock experienced. Consistent with previous results, low-performance analysts have a homogeneous effect on firms independently of the risk type. The findings corroborate that low performers are affected by available heuristics, while high performers seem to learn from experiencing a weather shock.

A concern is high-performance analysts are overestimating the risks of firms with high physical risk as the shock experienced. To further prove that high-performance analysts learn from the event, I exploit shock damage characteristics. 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 corroborate what channels that drive the results. Since analysts are trying to forecast 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 0.04 percentage points. While after experiencing a shock with economic damages, they have a 0.35 p.p. reduction in bias. Contrarily, low-performance analysts decrease their forecast bias of 0.13 p.p. only for shocks with health-related damages, but no effect is found for shocks with economic damages. No effect is found on forecast error after analysts experienced a shock that caused economic damages.

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, that experience extreme weather events, may not only change their beliefs about physical risks but also about transition risks: believing that stricter regulation policies will be implemented. If this hypothesis is true, I expect treated analysts to become more pessimistic about firms with higher transition risks than firms with lower transition risks.

To check for this channel, I repeat the analysis by dividing firms into high and low terciles of transition risks, proxied by "Unpriced Carbon Cost adjusted EBITDA" from Trucost. Table 10 reports the estimated results by dividing the sample by firms with high and low transition risks. The results indicate that high-performance analysts decrease their forecast bias by 0.24 percentage points only for firms with low transition risks. In contrast, low-performance analysts decrease their bias of 0.21 p.p. only for firms with high transition risk. This suggests that low-performance analysts may overreact and penalize firms with high carbon risks but disregarding firms' physical risks, high-performance analysts seem to only change their forecasts for firms with high physical risks.

8.2 Disaggregate Results

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.

Breakdown by Forecast Horizons. Table 11 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 2 years-ahead forecasts. Interestingly, analysts become 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.[27]

Table 12 reports the estimated coefficients of the baseline DID 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.

Exploiting shocks' damages and events' type, I try to disentangle what channels drive the results. For example, the first panel assumes that an analyst that has experienced a hurricane is now experiencing a heat wave. Similarly, an analyst that experienced a shock with a high number of fatalities is now experiencing a shock with high economic damages. Both examples suggest that analysts could extract some additional information from the event because they have distinct characteristics.

The hypothesis is that, if analysts are learning from events, experiencing a second shock with different information (different types of damage or different weather events) should lead to a statistical effect on analysts' forecasts. Contrarily, the heuristic hypothesis implies that experiencing an additional event (irrespective of its similarity to the previous event) may evoke relevant memories that could bias analysts' perceptions of climate change.

Table 13 reports the estimated coefficients for analysts experiencing different or similar weather events (Panel A) and different or similar events' damages (Panel B) to the first weather shock. The findings indicate that both high and low-performance analysts, after experiencing a 2nd shock with the same characteristics of the previously experienced shock (both in terms of damages or type of events), become more pessimistic and more accurate. No effect is found for weather shocks with different characteristics. The results highlight the possibility of the heuristic channels, however, given the small sample size additional analysis is required to corroborate the results.

8.3 Belief Diffusion Results

The previous 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 that 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.

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

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

error averaged over low-performance analysts. Figure 5 plots the estimated coefficients (blue dot) of pre and post periods 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.

Limitation. Ideally, I would have used All-Star analysts for my analysis on belief diffusion. 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.

9 Additional Effects and Robustness Tests

This section investigates if analysts, following extreme events, are more likely to change their firm's coverage or ask climate-related questions during earnings calls.

Analysts Coverage. Equity analysts have discretion in the number of forecasts they want to issue and what companies they want to cover.

Using the baseline staggered DID methodology, I investigate if treated analysts follow more firms with higher climate risks in the 2 years after the extreme event compared to the control group. To do so, I start by assigning to each firm its specific physical, transition, and ESG score and I define analyst coverage as the number of firms that an analyst forecasts in one year. The total analysts' climate portfolio score is the average total physical, transition, and ESG score for the firms an analyst covers in one year.

Table 14 reports the staggered DID for treated analysts for the number of firms forecasted, and average climate coverage scores. Panel A reports the result for all analysts, while panels B and C report the results for low and high-performance analysts separately. The only statistically significant result is the DID estimated coefficient for the average transition score. Indicating that analysts tend to cover fewer firms with high transition risk in the two years following an experience of a salient weather shock. Panels b and c divide the analysis into the high and low-performance analysts subgroups, showing that the results are driven by low-performance analysts covering fewer firms with high transition risks.

Earnings Calls' Questions. Li et al. (2022) provide evidence that female analysts are more likely to ask environmental and social issues questions during earnings calls. In my setting, I want to investigate if analysts that experience extreme weather events are more likely to ask climate-related questions during earnings calls.

I obtain earnings transcripts from 2000 to 2019 from WRDS. By matching the two samples by analysts' names, I am able to match 962 analysts. To identify climate-related questions I use the unigrams and bigrams constructed in Sautner et al. (2020).[28]

[28]Notice that the full list of bigrams is not publicly available, hence I rely on the bigrams reported in the table

The variable "climate-related questions" represents the share of questions in which analysts mention one of the unigrams or bigrams over the total number of questions asked in a year expressed in percentage points. Consequently, I construct the share of physical, regulatory, and opportunity risk questions. As a preliminary result, table 15 reports the estimated LPM where the variable of interests is asking climate-related questions during earnings calls. The table indicates that treated analysts are more likely to ask fewer questions concerning regulatory risks and to ask more questions related to climate opportunity. The two estimated coefficients are very similar in terms of magnitude, which explains why on average I do not find any statistical effect on the total share of climate-related questions.

Overall, the findings are in line with what was found when looking at analysts' coverage: analysts after experiencing weather shocks cover fewer firms with high transition risks and ask fewer climate transition questions. Further analysis is required to explain this mechanism.[29]

Robustness. 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 16 shows that the findings are robust by selecting only analysts working far away from New York. Second, table 17 shows that the results are also statically significant when the standard errors are clustered at the brokerage firms.

Placebo Analysis. I conduct a placebo exercise by exploiting terrorist attacks in the US that occurred 100 miles near analysts' locations. Similar to the weather shocks used in the analysis, I select salient terrorist attacks if they cause more than 10 fatalities or injured more than 100 people.[30] Table 18 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 0.2 p.p. and 0.4 p.p. after the event. Columns 3 to 10 repeat the analysts for subgroups of high and low-performance analysts forecasting firms with high and low physical risks. Interestingly, high-performance analysts decrease their bias and error for firms with both high and low physical risks, even if the estimated coefficient of forecast error is not statistically significant for firms with low physical risks. For low-performance analysts, I only find a statistically significant decrease in forecast errors for firms with high physical risks. Keeping in mind the very small number of observations, this placebo analysis seems to validate the previous results.

10 Conclusion

This study sheds light on how experiences of weather shocks affect beliefs about physical risks. In line with previous studies, I find that analysts become more pessimistic and accurate after experiencing a salient weather shock. Two channels can explain the results: a heuristic and an information effect.

"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 removed deceptive bigrams and I complemented these lists with additional bigrams and unigrams, see the full list in table A3.

[29] This effect could be also driven by an institutional ownership demand story. Since institutional owners disinvest in firms with high transition risks, analysts follow fewer firms with high carbon emissions.

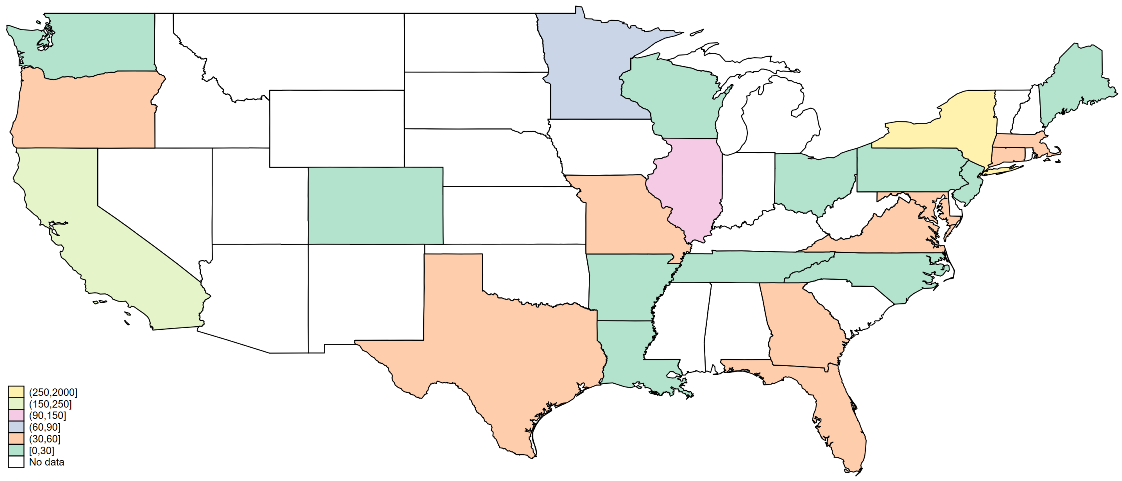
[30] Note that there is no information on the economic-related damages of a terrorist attack.

My findings suggest that both channels coexist. I find that high-performance analysts acquire new information from experiencing a salient weather event and hence change their forecasts for firms with high climate risks. In line with the *information hypothesis*, they become more pessimistic for firms with high physical risks as the type of weather events they experience. Contrarily, low-performance analysts become more pessimistic about all firms, disregarding the type or level of climate risks faced by the forecasted firm. Since high-performance analysts can extra new information about future economic damages caused by weather events, the results indicate that high-performance analysts are mainly affected by high-economic damages shocks. While low-performance analysts, which are affected by heuristics, update their forecasts for shocks with high health-related damages.

At last, I found no evidence that new information acquired by treated high-performance analysts diffuses their beliefs from other non-treated analysts.

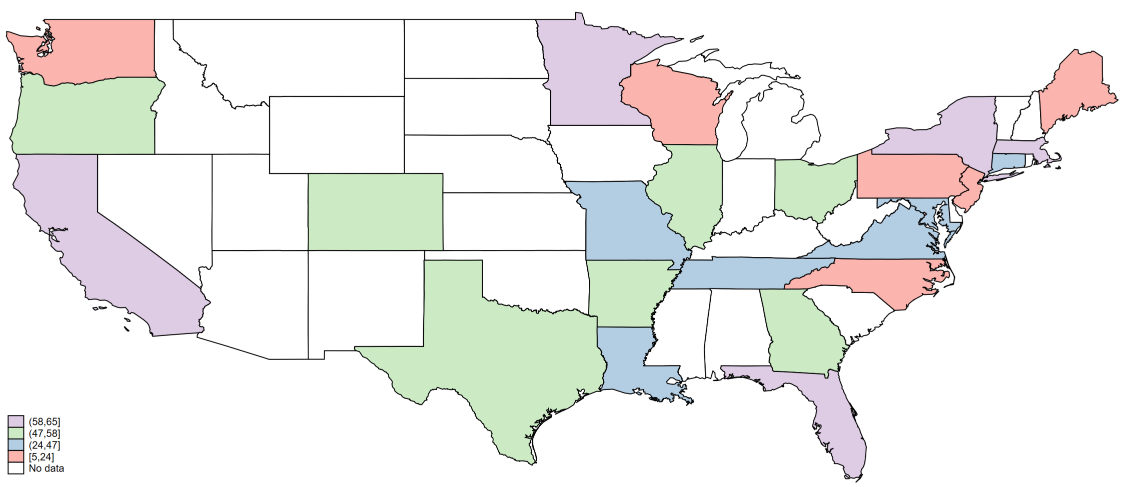
Figures

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



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

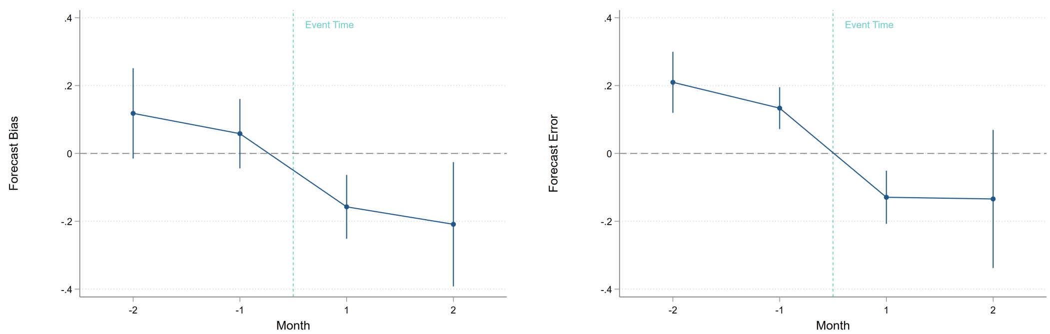
Figure 2: Salient Storm Events from 1999 to 2020 by State



Note: The graph maps the Selected Storm Events from 1999 to 2020 by US state. Notice that only weather shocks that take place 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.

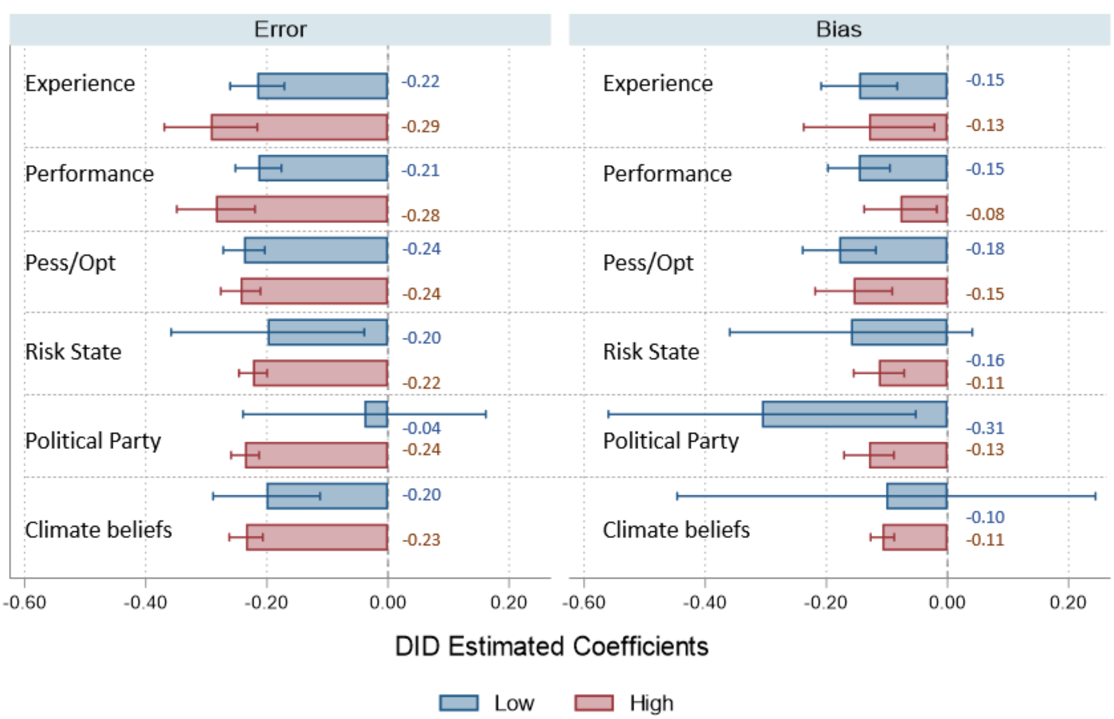
Figure 3: Parallel Trend

(a) Forecast BIAS (b) Forecast ERROR



Note: figures plot the estimated coefficients (blue dot) of pre and post periods interactions between treatment and time variable with 99% confidence interval (blue line). The omitted year is the year of the treatment (light blue dashed line). The specification includes all covariates. The fixed effects (analyst, year, and firm) interact with forecast horizon and event 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.

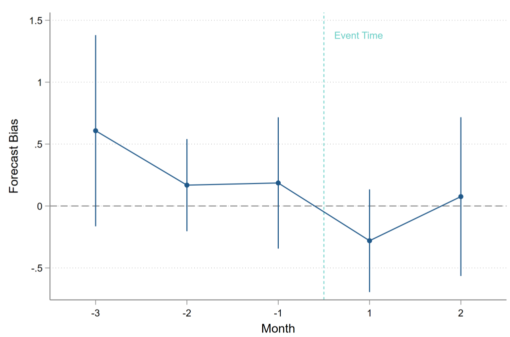
Figure 4: Analysts' Characteristics



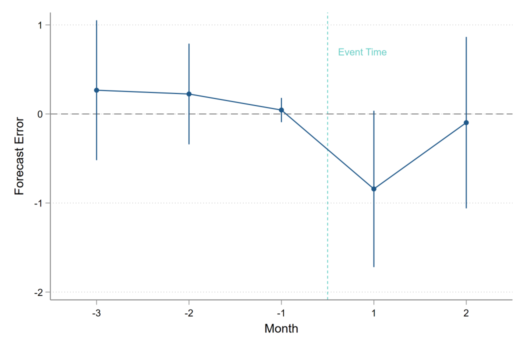
Note: figures plot the estimated coefficients from the staggered difference in difference in bar plots with 90% confidence intervals for error (left graph) and bias (right graph). The specification includes all covariates plus analyst, year, and firm fixed effects (interacted with horizon fixed effects).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

Figure 5: Belief Diffusion: effect on firms with one treated high performance analyst

(a) Forecast BIAS



(b) Forecast ERROR



Note: figures plot the estimated coefficients (blue dot) of pre and post periods interactions between treatment and time variables with a 99% confidence interval (blue line). The omitted year is the year of the treatment (light blue dashed 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 - Staggered DID

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

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 19 20 for a description of the variables used.

Table 2: Description Merged Salient Storm Event

Event Type	Av. Total Damage (Mil. $)	Av. Total Deaths	Av. Total injuries	Number of Events
Extreme Cold/Wind Chill	0	10	0	1
Thunderstorm Wind	0	1	100	1
Winter Weather	0	1	200	1
Excessive Heat	0	10	157	6
Heavy Snow	1	0	100	1
Winter Storm	10	2	250	1
Heat	61	15	79	11
Tornado	74	8	115	10
Debris Flow	289	15	59	3
Storm Surge/Tide	1082	0	0	1
Flood	1304	3	0	3
Hail	1753	0	0	2
Flash Flood	2321	4	25	4
Tropical Storm	3364	14	51	3
Hurricane (Typhoon)	4370	1	8	4
Coastal Flood	5073	1	0	1
Wildfire	15771	86	12	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. Notice that the arguably small number of selected shocks are driven by our 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).

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*			0.0150			-0.00475		
	(0.0496)			(0.0510)			(0.0517)		
Injuries		0.00942			-0.0182			-0.0225	
		(0.0868)			(0.0518)			(0.0508)	
1 bil. $ damages			0.0860**			-0.0727			-0.119*
			(0.0327)			(0.0687)			(0.0683)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	NO	NO	NO	NO	NO	NO
R^2	0.825	0.825	0.825	0.0000188	0.0000268	0.000244	0.0402	0.0402	0.0409
N	5028	5028	5028	4580	4580	4580	4484	4484	4484

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 Results - BIAS & FERROR

Dependent Variable:	Forecast Error				
	(1)	(2)	(3)	(4)	(5)
Treat*time	-0.237***	-0.234***	-0.239***	-0.0122	-0.241***
	(0.0202)	(0.0192)	(0.0204)	(0.0472)	(0.0242)
Controls	No	Yes	Yes	Yes	Yes
Analyst, Year, Horizon and Firm FE	Yes	Yes	Yes	Yes	Yes
Brokerage FE	No	No	Yes	Yes	Yes
Firm-Time FE	No	No	No	Yes	No
Group interacted FE	No	No	No	No	Yes
R^2	0.703	0.708	0.712	0.752	0.889
N	99781	92191	92188	72234	79263
Dependent Variable:	**Forecast Bias**				
	(1)	(2)	(3)	(4)	(5)
Treat*time	-0.157***	-0.134***	-0.131***	-0.0333	-0.158***
	(0.0318)	(0.0261)	(0.0260)	(0.0491)	(0.0233)
Controls	No	Yes	Yes	Yes	Yes
Analyst, Year, Horizon and Firm FE	Yes	Yes	Yes	Yes	Yes
Brokerage FE	No	No	Yes	Yes	Yes
Firm-Time FE	No	No	No	Yes	No
Group interacted FE	No	No	No	No	Yes
R^2	0.678	0.687	0.693	0.724	0.893
N	99781	92191	92188	72234	79263

Note: the table shows the baseline staggered differences-in-differences for yearly forecasts. 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 each fixed effect with the group of each singular shock. The standard errors are clustered at the office location.

Table 5: Z-test of coefficients

Dep. Var.:	Forecast Bias						Forecast Error					
Subgroups:	exp	perf	pess/opt	risky state	pol. party	climate beliefs	exp	perf	pess/opt	risky state	pol. party	climate beliefs
β_l	-0.15	-0.15	-0.18	-0.159	-0.31	-0.101	-0.216	-0.214	-0.238	-0.199	-0.039	-0.2
$SE\beta_l$	0.04	0.03	0.04	0.12	0.15	0.2	0.027	0.023	0.021	0.094	0.118	0.05
β_h	-0.13	-0.08	-0.16	-0.11	-0.13	-0.11	-0.293	-0.284	-0.243	-0.223	-0.236	-0.234
$SE\beta_h$	0.06	0.04	0.04	0.02	0.02	0.01	0.046	0.039	0.02	0.014	0.014	0.016
$\beta_l - \beta_h$	-0.02	-0.07	-0.02	-0.05	-0.18	0.01	0.077	0.07	0.005	0.024	0.197	0.034
$\sqrt{(SE\beta_l)^2 + (SE\beta_h)^2}$	0.07	0.05	0.05	0.12	0.15	0.2	0.053	0.045	0.028	0.095	0.119	0.053
z-test	-0.21	-1.45	-0.46	-0.38	-1.17	0.03	1.452	1.564	0.176	0.253	1.659	0.646

Note: the table reports the estimated coefficients and associated standard error of figure 4, respectively l and h for Low and High subgroups. The z-test is computed by dividing the difference between the two coefficients by the square roots of the squared sum of the standard errors. The null hypothesis is rejected at 10%, 5% and 1% for Z values above/below $\pm$ 1.645, $\pm$ 1.960 and $\pm$ 2.576.

Table 6: Analysts' Performance and Climate Sensitive Sector

	High performance analyst				Low performance analyst			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bias	Error	Bias	Error	Bias	Error	Bias	Error
Treat*time	-0.134**	-0.347***	0.0146	-0.223***	-0.123***	-0.226***	-0.170***	-0.214***
	(0.0584)	(0.0500)	(0.0271)	(0.0363)	(0.0354)	(0.0435)	(0.0537)	(0.0483)
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	0.770	0.797	0.870	0.873	0.686	0.734	0.779	0.740
N	14179	14179	7633	7633	38536	38536	31129	31129

Note: the table shows the baseline staggered differences-in-differences 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 a performance score in the top tercile in the previous year, otherwise, they are low-performance analysts. Firms' climate-sensitive sectors follow 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). 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 standard errors are clustered at the analysts' office location.

Table 7: Analysts' Performance and Firms' Physical Risk

	High performance analyst				Low performance analyst			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bias	Error	Bias	Error	Bias	Error	Bias	Error
Treat*time	-0.0804**	-0.254***	-0.0819	-0.361***	-0.146***	-0.204***	-0.161***	-0.267***
	(0.0371)	(0.0329)	(0.0787)	(0.0766)	(0.0338)	(0.0305)	(0.0565)	(0.0350)
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	0.798	0.814	0.861	0.875	0.725	0.736	0.731	0.757
N	16761	16761	5020	5020	54250	54250	15334	15334

Note: the table shows the baseline staggered differences-in-differences 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 a performance score in the top tercile in the previous year, otherwise, they are low-performance analysts. A firm's physical risk is a composite score of all 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 standard errors are clustered at the analyst's office location.

Table 8: Analysts' Performance and Shock Information

	High performance analyst				Low performance analyst			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bias	Bias	Error	Error	Bias	Bias	Error	Error
Treat*Time	-0.108**	0.0327	-0.231***	-0.211***	-0.190***	-0.116*	-0.249***	-0.0796*
	(0.0427)	(0.140)	(0.0268)	(0.0659)	(0.0539)	(0.0658)	(0.0353)	(0.0426)
Firm physical risks as the experienced shock	High	Low	High	Low	High	Low	High	Low
Analyst*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
Year*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y
r2	0.831	0.849	0.831	0.884	0.753	0.782	0.758	0.789
N	12425	3954	12425	3954	42065	11536	42065	11536

Note: the table shows the baseline staggered differences-in-differences 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. The analysis includes only firms with high physical risks (a composite score higher than 60 points). 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. while analysts' performance score is created following Hong et al. (2000). High-performance analysts are defined if analysts have a performance score in the top tercile in the previous year, otherwise, they are low-performance analysts. 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 standard errors are clustered at the analyst's office location.

Table 9: Analysts' Performance and Shock Characteristics

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

Note: the table shows the baseline staggered differences-in-differences 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 a performance score in the top tercile in the previous year, otherwise, they are low-performance analysts. 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 caused more than 1 billion in economic damages. Shocks with both economic and health-related damages are excluded. 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 standard errors are clustered at the analyst's office location.

Table 10: Analysts' Performance and Transition Risk

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

Note: the table shows the baseline staggered differences-in-differences for subgroups of high and low-performance analysts forecasting firms with high and low transition risks. Analysts' performance score is created following Hong et al. (2000). High-performance analysts are analysts that have a performance score in the top tercile in the previous year, otherwise, they are low-performance analysts. Transition risks are proxied by "Unpriced Carbon Cost adjusted EBITDA" estimated for the year 2020 in Carbon Earnings at Risk of Trucost/S&P. High transition risks firms are firms in the top terciles with respect to the number of carbon earnings at risk, otherwise they are low transition risks firms. 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 standard errors are clustered at the analyst's office location.

Table 11: Forecast Horizons Decomposition

	Forecast Error					Forecast Bias					LTG
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)
	1-Year	2-Year	3-Year	4-Year	5-Year	1-Year	2-Year	3-Year	4-Year	5-Year	LTG
Treat*post	-0.338***	-0.199***	-0.181***	0.0530	0.441**	-0.0639**	-0.254***	-0.0535	-0.178	-0.0175	-0.877***
	(0.0353)	(0.0424)	(0.0571)	(0.0963)	(0.179)	(0.0243)	(0.0518)	(0.0650)	(0.115)	(0.202)	(0.290)
Analyst	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.547	0.628	0.774	0.908	0.898	0.518	0.594	0.804	0.935	0.931	0.873
N	41699	37713	9896	1920	963	41699	37713	9896	1920	963	2173

Note: the table shows the baseline staggered differences-in-differences 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 12: Experiencing a 2nd Shock

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

Note: the table show the baseline staggered differences-in-differences for analysts that have experienced more than one weather shock. Column 1 includes analysts, firms, and year-fixed effects. Column 2 adds additional covariates: 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 adds firm*time fixed effects. At last, in column 5 each fixed effect interacted with the group of each singular shock. The standard errors are clustered at the analyst's office location.

Table 13: 2nd Shock and Shock's Information by Performance

Panel A	Different Weather Event				Same Weather Event			
	(1) Error	(2) Bias	(3) Error	(4) Bias	(5) Error	(6) Bias	(7) Error	(8) Bias
Treat*Time	-1.333**	-0.424	-0.479***	-0.142	-0.257***	-0.173***	-0.392***	-0.354***
	(0.468)	(0.756)	(0.0675)	(0.181)	(1.47e-16)	(3.20e-15)	(0.0773)	(0.0551)
Analysts Performance	High	High	Low	Low	High	High	Low	Low
R^2	0.906	0.925	0.907	0.939	0.908	0.928	0.917	0.951
N	202	202	751	751	384	384	1405	1405
Panel B	**Different Damage Type**				**Same Damage Type**			
	(1) Error	(2) Bias	(3) Error	(4) Bias	(5) Error	(6) Bias	(7) Error	(8) Bias
Treat*Time	-1.660	1.499	-0.312	0.0360	-0.618***	-0.443***	-0.399***	-0.307***
	(2.262)	(2.381)	(0.181)	(0.0723)	(0.00385)	(0.0119)	(0.0908)	(0.105)
Analysts Performance	High	High	Low	Low	High	High	Low	Low
R^2	0.915	0.936	0.920	0.938	0.900	0.921	0.907	0.950
N	150	150	527	527	428	428	1623	1623

Note: the table show the baseline staggered differences-in-differences for analysts that have experienced a second weather shocks. The standard errors are clustered at the analyst's office location.

Table 14: Firm's Coverage & Overall Climate Portfolio Score

Panel A	All Analysts			
	(1)	(2)	(3)	(4)
	N. of Firms Forecasted	Av. ESG Score	Av. Transition Risk	Av. Physical Risk
treat*time	-0.321	-0.105	-653.0*	-0.189
	(0.363)	(0.389)	(339.2)	(0.217)
R^2	0.705	0.778	0.734	0.663
N	25690	13165	24554	24670
Panel B	**Low Performance Analysts**			
	(5)	(6)	(7)	(8)
	N. of Firms Forecasted	Av. ESG Score	Av. Transition Risk	Av. Physical Risk
treat*time	-0.483	0.0588	-835.4**	-0.0760
	(0.467)	(0.362)	(339.3)	(0.231)
R^2	0.714	0.783	0.735	0.656
N	19685	9797	18674	18780
Panel C	**High Performance Analysts**			
	(9)	(10)	(11)	(12)
	N. of Firms Forecasted	Av. ESG Score	Av. Transition Risk	Av. Physical Risk
treat*time	-0.148	-0.474	-349.1	-0.437
	(0.500)	(0.709)	(678.1)	(0.497)
R^2	0.808	0.888	0.823	0.831
N	5853	3225	5721	5730

Note: the table show the baseline staggered differences-in-differences for analysts that have experienced more than one weather shock. The data is aggregated at the yearly level. The event year is discarded and I keep only 2 years before and after the year of the extreme weather shock. The table includes year and analyst ID fixed effects. The standard errors are clustered at the analyst level.

Table 15: Climate-Related Questions during Earnings Calls

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

Note: the table show the baseline staggered differences-in-differences for analysts that have experienced one weather shock. The data is aggregated at the yearly level. The event year is discarded and I keep only 2 years before and after the year of the extreme weather shock, the table shows that first-time treated analysts follow more firms compared to never-treated analysts. The table includes analysts, year, and firm fixed effects. The standard errors are clustered at the analyst level.

Table 16: Robustness Baseline - excluding NY

Dependent Variable:	Forecast Error				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.238***	-0.251***	-0.257***	0.0196	-0.282***
	(0.0501)	(0.0476)	(0.0469)	(0.0746)	(0.0581)
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	0.665	0.672	0.676	0.698	0.881
N	64931	60172	60170	44580	50710

Dependent Variable:	Forecast Bias				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.177**	-0.133*	-0.134*	-0.0421	-0.164*
	(0.0737)	(0.0752)	(0.0740)	(0.124)	(0.0830)
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	0.637	0.648	0.653	0.659	0.885
N	64931	60172	60170	44580	50710

Note: the table show the baseline staggered differences-in-differences 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 each fixed effect with the group of each singular shock. The standard errors are clustered at the analyst's office level.

Table 17: Robustness Baseline - s.e. clustered at the brokerage level

Dependent Variable:	Forecast Error				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.306***	-0.300***	-0.301***	-0.0379	-0.296***
	(0.0253)	(0.0250)	(0.0251)	(0.0386)	(0.0288)
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	0.703	0.711	0.714	0.753	0.891
N	118435	108206	108204	85977	93463
Dependent Variable:	Forecast Bias				
	(1)	(2)	(3)	(4)	(5)
treat*post	-0.153***	-0.143***	-0.151***	-0.0436	-0.180***
	(0.0281)	(0.0288)	(0.0300)	(0.0521)	(0.0289)
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	0.676	0.684	0.690	0.719	0.892
N	118435	108206	108204	85977	93463

Note: the table show the baseline staggered differences-in-differences for yearly forecasts. Column 1 includes analysts, firms, and year-fixed effects interacted with 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. At last, column 5 interacts each fixed effect with the group of each singular shock. The standard errors are clustered at the brokerage level.

Table 18: Placebo test - Terrorist Attack

	All analysts		High performance analysts				Low performance analysts			
	(1)	(2)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Bias	Error	Bias	Error	Bias	Error	Bias	Error	Bias	Error
Treat*post	-0.180*	-0.385***	-0.470*	-0.410***	-0.254**	-0.401	-0.139	-0.457***	0.0436	-0.106
	(0.0953)	(0.0764)	(0.223)	(0.0971)	(0.0589)	(0.313)	(0.130)	(0.106)	(0.102)	(0.173)
Firm Physical Risk	All	All	High	High	Low	Low	High	High	Low	Low
Analyst*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm*Horizon FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.943	0.926	0.963	0.958	0.902	0.903	0.954	0.955	0.982	0.974
N	1920	1920	358	358	159	159	911	911	321	321

Note: the table shows the baseline staggered differences-in-differences for yearly forecasts using the terrorist attack as a placebo shock. Terrorist attacks are salient events with at least 10 fatalities or 100 injured people. Columns 1 and 2 report the results for all analysts. while columns 3 to 10 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 standard errors are clustered at the analyst's office location.

Table 19: 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
Firm Experience	The difference in years between the first forecast issued for a firm j and the analyzed forecasts
Industry Followed	How many industries are forecasted by an analyst in a year
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
State Political Affiliation	The party with the highest number of votes in the previous election in a state: 1(Democrat)
County political ideology	the party (Democratic or Republican) with the majority of votes in the previous election (from Data and Lab, 2017).
Experienced analysts	analysts with more than the average years of experience in the sample (7 years).
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 in the previous year
County political ideology	the party (Democratic or Republican) with the majority of votes in the previous election (the data is obtained from Data and Lab, 2017).
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).

Table 20: 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 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 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 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).

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Appendix

Appendix

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 A1 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.

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

Table A3: 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'

Table A1: 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.

Table A2: 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).