Climate Change Expectations: Evidence from Earnings Forecasts*

Pietro Reggiani†

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Abstract

I study the effects of changes in climate change expectations on forecasts of cash flows of public firms. I use data on financial analysts' forecasts of firm earnings, and local temperatures as shifters of their perception of climate change. Analysts experiencing warmer temperatures tend to issue more pessimistic forecasts. The effect is correlated with firm exposure to both regulatory and physical climate change risks. The sensitivity of forecasts to temperatures is more negative for carbon-intensive industries, while for firms in the renewable sector the effect has an opposite, positive, sign. The negative effect is related to firm exposure to physical climate risks as well, especially for some risks such as hurricanes and storms. This effect is amplified for analysts that directly experience extreme weather events, consistently with a mechanism related to the salience of climate change. Exploiting forecasts issued for different future horizons, I pin down the timing at which climate risks are expected to materialize. The reaction of forecasts to temperatures is concentrated in horizons between eight and ten quarters in the future.

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†New York University Stern School of Business, 44 West 4th street, New York, NY 10012.
Email: preggian@stern.nyu.edu.

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1 Introduction

Climate change is one of the main challenges facing modern human society. The intensity and reach of its effects have increased at an alarming rate over the past years. This is demonstrated for instance by recurring wildfire and heatwave emergencies occurring also at latitudes traditionally unaffected by such events.[1] Due to its growing negative effects, climate change has risen to prominence in the media, policy forums, government, academia and industry. The *Inflation Reduction Act* approved by Congress in August 2022 is the first significant climate law in the United States and contains provisions for sizeable spending in favor of clean technologies, to an extent that was considered unthinkable until recently.[2]

The financial services industry is no exception to this trend. On the contrary, it has witnessed a growing interest in the topic, usually grouped under the category Environmental, Social and Governance (ESG) investing, or sustainable investing. On the one hand, this is the result of an attempt to cater to clients who are concerned about the broader social impact of their investments, in the spirit of stakeholder capitalism.[3] There is evidence (Riedl and Smeets (2017), Hartzmark and Sussman (2019), Anderson and Robinson (2019)) that such investor demand is growing, representing a business opportunity for intermediaries. Some of these intermediaries suffered from shrinking margins with the expansion of passive investing and see ESG as an opportunity to diversify.[4] On the other hand, it has become clear that the aggravating effects of climate change will impact the financial performance of all kinds of assets and businesses substantially. As a consequence, also traditional asset managers have started to prioritize the careful monitoring and forecasting of climate-related risks.

This work studies precisely how market participants take into account climate risks when forming cash flow forecasts. In particular, I study forecasts of public corporations' future earnings issued by sell-side financial analysts. These forecasts are important as a benchmark for forecasts of other market participants, and in aggregate constitute the "consensus forecasts", commonly considered a proxy for market-wide expectations of firm performance. My goal is to understand whether and how analysts adjust their projections as a result of shifting climate change perceptions.

[1]For instance, see Zachariah et al. (2022) for a discussion of heatwaves in the United Kingdom.

[2]https://www.economist.com/leaders/2022/08/08/americas-climate-plus-spending-bill-is-flawed-but-essential .

[3]https://www.economist.com/business/2020/09/17/what-is-stakeholder-capitalism

[4]https://hbr.org/2022/08/esg-investing-isnt-designed-to-save-the-planet .

I find that analysts become more pessimistic about future cash flows when experiencing warmer temperatures. This effect is stronger for firms in carbon intensive industries, and firms that are directly exposed to calamitous weather events related to climate change. This suggests that analysts do take into account both regulatory and physical risks when producing their estimates, and that they attach a positive probability to these risks affecting firm performance materially. I find that the magnitude of the effect increases after analysts experience large weather disasters, in line with the hypothesis that climate change salience drives the results.

The previous literature studying the impact of climate change risks on asset prices, could not distinguish between the role of cash flow expectations and discount rates. I provide a meaningful contribution by focusing exclusively on cash flow forecasts and showing that climate risks matter for them. This implies that movements in expected cash flows explain at least part of the price impact of climate change risks. Furthermore, I believe this is the first study able to infer how far in the future the market expects climate risks to materialize. I do so by exploiting variation in my dataset across forecasts of different horizons. I find that on average analysts expect climate risks to have a possible negative effect on earnings between 8 and 10 quarters in the future.

As a shifter of analysts' expectations of future climate change effects, I use temperatures at the analyst's location. I exploit variation across analysts that are forecasting the same firm's future earnings but are exposed to different temperature shocks, in order to identify the sensitivity of forecasts to temperature. I find that analysts experiencing a one standard deviation warmer temperature issue 0.3 percent more pessimistic earnings forecasts on average. This result shows that temperature is inducing some reaction on the part of the analyst. The mechanism I suggest is that analysts increase their subjective probability of climate change effects having material impact on the firm within the forecast horizon. If this is the case, we should observe variation in the effect across firms with different exposures to climate risks.

First, I focus on regulatory climate risk, that is the likelihood that a firm is affected by future policies aimed at reducing the economy's carbon footprint. Such policies should damage the more polluting sectors but may represent an opportunity for industries that will be pivotal in the transition to a more sustainable economy. Carbon dioxide emissions are the main culprit behind the greenhouse effect, and therefore also the main target of climate policies for emission reduction. Accordingly, I gather data on total carbon dioxide emissions by industry, and use them as a proxy for exposure to future regulatory climate risk. I find that the negative effect of warm temperatures on forecasts is five times stronger for firms belonging to the sectors with highest emissions. This suggests that emissions belong to the analysts' information set, and, importantly, that the analysts attach a positive probability to the event that regulatory risks affect firm performance within a short time horizon. Notice that earnings are not forward looking, as valuations would be, meaning that any effect observed must be expected to affect the company's bottom line within the horizon of the forecast.

Second, I consider physical climate risk. This is the risk that weather events related to climate change[5] might affect a firm directly, with a negative impact on its operations. The events that usually fall within this category are hurricanes, sea level rise, tropical storms, heatwaves, droughts, wildfires and floods. I obtain firm-level scores that measure the exposure to the risk of these events, and observe analysts' reaction to temperature across firms. I find that forecasts of earnings for firms in the highest quartile of risk are on average three times more sensitive to temperature shocks than the other firms. By breaking down the risk by event category, I observe that most of the difference is attributable to firms that are exposed to the risk of hurricanes and storms, and more mildly to heat stress risk. This result suggests that analysts are quite sophisticated in determining the risk exposure of firms, and that some weather events matter more than others. I find evidence that the regulatory and physical risks are correlated: the temperature effect correlates significantly with physical risk exposures only within high carbon emission industries. This indicates that carbon emissions probably remain the first-order variable analysts consider when evaluating climate risk exposures.

There is still considerable uncertainty around the speed with which climate change effects will occur. In the data, I observe a term structure of different forecast horizons for each analyst-firm pair. As a result, I can inspect the timing with which analysts expect climate change risks to materialize, which is one of the novel contributions of this work. To do so, I estimate the temperature effect on forecasts for different horizons separately. The results show that virtually all the effect is concentrated in forecasts with horizons between eight and ten quarters ahead. This is at the longest end of the horizons the analysts consider, but also remarkably soon for a risk that is typically regarded to be relevant only in the long run.

[5]Related in the sense that they are becoming more widespread, severe and frequent as a result of the climate change induced by humans.

To provide further evidence that the effect is due to perceptions of climate change risk, I run an event study following some large weather events which are becoming more frequent and severe as a result of climate change. I find that these events affect the temperature sensitivity. Analysts hit by large hurricanes, for instance, have a temperature sensitivity of the forecast that is 50 percent greater than others. This difference tends to revert to the mean after about a year after the event. Given that these large events affect the analyst location and should have no relation with the firm's operations, I deduce that they affect the forecasts through the salience of climate change, making analysts more sensitive to temperature shocks.

The remainder of the paper is structured as follows. The following Section 2 outlines the motivation for this work and the contribution in relation to the existing literature. Section 3 details the data sources used in the empirical analysis presented in Section 4. Section 5 concludes.

2 Motivation and Relation to Literature

This work belongs to the rising field of climate finance, which originated as a result of the increasing importance of climate change.[6] As these effect arise at an accelerating pace, more and more economic actors, public and private, have started to realize that the changing climate will have broad and reverberating effects on the whole economy, including financial markets.

Asset owners and managers are interested in understanding whether climate risks are correctly priced, and how to manage and predict these risks. Regulators would like to assess the efficiency of markets relative to climate risks in order to prevent systemic shocks. The belief that financial markets, if correctly managed, could become drivers of a more sustainable economy is spreading.

Academic work in finance has started to address some of these questions. In particular, a considerable amount of work has been devoted to understanding whether financial markets are efficient in pricing the risks of climate change.

[6] For extensive reviews of this literature, see Hong et al. (2020) and Giglio et al. (2020)

These risks are usually categorized in three types. The first is physical climate risk, that is the direct impact of climatic events on firm operations and real assets. These events can be floodings, droughts, tropical storms, extreme heat, and all other phenomena that are becoming more frequent and severe as a consequence of anthropogenic emissions. The second category is regulatory risk, meaning the effect of potential government interventions making greenhouse gas emissions more costly. Closely related to regulation, the third type is transition risk, that is the effects due to the gradual systemic shift to a more sustainable economic model. This shift will create winners and losers. For some sectors, for instance industries related to electrification, the transition may be beneficial, while others may lose considerable business opportunities. Some of the more polluting assets such as coal reserves are likely to lose most of their value, becoming "stranded".[7] I believe the latter two are so closely intertwined that it is preferable to consider them as a single category, as I will do in this paper. This comes from the consideration that in a world with abundant fossil fuel reserves, there can be no transition without regulation, at least in the initial phase where we are today.

Are market prices reflecting these risks in the current equilibrium? Numerous studies have tried to answer this question in different markets. Real estate, for obvious reasons, is one of the sectors that are more exposed to physical climate risk, in the form of sea level rise, flooding and the increasing likelihood of violent storms and hurricanes. Bernstein et al. (2019), Keys and Mulder (2020) and Giglio et al. (2021) find a significant difference in home valuations due to exposure to sea level rise. Baldauf et al. (2020) qualify these results by observing that the price of inundation risk depends crucially on the prevailing local climate change beliefs. Murfin and Spiegel (2020) however find no significant discount for properties with higher flood risk.

The impact of physical risk on prices has been studied in several asset classes. Goldsmith-pinkham et al. (2019) and Painter (2020) show that municipal bonds from places more likely to suffer from climate change tend to pay higher underwriting fees and yields. This difference is present exclusively in longer maturity bonds, consistent with the long term horizon of climate change. In contrast, my findings suggest that the horizon is not as long, at least in the context of corporate cash flows. I find that markets expect some material impact already within a few years. Acharya et al. (2022) study the pricing of physical risk too, finding a

[7] Interesting papers on stranded asset risk are Atanasova and Schwartz (2019), Barnett (2020) and De Greiff et al. (2020).

similar result for long term municipal bonds and corporate bonds, especially those of lower credit quality. Among the types of physical risks, Acharya et al. (2022) find that significant effects are only attributable to heat stress. In my analysis I distinguish different physical risks as well, finding that the risk of hurricanes and storms is the one with the largest impact on analyst forecasts. Seltzer et al. (2020) focus on the importance of regulatory risk for corporate bonds, finding that firms with poorer environmental profiles or higher emissions have higher yield spreads. This effect is stronger for firms located in States with stricter regulatory enforcement.

Stocks are by far the most studied asset class in this context. To what extent are risks induced by climate change reflected in valuations and excess returns? Ilhan et al. (2020) look at the option market to find evidence that uncertainty about climate policy is priced. The cost of option protection against downside tail risk is larger for firms with a more carbon-intensive business model. Bolton and Kacperczyk (2021) find a relationship between carbon emissions and the cross section of stock returns. Firms that pollute more earn higher returns, after controlling for common risk factors. This premium cannot be explained by differences in unexpected profitability. This suggests that some of the firm-level transition and regulatory risk are already reflected in prices. Sautner et al. (2021) reach a similar conclusion using a novel measure of firm climate exposure that is constructed using textual data from earnings calls. Hong et al. (2019) find an opposite conclusion when looking at the global food industry. They find that stock prices of firms that are more exposed to droughts tend to be too high and deliver consistently lower returns, evidence of mispricing of risk. The variability of results in the literature may be due to the choice of sample, but overall it appears that market valuations are gradually incorporating climate risks. My paper will consider similar risks affecting the performance of corporations, such as regulatory risk associated with carbon emissions, and direct physical risk. In particular, my focus will be on determining which risks matter most for market participants when they form expectations. I believe this work is the first to be able to study the impact of these risks on cash flow expectations separately from discount rates, something that would not be possible by focusing on prices only.

I will exploit abnormal temperatures and natural disasters as shifters of expectations of future climate change. This approach follows some pre-existing literature. Choi et al. (2020) show that, internationally, public attention to climate change is higher in places that experience warmer than usual temperatures. In addition, they show that retail investors tend to trade away from carbon intensive firms on such days. Alekseev et al. (2021) observe how fund managers trade after experiencing local extreme heat events. They exploit these trades as signals of which assets should be best as hedge of climate risks. Indeed, the trades should provide a good indication of which stocks will be preferentially bought and sold by institutional investors as a reaction to aggregate climate shocks or news. I will exploit similar local climatic shocks in my setting. The advantage of local shocks is that they shift the climate change risk perception of the affected agents, without at the same time introducing potential confounding factors as aggregate shocks would do.

Alok et al. (2020) show that following climatic disasters, affected money managers tend to overreact and underweight firms in the disaster region. They attribute this fact to salience bias, and they show that this effect tends to subside over time. Correa et al. (2022) focus on syndicated loans. They show how in the aftermath of large climate-change related disasters, lenders tend to charge higher spreads to firms that are unaffected but at risk of similar events in the future. Interestingly, only disasters related to climate change have such effect, suggesting that it is exactly the lenders' expectations about climate change that adjusted after the event. I will show that also my baseline result is strengthened following climatic disasters.

The main outcome variable of this study will be the earnings forecasts of sell side financial analysts. The analysts issue regular forecasts of future earnings of public corporations, which inform all other market participants, and contribute to the efficiency of financial markets. A vast literature, especially in accounting and finance, has studied the factors affecting the formation of these forecasts.

A number of papers (e.g. Hong et al. (2000) , Malmendier and Shanthikumar (2014), Horton et al. (2017) , Harford et al. (2018) , Kempf (2020)) have focused on the role of career incentives. Others study the cultural and political factors affecting analysts' forecasts. Jiang et al. (2015) observe how political orientation correlates with the precision and variation of the forecasts over time. Kempf and Tsoutsoura (2021) find a striking role for political partisanship in the formation of corporate credit ratings. Pursiainen (2021) studies the effect of trust between different european cultures on analysts stock recommendations. He finds a significant "trust bias" in recommendations which tend to favor countries considered reliable.

In this paper, I am interested in analyst forecasts as an important channel through which the expectations of market agents transmit to financial markets. In particular, I will analyze shifts in perceptions of future climate risk. The most closely related study is Cuculiza et al. (2021). They use a similar dataset on analyst forecasts, and consider similar temperature shocks in line with the previous literature. Cuculiza et al. (2021) categorize firms based on their sensitivity to temperatures. They find that analysts located close to those firms are more accurate at forecasting earnings in periods of temperature increases. This effect is concentrated precisely on those firms that are more sensitive to temperatures. The interpretation of this finding is that proximity makes analysts more accurate at forecasting earnings of temperature-sensitive firms. My research question and approach are quite different. I consider granular local temperature shocks, in a spirit similar to Alekseev et al. (2021), that affect the analysts and their climate risk expectations but, crucially, should not affect the current cash flow performance of the firms they analyze. My goal is to understand whether analysts expect climate risks to impact cash flows with some probability, which risks they consider more important and at what time horizons. I take as a given the capability of the analysts to form reliable forecasts, and exploit their reaction to climatic shocks as precious information about how markets incorporate these kinds of risks. I will not discuss whether the incorporation of climate risks in the forecasts was accurate or not, because this question is impossible to answer ex-post. Given that climate risks are low probability events, even if I observed that analysts were wrong in expecting a negative climate impact on cash flows, this could be due to a small sample problem, but I would not be able to infer the accuracy of the ex-ante probabilities.

3 Data and Summary Statistics

The data on analyst forecasts come from *Thomson Reuters Institutional Brokers' Estimate System* (I/B/E/S). This dataset has been widely used in previous literature. The sample includes all forecasts of earnings per share (EPS) of public corporations covered by analysts located in the United States, issued between 2000 and 2021. Forecasts can be for the quarterly or yearly earnings, for horizons up to 10 quarters ahead. I keep the most recent forecast issued for each analyst, month, firm and horizon. Following Cuculiza et al. (2021) I remove forecasts with an horizon shorter than one month, and firms which are covered by fewer than five analysts in a year.

The geographic locations of analysts' offices come from Gerken and Painter (2019).[8]

[8] I am grateful to the authors for kindly sharing the data.

The authors obtain the office locations thanks to a number of Freedom of Information Act requests to State securities regulators managing the database of all analysts' work histories. A more detailed account of the data retrieval process can be found in their paper. The office locations are at the Metropolitan Statistical Area (MSA) level and are updated at the yearly frequency.[9]

Monthly temperature data for all MSAs in the United States come from the National Oceanic and Atmospheric Administration (NOAA) *NClimdiv* database. [10] The main temperature variable of interest will be the monthly average temperature in each MSA. From NOAA I also collect extreme weather event data, as included in the *Spatial Hazard Events and Losses Database for the United States* (SHELDUS). These records provide MSA by month information about the damages caused by several types of weather events: heatwaves, droughts, wildfires, storms, hurricanes, floods and tornadoes. These events will be used as an additional shock to the climate change perceptions of the affected analysts.

Industry-level CO_2 emissions data come from *Thomson Reuters Refinitiv*. These include yearly observations, from 2002 to 2021, of total and direct carbon dioxide emissions for every industry among the Thomson Reuters business categories. I use this information to rank sectors based on their average total emissions over the past two decades.

The data on firm level exposure to physical climate risks come from *Four Twenty Seven*.[11] The physical risk scores measure the vulnerability of each firm to future direct effects of climate change, such as heat stress, water scarcity, sea level rise and hurricanes. They are the outcome of a forward looking proprietary model, and were already used in the literature, for instance by Engle et al. (2020).[12] I have access to one cross section of firm scores as of September 30, 2019.

The final sample consists of a panel of eight million monthly observations for 4,911 analysts and 10,209 firms. Each observation is a new or revised forecast made by an analyst

[9] I observe only analysts working in the U.S.. The sample period ends in 2015. For the subsequent years, I carry the locations forward assuming the analysts did not move. In this way, I do not observe new analysts that appear in the dataset since 2016.

[10] The NOAA is an agency within the United States Department of Commerce. The data are publicly available at `https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C00005` .

[11] Now part of *Moody's ESG Solutions* I thank Professor Johannes Stroebel and the *Volatility and Risk Institute* at *New York University* for making data access possible.

[12] More details on the score generation can be found on their website https://427mt.com/ .

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
EPS Forecast	8,278,959	2.750	4.146	−2.560	0.600	3.360	20.000
Avg. Temperature	8,278,959	0.015	1.000	−2.859	−0.722	0.902	2.351
Analyst Experience	8,278,959	4.636	0.919	0.000	4.220	5.287	5.966
Analyst-firm experience	8,278,959	3.257	1.344	0.000	2.504	4.253	5.962
Precipitation	8,278,959	1.395	0.460	0.000	1.153	1.720	3.253
Forecast horizon (months)	8,120,793	10.539	7.305	1.000	5.000	16.000	30.000
Industry Total CO2	6,788,395	12.964	1.369	9.820	11.959	13.640	15.701
High Physical Risk	2,406,703	0.252	0.434	0.000	0.000	1.000	1.000
High Heat Stress Risk	2,406,703	0.231	0.422	0.000	0.000	0.000	1.000
High Flood Risk	2,406,703	0.032	0.176	0.000	0.000	0.000	1.000
High Sea Level Rise Risk	2,406,703	0.082	0.275	0.000	0.000	0.000	1.000
High Hurricane Risk	2,406,703	0.006	0.074	0.000	0.000	0.000	1.000
High Water Stress Risk	2,406,703	0.317	0.465	0.000	0.000	1.000	1.000

Table 1: Summary statistics of main variables used in the empirical analysis.

for some firm's future EPS. Some summary statistics on the main variables are displayed in Table 1.

4 Empirical Results

4.1 Pooled Effect

The goal of the empirical analysis is to dissect the mechanisms driving the incorporation of climate change expectations into the forecasts. The object of the forecasts are future earnings, that is the firms' financial performance, not valuations or prices. This means that any effect we observe will be driven by shifts in beliefs about material impacts of climate change or related regulation on the firm's business, not on forward looking considerations about future growth. This observation is important as it implies we can infer the expected timing of the effects from the term structure of the forecasts.

The starting point of the empirical analysis is a pooled regression, where we test whether temperature shocks affect forecasts for the average firm. The empirical set-up presented here will be the foundation for most of the following empirical tests.

I estimate the following regression specification:

$$Forecast_{t,t+h,a,m,f,i} = \boldsymbol{\beta} \cdot Temperature_{m,t} + \boldsymbol{\Gamma} \cdot \boldsymbol{Controls_{t,a,f,m}} + \gamma_{f,t,t+h,i} + \theta_a + \varepsilon_{t,t+h,a,f,i} \tag{4.1}$$

for analyst a in MSA m issuing a forecast in month t of the future earnings of firm f published in month $t+h$. i is an indicator for whether the earnings figure is quarterly or yearly. The main coefficient of interest is β, that is the sensitivity of the forecast to the average temperature in the analyst's MSA in the month of issuance. The specification includes firm-month-horizon-type (γ) and analyst (θ) fixed effects. To identify the effect of the local temperature, I exploit variation in temperatures across forecasts of a firm's future earnings issued in the same month by analysts located in different MSAs. Results are presented in Table 2. The estimates suggest that analysts experiencing warmer temperatures tend to issue lower forecasts of future firm earnings. On average, according to the baseline estimates of column (4), one standard deviation warmer temperatures are associated with a 0.3 percent more negative forecast.

The granular fixed effects take into account the possible confounding factors that affect the process of forecasting the future earnings of a particular firm in a particular month, for a particular future horizon. The analyst fixed effects control for constant unobserved differences in the analysts, which include characteristics potentially related to their preference to reside in places with a warmer climate. The identifying assumption is that the monthly temperature at an analyst's city in month t is not correlated with any unobserved idiosyncratic shocks affecting the forecasts of that particular analyst in that month.

The distribution of the analysts is obviously not uniform across the country. Around 56% of the analysts in the sample are located in the State of New York, and 11% in California. One might worry that the results rely too much on what is happening in these places. To verify, I re-estimate the specification of column (4) excluding analysts in the State of New York, and analysts in both New York and California. Estimates for these two subsamples are reported in columns (5) and (6) of Table 2. Reassuringly, the effect of temperature remains significant and if anything stronger when excluding the most represented States.

Given that temperature is a local variable associated with the MSA of the analyst, it should have no direct effect on the firm, especially as firms in the sample tend to be large public corporations which are geographically diversified. This means that the observed effect must be due to a differential reaction specific to the analysts, and unrelated to the firm whose earnings they are forecasting.

So far, the baseline result tells us that warm temperatures induce some reaction in the analysts that makes them more pessimistic on future firm earnings. The goal for the rest of the paper will be to argue in favor of the following explanation. Warm temperatures operate by shifting analysts' perception of climate change upwards.[13] In turn, this increases analysts' subjective probability of climate change risks impacting firm cash flows, and therefore decreases expected earnings. If this climate change risk channel is at work, we should observe variation in the effect of temperature across firms with different exposures to climate change risk. This will be the focus of the following sections: first, we will focus on exposure to regulatory risk, then on physical risks.

4.2 Cross-section of Firms

4.2.1 Carbon Emissions and Regulatory Risk

For the purpose of this paper, I will consider transition risk to be part of regulatory risk, even though some studies separate them. I believe this is a sensible assumption because at least until fossil fuel resources are abundant, any meaningful transition towards a more sustainable economic system requires some form of regulatory incentive to reduce carbon emissions. Therefore, I use industry level carbon dioxide (CO_2) emissions as a proxy for firms' exposure to regulatory risk. The reduction of CO_2 emissions is the main target of policies aimed at containing climate change, being the greenhouse gas responsible for the greatest share of global warming. It is reasonable to expect that carbon-intensive sectors will incur higher costs and more stringent limitations once climate policies are implemented. For instance, the introduction of a carbon tax would force emitters to take into account their negative externality, potentially leading to the transformation or complete disappearance of some industries.

Table 3 displays OLS estimates of a specification similar to the one of equation 4.1, where we add the interaction between temperature in the analyst MSA and a dummy for

[13] The fact that temperatures can increase the salience of climate change has been studied by Choi et al. (2020).

	EPS Forecast					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Temperature	-0.008***	-0.004***	-0.008***	-0.008***	-0.014***	-0.021***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)
Analyst Experience			-0.003***	-0.001	-0.012***	-0.005**
			(0.000)	(0.001)	(0.002)	(0.003)
Analyst Firm Experience			0.002***	-0.000	0.001	0.001
			(0.000)	(0.000)	(0.001)	(0.001)
Precipitation			0.002**	0.007***	0.011***	0.016***
			(0.001)	(0.001)	(0.001)	(0.003)
Observations	8,278,959	8,278,959	8,278,959	8,278,959	3,438,980	2,649,097
R^2	0.9782	0.9786	0.9782	0.9786	0.9862	0.9857
Firm-Year-Month-Earnings Date-type fixed effects	✓	✓	✓	✓	✓	✓
Analyst fixed effects		✓		✓	✓	✓
Exclude New York					✓	✓
Exclude California						✓

Table 2: Results of OLS estimation of pooled effect of temperature on the Earnings per Share forecasts, as in equation (4.1). The dependent variable is the forecast of the earnings per share, expressed in millions of dollars. The independent variable of interest, *Avg. Temperature* is the monthly average temperature in the MSA of residence of the analyst, taken from *NOAA*. It is normalized to have zero mean and unit variance. In the fixed effects, *Year-Month* is the month of issuance of the forecast, *Earnings Date* is the date the earnings figure is made public by the firm (variable *fpedats* of *I.B.E.S.*) , and *type* is an indicator for whether the forecast is for yearly or quarterly earnings. *Analyst experience* refers to the number of years since the analyst appears in the sample, and *Analyst Firm experience* the number of years the analyst-firm pair appears in the sample. *Precipitation* is the monthly average precipitation at the analyst MSA, coming from *NOAA*. The two rightmost columns display estimates from the same specification as in column (4), but excluding from the sample all analysts who reside in the States of New York and California.

the industries with highest total CO_2 emissions. Emission data come from *Thomson Reuters Refinitiv*, thus the industry groups follow their classification.[14] The high carbon dummy variable is equal to one for the five industries with the highest average total CO_2 emissions over the 2002 to 2021 period. These industries are mineral resources, energy, consumer goods conglomerates, chemicals and applied resources.[15] The results indicate that the reaction to warm temperatures is significantly stronger for polluting sectors. This result is important, as it confirms our prior that the effect due to temperature is indeed due to climate risk perceptions and not to some other reaction to temperatures. In addition, this shows that emissions are a first order characteristic considered by analysts when assessing the firm exposure to such climate risks. This is in line with our hypothesis, but not obvious given the uncertainty around the size and timing of future policies. Not only do analysts seem to believe climate policies will have an effect of firm profits, but also that this will happen within the relatively short time horizon considered in these forecasts. I will discuss the timing in greater detail in the next sections.

To observe the cross-section of the effect, we estimate column (4) of Table 3 industry by industry, and plot the estimated $\beta_{industry}$ coefficients in Figure 1. Industries are ranked from top to bottom in increasing order of CO_2 emissions. The coefficients display a downward trend as we move towards the bottom of the chart, for industries such as transportation, energy and mining. Strikingly, the renewable energy industry stands out with a significantly positive beta, a sign opposite to the one of the average firm seen in Table 2. This observation is reassuring as it aligns with the mechanism I propose: temperature increases the probability assigned by analysts to the arrival of some climate regulation. Renewables are among the sectors which should benefit the most from such regulation, thus, accordingly, analysts revise earnings expectations upwards when revising upwards their perception of climate change risk.

4.2.2 Physical Risk

We have observed how the temperature effect varies across industries with different levels of carbon emissions. Emissions are a proxy for vulnerability to future regulatory climate change risk. In this section I apply a similar approach to physical risk. I study whether

[14] *Thomson Reuters Business Classification* (TRBC). More details can be found online at https://www.refinitiv.com/en/financial-data/indices/trbc-business-classification

[15] The applied resources category includes paper and forest products and containers and packaging.

	EPS Forecast			
	(1)	(2)	(3)	(4)
Avg. Temperature	-0.004***	-0.002	-0.004***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Avg. Temperature × High Carbon Industry	-0.017***	-0.027***	-0.018***	-0.024***
	(0.003)	(0.005)	(0.003)	(0.005)
Analyst Experience			-0.003***	0.002**
			(0.001)	(0.001)
Analyst Firm Experience			0.004***	0.001
			(0.000)	(0.000)
Precipitation			0.001	0.007***
			(0.001)	(0.001)
Observations	7,115,554	7,115,554	7,115,554	7,115,554
R^2	0.9790	0.9796	0.9790	0.9796
Firm-Year-Month-Earnings Date-type fixed effects	✓	✓	✓	✓
Analyst fixed effects		✓		✓

Table 3: Results of OLS estimation of effect of temperature on the earnings per share forecasts, interacted with industry-level carbon dioxide emissions. The emissions data are taken from *Thomson Reuters Refinitiv*. The *High Carbon Industry* variable is a dummy equal to one for firms belonging to the five industries that had highest yearly average emissions over the last twenty years. Firms are classified in industries based on the *Thomson Reuters Business Classification*. All other variables remain defined as in previous Table 2.

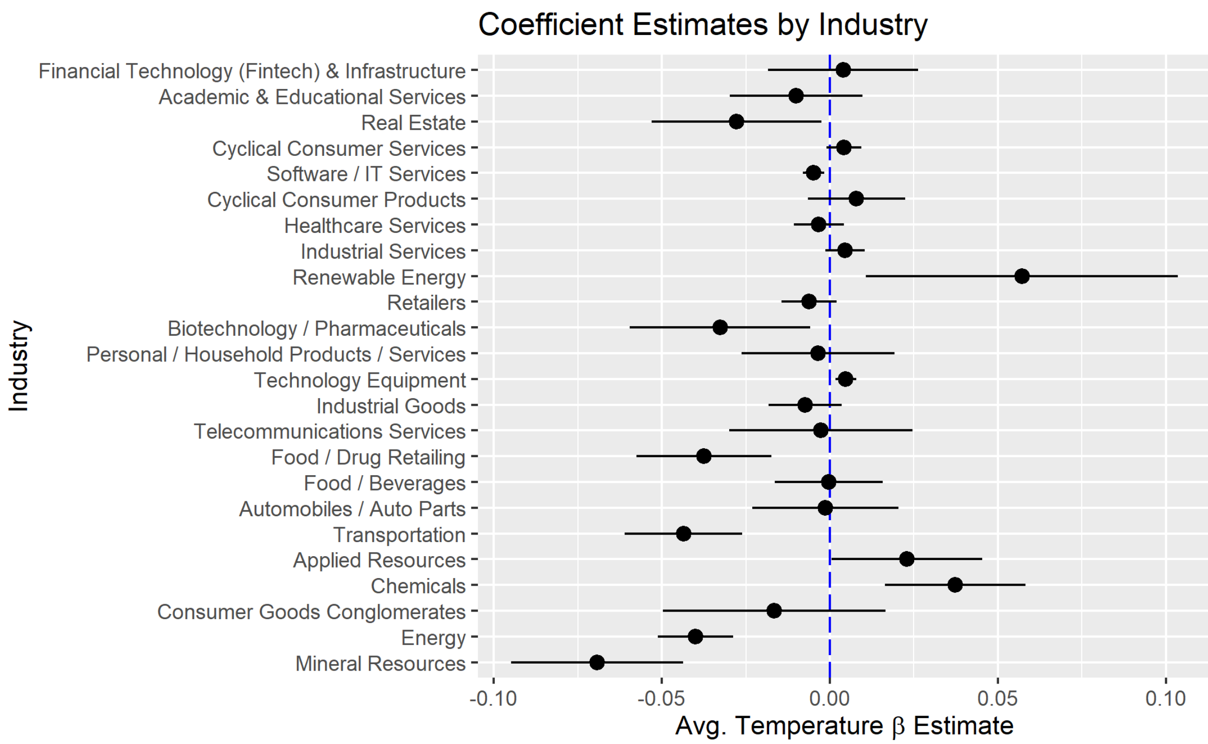

Figure 1: Estimates of the β coefficient by industry. The reported estimates refer to the specification of column (4) of Table 2, obtained considering firms in each industry separately. The dots are the point estimates, while black horizontal segments represent 95 percent confidence intervals. Industries are ordered based on average yearly total CO_2 emissions from 2002 to 2021 , as per *Thomson Reuters*. Highest emission industries appear at the bottom.

analysts' reaction to temperatures reflects also this risk, and whether they can differentiate among different types of risk.

As a measure of firm-level physical risk exposure, I use the scores provided by *FourTwoSeven*. I match the scores of $1,134$ firms in the sample, for which I have a snapshot of the risk exposure as of September 2019. I use this cross-section of scores to rank firms over all the years in the sample, relying on the relative risk exposure across firms to remain constant over time. This assumption does not seem unreasonable given the exposure is related to the geographic location and the business model of the firms, which are persistent over time. Results are reported in Table 4.

The first column reports estimates of a regression specification analogous to the one of Table 3 column (4), where now temperature at the analyst's MSA is interacted with a dummy "high physical risk" equal to one for firms in the 4th quartile of physical risk scores. The interaction coefficient is negative and significant, meaning that the temperature reaction is more marked for firms exposed to physical risk. The temperature sensitivity for high risk firms is roughly three times as large as for the other companies. I interpret this as additional evidence that temperature is really capturing climate change risk perceptions here, and in particular analysts seem to be aware of physical as well as regulatory risk.

In the second column, firms are split by type of risk. Temperature is interacted with dummies related to a specific category of weather events expression of physical climate risk. Each dummy is defined as in the previous case, as an indicator for the highest quartile of risk. Risk categories are hurricanes, floods, heat, sea level rise and water (droughts). The estimates suggest that hurricane risk is the most salient category: the temperature sensitivity of the forecasts for firms exposed to hurricanes is significantly more negative than that of other firms. Also firms exposed to heat stress have a significantly larger impact. The other categories do not appear to be as important. Overall, these tests support the mechanism I suggest: temperatures act as a catalyst for expectations of the severity of climate change, and analysts react differently for different firms as they can discern the risk exposures of the firms they cover.

So far the evidence shows that regulatory and physical risks matter. In the third column of Table 4, I test whether these two risks interact with each other. I estimate the same regression specification of column (1), adding the interaction of temperature with the high carbon emission dummy seen in Table 3, and a triple interaction of temperature with the two risk dummies. I observe a significant effect of physical risk exposure on the temperature sensitivity only within the highest emission industries. This result suggests that carbon dioxide emissions may be the first order characteristic the analysts take into account when concerned about climate change. Within the carbon intensive industries however, also exposure to physical risks becomes an important determinant of how they will adjust forecasts across firms.

4.3 Term Structure

The future distribution of the effects of climate change is highly uncertain. While the majority of the scientific community have no more doubts about the link between human activity and climate change, enormous uncertainty remains over the magnitude and especially the speed at which effects will materialize. From the point of view of financial markets, timing is essential in determining the impact on asset prices. My setting is ideal for studying at what time in the future market participants exactly expect climate change shocks to impact firm cash flows. I have information on how analysts revise their forecasts for each firm over a set of different forecast horizons. This leads to a term structure of earnings forecasts for the same analyst-firm pair, which can be used to infer the expected timing of the climate change impact. To do so, I investigate how the temperature sensitivity of the forecasts varies depending on how distant the earnings are in the future. I estimate the regression specification (4.1) separately for each forecast horizon. The estimated β coefficients are reported in Figure 2.

The results show that the average sensitivity to temperature shocks is not significantly different from zero for essentially all earnings forecasts with horizons shorter than 8 quarters. The effect is concentrated in the longer horizon forecasts issued at least two years ahead. On the one hand, it seems sensible that climate change is expected to impact profits only in the longer run, indeed the very short term earnings forecasts don't seem to react to temperatures. On the other hand, it is remarkable to observe that analysts already factor in a direct impact on earnings as soon as two years in the future on average. This suggests that climate change risk is not regarded only as a long run risk. On the contrary, analysts seem to consider a potential material impact on firm income well within the medium term. I believe this is the first attempt in the literature to dissect the expected timing of climate risk in such a granular

	EPS Forecast		
	(1)	(2)	(3)
Avg. Temperature	-0.006**	-0.007***	-0.001
	(0.002)	(0.002)	(0.002)
Avg. Temperature × High Physical Risk	-0.014***		0.004
	(0.004)		(0.003)
Avg. Temperature × Hurricane Risk		-0.215***	
		(0.068)	
Avg. Temperature × Flood Risk		-0.004	
		(0.008)	
Avg. Temperature × Heat Risk		-0.030***	
		(0.005)	
Avg. Temperature × Sea Level Rise Risk		0.014**	
		(0.006)	
Avg. Temperature × Water Risk		0.006*	
		(0.003)	
Avg. Temperature × High Carbon Industry			-0.029***
			(0.008)
Avg. Temp.×High Physical Risk×High Carbon Ind.			-0.047***
			(0.010)
Observations	2,541,453	2,541,453	2,403,763
R^2	0.9864	0.9864	0.9862
Firm-Year-Month-Earnings Date-type fixed effects	✓	✓	✓
Analyst fixed effects	✓	✓	✓

Table 4: Results of OLS estimation of effect of temperature on the earnings per share forecasts, interacted with firm-level exposure to physical climate risk. The firm-level risk scores come from *FourTwentySeven* and are a single cross section as of September 2019. All the risk variables are dummies indicating the quartile of most exposed risks. *High Physical Risk* considers the overall risk score, while column (2) breaks down each specific risk in a separate dummy. The breakdown of risks they provide includes the following types: hurricanes, floods, heat stress, sea level rise and water stress. Column (3) includes interactions with the high carbon emission dummy introduced in 3. All specifications include also the dummies alone, not interacted.

way. The results suggest that market participants are aware of material climate risks, and expect the first effects on cash flows to materialize sooner than we might have thought.

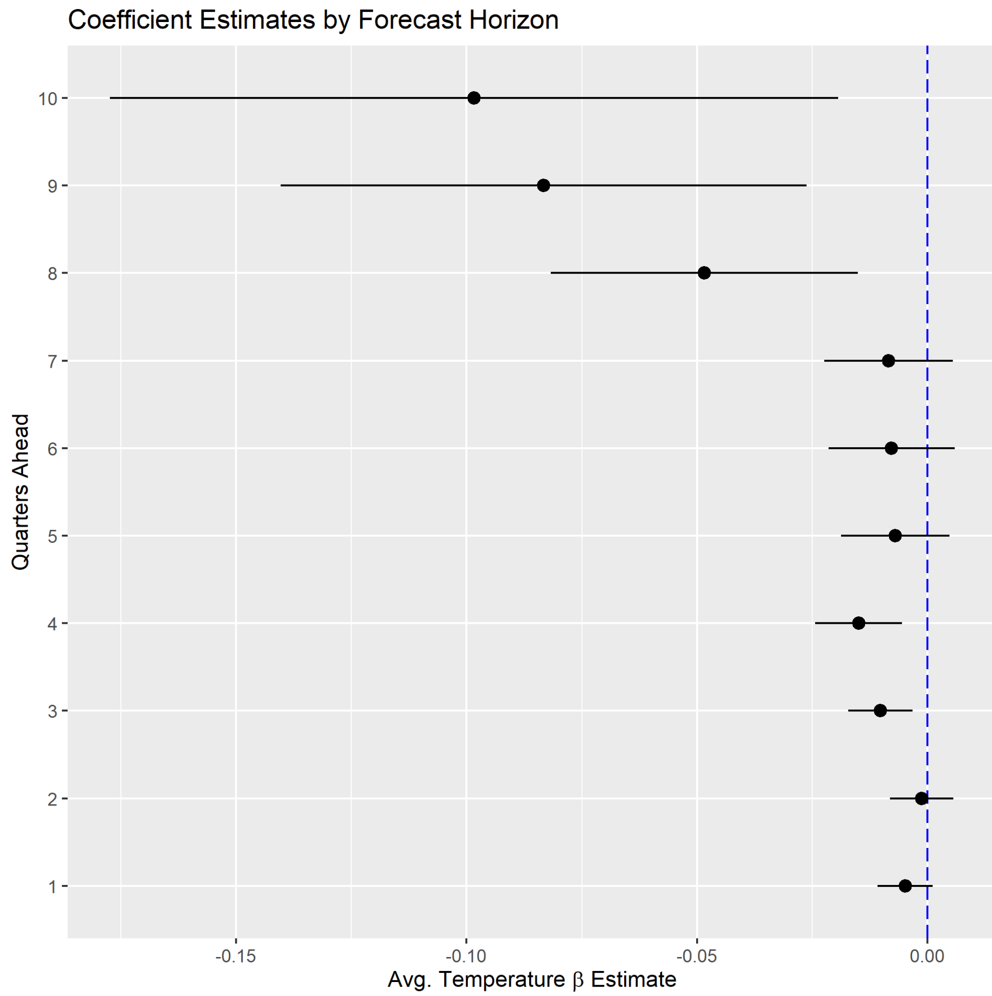

Figure 2: Estimates of the β coefficient by horizon. The reported estimates refer to the specification of column (4) of Table 2, obtained considering forecasts of different horizons separately. The vertical axis indicates the forecast horizon measured in quarters, rounded down. The dots are the point estimates, while black horizontal segments represent 95 percent confidence intervals.

4.4 Post-Disaster Effect

This section provides additional evidence in favor of the hypothesis that the temperature sensitivity of the forecasts is due to a shift in the analysts' perceptions of climate change risks. To do so, I exploit the arrival of extreme weather events which are becoming more frequent and destructive as a result of climate change. Similar events have been used in previous literature as an alternative to temperature as shocks to climate change expectations. For instance Alok et al. (2020) analyze the reaction of portfolio managers to the arrival of large disasters and show that they tend to trade against firms located in affected areas, suggesting a revised perception of risk.

In the following analysis, I study how the sensitivity of forecasts to temperature changes for analysts affected by large weather events related to climate change. I collect data from *SHELDUS* on large weather events in the U.S. and their associated damages, and link them to the MSA of residence of the analysts. Consequently, I re-estimate the main regression specification (4.1) adding the interaction of the local temperature at the analyst MSA with a post indicator that is equal to one after an analyst experiences a weather event in her MSA. The events I consider are hurricanes, storms and tornadoes leading to at least 50$ million in damages. I choose these particular events as results from Table 4 suggest that hurricane risks are the most salient for analysts. On average, between 14 and 15 MSAs are hit by similar events every year in the sample. Results are presented in Table 5. The estimates suggest that the temperature sensitivity of the forecasts becomes greater for analysts who experience a large weather event. This is in line with the hypothesis that they are becoming more aware of the potential effects of climate change, or simply that the salience of climate change has increased.

In order to understand the persistence of the effect, I split the post indicator in specific quarterly indicators: "Post02" for the month of the event and the following two, "Post35" for the third, fourth and fifth month since the event, and so on. Results are shown in column (2) of Table 5. I find a significant post-event difference in the temperature sensitivity, that lasts for about one year after the event before reverting to the mean.

Major weather events appear to induce analysts' to become more sensitive to warm temperatures. The effect is substantial and seems to last for several months after the event. A question naturally arises, related to the discussion of physical risk of Section 4.2.2. We observed that analysts' reaction to temperatures is more marked for firms exposed to some types of physical risks, such as hurricanes and heat stress. What happens when analysts experience the same type of events directly? Do they adjust their risk perception similarly for all firms, or differently for firms exposed to precisely those types of events? I try to address this question by combining the event study of Table 5 with the *FourTwentySeven* risk scores seen in Section 4.2.2, which allow a categorization of firms based on their exposure to different types of weather events.

	EPS Forecast	
	(1)	(2)
Avg. Temperature	-0.004***	-0.004***
	(0.001)	(0.001)
Avg. Temperature × Post	-0.003***	
	(0.001)	
Avg. Temperature × Post02		-0.023***
		(0.004)
Avg. Temperature × Post35		-0.010***
		(0.003)
Avg. Temperature × Post68		-0.019***
		(0.003)
Avg. Temperature × Post911		-0.008**
		(0.003)
Avg. Temperature × Post1214		-0.005
		(0.004)
Observations	8,294,476	8,294,476
R^2	0.9764	0.9764
Firm-Month-Earnings Date-type fixed effects	✓	✓
Analyst fixed effects	✓	✓

Table 5: Results of OLS estimation of event study examining how the temperature sensitivity changes after analysts experience large weather events. The *Post* indicator is a dummy indicating all the months after an analyst's MSA is hit by a hurricane or tropical storm engendering at least 50 million dollars of damages. Information on events and damages come from *SHELDUS*. Column (2) breaks down the indicator by quarter, so that *Post02* indicates the trimester starting on the month of the event, *Post35* the next, and so on.

I estimate the same specification of Table 5, adding a triple interaction between temperature, the post indicator and the firm-level physical risk indicator dummies. In table 6 I report the results. The weather events considered to build the post dummies are the same of Table 5: large hurricanes and storms leading to at least 50$ million in damages. The coefficient of interest here is the one on the triple interaction. In column (1), we notice that the effect of storms on temperature sensitivity is significantly stronger for firms exposed to hurricane risk. In column (2) I compare the effect for firms exposed to hurricane risk relative to firms exposed to any of the other physical risks. It seems that the temperature effect for firms that are not exposed to hurricane risk is unaffected by the arrival of the storms, if anything the effect gets reduced. It could be that the arrival of the storm "crowds out" other risks making the hurricanes the most salient in the analysts' mind. In column (3), I split firms more granularly among the categories of physical risk. The results confirm the finding that hurricane risk drives the effect, suggesting that the arrival of a storm makes storm risk exposures of firms more salient in the analysts' minds. It does not appear that a similar effect is present for firms exposed to other physical risks: there is a small reduction in the temperature sensitivity post event for firms exposed to water stress and sea level rise risks, possibly in line with the crowding out interpretation.

These tests suggest that direct experience of local weather events matters for the salience of climate change among analysts. Is this salience driven only by direct experience, or could it be that just receiving news of weather events is enough to increase the sensitivity of forecasts to temperature going forward? I attempt to answer this question by carrying out an exercise similar to the one of Table 5, but focusing on larger hurricanes and storms, and assuming that they are large enough so that also unaffected analysts would receive some news about them. I consider events leading to twice the damage from the previous tests, at least $100 million. I run a similar event study, but now treat these weather shocks as national, common to all analysts. The hypothesis I test is whether the temperature sensitivity of the forecasts across analysts is different in periods following a large storm happening anywhere in the U.S. . Results are presented in Table 7. Each post dummy indicates months since the arrival of the event. The coefficients are small and not statistically significant. Based on these estimates, I do not find evidence that news of large national events are enough to affect climate change salience. My analysis suggests that direct experience of local weather events is what matters to move analysts' sensitivity to temperatures.

	EPS Forecast		
	(1)	(2)	(3)
Avg. Temperature	-0.008***	-0.003	-0.003
	(0.002)	(0.003)	(0.002)
Avg. Temperature × Post	-0.003**	-0.009***	-0.011***
	(0.001)	(0.002)	(0.002)
Avg. Temperature × Post × Hurricane Risk	-0.042**	-0.036**	-0.043**
	(0.017)	(0.017)	(0.018)
Avg. Temperature × Post × Non-hurricane Risk		0.012***	
		(0.002)	
Avg. Temperature × Post × Heat Risk			0.002
			(0.003)
Avg. Temperature × Post × Water Risk			0.021***
			(0.003)
Avg. Temperature × Post × Flood Risk			-0.005
			(0.009)
Avg. Temperature × Post × Sea Level Rise Risk			0.008*
			(0.004)
Observations	2,401,012	2,401,012	2,401,012
R^2	0.9845	0.9845	0.9845
Firm-Month-Earnings Date-type fixed effects	✓	✓	✓
Analyst fixed effects	✓	✓	✓

Table 6: Results of OLS estimation expanding on the event study presented in Table 5 to differentiate across firms with different physical climate risk exposure. The goal is to test whether experiencing large weather events affects the analysts disproportionately for firms that are exposed to events similar to the one affecting the analyst. The physical risk dummies are defined as in Table 4, and the post indicators as in 5. Events remain large hurricanes and storms leading to at least 50 million dollars in damages. The coefficients of interest are the triple interactions of the post indicator with the average temperature and the firm risk dummies. These triple interactions estimate the differential change in the post event temperature sensitivity for firms exposed to certain types of events in the future. For the rest the specification is analogous to the one of Table 2 column (4). All the remaining double interactions are included in the specification but not reported in the table for reasons of space.

	EPS Forecast
	(1)
Avg. Temperature	-0.004**
	(0.002)
Avg. Temperature × Post0	-0.008*
	(0.004)
Avg. Temperature × Post1	0.008**
	(0.004)
Avg. Temperature × Post2	-0.006
	(0.005)
Avg. Temperature × Post3	-0.005
	(0.004)
Avg. Temperature × Post4	0.000
	(0.003)
Observations	6,564,149
R^2	0.9765
Firm-Month-Earnings Date-type fixed effects	✓
Analyst fixed effects	✓

Table 7: Results of OLS estimation of an event study related to the one of Table 5, but focused on large national events instead of local ones. The weather disasters considered remain hurricanes and storms, but of larger magnitude, inducing at least $100 million in damages. These events are treated as national, as they should affect all analysts through news, regardless of where they are located. The goal is to test whether receiving news of large weather events at the national level has effects on analysts' sensitivity to temperature that are comparable to those arising after experiencing local events directly. The post indicators are dummies for the months since the event, so that *Post0* is the month of the event, and *Post1* the following month. These dummies vary only in the time series and are constant across analysts.

5 Conclusion

In this paper, I investigate how changes in the perceptions of climate change risk affect professional forecasts of firms cash flows. In particular, I consider a sample of forecasts of firm earnings issued by sell-side financial analysts' in the United States. As a shifter of climate change beliefs, I exploit variation in temperatures across analyst locations. I show that analysts experiencing warmer temperatures become more pessimistic about future earnings on average. The negative effect is concentrated in firms exposed to regulatory climate risk, as proxied by carbon dioxide emissions. The sign of the effect for renewable energy firms is strongly positive, as opposed to the negative effect on the average firm. This supports the credibility of temperature as a shifter of climate change risk perceptions, and suggests that analysts are sensitive to exposures to regulatory risk in particular. In the cross-section of firms, also physical risks matter. The forecasts for firms which are most exposed are significantly more sensitive to warm temperatures. The kinds of risks that appear more salient to analysts are hurricane risk and heat stress risk.

For each analyst-firm pair, I observe a term structure of forecasts for earnings at different future horizons. I exploit this to investigate how soon analysts expect climate risk to impact earnings. I observe that the negative sensitivity of forecasts to temperature is concentrated in forecasts for earnings between eight and ten quarters in the future. Although these are the longest horizons for which analysts issue forecasts in the sample, it is remarkable that analysts expect a negative effect on earnings to happen with some probability within such a short time-horizon.

Finally, I exploit large weather disasters as additional evidence supporting the climate change risk explanation. I perform an event study to estimate whether analysts become more sensitive to temperatures after they experience a devastating storm in their city. I find that the temperature sensitivity is more marked for affected analysts, but that this effect fades over time. This pattern could be motivated by weather events increasing the salience of climate change risks. In line with this, I observe that the the sensitivity to temperature after the events increases exactly for firms exposed to weather disasters of the same kind.

Researchers are interested in understanding whether and how well markets incorporate climate change risks. This work is a step in that direction, and provides meaningful contributions to the previous literature. While several previous studies have focused on the impact of climate risks on prices, there is still limited evidence on whether it is cash flow expectations or discount rates that matter. I provide evidence that cash flow forecasts do react to changing climate change risk perceptions, thus contributing at least in part to the effects on prices found in the literature. Furthermore, I believe this is the first study to attempt a precise investigation on the timing at which markets expect climate change effects to materialize.

Future research may perform event studies around climate-related firm announcements. For instance to test what happens to analyst forecasts and prices when firms pledge to meet new sustainability standards. Moreover, one could focus on the asset pricing implications of the temperature sensitivity uncovered here, to inform investment decisions or to form portfolios that hedge temperature shocks. Using the textual content of equity research reports, researchers may extract better information on how analysts incorporate climate risk in their analysis. Generally, the sophistication of climate data and models employed by the financial industry will certainly increase, generating valuable new data for research.

Climate change is one of the main challenges facing modern human society.

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