Warming Trend, Falling Forecasts? High Temperature and Analyst Performance

Mengmeng Guo
Nanjing Agricultural University
gmm@njau.edu.cn

Liurong Liang
Southwestern University of Finance and Economics
121020204056@smail.swufe.edu.cn

Xiaoran Ni
Xiamen University
nxr@xmu.edu.cn

Warming Trend, Falling Forecasts? High Temperature and Analyst Performance

Abstract: This paper provides granular evidence on how rising temperatures affect the processing of financial information in view of sell-side analyst earnings forecast accuracy. We find that exposure to extreme heat significantly reduces the forecast accuracy of local analysts. We propose two potential channels. First, an increased frequency of extreme heat hinders information acquisition by discouraging site visits, which are important for accurate forecasting. Second, extreme heat contributes to analysts' cognitive biases. We also explore possible mitigating factors, and find that analyst experience, brokerage firm resources, and information transparency can buffer the negative effects of extreme heat. Our study offers important insights into how climate change may indirectly distort information flows in financial markets by altering analysts' behavior, and calls for more effective mitigation and adaptation strategies to cope with the adverse effects of global warming on highly skilled professionals.

Keywords: High temperature; Analyst forecast; Information processing; Cognitive ability; Site visit

JEL: G14; G30; D80; M41; Q54

1. Introduction

Climate change poses a profound and multifaceted global challenge. Notably, the global mean surface temperature has risen significantly above pre-industrial levels—a trend the IPCC (2021) deems irreversible. This warming has led to a 3.8-fold increase in the frequency of extreme high temperatures since the pre-industrial era (National Climate Assessment, 2023). Existing research shows clear evidence that high temperatures hinder economic growth and reduce labor supply, output, and productivity (e.g., Dell et al., 2012; Graff-Zivin and Neidell, 2014; Barreca et al., 2016; Somanathan et al., 2021; Callahan and Mankin, 2022; Heyes and Saberian, 2022; Sun et al., 2024; Akyapı et al., 2025; Jin et al., 2025). However, granular evidence on whether and how high temperatures affect highly skilled *financial* professionals, like financial analysts, is still rare.

Given their crucial role in capital markets, to say, collecting, analyzing, and disseminating financial information (Hope, 2003), understanding how high temperatures affect analysts' "productivity" is crucial for the well-function of information processing in financial markets. Specifically, we investigate two key questions: First, do high temperatures affect the accuracy of analyst earnings forecasts? Second, if so, what factors can mitigate such adverse effects?

To answer the questions above, we focus on city-level extreme heat exposure, which is constructed as the number of "Hot Days" experienced by an analyst's city, normalized by 100. We define a "Hot Day" as a day with a mean temperature of 32°C or higher (Zhang et al., 2018; Li et al., 2023). This 32°C threshold is chosen for its relevance to both human health and economic outcomes. Existing research indicates that exposure to 32°C heat is positively correlated with risks such as delivery complications (Auger et al., 2014) and negatively associated with adult economic well-being (Isen et al., 2017), which aligns closely with the

Wet-Bulb Globe Temperature (WBGT) threshold of 32.2°C, being considered an extreme threat to human health.

China provides a compelling setting to investigate our research questions for several reasons, which can generate important implications for other countries amid the global warming trend. First, situated in a region highly sensitive to global warming, China has experienced pronounced impacts from climate change. According to the Blue Book on Climate Change in China (2023), China's warming rate is higher than the global average, and a range of key indicators have reached record highs, such as the average summer temperature, coastal sea levels, and the thickness of the active layer in permafrost areas.[1] Second, owing to tremendous differences in latitude, longitude, and altitude, the climate of China is extremely diverse, ranging from tropical in the far south to subarctic in the far north, which creates large variations in extreme heat exposure.[2] Third, China offers a unique advantage in terms of data availability. Since 2009, the Shenzhen Stock Exchange has mandated the disclosure of all corporate site visits by analysts, a requirement absent in other major markets like the U.S. This granular data allows us to directly observe the impact of extreme heat on analysts' on-the-ground information gathering activities.

Empirically, we observe a decrease in forecast accuracy, both statistically and economically meaningful, when analysts experience additional days of extreme heat prior to issuing their annual forecasts. Our findings remain consistent across various measures of extreme heat, analyst locations, and forecast types. We also control for and exclude the potential influence of external shocks and cities with prolonged exposure to high temperatures. Additionally, our results hold when accounting for time-varying province-specific factors. To address potential concerns regarding omitted variable bias at the city level, we conduct a placebo test by randomizing extreme heat exposure within each

---

[1] Source: https://www.globaltimes.cn/page/202307/1294022.shtml.

[2] Source: https://en.wikipedia.org/wiki/Climate_of_China.

analyst-firm pairing, which further corroborates our main findings, indicating that our results are not driven by unobserved city-level factors.

To shed light on possible underlying channels, we investigate the impact of extreme heat on analysts' information acquisition and processing abilities. We begin by examining the impact of extreme heat on analysts' corporate site visits. Given that corporate site visits provide analysts with valuable and firsthand insights into firm performance through face-to-face interactions, they are known to enhance forecast accuracy (Cheng et al., 2016). Consequently, if extreme heat increases the disutility or cost of travel (e.g., Graff-Zivin and Neidell, 2014), and thereby reduces the frequency of site visits, we would expect a corresponding decrease in forecast accuracy. Our findings support this view, suggesting that analysts exposed to extreme heat conduct fewer site visits. We also find that the main effect is more pronounced for manufacturing firms and firms with a greater proportion of tangible assets, suggesting that the information acquisition constraints imposed by extreme heat are particularly salient in these contexts.

Next, we investigate the effect of extreme heat on analysts' cognitive abilities. High temperatures can negatively affect both mood and sleep quality (Keller et al., 2005; Obradovich et al., 2017; Heyes and Saberian, 2019), both of which are crucial for optimal cognitive function. Previous research has documented the detrimental impact of high temperatures on cognitive performance (Graff-Zivin et al., 2020; Heyes and Saberian, 2019; Park et al., 2020). We hypothesize that even indoor-working analysts might experience cognitive impairment due to high temperatures, leading to a reduction in forecast accuracy. Consistent with this hypothesis, our results show that extreme heat is associated with an increase in optimism bias, measured as the difference between an individual analyst's forecast and the consensus forecast.

To explore potential mitigating factors that can alleviate the negative effects of extreme heat on analyst forecast behavior, we split our full sample into subgroups based on a range of analyst, brokerage firm and visited firm characteristics and re-estimate our baseline models. First, we observe that more experienced and better-educated analysts, indicating stronger analytical skills, appeared better equipped to mitigate the negative cognitive effects of extreme heat. Analysts also can leverage their experience with a particular firm and the local advantage of being situated in the same region, which provides them with deeper insights into the firm's operations and context. Second, the negative impact of extreme heat on forecast accuracy is amplified when their brokerage firms don't possess an information advantage. Analysts can benefit from established information acquisition channels through their brokerage firms, such as brokerage firm site visits and reports and underwriting relationships, which grant them access to exclusive and critical information. Finally, we find a more reliable information environment, characterized by high analyst coverage and the presence of a Big 4 auditor, appears to attenuate the negative impact of extreme heat on forecast accuracy. These factors likely contribute to a greater quantity and higher quality of disclosed information, thereby reducing analysts' reliance on information acquisition activities that are hampered by extreme heat.

This paper mainly contributes to two strands of literature. First, it extends the research on the impact of high temperatures on labor productivity (e.g., Zhang et al., 2018; Somanathan et al., 2021; Heyes and Saberian, 2022). Although some research specifically focuses on highly skilled professionals, such as police officers, food safety inspectors, and immigration judges, etc. (Obradovich et al., 2018; Heyes and Saberian, 2019), evidence on how extreme heat affects the productivity of *financial* professionals is still rare. Our findings indicate that high temperatures can reduce the productivity of highly skilled professionals in financial markets. Relatedly, our evidence suggests that in addition to direct detrimental effects on firm operations, cash flows, and earnings (Brown et al., 2021; Addoum et al., 2023;

Gounopoulos and Zhang, 2024), and stimulating effects on the green transition (Long and Wang, 2025; Wang et al., 2025), which can be perceived by investors and reflected in asset prices (Balvers et al., 2017; Choi et al., 2020; Pankratz et al., 2023), high temperatures can affect the functioning of financial markets through a potentially significant, yet often overlooked channel: deterring the collecting, analyzing, and disseminating of financial information.

Second, this study contributes to the burgeoning body of research examining factors that influence analyst forecast accuracy (e.g., Clement, 1999; Hope, 2003; Tan et al., 2011; Dhaliwal et al., 2012; Beyhaghi et al., 2023). Our paper extends this research by specifically focusing on the impact of high temperatures on analyst forecasting behavior, revealing a significant decline in forecast accuracy.[3] Prior research has examined the impact of various geographical or climate-related factors on analyst forecasts, including air pollution (Li et al., 2020; Dong et al., 2021), earthquakes (Kong et al., 2021), and climate risks and disaster events (Han et al., 2024; Kim et al., 2024; Zhang and Kanagaretnam, 2024).[4] Our findings extend this research by showing that extreme heat also contributes to inaccurate forecasts.[5]

Specifically, several above studies mainly focus on *affected* firms rather than analysts. Dong et al. (2021) explore the relation between air pollution *during* corporate site visits by Chinese analysts and the earnings forecasts they issued. Kong et al. (2021) explore how earthquakes affect analysts' earnings forecasts for affected firms in China. Zhang and Kanagaretnam (2024) examine how climate disasters affect analysts' earnings forecasts for

---

[3] Previous studies have established links between sunshine exposure and biased earnings forecasts by managers (Chen et al., 2022) or seasoned equity offerings (Sun et al., 2023). Although sunshine is related with temperature, they are different factors, as cloudy days could also be very hot. Therefore, our study has a different angle.

[4] DeHaan et al. (2017) and Jiang et al. (2021) show that unpleasant weather, measured by cloud cover, rain, and wind speed, experienced by analysts and institutional investors leads to more delayed market responses to earnings news. They do not specifically consider either temperature or analyst forecast accuracy.

[5] Two recent studies also provide some discussions on extreme heat and analyst forecast. Pankratz et al. (2023) show that increased heat exposure impacts negatively on firm financial performance. As analysts do not anticipate this effect, their forecasts of revenue and operating income of affected firms tend to be systematically too high in periods when firms are affected by more extremely warm days than usual. Cuculiza et al. (2025) show that analysts issue less accurate forecasts for firms with higher temperature sensitivity. As they focus on extreme heat surrounding firms rather than analysts, our study has a fundamentally different research angle compared with theirs.

affected firms. Kim et al. (2024) also focus on the impact of climate risk surrounding the location of firms and whether analysts incorporate that information effectively into their forecasts. As we focus on the extreme heat of the location of analysts rather than the location of target firms, and our main results concentrate in the subsample where analysts and target firms are in *different* cities, our research angle is fundamentally different from theirs.

Compared with the two above studies focusing on analysts' locations, different from Han et al. (2024) who focus on how *salient* climatic disasters can mentally or physically constrain analysts, as temperature rise is relatively *gradual* while long-lasting compared with climate disasters like hurricanes, the underlying channel in our paper is different from theirs, where the short-term distraction effect is unlikely to drive our main findings. In addition, extreme heat is fundamentally different from air pollution, the main focus of Li et al. (2020). Particulate matter (PM) pollution in China has been significantly controlled due to strong environmental regulations, while extreme heat becomes more and more frequent, coinciding with the global warming trend. Given that extreme heat is more of a global issue compared with air pollution, our findings have broader implications for other countries.

In a concurrent study, Li et al. (2025) examine how exposure to temperature change during site visits can impair analysts' performance. Specifically, they focus on perceived temperature *change*, the difference between the temperature at the firms' location on the day of the site visit and the seven-day average temperature in the analysts' office city prior to the visit, and find that analysts' performance is adversely affected by the experiencing of abnormally high temperatures in summer and abnormally low temperatures in winter. By comparison, we focus on how ambient conditions of analysts' typical work environment affect their forecast performance. Our study complements to but is different from theirs, as we find that extreme heat of analysts' location reduces the frequency of corporate site visits in the first place, while they focus on temperature change *during* site visits. Also, their findings imply that analysts may *temporarily* lose their forecast precision due to perceived temperature change during site visits. By comparison, based on our findings, it is reasonable to conjecture that given the accelerated warming trend globally, without more effective mitigation and adaptation strategies, analysts may *increasingly* lose their forecast precision in the long run.

The remainder of the paper is organized as follows. Section 2 reviews the related literature and develops our hypotheses. Section 3 describes the empirical methodology and data. Section 4 presents the main results and robustness checks. Section 5 discusses mechanism analyses and provides additional analyses, respectively. Section 6 concludes the paper.

2. Related Literature and Hypothesis Development

2.1 Related literature

Rising global temperatures are increasing the frequency, intensity, and duration of extreme heat events (Meehl and Tebaldi, 2004; Callahan and Mankin, 2022), which poses a significant threat to human health, with extreme heat exacerbating cardiovascular and kidney diseases (De Blois et al., 2015; Kovats and Hajat, 2008) and impairing cognitive performance (e.g., Graff-Zivin et al., 2020; Park et al., 2020; Park, 2022; Escobar Carias et al., 2024). Extreme high temperatures also have a negative impact on mental health. Obradovich et al. (2018) find that a monthly temperature increase from the range of 25°C–30°C to the range above 30°C in the U.S. is correlated with a 0.5% rise in the probability of experiencing mental health difficulties. Similarly, Huang and Li (2023) linked an increase in monthly hot days during summer to heightened feelings of frustration, restlessness, hopelessness, and a diminished sense of meaning in life. Beyond direct psychological effects, temperature can indirectly influence mental well-being through its impact on sleep. High temperatures can disrupt sleep quality, thereby negatively affecting cognitive ability and mental health (Mullins and White, 2019; Graff-Zivin et al., 2020; Escobar Carias et al., 2024). In particular, the thermal environment is an extremely important determinant of sleep quality, and even moderate increases in temperature can disrupt the tightly coupled thermoregulation of sleep (Rifkin et al., 2018). These findings underscore the potential for widespread economic and social consequences stemming from the impact of extreme heat on cognitive and mental health.

Based upon the negative effects of extreme heat on cognitive ability and mood motivate, economic research has examined the effects of high temperatures on the labor productivity of both professional and non-professional workers. Previous research has established a robust relation between high temperatures and work-related activities. High temperatures can result in elevated injury rates (Dillender, 2021; Parks et al., 2020), and lead individuals to avoid work in unfavorable or unsafe conditions (Dillender, 2021). Graff-Zivin and Neidell (2014) show that high temperatures result in a decrease in labor time, particularly for individuals engaged in outdoor work. Heyes and Saberian (2019) find that for every 10°F increase in outdoor temperature, the grant rate of U.S. immigration judges decreased by 6.55%, attributed to the negative influence of heat on both mood and cognitive ability. Empirical evidence across diverse contexts underscores this negative relationship. Extreme heat also contributes to absenteeism, as workers may experience heat-related illnesses (Ireland et al., 2023) or suffer from reduced productivity (Somanathan et al., 2021). Similarly, Heyes and Saberian (2022) estimate a 7% reduction in individual work capacity over a month due to exposure to a single hot day. Furthermore, Huang and Li (2023) link high temperatures to increased labor activism, highlighting the broader socioeconomic consequences of extreme heat.

2.2 Hypothesis development

Financial forecasting is a cognitively demanding task that requires analysts to gather, synthesize, and interpret diverse sources of information (Jacob et al., 1999; Ivkovic and Jegadeesh, 2004; Piotroski and Roulstone, 2004). Given the established negative effects of high temperatures on physical health, cognitive function, and mood, we propose that exposure to extreme heat impairs analysts' ability to effectively process information and formulate accurate forecasts for at least two reasons.

First, while financial analysts acquire private information through a variety of corporate access activities (Mayew et al., 2013; Green et al., 2014), corporate site visits hold particular value (Cheng et al., 2016). These visits provide analysts with firsthand insights into firm operations, allowing for a deeper understanding of firm performance and contributing to more accurate forecasts (Han et al., 2018). As mentioned above, hot temperatures likely increase the disutility or cost of travel (e.g., discomfort, health risks, or reduced productivity), which can discourage site visits and limit analysts' information acquisition opportunities, ultimately hindering their ability to formulate accurate forecasts.

Second, high temperatures have been shown to increase physiological stress, which can negatively impact mental performance, information processing, and memory (Hocking et al., 2001; Hyde et al., 1997; Vasmatzidis et al., 2002), and have detrimental effects on individuals' decision-making that requires professional skills, even when their work is conducted primarily indoors (Graff-Zivin et al., 2020; Heyes and Saberian, 2019; Park et al., 2020). In particular, while analysts may have access to air conditioning during peak hours, given the known negative impacts of high temperatures on mood and sleep quality (e.g., Hsiang et al. 2013; Obradovich et al. 2017; Baylis, 2020; Escobar et al., 2024), higher daily average temperatures are still likely to have a persistent and pervasive effect on analysts' cognitive performance and overall well-being, and hinder their ability to effectively process and analyze financial information. Lo and Wu (2018) reveal the link between mood and forecasting by documenting the impact of Seasonal Affective Disorder (SAD) on analyst forecast accuracy, pessimism, and boldness. Financial decisions rely on higher-order cognitive processes, and sleep distortions can reduce analyst forecast accuracy (Kleppe et al., 2024; Bazley et al., 2025), while a reduction of decision fatigue can improve it (Hirshleifer et al., 2019). Therefore, the cognitive impairment, coupled with the potential impact of extreme heat on mood, may dampen analysts' information processing abilities and, consequently, their forecast accuracy.

Importantly, the decrease in forecast accuracy is not just a short-run "day-to-day" response of analysts. Rather, faced with the long-term trend in rising temperatures, analysts may fail to provide accurate forecasts even on days that are *not* themselves hot. Although global warming is a long-term trend usually not visible on a personal level, greater exposure to high temperatures in the past may revise local analysts' beliefs about climate change, and transform their perceived threats of climate change into a greater and more pressing concern (Choi et al., 2020; Li, 2025). Heat might shrink analysts' geographic scope by increasing the salience of local risks and constrain analysts' travel abilities, especially discouraging intercity travel.[6] Therefore, reducing site visits could be an adaptation strategy to new routines for individual analysts may adapt to new routines featured by fewer site visits in response to the rising trend in local temperatures. Also, while individual days may see extreme heat, high temperatures can persist for relatively long periods. Repeated exposure to extreme heat can create cumulative health risks (heat stress, cardiovascular strain) and induce cognitive biases for a long time. As the nature of climate change and its potential impact is highly uncertain,

---

[6] For example, firms in their home city may face heat-related disruptions, demanding more attention, which is akin to a "home bias" triggered by environmental stress. More frequent extreme temperatures can also induce more flight delays, disrupt air travel and increase in-flight safety risks.
Source: https://www.climatecentral.org/climate-matters/climate-change-is-disrupting-air-travel-2023

the resolution of climate-related uncertainties is slow, analysts may suffer behavioral biases for extended periods following their exposure to hot days (Zhang, 2006; Kruttli et al., 2025).

Considering the multifaceted impacts of extreme heat on outdoor activities, travel decisions, cognitive function, and potential biases in information processing, we propose the following hypothesis:

HA: Exposure to extreme heat decreases analyst forecast accuracy.

Alternatively, analyst forecast accuracy may improve when exposed to extreme heat. It is possible that extreme heat alerts analysts about climate change and induces them to rationally seek out and incorporate more climate-related information and improve forecasting ability, which can result in more accurate forecasts (Faralli, 2025). Also, Choi et al. (2020) show that local warm temperature mainly affects retail investors, while institutional investors that are more sophisticated is less affected. Almås et al. (2025) indicate that most major dimensions of economic decision-making are unaffected by temperature. In addition, as the actual temperature exposure is usually unobserved by researchers, given ex post adaptations, such as air conditioning, researchers have to use ambient temperature as a proxy for temperature exposure (Lai et al., 2023). It is probable that the widespread usage of air conditioning essentially improves adaptation capacity to climate change (Barreca et al., 2016), and the actual temperature exposure of financial analysts may not be as high as the level indicated by the extreme heat. What's more, only certain sectors exhibit sensitivity to extreme temperatures, and such sensitivities may be pronounced only during certain months or seasons, yielding no population-level effects associated with extreme heat (Addoum et al., 2020, 2023). Therefore, extreme heat may have no significant relation to the accuracy of analyst forecasts.

We provide the following competing hypothesis to summarize the arguments above:

HB: Extreme heat increases (or has no significant impact on) the accuracy of analyst forecast.

3. Research design

3.1 Model specification

Our main analyses are based on specifications of the following form:

$$Accuracy_{i,c,j,t} = \beta_0 + \beta_1 * Extreme\ Heat_{c,t} + \beta_2 * Controls_{i,c,j,t} + Year\ FE + Month\ FE\ + Analyst\ FE\ + Firm\ FE\ + \varepsilon_{i,j,t} \qquad (1)$$

where i indexes the analyst, c indexes the city of analyst, j indexes the firm covered by the analyst, and t indexes year.

Following So (2013) and Ham, Kaplan and Lemayian (2022), *Forecast error* is the absolute value of the difference between the forecasted EPS and the actual EPS, divided by the stock price at the end of the previous fiscal year t-1. To facilitate the interpretation of estimation results, *Accuracy* is defined as negative one times forecast error, which is a positive measure of analyst forecast accuracy. Therefore, a higher value for *Accuracy* indicates a more accurate forecast (i.e., less error).

Extreme Heat is calculated as the number of "Hot Days" in the analyst's city within the 365 days prior to the final forecast issuance in year *t*, normalized by 100. Following Zhang et al. (2018) and Li et al. (2023), a "Hot Day" is defined as a day with a mean temperature of 32°C or higher.[7] We expect a negative coefficient on *Extreme Heat*, indicating that analyst forecast accuracy decreases with greater exposure to extreme heat.

The vector *Controls* consists of a battery of control variables at both the analyst and firm levels, drawing upon prior research that highlights their influence on forecast behavior and accuracy (e.g., Kumar, 2010; Kim et al., 2011). These include: *Brokersize* is the number of

---

[7] We do not use maximum daily temperature to define "Hot Day" for the main specification, as it may not adequately capture the full exposure of temperature during the course of a day (Zhang et al., 2018). Our main findings remain robust if using maximum daily temperature to define "Hot Day".

analysts employed by the brokerage. *Experience* and *Star* control for the ability of analysts. *Experience* is the number of years between analyst *i'*s forecast of company *j'*s and the first forecast of this company. *Star* is a dummy variable that equals to one if the analyst is recognized as a "Star Analyst" by Institutional Investor magazine, reflecting analyst ability and reputation. Following Li, et al. (2020), we use *Num_Ind* and *Num_Firm* to measure the number of unique industries and the number of unique firms the analyst, capturing analyst breadth of coverage and workload separately. *Forhorizon* is the number of days between the forecast date and the fiscal year-end, controlling for the information advantage associated with later forecasts.

We include the following firm-level control variables to account for factors that may influence both forecast accuracy and extreme heat exposure: Firm size (*Size*), measured by the natural logarithm value of the firm's total assets. Larger firms tend to have more analyst coverage and greater transparency, potentially leading to higher forecast accuracy. Return on assets (*ROA*) is included to control for profitability. More profitable firms often face less uncertainty, potentially enhancing forecast accuracy. The book-to-market ratio (*BM*) is included as a proxy for growth opportunities and is used to control for the difficulty in valuing growth opportunities more than assets in place, as this may affect analyst earnings forecasts. *Loss* is a dummy variable equal to one if the firm experienced a loss in the previous year, capturing potential information asymmetry associated with poor performance. To control the effect of other market participants on analysts' forecast, following Lys and Soo (1995), Ljungqvist et al. (2007) and Behn et al. (2008), we measure the institutional holdings (*Proportion*) as the percentage of institutional ownership. Detailed definitions of variables are presented in Appendix A.

To further mitigate potential endogeneity concerns, our regression analysis incorporates four sets of fixed effects. First, *Analyst FE* are the fixed effects of analysts to capture unobserved time-invariant analyst characteristics, such as individual forecasting styles or their locations. Second, we include *Firm FE* to account for unobservable time-invariant firm characteristics. Third, we include *Year FE* in our regression specifications to account for macroeconomic fluctuations and potential trends in analyst skill levels over time. Lastly, *Month FE* are the fixed effects of months to capture systematic monthly variation in forecast accuracy related to the timing of annual report releases. The standard errors are clustered by firm.

3.2 Data and descriptive statistics

Our study utilizes data from various sources to comprehensively examine the relationship between extreme heat and analyst forecast accuracy. Daily weather data, including sunny hours, temperature, humidity, precipitation, and wind speed, are obtained from the National Meteorological Information Center (NMIC). Data on analyst forecasts, analyst characteristics, and firm characteristics are sourced from the China Stock Market and Accounting Research (CSMAR) database. To determine analyst locations, we leverage data on analyst reports, including cell phone and office landline numbers, obtained from the WIND database.

To ensure the accuracy of location data, we retain only observations where the reported cell phone and landline locations within a single report are consistent. To address potential concerns regarding analyst mobility within a given year, we pinpoint each analyst's location using two reports annually: the report issued closest to January 1st and the report issued closest to December 31st. We retain observations only if the locations reported in these two reports are consistent, effectively ensuring that our analyst-year observations do not include any instances where an analyst’s location changed within a single year. We focus on analysts' last forecasts issued prior to earnings announcements and exclude team forecasts and retain only the earnings forecast for the following year to avoid potential distortions from multiple-year forecasts within a single report.

Our sample period spans from 2007 to 2020. We select 2007 as our starting point due to the limited availability of reliable analyst reports and the relatively underdeveloped state of the Chinese analyst industry prior to this year. We exclude the following observations: (i) financial services firms, (ii) special treatment (ST/ST*/PT/T) firms, and (iii) observations without sufficient data to construct control variables for the regressions. Financial firms are excluded due to their distinct industry structure in the Chinese context. We further exclude observations without analyst location or temperature data. Our final sample comprises 92,339 analyst-firm-year observations. To mitigate the influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

Appendix Table A2 describes the geographic distribution of analyst forecasts and their exposure to extreme heat across Chinese cities. This table shows that our sample covers 27 cities, with a highly concentrated distribution: Shanghai, Beijing, and Shenzhen together account for approximately 88% of all forecasts and 90% of analysts. Specifically, Shanghai hosts the largest number of analysts (1,602), contributing 48% of the forecasts in our sample, followed by Beijing (28%) and Shenzhen (12%). We confirm that our main findings are not purely driven by any of these “big-three” cities.

Column (6) of Table A2 in Appendix reports the average number of hot days experienced in each city. Despite hosting the majority of analysts, Beijing and Shenzhen exhibit relatively low exposure to extreme heat, averaging only 0.42 and 0.27 hot days per year, respectively. In contrast, analysts in cities such as Wuxi, Hefei, and Hangzhou experience substantially more heat exposure, with annual averages of 7.88, 7.26, and 7.44 hot days, respectively. This substantial variation in extreme heat across analyst locations provides the basis for our identification strategy.

Table 1 presents descriptive statistics for all variables. The mean value of *Accuracy* is -0.03, suggesting a tendency for analysts to be slightly inaccurate in their predictions. On average, analysts in our sample experience 3 days of extreme heat (*Extreme Heat*) prior to issuing their last forecast each year. The remaining variables exhibit values within reasonable ranges. The average brokerage employs 38.98 analysts (*BrokerSize*), and analysts have an average experience of 2.94 years (*Experience*). The average firm size (*Size*) is 22.60 (natural logarithm of total assets), with an average leverage (*Lev*) of 0.42, book-to-market ratio (*BM*) of 0.92, return on assets (*ROA*) of 0.08, and institutional ownership (*Proportion*) of 16.87%. Approximately 3% of firms reported negative net profits in the previous year (*Loss*). These metrics are consistent with prior studies such as Kong et al. (2021) and Li et al. (2021).

[Insert Table 1 about here]

4. Empirical analysis

4.1 Baseline results

Table 2 presents the results of our baseline regression analysis, testing Hypothesis A. Column (1) reports estimates from a specification with analyst, firm, year, and month fixed effects but without other control variables. Our primary variable of interest, *Extreme Heat*, exhibits a negative and statistically significant coefficient (-0.013, $p < 0.01$). This suggests that, even after controlling for these fixed effects, analyst forecast accuracy decreases with greater exposure to extreme heat prior to issuing their forecasts. As shown in Column (2), this key result remains robust after adding all control variables. Given that the sample mean of *Accuracy* is -0.03, the estimation results are both statistically and economically meaningful. These findings provide robust support for Hypothesis A, indicating that extreme heat exposure has a detrimental effect on analyst forecast accuracy, even after accounting for a wide range of potential confounding factors. Our results carry significant economic implications, revealing a notable 1.3% decrease in forecast accuracy for each additional day of extreme heat experienced by analysts before issuing their final annual forecast.

Regarding control variables, we find a negative relationship between firm size (*Size*) and forecast accuracy, consistent with findings by Beyhaghi et al. (2023), who attribute this to the increased complexity often associated with larger firms. Aligned with Call et al. (2009) and Li et al. (2020), we observe positive associations between forecast accuracy and both *ROA* and *Cashflow*, while *BM* exhibits a negative relationship. In line with Ljungqvist et al. (2007), higher institutional ownership (*Proportion*) is positively related to forecast accuracy, suggesting that institutional investors contribute to a richer information environment. As expected, the inclusion of *Analyst Fixed Effects* absorbs much of the variation in analyst characteristics, rendering most of these controls statistically insignificant. However, *Forhorizon* remains negative and significant, indicating that forecasts made farther in advance of the fiscal year-end are less accurate.

[Insert Table 2 about here]

4.2 Robustness checks

To ensure the robustness of our findings and mitigate potential biases, we conduct several sensitivity analyses. First, we exclude observations in major cities (i.e., Shanghai, Beijing, Shenzhen) respectively. Second, we employ alternative measures for extreme heat, analyst locations and analyst forecasts, respectively. Third, we exclude the potential confounding effect of the COVID-19 pandemic. Fourth, we control for the influence of cities with prolonged exposure to high temperatures. Fifth, we employ a multiple fixed effects model to enhance the rigor of our analysis. Sixth, we control the potential effect of air pollution. Finally, we conduct a placebo test to further validate our results. The tests mentioned above are illustrated in detail as follows.

4.2.1 Additional Robustness Checks

First, to ensure that the main effect is not driven by a few dominant financial hubs, we exclude analysts located in Beijing, Shanghai, and Shenzhen—three cities that jointly host a disproportionate share of China's financial institutions and brokerage headquarters. Excluding them mitigates concerns that our findings are driven by urban outliers with systematically different baseline forecast performance. After excluding observations from each of these cities separately (as shown in Table 3), the results remain robust, suggesting that the adverse effect of extreme heat on forecast accuracy is not solely driven by analysts based in major metropolitan areas.

Second, in Column (1) of Table 4, we redefine extreme heat as the proportion of days within the past year during which the daily maximum temperature at the analyst's location exceeds 32°C. The results remain consistent with our baseline specification, confirming that the negative effect of extreme heat on forecast accuracy is robust to alternative definitions of heat exposure.

Third, we re-estimate model (1) with an alternative measure of analyst location. Our sample derives analyst location from both cell phone and office landline numbers. Recognizing the potential for error if analysts utilize SIM cards registered in previous locations, we conducted a robustness test. This test employed a subsample exclusively utilizing office landline numbers to determine analyst location. Re-examining our primary model with this refined dataset, as shown in Column (2) of Table 4, confirms the robustness of our initial findings.

Fourth, we re-estimate model (1) with an alternative measure of analyst forecast. While a single analyst report may contain multiple earnings forecasts spanning several years, this analysis focuses solely on the one-year-ahead earnings forecast for the primary regression.

This decision aligns with established practices in the field (Clement and Tse, 2003; Tan et al., 2011) and ensures consistency with prior research. To further validate the robustness of our findings, we replicate our primary model (Eq. (1)) using a subsample limited to current-year earnings forecasts. The results of this robustness test, presented in Column (3) of Table 4, continue to strongly support our initial hypotheses.

Fifth, we exclude the potential effects of the COVID-19 pandemic and heat adaptation. The COVID-19 pandemic, emerging within our sample period of 2007-2020, presents a potentially significant exogenous shock that warrants careful consideration. After excluding observations in 2020, we find that our main results remain largely unchanged, as reported in Column (4) of Table 4. Analysts located in cities with prolonged exposure to high temperatures might exhibit sensitivity or adaptation to extreme heat, potentially influencing their reactions and our findings. To address this, we exclude data from four cities known for long-term high temperatures (Wuhan, Chongqing, Changsha, and Nanchang) and re-estimate model (1). The results, reported in Column (5) of Table 4, confirm the robustness of our baseline findings even after excluding these cities.

Sixth, to address concerns that analysts may conflate localized economic shocks with broader trends, we control for time-varying province-level factors—such as economic conditions and cultural norms—that may correlate with extreme heat. Column (6) of Table 4 shows that the negative association between extreme heat and forecast accuracy remains statistically significant. We further include Year × Firm fixed effects to account for time-varying firm-specific shocks. As shown in Column (7), the results remain robust. Overall, these results indicate that the effect is not driven by local economic or political conditions, nor by firm-level heterogeneity.

Finally, we control for air pollution to address the concern that reduced forecast accuracy may be driven by environmental conditions other than temperature. *Air Pollution* is defined as the number of days within the past year during which the local Air Quality Index (AQI) exceeds 100. Including this control does not alter our main findings, suggesting that the observed effect is specific to extreme heat rather than general environmental degradation.

[Insert Table 3 about here]

[Insert Table 4 about here]

4.2.2 Placebo Tests

To address concerns that unobservable, city-specific analyst characteristics might be driving our results, we conduct a placebo test. We randomly assign each analyst to a different city within China and recalculate the extreme heat measure based on the new location. This approach retains the influence of time-variant characteristics present in our data structure. If extreme heat is the primary driver of our findings, the observed results should be significantly different from those estimated from the placebo test.

We repeat this randomization and re-estimation process 150 times, applying it to model (1) each time to generate a distribution of placebo coefficients for extreme heat. Figure 1 displays the distribution of the placebo coefficients, with the solid line representing the true coefficient and the dashed line showing the mean of the placebo coefficients. While the mean of placebo coefficients is centered around zero, the true coefficient is significantly different from zero, indicating that our findings are indeed primarily driven by extreme heat. The observed effect is significantly larger in magnitude than any coefficient from the placebo distribution.

[Insert Figure 1 about here]

5. Further Analyses

5.1 Possible channels

5.1.1 The impact on site visits

This subsection explores the hypothesis that analysts exposed to extreme heat are less likely to attend corporate site visits, resulting in a decrease in forecast accuracy. If the reduction in forecast accuracy is driven by diminished information acquisition by analysts, we would expect to observe a negative correlation between the frequency of analysts' corporate site visits and increases in extreme heat. To test the effects of extreme heat on analysts' corporate site visits, we re-estimate model (1) by using *Site Visit* as the dependent variable. *Site Visit* is defined as the number of site visits conducted by analyst *i* to firm *j* within the 365 days prior to issuing their final forecast in year *t*, scaled by the total number of site visits and conference calls. The estimation results are reported in the Column (1) of Table 5. The coefficient of *Extreme Heat* is significantly negative, thereby suggesting that extreme heat reduces the frequency of analysts' corporate site visits. This limitation in outdoor information-seeking activities may explain the observed decrease in forecast accuracy among analysts affected by extreme heat.

5.1.2 The impact on cognitive bias

Previous studies have linked environmental stressors like air pollution and natural disasters to cognitive bias in analyst forecasts (Li et al., 2010; Kong et al., 2021). Our study expands on this by examining the impact of extreme heat. We hypothesize that extreme heat, by impairing mood and cognitive function, reduces analysts' information processing efficiency, thereby increasing cognitive biases in their forecasts. This effect differs from limitations in information acquisition, as analysts can access various resources, such as publicly available data and online conferences, to improve accuracy. Thus, we argue that cognitive impairment due to extreme heat represents a distinct factor influencing forecast accuracy. To provide evidence that extreme hear has a larger effect on analyst optimism bias, we re-estimate model (1) by using *Optimism Bias* as the dependent variable. *Optimism Bias* is defined as the difference between the forecast and consensus forecast. The consensus forecast is the mean value of forecasts issued by all analysts following firm *j* except analyst *i* in year *t*. The result is shown in Column (2) of Table 5. The coefficient of *Extreme Heat* is significantly positive, thereby suggesting that extreme heat can increase analysts' optimism bias.

[Insert Table 5 about here]

5.1.3 The impact of manufacturing firms and firms with more tangible assets

Site visits facilitate analysts' information acquisition through observing firms' operations. Consistent with this notion, Cheng et al. (2016) find that the effect of site visits on analyst forecast accuracy is greater for manufacturing firms and firms with more tangible assets. If extreme heat disrupts information acquisition through corporate site visits, as we hypothesize, then we expect forecast accuracy to decrease more for firms in manufacturing industries and those with higher asset tangibility. To test this, we construct indicator variables for manufacturing firms (*Manufacture*) and for firms with more tangible assets (*Tangibility*). If the visited firm belongs to the manufacturing industry, *Manufacture* is equal to 1, and 0 otherwise. *Tangibility* is equal to 1 when the ratio of tangible assets to total assets exceeds the sample median, and 0 otherwise. As shown in Table 6, Columns (1)-(4), regression results confirm that the negative impact of extreme heat on analysts' forecast accuracy is indeed more pronounced for subsamples of manufacturing firms and those with high tangible assets. These findings support our hypothesis and underscore the critical role of corporate site visits in generating accurate earnings forecasts, particularly during periods of extreme heat. Extreme heat disrupts analysts' information acquisition for manufacturing firms or those with more tangible assets by reducing visit frequency, leading to a decline in forecast accuracy.

[Insert Table 6 about here]

5.2 Further analyses

5.2.1 The characteristics of analyst: Analyst ability

Prior research documents that star analysts possess superior firm-specific knowledge, exhibit greater forecast accuracy, and have stronger performance compared to their non-star counterparts (Xu et al., 2013; Jin et al.,2023). Hence, we hypothesize that star analysts' enhanced information acquisition and decision-making capabilities render them less susceptible to the negative effects of extreme heat on forecasting accuracy. To investigate this argument, we follow Dong et al. (2021) and Li et al. (2020) and identify star analysts as those who have received the prestigious Best Analyst Award from New Fortune magazine. Forecasts made by these analysts are grouped into a star analyst subsample, while forecasts from other analysts constitute the non-star sub-sample. Columns (1)-(2) of Table 7 presents the results. Notably, the coefficient of *Star* is consistently negative and significant at the 0.01 level within the non-star analyst subsample. Conversely, this coefficient is statistically insignificant within the star analyst subsample. This finding suggests that extreme heat has a diminished impact on the forecasting behavior of star analysts compared to their non-star peers.

Analysts with advanced degrees often possess a wider and deeper knowledge base, providing them with a distinct advantage, particularly in challenging circumstances such as extreme heat events. This advantage stems from their ability to draw upon their extensive knowledge to mitigate the negative impacts of such conditions. Therefore, we hypothesize that extreme heat exposure will disproportionately affect the forecasting accuracy of analysts with lower educational attainment compared to their highly educated peers. To examine this hypothesis, we estimate model (1) on separate subsamples of analysts with and without high education. *High education* is defined as possessing a Master's degree or a doctorate, represented by a dummy variable equal to 1, and 0 otherwise. As depicted in Columns (3) and (4) of Table 7, the coefficient of *Extreme Heat* is negative and statistically significant for the low education group. Specifically, analysts without high education exhibit a 0.027 point reduction in forecast accuracy relative to those with high education. This supports the hypothesis that educational attainment moderates the negative impact of extreme heat on analyst forecast accuracy.

[Insert Table 7 about here]

5.2.2 The characteristics of analyst: Information advantage

Prior research, grounded in learning-by-doing theory (Arrow, 1962), suggests a positive correlation between forecast accuracy and analyst experience, both general and firm-specific (Clement, 1999). Analysts are likely to develop superior private information about a company's economics the longer they follow it, potentially reducing bias in forecasts. Extending this, we hypothesize that analysts with greater firm-specific experience are better positioned to mitigate the adverse effects of extreme heat on forecasting accuracy. To test this, we define *Firm experience* as the natural logarithm of one plus the number of years an analyst has issued forecasts for a specific company. We then partition our sample into two groups based on the median *Firm Experience*. As depicted in Table 8, Columns (1) and (2) present results for the subsamples below and above the median *Firm experience*, respectively. Consistent with our hypothesis, the coefficient on *Extreme Heat* is negative and statistically significant at the 1% level only in the subsample with lower *Firm Experience*. This suggests that greater firm-specific experience attenuates the adverse effect of extreme heat.

Local analysts, often possessing information advantages through established social networks and intimate knowledge of local market dynamics (Chen et al., 2024; Malloy, 2005), may rely less on site visits than their non-local counterparts. Conversely, non-local analysts, lacking such informal networks and localized understanding (Cheng et al., 2016), may depend more heavily on site visits to gather information. We therefore hypothesize that extreme heat will negatively impact forecast accuracy more significantly for non-local analysts. Table 8 further examines the role of geographic proximity in mitigating the negative effects of extreme heat on forecast accuracy. *Local* is equal to 1 if the analyst resides in the same city as the covered firm, and 0 otherwise. Columns (3) and (4) present the regression results for subsamples of non-local and local analysts, respectively. As hypothesized, the coefficient of *Extreme Heat* is significantly negative only within the non-local analyst subsample. This key finding provides support for the idea that local analysts, by virtue of their geographic advantage, are better positioned to mitigate the detrimental impacts of extreme heat on forecast accuracy.

[Insert Table 8 about here]

5.2.3 The characteristics of analyst: Brokerage firm’s information advantage

The existing literature highlights the positive impact of knowledge spillovers and information sharing within brokerage firms on analysts' forecast accuracy (e.g., Hwang et al., 2019; Hope et al., 2021). This means, even analysts who do not personally conduct corporate site visits before issuing forecasts can still benefit from their brokerage firm's resources, such as site visit insights and internal reports. To explore how knowledge spillovers or information sharing might mitigate the adverse effects of extreme heat on forecast accuracy, we examine the moderating role of a brokerage firm’s information advantage.

We hypothesize that more frequent site visits and a greater number of research reports by brokerage firms improve analysts' forecasting performance, even under extreme heat. To test this, we divide the sample into two groups based on the median value of the number of site visits by the brokerage firm and the number of reports by the brokerage firm. Columns (1) and (2) of Table 9 show that the negative impact of extreme heat on forecast accuracy is significantly reduced for analysts at firms with above-median site visit frequencies. Similarly, Columns (3) and (4) indicate that extreme heat negatively affects forecast accuracy only for firms with a below-median number of reports. These results suggest that information sharing within brokerage firms helps mitigate the detrimental effects of extreme heat on analyst performance.

We also explore the effect of underwriting relationships on analysts' performance. Affiliated analysts, benefiting from their brokerage firms' connections, are known for providing more accurate forecasts (Li et al., 2021). However, such affiliations may expose them to client pressures, leading to potential optimism bias. Lin and McNichols (1998) show that analysts from lead underwriters and co-underwriters often issue more optimistic growth forecasts and stock recommendations, selectively highlighting positive information about affiliated firms. Under extreme heat, affiliated analysts may leverage their internal information advantage to issue more accurate forecasts or, alternatively, prioritize client preferences at the expense of accuracy.

To examine the role of underwriting relationships, we categorize firms based on analyst affiliations. If an analyst belongs to a brokerage with an existing underwriting relationship with the firm being analyzed, *Affiliated brokerage firm* is equals to 1 and 0 otherwise. Columns (5) and (6) of Table 9 reveal that the coefficient for *Extreme Heat* is negative and significant for non-affiliated analysts but not significant for affiliated analysts. This implies that affiliated analysts’ information advantage may help them mitigate the negative effects of extreme heat on information processing, whereas non-affiliated analysts, lacking such support, are more vulnerable to cognitive biases induced by extreme heat.

[Insert Table 9 about here]

5.2.4 The characteristics of visited firm: Information environment

A firm's information environment plays a crucial role in the accuracy of analyst forecasts. Analyst coverage and financial report quality, are widely accepted indicators of information environment quality (Bushman et al., 2004; Irani and Oesch, 2013; Lang et al., 2004). Increased analyst coverage is associated with greater disclosure transparency and, consequently, more accurate forecasts (Lys and Soo, 1995; Weiss, 2010). We hypothesize that analysts covering firms with lower analyst coverage, particularly those facing extreme heat conditions, may encounter significant difficulties in obtaining sufficient information. This, in turn, could lead to a more pronounced decline in forecast accuracy. To investigate this hypothesis, we divide our sample into two groups based on the median analyst coverage (defined as the number of analysts covering a firm in a given year). Columns (1) and (2) of Table 10 present the results for the low and high analyst coverage subgroups, respectively. In line with our expectations, the negative impact of extreme heat on forecast accuracy is significantly more pronounced for firms with lower analyst coverage.

We further examine the role of financial reporting quality in mitigating the adverse effects of extreme heat on analyst forecast accuracy. We utilize *Big 4 Auditor* status (an indicator variable equal to one if a firm is audited by a Big 4 accounting firm) as a proxy for financial reporting quality. Prior research suggests that high-quality financial reporting, often associated with *Big 4 Auditor* status, reduces information asymmetry and analyst information acquisition costs (Archambault and Archambault, 2003). This suggests that the enhanced transparency and reliability of financial information provided by Big 4 audited firms may partially offset the limitations extreme heat imposes on private information gathering. Columns (3) and (4) of Table 10 present the results of our analysis, segregating the sample based on *Big 4 Auditor* status. Consistent with our hypothesis, the negative impact of extreme heat on forecast accuracy is amplified for firms audited by non-Big 4 auditors.

In sum, these findings highlight the critical importance of both public and private information channels for accurate analyst forecasting, particularly under environmental stress. A strong information environment, defined by high analyst coverage and high-quality financial reporting, appears to be instrumental in mitigating the adverse effects of extreme heat on forecast accuracy.

[Insert Table 10 about here]

5.3 The short term effect of hot days

While our main focus is how the long-term trend in rising temperatures affects analysts' forecast behavior, and our baseline specification defines extreme heat exposure as the number of hot days experienced in the 365 days prior to an analyst's final forecast, this relatively long window may obscure shorter-term effects. To assess the immediacy of extreme heat's impact, we re-estimate our model using alternative exposure windows of 45 and 90 days. As reported in Table 11, the coefficients on extreme heat remain negative and statistically significant across both specifications. These findings suggest that the adverse effect of extreme heat on forecast accuracy is not only persistent in the long term, but also salient in the short term.

[Insert Table 11 about here]

6. Conclusion

Rising global temperatures and the escalating frequency of extreme heat events have spurred growing concern about their potential impact on human capital and economic productivity. This study delves deeper into this issue by investigating the effects of extreme heat on the forecasting behavior of financial analysts, a crucial element of the capital market specializing in processing financial information. Our findings reveal a significant negative relationship between exposure to high temperatures and the accuracy of analyst forecasts.

This relationship is driven, at least in part, by not only decreased site visits, but also heightened cognitive biases. The main effect is particularly pronounced for manufacturing firms and those with high asset tangibility, consistent with the reliance on visual inspection and on-site observation for assessing these companies. We also identify mitigating factors that can buffer the baseline negative effects. Analysts with greater firm-specific experience, stronger information networks, and access to higher-quality public information exhibit resilience to extreme heat. This resilience is evident in analysts with extensive company-specific knowledge, those embedded in robust research environments, and those covering firms subject to higher levels of scrutiny and transparency. These findings underscore the vital role experience, information access, and robust information environments play in mitigating the adverse effects of extreme heat on financial analysis.

Our findings have significant policy implications. First, regulators should consider the impact of extreme heat on the reliability of financial information when assessing market integrity and investor protection. This could involve incorporating climate-related risks into existing regulatory frameworks, potentially necessitating adjustments to disclosure requirements or the timing of reporting deadlines during periods of extreme heat. Second, investments in improved data infrastructure and access to high-quality public information could mitigate the negative impacts of extreme heat on forecast accuracy, particularly for analysts with fewer resources. Third, promoting robust research environments and incentivizing analyst training programs that emphasize critical thinking and data analysis skills may enhance resilience to cognitive biases exacerbated by extreme heat. Our findings underscore the need to incorporate climate-related factors into assessments of information environments and their implications for financial market functioning and regulatory oversight.

Reference

Addoum, J. M., Ng, D. T., & Ortiz-Bobea, A. (2020). Temperature shocks and establishment sales. *Review of Financial Studies*, 33(3), 1331-1366.

Addoum, J. M., Ng, D. T., & Ortiz-Bobea, A. (2023). Temperature shocks and industry earnings news. *Journal of Financial Economics*, 150(1), 1-45.

Akyapı, B., Bellon, M., & Massetti, E. (2025). Estimating Macrofiscal Effects of Climate Shocks from Billions of Geospatial Weather Observations. *American Economic Journal: Macroeconomics*, 17(3), 114-159.

Almås, I., Auffhammer, M., Bold, T., Bolliger, I., Dembo, A., Hsiang, S. M., ... & Pickmans, R. (2025). Destructive Behaviour, Judgement, and Economic Decision-making under Thermal Stress. *The Economic Journal*, ueae116.

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, 29(3), 155-173.

Archambault, J. J., & Archambault, M. E. (2003). A multinational test of determinants of corporate disclosure. *The International Journal of Accounting*, 38(2), 173-194.

Auger, N., Naimi, A. I., Smargiassi, A., Lo, E., & Kosatsky, T. (2014). Extreme heat and risk of early delivery among preterm and term pregnancies. *Epidemiology*, 25(3), 344-350.

Balvers, R., Du, D., & Zhao, X. (2017). Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *Journal of Banking & Finance*, 77, 18-34.

Barnett, M., Brock, W., & Hansen, L. P. (2020). Pricing uncertainty induced by climate change. *Review of Financial Studies*, 33(3), 1024-1066.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., & Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1), 105-159.

Baylis, P. (2020). Temperature and temperament: Evidence from Twitter. *Journal of Public Economics*, 184, 104161.

Bazley, W., Cuculiza, C., & Pisciotta, K. (2025). Sleep disruptions and information processing in financial markets. *Management Science*, 71(4), 3146-3165.

Behn, B. K., Choi, J. H., & Kang, T. (2008). Audit quality and properties of analyst earnings forecasts. *The Accounting Review*, 83(2), 327-349.

Beyhaghi, M., Khashabi, P., & Mohammadi, A. (2023). Pre-grant Patent Disclosure and Analyst Forecast Accuracy. *Management Science*, 69(5), 3140-3155.

Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1), 3-18.

Bradley, D., Gokkaya, S., & Liu, X. (2020). Ties that bind: The value of professional connections to sell-side analysts. *Management Science*, 66(9), 4118-4151.

Brown, J. R., Gustafson, M. T., & Ivanov, I. T. (2021). Weathering cash flow shocks. *The Journal of Finance*, 76(4), 1731-1772.

Bourveau, T., & Law, K. K. (2021). Do disruptive life events affect how analysts assess risk? Evidence from deadly hurricanes. *The Accounting Review*, 96(3), 121-140.

Bushman, R., Chen, Q., Engel, E., & Smith, A. (2004). Financial accounting information, organizational complexity and corporate governance systems. *Journal of Accounting and Economics*, 37(2), 167-201.

Call, A. C., Chen, S., & Tong, Y. H. (2009). Are analysts' earnings forecasts more accurate when accompanied by cash flow forecasts?. *Review of Accounting Studies*, 14, 358-391.

Callahan, C. W., & Mankin, J. S. (2022). Globally unequal effect of extreme heat on economic growth. *Science Advances*, 8(43), eadd3726.

Calvet, L., Gianfrate, G., & Uppal, R. (2022). The finance of climate change. *Journal of Corporate Finance*, 73, 102162.

Chen, C., Chen, Y., Pittman, J. A., Podolski, E. J., & Veeraraghavan, M. (2022). Emotions and managerial judgment: Evidence from sunshine exposure. *The Accounting Review*, 97(3), 179-203.

Chen, Q., Mayew, W. J., & Yan, H. (2024). Equity analyst social interactions and geographic information transmission. *Review of Accounting Studies*, 29(1), 327-353.

Cheng, Q., Du, F., Wang, X., & Wang, Y. (2016). Seeing is believing: Analysts' corporate site visits. *Review of Accounting Studies*, 21, 1245-1286.

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

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?. *Journal of Accounting and Economics*, 27(3), 285-303.

Clement, M. B., & Tse, S. Y. (2003). Do investors respond to analysts' forecast revisions as if forecast accuracy is all that matters?. *The Accounting Review*, 78(1), 227-249.

Cuculiza, C., Kumar, A., Xin, W., & Zhang, C. (2025). Temperature sensitivity, mispricing, and predictable returns. *Management Science*.

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

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3), 66-95.

De Blois, J., Kjellstrom, T., Agewall, S., Ezekowitz, J. A., Armstrong, P. W., & Atar, D. (2015). The effects of climate change on cardiac health. *Cardiology*, 131(4), 209-217.

Dhaliwal, D. S., Radhakrishnan, S., Tsang, A., & Yang, Y. G. (2012). Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The Accounting Review*, 87(3), 723-759.

Dong, R., Fisman, R., Wang, Y., & Xu, N. (2021). Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. *Journal of Financial Economics*, 139(3), 971-984.

Dillender, M. (2021). Climate change and occupational health: Are there limits to our ability to adapt?. *Journal of Human Resources*, 56(1), 184-224.

Escobar Carias, M., Johnston, D. W., Knott, R., & Sweeney, R. (2024). Temperature's toll on decision-making. *The Economic Journal*, 134(663), 2746-2771.

Faralli, M. (2025). What drives beliefs about climate risks? Evidence from financial analysts. Available at SSRN: https://ssrn.com/abstract=4700558

Gounopoulos, D., & Zhang, Y. (2024). Temperature trend and corporate cash holdings. *Financial Management*, 53(3), 471-499.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1), 1-26.

Graff Zivin, J., Song, Y., Tang, Q., & Zhang, P. (2020). Temperature and high-stakes cognitive performance: Evidence from the national college entrance examination in China. *Journal of Environmental Economics and Management*, 104, 102365.

Green, T. C., Jame, R., Markov, S., & Subasi, M. (2014). Access to management and the informativeness of analyst research. *Journal of Financial Economics*, 114(2), 239-255.

Ham, C. G., Kaplan, Z. R., & Lemayian, Z. R. (2022). Rationalizing forecast inefficiency. *Review of Accounting Studies*, 1-31.

Han, B., Kong, D., & Liu, S. (2018). Do analysts gain an informational advantage by visiting listed companies?. *Contemporary Accounting Research*, 35(4), 1843-1867.

Han, Y., Mao, C. X., Tan, H., & Zhang, C. (2024). Climatic disasters and distracted analysts. *Contemporary Accounting Research*, 41(2), 1120-1150.

Heyes, A., & Saberian, S. (2019). Temperature and decisions: evidence from 207,000 court cases. *American Economic Journal: Applied Economics*, 11(2), 238-265.

Heyes, A., & Saberian, S. (2022). Hot Days, the ability to Work and climate resilience: Evidence from a representative sample of 42,152 Indian households. *Journal of Development Economics*, 155, 102786.

Hirshleifer, D., Levi, Y., Lourie, B., & Teoh, S. H. (2019). Decision fatigue and heuristic analyst forecasts. *Journal of Financial Economics*, 133(1), 83-98.

Hocking, C., Silberstein, R. B., Lau, W. M., Stough, C., & Roberts, W. (2001). Evaluation of cognitive performance in the heat by functional brain imaging and psychometric testing. *Comparative Biochemistry and Physiology Part A: Molecular & Integrative Physiology*, 128(4), 719-734.

Hope, O. K. (2003). Disclosure practices, enforcement of accounting standards, and analysts' forecast accuracy: An international study. *Journal of Accounting Research*, 41(2), 235-272.

Hope, O. K., & Su, X. (2021). Peer-level analyst transitions. *Journal of Corporate Finance*, 70, 102072.

Hsiang, S. M., Burke, M., & Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151), 1235367.

Huang, Y., & Li, Y. (2023). Labor activism over searing heat. *Journal of Environmental Economics and Management*, 122, 102888.

Hwang, B. H., Liberti, J. M., & Sturgess, J. (2019). Information sharing and spillovers: Evidence from financial analysts. *Management Science*, 65(8), 3624-3636.

Hyde, D., Thomas, J. R., Schrot, J., & Taylor, W. F. (1997). Quantification of special operations mission-related performance: Operational evaluation of physical measures. *Naval Medical Research Institute*. NMRI, 97-01.

Irani, R. M., & Oesch, D. (2013). Monitoring and corporate disclosure: Evidence from a natural experiment. *Journal of Financial Economics*, 109(2), 398-418.

Ireland, A., Johnston, D., & Knott, R. (2023). Heat and worker health. *Journal of Health Economics*, 91, 102800.

Isen, A., Rossin-Slater, M., & Walker, R. (2017). Relationship between season of birth, temperature exposure, and later life wellbeing. *Proceedings of the National Academy of Sciences*, 114(51), 13447-13452.

Ivković, Z., & Jegadeesh, N. (2004). The timing and value of forecast and recommendation revisions. *Journal of Financial Economics*, 73(3), 433-463.

Jacob, J., Lys, T. Z., & Neale, M. A. (1999). Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics*, 28(1), 51-82.

Jannati, S. (2025). Rest and financial judgments: The impact of holidays on analyst accuracy. *Journal of Banking & Finance*, 173, 107399.

Jin, H., Mazouz, K., Wu, Y., & Xu, B. (2023). Can star analysts make superior coverage decisions in poor information environment?. *Journal of Banking & Finance*, 146, 106650.

Jin, Z., Li, F. W., Lin, Y., & Zhang, Z. (2025). How firms adapt to rising temperatures: Evidence from US establishments. *Journal of Business Ethics*, 1-29.

Jiang, D., Norris, D., & Sun, L. (2021). Weather, institutional investors and earnings news. *Journal of Corporate Finance*, 69, 101990.

Keller, M. C., Fredrickson, B. L., Ybarra, O., Côté, S., Johnson, K., Mikels, J., ... & Wager, T. (2005). A warm heart and a clear head: The contingent effects of weather on mood and cognition. *Psychological Science*, 16(9), 724-731.

Kim, I., Lee, S., & Ryou, J. (2024). Does climate risk influence analyst forecast accuracy?. *Journal of Financial Stability*, 75, 101345.

Kim, Y., Lobo, G. J., & Song, M. (2011). Analyst characteristics, timing of forecast revisions, and analyst forecasting ability. *Journal of Banking & Finance*, 35(8), 2158-2168.

Kleppe, T. J., Pierce, A. T., Wiebe, Z., & Yohn, T. L. (2024). The effects of daylight saving time adjustments on investor information processing. *The Accounting Review*, 99(2), 249-277.

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

Kovats, R. S., & Hajat, S. (2008). Heat stress and public health: a critical review. *Annu. Rev. Public Health*, 29(1), 41-55.

Kruttli, M. S., Tran, B. R., & Watugala, S. W. (2025). Pricing Poseidon: Extreme weather uncertainty and firm return dynamics. *Journal of Finance*, 80(2), 783-832.

Kumar, A. (2010). Self ‐ selection and the forecasting abilities of female equity analysts. *Journal of Accounting Research*, 48(2), 393-435.

Lai, W., Qiu, Y., Tang, Q., Xi, C., & Zhang, P. (2023). The effects of temperature on labor productivity. *Annual Review of Resource Economics*, 15(1), 213-232.

Lang, M. H., Lins, K. V., & Miller, D. P. (2004). Concentrated control, analyst following, and valuation: do analysts matter most when investors are protected least?. *Journal of Accounting Research*, 42(3), 589-623.

Lee, J. J., Gino, F., & Staats, B. R. (2014). Rainmakers: Why bad weather means good productivity. *Journal of Applied Psychology*, 99(3), 504.

Li, C. K., Luo, J. H., & Soderstrom, N. S. (2020). Air pollution and analyst information production. *Journal of Corporate Finance*, 60, 101536.

Li, F. W., Mukherjee, A., & Sen, R. (2021). Inside brokers. *Journal of Financial Economics*, 141(3), 1096-1118.

Li, X. (2025). Physical climate change exposure and firms' adaptation strategy. *Strategic Management Journal*, 46(3), 750-789.

Li, X., Smyth, R., Xin, G., & Yao, Y. (2023). Warmer temperatures and energy poverty: Evidence from Chinese households. *Energy Economics*, 120, 106575.

Li, Z., Xue, S., Mao, X., & Zhang, Y. (2025). Temperature anomalies and analyst forecast: Empirical evidence from Chinese financial analysts. Available at SSRN: https://ssrn.com/abstract=5093251

Lin, H. W., & McNichols, M. F. (1998). Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics*, 25(1), 101-127.

Ljungqvist, A., Marston, F., Starks, L. T., Wei, K. D., & Yan, H. (2007). Conflicts of interest in sell-side research and the moderating role of institutional investors. *Journal of Financial Economics*, 85(2), 420-456.

Lo, K., & Wu, S. S. (2018). The impact of seasonal affective disorder on financial analysts. *The Accounting Review*, 93(4), 309-333.

Long, X., & Wang, Z. (2025). From heat to high-tech: How innovation responds to climate change. *Journal of Development Economics*, 103525.

Lys, T., & Soo, L. G. (1995). Analysts' forecast precision as a response to competition. *Journal of Accounting, Auditing & Finance*, 10(4), 751-765.

Malloy, C. J. (2005). The geography of equity analysis. *The Journal of Finance*, 60(2), 719-755.

Mayew, W. J., Sharp, N. Y., & Venkatachalam, M. (2013). Using earnings conference calls to identify analysts with superior private information. *Review of Accounting Studies*, 18, 386-413.

Meehl, G. A., & Tebaldi, C. (2004). More intense, more frequent, and longer lasting heat waves in the 21st century. *Science*, 305(5686), 994-997.

Mullins, J. T., & White, C. (2019). Temperature and mental health: Evidence from the spectrum of mental health outcomes. *Journal of Health Economics*, 68, 102240.

Obradovich, N., Migliorini, R., Mednick, S. C., & Fowler, J. H. (2017). Nighttime temperature and human sleep loss in a changing climate. *Science Advances*, 3(5), e1601555.

Obradovich, N., Tingley, D., & Rahwan, I. (2018). Effects of environmental stressors on daily governance. *Proceedings of the National Academy of Sciences*, 115(35), 8710-8715.

Pankratz, N., Bauer, R., & Derwall, J. (2023). Climate change, firm performance, and investor surprises. *Management Science*, 69(12), 7352-7398.

Park, R. J., Goodman, J., Hurwitz, M., & Smith, J. (2020). Heat and learning. *American Economic Journal: Economic Policy*, 12(2), 306-39.

Park, R. J. (2022). Hot temperature and high-stakes performance. *Journal of Human Resources*, 57(2), 400-434.

Parks, R. M., Bennett, J. E., Tamura-Wicks, H., Kontis, V., Toumi, R., Danaei, G., & Ezzati, M. (2020). Anomalously warm temperatures are associated with increased injury deaths. *Nature Medicine*, 26(1), 65-70.

Piotroski, J. D., & Roulstone, D. T. (2004). The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm - specific information into stock prices. *The Accounting Review*, 79(4), 1119-1151.

Rifkin, D. I., Long, M. W., & Perry, M. J. (2018). Climate change and sleep: A systematic review of the literature and conceptual framework. Sleep Medicine Reviews, 42, 3-9.

Schlenker, W., & Taylor, C. A. (2021). Market expectations of a warming climate. *Journal of Financial Economics*, 142(2), 627-640.

Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy*, 129(6), 1797-1827.

So, E. C. (2013). A new approach to predicting analyst forecast errors: Do investors overweight analyst forecasts?. *Journal of Financial Economics*, 108(3), 615-640.

Sun, Q., Cheng, X., Gao, S., Chen, T., & Liu, J. (2023). Sunshine-induced mood and SEO pricing: Evidence from detailed investor bids in SEO auctions. *Journal of Corporate Finance*, 80, 102411.

Sun, Y., Zhu, S., Wang, D., Duan, J., Lu, H., Yin, H., ... & Guan, D. (2024). Global supply chains amplify economic costs of future extreme heat risk. *Nature*, 627(8005), 797-804.

Tan, H., Wang, S., & Welker, M. (2011). Analyst following and forecast accuracy after mandated IFRS adoptions. *Journal of Accounting Research*, 49(5), 1307-1357.

Vasmatzidis, I., Schlegel, R. E., & Hancock, P. A. (2002). An investigation of heat stress effects on time-sharing performance. *Ergonomics*, 45(3), 218-239.

Wang, J., Zhuang, J., Yan, C., & Chan, K. C. (2025). Standing up or standing by: Abnormally hot temperatures and corporate environmental engagement. *Journal of Business Ethics*, 196(1), 93-127.

Xu, N., Chan, K. C., Jiang, X., & Yi, Z. (2013). Do star analysts know more firm-specific information? Evidence from China. *Journal of Banking & Finance*, 37(1), 89-102.

Zhang, L., & Kanagaretnam, K. (2024). Climate Disasters and Analysts' Earnings Forecasts: Evidence from the United States. *European Accounting Review*, 1-28.

Zhang, P., Deschenes, O., Meng, K., & Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, 88, 1-17.

Zhang, X. F. (2006). Information uncertainty and analyst forecast behavior. *Contemporary Accounting Research*, 23(2), 565-590.

Appendix

Table A1 Variable Definitions

Variables	Definitions
Accuracy	It is defined as negative one times forecast error. Forecast error is the absolute value of the difference of the forecasted EPS and the actual EPS, divided by the stock price at the end of the previous fiscal year *t-1*.
Extreme Heat	The number of days when daily mean temperature exceed 32° C of the location of the analyst, and divided by 100.
Size	Firm size (the natural logarithm value of the firm’s total assets).
Lev	The firm’s leverage ratio (total debts divided by total assets).
BM	The book-to-market ratio (book value divided by market capitalization).
ROA	The firm’s profitability ratio (net income divided by total assets).
Loss	Net loss, which is an indicator variable that equals one if the firm reports a net loss for the year, and zero otherwise.
Cashflow	The ratio of cash holdings defined as the value of cash and cash equivalent divided by the value of total assets.
Proportion	The ratio of institutional holdings on outstanding shares. Institutional holdings include holdings from mutual funds, brokerage firms, insurance firms, social insurance funds, and qualified foreign institutional investors (QFII).
Brokersize	The number of analysts employed by a broker.
Experience	The number of years for an analyst between his first forecast report date recorded in the CSMAR database and the current earnings announcement date, plus one and take natural logarithm.
Forhorizon	The number of days between the analyst forecast date and the forecast period end date.
Num_Ind	The number of industries the analyst follows.
Num_Firm	The number of firms the analyst follows.
Site visit	It is defined as the number of site visit for analyst i in firm j before she/he issued the last forecast in year t, scaled by the total number of site visits and conference calls.
Optimism bias	It is defined as the difference of the forecast and consensus forecast. Consensus forecast is the mean value of forecasts issued by all analysts followed firm *j* expect analyst *i* in year *t*.
Manufacture	If the visited firm belongs to manufacturing industry, it is equal to 1, and 0 otherwise.
Tangibility	It is equal to 1 when the ratio of tangible assets to total assets exceeds the sample median, and 0 otherwise.

Star	An indicator variable that equals 1 if one analyst was awarded the title of star analyst by the NEW FORTURE magazine in the preceding calendar year, otherwise 0.
High education	It becomes a dummy variable equal to 1 if the analyst owns a Master's degree or a doctorate degree, and 0 otherwise.
Firm experience	Analyst's firm-specific experience measured as the number of prior years he has issued annual earnings forecasts for a given firm.
Local	It equals to 1 if the analyst is located in the same city as firm *j*.
The number of site visits of brokerage firm	It is defined as the number of site visit for brokerage firm in firm *j* in year *t*.
The number of reports of brokerage firm	It is defined as the number of reports of brokerage firm in year *t*.
Affiliated brokerage firm	An indicator variable that takes the value of 1 if an analyst works for a broker that is either a co-underwriter of a firm's initial public offering or a secondary equity offering during the current year.
Analyst Coverage	The number of analysts focusing on the same listed firm.
Big4	A dummy variable that equals one if firm *i* in year *t* is audited by one of the Big-4, which refer to the biggest four international auditors, Deloitte, PwC, EY, and KPMG, and zero otherwise.

Table A2. Sample Distribution by Cities

Cityname	Num_Forecast	Percent_Forecast	Num_Analyst	Percent_Analyst	Mean_HotDays
Shanghai	44,713	0.48	1602	0.48	4.85
Beijing	25,417	0.28	940	0.28	0.42
Shenzhen	11,365	0.12	460	0.14	0.27
Nanjing	1,868	0.02	69	0.02	4.27
Wuhan	1,575	0.02	20	0.01	5.13
Wuxi	1,193	0.01	46	0.01	7.88
Guangzhou	1,177	0.01	64	0.02	1.41
Chongqing	1,117	0.01	20	0.01	4.12
Changsha	1,020	0.01	34	0.01	3.84
Dongguan	875	0.01	23	0.01	0.51
Tianjin	524	0.01	19	0.01	0.41
Taiyuan	491	0.01	19	0.01	0.00
Hangzhou	275	0.00	14	0.00	7.44
Xiamen	172	0.00	8	0.00	0.12
Hefei	160	0.00	6	0.00	7.26
Xian	116	0.00	8	0.00	0.79
Jinan	105	0.00	9	0.00	2.56
Dalian	92	0.00	4	0.00	0.00
Shijiazhuang	38	0.00	8	0.00	0.08
Jiaxing	13	0.00	1	0.00	4.00
Lanzhou	8	0.00	3	0.00	0.00
Nanchang	7	0.00	2	0.00	7.43
Chengdu	5	0.00	1	0.00	0.00
Xuzhou	4	0.00	1	0.00	4.75
Kunming	4	0.00	3	0.00	0.00
Zhengzhou	4	0.00	3	0.00	6.00
Shenyang	1	0.00	1	0.00	0.00
Total	92,339	100	3,388	100	

This table reports the sample distribution by cities. Column (1) shows the city name. Column (2) reports the number of forecasts (*Num_Forecast*) issued for each city. Column (3) presents the percentage of total forecasts (*Percent_Forecast*) represented by each city. Column (4) provides the number of analysts (*Num_Analyst*) covering each city. Column (5) shows the percentage of analysts (*Percent_Analyst*) relative to the total analysts covering all cities. Finally, Column (6) indicates the average number of hot days (*Mean_HotDays*) recorded for each city during the sample period.

Table 1. Descriptive statistics

Variable name	Obs	Mean	SD	P25	P75
Accuracy	92,339	-0.03	0.04	-0.04	-0.01
Extreme Heat	92,339	0.03	0.05	0.00	0.03
Size	92,339	22.60	1.46	21.54	23.44
Lev	92,339	0.42	0.20	0.26	0.57
ROA	92,339	0.08	0.05	0.04	0.11
BM	92,339	0.92	1.07	0.32	1.04
Loss	92,339	0.03	0.16	0.00	0.00
Proportion	92,339	16.87	22.07	1.80	24.00
Cashflow	92,339	0.07	0.07	0.02	0.11
Brokersize	92,339	38.98	20.68	22.00	54.00
Experience	92,339	2.94	2.73	1.00	4.00
Num_ind	92,339	3.18	2.03	2.00	4.00
Num_firm	92,339	24.51	21.69	10.00	31.00
Forhorizon	92,339	509.53	92.85	430.00	604.00

This table reports the descriptive statistics of the variables, which are defined in Table A1 of the Appendix. Columns (2)–(6) provide the sample size, mean value, standard deviations, 25% value and 75% value, respectively.

Table 2. Extreme heat and forecast accuracy

	Dependent variable: *Accuracy*	
	(1)	(2)
Extreme Heat	-0.013***	-0.013***
	(-3.73)	(-4.00)
Size		-0.012***
		(-9.47)
Lev		0.013***
		(3.29)
ROA		0.030***
		(2.74)
Loss		-0.003
		(-0.92)
BM		-0.011***
		(-11.34)
Proportion		0.000**
		(2.07)
Cashflow		0.016**
		(2.56)
Brokersize		-0.000
		(-1.22)
Experience		0.001
		(0.66)
Num_ind		0.000
		(1.28)
Num_firm		-0.000
		(-0.36)
Forhorizon		-0.000***
		(-3.35)
Year FE	YES	YES
Month FE	YES	YES
Analyst FE	YES	YES
Firm FE	YES	YES
Observations	92,339	92,339
Adj. R-squared	0.378	0.405

This table presents OLS regression results using *Accuracy* as the dependent variable. It is defined as negative one times forecast error. In column (1), we do not control any variables. In column (2), we include all control variables to the model. For all the analysis we employ OLS estimation with year, month, analyst and firm fixed effects. All standard errors are corrected for firm level correlation. The sample period spans 2007-2020. The superscripts *, ** and *** denote 10%, 5%, and 1% significance levels, respectively. The robust t-statistics are shown in brackets. See the appendix for variable definitions.

Table 3. Excluding Observations in Major Cities

	Dependent variable: *Accuracy*		
	Excluding Shanghai	Excluding Beijing	Excluding Shenzhen
	(1)	(2)	(3)
Extreme Heat	-0.025***	-0.010***	-0.013***
	(-3.54)	(-2.75)	(-4.10)
Controls	YES	YES	YES
Year FE	YES	YES	YES
Month FE	YES	YES	YES
Analyst FE	YES	YES	YES
Firm FE	YES	YES	YES
Observations	47,739	67,032	81,087
Adj. R-squared	0.409	0.407	0.402

This table reports results of excluding observations in major cities. For all the analysis we employ OLS estimation with year, month, analyst and firm fixed effects, and control for analyst and firm specific variables. In Column (1), we exclude observations in Shanghai. In Column (2), we exclude observations in Beijing. In Column (3), we exclude observations in Shenzhen. Definitions for all variables are provided in the Appendix. The t-statistics, reported in parentheses, are calculated using standard errors clustered by firm. The superscripts *, ** and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 4. Other Robustness Checks

	Dependent variable: *Accuracy*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Extreme Heat	-0.002***	-0.014***	-0.006***	-0.016***	-0.015***	-0.017***	-0.011***	-0.015***
	(-4.16)	(-4.28)	(-3.19)	(-4.67)	(-4.24)	(-3.68)	(-4.84)	(-4.51)
Air Pollution								-0.000***
								(-5.09)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	NO	YES	YES
Month FE	YES	YES	YES	YES	YES	NO	YES	YES
Analyst FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year * Province FE	NO	NO	NO	NO	NO	YES	NO	No
Year* Firm FE	NO	NO	NO	NO	NO	NO	YES	No
Observations	92,339	89,743	85,406	86,400	88,620	92,339	92,339	91,637
Adj. R-squared	0.405	0.405	0.472	0.408	0.405	0.405	0.835	0.404

This table reports results of other robustness tests. For all the analysis we employ OLS estimation with year, month, analyst and firm fixed effects, and control for analyst and firm specific variables. In Column (1), we define *Extreme Heat* as the number of days within a given period where the daily maximum temperature at the analyst's location exceeds 32° C, divided by100. In Column (2), we employ an alternative measure of analyst's location which only uses office landline numbers to determine analyst location. In Column (3), we employ an alternative measure of analyst forecast which focuses solely on the one-year-ahead earnings forecast. Columns (4) and (5) report the estimation results by excluding the effect of Covid-19 and heat adaptation. In Column (4), we employ a sub-sample without 2020 to re-examine our basic model. In Column (5), we exclude data from four cities known for long-term high temperatures (Wuhan, Chongqing, Changsha, and Nanchang). In Columns (6) and (7), we include interaction terms Year × Province FE and Year × Firm FE to control for time-varying province-specific and firm-specific factors, respectively. In Column (8), we add *Air pollution* to control the potential effect of air pollution on analysts. *Air pollution* is defined as the number of days within a given period where the AQI index is higher than 100. Definitions for all variables are provided in the Appendix. The t-statistics, reported in parentheses, are calculated using standard errors clustered by firm. The superscripts *, ** and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 5. The Effect on Site Visit and Optimism Bias

Dependent variable:	*Site Visit* (1)	*Optimism Bias* (2)
Extreme Heat	-0.172***	0.089**
	(-5.45)	(2.51)
Controls	YES	YES
Year FE	YES	YES
Month FE	YES	YES
Analyst FE	YES	YES
Firm FE	YES	YES
Observations	28,896	86,656
Adj.R-squared	0.666	0.169

The regressions in this table address the question whether extreme heat has a larger impact on the frequency of corporate site visit for analyst and forecast optimism bias. *Site Visit* is defined as the number of site visit for analyst *i* in firm *j* before she/he issued the last forecast in year *t*, scaled by the total number of site visits and conference calls. *Optimism Bias*, is defined as the difference between the forecast and consensus forecast. Consensus forecast is the mean value of forecasts issued by other analysts excluding analyst *i* followed firm *j*. Definitions for all variables are provided in the Appendix. The t-statistics, reported in parentheses, are calculated using standard errors clustered by firm. The superscripts *, ** and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 6. The characteristics of visited firm: Manufacture firm and Tangible assets

	Dependent variable: *Accuracy*			
	Manufacture		Tangibility	
	(1)	(2)	(3)	(4)
	Yes	No	High	Low
Extreme Heat	-0.015***	-0.007	-0.018***	-0.007
	(-3.64)	(-1.18)	(-3.79)	(-1.42)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	58,052	34,287	46,169	46,170
Adj.R-squared	0.434	0.389	0.439	0.410
Difference (bootstrapped p-values)	0.008** (0.043)		0.012*** (0.000)	

This table reports the mitigation effect of the characteristics of visited firm on the relationship between extreme heat and forecast accuracy. If the visited firm belongs to manufacturing industry, *Manufacture* is equal to 1, and 0 otherwise. *Tangibility* is set to 1 when the ratio of tangible assets to total assets exceeds the sample median, and 0 otherwise. The standard errors are clustered by firms. * **, * * and * indicate 1%, 5% and 10% significant level, respectively. Appendix A outlines definitions for all variables. The t-statistics are shown in brackets. The last row reports tests of the coefficient of the variable *Extreme Heat* between those two sub-samples, using a bootstrapping approach in which we randomly select, with replacement, observations from each of the sub-samples. The procedure was repeated 1000 times.

Table 7. The characteristics of analyst: Analyst Ability

	Dependent variable: *Accuracy*			
	Star		High education	
	(1)	(2)	(3)	(4)
	Yes	No	Yes	No
Extreme Heat	-0.023	-0.011***	-0.011***	-0.027**
	(-1.31)	(-3.10)	(-3.24)	(-2.45)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	5,346	86,993	75,783	16,556
Adj. R-squared	0.421	0.406	0.399	0.445
Difference	-0.013***		-0.016**	
(bootstrapped p-values)	(0.000)		(0.017)	

This table reports the mitigation effect of analyst's ability on the relationship between extreme heat and forecast accuracy. If analyst has received the prestigious Best Analyst Award from New Fortune magazine. Forecasts, *Star* is equal to 1 and 0 otherwise. *High education* is defined as possessing a Master's degree or a doctorate, represented by a dummy variable equal to 1, while analysts without such qualifications are coded as 0. The standard errors are clustered by firms. * **, * * and * indicate 1%, 5% and 10% significant level, respectively. Appendix A outlines definitions for all variables. The t-statistics are shown in brackets. The last row reports tests of the coefficient of the variable *Extreme Heat* between those two sub-samples, using a bootstrapping approach in which we randomly select, with replacement, observations from each of the sub-samples. The procedure was repeated 1000 times.

Table 8. The characteristics of analyst: Information advantage

	Dependent variable: *Accuracy*			
	Firm experience		Local	
	(1)	(2)	(3)	(4)
	High	Low	Yes	No
Extreme Heat	-0.008	-0.016***	0.010	-0.016***
	(-1.29)	(-3.89)	(0.73)	(-4.30)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	30,690	61,612	10,379	81,960
Adj. R-squared	0.424	0.415	0.362	0.409
Difference	-0.009***		-0.025***	
(bootstrapped p-values)	(0.000)		(0.000)	

This table reports the mitigation effect of analyst's information advantage on the relationship between extreme heat and forecast accuracy. *Firm Experience* as the natural logarithm of one plus the number of years an analyst has issued forecasts for a specific company. We then partition our sample into two groups based on median *Firm Experience*. *Local* is equal to 1 if the analyst resides in the same city as the covered firm, and 0 otherwise. The standard errors are clustered by firms. * **, * * and * indicate 1%, 5% and 10% significant level, respectively. Appendix A outlines definitions for all variables. The t-statistics are shown in brackets. The last row reports tests of the coefficient of the variable *Extreme Heat* between those two sub-samples, using a bootstrapping approach in which we randomly select, with replacement, observations from each of the sub-samples. The procedure was repeated 1000 times.

Table 9. The characteristics of analyst: Brokerage firm's information advantage

	Dependent variable: *Accuracy*					
	The number of site visits of brokerage firm		The number of reports of brokerage firm		Affiliated brokerage firm	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	High	Low	Yes	No
Extreme Heat	-0.003	-0.023***	-0.004	-0.022***	0.009	-0.013***
	(-0.77)	(-3.41)	(-1.06)	(-4.12)	(0.31)	(-3.92)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	46,108	46,231	45,242	47,097	2,648	89,691
Adj. R-squared	0.407	0.471	0.475	0.427	0.099	0.406
Difference (bootstrapped p-values)	-0.020*** (0.000)		-0.017*** (0.000)		-0.022*** (0.000)	

This table reports the mitigation effect of brokerage firm's information advantage on the relationship between extreme heat and forecast accuracy. In Column (1) and (2), we divide the sample into two groups based on the median value of the number of onsite visits of brokerage firm. In Column (3) and (4), we divide the sample into two groups based on the median value of the number of reports of brokerage firm. In Column (5) and (6), if analyst is belong to a brokerage with an existing underwriting relationship with the firm being analyzed, *Affiliated brokerage firm* is equals to 1 and 0 otherwise. The standard errors are clustered by firms. * **, * * and * indicate 1%, 5% and 10% significant level, respectively. Appendix A outlines definitions for all variables. The t-statistics are shown in brackets. The last row reports tests of the coefficient of the variable *Extreme Heat* between those two sub-samples, using a bootstrapping approach in which we randomly select, with replacement, observations from each of the sub-samples. The procedure was repeated 1000 times.

Table 10. The characteristics of visited firm: Information environment

	Dependent variable: *Accuracy*			
	Analyst Coverage		Big4	
	(1)	(2)	(3)	(4)
	High	Low	Yes	No
Extreme Heat	-0.002	-0.024***	-0.005	-0.014***
	(-0.33)	(-4.77)	(-0.44)	(-4.08)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	43,661	48,677	10,299	82,040
Adj. R-squared	0.493	0.413	0.421	0.414
Difference	-0.022***		-0.009***	
(bootstrapped p-values)	(0.000)		(0.000)	

This table reports the mitigation effect of corporate information environment on the relationship between extreme heat and forecast accuracy. *Analyst Coverage* is defined as the number of analysts covering a firm in a given year. *Big4* is an indicator variable equal to one if a firm is audited by a Big 4 accounting firm. The standard errors are clustered by firms. * **, * * and * indicate 1%, 5% and 10% significant level, respectively. Appendix A outlines definitions for all variables. The t-statistics are shown in brackets. The last row reports tests of the coefficient of the variable *Extreme Heat* between those two sub-samples, using a bootstrapping approach in which we randomly select, with replacement, observations from each of the sub-samples. The procedure was repeated 1000 times.

Table 11. The short term effect of hot days

	Dependent variable: Accuracy (1)	Dependent variable: *Accuracy* (2)
HotDays_last45days	-0.016**	
	(-2.00)	
HotDays_last90days		-0.023***
		(-3.64)
Observations	92,129	92,129
Controls	YES	YES
Year FE	YES	YES
Month FE	YES	YES
Analyst FE	YES	YES
Firm FE	YES	YES
Observations	92,129	92,129
Ad. R-squared	0.405	0.405

This table reports the short term effect of hot days. *HotDays_last45days* and *HotDays_last90days* are defined as the number of hot days experienced in the 45 and 90 days prior to the analyst's forecast release, divided by 100. The standard errors are clustered by firms. * **, * * and * indicate 1%, 5% and 10% significant level, respectively. Appendix A outlines definitions for all variables. The t-statistics are shown in brackets.

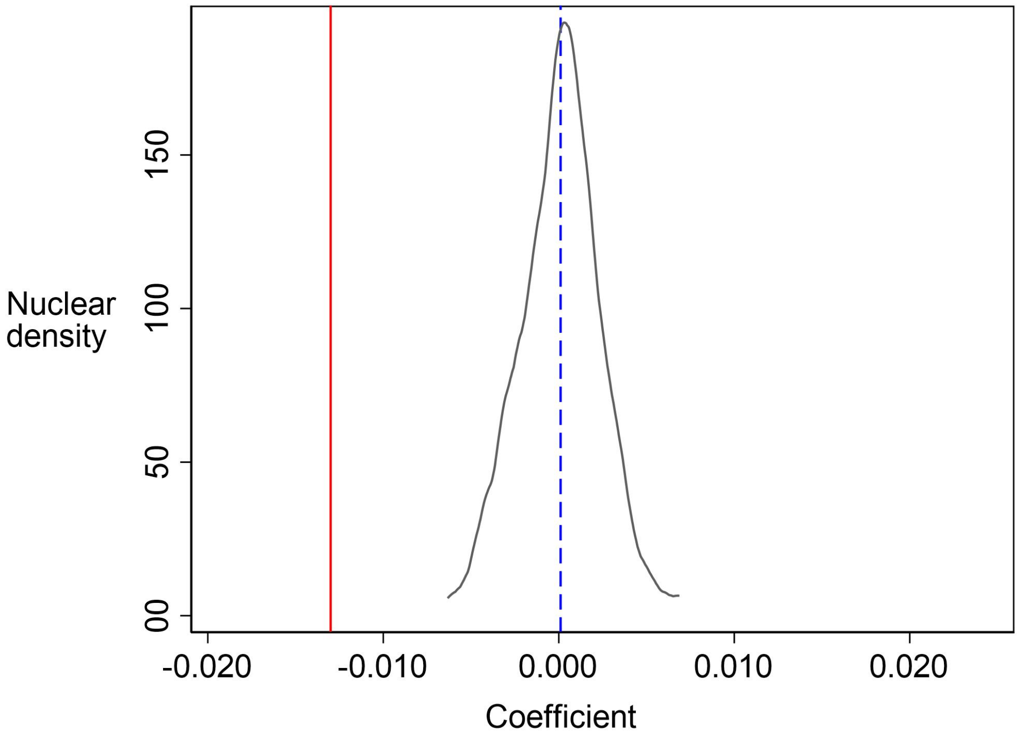

Figure 1. Placebo coefficient distribution of placebo test

This figure illustrates the distribution of the placebo coefficients of *Extreme Heat* from 1000 times placebo tests in placebo test, where we randomly assign each analyst to a different city within China and recalculate the extreme heat measure based on the new location. The x-axis reports the coefficient value, where the y-axis reports nuclear density. The red and solid line is the real value of the coefficient, and the blue and dashed line is the mean of the false coefficient of *Extreme Heat* from 1000 times placebo tests.