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Does climate risk influence analyst forecast accuracy?

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ABSTRACT

We examine how climate risk influences analyst forecast accuracy proxied by forecast error and dispersion. Using country-level climate risk estimated with time trends in droughts, we find that analyst forecasts are less accurate for firms in drought-prone countries. This effect of climate risk is stronger when climate risks are denoted in earnings forecasts, and when firms' home countries have greater reliance on hydroelectric sources in electricity generation, more important agricultural and food industries, and active stances concerning climate change. Overall, our findings suggest noteworthy implications of climate risk on the financial markets via analyst forecast accuracy.

1. Introduction

Since the Industrial Revolution, world economies have rapidly advanced but overlooked the negative externalities of industrial pollution, which is intimately linked to climate change. The United Nations (UN) defines climate change as "long-term shifts in temperatures and weather patterns."[1]; While these shifts might be caused by a change in the solar cycle to some degree, the UN attributes the main cause of climate change to human activities such as burning fossil fuels, including coal and oil. In turn, climate change is expected to intensify the incidence and severity of both acute and prolonged climate events, presenting rigorous challenges for society at large. Unquestionably, business stakeholders are also exposed to climate risk to a momentous extent as climate change causes unprecedented disruptions to firms' operations, investments, and financial performance. A CDP report issued in 2018, which analyzed 215 submissions from the world's 500 large corporations, indicates that global businesses are potentially subject to around $1 trillion costs related to climate change in the near future unless preemptive measures are taken.[2]

Concerns about worldwide climate change have brought a burgeoning literature on the importance of climate issues in business. Growing evidence indicates that climate risks, often represented by long-run temperature shifts, droughts, or sea-level rise, have substantial implications for financial markets, such as stock returns (Bansal et al.,

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[1] https://www.un.org/en/climatechange/what-is-climate-change#:~:text=Climat%20change%20refers%20to%20long,like%20coal%2C%20oil%20and%20gas.

[2] CDP, formerly known as the Carbon Disclosure Project, is an international nonprofit organization that works with companies around the world to publicly reveal the opportunities and risks associated with climate change. For more information, find the full report (Global Climate Change Analysis 2018) available on the CDP website (https://www.cdp.net/en/research/global-reports/global-climate-change-report-2018).

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2016; Hong et al., 2019), return comovement (Ma et al., 2022), currency exchange rates (Bonato et al., 2023), and bond returns (Painter, 2020), among many others. There are also studies focusing on the effect of policy risks that address extreme weather changes on focal firms.[3] Despite this accumulating evidence highlighting the impact of climate change on firms, it is largely yet to be unearthed how climate change as a risk is incorporated into financial markets. In this paper, we explore this relatively new research area of climate issues by providing evidence about the effects of climate risk on financial analysts' accuracy in forecasting corporate earnings around the world.

A financial analyst is an expert in interpreting and analyzing relevant information as well as assessing risks related to corporate earnings, and therefore, is often referred to as a financial intermediary promoting price discovery between information suppliers and demanders. In existing studies of analyst forecasting accuracy, however, there is ample evidence showing the limited ability of analysts to incorporate market-wide information (Chuang and Lee, 2011) or a systematic bias in analysts' earnings forecasts that is generally in an upward direction. Prior researchers find causes of forecasting inaccuracy from analysts' characteristics (e.g., career concerns (Hong and Kubik, 2003), ability (Clement, 1999), industry experience (Bradley et al., 2017), and overconfidence (Hilary and Menzly, 2006)), firm characteristics (e.g., corporate disclosure quality (Hope, 2003) and product market competition (Mattei and Platikanova, 2017)), and external environments (for example, macroeconomic uncertainty (Hope and Kang, 2005) and accounting standard (Tan et al., 2011)), but shows relatively little evidence on the role of non-financial factors in this framework. By integrating the analysts' forecast literature with climate studies, we investigate whether and how climate change, as a non-traditional financial factor, relates to the inaccuracy of analysts' forecasts around the world. We then study how the influence of climate risk on the accuracy of earnings forecasts varies with country and analyst attributes.

To test our inquiries, we adopt a cross-country empirical setting to exploit geographical heterogeneity in the magnitude of climate change. Climate risk is broadly divided into two categories: physical risk, which pertains to the direct costs and damages caused by climatic events and conditions, and transition risk, which is owing to growing awareness of climate changes and the political efforts to address them (e.g., Gu and Hale, 2023; Battiston et al., 2021). As a proxy of the physical aspect of climate risk in particular, we focus on droughts since droughts, which are highly correlated with a level of temperature and moisture, could reflect multiple types of climate change. Moreover, unlike other natural disasters such as hurricanes and floods, droughts are more global than regional phenomena, which influence firm operations in several ways and thus require analysts' attention and meticulous incorporation into their forecasting. In the U.S., for instance, the water levels of the Mississippi River exhibit near record lows, which decrease southbound shipments of corn, soybeans, wheat, and oil by 20 % due to the lack of adequate water levels.[4] France, which is also dealing with severe drought, is forced to reduce power generation of nuclear plants that use river water to cool reactors.[5] Shallow water levels on the Rhine River raise shipping costs for coal by preventing shipping vessels from being fully loaded in Germany. In short, water scarcity has extensively been influencing multifarious business settings.

To quantify drought risk, we attain our country-level climate risk measure by estimating the time trend in droughts across countries based on the Palmer Drought Severity Index (PDSI), a metric widely used in climate studies (Palmer, 1965). More specifically, we utilize a long time series of PDSI for each of the 36 countries in our international sample and use a trend-stationary model to estimate the time trend in droughts for each country, following the work of Hong et al. (2019). Thenceforth, a country with greater climate risk (i.e., a higher score on the climate risk) is identified as the one with more significant trends toward drought-like conditions. Although there may be a common perception that the effects of drought would be relevant primarily to water-dependent sectors, such as food and agriculture industries, the key message of the review by Wlostowski et al. (2022) highlights drought as an impactful factor with significant damages on a wide range of nonagricultural sectors of the economy. Moreover, considering important interconnections between firms and sectors in the economy (e.g., Acemoglu et al., 2012), climate risk bringing negative shocks to a particular industry could also lead to large ripple effects in other sectors. Accordingly, several papers (e.g., Huynh et al., 2020; Javadi and Masum, 2021) use the Palmer Drought Severity Index (PDSI) to construct climate-related variables for the investigations spanning across diverse sectors.

Our main finding is that analyst earnings forecasts are less accurate for firms located in countries with greater climate risk or more vulnerability to droughts due to climate change, where the accuracy of analyst earnings forecasts is proxied by forecast error and forecast dispersion. The size of the relationship between climate risk and analyst forecast accuracy is substantial as well. In our sample, the mean values of forecast error and dispersion are 0.1582 and 0.0568, respectively. One standard deviation increase in the degree of climate risk corresponds to a 0.0911 and 0.0282 increase in forecast error and dispersion, respectively. This finding concurs with prior evidence documenting higher inaccuracy in analyst forecasts for firms with complicated nonfinancial attributes (e.g., Chen et al., 2010). We also perform a battery of robustness checks, including tests based on alternative measures of climate risk[6] and within-country variation in climate risk. For example, we use the current abnormality of drought conditions based on deviation from the mean of the past 10-year drought in a given country as an alternative proxy for climate risk and get support for our conjecture with copious evidence. We also acknowledge the view that extremely wet conditions, which are likely associated with floods and mudslides, might be indicative of severe climate change. We thus employ a climate risk variable measuring exceptionally wet conditions in our robustness test and find that severe wetness as a climate risk has a comparable effect as in our main result.

Climate change could be an influential factor for forecast accuracy, depending on how analysts perceive climate risk, a crucial yet nonfinancial factor. Especially, since climate risk has started getting attention in relatively recent periods, it is highly probable that this nonfinancial information is either less recognizable (limited attention) or understandable (limited understanding). Our analysis distinguishes between these, revealing that the negative relation between climate risk and forecast accuracy is more concentrated for firms about which analysts recognize their exposure to climate change, as identified by the climate-related words included in analyst reports. This suggests that analysts' limited understanding, rather than limited attention, primarily drives forecast inaccuracy linked to climate risk. Consequently, climate risk, although acknowledged by analysts, is not effectively integrated

[3] For example, Calel and Dechexlepretre (2016) find that the European Union Emissions Trading System increases eco-friendly innovations for compliant firms by 10 % compared to non-compliant peers. Ehlers et al. (2022) show the cost of equity capital increases for firms in the fossil fuel industry after the Paris agreement.

[4] https://www.fox10phoenix.com/news/mississippi-river-drought-hits-record-level-revives-supply-chain-concerns-report

[5] https://journalrecord.com/2022/08/05/drought-may-force-nuclear-power-production-cut/

[6] In our robustness tests, we use several alternative measures of climate risk, including raw values of PDSI, measures indicating extreme climate conditions, and measures related to alternative dimensions of vulnerability to climate change.

Table 1
Descriptive Statistics. This table presents descriptive statistics for our sample of firms, 161,853 firm-year observations that range from 1990–2014. Refer to Appendix A for detailed variable descriptions.

	N	Mean	P25	P50	P75	Std
Climate Risk	161,853	0.0232	−0.0463	−0.0157	0.0756	0.1130
ForeError	161,853	0.1582	0.0032	0.0159	0.0699	0.6263
ForeDisp	161,853	0.0568	0.0033	0.0096	0.0254	0.2156
Ln (Assets)	161,853	5.9752	4.6392	5.9064	7.1912	1.8876
Q	161,853	1.8679	1.0284	1.3658	2.0639	1.5310
ROA	161,853	0.0492	0.0250	0.0689	0.1159	0.1484
Loss	161,853	0.1699	0.0000	0.0000	0.0000	0.3756
Leverage	161,853	0.2057	0.0379	0.1826	0.3259	0.1772
Tangibillity	161,853	0.2901	0.1073	0.2402	0.4230	0.2228
Std(ROA)	161,853	0.0700	0.0157	0.0316	0.0705	0.1125
HHI	161,853	0.1881	0.0496	0.0999	0.2460	0.2097
IFRS	161,853	0.2015	0.0000	0.0000	0.0000	0.4011
TopAudit	161,853	0.6966	0.0000	1.0000	1.0000	0.4597
Ln (AnalyFollow)	161,853	1.4597	0.6931	1.3863	2.1972	0.9888
Ln (BrokSize)	161,853	3.7931	3.2387	3.9120	4.4148	0.9708
Ln (AnalyExp)	161,853	1.8168	1.4469	1.9279	2.3026	0.6801
GDPGrow	161,853	0.0207	0.0080	0.0187	0.0320	0.0273
FDI	161,853	0.0247	0.0090	0.0172	0.0304	0.0389
Hydro	161,853	11.822	5.911	7.292	9.611	16.300
Agr&Food	161,848	7.794	4.565	7.957	10.302	5.463
InvCO2Emiss	141,629	−20.735	−14.799	−9.027	−0.853	46.406
NonConservative	133,302	0.533	0.000	1.000	1.000	0.499
AnalyExp	1147,502	7.436	2.000	6.000	11.000	6.222
AnalyCover	1147,502	6.928	1.000	3.000	7.000	18.592

into forecasting, which is consistent with the view of Friesen and Weller (2006) showing analysts' limited role as information intermediaries.[7] Concerning the analysts' limited comprehension of climate risk, we further demonstrate that climate risk tends to increase firms' earnings volatility. Hence, we claim that a substantial degree of climate risk could have the effect of augmenting the inherent vagueness of earnings, which thus would confound the analysts' task of producing earnings forecasts.

We then explore the moderating effects on the relation between climate risk and analysts' forecasts, examining whether our main finding varies across different country characteristics that might impact the degree to which businesses are vulnerable to climate change. We find that firms in countries with a greater reliance on hydroelectric sources for electricity production and a greater importance of agricultural and food product sectors in the economy display a stronger positive relation between climate risk and forecast error (or dispersion). In addition, the effect of climate risk on forecast accuracy is particularly pronounced in countries that are more likely to implement environment-related regulations or policies. Regarding this distinction, we argue that when a country and its local economy are more sensitive to climate change, companies in that country would be more substantially influenced by climate change and thus make it more challenging to forecast earnings.

We then examine what attributes of analysts can lessen the effect of climate change on forecasting inaccuracy. Extant literature indicates that analysts' past industry experience (Bradley et al., 2017) and tenure (Clement, 1999) influence their forecasting accuracy. As such, we examine whether the relation we present in this study is influenced by analysts' (industry) expertise and tenure. We find evidence that the impact of climate risk on forecast accuracy is moderated by analysts' experience and expertise, highlighting these features of analysts as helpful factors in comprehending the influence of climate risk as a new and unique type of factor on businesses.

To summarize, this paper contributes to a new and emerging line of research on climate risk or weather-related issues and various financial outcomes. For example, several studies assess the effects of climate shocks on financial markets (e.g., Bansal et al., 2016; Daniel et al. 2016; Hong et al., 2019; among many others). By extending this line of research, we contribute to the literature by documenting a link between country-level climate risk depicted by drought trends and analyst's earnings forecasts. This study reveals that climate risk is not adequately incorporated into the generation of analyst earnings forecasts.

In particular, this research contributes to the growing literature examining climate-related factors influencing analyst forecasts (e.g., Addoum et al., 2023; Cuculiza et al., 2021; Pankratz et al., 2023). For instance, Cuculiza et al. (2021) show that analysts located in states where firms exhibit greater sensitivity to past abnormal temperature changes issue less optimistic earnings forecasts and thus result in greater accuracy, indicating those analysts' ability to assess climate change's negative impact on earnings. Pankratz et al. (2023) contend that capital market participants do not fully estimate the adverse economic effects of heat exposure, as increased heat exposure negatively affects firm performance compared to analyst predictions and earnings announcement returns. Many of these prior studies predominantly base their arguments on the negative impact of climate risk on firm performance. Instead, we turn our attention to a more equivocal aspect of climate risk as a factor increasing the uncertainty inherent in earnings rather than its negative or uni-directional impact on earnings[8] and demonstrate its linkage with analysts' forecasting ability. Also, while both highlighting the negative linkage between climatic issues and analyst forecast accuracy, our approach and argument are distinct from those of Han et al. (2024) in that, while Han et al. (2024) claim climate disaster events in the

[7] In our robustness test, we employ a quasi-experimental setting to further confirm our findings. Specifically, we exploit the release of the Stern Review on the Economics of Climate Change (Stern, 2008) as an event that significantly increases people's awareness of climate change and find that the accuracy of forecasts does not improve despite increased attention to climate risk among analysts after the release of the Stern Review. This is in line with our result from the test using climate risk keywords in analyst reports, which shows that the relevance of climate risk is recognized yet not effectively incorporated into the task of forecasting.

[8] Climate change may not always negatively impact firm performance and could rather offer a new opportunity for some industries. Addoum et al. (2023) show the bi-directional effects of climate risk on industry earnings.

analysts' locations as a source of distraction, our study hinges on showing how trends[9] in local climate change make firms in the area "harder-to-value" and influence forecast accuracy.[10] Going beyond prior studies, we find that analysts' limited understanding of climate risk, despite paying attention to it, drives the linkage between climate risk and analyst forecast inaccuracy.

Our study is also closely related to the literature that examines the incorporation of non-financial information into analyst forecasts. Contrary to Dhaliwal et al. (2012) showing a positive association between the issuance of corporate social responsibility report, as a proxy for disclosure of non-financial information, and better analysts forecast accuracy, we find that analyst forecasting errors are greater for firms about which analysts recognize the relevance of climate risk, as evidenced by the inclusion of climate-related keywords in reports, implying inefficient incorporation of climate risk into forecasts. Collectively, we complement this line of literature by presenting climate change as a potential source of over- or under-estimation embedded in analyst forecasts on earnings.

The findings of this study carry significant implications for policymakers and regulators, particularly in light of the rising impact of global climate change on businesses across various regions worldwide. Our findings echo recent initiatives aimed at standardizing and improving climate-related disclosures, and policymakers and regulators may consider imposing requirements for more accurate and in-depth reporting on the effects of climate risk on businesses. That is, our results suggest that recent regulatory moves to expand requirements on climate-related disclosure and improve its consistency and reliability are likely to benefit market participants and enhance the information landscape. Furthermore, policymakers may consider these results in the design of effective strategies for addressing climate-related financial risks.

The remainder of the paper is organized as follows. Section 2 discusses the related literature and prior findings. Section 3 explains our measure of climate risk and describes the data. Section 4 explains the empirical results. The last section presents our conclusions.

[9] Since the nature of financial analyst jobs involves projecting future revenues and earnings based on an analysis of cost structure, we contend that using trends in climate risk, which would include concurrent information as well, is more suitable for this line of studies than employing past climatic risk or events.

[10] More specifically, while Han et al. (2024) center their argument on the distracting effect of climatic events within the location of analysts on forecast accuracy as disasters could constrain analysts' attention that is a scarce or limited resource important for forecasting task, our work is focused on the impact of climate risk surrounding the location of businesses and whether analysts incorporate that information effectively into their forecasts for better precision. In addition, our work is on international setting with a measure of concurrent trend in climate risk with a progressive nature, whereas Han et al. (2024) examine the impact of climate disaster events on a single country (U.S.) setting. Hence, unlike climatic disasters that occur sporadically with typically short-term durations in the work of Han et al. (2024), the climate risk in our study is a progressive measure capturing the country-level continuous trajectories of climate change as a factor influencing businesses. Another closely related work is done by Addoum et al. (2023), who investigate how extreme temperatures influence industry earnings with a sample of U.S. firms. In their study, the analysis is on whether analyst forecasts are significantly changed when local firms experience the earnings shocks associated with extreme temperatures, and the authors find no meaningful difference in analyst forecasts around temperature shocks and argue that analysts expect at least a portion of the earnings shocks in advance. However, Addoum et al. (2023) do not directly test the effect of climate risk on the accuracy of analyst forecasts, which distinguishes our study.

2. Literature review

2.1. The effect of climate changes on corporations

With accumulating scientific evidence regarding global climate change, one type of non-financial information relevant to diverse aspects of firms is the one arising from climate change. As Krueger et al. (2020) illustrate with their survey-based analysis, a growing number of investors already recognize that weather and climate change pose a critical risk to global business. Indeed, there is a rapidly growing list of finance studies focusing on the impact of climate change, mainly identifying climate change as a risk. Remarkably, Bansal et al. (2016) highlight the importance of climate risks as a long-run risk factor, and Bolton and Kacperczyk (2021) also assert the importance of carbon risks in the cross-section of stock returns by showing that stocks of firms with higher total CO_2 emissions earn higher returns. Likewise, Hsu et al. (2023) find that highly polluting firms are more exposed to environmental regulation risk and command higher average returns as a reward for investors taking additional risks. At the same time, several studies, such as Daniel et al. (2016) and Hong et al. (2019), present mounting shreds of evidence that climate risks may be mispriced in financial markets. For instance, Hong et al. (2019) focus on publicly traded food companies around the world and find that the intensifying drought risk caused by climate change is not efficiently priced by stock markets. Meanwhile, focusing on the investor side, Gibson Brandon and Krueger (2018) and Hoepner et al. (2024) show that better environmental policies are related to lower downside and overall portfolio risk. In a related spirit, Jagannathan et al. (2017) claim that investors can reduce portfolio risk by incorporating climate criteria into their investment processes.

Another category of studies examines the effects of climate change on overall economic outcomes and firm-level outcomes like sales, earnings, or investments. To some degree, the results are mixed, suggesting that some firms may be better at mitigating the impact of weather or climate change on their operations. For example, focusing on aggregate economic outcomes, Dell et al. (2012) find that, although higher temperatures substantially reduce economic growth in developing countries, there is no discernible impact of higher temperatures on economic growth among the more affluent countries in their sample. Hsiang (2010) also finds that countries with higher temperatures exhibit greater reductions in national output. Then, analyzing establishments owned by publicly listed firms in the United States, Addoum et al. (2020) hypothesize that extreme temperatures may influence local establishments' sales, productivity, and profitability, but find little economic effect. Additionally, Hugon and Law (2019) examine the impact of climate change on firm earnings and find that an unusually warm climate tends to have a negative impact on firms' earnings, although there are also some "winners" benefiting from a warmer climate. Further, some studies have looked at climate change and investments. Focusing on electricity-producing firms, Lin et al. (2019) find that those firms increase their investment in flexible power plants in areas where weather conditions are becoming more extreme and leading to more volatile electricity demand and prices. Thus, the authors show that firms react to higher volatility by investing in a way that improves their operating flexibility, implying that climate change is becoming a consequential factor influencing firms' behavior. In sum, there is an ever-increasing amount of evidence regarding the impact of climate change on different realms of the economy and businesses.

2.2. The effect of climate changes on analyst predictability

The accuracy of earnings forecasts is generally regarded as a reflection of the degree of information asymmetry between sophisticated investors and managers (Krishnaswami and Subramaniam, 1999; Duru and Reeb, 2002; among many others). Various factors improving or limiting analysts' forecasting ability have been uncovered, including firm-level and institutional factors that influence analyst forecasts (e.g., Brown, 1993; Clarke and Subramanian, 2006). For instance, Duru and Reeb (2002) find that greater corporate international diversification, reflecting unique dimensions of forecasting difficulty, is associated with less accurate forecasts. Often, analyst performance has been linked with experience. Mikhail et al. (1997), for example, discover that analysts who cover a firm for a longer period produce better forecasts. Other studies have found that general analyst forecasting experience and industry experience lead to more accurate forecasts (e.g., Clement, 1999; Clement et al., 2007; Bradley et al., 2017). In addition, proximity to firms in terms of geography and culture has been found to boost precision in analysts' forecasting (Bae et al., 2008; Du et al., 2017). Overall, this line of research concurs with the view of Easley et al. (1998), showing that analyst following is not positively associated with information-based trading.

Furthermore, while it is unquestionable that analyzing financial information is vital in generating accurate forecasts of earnings (Brown et al., 1987; Abarbanell and Bushee, 1997; Hope, 2003), the impact of non-financial information on analyst forecasts has also been the subject of several studies. For example, Dhaliwal et al. (2012) use the issuance of stand-alone corporate social responsibility (CSR) reports as a proxy for disclosure of non-financial information, and they find that the issuance of stand-alone CSR reports improves analyst forecast accuracy. In a similar vein, Muslu et al. (2019) find that CSR reporting firms with better disclosure qualities are associated with more accurate forecasts. On the contrary, some non-financial traits of firms make it more challenging to forecast earnings. For instance, according to Chen et al. (2010), analysts experience greater difficulty in predicting the earnings of firms with political connections, which supports the authors' argument based on the idea that political favoritism is usually granted covertly and often comes in a windfall fashion.

More recently, there are further studies relating environmental or climatic issues with financial analysts' tasks, and mixed evidence on the matter is accumulating. Dong et al. (2019) argue that there is a negative relation between air pollution during investment analysts' corporate site visits and subsequent earnings forecasts. Their result shows that the effect of air pollution pertains only to forecasts announced in the weeks immediately following a visit, implying that the impact of environmental conditions on mood likely plays a role. Similarly focusing on air pollution issues, Li et al. (2020) present evidence that air pollution deters analysts from producing information, as analysts exposed to severe air pollution are less likely to issue timely forecasts or improve their forecast accuracy. Their finding accords with the argument regarding the negative effect of air pollution on labor productivity. Additionally, utilizing major climatic disasters in the U.S. as exogenous shocks, Han et al. (2024) reveal that earnings forecast errors increase substantially when analysts are affected by a disaster. Their analyses show that the disaster effect is driven by distracted attention among analysts, as analysts distracted by climatic disasters need to allocate their scarce attention in a strategic way. While these studies center their argument on the effect of environmental or climatic issues as a trigger of mood, reduction in labor productivity, or distraction, there is also emerging research questioning whether analysts understand the impact of climate issues. Addoum et al. (2023), for example, investigate how extreme temperatures influence earnings, and they find that analysts expect at least a portion of the earnings shocks associated with extreme temperatures. Relatedly, Cuculiza et al. (2021) show that analysts in states where firms are more responsive to abnormal temperature changes issue less optimistic forecasts in periods following large temperature increases. They posit that analysts in areas where firms are more susceptible to the adverse effects of climate change would be more sensitive to large temperature changes and thus be more conservative in their forecasts.

We complement these findings by further investigating how the effect of climate change as an amplifier of uncertainty inherent in earnings, rather than its uni-directional or adverse impact on earnings or analysts' behavior, is associated with analysts' ability to predict earnings. Moreover, instead of past climate events such as abnormal temperatures, we employ a measure of concurrent trend in climate risk, the outcome of which could be more enigmatic and perplexing due to its progressive nature. Thence, we view firms' exposure to climate change as risks increasing uncertainty in earnings and examine its implications for financial analysts' ability to forecast by testing the relation between climate change and analyst forecast accuracy. Distinctively, we document a link between country-level climate risk and analysts' earnings forecasts by using an international sample and also look into its heterogeneity in relation to country characteristics.

3. Data and Variables

3.1. Sample selection

In this section, we illustrate our sample composition. To carry out our empirical analyses, we compile our datasets from multiple data sources. For our measure of climate risk, about which we provide a more detailed description in the following section, we obtain the Palmer Drought Severity Index (PDSI) data from the website of the National Centers for Environmental Information (NCEI), the National Oceanic and Atmospheric Administration (NOAA). Our analyst forecast variables are then constructed using the Institutional Brokers' Estimate System (I/B/E/S) database. We begin with all analysts' annual EPS forecasts from 1990 to 2014 from the I/B/E/S detail history file, which approximately results in 9.86 million observations. To minimize the time effect, in which forecast accuracy is inversely related to the time distance from the actual earnings announcement date, we include the latest forecast from an analyst before the actual earnings are announced if there are multiple forecasts per firm, which yields 391,569 observations. We also retain analyst EPS forecasts for the very next year (i.e., FPI=1). To calculate forecast error and dispersion, we require a minimum of two analyst forecasts in a given firm and year, which renders 330,340 observations. We then obtain financial and accounting information from Global Compustat and merge our analyst sample with firms that have information available for the variables employed in our baseline regression models. We exclude firms in regulated sectors (e.g., finance and utility industries) using two-digit SIC codes (49 and 60–69). Non-U.S. firms' market capitalization values are converted to U.S. dollars using exchange rate data from Compustat. We winsorize all continuous variables at the top and bottom 1 % levels. After dropping observations with missing firm-, analyst-, and country-specific variables, we end up with a sample of 161,853 firm-year observations (involving 24,879 unique firms and 45,097 unique analysts) from 36 countries for the period of 1990–2014. Our sample ends in 2014 due to PDSI data limitations.

3.2. Measure of climate risk

Following how drought trends are measured in Hong et al. (2019), we measure country-level climate risk by estimating time trends in droughts across countries. For this estimation, we use the Palmer

Drought Severity Index (PDSI) developed by Palmer (1965), a monthly metric broadly used in climate studies.[11] The data is updated monthly on the NOAA's website, and the index value extends back to the early 1900s. The index grades drought (dryness) and moist (wetness) conditions, and it is normalized using local surface moisture conditions. The index ranges from −10 to +10, with a lower PDSI indicating a more severe drought. Thus, the extreme values for PDSI, −10 and +10, signify extreme drought and highly moist conditions, respectively. However, in this study, we reverse the sign of PDSI so that higher or more positive values imply more severe drought-like conditions for a more straightforward interpretation of the results.[12]

To capture differential trends in climate change (droughts) across countries over time, we construct a measure of a country's vulnerability to droughts resulting from climate change for each of the 36 countries in our international sample. Employing long time series of PDSI for each country going back to the early 1900s and using a trend-stationary model, the following AR(1) model for PDSI that is augmented with a deterministic time trend t, we measure *Climate Risk* as the time trend of drought for each country i.

$$PDSI_{i,t} = a_i + b_i t + c_i PDSI_{i,t-1} + \epsilon_{i,t}$$

Here, the trend term (b_i), estimated using data from 1900 (or earliest date available) up to time t, is our parameter of interest that picks up the long-run effect of climate change on a country's drought vulnerability or the differential time trends in droughts for a country. We estimate this trend model for our sample of 36 countries on a rolling basis. In other words, in each year t from 1990 to 2014,[13] we use the annual PDSI values (annual average based on monthly values) for a country i from 1900 (or the earliest starting date) up to year t and estimate the time trend for the country. We denote this estimated time trend for a country i as $Climate\ Risk_{i,t}$, which has been used for a proxy for climate risk research in finance (e.g., Javadi and Masum, 2021; Javadi et al., 2023). Not only does this time trend differ among countries, but it also varies across time within each country. Furthermore, in contrast to other climate-related metrics such as historical climatic events, it is a progressive measure that captures the concurrent rise or decline in climate risk based on the continuous trajectories of climate change in each country. Then, we use these time trends to identify the countries that are more susceptible to droughts (i.e., more positive time trends in droughts) and the ones that are less vulnerable to droughts (i.e., more negative time trends in droughts).

3.3. Analyst forecast accuracy and control variables

In the literature on financial analyst forecasting, the absolute value of forecast error is often deemed as a proxy for analyst ability to forecast earnings accurately, and dispersion of forecasted earnings is utilized as a measure of the disagreement among analysts. To make this study complete and inclusive, we utilize both forecast error and forecast dispersion in this research. Following previous studies (e.g., Tan et al., 2011), forecast error (*ForeError*) is measured as the absolute value of the difference between the median forecasts of EPS and actual EPS, scaled by the stock price at the end of year t-1.[14] Also, forecast dispersion (*ForeDisp*) is defined as the standard deviation of all analyst EPS forecasts in a given year.

To control for factors that have already been identified as systematically affecting analyst forecast accuracy by previous studies, we include a set of firm-specific control variables, following Cao et al. (2022). For firm characteristics, we control for firm size (Ln *(*Assets)) as a proxy for a firm's general information environment (Atiase, 1987), Tobin's Q (*Q*) as a measure of firm value, return on assets (*ROA*) as a measure of profitability, whether the return on assets is negative (*Loss*) given that analysts tend to issue more optimistic forecasts in loss periods (Brown, 2001), debts (*Leverage*) as financial leverage can induce higher levels of earnings volatility by increasing financial risk (Parkash et al., 1995), tangibility (*Tangibility*) as tangible assets' values are less likely subject to information asymmetry and uncertainty (Barth et al., 2001; Gu and Wang, 2005), standard deviation of past three years' return on assets (*Std(ROA)*) as a proxy for forecast difficulty (Dichev and Tang, 2009), and Herfindahl index (*HHI*) to control for the effect of market competition on analyst forecast precision (Mattei and Platikanova, 2017). In addition, we include whether a firm's financial statements follow IFRS accounting standards (*IFRS*) as Horton et al. (2013) show that IFRS adoption is associated with improvements in analyst forecast accuracy, whether a firm's auditor is one of the top 4 auditors (*TopAudit*) considering their more substantial reputation incentives and stricter requirements (DeAngelo, 1981), and the number of analysts following a firm's EPS forecast (Ln *(*AnalyFollow)) as Lys and Soo (1995) suggest that greater analyst following indicates more intense competition among analysts and therefore greater incentives for analysts to improve forecast accuracy. For analyst characteristics, we include the number of analysts associated with a brokerage (Ln *(*BrokSize)) to measure analysts' available resources and number of years since an analyst first appeared in the I/B/E/S (Ln *(*AnalyExp)) to control for analyst general forecast experience.

Further, we also control for country-specific characteristics that could affect analyst forecast accuracy. As a country's financial reporting regime is likely associated with the development of economic and institutional characteristics, we include annual GDP growth rate (*GDPgrow*) to control for the growth of the economy. Moreover, Chen et al. (2021) find that stock market openness is negatively associated with analyst forecast errors due to the influx of foreign investors. To control for the governance effect of foreign investors, we include percentage of foreign direct investment in GDP (*FDI*) as well. A more detailed description of variable definitions is available in Appendix A.

3.4. Summary statistics

Table 1 presents the summary statistics of our sample. It shows that the average estimate of climate risk is 0.0232 with a standard deviation of 0.1130, which implies that there is an overall vulnerability to droughts, yet with substantial variations, around the globe. The mean

[11] The PDSI was initially created by Palmer (1965) for the purpose of evaluating the severity and frequency of abnormally dry periods. It is based on information about temperature and moisture in the soil, and this index enables the comparison of how severe the drought conditions are across regions. The key strength of this index is that it considers not only the degree of temperature and the amount of moisture in the soil but also some other factors that are hard to calibrate, such as evapotranspiration. Globally, it is available at the country-level and goes back to the early 1900s. Since the index is very robust for identifying drought, it is one of the most popular data in climate studies (Alley, 1984). Using PDSI, Hong et al. (2019) examine whether the prices of food stocks efficiently discount climate risks related to droughts, and Huynh et al. (2020) find that there is a positive relation between drought risk and the cost of equity capital.

[12] Originally, lower values of PDSI signify more drought-like conditions. Accordingly, Hong et al. (2019) classify countries with negative trends in droughts and countries with positive trends in droughts as the ones experiencing worsening droughts over time and improving climate conditions, respectively. On the contrary, in this study, we reverse the sign of PDSI so that higher values imply more severe drought-like conditions, and countries with more positive trends in drought are identified as the ones with more serious drought-related climate risk.

[13] The sample period ends in 2014 in this study due to data availability.

[14] Gu and Wu (2003) suggest using the median value of analyst forecasts to minimize a potential bias in forecasting. The results with forecast error and forecast dispersion with the mean forecasts of EPS are qualitatively the same as those with the median forecasts of EPS.

Table 2

Correlation Matrix. This table presents the Pearson and Spearman correlations of all variables used in our regression models. Pearson correlations appear below the diagonal, and Spearman correlations appear above the diagonal. Correlation coefficients that are significant at least at the 0.05 level appear in bold. All variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) *ForeError*	1	0.03	0.00	0.08	−0.14	−0.07	−0.10	−0.02	−0.03	−0.21	0.01	0.03	−0.45	0.08	0.05	0.28	−0.17	−0.20
(2) *ForeDisp*	0.12	1	0.44	−0.24	−0.17	−0.15	0.16	0.08	0.06	0.10	0.06	−0.03	−0.13	−0.18	−0.09	−0.09	0.04	0.00
(3) *Climate Risk*	0.11	0.77	1	−0.22	−0.23	−0.19	0.15	0.09	0.06	0.16	0.13	0.07	−0.06	−0.06	−0.07	−0.07	0.01	0.07
(4) Ln (Assets)	0.05	−0.07	−0.07	1	0.37	0.30	−0.29	0.08	0.10	−0.26	0.00	0.03	0.07	0.61	0.33	0.10	0.03	0.01
(5) *Q*	−0.11	0.00	−0.01	0.28	1	0.35	−0.01	−0.27	−0.19	0.16	−0.16	−0.06	0.15	0.14	0.01	−0.17	0.14	0.11
(6) *ROA*	0.03	−0.04	−0.05	0.30	0.00	1	−0.65	−0.08	0.07	−0.28	0.06	0.00	0.08	0.16	0.04	0.00	0.09	0.04
(7) *Loss*	−0.11	0.04	0.06	−0.29	0.08	−0.71	1	−0.12	−0.15	0.46	−0.10	−0.01	0.08	−0.15	−0.08	−0.10	−0.07	0.04
(8) *Leverage*	−0.02	0.04	0.05	0.05	−0.23	0.03	−0.09	1	0.35	−0.18	0.14	0.01	−0.01	0.07	0.11	0.04	0.00	−0.01
(9) *Tangibility*	−0.04	0.01	0.01	0.08	−0.16	0.11	−0.11	0.33	1	−0.20	0.16	−0.08	−0.05	0.05	0.08	−0.02	0.09	−0.01
(10) *Std(ROA)*	−0.16	0.04	0.04	−0.23	0.22	−0.54	0.47	−0.16	−0.19	1	−0.10	0.02	0.19	−0.13	−0.14	−0.15	−0.02	0.12
(11) *HHI*	−0.04	0.05	0.07	0.04	−0.08	0.08	−0.07	0.10	0.11	−0.10	1	0.40	0.03	0.10	0.06	0.13	−0.07	0.20
(12) *IFRS*	−0.02	−0.04	−0.01	0.04	−0.04	0.02	−0.01	−0.01	−0.07	−0.02	0.35	1	0.06	0.05	−0.07	0.18	−0.15	0.19
(13) *TopAudit*	−0.54	−0.08	−0.07	0.07	0.08	−0.02	0.08	−0.01	−0.01	0.12	0.05	0.06	1	0.10	0.02	−0.15	−0.07	0.23
(14) Ln (AnalyFollow)	0.01	−0.03	−0.02	0.61	0.08	0.16	−0.15	0.05	0.05	−0.13	0.11	0.06	0.10	1	0.43	0.05	−0.03	0.08
(15) Ln (BrokSize)	0.06	−0.05	−0.04	0.26	−0.02	0.07	−0.08	0.09	0.05	−0.11	0.04	−0.06	0.00	0.41	1	0.03	0.03	0.05
(16) Ln (AnalyExp)	0.28	0.01	0.01	0.11	−0.13	0.08	−0.10	0.03	−0.03	−0.11	0.08	0.15	−0.10	0.12	0.06	1	−0.25	−0.16
(17) *GDPgrow*	−0.04	−0.03	−0.04	0.05	0.12	0.07	−0.09	−0.01	0.07	−0.05	−0.06	−0.13	−0.15	−0.02	0.04	−0.25	1	0.36
(18) *FDI*	−0.10	−0.02	−0.01	0.00	0.02	0.00	0.01	0.00	−0.01	0.01	0.21	0.20	0.11	0.05	0.02	0.01	0.13	1

Table 3

Climate Risk and Analyst Forecast Accuracy by Country. The table presents climate risk and measures of analyst forecast accuracy (forecast error and forecast dispersion) by country.

Country	N	*Climate Risk*	*ForeError*	*ForeDisp*
Australia	4955	−0.1002	0.0659	0.0365
Austria	326	0.2346	0.1196	0.0502
Belgium	701	0.0320	0.0889	0.0374
Brazil	1222	0.2072	1.9614	0.7038
Canada	3882	−0.1209	0.1156	0.0385
Chile	427	0.1067	0.0892	0.0483
China	10,171	0.0988	0.0711	0.0296
Denmark	1115	−0.0995	0.2721	0.0976
Egypt	166	−0.1847	0.3701	0.1033
Finland	1444	0.0141	0.1161	0.0491
France	4967	0.0660	0.1400	0.0506
Germany	4901	0.0529	0.1712	0.0646
Greece	593	0.1471	0.0813	0.0367
India	2791	−0.1493	0.1724	0.0576
Indonesia	1141	0.0017	0.6469	0.2160
Ireland	360	0.0339	0.1224	0.1610
Israel	483	0.2622	0.0699	0.0341
Italy	1850	0.2004	0.0803	0.0401
Japan	19,541	0.2523	0.3146	0.1035
Malaysia	3463	0.0123	0.1383	0.0508
Mexico	816	−0.1771	0.1326	0.0814
Netherlands	1916	0.0422	0.1188	0.0546
New Zealand	535	−0.1638	0.0612	0.0262
Norway	1752	−0.1532	0.1905	0.0824
Philippines	458	0.1845	0.2463	0.1082
Poland	664	0.1281	0.0785	0.0361
Russia	325	−0.0920	0.1848	0.2436
South Africa	1682	0.0322	0.0875	0.0372
South Korea	2723	−0.0717	0.2961	0.0902
Spain	1027	−0.0029	0.1588	0.0527
Sweden	2694	−0.0291	0.1471	0.0550
Switzerland	2279	0.1358	0.4669	0.1347
Thailand	1841	0.1402	0.4250	0.1545
Turkey	842	−0.0540	0.6942	0.2669
United Kingdom	14,814	−0.0260	0.0870	0.0374
United States	62,986	−0.0306	0.0829	0.0277

values of forecast error and forecast dispersion are 0.1582 and 0.0568, respectively. Regarding the firm-level characteristics, this table shows that the mean values of (log-transformed) firm size, Tobin's Q, ROA, leverage, and tangibility are 5.9752, 1.8679, 0.0492, 0.2057, and 0.2901, respectively. About 17 % of the observations experience negative ROA (loss), the standard deviation of the past three years' ROAs is 0.0700, and the Herfindahl index is 0.1881, on average. Approximately 20.15 % of firms' financial statements follow IFRS accounting standards, and about 69.66 % of firms' auditors are among the top 4 auditors.

Concerning analyst characteristics, the mean log-transformed values of the number of analysts associated with a brokerage and the number of years since an analyst first appears in the I/B/E/S EPS forecasts file are 3.7931 and 1.8168, respectively. Lastly, the table also shows the descriptive statistics for country-level characteristics. On average, the annual GDP growth rate is 2.07 %, while foreign direct investment value is about 2.47 % of GDP.

Table 2 shows the Pearson and Spearman correlations among the variables included in our regressions. Not surprisingly, the two analyst forecast inaccuracy measures (*ForeError* and *ForeDisp*) are highly correlated. The positive correlations between *Climate Risk* and analyst forecast inaccuracy measures indicate that forecast error and dispersion tend to increase with higher climate risk or more vulnerability to drought-like conditions. Also, analyst forecast inaccuracy is negatively correlated with the adoption of IFRS accounting standards and the top 4 auditors.

Table 3 summarizes the results of the trend estimates along with the sample mean of forecast errors and dispersions for each country included in our sample. Notably, we observe a considerably large

Table 4
Climate Risk and Analyst Forecast Accuracy. This table presents the results estimated from OLS regressions where the dependent variable is analyst forecast accuracy: *ForeError* and *ForeDisp*. *ForeError* is measured as (median analyst EPS forecasts_t - actual EPS_t)/stock price at the end of year *t*-1. *ForeDisp* is measured as the standard deviation of all analyst EPS forecasts in a given year. *Climate Risk* is a country-level drought risk measure estimated from an AR (1) model (Hong et al., 2019). *Quintile 1–5* is a set of indicator variables that divide climate risk into five groups, with *Quintile 1* (lowest) and *Quintile 5* (highest). The definitions of other variables are available in Appendix A. All regressions include industry, year, and country fixed effects. The numbers shown in parentheses are *t*-statistics clustered at the country level. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	(1)	(2)	(3)	(4)
	$ForeError_t$		$ForeDisp_t$	
$Climate\ Risk_t$	0.8065		0.2495	
	(3.50)***		(3.13)***	
$Quintile\ 2_t$		−0.0287		−0.0105
		(−0.93)		(−0.97)
$Quintile\ 3_t$		−0.0209		−0.0136
		(−0.50)		(−0.91)
$Quintile\ 4_t$		0.0317		0.0094
		(0.77)		(0.71)
$Quintile\ 5_t$		0.2466		0.0748
		(2.87)***		(2.56)**
Ln $(Assets)_{t-1}$	−0.0366	−0.0354	−0.0141	−0.0138
	(−2.38)**	(−2.32)**	(−2.67)**	(−2.63)**
Q_{t-1}	0.0110	0.0095	0.0026	0.0021
	(0.77)	(0.67)	(0.63)	(0.50)
ROA_{t-1}	0.0682	0.0647	0.0308	0.0291
	(0.39)	(0.37)	(0.66)	(0.62)
$Loss_{t-1}$	0.0532	0.0550	0.0298	0.0303
	(1.86)*	(1.89)*	(3.17)***	(3.19)***
$Leverage_{t-1}$	0.1203	0.1204	0.0611	0.0609
	(2.93)***	(2.93)***	(3.22)***	(3.21)***
$Tangibility_{t-1}$	−0.0881	−0.0677	−0.0348	−0.0283
	(−1.14)	(−0.87)	(−1.39)	(−1.12)
$Std(ROA)_{t-1}$	0.2700	0.2765	0.0885	0.0906
	(2.88)***	(2.90)***	(2.36)**	(2.38)**
HHI_{t-1}	0.0460	0.0540	0.0131	0.0158
	(0.70)	(0.84)	(0.70)	(0.87)
$IFRS_{t-1}$	−0.1563	−0.1514	−0.0478	−0.0466
	(−1.94)*	(−1.85)*	(−1.80)*	(−1.73)*
$TopAudit_{t-1}$	0.0236	0.0232	0.0125	0.0123
	(0.97)	(0.93)	(1.61)	(1.53)
Ln $(AnalyFollow)_{t-1}$	0.0244	0.0241	0.0109	0.0111
	(1.11)	(1.16)	(1.21)	(1.31)
Ln $(BrokSize)_{t-1}$	−0.0317	−0.0303	−0.0076	−0.0072
	(−1.52)	(−1.48)	(−1.23)	(−1.17)
Ln $(AnalyExp)_{t-1}$	−0.0041	−0.0027	−0.0018	−0.0012
	(−0.56)	(−0.36)	(−0.90)	(−0.57)
$GDPgrow_{t-1}$	−0.9054	−0.9339	−0.3612	−0.3919
	(−1.42)	(−1.84)*	(−1.72)*	(−2.39)**
FDI_{t-1}	−0.1557	−0.1009	0.0294	0.0420
	(−0.78)	(−0.50)	(0.42)	(0.60)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	161,853	161,853	161,853	161,853
Adj. R2	0.048	0.051	0.047	0.050

dispersion in the drought trend estimates across countries, which accords with earlier climate studies.[15] For instance, Israel, Japan, and Austria are among the countries with the most significant degree of climate risk (trend estimates of 0.2622, 0.2523, and 0.2346, respectively). On the contrary, Egypt, Mexico, and New Zealand are among those with the lowest degree of climate risk and the slightest vulnerability to droughts (trend estimates of −0.1847, −0.1771, and −0.1638, respectively). There are also notable differences in the average values of forecast errors and dispersions across countries, which allows us to make some initial inferences regarding the relationship between climate risk and forecast accuracy. Although the clear relation cannot be identified here, it is discernible that numerous countries with more susceptibility to droughts (more positive estimates of *Climate Risk*) are often associated with greater average values of forecast inaccuracy measures, and vice versa. The country with the highest average values of forecast error and dispersion (1.9614 and 0.7038, respectively) is Brazil, which is also more vulnerable to droughts (climate risk of 0.2072) than many other countries. On the contrary, New Zealand, the nation with the lowest average values of forecast error and dispersion (0.0612 and 0.0262, respectively), shows one of the lowest climate risk estimates in our sample. Nevertheless, this comparison is only preliminary and cannot provide a complete and clear picture, at the univariate level, of how climate risk and forecast accuracy are related, leading us to conduct multivariate analysis in the following section.

4. Empirical results

4.1. Climate risk and analyst forecast accuracy

In this section, we examine whether climate risk affects analyst forecast accuracy. We run OLS regressions where the dependent variable is analyst forecast accuracy, measured as either forecast error (the absolute value of the difference between the median forecasts of EPS and actual EPS, scaled by the stock price at the end of year *t*-1) or analyst forecast dispersion (standard deviation of all analyst EPS forecasts in a given year). The variable of interest is our proxy for the country-level climate risk, estimated as time trends in drought-like conditions. The regressions include several firm, analyst, and country characteristics that are expected to be related to analyst forecast accuracy as control variables. To ensure that our findings are not swayed by any invisible time-invariant industry or country characteristics or unobserved differences in temporal trends, we employ industry-, country- and year-fixed effects in each of our regressions. Also, throughout the analyses, standard errors are adjusted for country clustering to account for a correlation in error terms across domestic firms whose responses to climate change might be dependent on one another (e.g., Petersen, 2009).

We report the regression results in Table 4. In the first model of Table 4, with forecast error employed as a dependent variable, the coefficient of the climate risk measure is positive and statistically significant. This result indicates that forecast error tends to increase with higher climate risk or more vulnerability to drought-like conditions. In the third model, where the dependent variable is replaced with forecast dispersion, the climate risk variable has a positive coefficient with statistical significance. Thus, these results from the two models imply that more severe time trends in droughts are associated with less accuracy in analyst forecasts, as denoted by higher analyst forecast error and greater dispersion in forecasted earnings. Also, the size of the relationship between climate risk and analyst forecast accuracy is substantial as one standard deviation increase in the degree of climate risk corresponds to a 0.0911 and 0.0282 increase in forecast error and dispersion, respectively. The control variables also display coefficients that are largely consistent with the existing literature. Larger firms generally have more accurate forecasts, while past earnings volatility is positively associated with forecast errors and dispersions. Also, with the adoption of IFRS

[15] In general, our estimates of climate risk as time trends in droughts are compatible with those presented in Hong et al. (2019), except that our estimates tend to be in opposite directions since we reverse the sign of PDSI.

accounting standards, lower forecast errors and dispersions are displayed. [16]

In the second and fourth models, we repeat our main analysis by employing an alternative approach to examine the relationship between climate risk and earnings forecast accuracy. The sample is sorted into quintiles based on climate risk, and then we generate a set of indicator variables, signifying the lowest degree of climate risk (*Quintile 1*) through the highest degree of climate risk (*Quintile 5*), to be included in the regressions in lieu of *Climate Risk*. In both Columns (2) and (4), the coefficients of the climate risk indicators generally exhibit a monotonic increase in size following the severity of climate risk (from *Quintile 2* towards *Quintile 5*). Above all, the variable indicative of the highest degree of climate risk (*Quintile 5*) is the one most positively and significantly associated with forecast errors and dispersions, in terms of both the magnitude and statistical significance of the coefficient.

Overall, the results presented in Table 4 suggest that analysts' forecasts of earnings tend to be less precise with a substantial degree of climate risk represented by time trends in droughts. Our results show that climate risk not only deteriorates analysts' ability to forecast earnings with accuracy (higher forecast error) but also heightens disagreement among analysts (higher forecast dispersion). We also explore the relation between climate risk and forecast accuracy using alternative measures of climate risk. With more details available in Section 4.6, the results are in line with those in Table 4, adding more validity to our findings.

4.2. Climate risk keywords in analyst report and analyst forecast accuracy

As presented in the previous section, there exists a significantly negative relation between climate risk and forecast accuracy. Regarding the plausible mechanism through which climate risk affects forecast accuracy, we suggest it could be related to analysts' handling of climate risk as non-financial information in their forecasting task. On one hand, analysts may tend to overlook the relevance of climate risk and generate incorrect forecasts, especially as climate change has been perceived as a critical factor for businesses only recently.[17] On the other hand, it is also likely that analysts recognize the importance of climate risk for firms, yet they lack a thorough grasp of how climate change would affect earnings and hence fail to properly incorporate climate risk into their forecasts of earnings. In this case, somewhat paradoxically, analysts who consider climate risk may produce more inaccurate forecasts since including non-financial information that they cannot comprehend well could rather magnify the complexity and even lead to incorrect direction in forecasting. On top of that, when analysts recognize the relevance of climate risk for some firms in their reports, those particular businesses would tend to be more vulnerable to climate risk and thus have earnings that are harder to predict.

Our premise is that when analysts acknowledge the influence of climate change, they would be more likely to add relevant statements explicitly to their reports. Thus, we extract analyst reports from the Refinitiv Thomson One database and identify the reports that contain keywords related to climate change. In order to identify diverse and inclusive information related to climate change, we consider five terms: climate, weather, global warming, carbon, and renewable energy.[18] Then, we run the main regression of Table 4 separately for two groups, sorted by whether the analyst report contains climate keywords or not.[19] If our main result is primarily due to analysts' inattention to the importance of climate risk, then a more significant relation between climate risk and analyst forecast accuracy is expected in the subsample in which climate keywords are absent. On the contrary, if analysts recognize the relevance of climate risk but are unable to incorporate the information adequately into their forecasts, they would attribute inaccurate forecasts to climate risk in the analyst report. In that case, we would expect to observe a stronger link between climate risk and forecast accuracy in the group with climate keywords in analyst reports.

Table 5 presents the outcome. When climate-related keywords are mentioned in analyst reports, the link between climate risk and forecast inaccuracy (forecast error and forecast dispersion) becomes more powerful. In contrast, when analyst reports do not include any of the climate keywords, the relation between climate risk and analyst forecast inaccuracy still remains, but it is much weaker, as supported by the

Table 5
Climate Risk Keywords in Analyst Report and Analyst Forecast Accuracy. This table presents the results estimated from subsample analyses based on whether the relevance of climate risk is mentioned in analyst reports. The sample is sorted by whether analyst report contains any of the five keywords related to climate risk, and those five climate risk keywords are climate, weather, global warming, carbon, and renewable energy. The dependent variable is analyst forecast accuracy: *ForeError* and *ForeDisp*. *ForeError* is measured as (median analyst EPS forecasts$_t$ - actual EPS$_t$)/stock price at the end of year *t*-1. *ForeDisp* is measured as the standard deviation of all analyst EPS forecasts in a given year. *Climate Risk* is a country-level drought risk measure estimated from an AR (1) model (Hong et al., 2019). The definitions of other variables are available in Appendix A. All regressions include the same set of control variables (used in Table 4), industry, year, and country fixed effects. The numbers shown in parentheses are *t*-statistics clustered at the country level. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	(1)	(2)	(3)	(4)
	ForeError$_t$		*ForeDisp$_t$*	
	Keywords	No Keyword	Keywords	No Keyword
Climate Risk$_t$	5.5961	0.7939	1.7431	0.2460
	(2.15)**	(5.27)***	(2.08)*	(5.08)***
	H0: β(1) = β (2)		H0: β(3) = β (4)	
	[2.65]***		[2.54]* *	
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	4951	143,119	4951	143,119
Adj. R2	0.220	0.050	0.208	0.047

[16] In unreported tests, the analyses are repeated with geographical fixed effects, based on latitudes of the country, employed instead of country-fixed effects to control for the effect of time-invariant geographic characteristics on analyst forecasting accuracy in an alternative way. The results mirror the ones with country-fixed effects, supporting that our findings are not swayed by certain geographic characteristics. Using geographical fixed effects based on latitudes and longitudes also generates similar results.

[17] Also, according to prior findings, a possible explanation for the association between climate change and analyst forecast accuracy could be based on the effect of climate change on analyst mood or distraction (e.g., Dong et al., 2019; Han et al., 2024; Li et al., 2020).

[18] For instance, an analyst report from the Canadian Imperial Bank of Commerce (issued in April 2012) about Mullen Group Ltd. mentions "changes in climate change regulations or carbon pricing and taxes" as part of the key risks to the covered firm. In addition, an analyst report from the DBS Bank (issued in July 2020), covering 29 stocks in the oil & gas exploration, coal mining, and power generation sectors in China, Hong Kong, Indonesia, Malaysia, and Thailand, contains several sections discussing climate issues such as increasing carbon emissions in developing countries, how climate change will affect businesses, and the risk of carbon emissions.

[19] In 4951 firm-year analyst report observations, terms related to climate risk are mentioned at least once. Considering each keyword, the number of firm-year observations mentioning climate is 1926, and the number of firm-year observations mentioning weather is 3671. The number of firm-year observations mentioning global warming, carbon, and renewable energy is 153, 632, and 161, respectively.

Table 6
Climate Risk and Earnings Volatility. This table presents the results estimated from OLS regressions where dependent variable is a measure of a firm's earnings volatility: $Std(QtrROA)_t$, $Std(ROA)_{[t,t+2]}$, and $Std(ROA)_{[t,t+4]}$. $Std(QtrROA)_t$ is the standard deviation of quarterly ROA in a given year. $Std(ROA)_{[t,t+2]}$ is the standard deviation of ROA for the next three years. $Std(ROA)_{[t,t+4]}$ is the standard deviation of ROA for the next five years. *Climate Risk* is a country-level drought risk measure estimated from an AR (1) model (Hong et al., 2019). The definitions of other variables are available in Appendix A. All regressions include industry, year, and country fixed effects. The numbers shown in parentheses are *t*-statistics clustered at the country level. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	(1)	(2)	(3)
	$Std(QtrROA)_t$	$Std(ROA)_{[t,t+2]}$	$Std(ROA)_{[t,t+4]}$
Climate Risk	0.2648	0.2070	0.4818
	(3.31)***	(2.95)***	(2.07)**
Ln (Assets)	0.0047	0.0089	−0.0005
	(1.97)*	(3.64)***	(−0.17)
Q	−0.0063	−0.0141	0.0043
	(−3.91)***	(−4.74)***	(2.39)**
ROA	1.3640	1.1631	0.1160
	(22.48)***	(16.59)***	(1.14)
Loss	0.0221	0.0009	−0.0147
	(0.95)	(0.03)	(−0.92)
Leverage	−0.0486	−0.0650	−0.0364
	(−4.61)***	(−4.38)***	(−1.77)*
Tangibility	−0.0112	0.1111	0.0270
	(−1.15)	(5.47)***	(0.87)
Std(ROA)	−0.6404	−0.3657	−0.0861
	(−19.80)***	(−21.97)***	(−1.05)
HHI	−0.0192	0.0032	0.0237
	(−1.15)	(0.10)	(0.88)
IFRS	−0.0398	−0.0601	−0.0841
	(−2.48)**	(−3.72)***	(−3.14)***
TopAudit	0.0080	0.0223	0.0233
	(1.13)	(2.49)**	(1.85)*
Ln (*AnalyFollow*)	−0.0136	−0.0018	−0.0042
	(−3.73)***	(−0.35)	(−0.47)
Ln (BrokerSize)	0.0065	0.0059	−0.0174
	(1.85)*	(1.40)	(−1.78)*
Ln (*AnalyExp*)	0.0103	0.0140	0.0167
	(2.16)**	(3.12)***	(3.11)***
GDPgrow	0.7855	0.4243	−0.4347
	(4.75)***	(3.02)***	(−0.83)
FDI	−0.2250	−0.3603	−0.2327
	(−1.75)*	(−1.94)*	(−1.46)
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Country FE	YES	YES	YES
Observations	161,853	161,853	161,853
Adj. R2	0.299	0.168	0.202

smaller size of the coefficient in every specification. Further, the differences in the two subsamples' coefficients are statistically significant. The inclusion of the keywords related to climate change could manifest that analysts are aware of the nontrivial impact of climate risk on businesses. However, those analysts seem to face more serious difficulty in understanding the impact of climate risk and incorporating the information into earnings forecasts, as corroborated by greater forecast inaccuracy. Hence, by showing that the adverse effect of climate risk on forecast accuracy is more substantial for the firms about which analyst reports mention climate-related words, the results demonstrate that analysts recognize some businesses to be more susceptible to climate risk and acknowledge the importance of climate risk but do not correctly integrate it into forecasting.

4.3. Climate risk and earnings volatility

We have demonstrated a notably adverse association between climate risk and forecast accuracy, primarily stemming from analysts' limited comprehension of climate risk. The next inquiry pertains to how climate risk hinders the task of analysts. While prior studies often emphasize the negative or one-sided influence of climate change on earnings (e.g., Cuculiza et al., 2021; Pankratz et al., 2023), it has also been suggested that certain firms might benefit from climate change (e.g., Hugon and Law, 2019). Thus, we propose that climate risk, with its bi-directional nature, contributing to heightened earnings uncertainty rather than solely negative impacts, could undermine analysts' ability to forecast earnings, thereby promoting the relationship posited in this study.

To investigate whether the negative relationship between climate risk and forecast accuracy is driven, at least to a certain extent, by increased uncertainty of earnings, we conduct an additional test in this section. We perform this test by running regressions where the dependent variable is a measure of a firm's earnings volatility, and we consider a number of ways to measure earnings volatility. It is measured as the standard deviation of quarterly ROA in a given year ($(Std(QtrROA)_t)$, the standard deviation of ROA for the next three years $(Std(ROA)_{[t,t+2]})$, or standard deviation of ROA for the next five years $((Std(ROA)_{[t,t+4]})$. The variable of interest is our measure of the country-level forward-looking climate risk, estimated as time trends in droughts.

The results are presented in Table 6. Throughout different specifications, the coefficient of our proxy for climate risk is positive with robust statistical significance. Hence, irrespective of how earnings volatility is measured, the results consistently demonstrate that earnings are more volatile when a firm is located in a country with more solid time trends in drought-like conditions (higher climate risk). This result is in accordance with Huang et al. (2018), showing that firms in countries experiencing higher climate risk are associated with higher earnings volatility.[20] Overall, the results lend support for our view that a substantial degree of climate risk has the effect of augmenting the inherent vagueness of earnings, which thus would confound the analyst's task of producing earnings forecast.

4.4. Country characteristics and the effect of climate risk on forecast accuracy

In this section, we examine whether country characteristics influence the effect of climate risk on forecast accuracy. We pay special attention to four different types of country characteristics that potentially could affect the extent to which climate risk impacts firms' earnings. First, we consider country-level dependency on hydroelectric sources for electricity generation and assume that firms would be more severely struck by drought-like conditions when their home countries are more heavily reliant on hydroelectric sources for electricity generation. In summer 2022, for example, dry weather and extreme drought in southwestern China crippled huge hydroelectric dams, forcing cities to impose rolling blackouts and blocking off ships transporting supplies.[21] So, when a country relies more on hydroelectric sources to generate electricity, businesses would be more vulnerable to business disruptions caused by droughts. Second, we identify countries where agricultural and food production sectors play more vital roles in the economy by computing the percentage of agricultural products and food merchandises in total exports in each country. While agricultural and food industries are evidently the ones that are more heavily affected by climate change (e.

[20] In Huang et al. (2018), climate risk is based on the extent of economic losses from extreme weather events (e.g., major storms, flooding, and heat waves).

[21] An article in the New York Times, titled "China's Record Drought Is Drying Rivers and Feeding Its Coal Habit," covers more details. The full article can be found at https://www.nytimes.com/2022/08/26/business/economy/china-drought-economy-climate.html?campaign_id=9&emc=edit_nn_20220907&instance_id=71265&nl=the-morning&regi_id=84823470&segment_id=105577&te=1&user_id=7178643657c965e1e1ae10f770b76e84.

g., Wilbanks et al., 2007),[22] we posit that earnings of firms in other industries can also be more greatly affected by climate change when they are located in countries where agricultural and food products industries are more important. When agricultural and food manufacturing industries are dominant, the overall industrial structure is very likely to be centered on those sectors, and firms in other non-agricultural and non-food industries would be more likely to have significant operations and business relations with companies in those agricultural and food manufacturing industries. As a result, when agricultural and food manufacturing sectors, which are highly sensitive to climate conditions, are more essential in a country, businesses in other industries in that country will also have earnings more impacted by climate change, owing to the chain effect.

In addition, while our primary focus is on the effect of physical climate risk denoted by drought trends, we now question how the effect of physical climate risk could interact with transition climate risk (i.e., a type of climate risk that arises from increased awareness of climate changes and political movement to mitigate them) in the context of our research since the level of transition climate risk may vary even among countries with a high degree of physical climate risk. To capture transition climate risk, we consider country characteristics that would be relevant to the likelihood of taking more proactive approaches to climate issues, which are country-level total CO_2 emissions and political ideology. Specifically, countries often have big bipartisan divides on climate issues, with more liberal, non-conservative, or left-of-center parties often expressing more intense concerns and active efforts regarding climate change.[23] We argue that countries with lower total CO_2 emissions and governments with non-conservative political ideologies, which are more likely to take a preemptive approach to climate issues, will tend to implement more environment-related regulations or policies that may cause more uncertainties in firms' earnings due to greater exposure to transition risks.

To examine how these country characteristics influence the effect of climate risk on forecast accuracy, we add variables indicating each country's reliance on hydroelectric sources in electricity generation, the importance of agricultural and food production industries in the economy, total CO_2 emissions, and non-conservative government to the main regression in Table 4. We also include interaction terms between each of those country characteristic variables and our measure of climate risk. The regressions use the same set of control variables as in Table 4, as well as year-, industry-, and country-fixed effects.

We present the results in Table 7. In Panel A, the results generally follow the prior findings; in the presence of sizable climate risk, forecast

[22] According to Wilbanks et al. (2007), industries' vulnerability and challenges to adapting to variations in environmental conditions depend on businesses' flexibility and capacity to adapt. They claim that industries with longer-lived capital assets (e.g., energy) are especially susceptible to losses caused by extreme weather. They also show that industries with weather-dependent resources and extended supply-chain are more likely to be vulnerable to climate change impacts. Examples of such industries are mining, agriculture, and food manufacturing. Huang et al. (2018) find that some industries are less vulnerable to extreme weather and thus face less climate-related risk. Mainly, they consider agriculture, energy (including mining and oil extraction), food products, healthcare, communications, business services, and transportation to be vulnerable industries.

[23] For example, the Pew Research Center provides an article, titled "The U.S. isn't the only nation with big partisan divides on climate change," about how several nations have strong political divisions on the climate issue. The full article can be found at https://www.pewresearch.org/fact-tank/2015/11/06/the-u-s-isnt-the-only-nation-with-big-partisan-divides-on-climate-change/. As stated in the article, followers of right-of-center parties tend to be less likely to be worried about climate change, compared to those with left-leaning parties. In addition, Farstad (2018) finds that left-right political ideology is more critical than any other party characteristic in explaining the differences in political parties' climate change salience tendency cross-nationally.

Table 7

By Country Characteristics. This table presents the results estimated from subsample analyses based on the firm's home country characteristics. *Hydro* is the percentage of reliance on hydroelectric sources to generate electricity at home country. *Agr&Food* is the percentage of the sum of agricultural products and food merchandizes in all export at home country. *InvCO2Emiss* is the inverse value of total CO2 emission at home country. *NonConservative* is an indicator variable that takes the value of one if the incumbent government's political ideology is either left or central and zero otherwise. *Climate Risk* is a country-level drought risk measure estimated from an AR (1) model (Hong et al#, 2019). All regressions include the same set of control variables (used in Table 4), industry, year, and country fixed effects, but their coefficients and *t*-statistics are omitted for brevity. The numbers shown in parentheses are *t*-statistics clustered at the country level. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Panel A. Analyst Forecast Error

	(1)	(2)	(3)	(4)
	ForeError			
Climate Risk	0.1723	0.6767	1.0725	0.7703
	(0.88)	(3.67)***	(5.76)***	(4.34)***
Climate Risk x Hydro	0.0437			
	(6.03)***			
Hydro	0.0068			
	(7.80)***			
Climate Risk x Agr&Food		0.0660		
		(3.95)***		
Agr&Food		0.0116		
		(4.66)***		
Climate Risk x InvCO2Emiss			0.0067	
			(4.22)***	
InvCO2Emiss			−0.0001	
			(−1.06)	
Climate Risk x NonConservative				0.3721
				(3.78)***
NonConservative				0.0247
				(4.24)***
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	161,853	161,848	141,629	133,302
Adj. R-squared	0.086	0.062	0.051	0.051

Panel B. Analyst Forecast Dispersion

	(1)	(2)	(3)	(4)
	ForeDisp			
Climate Risk	0.0395	0.1927	0.3281	0.2329
	(0.66)	(3.36)***	(5.74)***	(4.19)***
Climate Risk x Hydro	0.0145			
	(6.31)***			
Hydro	0.0022			
	(8.13)***			
Climate Risk x Agr&Food		0.0248		
		(4.71)***		
Agr&Food		0.0040		
		(5.04)***		
Climate Risk x InvCO2Emiss			0.0019	
			(4.01)***	
InvCO2Emiss			−0.0000	
			(−0.76)	
Climate Risk x NonConservative				0.0999
				(3.61)***
NonConservative				0.0060
				(2.96)***
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	161,853	161,848	141,629	133,302
Adj. R-squared	0.082	0.063	0.050	0.047

Table 8

By Analyst Characteristics. This table presents the results estimated from subsample analyses at the analyst level. The dependent variable is analyst forecast accuracy: *AnalyError*. *AnalyError* is measured as (analyst's individual EPS forecast$_t$ - actual EPS$_t$)/stock price at the end of year *t*-1. *Climate Risk* is a country-level drought risk measure estimated from an AR (1) model (Hong et al., 2019). *Ln(AnalyExp)* is the logarithm-transformed number of years since an analyst first appears in the I/B/E/S EPS forecast file. *Ln(AnalyCover)* is the logarithm-transformed number of firms that analyst follows in a given industry (SIC2). All regressions include the same set of control variables (used in Table 4), industry, year, and country fixed effects, but their coefficients and *t*-statistics are omitted for brevity. The numbers shown in parentheses are *t*-statistics clustered at the country level. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	(1)	(2)	(3)
	AnalyError		
Climate Risk	0.7063	0.9335	0.9167
	(6.41)***	(6.95)***	(6.59)***
Climate Risk x Ln(AnalyExp)		−0.0654	
		(−4.17)***	
Ln (AnalyExp)		−0.0092	
		(−5.01)***	
Climate Risk x Ln(AnalyCover)			−0.1069
			(−2.90)***
Ln (AnalyCover)			−0.0039
			(−2.31)**
Controls	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Country FE	YES	YES	YES
Observations	1147,502	1147,502	1147,502
Adj. R-squared	0.060	0.061	0.060

error tends to be greater, signifying less accurate forecasts. Moreover, according to the positive and statistically significant coefficients of the interaction terms, this effect appears more robust when firms' home countries rely more on hydroelectric sources in electricity generation and have economies where agricultural and food manufacturing sectors are more important. Additionally, supporting the notion of an interaction effect between physical and transition risks, the impact of physical climate risk in making forecasts harder is more evident when firms' home countries are also more likely to have a greater degree of transition climate risk, denoted by lower total CO2 emissions and non-conservative governments. Similar findings are obtained in Panel B, where the dependent variable is substituted by analyst forecast dispersion. In sum, while there is a general relation between climate risk and forecast accuracy, the intensity of the relationship is affected by country characteristics.

4.5. Analyst characteristics and the effect of climate risk on forecast accuracy

Concerning the effect of climate risk deteriorating forecast accuracy, an interesting follow-up question would be whether the observed association between climate risk and forecast inaccuracy is moderated by analyst attributes. We propose two variables of analyst characteristics, based on several papers suggesting that experience matters in the context of analyst forecasting performance. A number of papers suggest that general analyst experience translates into more accurate forecasts (e.g., Clement, 1999; Clement et al., 2007). Hence, we consider the analyst's general forecast experience, which we measure with the number of years since an analyst first appears in the I/B/E/S EPS forecast file. In addition, it is commonly known that analysts tend to specialize in particular industries, which is related to analysts' forecasting. For instance, Clement (1999) and Bradley et al. (2017) show that analysts' forecast accuracy increases with their industry specialties. Thus, we also consider the analyst's industry-specific forecast specialty, which is measured as the number of firms followed by the analyst in a given industry and year, where an industry is classified based on the first two digits of the SIC code.

Then, we add these variables reflecting analysts' general experience and industry-specific specialty to the regressions. We also include interaction terms between each of these analyst attribute variables and our measure of climate risk in the regressions. Here, the difference between these tests and our prior regressions is that the analyses in this section are conducted at the analyst level, since our interest is in whether individual analysts' characteristics matter for how their forecasts are affected by climate risk. Accordingly, the dependent variable in these regressions is forecast error at the analyst level, which is computed as (individual analyst's EPS forecast$_t$ – actual EPS$_t$)/stock price at the end of year *t*-1.

Table 8 presents the outcome. The result in Column (1) confirms our main argument on the impact of climate risk on analyst forecast error by providing analyst-level evidence. More notably, in Columns (2) and (3), the interaction terms between our climate risk variable and analyst experience measures generate negative coefficients with statistical significance. As a consequence, the results in this table suggest that the role of analysts' tenure and industry experience is effective in generating more accurate earnings forecasts given the complications induced by climate risk. These results suggest that analysts' experience is helpful to better comprehension in navigating the impacts of climate risk as a novel type of factor. [24]

Numerous papers in the literature on forecast accuracy point to analysts' limited skills or limited information available to them as significant factors influencing forecast accuracy. In Table 5, where we run subsample analyses based on the inclusion of climate-related keywords in the analyst report, the results imply that analysts who acknowledge the importance of climate risk, potentially based on the information provided to them, face serious difficulty in understanding the impact of climate risk and incorporating the information into earnings forecasts. Furthermore, in Table 8, the results suggest that analysts' experience, which is closely related to their general or industry-specific skills, is useful for better comprehension in navigating the impacts of climate risk as a novel type of factor. Hence, based on the results in Tables 5 and 8, we infer that analysts' limited understanding specifically about climate risk as a new type of factor is a contributor to the linkage between climate risk and forecast accuracy, which can be at least partially alleviated with their general or industry-specific skills.

4.6. Robustness tests

We conduct robustness tests based on alternative measures of climate risk and include the results in Table 9. First, we consider raw values of the weighted Palmer Drought Severity Index, which is calculated on the wetness and dryness index terms using probability as the weighting factor (*PDSI*). As in our previous analyses, we reverse the sign of PDSI so that higher values of *PDSI* imply more dry conditions. We also use *Abn_PDSI10* and *Abn_PDSI20*, calculated as the difference between the concurrent value of PDSI and the average value of PDSI in a country during the past 10 and 20 years, respectively. In Panel A, Models (1) through (3) present that these alternative measures of climate risk are

[24] In untabulated results, we also examine if corporate earnings quality influences how strong the relation between climate risk and forecast accuracy is. We focus on discretionary accruals and disclosure quality to analyze the relation between our main finding and a firm's earnings quality. The results show that, even with a considerable degree of climate risk potentially complicating the forecasts, the adverse impact on forecast accuracy is less severe when firms produce a better quality of earnings. In other words, the results imply that corporate earnings quality moderates the negative relation between climate risk and how precise analyst forecasts are.

Table 9
Alternative measurements of Climate Risk. This table presents the results with alternative climate-risk variables. Panel A uses raw and abnormal PDSI measures. *PDSI* is the weighted Palmer Drought Severity Index by the wet and dry index terms using probability as the weighting factor (PDSI). *Abn_PDSI10 (or Abn_PDSI20)* is difference the concurrent PDSI index and average PDSI index from past 10 (or 20) years. *Abs(Abn_PDSI20>0) (or Abs(Abn_PDSI20<0))* is the absolute value of the positive (or negative) difference between the concurrent PDSI and the country's average PDSI from the past 20 years. Panel B uses an alternative measurement of climate risk developed by Notre Dame Global Adaptation Initiative. *GAIN* is the inverse of the ND-Gain Country index, which measures a country's vulnerability to climate change by reflecting a heterogeneous level of geographical location or socioeconomic condition across countries. *SENSITIVITY* is the degree to which people and the sectors they depend upon are affected by climate-related perturbations. The factors increasing sensitivity include the degree of dependency on sectors that are climate-sensitive and the proportion of populations sensitive to climate hazards due to factors such as topography and demography. A greater value of *GAIN* and *SENSITIVITY* signifies higher climate risk, and vice versa. The definitions of other variables are available in Appendix A. All regressions include control variables (used in Table 4), industry, year, and country fixed effects, but are omitted for brevity. The numbers shown in parentheses are *t*-statistics clustered at the country level. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Panel A. Abnormal drought

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ForeError				*ForeDisp*			
PDSI	0.0036				0.0015			
	(3.24)***				(4.65)***			
Abn_PDSI10		0.0038				0.0009		
		(3.78)***				(2.77)***		
Abn_PDSI20			0.0053				0.0015	
			(3.65)***				(2.99)***	
Abs(Abn_PDSI20>0)				0.0129				0.0033
				(4.44)***				(3.37)***
Abs(Abn_PDSI20<0)				0.0199				0.0053
				(6.94)***				(5.93)***
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	161,853	161,853	161,853	161,853	161,853	161,853	161,853	161,853
Adj. R2	0.0235	0.0293	0.0294	0.0303	0.0255	0.0255	0.0310	0.0316

Panel B. ND-Gain Country index

	(1)	(2)	(3)	(4)
	ForeError		*ForeDisp*	
GAIN	0.0067		0.0029	
	(3.06)***		(5.28)***	
SENSITIVITY		3.6998		1.0470
		(7.86)***		(7.52)**
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	171,253	171,253	171,253	171,253
Adj. R2	0.057	0.058	0.143	0.144

positively related to forecast errors, while Models (5) through (7) also support the idea that severe time trends in droughts as a result of climate change tend to increase forecast dispersion.

Concerning the view that not only extreme dryness but also extreme wetness can be viewed as severe climate change, we try considering both extreme dryness and extreme wetness as climate risk since PDSI provides information on the degree of dryness as well as the level of wetness. When the difference between the concurrent PDSI and the country's average PDSI from the past 20 years is positive (*Abn_PDSI20>0*), it signifies a more drought-like condition. Conversely, when the difference between the concurrent PDSI and the country's average PDSI from the past 20 years is negative (*Abn_PDSI20<0*), it implies an exceptionally wetter condition. Then, by taking the absolute values of each, higher values of *Abs(Abn_PDSI20>0)* and *Abs(Abn_PDSI20<0)* represent the significantly dry condition and substantially wet condition, respectively. We add these two different measures in Models (4) and (8) in Panel A. The results are in line with those presented in our main tables and confirm our finding of an adverse effect of vulnerability to droughts on forecast accuracy. In addition, the results also imply that extreme wetness as a climate risk has a similar effect.

In Panel B, to further confirm the soundness of our results, the main analysis is repeated with alternative measure of climate risk employed as a key independent variable. We obtain the country-level climate data from the website of the Notre Dame Global Adaptation Initiative (ND-Gain) (https://gain.nd.edu/our-work/country-index/). The ND-Gain Country index measures a country's vulnerability to climate change by reflecting a heterogeneous level of geographical location or socioeconomic condition across countries, ranging from 0 (highest climate risk) to 100 (lowest climate risk), and is available annually from 26.98 to 77.83.[25] Another climate measure is *SENSITIVITY*, which is the degree to which people and the sectors they depend upon are affected by climate-related perturbations. The factors increasing sensitivity include the degree of dependency on sectors that are climate-sensitive and the proportion of populations sensitive to climate hazards due to factors such as topography and demography, and a greater value of *SENSITIVITY* signifies a higher degree of climate risk. We use the inverse ND-Gain Country index (*GAIN*) and *SENSITIVITY* as alternative measures of

[25] More precisely, the ND-Gain climate risk quantifies a country's vulnerability in six life-supporting sectors (food, water, health, ecosystem, human habitat, and infrastructure) against climate hazard. See the manual for a more detailed description of the data via https://gain.nd.edu/assets/254377/nd_gain_technical_document_2015.pdf.

Table 10
Country Variation. This table divides our sample into U.S. vs. non-U.S. firms. *Climate Risk* is a country-level drought risk measure. *Climate Risk_State* is a state-level drought risk measure based on the state where U.S. firms' headquarters reside. The definitions of other variables are available in Appendix A. All regressions include industry, year, and country fixed effects. The numbers shown in parentheses are *t*-statistics clustered at the country level or state level. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ForeError				*ForeDisp*			
	US	Non-US	Non-US	US	US	Non-US	Non-US	US
Climate Risk	0.3878	0.7422	0.6731		0.1851	0.2172	0.1975	
	(1.33)	(3.17)***	(2.89)***		(2.65)**	(2.78)**	(2.46)**	
Climate Risk_State				0.0754				0.0116
				(3.07)***				(1.66)*
Ln (Assets)	−0.0163	−0.0499	−0.0515	−0.0124	−0.0065	−0.0193	−0.0201	−0.0058
	(−3.23)***	(−2.25)**	(−2.34)**	(−5.25)***	(−4.50)***	(−2.66)**	(−2.83)***	(−8.17)***
Q	−0.0075	0.0228	0.0239	−0.0073	−0.0026	0.0060	0.0066	−0.0023
	(−2.65)**	(1.09)	(1.14)	(−2.74)***	(−4.80)***	(0.95)	(1.04)	(−5.43)***
ROA	−0.1782	0.2449	0.2508	−0.2062	−0.0303	0.0521	0.0551	−0.0356
	(−3.35)***	(1.00)	(1.02)	(−5.17)***	(−1.89)*	(0.79)	(0.84)	(−2.71)***
Loss	0.0042	0.0930	0.0905	0.0051	0.0138	0.0413	0.0402	0.0136
	(0.22)	(3.12)***	(3.11)***	(0.28)	(2.69)**	(4.12)***	(4.18)***	(2.89)***
Leverage	0.0898	0.1376	0.1377	0.0840	0.0352	0.0785	0.0786	0.0339
	(2.94)***	(2.54)**	(2.55)**	(6.60)***	(4.34)***	(3.88)***	(3.93)***	(9.06)***
Tangibility	0.0467	−0.1317	−0.1259	0.0317	0.0122	−0.0506	−0.0486	0.0100
	(2.45)**	(−1.35)	(−1.27)	(1.48)	(3.03)***	(−1.65)	(−1.56)	(2.46)**
Std(ROA)	0.1489	0.5219	0.5219	0.1621	0.0410	0.1939	0.1934	0.0434
	(4.26)***	(3.31)***	(3.32)***	(8.88)***	(5.77)***	(3.07)***	(3.11)***	(8.52)***
HHI	0.0270	0.0602	0.0657	0.0539	0.0158	0.0179	0.0200	0.0219
	(0.23)	(0.81)	(0.90)	(0.89)	(0.52)	(0.80)	(0.91)	(1.18)
IFRS	0.0084	−0.1215	−0.1454	0.0381	−0.0143	−0.0371	−0.0473	−0.0088
	(0.28)	(−1.27)	(−1.53)	(1.58)	(−1.76)*	(−1.15)	(−1.52)	(−1.22)
TopAudit	0.0026	0.0193	0.0210	−0.0119	0.0016	0.0101	0.0111	−0.0006
	(0.19)	(0.74)	(0.82)	(−1.17)	(0.40)	(1.21)	(1.34)	(−0.19)
Ln (AnalyFollow)	−0.0113	0.0502	0.0505	−0.0066	−0.0052	0.0243	0.0246	−0.0046
	(−2.78)**	(1.74)*	(1.79)*	(−2.80)***	(−4.56)***	(2.46)**	(2.57)**	(−6.06)***
Ln (BrokerSize)	0.0054	−0.0556	−0.0519	0.0025	0.0016	−0.0140	−0.0124	0.0011
	(1.83)*	(−2.86)***	(−2.66)**	(1.00)	(1.92)*	(−2.20)**	(−1.93)*	(1.50)
Ln (AnalyExp)	−0.0138	−0.0009	−0.0033	0.0034	−0.0002	−0.0010	−0.0020	0.0033
	(−1.49)	(−0.07)	(−0.27)	(1.04)	(−0.11)	(−0.33)	(−0.69)	(3.75)***
GDPgrow			−1.1771				−0.4814	
			(−2.06)*				(−2.72)**	
FDI			−0.4174				−0.0647	
			(−1.88)*				(−0.92)	
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	NO	YES	YES	YES	NO
Observations	62,986	98,866	98,866	62,986	62,986	98,866	98,866	62,986
Adj. R2	0.0569	0.058	0.0602	0.0785	0.0513	0.0525	0.0538	0.0620

climate risk and find that our results continue to hold, adding more credibility to the main findings of this study and alleviating concerns about the generalizability of our results due to the limited sample period. In sum, the results in Table 9 indicate that the findings of this study are consistent even with alternative measures of climate risk.[26]

Then, in Table 10, we divide our international sample into two categories, U.S. firms and non-U.S. firms, and run our baseline regressions separately for the two groups. Models (1), (2), (5), and (6) show that climate risk deteriorates forecast precision in both U.S. and non-U.S. groups. Even with the inclusion of country characteristics as control variables (Models (3) and (7)), the association between climate risk and forecast accuracy remains robust for non-U.S. firms. Also, considering only U.S. firms, we compute state-level drought risk measure (*Climate Risk_State*) employing the same method we use to compute country-level measure but based on the states where U.S. firms' headquarters are resided in. Then, the results in Models (4) and (8) show that state-level drought risk increases forecast error and forecast dispersion, respectively. In sum, these results confirm that the overall relation between country-level time trends in droughts resulting from climate change and analyst forecast accuracy is applicable around the globe, both U.S. and non-U.S. countries. Moreover, even within the U.S., state-level variations in susceptibility to drought-like conditions reduce precision in earnings forecasts.

In addition, we confirm our finding of the relation between climate risk and analyst forecast accuracy in a quasi-experimental setting. Specifically, the event that we exploit in this test is based on the *Stern Review on the Economics of Climate Change* (Stern, 2008), a report released in 2006. The report warns that potential damage from climate change could be greater if climate change is not properly recognized. Then, in determining whether investors take climate risks into account, Painter (2020) uses the release of the Stern Review as an event that significantly

[26] In untabulated results, we repeat our main analysis, considering the distinctions between primary EPS and diluted EPS. The coefficient of the climate risk variable is invariably positive and statistically significant across all specifications, implying that both forecast errors and forecast dispersions increase with climate risk, regardless of whether EPS is primary or diluted. Thus, these results confirm the soundness of our findings regarding the negative relation between climate risk and analyst forecast accuracy.

Table 11
Difference-in-Difference. This table reports the result of a difference-in-difference regression. *Treat* takes the value of one if a firm is in the top quintile of climate risk (based on our country level measure of drought trends) and zero if a firm is in the bottom quintile of climate risk. *Post* equals one for years after the release of the Stern Report (2006 – 2009) and zero for years before the release of the Stern Report (2002 – 2005). *Treat x Post* is an interaction term of *Post* and *Treat*. The definitions of other variables are available in Appendix A. All regressions include industry, year, and country fixed effects. The numbers shown in parentheses are *t*-statistics clustered at the country level. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

	(1)	(2)
	ForeError	*ForeDisp*
Treat x Post	0.0908	0.0332
	(2.88)***	(3.33)***
Treat	0.4068	0.1273
	(9.24)***	(9.47)***
Ln (Assets)	−0.0821	−0.0282
	(−7.13)***	(−7.74)***
Q	0.0284	0.0042
	(1.59)	(0.81)
ROA	0.3476	0.1069
	(3.04)***	(3.40)***
Loss	0.0861	0.0386
	(3.37)***	(4.34)***
Leverage	0.1553	0.0772
	(2.38)**	(3.58)***
Tangibility	−0.2170	−0.0845
	(−3.51)***	(−4.44)***
Std(ROA)	0.1760	0.0916
	(2.72)***	(4.08)***
HHI	0.2522	0.0441
	(2.65)***	(1.39)
IFRS	−0.2388	−0.0811
	(−7.97)***	(−7.82)***
TopAudit	0.0546	0.0201
	(2.90)***	(3.05)***
Ln (AnalyFollow)	0.0150	0.0093
	(1.35)	(2.49)**
Ln (BrokerSize)	0.0298	0.0113
	(3.21)***	(3.83)***
Ln (AnalyExp)	0.0161	0.0116
	(1.17)	(2.62)***
GDPgrow	2.9242	1.2314
	(7.12)***	(6.90)***
FDI	−0.6135	−0.1681
	(−1.89)*	(−1.61)
Year FE	YES	YES
Industry FE	YES	YES
Country FE	YES	YES
Observations	48,863	48,863
Adj. R2	0.098	0.100

draws people's attention to climate change.[27] Based on the same rationale, we also utilize the release of the Stern Review as an event that considerably increases financial analysts' attention on climate change. In other words, the climate risk, which might not have been recognized before the release of the Stern Review, could receive substantially greater attention from market participants, including financial analysts, after the release of the review. Therefore, we set up our difference-in-difference model as follows:

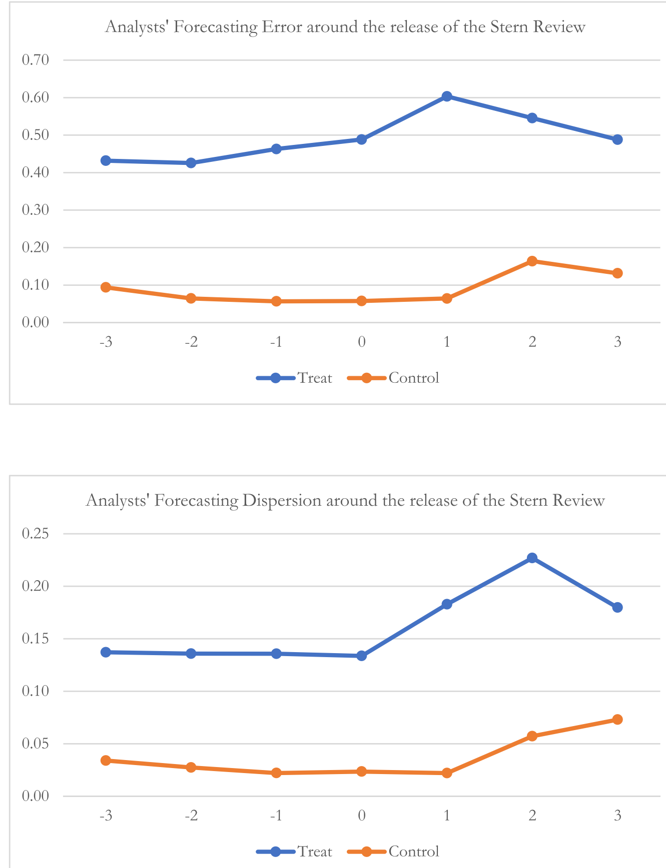

Fig. 1. Analysts' Forecasting Error and Dispersion around the release of the Stern Review.

$$\text{ForeError (or ForeDisp)} = \beta_0 + \beta_1\text{Post} + \beta_2\text{Treat} + \beta_3\text{PostxTreat} + X + \text{Industry FE} + \text{Year FE} + \varepsilon$$

The dependent variable is analyst forecast accuracy, either forecast error or analyst forecast dispersion. *Treat* is a categorical variable that equals one if a firm is in the top quintile based on our measure of country-level climate risk and zero if a firm is in the bottom quintile based on climate risk. *Post* is a categorical variable that equals one for years after the release of the Stern Review and zero otherwise. To avoid the confounding effect, we limit our analysis to a short window around the release of the Stern review (i.e., −4 and +4 years around the release in 2006). *Post x Treat* is an interaction term between *Post* and *Treat*.

The regression results are reported in Table 11. As evidenced by the positive and significant coefficient of the interaction term (*Post x Treat*), we find that analysts' forecasting errors and dispersion are significantly greater for firms in the treatment group (high climate risk) than those in the control group (low climate risk) after the release of the Stern Review in 2006. This finding confirms that analysts' increased attention to climate risk does not actually lead to its effective incorporation into their task of forecasting. This result is in line with what we find in our test utilizing climate risk keywords in analyst reports in Section 4.2, suggesting that analysts' recognition of the relevance of climate risk does not match their correct understanding of how climate risks impact firms' earnings. To validate our test, we plot average forecasting errors and dispersion around the release of the Stern review in Fig. 1 and find no significant differences in the trend of analyst forecasting accuracy between the treatment and control groups.

[27] Painter (2020) shows that the difference in the total annualized cost of issuing long-term climate bonds and long-term non-climate bonds has increased significantly after the release of the Stern Review, suggesting that investors became more aware of the risks of climate change after the review was released and started pricing these risks into their investments. Schmidt et al. (2013) present a comparative analysis of media coverage of climate change in 27 countries and find a significant rise in issue attention between 1996 and 2010, about which the authors mention the release of the Stern Review as one of the relevant events.

5. Conclusion

In this paper, we examine the effect of climate risk on analyst forecast accuracy in a cross-country empirical setting. Using a country-level measure of climate risk obtained from estimating the time trend in droughts based on the Palmer Drought Severity Index (PDSI), this study finds that both forecast error and forecast dispersion are greater when firms are located in countries with higher climate risk or more severe vulnerability to droughts. We show that the effect of climate risk is more pronounced for the firms about which analyst reports mention keywords related to climate risk, suggesting that the relevance of climate risk is recognized by analysts but not incorporated well into the forecasts. Furthermore, we present evidence that climate risk tends to increase firms' earnings volatility, which accordingly would complicate analysts' tasks. Considering country characteristics, we find that the effect of climate risk in inducing forecast inaccuracy is sturdier among countries with heavy reliance on hydroelectric sources for producing electricity, greater importance of agricultural and food products industries in economy, and higher likelihood of having environment-related policies or regulations.

In summary, we document that climate risks have critical consequences for analyst forecast accuracy, thus limiting analysts' forecasting ability and their role as information agents in capital markets. Specifically, the findings presented in this study provide evidence that climate risk, as an essential piece of non-financial information, is not adequately incorporated into the creation of earnings forecasts. Subsequently, our findings have implications for a better understanding of the effect of climate risks on firms and the treatment of climate change in the tasks of financial analysts.

This study has certain limitations. In particular, since our findings are based on the limited sample period originating from the data availability of the PDSI data, the generalizability of our results may be limited, especially considering the heightened awareness and impact of climate change in more recent years. While we attempt to alleviate the concerns by employing alternative measures of climate risk that are available in a more recent time period, the sample can be further expanded in future research to make the study's conclusions more rigorous.

CRediT authorship contribution statement

Incheol Kim: Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Suin Lee:** Writing – review & editing, Writing – original draft. **Jiwoo Ryou:** Methodology, Investigation, Formal analysis.

Appendix A

Definitions of Variables

Variable	Definition
Climate Risk	A country-level drought risk measure based on the Palmer Drought Severity Index (PDSI) of a firm's home country (Hong et al., 2019).
ForeError	(Median analyst EPS forecasts$_t$ - actual EPS$_t$)/stock price at the end of year t−1.
ForeDisp	The standard deviation of all analyst EPS forecasts in a given year.
Ln *(Assets)*	The logarithm of book-value assets.
Q	Tobin's q measured as the sum of the market value of equity, the liquidating value of preferred stock, and the value of debts divided by the book value of assets (Chung and Pruitt, 1994).
ROA	Earnings before interests and taxes scaled by assets.
Loss	An indicator variable that is equal to one if *ROA* is negative and zero otherwise.
Leverage	(Long-term debts + debts in current liabilities)/assets.
Tangibility	Net property, plant, and equipment divided by assets.
Std(ROA)	The standard deviation of the past three years' ROAs.
HHI	Herfindahl index based on sales across the first two digits of SIC code.
IFRS	An indicator variable that is equal to one if a firm's financial statements are followed by IFRS accounting standards and zero otherwise.
TopAudit	An indicator variable that is equal to one if a firm's auditor is one of the top 4 auditors and zero otherwise.
Ln *(AnlaystFollow)*	A log-transformed number of analysts following for a firm's EPS forecast in a given year.
Ln *(BrokSize)*	A log-transformed number of analysts associated with a brokerage in a given year.
Ln *(AnalyExp)*	A log-transformed number of years since an analyst first appears in the I/B/E/S EPS forecast file.
GDPGrow	Annual GDP growth rate from the prior year.
FDI	The percentage of foreign direct investment in GDP.

References

Abarbanell, Jeffrey S., Bushee, Brian J., 1997. Fundamental analysis, future earnings, and stock prices. J. Account. Res. 35, 1–24.
Acemoglu, Daron, Vasco, M.Carvalho, Ozdaglar, Asuman, Tahbaz-Salehi, Alireza, 2012. The network origins of aggregate fluctuations. Econometrica 80, 1977–2016.
Addoum, Jawad M., Ng, David T., Ortiz-Bobea, Ariel, 2020. Temperature shocks and establishment sales. Rev. Financ. Stud. 33, 1331–1366.
Addoum, Jawad M., Ng, David T., Ortiz-Bobea, Ariel, 2023. Temperature Shocks and Industry Earnings News. J. Financ. Econ. 150, 1–45.
Alley, William M., 1984. The Palmer drought severity index: limitations and assumptions. J. Appl. Meteorol. Climatol. 23, 1100–1109.
Atiase, Rowland Kwame, 1987. Market implications of predisclosure information: Size and exchange effects. J. Account. Res. 168–176.
Bae, Kee-Hong, Stulz, René M., Tan, Hongping, 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. J. Financ. Econ. 88, 581–606.
Bansal, Ravi, Dana Kiku, and Marcelo Ochoa, 2016, Price of long-run temperature shifts in capital markets, *National Bureau of Economic Research*, No. w22529.
Barth, Mary E., Kasznik, Ron, McNichols, Maureen F., 2001. Analyst coverage and intangible assets. J. Account. Res. 39, 1–34.
Battiston, Stefano, Dafermos, Yannis, Monasterolo, Irene, 2021. Climate risks and financial stability. J. Financ. Stab. 54, 100867.
Bolton, Patrick, Kacperczyk, Marcin, 2021. Do investors care about carbon risk? J. Financ. Econ. 142, 517–549.
Bonato, Matteo, Cepni, Oguzhan, Gupta, Rangan, Pierdzioch, Christian, 2023. Climate risks and realized volatility of major commodity currency exchange rates. J. Financ. Mark. 62, 100760.
Bradley, Daniel, Gokkaya, Sinan, Liu, Xi, 2017. Before an analyst becomes an analyst: does industry experience matter? J. Financ. 72, 751–792.
Brown, Lawrence D., 1993. Earnings forecasting research: its implications for capital markets research. Int. J. Forecast. 9, 295–320.
Brown, Lawrence D., 2001. A temporal analysis of earnings surprises: profits versus losses. J. Account. Res. 39, 221–241.

Brown, Lawrence D., Richardson, Gordon D., Schwager, Steven J., 1987. An information interpretation of financial analyst superiority in forecasting earnings. J. Account. Res. 49–67.
Calel, Raphael, Dechezleprêtre, Antoine, 2016. Environmental policy and directed technological change: evidence from the European carbon market. Rev. Econ. Stat. 98, 173–191.
Cao, Ying, Keskek, Sami, Myers, Linda A., Tsang, Albert, 2022. The effect of media competition on analyst forecast properties: cross-country evidence. J. Account., Audit. Financ. 37, 378–406.
Chen, Charles J.P., Ding, Yuan, Kim, Chansog Francis, 2010. High-level politically connected firms, corruption, and analyst forecast accuracy around the world. J. Int. Bus. Stud. 41, 1505–1524.
Chen, S., Lin, B., Lu, R., Ma, H., 2021. Stock market openness and analyst forecast bias. J. Account. Public Policy 40 (6), 106874.
Chuang, Wen-I., Lee, Bong-Soo, 2011. The informational role of institutional investors and financial analysts in the market. J. Financ. Mark. 14, 465–493.
Chung, Kee H., Pruitt, Stephen W., 1994. A simple approximation of Tobin's q. Financ. Manag. 70–74.
Clarke, Jonathan, Subramanian, Ajay, 2006. Dynamic forecasting behavior by analysts: theory and evidence. J. Financ. Econ. 80, 81–113.
Clement, Michael B., 1999. Analyst forecast accuracy: do ability, resources, and portfolio complexity matter? J. Account. Econ. 27, 285–303.
Clement, Michael B., Koonce, Lisa, Lopez, Thomas J., 2007. The roles of task-specific forecasting experience and innate ability in understanding analyst forecasting performance. J. Account. Econ. 44, 378–398.
Cuculiza, Carina, Alok Kumar, Wei Xin, and Chendi Zhang, 2021, Climate Change, Analyst Forecasts, and Market Behavior, Available at SSRN 3781157.
Daniel, Kent D., Robert B.Litterman, and Gernot Wagner, 2016, Applying asset pricing theory to calibrate the price of climate risk, *National Bureau of Economic Research*, No. w22795.
DeAngelo, Linda Elizabeth, 1981. Auditor size and audit quality. J. Account. Econ. 3, 183–199.
Dell, Melissa, Jones, Benjamin F., Olken, Benjamin A., 2012. Temperature shocks and economic growth: evidence from the last half century. Am. Econ. J.: Macroecon. 4, 66–95.
Dhaliwal, Dan S., Radhakrishnan, Suresh, Tsang, Albert, Yang, Yong George, 2012. Non-financial disclosure and analyst forecast accuracy: international evidence on corporate social responsibility disclosure. Account. Rev. 87, 723–759.
Dichev, Ilia D., Tang, Vicki Wei, 2009. Earnings volatility and earnings predictability. J. Account. Econ. 47, 160–181.
Dong, Rui, Fisman, Raymond, Wang, Yongxiang, Xu, Nianhang, 2019. Air pollution, affect, and forecasting bias: Evidence from Chinese financial analystsm. J. Financ. Econ.
Du, Qianqian, Yu, Frank, Yu, Xiaoyun, 2017. Cultural proximity and the processing of financial information. J. Financ. Quant. Anal. 52, 2703–2726.
Duru, Augustine, Reeb, David M., 2002. International diversification and analysts' forecast accuracy and bias. Account. Rev. 77, 415–433.
Easley, David, O'Hara, Maureen, Paperman, Joseph, 1998. Financial analysts and information-based trade. J. Financ. Mark. 1, 175–201.
Ehlers, Torsten, Packer, Frank, de Greiff, Kathrin, 2022. The pricing of carbon risk in syndicated loans: which risks are priced and why? J. Bank. Financ. 136, 106180.
Farstad, Fay M., 2018. What explains variation in parties' climate change salience? Part. Polit. 24, 698–707.
Friesen, Geoffrey, Weller, Paul A., 2006. Quantifying cognitive biases in analyst earnings forecasts. J. Financ. Mark. 9, 333–365.
Gibson Brandon, Rajna, and Philipp Krueger, 2018, The sustainability footprint of institutional investors, *Swiss Finance Institute Research Paper*.
Gu, Grace Weishi, Hale, Galina, 2023. Climate risks and FDI. J. Int. Econ. 146, 103731.
Gu, Feng, Wang, Weimin, 2005. Intangible assets, information complexity, and analysts' earnings forecasts. J. Bus. Financ. Account. 32, 1673–1702.
Gu, Zhaoyang, Wu, Joanna Shuang, 2003. Earnings skewness and analyst forecast bias. J. Account. Econ. 35, 5–29.
Han, Yuqi, Mao, Connie X., Tan, Hongping, Zhang, Chi, 2024. Climatic disasters and distracted analysts. Contemp. Account. Res. 41, 1120–1150.
Hilary, Gilles, Menzly, Lior, 2006. Does past success lead analysts to become overconfident? Manag. Sci. 52, 489–500.
Hoepner, Andreas G.F., Oikonomou, Ioannis, Sautner, Zacharias, Starks, Laura T., Zhou, Xiao Y., 2024. ESG shareholder engagement and downside risk. Rev. Financ. 28, 483–510.
Hong, Harrison, Kubik, Jeffrey D., 2003. Analyzing the analysts: career concerns and biased earnings forecasts. J. Financ. 58, 313–351.
Hong, Harrison, Li, Frank Weikai, Xu, Jiangmin, 2019. Climate risks and market efficiency. J. Econ. 208, 265–281.
Hope, Ole-Kristian, 2003. Disclosure practices, enforcement of accounting standards, and analysts' forecast accuracy: an international study. J. Account. Res. 41, 235–272.
Hope, Ole-Kristian, Kang, Tony, 2005. The association between macroeconomic uncertainty and analysts' forecast accuracy. J. Int. Account. Res. 4, 23–38.
Horton, Joanne, Serafeim, George, Serafeim, Ioanna, 2013. Does mandatory IFRS adoption improve the information environment? Contemp. Account. Res. 30, 388–423.
Hsiang, Solomon M., 2010. Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. Proc. Natl. Acad. Sci. 107, 15367–15372.
Hsu, Po-Hsuan, Li, Kai, Tsou, Chi-Yang, 2023. The pollution premium. J. Financ. 78, 1343–1392.
Huang, Henry He, Kerstein, Joseph, Wang, Chong, 2018. The impact of climate risk on firm performance and financing choices: An international comparison. J. Int. Bus. Stud. 49, 633–656.
Hugon, Artur, and Kelvin Law, 2019, Impact of climate change on firm earnings: evidence from temperature anomalies, Available at SSRN 3271386.
Huynh, Thanh D., Nguyen, Thu Ha, Truong, Cameron, 2020. Climate risk: The price of drought. J. Corp. Financ. 65, 101750.
Jagannathan, Ravi, Ashwin Ravikumar, and Marco Sammon, 2017, Environmental, social, and governance criteria: why investors are paying attention, *National Bureau of Economic Research*, No. w24063.
Javadi, S., Masum, A.A., 2021. The impact of climate change on the cost of bank loans. J. Corp. Financ. 69, 102019.
Javadi, S., Masum, A.A., Aram, M., Rao, R.P., 2023. Climate change and corporate cash holdings: Global evidence. Financ. Manag. 52 (2), 253–295.
Krishnaswami, Sudha, Subramaniam, Venkat, 1999. Information asymmetry, valuation, and the corporate spin-off decision. J. Financ. Econ. 53, 73–112.
Krueger, Philipp, Sautner, Zacharias, Starks, Laura T., 2020. The importance of climate risks for institutional investors. Rev. Financ. Stud. 33, 1067–1111.
Li, Chao Kevin, Luo, Jin-hui, Soderstrom, Naomi S., 2020. Air pollution and analyst information production. J. Corp. Financ. 60, 101536.
Lin, Chen, Thomas Schmid, and Michael S. Weisbach, 2019, Climate change, operating flexibility and corporate investment decisions, *National Bureau of Economic Research*, No. w26441.
Lys, Thomas, Soo, Lisa Gilbert, 1995. Analysts' forecast precision as a response to competition. J. Account., Audit. Financ. 10, 751–765.
Ma, Rui, Marshall, Ben R., Nguyen, Hung T., Nguyen, Nhut H., Visaltanachoti, Nuttawat, 2022. Climate events and return comovement. J. Financ. Mark. 61, 100731.
Mattei, Marco Maria, Platikanova, Petya, 2017. Do product market threats affect analyst forecast precision? Rev. Account. Stud. 22, 1628–1665.
Mikhail, Michael B., Walther, Beverly R., Willis, Richard H., 1997. Do security analysts improve their performance with experience? J. Account. Res. 35, 131–157.
Muslu, Volkan, Mutlu, Sunay, Radhakrishnan, Suresh, Tsang, Albert, 2019. Corporate social responsibility report narratives and analyst forecast accuracy. J. Bus. Ethics 154, 1119–1142.
Painter, Marcus, 2020. An inconvenient cost: The effects of climate change on municipal bonds. J. Financ. Econ. 135, 468–482.
Palmer, Wayne C., 1965, Meteorological drought, US Department of Commerce, Weather Bureau.
Pankratz, Nora, Bauer, Rob, Derwall, Jeroen, 2023. Climate change, firm performance, and investor surprises. Manag. Sci. 69, 7352–7398.
Parkash, Mohinder, Dhaliwal, Dan S., Salatka, William K., 1995. How certain firm-specific characteristics affect the accuracy and dispersion of analysts' forecasts: A latent variables approach. J. Bus. Res. 34, 161–169.
Petersen, Mitchell A., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Rev. Financ. Stud. 22, 435–480.
Schmidt, Andreas, Ivanova, Ana, Schäfer, Mike S., 2013. Media attention for climate change around the world: A comparative analysis of newspaper coverage in 27 countries. Glob. Environ. Change 23, 1233–1248.
Stern, Nicholas, 2008. The economics of climate change. Am. Econ. Rev. 98, 1–37.
Tan, Hongping, Wang, Shiheng, Welker, Michael, 2011. Analyst following and forecast accuracy after mandated IFRS adoptions. J. Account. Res. 49, 1307–1357.
Wilbanks, Thomas J., Lankao, P.Romero, Bao, Manzhu, Berkhout, F.G.H., Cairncross, Sandy, Ceron, Jean-Paul, Kapshe, Manmohan, Muir-Wood, Robert, Zapata-Marti, Ricardo, 2007. Industry, settlement and society. Clim. Change 357–390.
Wlostowski, Adam N., Jennings, Keith S., Bash, Rachel E., Burkhardt, Jesse, Wobus, Cameron W., Aggett, Graeme, 2022. Dry landscapes and parched economies: a review of how drought impacts nonagricultural socioeconomic sectors in the US Intermountain. West, *Wiley Interdiscip. Rev.: Water* 9, e1571.