Climate Disasters and Analysts' Earnings Forecasts: Evidence from the United States

Lei Zhang
International Business School Suzhou
Xi'an Jiaotong-Liverpool University
Suzhou, China
Lei.Zhang02@xjtlu.edu.cn

Kiridaran Kanagaretnam
Schulich School of Business
York University
KKanagaretnam@schulich.yorku.ca

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Abstract

We examine the relation between climate disasters and analysts' earnings forecasts in the U.S. We find that climate disasters are associated with deteriorated analyst forecast properties proxied by forecast errors and forecast dispersion. We reason that the volatility of ROA, the volatility of cash flows, and lower financial statement comparability are three potential channels through which climate disasters influence analyst forecast properties. We also find that the relation between climate disasters and analyst forecast properties is more pronounced for firms in climate-vulnerable industries. Results from the market reaction tests further support our main findings by showing that the stock market responds less strongly to positive earnings surprises during periods of high climate disasters. Our results are robust to a battery of sensitivity tests, including two-stage least squares (2SLS) approach and a difference-in-differences specification. Overall, the results shed light on the association between climate disasters and analysts' earnings forecasts, which has significant implications for academics, investors, and standard setters.

Keywords: Climate disasters, Analyst forecast errors, Analyst forecast dispersion

JEL classification: G40, Q54, M21

1. Introduction

The growing concerns about climate change have attracted much attention in the broad economics literature investigating the impact of climate change on various economic activities (e.g., Dell et al., 2012; Gallagher and Hartley, 2017; Noy, 2009; Raddatz, 2006). In particular, an emerging strand of literature suggests that climate risk affects capital markets by influencing firm-level economic behaviors and outcomes (e.g., Addoum et al., 2020; Hsu et al., 2018; Huang et al., 2018; Krueger et al., 2020). Somewhat surprisingly, relatively little is known about the impact of climate disasters on analyst forecast properties, with a few exceptions (e.g., Kong et al., 2021). To the extent that climate risks play an increasingly important role in the capital markets (e.g., Hong et al., 2019; WEF, 2020), a better understanding of whether and to what extent climate disasters are associated with analyst forecast properties is particularly important, especially against the backdrop of climate change.

Motivated by the gap in the literature, the purpose of this study is to explore whether and to what extent climate disasters are associated with analyst forecast properties. The notion that limited attention affects analysts' forecasting performance is prevalent in the literature (e.g., Han et al., 2020; Harford et al., 2019). Nevertheless, less is known about how uncertainty arising from climate disasters increases the complexity of analysts' forecasting tasks, particularly given that firms are directly affected by physical damages inflicted by climate disasters and indirectly affected by the policies and regulations on climate change. Unlike existing studies that typically focus on a certain type of natural disasters (e.g., Kong et al., 2021), we focus on climate disasters because most disaster damages in the U.S. are caused by climate disasters rather than geophysical disasters (CEMHS, 2018; Cutter and Emrich, 2005). In addition, prior studies suggest that climate disasters may have different impacts on economic activities relative to geophysical disasters (e.g., Felbermayr and Gröschl, 2014; Klomp, 2017; Loayza et al., 2012; Skidmore and Toya, 2002).

We posit that climate disasters are associated with deteriorated analyst forecast properties. The uncertainty inherent in climate disasters increases the complexity of forecasting for several reasons. First, prior studies suggest that analysts have difficulty comprehending a range of uncertainties and thus are more inclined to issue biased and dispersed forecasts (Amiram et al., 2018; Hann et al., 2012; Mattei and Platikanova, 2017). Climate disasters induce uncertainty and complexity in the business environment because the magnitude, duration, and economic consequences of climate disasters are extremely difficult for analysts to quantify ex-ante, making it challenging for analysts to issue accurate earnings forecasts. Second, climate disasters typically bring about business and supply chain disruptions (e.g., Carvalho et al., 2021; Park et al., 2013), which makes it difficult for analysts to forecast sales, margins, cash flows, and other key financial metrics, leading to greater forecast errors and dispersion. Third, the volatility of key financial metrics makes historical financial data less useful, adding a further layer of difficulty to analysts' forecasting activities (e.g., Dichev and Tang, 2009; Duru and Reeb, 2002). Fourth, climate disasters may lead to unpredictable changes in climate-related policies, which in turn affect firms in multiple ways (e.g., compliance costs, and investment decisions) and add another layer of forecasting difficulty for analysts.

In terms of forecast dispersion, prior research suggests that the enhanced complexity of forecasting tasks positively impacts forecast dispersion by generating divergent views toward the same climate-induced extreme weather event because different analysts may interpret the same phenomenon differently (Barry and Jennings, 1992). Based on the above arguments, we predict a positive association between climate disasters and analyst forecast errors and dispersion.

Alternatively, in response to more complex forecasting tasks during high-climate-disaster periods, analysts are more likely to work harder due to career and reputational concerns (Loh and Stulz, 2018), thus partially offsetting forecasting challenges imposed by climate disasters. Moreover, climate uncertainty reduces the optimism bias by making analysts less likely to issue over-optimistic earnings forecasts. In addition, given that some analysts may have difficulty issuing accurate earnings forecasts during periods of high uncertainty arising from climate disasters, it could be an optimal strategy for them to issue forecasts following more experienced analysts (i.e., star/lead analysts). These arguments suggest that climate disasters may not be associated with analyst forecast errors and dispersion. Therefore, whether and how climate disasters are associated with analyst forecast properties is ultimately an empirical question.

We begin by examining the influence of climate disasters on analyst forecast properties by employing a sample of 382,387 analyst-firm-year observations over the period 2001-2017.[1] In particular, we focus on analyst forecast errors and analyst forecast dispersion, both of which are important metrics of analyst forecast properties. Following prior literature (e.g., Eckstein et al., 2019; Miao et al., 2018), we measure the severity of climate disasters as the total amount of annual state-wide monetary property damages caused by climate hazards.

Our empirical findings across multiple specifications are consistent with the notion that climate disasters are significantly positively associated with both analyst forecast errors and analyst forecast dispersion, implying deterioration in the quality of analyst forecasts. Our results are also economically meaningful. Specifically, a one standard deviation increase in the severity of climate disasters is related to an increase in forecast errors of 3.05% and an increase in forecast dispersion of 5.25%. This finding suggests that climate disasters could play an important role in

[1] Our data ends in 2017 because this is the latest year when climate disaster data from SHELDUS are available.

shaping analyst forecast properties. Furthermore, we identify possible channels through which climate disasters influence analysts' performance. Specifically, we find that climate disasters increase earnings volatility and cash flow volatility, and lower financial statement comparability, all of which are likely to further increase the complexity of the forecasting tasks of analysts, leading to deterioration in analyst forecast performance.

Having established the positive association between climate disasters and analyst forecast properties, we next examine whether the relationship is more pronounced for firms belonging to climate-vulnerable industries. Prior studies (e.g., Huang et al., 2018; Krueger et al., 2020) document that some industries are more susceptible to climate disasters than others. We thus partition our sample into climate-vulnerable industries and non-climate-vulnerable industries based on the Fama French 48 industry classification framework and the PPE intensity, respectively. Consistent with our expectation, we find that the positive relation between climate disasters and analyst forecast properties is more pronounced in climate-vulnerable industries.

To further validate our baseline results, we investigate how the stock market responds to earnings surprises around the earnings announcement date. If climate disasters are positively associated with forecast errors and dispersion indicating higher information asymmetry, we anticipate that market responses are likely to be weaker because investors tend to discount the role of earnings in valuing firms in higher-climate-disaster states (i.e., investors perceive earnings to be noisier). Consistent with our expectations, we find that the positive association between positive earnings surprises and abnormal returns is attenuated due to the influence of climate disasters. In contrast, the market reaction to negative earnings surprises is unlikely to be influenced by climate disasters, consistent with the notion of loss aversion suggested by prospect theory (Kahneman and Tversky, 1979).[2]

To address the potential endogeneity concerns arising from correlated omitted variables, we first employ an instrumental variable approach that uses population density at the state level in the U.S. as an instrument for climate disasters (Albouy et al., 2016; Huang et al., 2018). The results from the two-stage least squares regressions (2SLS) support our baseline findings. Moreover, we employ the occurrence of Superstorm Sandy as a plausibly exogenous shock and further investigate the potential causal relationship between climate disasters and analyst forecast properties by using a propensity score matching based difference-in-differences research design. Furthermore, we mitigate the endogeneity concerns by controlling for additional firm-level and analyst-level characteristics, as well as analyst- and firm-level fixed effects. As anticipated, our main findings continue to hold under all these different model specifications.

We also conduct a battery of sensitivity tests. We use various alternative measures to capture climate disasters. Specifically, we proxy for climate disasters using four additional measures: (1) the frequency of climate disasters, (2) the per capita monetary value of damages caused by climate disasters, (3) the rank of climate disaster damages, and (4) the county-level property damages from all types of climate disasters. Overall, the results show that our baseline findings are robust to all these alternative measures.

Finally, we rule out potential confounding factors that may drive our baseline results. It is plausible that our findings may be caused by observations during the financial crisis periods (Loh and Stulz, 2018), by firms in high-climate-disaster years (Bourveau and Law, 2021), by firms located in the Gulf Coast states, and by firms with a more dispersed workforce. To eliminate these

[2] According to loss aversion, investors have a greater aversion toward losses than equivalent gains, indicating a stronger response to losses than to gains, which is supported by our asymmetrical findings.

alternative explanations, we drop the corresponding subsamples, respectively, which are likely to drive our findings. Analyses based on the reduced samples show that the baseline results are robust to all these scenarios, indicating that the effects of climate disasters on analyst forecast properties are unlikely to be driven by these factors.

This study contributes to the literature in several ways. First, it contributes to a growing body of literature assessing the micro-level economic impact of climate risk (e.g., Addoum et al., 2020; Ding et al., 2021; Hsu et al., 2018; Huang et al., 2018) by focusing on the influence of climate disasters on analyst forecast properties. Specifically, we extend the study of Krueger et al. (2020) which serves as a good starting point to justify looking beyond investors and explore whether climate disasters in the U.S. influence analyst forecast performance in terms of greater analyst forecast errors and dispersion. To the best of our knowledge, we are among the first to show that climate disasters are related to deteriorated analyst forecast properties in the U.S., which has significant implications for academics, regulators, and investors.

Second, our study adds to the established literature on the determinants of analyst forecast properties (e.g., Duru and Reeb, 2002; Hope and Kang, 2005; Zhang, 2006) and the literature addressing the relation between uncertainty and analyst forecast properties (e.g., Amiram et al., 2018; Chourou et al., 2021). As suggested by Kozeniauskas et al. (2018), various measures of uncertainty are distinct, either statistically or conceptually. Climate change uncertainty is unique in terms of its far-reaching impact, unforeseeable nature, and irreversibility (Chenet et al., 2021).[3]

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[3] Oh and Oetzel (2022) argue that climate change uncertainty is highly unpredictable and unknowable due to a mixture of natural forces and human involvement. In contrast, natural forces play a much less important role in other types of uncertainties, such as economic policy uncertainty or political uncertainty.

In this sense, we contribute to these two strands of literature by identifying climate disasters as a significant source of information complexity that negatively affects analysts' forecasts.

Finally, our study contributes to the literature on the relationship between climate disasters and analyst forecasts based on complexity explanation. Prior research has suggested that distraction may influence analysts' forecasting tasks (e.g., Bourveau and Law, 2021; Han et al., 2021). For example, Han et al. (2021) demonstrate that analyst forecast accuracy decreases when analysts are distracted by climate disasters. Nevertheless, another strand of literature suggests that analysts are unlikely to be distracted (Groysberg and Healy, 2013; Murphy and Smith, 2015).[4] Consistent with this notion, we document that it is most likely that complexity rather than distraction that influences analyst forecast properties, lending support to and extending the complexity explanation literature (e.g., Clement, 1999; Francis et al., 2019; Plumlee, 2003).

Our paper is related to the contemporaneous work of Kong et al. (2021); however, our paper differs from theirs in several different dimensions. First, Kong et al. (2021) focus directly on the effect of disaster events on analyst forecast optimism, while we shed light on the impact of climate disasters on analyst forecast errors and dispersion. Second, Kong et al. (2021) focus on earthquakes which tend to cluster in some confined regions. As suggested by Oh and Oetzel (2022), countries experience significant variations in the types and severities of natural disasters. While hydrological disasters are a global concern, other types of natural disasters are more localized. In contrast, we focus on climate disasters, which caused most damages and can occur randomly

[4] There is a strand of literature suggesting that analysts may be unlikely to be distracted under the influence of natural disasters. Murphy and Smith (2015) find that analysts are likely to escape inattention since they are trained to deal with chaos and multitask. They also find that analysts are totally immersed themselves in their work and have little free time. Groysberg and Healy (2013) demonstrate that analysts are typically supported by their brokerages that outsource certain works to increase their attention capacity. Finally, analysts normally cover related firms. That is, the information garnered from one firm can be applied to another, making their work more efficient.

across the U.S., relative to geophysical hazards. Moreover, it is widely acknowledged that the economic impact of earthquakes is likely to be different from that of other climate disasters, as documented in the prior economics literature (e.g., Klomp, 2017; Loayza et al., 2012). Even for the same type of disaster, its impact is likely to differ across developed and developing countries (e.g., Felbermayr and Gröschl, 2014; Noy, 2009). Third, given that U.S. and emerging economies such as China differ significantly in terms of institutional setup, investor protection, and legal environment, all of which could substantially influence analyst forecasts (Bradshaw et al., 2019), it is thus very likely that Kong et al. (2021)'s findings may not be extended directly to a U.S. setting.

The remainder of this paper is organized as follows. Section 2 discusses the background literature and develops the hypotheses. Section 3 describes the data sources and research design. Section 4 discusses the empirical results, and Section 5 discusses the results of additional analyses and sensitivity checks. Section 6 concludes the study.

2. Background Literature and Hypotheses Development

2.1 The economic impact of climate disasters

Climate change has led to widespread concerns recently. As suggested by the World Economic Forum's Global Risk Report (2020), extreme weather events are ranked as the top risk faced by firms around the globe in the next decade. Globally, disaster damages grew 15-fold from the 1950s to the 1990s (Benson and Clay, 2004) and reached more than 113 billion dollars each year during the 2000s (Rauch, 2012). It is projected that global warming will significantly increase extreme weather events (IPCC, 2008). As far as the U.S. is concerned, the economic cost of disasters has been steadily increasing, and climate disasters account for most of these damages

(CEMHS, 2018; Cutter and Emrich, 2005). As pointed out by Hsiang et al. (2017), it is estimated that a 1-Celsius-degree rise in temperature is associated with a 1.25% decline in GDP in the U.S.

The economic impacts of climate disasters have been well documented in the broad economics literature with mixed findings (e.g., Dell et al., 2012; Gallagher and Hartley, 2017; Raddatz, 2006; Skidmore and Toya, 2002). Dell et al. (2012) find that the negative impacts of temperature on economic growth and export mainly exist in developing countries. Gallagher and Hartley (2017) investigate the impact of hurricane-induced floods on household finance in the U.S. They find that due to the influence of flooding, homeowners are more likely to repay their existing debt using flood insurance rather than rebuild, leading to a decline in total debts. Raddatz (2006) explores the effects of several kinds of natural shocks, including climate disasters. He finds that climate disasters lead to a roughly 2% decrease in per capita GDP one year following a disaster, but this effect disappears within five years. In contrast, Skidmore and Toya (2002) suggest that geologic disasters are negatively associated with economic growth, whereas climate disasters are positively related to economic growth.

Although the literature primarily focuses on climate disasters at the individual and national levels, an emerging strand of literature examines the firm-level impact of climate risk (e.g., Addoum et al., 2020; Hsu et al., 2018; Huang et al., 2018). Addoum et al. (2020) find that abnormal temperature exposure is inversely associated with earnings at the firm level. Using U.S. data, Hsu et al. (2018) investigate the association between natural disasters and firm-level operating performance. Their findings suggest that firms in states affected by natural disasters are less likely to be profitable than firms in other states. Huang et al. (2018) investigate the relation between climate risk and financial performance and financing choices in a global context. Using the climate risk index constructed by Germanwatch based on the number of deaths and economic losses resulting from natural disasters, the authors show that climate risk is negatively associated with financial performance in terms of reduced ROA, increased earnings volatility, and short-term debt, while positively associated with long-term debt.

Overall, despite the sizeable impact of climate disasters at the individual, firm, and country levels, there is limited understanding of how climate disasters are associated with analyst forecast properties. Given the potential impact of climate change on the capital market, a better understanding of how climate disasters influence analyst forecast properties is important and has significant implications, not only for capital allocation at the micro level but also for the overall economic growth at the macro level.

2.2 Climate disasters and analyst forecast properties

We posit that climate disasters are associated with deteriorated analyst forecast properties. Prior literature documents evidence of the negative impact of conventional uncertainty on analyst forecast properties. For example, Hope and Kang (2005) show that macroeconomic uncertainty is negatively associated with analysts' forecast accuracy, with macroeconomic uncertainty proxied by inflation and exchange rate volatility. Zhang (2006) documents that greater information uncertainty can lead to more analyst forecast errors. Unlike conventional uncertainties, uncertainty originating from climate disasters consists of scientific and socio-economic uncertainty (Heal and Millner, 2014).[5] Scientific uncertainty arises from the lack of knowledge to understand the inherently complex nature of climate change. In contrast, socio-economic uncertainty stems from a lack of understanding of the economic or social impact of climate change. Scientific and socio-economic uncertainty stemming from climate disasters adds much difficulty to analysts' forecasting. Consistent with this view, Oh and Oetzel (2022) suggest that climate change

[5] There is no universally accepted definition of uncertainty. We therefore follow prior literature (e.g., Bloom, 2014) and define it as the difficulty in forecasting the likelihood of unknown outcomes.

uncertainty is highly unpredictable and unknowable due to a mixture of natural forces and human involvement.

The uncertainty inherent in climate disasters increases the complexity of forecasting for several reasons. First, climate disasters induce uncertainty and complexity in the business environment, making it challenging for analysts to issue accurate earnings forecasts. For example, in the tourism and hospitality industry, natural disasters, such as hurricanes or wildfires, can disrupt tourism patterns, cause cancellations, and damage infrastructures (e.g., Laws and Prideaux, 2006). These events lead to uncertainty regarding visitor numbers, tourism demand, and tourism revenues (e.g., Rosselló et al., 2020), which in turn makes revenue forecasting more challenging. Second, climate disasters typically bring about business and supply chain disruptions (e.g., Carvalho et al., 2021), which makes it difficult for analysts to forecast sales, margins, cash flows, and other key financial metrics, leading to greater forecast errors and dispersion. Third, the volatility of key financial metrics makes historical financial data less useful, adding a further layer of difficulty to analysts' forecasting activities (e.g., Dichev and Tang, 2009; Duru and Reeb, 2002). Finally, climate disasters may lead to changes in climate-related policies, which in turn affect firms in multiple ways (e.g., compliance costs, and investment decisions) and add another layer of forecasting difficulty for analysts.

As economic agents, analysts are subject to limited attention and resources (Harford et al., 2019; Kahneman, 1973). Firms may become more conservative and deliberately reduce the quantity and quality of their voluntary disclosures because of some mitigating effects from competition, litigation risk, and proprietary costs (Hodges et al., 2018; Leuz and Wysocki, 2016). Managers are, therefore, more likely to respond to negative performance shocks arising from climate disasters by engaging in earnings big baths (Ng et al., 2020), degrading the informativeness of earnings that analysts normally use. Amiram et al. (2018) suggest that analysts struggle with market-level uncertainty, which leads to greater forecast errors. Consequently, climate disasters that encompass much complexity and uncertainty prevent analysts from assimilating and incorporating climate-related information into earnings forecasts because analysts have difficulty analyzing firms' future financial performance under such an uncertain context (Amiram et al., 2018) or because the costs to do so exceed the benefits (Plumlee, 2003). Taken together, we expect that climate disasters, by increasing the complexity of forecasting tasks, are positively associated with analysts' forecast errors. We propose our first hypothesis as follows (in alternate form):

H1: Climate disasters are positively associated with analyst forecast errors.

Alternatively, prior literature indicates that analysts' forecast accuracy significantly influences their career upward mobility and reputation (Groysberg et al., 2011; Hong and Kubik, 2003; Jackson, 2005). In addition, analysts have monetary incentives to generate trading commissions by inducing more trades for their brokerage firms (e.g., Hayes, 1998; Irvine, 2000). Further, forecast accuracy is also tied to analysts' reputation and job turnover (Groysberg et al., 2011; Hong and Kubik, 2003), which indirectly affects their brokerage commissions (Jackson, 2005). For example, Mikhail et al. (1999) find that the probability of leaving her current job increases if an analyst is less accurate than her peers. Lehmer et al. (2022) find that forecast accuracy is positively associated with trading volume. Therefore, career and reputational concerns induce analysts to improve their forecast accuracy (Loh and Stulz, 2018).[6] Furthermore, anecdotal evidence suggests that firms that miss analyst forecasts are likely to experience a significant drop

[6] There is also a vast literature documenting that analysts are on average optimistically biased to achieve certain goals such as increasing upward mobility and pleasing the management (e.g., Abarbanell, 1991; Lim, 2001). Although analysts are less likely to be penalized for issuing optimistic forecast during high uncertainty periods, continuous opportunistic behaviors are constrained by career and reputational concerns.

in their stock prices. In addition, empirical evidence documents that the capital market rewards firms that meet/beat analyst forecasts and penalizes firms that do not (Bartov et al., 2002; Brown and Caylor, 2005; Lopez and Rees, 2002; Skinner and Sloan, 2002). Consequently, when climate disasters increase, analysts are less likely to issue optimistic forecasts than they do in normal periods, due to career or reputational concerns. The systematic downward bias can enhance their forecast accuracy to some extent (Hugon and Muslu, 2010; Walther and Willis, 2013).[7] In addition, although analysts' tendency to issue optimistic earnings forecasts has been well documented in the literature (e.g., Abarbanell, 1991; Lim, 2001), Keskek and Tse (2018) find that forecasts issued by analysts are much less optimistic for firms in poor information environment. Consequently, climate risk may not be an important factor in influencing analyst forecast accuracy. The above reasoning provides some tension to our first hypothesis and warrants the empirical analysis.

In line with the previous discussion of Hypothesis 1, we argue that climate disasters are associated with not only greater analyst forecast errors but also greater analyst forecast dispersion. Climate disasters are likely to lead to more divergent earnings forecasts because different analysts may interpret the same complex climate-related event differently, thus engendering disparate views on firms' future performances. In addition, analyst forecasts are more dispersed when the quality and quantity of information disclosed by firms decrease (Healy et al., 1999). Based on the above discussions, we propose our second hypothesis as follows (in alternate form):

H2: Climate disasters are positively associated with analyst forecast dispersion.

In contrast, prior literature documents herding behaviors among financial analysts (e.g., Welch, 2000). Following more experienced (i.e., star/lead analysts) would be an optimal strategy

[7] Given that our sample is collected in the post-Reg FD period, analysts have less incentive to issue optimistic forecasts to please the firm they covered to obtain private information. However, we acknowledge that there is still some room for analysts to obtain some private information from managers, as suggested by existing studies.

for unsophisticated analysts who have fewer resources and are highly concerned with their career prospects.[8] Thus, an enhanced level of climate risk may encourage analysts to be more conservative and issue forecasts that are less likely to deviate significantly from those issued by more experienced analysts, leading to a relatively lower level of forecast dispersion. As before, these arguments provide some tension to our second hypothesis.

2.4 Climate-vulnerable industries versus non-climate-vulnerable industries

Prior research documents that some industries are more likely to be negatively affected by climate change than others (Huang et al., 2018; Krueger et al., 2020). Krueger et al. (2020) find that as the exposure to climate change likely varies across industries, the extent to which climate risk is incorporated into equity valuation could vary across industries. Huang et al. (2018) find that firms in climate-vulnerable industries are more susceptible to greater earnings volatility when climate risk increases. Greater earnings volatility inevitably adds an additional layer of difficulty to analysts' work. Therefore, we follow Huang et al. (2018) and partition industries into climate-vulnerable industries and non-climate-vulnerable industries using the Fama French 48 industry classification framework.

We conjecture that analysts will have more difficulty forecasting earnings for firms in climate-vulnerable industries due to the enhanced level of complexity imposed by potential climate disasters. In addition, when a climate disaster strikes, managers from climate-vulnerable industries are more likely to exercise their discretion in financial reporting to meet some specific goals (e.g., meet or beat the earnings benchmark). Earnings manipulation in climate-vulnerable industries may further aggravate firms' information environment by leading to deterioration in analysts'

[8] Prior research finds that *Institutional Investor*-ranked analysts possess higher ability as evidenced by higher forecasting accuracy, stock recommendation profitability, and report readability (e.g., De Franco et al., 2015; Stickel, 1990, 1992).

performances (e.g., Richardson, 2000; Wilson and Wu, 2011). For example, Wilson and Wu (2011) find that analyst forecast accuracy declines with the level of earnings management. Relative to firms in non-climate-vulnerable industries, firms in climate-vulnerable industries are more likely to suffer from losses when climate-related events strike. In addition, Ciccone (2003) suggests that more disagreement in earnings forecasts occurs following negative news. Based on these discussions, we propose our third hypothesis (in alternate form):

> H3: The positive relation between climate disasters and analyst forecast errors (dispersion) is more pronounced for firms in climate-vulnerable industries.

3. Data and Research Design

3.1 Sample selection

The data used in the analysis are compiled from multiple sources: (1) climate disasters data are based on weather-related events from the Spatial Hazard Events and Losses Databases for the United States (SHELDUS) maintained by the Arizona State University; (2) annual earnings analyst forecast data are from Institutional Brokers Estimate System (I/B/E/S) detail U.S. file; (3) financial data are from Compustat, and (4) stock price data are from Center for Research in Security Prices (CRSP). Our sample starts from 2001 because this is the first year when the Regulation Fair Disclosure (hereafter Reg FD)[9] took into effect and ends in 2017 because this is the latest year when climate disasters data from SHELDUS are available. In terms of the financial statement data and stock price data, we delete all observations with missing or negative information on total assets, and all observations with stock prices less than one dollar.

[9] Reg FD was passed in 2000 to prohibit firms from disclosing private information to market participants such as security analysts. Given that the private information disclosed by managers to analysts may influence their forecast accuracy as indicated in the prior literature, limiting our sample to the post-Reg FD period can eliminate the distortion caused by private disclosures.

We merge the firm-level financial data with the state-level climate disasters data based on the locations of firms' headquarters.[10] The intersection of these data sets leads to a final sample consisting of 382,387 firm-analyst-year observations, representing 11,905 analysts and 4,822 distinct firms over the period 2001-2017. Table 1 reports the sample distribution by state and year. As shown in Table 1, California has the largest number of observations (74,104), followed by Texas (44,211), New York (28,536), Massachusetts (20,993), Illinois (18,237), and Pennsylvania (15,728), while at the lower end are Alaska (88), Wyoming (133), and New Mexico (185).

[Insert Table 1 Here]

3.2 Measure of climate disasters

We derive our measure of the severity of climate disasters using the weather-related climate disasters data from the SHELDUS database for each state and year (CEMHS, 2018). We adopt the state-level measure to avoid the potential limitation of the SHELDUS data (i.e., county-level data are averaged out) because it is highly unlikely that all counties are equally affected by the same disaster, as suggested by Gall et al. (2009).[11] The SHELDUS database covers county-level natural disaster losses resulting from a group of 18 different categories of natural hazards, such as hurricanes, droughts, floods, and tornados. In calculating our measure of climate disasters, we

[10] We obtain a firm's headquarters location using the data and code provided by Gao et al. (2021) since Compustat doesn't report firms' historical headquarters locations.

[11] As pointed out by Gall et al. (2009), one potential limitation of the SHELDUS data is that economic losses are equally distributed across counties if they are simultaneously impacted by a climate event. Put it differently, using the county-level data is based on the tenuous assumption that all counties are equally affected by the same climate disaster. However, adopting a state-level climate disasters measure can avoid this potential drawback. As a robustness test, we also replicate our regression using the county-level measure and the results (which are reported in Section 5.2.2) are qualitatively unchanged.

focus on weather-related events and exclude geophysical disaster events in our analysis.[12] For each climate disaster event recorded in SHELDUS, we collect data on the date of the event and monetary property losses related to that event.[13] Following the spirit of the prior literature (e.g., Eckstein et al., 2019; Miao et al., 2018), we proxy for the severity of climate disasters by summing the total amount of annual state-wide monetary property damages (constant 2017 US dollars) caused by climate hazards and denote it as *CDD*. Thus, the increasing magnitude of *CDD* indicates a higher level of climate disaster risk. We also use several alternative measures of climate disasters and the results are reported in Section 5.2.2.

Table 2 shows the climate disasters proxied by the total annual climate disaster property damages (in millions of U.S. dollars) at the state level from 2001 to 2017. Texas has the greatest climate damage, with estimated property damages of 106,345 million U.S. dollars over 2001-2017, followed by Louisiana (64,176), Florida (33,189), and Mississippi (27,271), all situated on the Gulf Coast.

[Insert Table 2 Here]

We also provide a snapshot of the annual total property damages caused by weather-related disasters from 2001 to 2017 in Figure 1. As can be visualized from Figure 1, Year 2005 has the

[12] As mentioned earlier, one of the reasons why we focus on climate disasters rather than geophysical disasters is that prior studies suggest that climate disasters may have a different impact on economic activities relative to geophysical disasters (e.g., Klomp, 2017; Skidmore and Toya, 2002). Thus, our study covers a total of 13 types of climate-related events including coastal events, drought, flooding, hail, heat, hurricane, landslide, lightning, severe storm, tornado, wildfire, wind, and winter weather. Geophysical natural hazards, such as earthquake and volcano, are excluded from the analysis. In fact, there was no major earthquakes or volcano eruptions taking place over the period 2001-2017 in the mainland U.S.

[13] Although employing a single index can potentially camouflage the heterogeneity in the effects of disparate disasters, arguably total economic damages is one of the most important indicators in evaluating the severity of natural disasters. For example, Eckstein et al. (2019) create a global climate risk index (including the U.S.) in which economic losses and the number of deaths are the main factors in constructing the index. In addition, unlike Miao et al. (2018) who focus on the total of crop and property damages when investigating the dynamic fiscal response to natural disasters, we focus only on property damages in our baseline regressions because firms are mostly concerned with property economic damages rather than crop damages. However, as a robustness test, we also construct a new measure which includes both property and crop damages.

highest climate disaster losses with an estimated damage of 118,732 million U.S. dollars because of Hurricane Katrina, which is the most destructive climate disaster event in the U.S. history. It is worth noting that climate disaster risk has been increasing in recent years and peaked in the Year 2017 with an estimated damage of 116,693 million U.S. dollars, suggesting the increasingly devastating power of climate disasters.

[Insert Figure 1 Here]

3.3 Measures of analyst forecast properties

Given the critical role of security analysts in the capital market in disseminating, monitoring, and providing firm-level financial information, we focus on two main measures of analyst forecast properties: analyst forecast errors and analyst forecast dispersion. In line with the prior literature on security analysts (e.g., Clement and Tse, 2005), we eliminate all observations with missing information on the forecast announcement date, earnings announcement date, forecast value, actual value, and firm ticker. We delete observations for which the forecast announcement date is later than the earnings announcement date. In addition, to be included in our sample, a firm is required to have at least three observations in a specific year to construct analyst forecast dispersion. We eliminate observations with unidentified analysts (i.e., analyst identifier is equal to zero).

Following the prior literature, we measure analyst forecast errors using the following formula:

$$AFE_{a,i,t} = 100 * \frac{|Forecast_{a,i,t} - Earnings_{i,t}|}{Price_{i,t-1}}$$

where $Forecast_{a,i,t}$ is the latest analyst forecast issued by analyst a for firm *i* for period *t* before the earnings announcement, $Earnings_{i,t}$ is the actual value released on the earnings announcement date for firm *i* for period *t*, and $Price_{i,t-1}$ is the stock price for firm *i* at the beginning of the year. Given that analysts can issue multiple forecasts before the earnings announcement date, we retain the latest earnings forecast issued by each analyst before the earnings announcement date and use it to calculate analyst forecast error. As in prior research, we measure analyst forecast dispersion using the standard deviation of analyst forecast values for a given firm scaled by the stock prices at the beginning of the year.

3.4 Empirical methodology

We estimate the influence of climate disasters on analyst forecast properties using the following model:

$$\begin{aligned} AFP_{(a)it} = {} & \beta_0 + \beta_1\, CDD_{it} + \beta_2\, Size_{it} + \beta_3\, Loss_{it} + \beta_4\, ROA_{it} + \beta_5\, MTB_{it} + \beta_6\, Sgrowth_{it} \\ & + \beta_7\, Age_{it} + \beta_8\, SDret_{it} + \beta_9\, HOR_{ait} + \beta_{10}\, NOA_{it} + \beta_{11}\, NOC_{ait} + \beta_{12}\, NOF_{ait} \\ & + \beta_{13}\, Firmexp_{ait} + \beta_{14}\, Genexp_{ait} + \alpha_y + \alpha_{ind} + \alpha_{sta} + \varepsilon_{ait} \qquad (1) \end{aligned}$$

where subscripts *a*, *i*, and *t* refer to analyst, firm, and year, respectively. α_y , α_{ind} and α_{sta} are year, industry, and state fixed effects, respectively. We consider two analyst forecast properties (henceforth *AFP*): analyst forecast errors (henceforth *AFE*) and analyst forecast dispersion (henceforth *DISP*). *CDD* denotes climate disaster property damages, measured by the total amount of annual state-wide monetary property damages caused by climate hazards. Our variable of interest in equation (1) is *CDD*. We predict that the coefficient on *CDD* will be positive, implying that climate disasters cause deterioration of analyst forecast properties.

When estimating equation (1), we include a wide set of control variables that could potentially affect analyst forecast properties.[14] Prior research (e.g., Duru and Reeb, 2002; Mattei and Platikanova, 2017) indicates that firm size and age are associated with more accurate analyst forecasts and less analyst forecast dispersion. We include firm size proxied by the natural

[14] Detailed definitions of each variable used in this study can be found in the Appendix.

logarithm of total assets, and firm age, proxied by the number of years since a firm first appeared in the Compustat database. Following the extant literature, we control for other firm-level characteristics such as *ROA*, whether a firm is a loss firm (*Loss*), the market-to-book ratio (*MTB*), and sales growth (*Sgrowth*) in the model. Other than firm-level attributes, we also control for some analyst-level characteristics that prior literature identifies as determinants of analyst forecast properties. Prior literature shows that the number of analysts following a firm is positively associated with analyst forecast accuracy. We include the number of analysts following a firm (*NOA*). In addition, we include the variable of *Horizon*, which is defined as the distance between the earnings forecast issuance date and the actual earnings announcement date. We measure the involvedness in analysts' tasks using the number of firms they follow (*NOC*) and the number of earnings forecasts issued by an analyst (*NOF*). Prior literature has highlighted the role of general and firm-specific experience in influencing analyst forecast performance (e.g., Clement, 1999; Mikhail et al., 1999), we therefore include analysts' general experience (*Genexp*) and firm experience (*Firmexp*) as two additional control variables in our regression model. Specifically, *Genexp* is the number of years since an analyst initially appeared in the I/B/E/S database, and *Firmexp* is the number of years an analyst has provided coverage for a given firm.

To control for a variety of uncertainties that could influence our dependent variables and disentangle the effects of these uncertainties and that of climate disasters, we control for the following three types of uncertainty measures that are widely used in the literature: (1) economic policy uncertainty from Baker et al. (2016); (2) general macroeconomic uncertainty obtained from Jurado et al. (2015); and (3) Chicago Board Options Exchange volatility index (*VIX*).[15] We include them individually in our regression model to assess the robustness of our main findings.

[15] Untabulated results suggest that our findings continue to hold when we control for uncertainty arising from infectious disease using the Infectious Disease Equity Market Volatility Tracker data from Baker et al. (2020).

To control for time-invariant industry-, year-, and state-level characteristics, we control for industry-, year-, and state-level fixed effects. We winsorize all continuous variables at the top and bottom percentiles to eliminate the impact of outliers. We double cluster standard errors at the state and analyst levels to control for potential cross-sectional correlation.

4. Empirical Results

4.1 Descriptive statistics

Table 3 reports the descriptive statistics and pairwise correlations for the variables used in the baseline regression models. As shown in Panel A of Table 3, the mean (median) for analyst forecast errors and analyst forecast dispersion are 0.765 (0.164) and 0.008(0.003), respectively, which are largely consistent with those reported in the prior literature. The fact that the mean (median) of the property damages resulting from climate disasters is 570.20 (3.87) million U.S. dollars and that the standard deviation of property damages is 2811.74 million U.S. dollars suggests significant variation in climate disasters across the sample.

Table 3 Panel B reports the pairwise correlations between the variables used in our main analysis. It is worthwhile to note that: (1) climate disasters are positively and significantly correlated with both analyst forecast errors and analyst forecast dispersion, and (2) analyst forecast errors are positively and significantly correlated with analyst forecast dispersion.

[Insert Table 3 Here]

4.2 Baseline regression results

We report our baseline regression results on the relation between climate disasters and analyst forecast properties in Table 4. Columns (1) and (2) of Table 4 report the relation between climate disasters and analyst forecast errors after controlling for firm-level characteristics and analyst-level characteristics, respectively. Column (3) report our baseline regression results.

Columns (4) through (6) report results when three additional uncertainty measures are controlled for in the regressions.

As indicated in Table 4 Panel A, we document that climate disasters are positively and significantly related to analyst forecast errors across different specifications (coefficients range from 0.745 to 0.982). Specifically, we find that the coefficient on *CDD* is positive and statistically significant (coef. =0.830, t-stat. =7.05) at the 1% level in our baseline regression model. In terms of economic magnitude, a one standard deviation increase in climate disasters is associated with a 3.05% increase in analyst forecast errors.[16] This represents an increase of 0.023 in forecast errors for an average forecast error of 0.765. The signs of the coefficients on control variables are largely in line with those in the prior literature. As shown in Columns (4) through (6), our results are quantitatively similar when we control for those three types of uncertainty measures separately in our regression models.[17] Overall, these findings are consistent with H1, which states a positive association between climate disasters and analyst forecast errors.

Turning to Panel B of Table 4, we examine the relation between climate disasters and analyst forecast dispersion. Similarly, Columns (7) and (8) of Table 4 report the relation between climate disasters and analyst forecast dispersion after controlling for firm-level characteristics and analyst-level characteristics, respectively. Column (9) reports our baseline regression result for analyst forecast dispersion. Columns (10) through (12) report results when three additional uncertainty measures are controlled for in the regressions.

[16] Our illustration of economic magnitude is based on results reported in Column (3). The impact of a one standard deviation increase in climate disaster risk on analyst forecast errors is calculated as:1.0e-11∗0.830(coefficient reported in Table 4 Column (3)) *2811.74e+06 (standard deviation of climate disaster risk as reported in Table 3)/0.765(mean of forecast errors as reported in Table 3) =3.05%.

[17] We drop year fixed effects because it absorbs the effect of these uncertainty measures (uncertainty is year-specific).

An overview of our findings shows that climate disasters are positively and significantly associated with analyst forecast dispersion across all specifications (coefficients range from 0.013 to 0.014). Specifically, we find that the coefficient on *CDD* is positive and statistically significant (coef. =0.013, t-stat. =6.83) at the 1% level in the baseline regression model. In terms of economic magnitude, a one standard deviation increase in climate disasters is associated with an increase in forecast dispersion of 4.57%.[18] This represents an increase of 0.0004 in forecast dispersion for an average forecast dispersion of 0.008. Our finding is consistent with H2, which states a positive association between climate disasters and analyst forecast dispersion.

[Insert Table 4 Here]

4.3 Climate-vulnerable industries versus non-climate-vulnerable industries

Prior literature documents the disproportionate impact of climate change on firms in climate-vulnerable industries as opposed to non-climate-vulnerable industries (Huang et al., 2018; Krueger et al., 2020). We extend our analysis by focusing on the potential heterogeneous impact of climate disasters on analyst forecast properties in different industries.

In our research context, both analyst forecast errors and analyst forecast dispersion are influenced by the uncertainty associated with climate disasters. Compared to analyst forecasts for firms in non-climate-vulnerable industries, analyst forecasts for firms in climate-vulnerable industries are more likely to be influenced by climate disasters. Following Huang et al. (2018), we classify Agriculture, Business Services, Communication, Energy, Food Products, Health Care, and Transportation as climate-vulnerable industries while the rest are classified as non-climate-vulnerable industries. We drop the industry fixed effects because the indicator variable

[18] Our illustration of economic magnitude is based on results reported in Column (9). The impact of a one standard deviation increase in climate disaster risk on analyst forecast dispersion is calculated as:1.0e-11∗0.013(coefficient reported in Table 4 Column (9)) * 2811.74e+06 (standard deviation of climate disaster risk as reported in Table 3)/0.008(mean of forecast dispersion as reported in Table 3) =4.57%.

Vulnerability partially captures the industry fixed effects.[19] All other variables employed in the analysis are the same as those specified in the baseline regression model. In addition, given the potential drawbacks of the Fama-French industry classification as suggested in Bhojraj et al. (2003), we construct an alternative measure of climate vulnerability by using a firm's PPE intensity. The intuition behind this measure is that firms with higher PPE intensity are more likely to suffer when a disaster strikes, everything else being equal.

We present the regression results in Table 5. Columns (1) and (2) report results based on the Fama-French industry classification, while Columns (3) and (4) report results based on the PPE intensity. As predicated, we find that the coefficients on the interaction terms between climate disasters and vulnerability (Fama-French 48 and PPE intensity) are positive and statistically significant for both analyst forecast errors (coef. =0.923, t-stat. =1.75; and coef. =2.405, t-stat. =3.07) and dispersion (coef. =0.016, t-stat. =2.02; and coef. =0.042, t-stat. =2.19) at the conventional levels of significance. These findings indicate that industry vulnerability moderates the relation between climate disasters and analyst forecast properties, and that the positive relation between climate disasters and examined analyst forecast properties is more pronounced for firms in climate-vulnerable industries, thus lending support to H3.

[Insert Table 5 Here]

4.4 Potential economic channels

Having established the positive relationship between climate disasters and analyst forecast properties, we provide further evidence by examining the potential channels through which climate disasters may influence analyst forecast properties. Unlike a non-climate disaster, such as the sudden fire of a firm's factory, climate disasters, such as hurricanes and floods, can affect large

[19] Our results are qualitatively unchanged if we include industry fixed effects in the model.

areas and lead to widespread destruction, such as damaging infrastructure, displacing populations, and disrupting ecosystems. In this sense, the impact of climate disasters can be tremendous and long-lasting. Climate disasters affect not only the focal firm but also upstream and downstream firms along supply chains (Carvalho et al., 2021; Park et al., 2013), such as suppliers and customers, on which the firm's normal production and financial performance depend. By contrast, the impact of a sudden fire in a factory is generally more localized. A sudden fire in a factory primarily affects the immediate vicinity and the individuals working or living nearby. Relative to the sudden fire of a factory, climate disasters provide firms with a cover to take earnings big bath, for which potential losses can be blamed. In addition, by taking a big bath, managers can set a lower future earnings benchmark, against which improved earnings results can be obtained in subsequent periods. Prior literature suggests that firms may engage in earnings big baths when facing uncertainty (e.g., Ng et al., 2020; Yao et al., 2022). For example, Yao et al. (2022) find that Knightian uncertainty induces managers to engage in more downward earnings management. In a similar vein, Byard et al. (2007) find that in the aftermath of Hurricanes Katrina and Rita, large US-based companies engage in income-decreasing earnings management. We, therefore, argue that managers are more likely to respond to negative performance shocks arising from climate disasters by engaging in earnings big baths (Ng et al., 2020) degrading the informativeness of earnings that analysts normally use. Thus, it is reasonable to expect that analysts' forecasting tasks become more difficult due to the volatilities in ROA and cash flows.

Regarding our first channel, we exploit the link between climate disasters and the volatility of firms' performance in terms of ROA. We posit that climate disasters are positively associated with the volatility of ROA, making analyst forecasts more difficult and engendering divergent interpretations regarding firms' future performances. Similarly, the second channel, the volatility of cash flows, can also result from climate disasters and complicates analysts' forecasting job, leading to deterioration in analyst forecast quality. To test our conjectures, we estimate equation (1), with the dependent variable being either the volatility of ROA (ROA_SD) or the volatility of cash flows (CF_SD). Our variable of interest is still CDD.

Columns (1) and (2) in Table 6 present the results. We find that the coefficients on *CDD* are significant at the 1% level (coef. =0.678, t-stat. =5.28; coef. =0.136, t-stat. =2.73) for both models, suggesting that climate disasters increase the volatility of both *ROA* and cash flows. These findings indicate that the volatility of *ROA* and cash flows are two potential channels through which climate disasters influence analyst forecast properties.

Prior literature finds that corporate disclosures influence analyst forecast performance (e.g., Lang and Lundholm, 1996), and analysts often utilize corporate disclosure when making forecasts. More recently, De Franco et al. (2011) find that financial statement comparability is positively associated with analyst forecast accuracy but negatively associated with analyst forecast dispersion. Following this line of research, if climate disasters lead to deterioration in firms' financial statement comparability, we can argue that complexity arising from less comparable financial reports makes forecasting tasks more challenging, leading to worsened forecast accuracy and enlarged forecast dispersion, thereby supporting a complexity explanation.

Columns (3) through (6) in Table 6 present the regression results on financial statement comparability. We calculate financial statement comparability following De Franco et al. (2011) using four different measures. We find that the coefficients on *CDD* are significantly negative at the 1% level across all specifications, regardless of the comparability measure we examine. These findings provide strong evidence that complexity arising from climate disasters leads analysts to have more difficulty forecasting earnings because analysts tend to cover comparable firms in the same industry and anecdotal evidence and economic theory suggest that industries are geographically concentrated (e.g., Ellison and Glaeser,1997).

[Insert Table 6 Here]

4.5 An Additional test supporting the alternative complexity explanation

Our main findings and results from mechanism tests suggest that analyst forecast properties deteriorate due to the complexity arising from climate disasters. In this section, we perform an additional test to further disentangle the complexity explanation from the distraction explanation. Given that the main empirical challenge is to identify the location of each analyst, we take an alternative approach to circumvent this problem.[20] Specifically, we drop firms in the top 5/10 cities[21] where most financial analysts are located. Under this context, for the remaining sample of firms, if a disaster strikes, analysts are less likely to be distracted because they are mostly not located in the disaster-stricken areas, lending support to the complexity explanation.

As expected, we document a significant and positive relationship between climate disasters and analyst forecast properties after dropping firms located in either top 5/10 cities where analysts are located, consistent with the complexity explanation.

[Insert Table 7 Here]

4.6 Corroborating evidence from earnings surprises and market reaction tests

We further validate the relationship between climate disasters and analyst forecast properties by implementing a market reaction test similar to that of Nagar et al. (2019). Specifically, we measure earnings surprises using the actual earnings minus the analyst consensus mean

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[20] According to the literature, for the years prior to 2008, it is plausible to hand-collect these data from the *Nelson's Directory of Investment Research (NDIR)*. Post-2008 location is difficult to collect because *NDIR* has stopped updating since 2008. Therefore, we take an indirect approach to circumvent this obstacle.

[21] The data is obtained from https://www.zippia.com/advice/best-cities-for-finance-analysts/. These cities include New York, NY, Boston, MA, Chicago, IL, Los Angeles, CA, Dallas, TX (Top 5), Houston, TX, San Francisco, CA, Atlanta, GA, Charlotte, NC, San Jose, CA.

earnings forecasts.[22] Our return measure is the three-day (-1, +1) abnormal return, where day 0 is the earnings announcement date. We conjecture that when the likelihood of climate disasters is high, investors' responses to earnings surprises are weaker because they discount the usefulness of earnings in valuing firms. In contrast, if investors view earnings as a more valuable signal to value firms, the market response tends to be stronger. Specifically, we use the following model to test the market reaction:

$$CAR(-1{,}1)_{it} = \beta_0 + \beta_1\, CDD_{it} + \beta_2\, Sur_{it} + \beta_3\, CDD_{it} * Sur_{it} + \beta_4\, Size_{it} + \beta_5\, Loss_{it} + \beta_6\, ROA_{it} + \beta_7\, MTB_{it} + \beta_8\, Sgrowth_{it} + \beta_9\, Age_{it} + \beta_{10}\, SDret_{it} + \alpha_y + \alpha_f + \varepsilon_{it} \qquad (2)$$

where subscripts *i* and *t* refer to firm and year, respectively. The dependent variable *CAR* (-1,1) is the cumulative market-adjusted abnormal returns over a three-day event window (-1, 1) centered on the earnings announcement date. *Sur* is the earnings surprises. The independent variable of interest is the interaction term between *CDD* and *Sur*. We predict that the coefficient on the interaction term will be negative, suggesting that the magnitude of market response is mitigated when climate disaster risk is high. Specifically, we examine whether market reaction depends on the type of earnings news by partitioning earnings surprises into positive and negative ones.

Consistent with the prior literature (e.g., Nagar et al., 2019), in our simplest specifications, the results reported in Columns (1), (2), and (4) in Table 8 indicate that the coefficients on earnings surprises are positive and statistically significant at the 5% level (coef. =0.002, t-stat. =1.98; coef. =0.005, t-stat. =2.36) and at the 1% level (coef. =0.003, t-stat. =3.56), respectively, suggesting that,

[22] Analyst consensus mean earnings forecasts are constructed based on the average earnings forecast issued by each following analysts. Untabulated results show that our findings are robust to: (1) using a number of alternative windows such as (-3, 3), (0, 1), and (0, 3), and (2) using the median earnings forecast to calculate the earnings surprises.

as expected, the market responds positively to positive earnings surprises and negatively to negative earnings surprises.

More importantly, in line with our expectation, we find that the coefficient on the interaction term is negative and statistically significant at the 5% level (coef. =-0.450, t-stat. =-2.26), suggesting that the market response to positive earnings surprises is less pronounced for firms headquartered in high-climate-disaster states, due to investors tending to discount the role of earnings in valuing firms in these states. This finding implies that investors do not expect analyst forecasts to be accurate when the possibility of climate disasters is high, further corroborating our baseline findings. In contrast, we find that the coefficient on the interaction term is insignificant at the conventional level (coef. =0.058, t-stat. =0.66) for negative earnings surprises. This finding implies that the negative market response to negative earnings surprises is less likely to be affected by climate disasters, which is consistent with the concept of loss aversion suggested by prospect theory (Kahneman and Tversky, 1979).

[Insert Table 8 Here]

5. Additional Analyses and Robustness Tests

5.1 Endogeneity tests

5.1.1 Instrumental variable test

Like other empirical studies, one potential concern regarding our baseline model is endogeneity resulting from correlated omitted variables. Our estimates may be biased if there are correlated omitted variables that influence both climate disasters and analyst forecast properties simultaneously. It is also plausible that the measurement errors of our key variable may lead to biased estimates. To address these endogeneity concerns, we, therefore, employ two approaches. First, we adopt a 2*SLS* approach. Following prior literature (Albouy et al., 2016; Huang et al., 2018), we use population density, defined as the ratio of the annual population at the state level and the land area, as an instrumental variable for climate disasters. We obtain both state-level population and land area data from the U.S. Census Bureau. In our context, population density is correlated with climate disasters, thus satisfying the relevance condition. In addition, a thorough literature search indicates that there is no documented evidence on the relation between the instrument and analyst forecast properties. Put differently, it is unlikely that population density is associated with analyst forecast properties, satisfying the exclusion condition.

As shown in Table 9 Panel A, we find that population density is negatively associated with climate disasters at the 1% level in the first stage regression (coef. =-0.001, t-stat. =-2.88; coef. =-0.001, t-stat. =-4.01), which is consistent with Huang et al. (2018). Furthermore, the Cragg-Donald F (*CD-F*) statistics are 9.022 and 9.989, respectively, both of which are greater than the suggested cutoff value of 8.96 as identified in Stock and Yogo (2005), satisfying the relevance criteria of the instrument. In the second stage, we find that the coefficients on climate disasters are positive and statistically significant for both *AFE* (coef. =1.315, t-stat. =4.72) and *DISP* (coef. =0.004, t-stat. =2.00) at the 1% and 5% levels, respectively. Therefore, the 2*SLS* regression results indicate that our baseline results are not biased, lending further support to our main findings.

5.1.2 Firm-/analyst- level fixed effects

Second, to further mitigate the correlated omitted variable concern, we augment our model with firm-level rather than industry-level fixed effects to control for unobservable time-invariant firm-level characteristics. In addition, we also include analyst-level fixed effects to control for unobservable time-invariant analyst-level characteristics. The results reported in Panel B of Table 9 show that the coefficients are significant at the 1% level in both specifications,[23] suggesting that our baseline results continue to hold when controlling for either firm- or analyst- level fixed effects.

[23] One exception is Model 1, where the coefficient on *CDD* is marginally significant at the 10% level.

5.1.3 The impact of climate change regulation

Another potential concern with our study is that climate change regulation, which could influence the impact of climate disasters through climate mitigation and adaptation activities, is missing in our baseline regression models. To address this concern, we collect data on the adoption of a state-level climate adaptation plan[24] and generate an indicator variable for climate change regulation (*CCR*) that equals one if a state has a climate adaptation plan in place or is in the process of designing one, and zero otherwise.

We report the regression results in Panel C of Table 9 after controlling for *CCR*. The results indicate that climate change regulation has a negative and insignificant impact on analyst forecast properties. More importantly, our baseline results continue to hold after including the *CCR* variable, further mitigating the correlated omitted variables concern.

[Insert Table 9 Here]

5.2 Robustness tests

5.2.1 A propensity score matching based difference-in-differences (PSM-DiD) analysis

To bolster a potential causal inference between climate disasters and analyst forecast properties, we further investigate how analyst forecast properties change in response to a climate disaster event using a difference-in-differences model. Using hurricanes as exogenous shocks has been substantiated in the existing literature (e.g., Bourveau and Law, 2021; Dessaint and Matray, 2017), because the occurrence of hurricanes is largely not affected by firms' behaviors. Following this stream of literature, we focus on the Superstorm Sandy and investigate how it affects analyst forecast properties. We choose Superstorm Sandy because it caused the most devastating damages

[24] Data is obtained from https://www.c2es.org/document/climate-action-plans/.

in terms of employment (22.08 percent vs. 9.21 percent of Hurricane Katrina in 2005) to the U.S. economy and has been identified as one of the largest storms in the U.S. history.

We define a firm as affected if its headquarters is located within the state hit by Superstorm Sandy in 2012, otherwise we treat the firm as unaffected. The year of disaster, 2012, is excluded from the analysis. We follow prior literature (e.g., Bourveau and Law, 2021) to choose the length of the event window. Given we employ the arrival of Hurricane Sandy, the second costliest hurricane in U.S. history, we first restrict our analysis to three years before and three years after the disaster to mitigate the concern about the potential effects of confounding events. We further delete the year of 2009 to mitigate the influence of financial crisis. We apply the propensity score matching technique to construct the affected and control groups using a logit regression model based on the same set of variables and fixed effects used in the baseline regression model. We compare the analyst forecast properties of affected and unaffected firms before and after the Superstorm Sandy using the following difference-in-differences (DiD) specification:

$$AFP_{it(k)} = \alpha_1 Affected_{it} + \alpha_2 Post_{it} + \alpha_3 Affected_{it} * Post_{it} + \sum X_{it} + \gamma_i + \delta_t + \theta_k + \varepsilon_{it} \quad (3)$$

where *i*,*t*,*k* denotes firms, years, and analysts, respectively. Control variables are the same as defined in the baseline model. *Affected* is a dummy variable taking the value of one if a firm's headquarters is located in the state hit by Superstorm Sandy, zero otherwise. *Post* is an indicator variable that takes the value of one for the years 2013-2015, and zero for the years 2010-2011. γ_i, δ_t, θ_k are firm-, year-, and analyst-level fixed effects. Our variable of interest is the interaction between *Affected* and *Post*. If Superstorm Sandy worsens analyst forecast properties, the coefficient on the interaction term (α_3) is expected to be positive.

Table 10 Panel A reports the results for the PSM-DiD analysis. The coefficients on *Post* and *Affected* are suppressed due to the introduction of firm-, year-, and analyst-level fixed effects.

As shown in Panel A of Table 10, the coefficients on the interaction term in both models are statistically significant at the 5% significance level (coef. =0.001, t-stat.= 3.16 and coef. =0.001, t-stat.= 2.07), which further corroborates our baseline findings as well as lends support to a causal interpretation between climate disasters and analyst forecast properties.

Our PSM-DiD results are based on an important underlying assumption of parallel trends, which states that firms in both treated and control groups should have similar analyst forecast properties before experiencing Superstorm Sandy. To validate this important assumption, we generate a set of indicator variables *D(t=i)* including *D(t=-2)*, *D(t=-1)*, *D(t=1)*, *D(t=2)*, *D(t=3)*, and interact them with the *Affected* variable. Table 10 Panel B reports the verification of the parallel trends assumption.

As can be seen from Panel B of Table 10, we find that the coefficient on the interaction term *D(t=-1)*Affected* is insignificant at the conventional level, suggesting that there is no significant trending difference in analyst forecast properties between treated and control firms before the hurricane.[25] However, the differences appear after the occurrence of Hurricane Sandy, as reflected in the significant coefficients on *D(t=1)*Affected*, and *D(t=2)*Affected*.[26] However, the effect starts to decay after two years, as indicated by the magnitude and significance of the coefficient on *D(t=3)*Affected*.

[Insert Table 10 Here]

5.2.2 Alternative measures for climate disasters

[25] *D(t=-2)*Affected* is automatically dropped in the regression due to multicollinearity.

[26] Although the coefficient on *D(t=1)*Affected* is insignificant in column (1) of Table 10 Panel B, we conducted an F-test and the results show that coefficients on *D(t=1)*Affected* and *D(t=2)*Affected* are not statistically different from each other (F-stat.=1.33 and p-value=0.2546). Thus, one possible explanation is that the damages brought about by Superstorm Sandy are long-lasting because it damages infrastructure, displaces populations, and leads to changes in climate-related policies, all of which will affect firms' performance in the long term (more than one year).

In our main analysis, climate disasters are proxied by the total property damages caused by climate disasters. In this subsection, we use several alternative measures for climate disasters to re-examine the relation between climate disasters and analyst forecast properties. First, we focus on the frequency rather than the severity of the climate disasters. Specifically, we generate an indicator variable (*CDF*) that is equal to one if the frequency of climate disasters in a state is greater than the median in a year, and zero otherwise. We report the results in Columns (1) and (2) of Panel A of Table 11.

Second, given that the same disaster may have differential impact to different states, we replace our original disaster variable *CDD* with the per capita damages caused by each disaster (*CDDP*). In addition, the same set of explanatory variables as employed in the baseline regression is used. We report the results in Columns (3) and (4) of Panel A of Table 11.

Third, we generate a rank score based on the amount of total monetary damages incurred each year. To this end, we first sort and rank state-level weather-related damages by year from 1 to 52 and re-scale using the formula *CDD* rank (hereafter *CDDR*) = (53-rank)/52 to make sure that the transformed ranking score is within the range from 0 and 1.[27] Consistent with the non-transformed index, a higher *CDDR* score indicates greater risk and vice versa. We report the results in Columns (5) and (6) of Panel A of Table 11.

Finally, we replicate our regression using the county-level total property disaster damages (*CDDC*) and report the results in the last two columns of Panel A of Table 11. As mentioned earlier, a major caveat of this measure is that the total disasters damages are averaged out across all counties in the disaster-stricken state even if some counties are not directly hit by the disaster.

[27] The economic losses data for U.S. territories such as Puerto Rico is only available from 2010-2018. The *CDD* rank is calculated as *CDDR*= (52-rank)/51 for the period prior to 2010.

Across all specifications, we document that all alternative measures of climate disasters are significantly positively associated with both analyst forecast errors and dispersion, further bolstering our baseline results. Overall, the findings demonstrate that the positive relation between climate disaster risk and analyst forecast properties is unchanged for all these alternative measures.

5.2.3 Additional analysis

One potential concern related to our study is that our findings may be driven by observations during the financial crisis periods (Loh and Stulz, 2018). Analysts face more performance challenges during these periods since the financial crisis fundamentally complicated their forecasting tasks. To address this concern, we conduct a subsample analysis by excluding observations during the financial crisis periods of 2007-2009. Columns (1) and (2) of Panel B of Table 11 report the results for the non-financial crisis periods. We find that, as expected, there is still a positive relation between climate disasters and analyst forecast properties during the non-financial crisis periods, consistent with our main findings.

Another concern in our study is that our results may be driven by firms in high-climate-disaster years. Bourveau and Law (2021) demonstrate a negative association between Hurricane Katrina and analyst performance. It is well known that monster hurricanes Katrina and Harvey struck the U.S. in 2005 and 2017, respectively, causing disproportionally significantly large damages in these two years, as already reflected in Figure 1. These two catastrophic events may significantly exacerbate the forecasting challenges. To alleviate this concern, we delete observations in years 2005 and 2017 and re-estimate the model. Results presented in Columns (3) and (4) of Panel B of Table 11 suggest that our baseline findings are not driven by these two abnormal years.

Furthermore, Gulf Coast states, including Florida, Louisiana, Mississippi, and Texas, suffer significantly from weather-related disasters. As illustrated by the statistics listed in Table 2, these four states rank as the top four in terms of economic damages stemming from climate disasters. Therefore, it is plausible that our findings are driven by observations from firms located in the Gulf Coast states. To address this concern, we exclude firms located in the Gulf Coast states and re-examine our findings. The results reported in Columns (5) and (6) of Panel B of Table 11 suggest that our main findings continue to hold even when focusing on non-Gulf Coast states.

It is also plausible that some firms in the U.S. operate across states and even countries for various reasons such as business purposes. Thus, all firms can be divided into either single-segment or multiple-segment firms based on different criteria. Our main findings may be biased if we treat both types of firms equally because the place where a firm is headquartered may not coincidentally be the same place where its major plant operates. To mitigate this concern, we follow Agrawal and Matsa (2013) and distinguish between firms in industries with more and less dispersed workforce. Specifically, we drop firms in wholesale, retail, and transportation industries, all of which have more dispersed workforce. The results reported in the Columns (7) and (8) of Panel B of Table 11 suggest that our main findings continue to hold when dropping industries with more dispersed workforce.[28] Columns (9) and (10) report the results for more-disperse subsamples, where our main findings are not fully supported.

[Insert Table 11 Here]

Finally, we implement additional tests to further corroborate our baseline findings. First, prior literature has shown differential impacts of various natural disasters (e.g., Felbermayr and Gröschl, 2014; Skidmore and Toya, 2002). Although geophysical disasters have been excluded from our analysis, we follow the prior literature and divide all climate disasters into two subcategories: “hurricane and tropical storms” and “non-hurricane and tropical storms disasters”.

[28] Our results are quantitatively similar when we focus on single-segment firms based on the Geographic and State Segment data (Compustat Segments Data).

Second, we replace the main independent variable *CDD*, with its corresponding one-year lag variable. Third, given that certain industry characteristics that are affected by climate change can change over time, we control for industry-by-year fixed effects. Finally, unlike the main regression model where we cluster standard errors at the state and analyst level, as a robustness test we cluster standard errors at the analyst-, brokerage-, and state-level. Untabulated results suggest our baseline findings are qualitatively unchanged under all these different specifications and subsamples. Overall, these findings highlight the robustness of our main findings.

6. Conclusions

Climate change has started to exert an increasingly significant impact on firms' behaviors and outcomes. Recently more academic attention has been devoted to exploring the firm-level effects of natural disasters. We extend the literature by concentrating on the effects of climate disasters on analyst forecast properties.

Using a large sample of 382,387 observations in the U.S. over 2001-2017, we document that climate disasters are associated with deteriorated analyst forecast properties. The results from market reaction tests provide further support for our main findings. In additional tests, we find that the positive relation between climate disasters and analyst forecast properties is more pronounced for firms in the climate-vulnerable industries and identify the volatility of ROA and cash flows as well as financial statement comparability as three possible channels through which climate disasters influence analyst forecast properties. Our findings are robust to alternative measures of climate disasters, different model specifications, and different subsamples.

Our study contributes to the literature in several important ways. First, we extend the micro-effect of climate risk studies by focusing on its effect on analyst forecast properties. To the best of our knowledge, we are among the first to address this important issue. Understanding how and to what extent climate disasters are associated with analyst forecast properties has significant implications for market participants, firms, and regulators. Second, our study also adds to the literature focusing on the micro-level impact of uncertainty. Unlike this literature which extensively focuses on conventional uncertainties, such as economic policy uncertainty and political uncertainty, our study extends this line of literature by focusing on uncertainty arising from climate disasters. Although not the focus of our study, we also add to the analyst forecast literature by identifying a potential environmental exogenous determinant which is largely neglected in the prior literature.

Our findings that climate disasters are associated with deteriorated analyst forecast properties have significant implications for academics, standard setters, analysts, and investors. In particular, considering the recent move of the Securities and Exchange Commission (SEC) toward the rulemaking of climate risk disclosures, our results suggest that climate risk-related disclosures are a feasible means that can compensate for the deteriorated analyst forecast properties caused by climate disasters. Under the context of climate change, investors who heavily rely on analysts to translate an overwhelming amount of information into meaningful implications may exercise caution based on our findings.

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Appendix: Definitions of variables

Variables	Definitions
Measures of analyst forecast properties	
AFE	Analyst forecast error, defined as the absolute difference between actual annual earnings and the most recent individual analyst forecast value before the earnings announcement date, which is multiplied by 100 and scaled by the stock price at the beginning of the year. Source: I/B/E/S.
DISP	The standard deviation of annual analyst forecast values for a given firm scaled by the stock price at the beginning of the year. Source: I/B/E/S.
Measures of climate disasters	
CDD	Total annual state-wide property damages from all hazard types of climate disasters. Source: SHELDUS.
Others:	
CDF	An indicator variable equal to one if the frequency of climate disasters in a state is greater than the median in a year, and zero otherwise. Source: Federal Emergency Management Agency(FEMA).
CDDP	Total annual state-wide property damages from all hazard types of climate disasters per capita. Source: SHELDUS.
CDDR	The rank of the CDD. CDDR ranges from 0 to 1. A higher score indicates more climate disaster damages in the year, and vice versa. Source: SHELDUS.
CDDC	Total annual county-wide property damages from all hazard types of climate disasters. Source: SHELDUS.
Other variables	
Size	Natural logarithm of total Assets (AT). Source: Compustat.
Loss	An indicator variable equal to one if a firm's net income is negative, and 0 otherwise. Source: Compustat.
ROA	Return on assets. Net income scaled by total assets. Source: Compustat.
MTB	Market-to-book ratio, measured as market value of equity divided by book value of equity. Source: Compustat.
Sgrowth	Percentage change of Sales (SALE). Source: Compustat.
Age	Firm age, which is computed based on the number of years the firm appears in Compustat. Source: Compustat.
SDret	The standard deviation of stock returns over 30 days leading up to the forecast. Source: CRSP.
Sur	The difference between actual earnings and analyst mean consensus forecast value. Source: I/B/E/S.
Horizon	The time between analyst forecast reporting date and actual EPS announcement date. Source: I/B/E/S.
NOA	The number of analysts following a firm. Source: I/B/E/S.
NOC	The number of firms followed by an analyst in a year. Source: I/B/E/S.
NOF	The number of earnings forecasts issued by an analyst in a year. Source: I/B/E/S.
Firmexp	The number of years an analyst has provided coverage for a given firm. Source: I/B/E/S.
Genexp	The number of years since an analyst initially appeared in the I/B/E/S database. Source: I/B/E/S.
CAR (-1,1)	Cumulative abnormal return for a three-day event window centered on the earnings announcement date. Source: CRSP.
CF_SD	The volatility of cash flows, measured as the standard deviation of cash flows over the past three years.
ROA_SD	The volatility of ROA, measured as the standard deviation of ROA over the past three years.
EPU	Economic policy uncertainty index developed by Baker et al. (2016).
VIX	VIX index data obtained from Chicago Board Options Exchange.
Macro	An aggregated measure of macroeconomic uncertainty index obtained from Jurado et al. (2015).
M4_comp	Average of the four highest comparability value calculated following De Franco et al. (2011) for firm i.
M10_comp	Average of the ten highest comparability value calculated following De Franco et al. (2011) for firm i.
M_comp	Average of comparability value for firm i for all firms in firm i's industry.
Md_comp	Median of comparability value for firm i for all firms in firm i's industry.
Vul	Climate vulnerability industry membership. An indicator variable that equals 1 for Agriculture (Fama–French Industry Code 1), Business Services (Code 34), Communication (Code 32), Energy [Mines

	(code 28), Coal (Code 29), Oil (Code 30)], Food Products (Code 2), Health Care (Code 11), and Transportation (Code 40), and 0 otherwise. Source: Compustat.
PPEinten	PPE intensity, measured as the value of property, plant, and equipment divided by total assets. Source: Compustat.
Population	The annual population of each state. Source: U.S. Census Bureau.
Land	The land area of each state. Source: U.S. Census Bureau.
Density	Population density: number of people per square mile of land area. Source: U.S. Census Bureau.
CCR	An indicator variable equal to one if a state has a climate adaptation plan in place or in the process of designing one, and zero otherwise. Source: https://www.c2es.org/document/climate-action-plans/.
Post	An indicator variable that equals one for years 2013-2015, and zero for years 2010-2011.
Affected	An indicator variable that equals one if a firm's headquarters is located in a state hit by Superstorm Sandy, and zero otherwise.
D(t=-2)	An indicator variable equal to one for year 2010, and zero otherwise.
D(t=-1)	An indicator variable equal to one for year 2011, and zero otherwise.
D(t=1)	An indicator variable equal to one for year 2013, and zero otherwise.
D(t=2)	An indicator variable equal to one for year 2014, and zero otherwise.
D(t=3)	An indicator variable equal to one for year 2015, and zero otherwise.

Figure 1: Trends in climate disaster damages in the U.S. 2001-2017

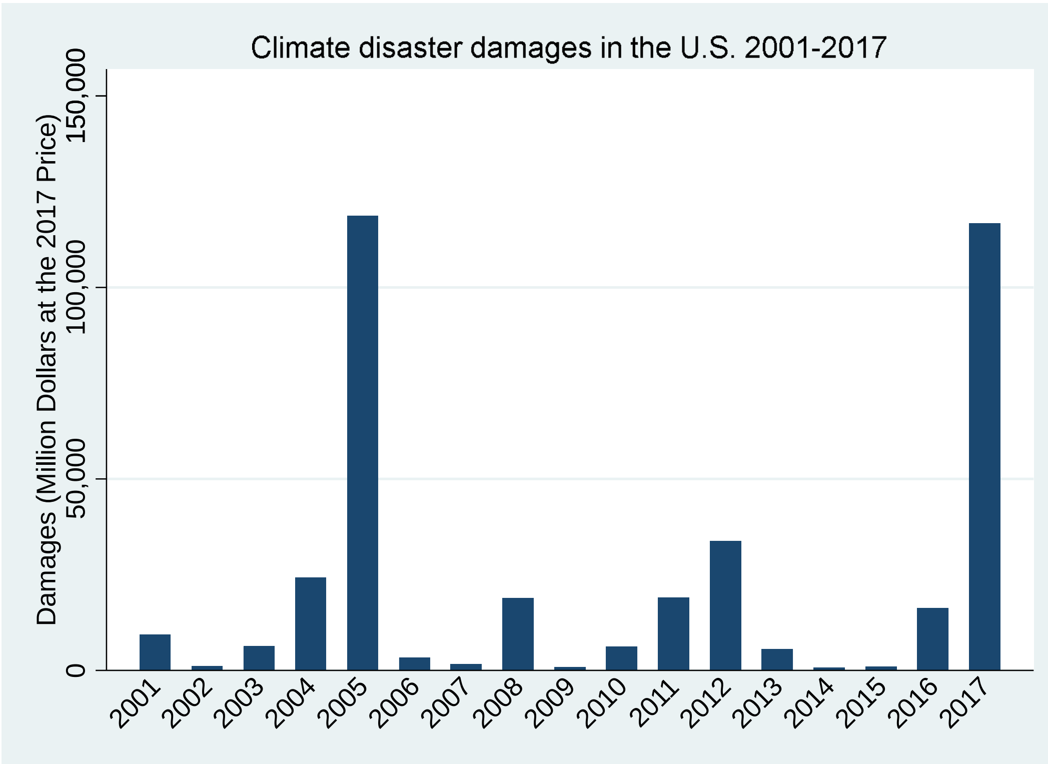

Table 1: Sample distribution by state and year

State	Year																	
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
AK	5	6	4	5	12	13	8	8	5	5	5	5	4	3	0	0	0	88
AL	75	53	69	77	148	151	153	158	139	144	177	182	183	158	153	155	148	2323
AR	97	166	141	159	147	135	114	119	123	124	130	126	125	160	157	160	159	2342
AZ	260	326	372	363	384	408	398	393	364	366	378	298	328	359	293	310	328	5928
CA	2651	3555	3726	3979	4526	4484	4486	4403	4258	4427	4637	4673	4786	4958	4865	4847	4843	74104
CO	270	290	347	357	373	339	391	406	418	493	563	632	660	658	681	634	670	8182
CT	187	203	254	246	253	300	306	303	319	326	370	419	431	437	483	520	482	5839
DC	58	84	101	111	132	131	130	96	76	93	87	98	111	96	108	97	81	1690
DE	67	54	57	61	83	79	77	72	65	69	58	72	68	67	78	71	62	1160
FL	455	497	564	639	736	803	835	822	813	834	863	835	921	1003	1030	1025	964	13639
GA	295	399	473	492	611	555	547	517	511	598	632	587	688	729	711	705	765	9815
HI	6	4	5	8	19	15	17	21	19	29	45	57	58	55	52	56	51	517
IA	40	63	74	88	101	98	97	95	99	89	89	92	96	95	106	109	102	1533
ID	35	51	64	70	70	47	48	39	45	47	54	65	59	65	62	58	66	945
IL	645	635	744	718	882	946	1016	1022	1056	1124	1197	1346	1417	1373	1372	1391	1353	18237
IN	109	132	157	156	241	228	235	243	252	288	309	334	356	388	436	397	372	4633
KS	86	116	128	79	83	60	88	93	84	83	87	79	118	112	140	159	163	1758
KY	68	105	120	128	157	131	133	169	164	192	176	169	189	183	176	165	170	2595
LA	142	148	105	87	105	170	178	202	190	207	163	144	119	108	130	123	135	2456
MA	832	839	916	1055	1161	1245	1219	1261	1188	1255	1271	1367	1314	1464	1525	1471	1610	20993
MD	174	209	273	276	354	388	363	412	409	445	460	405	383	376	333	387	361	6008
ME	7	4	6	6	7	6	7	8	9	15	17	14	23	22	31	31	28	241
MI	336	341	307	297	381	406	442	402	392	399	450	415	449	458	454	494	471	6894
MN	264	391	481	504	567	577	579	606	584	539	559	564	536	542	555	511	456	8815
MO	268	309	315	302	352	327	334	327	357	376	420	457	470	476	437	452	410	6389
MS	0	3	5	13	34	36	30	40	61	64	60	48	49	50	54	52	55	654
MT	4	4	7	6	41	47	48	41	33	12	6	11	6	0	0	7	7	280
NC	262	341	338	370	458	471	495	487	512	512	581	576	593	627	598	609	598	8428
ND	0	0	13	9	8	12	11	13	13	15	16	14	22	20	20	16	14	216
NE	23	37	43	46	58	69	69	86	126	158	158	149	147	164	160	161	122	1776
NH	26	33	31	30	27	31	26	21	29	27	19	43	42	31	33	40	39	528
NJ	456	539	599	702	792	748	801	700	692	767	829	804	846	858	822	835	849	12639
NM	5	6	6	9	20	19	17	20	13	13	11	8	6	5	7	9	11	185
NV	114	154	202	232	213	264	236	238	225	264	293	266	234	207	161	168	181	3652
NY	888	1069	1119	1165	1437	1528	1645	1670	1657	1837	1950	2097	2056	2106	2087	2140	2085	28536
OH	451	510	521	505	684	714	700	667	677	752	788	868	919	913	943	942	963	12517
OK	131	144	156	149	162	194	206	268	260	256	295	309	386	425	460	425	434	4660
OR	157	189	230	230	282	268	238	240	201	213	231	247	246	232	213	162	150	3729

PA	542	577	701	687	878	994	1021	988	979	1008	1035	1048	1016	1036	1111	1078	1029	15728
PR	0	0	0	0	13	12	5	11	9	7	10	17	22	32	29	31	31	229
RI	72	62	59	68	84	81	79	93	87	97	100	90	95	97	111	119	112	1506
SC	38	34	33	39	95	102	105	96	97	91	91	94	103	130	131	135	142	1556
SD	5	17	18	21	19	17	42	19	14	18	20	19	21	15	16	27	31	339
TN	294	348	377	402	423	440	388	427	430	483	454	474	484	483	512	487	503	7409
TX	1407	1782	1843	1913	2189	2340	2350	2493	2489	2511	2721	2886	3281	3393	3651	3579	3383	44211
UT	28	44	74	103	148	144	143	149	138	153	169	178	186	140	144	146	141	2228
VA	411	387	506	548	567	619	612	560	574	607	627	559	561	530	580	605	596	9449
VT	24	18	21	22	20	21	8	7	7	10	11	9	8	0	7	9	7	209
WA	287	283	412	442	520	570	568	571	569	586	606	605	621	589	582	590	624	9025
WI	174	186	220	230	275	276	288	323	312	319	308	322	338	336	350	354	326	4937
WV	0	5	7	6	27	32	37	43	49	60	49	41	43	35	27	21	22	504
WY	0	0	0	0	0	0	0	0	0	13	20	19	25	20	16	10	10	133
Total	13231	15752	17344	18210	21359	22091	22369	22468	22192	23420	24655	25236	26248	26819	27193	27085	26715	382387

Table 2: Cumulative climate disaster property damages by state over 2001-2017(in million U.S. dollars)

State	Code	Total property damages	State	Code	Total property damages
ALABAMA	AL	8180.15	MONTANA	MT	19.84
ALASKA	AK	2.48	NEBRASKA	NE	895.21
ARIZONA	AZ	2894.01	NEVADA	NV	44.56
ARKANSAS	AR	1463.97	NEW HAMPSHIRE	NH	19.05
CALIFORNIA	CA	4544.62	NEW JERSEY	NJ	25376.66
COLORADO	CO	4067.83	NEW MEXICO	NM	456.65
CONNECTICUT	CT	94.0115	NEW YORK	NY	2241.08
DELAWARE	DE	33.64	NORTH CAROLINA	NC	1885.89
DISTRICT OF COLUMBIA	DC	0.03	NORTH DAKOTA	ND	15.31
FLORIDA	FL	33189.29	OHIO	OH	1113.42
GEORGIA	GA	798.27	OKLAHOMA	OK	3909.66
HAWAII	HI	0	OREGON	OR	0.70
IDAHO	ID	486.14	PENNSYLVANIA	PA	1383.88
ILLINOIS	IL	1844.10	PUERTO RICO	PR	19012.50
INDIANA	IN	948.643	RHODE ISLAND	RI	99.48
IOWA	IA	8040.71	SOUTH CAROLINA	SC	399.37
KANSAS	KS	715.66	SOUTH DAKOTA	SD	4.49
KENTUCKY	KY	544.74	TENNESSEE	TN	4835.65
LOUISIANA	LA	64175.74	TEXAS	TX	106344.90
MAINE	ME	46.10	UTAH	UT	0.70
MARYLAND	MD	732.11	VERMONT	VT	815.00
MASSACHUSETTS	MA	240.28	VIRGINIA	VA	906.00
MICHIGAN	MI	599.66	WASHINGTON	WA	14.45
MINNESOTA	MN	231.11	WEST VIRGINIA	WV	366.33
MISSISSIPPI	MS	27270.65	WISCONSIN	WI	1944.16
MISSOURI	MO	5033.61	WYOMING	WY	12.31

Table 3:

Panel A: Summary statistics (N=382, 387)

	Mean	Std. Dev.	p25	Median	p75
AFE	0.765	2.201	0.052	0.164	0.524
DISP	0.008	0.017	0.001	0.003	0.007
CDD	5.702e+08	2.811e+09	0	3868000	76551000
CDF	0.5	0.5	0	1	1
CDDP	35.817	219.11	0	0.286	4.409
CDDR	11619.195	6906.973	5583	11070	17435.5
CDDC	1.107e+08	1.345e+09	0	0	20000
Size	7.965	1.86	6.611	7.895	9.196
Loss	0.203	0.402	0	0	0
ROA	0.027	0.119	0.008	.043	0.083
MTB	3.351	5.548	1.515	2.475	4.132
Sgrowth	0.128	0.3	-0.004	0.079	0.196
Age	26.879	20.007	11	20	39
SDret	0.027	0.019	0.015	0.021	0.032
PPEint	0.245	0.252	0.051	0.142	0.368
ROA_SD	0.025	0.04	0.003	0.011	0.029
CF_SD	0.023	0.029	0.005	0.015	0.031
Sur	-0.011	0.902	-0.028	0.014	0.061
CAR(-1,1)	0.003	0.082	-0.035	0.002	0.042
Post	0.417	0.493	0	0	1
Affected	0.324	0.468	0	0	1
Horizon	116.044	88.022	62	98	121
NOA	18.745	11.156	10	17	25
NOC	16.617	8.664	11	16	21
NOF	4.164	2.577	2	4	5
Firmexp	3.858	3.327	2	3	5
Genexp	8.075	6.186	3	6	11
Vul	0.279	0.448	0	0	1
CCR	0.736	0.441	0	1	1
Density	324.25	695.308	103.22	228.365	285.684

Panel B: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)AFE	1.00																	
(2)DISP	0.67	1.00																
(3)CDD	0.02	0.03	1.00															
(4)CDF	-0.01	-0.01	0.16	1.00														
(5)CDDP	0.01	0.02	0.78	0.13	1.00													
(6)CDDR	0.02	0.04	0.32	0.20	0.27	1.00												
(7)CDDC	0.02	0.03	0.60	0.07	0.31	0.15	1.00											
(8)Size	-0.11	-0.11	0.03	-0.00	0.02	0.07	0.03	1.00										
(9)Loss	0.34	0.42	0.00	-0.02	-0.01	0.01	0.03	-0.28	1.00									
(10)ROA	-0.30	-0.37	0.00	0.04	0.01	-0.00	-0.01	0.24	-0.69	1.00								

(11)MTB	-0.09	-0.11	-0.02	0.01	-0.01	-0.00	-0.02	-0.05	-0.00	0.03	1.00							
(12)Sgrowth	-0.04	-0.07	0.06	0.03	0.03	-0.01	0.05	-0.12	-0.04	0.01	0.11	1.00						
(13)Age	-0.06	-0.07	-0.00	-0.02	0.01	0.02	0.00	0.57	-0.19	0.13	-0.05	-0.19	1.00					
(14)SDret	0.32	0.39	-0.03	0.01	-0.02	-0.03	-0.02	-0.32	0.32	-0.30	-0.05	0.03	-0.25	1.00				
(15)PPEint	0.02	0.05	0.11	0.06	0.06	0.12	0.09	0.09	-0.01	0.06	-0.06	-0.03	0.01	-0.03	1.00			
(16)ROA_SD	0.13	0.17	0.04	0.03	0.02	0.01	0.05	-0.24	0.24	-0.19	0.04	0.05	-0.15	0.15	-0.02	1.00		
(17)CF_SD	0.08	0.10	0.03	0.03	0.02	0.01	0.03	-0.25	0.15	-0.12	0.06	0.09	-0.15	0.10	-0.06	0.53	1.00	
(18)Sur	-0.26	-0.18	-0.00	-0.00	-0.00	0.00	-0.01	0.00	-0.12	0.10	0.02	0.05	-0.00	-0.10	-0.01	0.00	0.01	1.00
(19)CAR(-1,1)	-0.18	-0.12	0.00	0.00	0.00	0.01	0.00	-0.00	-0.08	0.07	0.02	0.03	-0.00	-0.06	-0.01	0.00	0.01	0.04
(20)Post	-0.02	-0.01	-0.00	-0.00	-0.00	-0.01	-0.01	-0.01	-0.04	0.04	0.00	0.02	-0.01	-0.00	-0.02	-0.00	0.00	0.01
(21)Affected	-0.03	-0.02	0.02	-0.22	0.02	0.20	0.01	0.14	0.00	-0.01	0.06	-0.08	0.11	-0.20	0.00	-0.05	-0.03	0.00
(22)Horizon	-0.00	-0.02	-0.05	-0.10	-0.01	-0.05	-0.04	0.05	-0.03	-0.01	-0.00	-0.01	0.10	-0.05	-0.17	-0.02	-0.01	-0.01
(23)NOA	0.17	0.03	-0.00	-0.00	-0.01	-0.03	-0.00	-0.11	0.05	-0.06	0.00	0.00	-0.06	0.05	-0.06	0.02	0.01	0.02
(24)NOC	-0.14	-0.11	0.01	0.01	-0.01	0.10	0.00	0.56	-0.10	0.16	0.10	-0.02	0.15	-0.13	0.12	-0.03	-0.05	-0.01
(25)NOF	-0.01	0.01	0.01	-0.01	0.01	0.10	0.00	0.10	-0.02	-0.00	-0.02	-0.02	0.07	-0.07	0.09	-0.03	-0.03	-0.01
(26) Firmexp	-0.04	0.06	0.01	0.01	0.01	0.09	0.00	0.18	-0.01	0.03	-0.04	-0.04	0.09	-0.02	0.17	0.01	0.01	0.01
(27)Genexp	-0.05	-0.05	-0.00	-0.02	-0.00	0.04	-0.00	0.20	-0.09	0.09	-0.01	-0.11	0.23	-0.13	0.02	-0.02	-0.02	0.00
(28)Vul	-0.03	-0.03	-0.01	-0.03	-0.00	0.05	0.00	0.07	-0.04	0.04	0.00	-0.04	0.08	-0.07	-0.02	-0.03	-0.02	-0.00
(29)CCR	0.00	0.01	0.03	0.04	0.02	0.10	0.00	-0.03	0.06	-0.01	0.03	0.05	-0.18	0.04	0.24	0.00	-0.03	0.01
(30)Density	0.13	0.16	-0.02	-0.03	-0.00	-0.07	-0.01	-0.05	0.09	-0.07	-0.08	-0.07	-0.03	0.39	0.02	0.01	0.01	-0.01

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(19)CAR(-1,1)	1.00											
(20)Post	-0.00	1.00										
(21)Affected	0.00	0.00	1.00									
(22)Horizon	-0.01	-0.02	0.01	1.00								
(23)NOA	-0.01	0.11	-0.09	-0.07	1.00							
(24)NOC	-0.00	0.17	-0.01	-0.10	0.01	1.00						
(25)NOF	0.00	0.07	-0.04	-0.47	0.17	0.13	1.00					
(26) Firmexp	0.00	0.17	0.01	-0.01	0.10	0.15	0.16	1.00				
(27)Genexp	0.00	0.19	0.01	-0.03	0.01	0.26	0.08	0.58	1.00			
(28)Vul	-0.01	0.02	-0.09	-0.00	0.14	0.01	0.05	-0.05	-0.03	1.00		
(29)CCR	0.00	-0.03	0.17	0.03	-0.06	-0.09	-0.10	-0.01	-0.01	-0.14	1.00	
(30)Density	-0.00	0.01	0.21	0.01	-0.03	-0.00	-0.04	0.00	0.01	-0.00	0.14	-0.01

Table 4: Relation between climate disasters and analyst forecast properties: Baseline OLS regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			Panel A (AFE)						Panel B (DISP)			
CDD	0.841***	0.982***	0.830***	0.745***	0.868***	0.892***	0.013***	0.013***	0.013***	0.013***	0.014***	0.014***
	(6.87)	(7.24)	(7.05)	(2.95)	(3.30)	(3.43)	(7.38)	(5.36)	(6.83)	(4.27)	(4.84)	(4.46)
EPU				0.006**						0.015***		
				(2.64)						(4.59)		
VIX					0.029						0.023	
					(0.89)						(0.75)	
Macro						0.495**						0.070
						(2.59)						(0.43)
Size	-0.022*		0.104***	0.105***	0.106***	0.103***	0.003		0.088***	0.085***	0.086***	0.086***
	(-1.87)		(8.22)	(7.57)	(7.50)	(7.19)	(0.23)		(4.86)	(4.44)	(4.51)	(4.44)
Loss	0.011***		0.011***	0.011***	0.011***	0.011***	0.013***		0.012***	0.013***	0.013***	0.013***
	(8.29)		(8.17)	(8.15)	(8.20)	(8.29)	(11.30)		(11.16)	(11.27)	(11.27)	(11.32)
ROA	-0.015***		-0.013***	-0.013***	-0.013***	-0.013***	-0.021***		-0.020***	-0.020***	-0.020***	-0.020***
	(-5.08)		(-4.95)	(-4.74)	(-4.84)	(-4.87)	(-7.59)		(-7.60)	(-7.59)	(-7.72)	(-7.66)
MTB	-0.183***		-0.142***	-0.148***	-0.147***	-0.146***	-0.211***		-0.177***	-0.180***	-0.181***	-0.182***
	(-5.47)		(-4.70)	(-4.77)	(-5.02)	(-5.03)	(-7.01)		(-6.06)	(-6.00)	(-6.30)	(-6.29)
Sgrowth	-0.002***		-0.002***	-0.002***	-0.002***	-0.002***	-0.003***		-0.003***	-0.003***	-0.003***	-0.003***
	(-3.25)		(-2.97)	(-2.92)	(-3.06)	(-3.03)	(-7.50)		(-6.68)	(-7.11)	(-6.92)	(-7.21)
Age	0.004		-0.013	-0.011	-0.011	-0.010	0.006		-0.003	0.000	0.002	0.002
	(0.36)		(-1.42)	(-1.26)	(-1.21)	(-1.17)	(0.47)		(-0.23)	(0.04)	(0.15)	(0.15)
SDret	0.238***		0.238***	0.230***	0.228***	0.219***	0.271***		0.269***	0.255***	0.255***	0.257***
	(12.87)		(12.40)	(11.24)	(9.85)	(9.73)	(14.83)		(14.68)	(14.49)	(13.42)	(12.82)
Horizon		0.044***	0.037***	0.037***	0.038***	0.038***		0.027***	0.016***	0.017***	0.017***	0.017***
		(20.24)	(17.83)	(17.31)	(17.16)	(17.25)		(16.67)	(11.13)	(11.52)	(11.67)	(11.60)
NOA		-0.296***	-0.236***	-0.238***	-0.237***	-0.232***		-0.343***	-0.215***	-0.210***	-0.209***	-0.208***
		(-12.60)	(-8.50)	(-8.38)	(-8.46)	(-8.10)		(-12.91)	(-6.08)	(-5.70)	(-5.80)	(-5.69)

NOC		0.010	0.005	0.019*	0.020*	0.021**		0.043***	0.023*	0.037**	0.039**	0.038**
		(0.94)	(0.47)	(1.83)	(1.99)	(2.05)		(2.91)	(1.73)	(2.49)	(2.60)	(2.56)
NOF		0.374***	0.134**	0.194***	0.195***	0.194***		0.831***	0.489***	0.560***	0.565***	0.565***
		(5.44)	(2.47)	(3.04)	(3.04)	(3.04)		(10.93)	(7.83)	(9.48)	(9.55)	(9.53)
Firmexp		-0.188***	-0.017	0.005	0.007	0.006		-0.281***	-0.093**	-0.072*	-0.069*	-0.069*
		(-8.31)	(-1.03)	(0.27)	(0.38)	(0.34)		(-5.21)	(-2.31)	(-1.79)	(-1.68)	(-1.71)
Genexp		-0.047***	-0.058***	-0.043***	-0.040***	-0.038***		-0.029	-0.022	-0.010	-0.004	-0.005
		(-4.12)	(-6.27)	(-5.06)	(-4.57)	(-4.39)		(-1.10)	(-1.29)	(-0.48)	(-0.19)	(-0.25)
Constant	0.198	0.747***	-0.790***	-0.927***	-0.912***	-1.150***	0.000	0.008***	-0.007***	-0.009***	-0.008***	-0.008***
	(1.32)	(8.75)	(-6.57)	(-7.39)	(-7.62)	(-8.27)	(0.07)	(16.19)	(-4.28)	(-5.52)	(-5.24)	(-5.73)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	No	No	No
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	382387	382420	382387	382387	382387	382387	32240	32246	32240	32240	32240	32240
R^2	0.1968	0.0999	0.2274	0.2190	0.2189	0.2196	0.2898	0.0961	0.2977	0.2909	0.2904	0.2904

This table presents the regression results of the relation between climate disasters and analyst forecast properties. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 5: Relation between climate disasters and analyst forecast properties: Impact of climate vulnerability and PPE intensity

	(1) AFE	(2) DISP	(3) AFE	(4) DISP
CDD	0.468	0.007*	-0.166	-0.002
	(1.47)	(1.97)	(-0.30)	(-0.20)
Vul	-0.000	0.000		
	(-0.44)	(0.51)		
CDD*Vul	0.923*	0.016**		
	(1.75)	(2.02)		
PPEint			0.004***	0.005***
			(5.19)	(5.90)
CDD*PPEint			2.405***	0.042**
			(3.07)	(2.19)
Size	0.144***	0.132***	0.102***	0.083***
	(8.50)	(6.59)	(8.00)	(4.57)
Loss	0.011***	0.013***	0.011***	0.012***
	(8.44)	(11.26)	(8.15)	(11.28)
ROA	-0.014***	-0.020***	-0.013***	-0.021***
	(-5.30)	(-7.84)	(-5.09)	(-7.63)
MTB	-0.172***	-0.214***	-0.140***	-0.173***
	(-5.52)	(-8.13)	(-4.56)	(-5.73)
Sgrowth	-0.001**	-0.002***	-0.002***	-0.003***
	(-2.46)	(-5.78)	(-3.12)	(-6.24)
Age	-0.017**	-0.014*	-0.012	-0.002
	(-2.02)	(-1.68)	(-1.46)	(-0.18)
SDret	0.242***	0.270***	0.238***	0.269***
	(12.68)	(15.68)	(12.47)	(14.65)
Horizon	0.038***	0.017***	0.037***	0.016***
	(17.24)	(10.91)	(17.82)	(11.20)
NOA	-0.254***	-0.243***	-0.236***	-0.211***
	(-12.23)	(-8.02)	(-8.03)	(-5.72)
NOC	0.013	0.036***	0.005	0.024*
	(1.26)	(2.80)	(0.50)	(1.79)
NOF	0.242***	0.614***	0.120**	0.473***
	(4.90)	(8.01)	(2.05)	(7.71)
Firmexp	-0.048**	-0.129***	-0.017	-0.094**
	(-2.32)	(-3.16)	(-1.07)	(-2.44)
Genexp	-0.051***	-0.022	-0.057***	-0.022
	(-4.31)	(-1.19)	(-6.12)	(-1.29)
Constant	-1.126***	-0.010***	-0.869***	-0.008***
	(-7.13)	(-5.45)	(-7.19)	(-4.66)
Industry	No	No	Yes	Yes
Year	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes

N	382387	32240	382387	32240
R^2	0.2156	0.2841	0.2282	0.2991

This table presents the regression results of the impact of climate vulnerability on the relation between climate disasters and analyst forecast properties. Climate vulnerability is proxied by the Fama French 48 industry framework in the first two columns and the PPE intensity in the last two columns. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 6: Channel analyses

	(1) ROA_SD	(2) CF_SD	(3) M4_comp	(4) M10_comp	(5) M_comp	(6) Md_comp
CDD	0.678***	0.136***	-0.543**	-0.817***	-0.244**	-0.226**
	(5.28)	(2.73)	(-2.32)	(-2.96)	(-2.34)	(-2.40)
Size	-0.610***	-0.649***	1.292*	1.712*	3.406**	5.806***
	(-19.00)	(-25.67)	(1.69)	(1.73)	(2.16)	(3.13)
Loss	0.015***	0.004***	-0.388***	-0.510***	-0.589***	-0.832***
	(8.55)	(5.98)	(-7.06)	(-7.64)	(-6.07)	(-8.34)
ROA	-0.046***	-0.029***	0.559***	0.826***	2.017***	3.428***
	(-6.81)	(-6.36)	(3.77)	(4.45)	(7.61)	(10.56)
MTB	0.260***	0.360***	5.553**	6.826**	9.463**	8.782*
	(3.28)	(3.70)	(2.63)	(2.60)	(2.30)	(1.75)
Sgrowth	0.002	0.009***	0.016	0.006	-0.014	-0.120
	(1.00)	(5.92)	(0.49)	(0.14)	(-0.18)	(-1.47)
Age	-0.004	-0.003	0.412	0.715	0.551	0.551
	(-0.17)	(-0.11)	(0.60)	(0.81)	(0.44)	(0.40)
SDret	0.338***	0.136***	-6.278***	-8.481***	-15.074***	-16.046***
	(9.99)	(3.13)	(-7.78)	(-8.46)	(-12.25)	(-12.69)
Constant	0.072***	0.079***	-0.329***	-0.502***	-2.815***	-1.948***
	(27.46)	(42.73)	(-5.07)	(-5.79)	(-21.22)	(-12.37)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
N	22831	22831	20553	20553	20553	20553
R^2	0.2475	0.2425	0.1746	0.2513	0.3837	0.3279

This table presents the regression results of the channel analyses. The dependent variable in column (1) is *ROA_SD*, and the dependent variable in column (2) is *CF_SD*. The dependent variables in columns (3) to (6) are four major financial statement comparability measures calculated following De Franco et al. (2011). The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 7: Further evidence on the complexity explanation

	(1)	(2)	(3)	(4)
	Drop Top 5 cities		Drop Top 10 cities	
	AFE	DISP	AFE	DISP
CDD	0.768***	0.011***	0.996***	0.009***
	(5.72)	(5.69)	(6.95)	(4.24)
Size	0.109***	0.096***	0.109***	0.090***
	(7.36)	(4.61)	(6.99)	(4.19)
Loss	0.011***	0.013***	0.011***	0.013***
	(7.03)	(10.21)	(7.80)	(11.82)
ROA	-0.014***	-0.020***	-0.012***	-0.018***
	(-4.66)	(-7.19)	(-5.22)	(-7.74)
MTB	-0.149***	-0.172***	-0.153***	-0.182***
	(-4.95)	(-6.43)	(-5.08)	(-7.75)
Sgrowth	-0.001**	-0.003***	-0.002***	-0.003***
	(-2.43)	(-6.71)	(-3.11)	(-5.08)
Age	-0.013	-0.003	-0.007	0.004
	(-1.30)	(-0.32)	(-0.68)	(0.41)
SDret	0.239***	0.269***	0.243***	0.271***
	(11.03)	(13.13)	(12.27)	(13.32)
Horizon	0.038***	0.016***	0.038***	0.016***
	(21.83)	(10.68)	(19.97)	(10.99)
NOA	-0.236***	-0.218***	-0.226***	-0.209***
	(-6.80)	(-5.22)	(-7.55)	(-6.26)
NOC	0.003	0.027*	0.002	0.022
	(0.30)	(1.88)	(0.13)	(1.19)
NOF	0.141**	0.481***	0.158***	0.502***
	(2.46)	(7.04)	(3.71)	(6.67)
Firmexp	-0.012	-0.083**	-0.011	-0.080**
	(-0.84)	(-2.07)	(-0.77)	(-2.03)
Genexp	-0.062***	-0.035**	-0.056***	-0.027
	(-6.84)	(-2.10)	(-5.33)	(-1.40)
Constant	-0.008***	-0.008***	-0.009***	-0.008***
	(-6.36)	(-4.04)	(-6.67)	(-3.93)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
N	343212	29087	295410	25967
R^2	0.2294	0.2992	0.2336	0.2964

This table presents the regression results of the relation between climate disasters and analyst forecast properties after dropping the top 5/10 cities where most analysts are located. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 8: Market reaction tests

	(1) Sur	(2) Sur>=0	(3) Sur>=0	(4) Sur<0	(5) Sur<0
CDD		0.075**	0.076**	-0.014	-0.012
		(2.62)	(2.65)	(-0.44)	(-0.36)
Sur	0.002**	0.005**	0.005**	0.003***	0.002***
	(1.98)	(2.36)	(2.41)	(3.56)	(3.38)
CDD*Sur		-0.423**	-0.450**	0.065	0.058
		(-2.19)	(-2.26)	(0.73)	(0.66)
Size			-0.007***		-0.011***
			(-2.70)		(-4.63)
Loss			-0.004		-0.000
			(-1.09)		(-0.10)
ROA			-0.047*		-0.002
			(-1.72)		(-0.11)
MTB			-0.055		-0.317*
			(-0.35)		(-1.68)
Sgrowth			0.007**		0.003
			(2.43)		(1.07)
Age			-0.215		-1.294**
			(-0.53)		(-2.27)
SDret			0.056		-0.060
			(0.79)		(-0.93)
Constant	0.004***	0.016***	0.073***	-0.014***	0.096***
	(7.11)	(75.19)	(3.57)	(-61.44)	(5.23)
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	29635	16691	16682	11638	11618
R^2	0.1643	0.2194	0.2212	0.2703	0.2724

This table presents the regression results of the market reaction tests. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 9: Relation between climate disasters and analyst forecast properties: Endogeneity tests

	(1) 1st stage	(2) 2nd stage	(3) 1st stage	(4) 2nd stage
Panel A	AFE		DISP	
CDD		1.315***		0.004**
		(4.72)		(2.00)
Density	-0.001***		-0.001***	
	(-2.88)		(-4.01)	
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
N	382393	382387	32258	32240
R^2	0.2039		0.1881	
CD-F	9.022		9.989	
Panel B				
	AFE	DISP	AFE	DISP
CDD	0.408*	0.009***	0.625***	0.009**
	(1.93)	(3.17)	(4.06)	(2.31)
Controls	Yes	Yes	Yes	Yes
Industry	No	No	Yes	Yes
Firm	Yes	Yes	No	No
Analyst	No	No	Yes	Yes
Year	Yes	Yes	Yes	Yes
State	No	No	Yes	Yes
N	382352	31511	380955	29960
R^2	0.402	0.518	0.284	0.433
Panel C	AFE		DISP	
CDD	0.899***		0.014***	
	(5.70)		(6.35)	
CCR	-0.001		-0.001	
	(-1.53)		(-1.63)	
Controls	Yes		Yes	
Industry	Yes		Yes	
Year	Yes		Yes	
State	No		No	
N	382387		32240	
R^2	0.2254		0.2956	

This table reports the regression results for endogeneity tests. Panel A reports the results based on the instrument variable approach. The dependent variable in the first stage regression is climate disasters (*CDD*). The instrumental variable is population density. *CD-F* represents *Cragg-Donald F statistic*. Panel B reports results when either firm- or analyst- level fixed effects are controlled for. Panel C reports the regression results on the relationship between climate disaster and analyst forecast properties after controlling for the impact of climate change regulation. All other variables are defined in the appendix. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 10: Relation between climate disasters and analyst forecast properties: A PSM-DiD analysis

Panel A: PSM-DID analysis

	(1) AFE	(2) DISP
Affected*Post	0.001***	0.001**
	(3.16)	(2.07)
Controls	Yes	Yes
Firm	Yes	Yes
Year	Yes	Yes
Analyst	Yes	Yes
N	76952	7317
R^2	0.5143	0.7513

Panel B: Parallel trends assumption

	(1) AFE	(2) DISP
D(t=-2)*Affected	0.000	0.000
	(.)	(.)
D(t=-1)*Affected	0.001	0.001
	(1.35)	(1.07)
D(t=1)*Affected	0.001	0.002*
	(1.46)	(1.86)
D(t=2)*Affected	0.002**	0.002*
	(2.50)	(1.88)
D(t=3)*Affected	0.001	0.002
	(0.87)	(1.44)
Controls	Yes	Yes
Firm	Yes	Yes
Year	Yes	Yes
Analyst	Yes	Yes
N	76952	7317
R^2	0.5144	0.7514

Panel A presents the regression results of the relation between climate disasters and analyst forecast properties using the PSM-DiD analysis. Panel B presents the regression results of the verification of the parallel trends assumption. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 11: Relation between climate disasters and analyst forecast properties

Panel A: Alternative measures of climate disasters

	(1) AFE	(2) DISP	(3) AFE	(4) DISP	(5) AFE	(6) DISP	(7) AFE	(8) DISP
CDF	0.135**	0.042*						
	(1.99)	(1.85)						
CDDP			0.194***	0.020*				
			(2.95)	(1.92)				
CDDR					0.316**	0.032**		
					(2.42)	(2.03)		
CDDC							0.846***	0.018***
							(3.31)	(5.79)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	No	No	Yes	Yes	Yes	Yes	Yes	Yes
N	382387	32240	382387	32240	382387	32240	382387	32243
R^2	0.2273	0.2976	0.2274	0.2977	0.2274	0.2976	0.2273	0.2939

Panel B: Additional robustness tests

	(1) Non-financial crisis period (AFE)	(2) Non-financial crisis period (DISP)	(3) Exclude high climate disaster Year (AFE)	(4) Exclude high climate disaster Year (DISP)	(5) Non-Gulf Coast (AFE)	(6) Non-Gulf Coast (DISP)	(7) Firms with a less dispersed workforce (AFE)	(8) Firms with a less dispersed workforce (DISP)	(9) Firms with a more dispersed workforce (AFE)	(10) Firms with a more dispersed workforce (DISP)
CDD	0.607***	0.011***	0.950***	0.013***	1.196***	0.010**	0.798***	0.014***	0.851**	0.009
	(5.03)	(6.87)	(3.18)	(3.41)	(3.71)	(2.22)	(4.83)	(6.04)	(2.35)	(1.38)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	315358	26294	382387	32240	321427	27467	332624	28534	49763	3705
R^2	0.1996	0.2732	0.2274	0.2976	0.2303	0.2968	0.2254	0.2915	0.2882	0.4100

This table presents the regression results of the relation between climate disasters and analyst forecast properties, using four alternative measures for climate disasters, and additional robustness tests. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.