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Climate policy uncertainty and analyst earnings forecasts: Evidence from the Chinese energy sector

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ABSTRACT

We investigate whether climate policy uncertainty affects analysts' earnings forecasts. Using 51,986 analyst forecasting data from China's energy sector for 2009–2021, we find that climate policy uncertainty results in lower analysts' earnings forecasts. Our finding is consistent with the deterioration of the company's fundamentals. Heterogeneity analysis shows that climate policy uncertainty's "correction effect" on analysts' optimistic forecasts is more effective among firms with worse ESG performance and higher pollution levels. Additional analysis suggests that analysts' revision behavior is only present in the sample of optimistic forecasts and that the "correction effect" improves the accuracy of analysts' forecasts.

1. Introduction

In recent years, frequent climate disasters have posed a significant challenge globallyd, which have had a significant impact on thesocio-economic development and human health (Gong & Liao, 2024; Nordhaus, 2019). Environmental policies enacted by many countries to mitigate the effects of climate change, which have effectively mitigated pollutant emissions but have also created considerable uncertainty in the capital markets (Abudu et al., 2024; Cao et al., 2023; Chai et al., 2023; Shen & Zhang, 2024). The literature on climate policy uncertainty (CPU) focuses on the effects on stock markets (Ren et al., 2022; Treepongkaruna et al., 2023), investments (Dutta et al., 2023; Huang & Sun, 2023), financial risk (Liu, Wang, et al., 2024; Zhang & Chen, 2024), corporate innovation (Liu, Chen, et al., 2024;, energy consumption (Lin & Cheung, 2024; Zhang et al., 2024) and energy prices (Syed et al., 2023). The literature needs to be more transparent on the consequences for external corporate stakeholders of climate policy uncertainty, especially for analysts.

According to Chen et al. (2017) proposed that analysts fulfill the functions of "information intermediary", "monitoring agent", and "market pressure" within capital markets. And the accuracy of their forecasts not only affects investors' investment decisions but also affects the company's governance ability (Chen et al., 2015). As a result, analyst forecasting has become an object of interest for scholars in recent years. Analysts function as information intermediaries bridging companies and investors. They typically receive professional training and are often called upon to exercise professional judgment in a multiplicity of circumstances. However, scholars have found that analysts make overly optimistic predictions due to cognitive biases (Malmendier & Shanthikumar, 2014). Thus, they may adjust their forecasting behavior when new information becomes available (Li et al., 2023; Zhao et al., 2022). In light of the fact that the recurrent shocks to capital markets caused by climate policy alterations furnish new data for analysts' forecasts, analysts are likely to respond to climate policy uncertainty.

There are several reasons why uncertainty about climate policy can affect analysts' forecasts. On the one hand, the economic shock of climate policy uncertainty could trigger pessimism among analysts, leading them to lower their forecasts and revise their previous optimistic bias, i.e., CPU has a "corrective effect" on analysts' forecasts. There is a consensus that policy uncertainty has hindered the development of financial markets (Gong et al., 2022; Matousek et al., 2020; Wen et al., 2022). Specifically, climate policy uncertainty reduces corporate valuations (Azimli, 2023). Ilhan et al. (2021) claim that to mitigate the shock of climate policy, banks may reduce funding, resulting in financing constraints for firms. CPU is negatively associated with a firm's total factor productivity (Ren et al., 2022). Frequent changes in climate policy

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directly affect company performance, which causes analysts to recognize their optimistic bias and, in turn, make more pessimistic forecasts. Meanwhile, enacting climate policy may increase the declaration of non-financial information, like pollutant emissions, providing analysts with more potential bad news. Therefore, we hypothesize that the increase in climate policy uncertainty is accompanied by analysts revising their forecasts downwards. Referring to Zhao et al. (2022), we describe this behavior as a “correction effect” on analysts' optimism bias, which implies that analysts will revise their overly optimistic forecasts and reduce the degree of optimism in their forecasts.

On the other hand, climate policy uncertainty could lead analysts to make more optimistic forecasts. Kumar (2009) proves that behavioral biases are stronger when uncertainty increases. Frequent changes in climate policy make it more difficult for analysts to forecast, and climate policy uncertainty makes analysts rely more on their subjective speculation when making forecasts so that analysts may amplify optimistic beliefs. In addition, as mentioned above, analysts often tend to make optimistic forecasts out of professional concern. Specifically, Easterwood and Nutt (1999) claim that analysts may underreact to negative news. A work closer in line with this paper is that Lim (2001) finds that in the face of high uncertainty about the firm, to maintain a relationship with a company, analysts make more positive bias forecasts to gain more information on the future of the company. As a result, analysts' forecasts may become more optimistic when climate policy uncertainty increases. We describe this behavior as an “amplification effect” on analysts' optimism bias. In summary, the effect of CPU on analysts' sentiment needs to be explored as an empirical question.

Using the sample of the Chinese energy sector during 2009–2021, we investigates the effect of CPU on analysts' forecasts. Several reasons for China's energy sector are suitable for our research. First, climate policy aims to reduce carbon emissions, but in the process inevitably affects the profitability of companies (Hsu et al., 2022). In addition, Dong et al. (2021) indicate that pollution results in lower profit forecasts. Energy-related enterprises usually have more carbon emissions, and climate policy uncertainty may be most relevant for energy-related enterprises (Ilhan et al., 2021). Hence, the causal link between CPU and analyst forecast bias is more acute in the energy sector. Second, as climate change has become a global issue, investors increasingly focus on corporate environmental performance. Bolton and Kacperczyk (2021) find that investors may punish energy-related enterprises as less environmentally friendly in the high climate policy uncertainty period, and investors may seek higher equity returns as compensation for carbon risk. Similarly, analysts who value environmental sustainability may also overreact to environmental investors' impact on companies and therefore cause negative forecast bias. Above all, the energy sector is ideal for examining this connection. Third, with the rapid economic development, China has progressively attached great significance to the green transition of the economic and social arenas and has enacted policies like the “Interim Regulations on the Administration of Carbon Emission Rights Trading”, spurring analysts to take into account the ramifications of the incessant fluctuations in climate policies when formulating earnings projections.

We use the CPU index developed by Ma et al. (2023) as a proxy of climate policy uncertainty for China. To increase the reliability of the results, this paper uses provincial data on climate policy uncertainty. Our results demonstrate a negative causal relationship between climate policy uncertainty and analysts' forecasts. After controlling for the firm and analyst characteristics, including firm fixed effects and time trends, the coefficient on climate policy uncertainty is estimated to be -0.102, which implies that an increase of one standard deviation in the independent variable reduces analysts' forecast earnings per share by 9.31 % of actual earnings. That is, CPU has led analysts to reduce their optimistic forecasts, confirming our “correction effect” hypothesis.

In the following, to verify analysts' pessimistic forecast is due to the negative news from CPU. We verify the effect of CPU on the company's profitability. The result shows that CPU harms the company's profitability. Accordingly, we believe that analysts' pessimistic behavior is due to analysts' awareness that CPU hurts companies, increasing their perception of negative news and thus correcting for optimism bias. To further test our conjecture, we examine the heterogeneous performance of analysts across firms to explore whether a ‘corrective effect’ of climate policy on analysts' optimism differs between firms with different climate policy sensitivities. We find that analysts' corrective behavior is more pronounced among companies with lower ESG (Environmental, Social and Governance) scores and those in highly polluting industries. These results align with our expectations, as high ESG and cleaner companies are less vulnerable to climate policy penalties. At the same time, better environmental performers are more favored by investors as public attention to climate issues grows. The study reveals high environmental performance companies have a financing cost advantage and are more resilient to climate policies. Thus, the adverse causal relationship between CPU and analysts' forecasts is more pronounced in the environmentally underperforming sample, and the results further suggest that analysts are revising their optimistic forecasts.

We then conduct several robustness checks to improve the reliability of the results. Initially, we have substituted measures of key variables and re-run baseline regressions. Second, we added analyst-fixed effects to alleviate concerns about the endogeneity of the results due to missing analyst characteristics variables. And then we exclude the effect of significant health events on analysts' pessimistic forecasts by removing observations from the 2020–2021 COVID-19 period. Finally, we conducted a 2SLS (two stage least square) regression using Global Mean Surface Temperature as an instrumental variable. After a battery of robustness tests, the negative impact of climate policy uncertainty on analysts' forecasts continues to play a role.

To enhance our knowledge of the role that “correction effects” play in the causal relationship between CPU and analysts' forecasts, we further examine analysts' revision behavior and the consequences of their optimistic revisions. For analysts' revisionary behavior, we test the possibility that uncertainty about climate policy is a corrective to both optimistic and pessimistic analyst forecasts. Analysts tend to correct for optimism bias as climate policy uncertainty brings more negative news to analysts. The empirical results show that CPU merely has a corrective effect on analysts' optimistic forecasts, and has an insignificant effect on analysts' pessimistic forecasts. We then explore the consequences of the “correction effect” by examining the impact of CPU on the accuracy of analysts' forecasts. If the analysts' optimistic revisions are due to the acquisition of additional negative news, it would be reasonable to presume that the analyst's forecast becomes more accurate with the revised behavior. The results demonstrate a negative relationship between climate policy uncertainty and analysts' forecast bias, suggesting an improvement in analysts' forecast accuracy and further supporting the hypothesis of a “correction effect”.

Our contributions are mainly twofold. Our findings deepen the understanding of the economic consequences of climate policy uncertainty, in particular by adding research on its impact on capital markets. With frequent changes in environmental regulation, climate policy uncertainty is amplified. Some works of literature investigate the influence of CPU on firms, with Donadelli et al. (2020) finding that it reduces the value of fossil fuel businesses. Climate policy uncertainty is priced by banks (Delis et al., 2019) and option markets (Ilhan et al., 2021). Our findings extend these studies by exploring the implications of CPU for financial information intermediaries, which focuses on the analysts' forecasts. Thus, climate policy uncertainty affects external stakeholders in addition to firms, providing new evidence that climate policy uncertainty affects capital markets. In particular, climate policy uncertainty has been criticized for its potential risks, but this paper finds that it corrects analysts' optimistic forecast bias, providing evidence for its positive externalities.

Meanwhile, our work complements the understanding of analysts' forecasts. Prior researches focus on the firm factors and analysts' characteristic, such as educational background (Fracassi et al., 2016), experience (Bradley, Gokkaya, & Liu, 2017), competition (Hong & Kacperczyk, 2010), and corporate governance (Byard et al., 2006). Recently, scholars are beginning to focus on the impact of external factors on analysts, such as terrorist attacks (Cuculiza et al., 2021), air pollution (Dong et al., 2021), and natural disasters (Kong et al., 2021). However, the literature examines analysts' pessimistic forecasts from a sentiment perspective, and less literature examines analysts' revisions to optimistic forecasts (Zhao et al., 2022). We examine analyst behavior from the perspective of frequent changes in climate policy, providing new evidence that external factors can revise analysts' optimistic forecasts. In addition, our study also identifies a new driver that influences the accuracy of analysts' forecasts. Literature suggests that analyst experience, decision fatigue (Hirshleifer et al., 2019), the number of analysts following companies (Clement, 1999), and the number of analysts in the same industry (Kumar et al., 2022) affect the accuracy of analysts' forecasts. We complement the documentation by presenting evidence on the impact of CPU on the accuracy of analysts' forecasts.

The rest of this paper is organized as follows: Section 2 reviews the relevant literature and develops the hypotheses. Section 3 describes the data sources and reports the summary statistics. Section 4 presents our study design, shows the results of the baseline regressions, and reports the results of the study on firm performance and the results of the heterogeneity analysis. Section 5 conducts robustness tests and additional analysis. Section 6 concludes.

2. Literature and hypotheses

2.1. Literature review

Under the scenarios of climate change, policymakers have taken many steps to reduce carbon emissions. Frequent changes in climate policy impose additional costs on firms (Li et al., 2024; Seltzer et al., 2022; Song, Xu, Qu, & Gong, 2024). Moreover, the shock of climate regulation change has proven to become a challenge that the financial market faces, priced by banks and the option market (Ehlers et al., 2022; Ilhan et al., 2021). In addition, some scholars cite the Paris Agreement to represent a climate policy shock. The Paris Agreement, signed by several countries around the world in December 2015, limits global warming to 2 °C (preferably 1.5 °C). The policy facilitates the research of scholars. They document that climate risk is associated with lower firms' leverage (Ginglinger & Moreau, 2019; Nguyen et al., 2022) and relates to credit ratings and bond yield spread (Seltzer et al., 2022). In summary, CPU has proven to affect the financial market negatively.

While most studies measure climate policy risk by firms' carbon intention or using a climate policy as an event that increases climate policy uncertainty, few documents use numerical indicators to examine the economic consequences of climate policy uncertainty. More recently, Gavriilidis (2021) uses newspaper news to construct a CPU index to measure climate policy uncertainty. Based on this data, Liang et al. (2022) identify the CPU as a factor in predicting fluctuations in the renewable energy index. Zhang et al. (2022) argue that uncertainty from climate regulation inhibits a firm's investment in the United Kingdom. Using Chinese capital markets as a research target, Ren et al. (2022) find that CPU reduces firms' total factor productivity by reducing their R&D investment and free cash flow. We complement the CPU study with findings on the impact of the CPU on analysts. In what follows, we review the literature on analyst forecasts to explain why climate policy uncertainty affects analysts' forecasts.

Analysts use their expertise to mitigate the information barriers that separate companies from investors through information mining and processing. However, analysts' forecasts may also be biased. For example, an analyst's education, experience, tenure, and previous industries worked in and the governance capabilities of the company can affect the accuracy of their forecasts (Bradley, Gokkaya, & Liu, 2017; Byard et al., 2006; Cao et al., 2022; Fracassi et al., 2016; Mamatzakis & Bagntasarian, 2021; Miah et al., 2023). Several empirical studies support that analysts tend to be over-optimism. To maintain relationships with clients, analysts respond more quickly to good news and slow down the delivery of bad news (O'brien et al., 2005). To increase commission income (Malmendier & Shanthikumar, 2014), be affected by the herding effects (Welch, 2000), and for their career concerns, they may issue optimistic forecasts (Ke & Yu, 2006). The above research confirms the claim that analysts make positively biased forecasts for both "strategic" and "non-strategic" reasons (Malmendier & Shanthikumar, 2014).

Since analysts are professionally trained, they will adjust their forecasts when acquiring new information. For example, Kumar et al. (2022) claim that analysts draw lessons from their peers' actions and adapt their forecasts to their peers' analytical errors. Beyer and Guttman (2011) claim analysts make upward predictions when given private information that is good news, and they make downward predictions when their private information is terrible. Specifically, the CDS deal provided negative information and dampened analysts' optimism (Zhao et al., 2022). Analysts downgrade their forecasts for companies accused of securities fraud after their corrective disclosures (Griffin, 2003). In addition, anti-corruption campaigns conceal bad corporate news, making analysts' optimism more pronounced (Li, Liu, et al., 2021; Li, Xu, et al., 2021). This literature finds a consistent conclusion that analysts have a positive forecast bias in that many factors influence their optimistic forecasts. Whether analysts react to climate policy uncertainty, an essential exogenous shock that significantly impacts financial markets is the question of our research.

2.2. Hypotheses development

Analysts are financial practitioners with professional knowledge (Bradley, Gokkaya, Liu, & Xie, 2017). In most cases, they consider a variety of valid information to reduce forecast bias when making predictions. Although the effect of CPU on analysts' forecasts may be multifaceted, we speculate that corrections play a crucial role. The explanation for the link between climate policy uncertainty and analysts' forecast is that climate policy uncertainty provides analysts with more negative news, leading analysts to revise optimistic forecasts. By combing through the previous literature, we learn that analysts tend to release optimistic forecasts for various reasons, making analysts' forecasts tend to be higher than the company's actual performance. Climate policy uncertainty is an exogenous shock that mitigates analysts' optimism bias. Because climate regulations are enacted to reduce environmental pollution, the policy risk to firms increases during climate policy implementation. The enactment of climate policy provides analysts with potentially bad news, analysts' optimistic beliefs are adjusted, and climate policy uncertainty acts as a "correction effect" in analysts' forecasts. Therefore, we consider a negative causal connection between climate policy uncertainty and analysts' forecasts as our first hypothesis:

H1. Climate policy uncertainty has acted as the corrective to analysts' optimistic forecasts.

Regarding the "correction effect" of climate policy uncertainty, previous literature suggests that climate policies typically negatively impact firms. Regulations like carbon taxes restrict the operation of firms, especially energy-related firms. Restrictions on emissions reduce firms' output, total factor productivity, and free cash flow and increase the production cost (Lin & Li, 2011). In particular, climate policy change has reduced the value of fossil fuel firms (Donadelli et al., 2020). Considering the climate policy exposure, dirty companies are charged higher loan rates (Delis et al., 2019). From the PV model, it is clear that investors may demand compensation for climate regulation due to the cost of understanding the new policy (Ilhan et al., 2021). These causes worsen firm profitability, and analysts revise their optimistic beliefs to recognize the negative impact of CPU on firms. We examine the relationship between CPU and firm profitability to test the analysts' behavior in revising expectations. If the "revision effect" hypothesis is valid, CPU should reduce firms' profitability.

H2. Climate policy uncertainty has weakened corporate performance.

Previous studies have found that people tend to have a higher tolerance for companies that perform better in ESG. As investors become more environmentally conscious, corporate ESG performance, a measure of corporate environmental performance, has become a focus of attention. When ESG scores are higher, companies have superior environmental performance, are less likely to be administratively penalized, and are less exposed to adverse shocks from climate policy uncertainty. Meanwhile, Atif and Ali (2021) document that higher ESG disclosure is related to lower default risk for companies. It is widely believed that ESG-performing companies are favored by investors (Huynh & Xia, 2021). Therefore, ESG-performing companies are unlikely to be penalized by investors. In addition, companies with higher ESG performance have lower debt financing costs (Eliwa et al., 2021). They are more resilient to CPU because they can cope with the adverse effects of climate policy at a lower cost. In summary, climate policy uncertainty significantly impacts poor ESG performers, so analysts are more likely to adjust their expectations of poor ESG performers downward.

Furthermore, we tested the difference in analysts' performance between dirty and clean companies. In addition, we tested the difference in analysts' performance between dirty and clean companies. Consistent with our shared knowledge, companies in high-polluting sectors are more affected by climate policies as they are more likely to be penalized by policies and investors for high emissions (Seltzer et al., 2022). Simultaneously, it has also been found that when climate policies are enacted, firms in high-polluting industries adjust their corporate decisions, such as reducing the size of their credit, which may reduce their ability to respond to a risky shock. Thus, climate policy uncertainty poses a greater risk to high-polluting firms, and analysts' corrective behavior is more pronounced.

H3. The analyst correction effect caused by climate policy uncertainty is more pronounced among companies with worse ESG performance and those in polluting industries.

As was discerned by Zhao et al. (2022), the emergence of adverse news exerts a rectifying impact on both strategic and non-strategic optimistic prognostications proffered by analysts. In consonance with the “correction effect” hypothesis, the uncertainty of climate policies is instigating analysts to effectuate adjustments towards more sanguine forecasts. The revisionary effect of climate policy uncertainty on analysts' forecasts is anticipated to be more salient within the cohort of optimistic forecasts.

Meanwhile, one of the cardinal premises of our investigation is that an optimistic predilection exists in analysts' forecasts, and the uncertainty of climate policies functions to redress this partiality. Thereby, this revisionary effect is efficacious in attenuating the forecast bias of analysts.

Hence, we hereby postulate the fourth hypothesis for this paper:

H4. The corrective effect of climate policy uncertainty on analysts' forecasts can improve the accuracy of analysts' forecasts, and its effect is more pronounced among companies with optimistic forecasts.

3. Data and summary statistics

3.1. Data sources

Our dataset is based on analyst reports published by Chinese analysts, and the data comes from the China Stock Market and Accounting Research (CSMAR) database. We construct our dependent variable, Sentiment, using the analyst forecast data and firms' actual earning data. The primary independent variable *CPU* index is from Ma et al. (2023). Since the relatively small amount of data available for analysts' forecasts before 2008, and to reduce concerns about the impact of the economic crisis in 2008, our sample period is 2009 to 2021. This paper is mainly examining the effect in energy-related industries. Therefore, our sample includes companies in the mining, energy production, transportation, and construction sectors, which aligns with the Industry Classification Guidelines for Listed Companies issued by the China Securities Regulatory Commission in 2012. We process the data as follows: 1) We dismiss observations on missing analyst characteristics; 2) We dismiss observations on missing company characteristics; 3) We exclude companies that are subject to special treatment. Since analysts make multiple predictions a year, consistent with existing papers, for each analyst, we only consider their first prediction of the same company each year. Ultimately, our sample consists of 51,986 analyst forecast observations involving 1259 firms.

3.2. Measuring analyst pessimism

Referring to the research of Kong et al. (2021) and several works of literature on the calculation of analyst sentiment, this paper defines analysts' sentiment as follows:

$$Sentiment_{ijt} = \frac{FEPS_{ijt} - EPS_{ijt}}{|EPS_{ijt}|} \quad (1)$$

where *FEPS* is the firm's earnings per share forecast by analysts, and *EPS* is the actual earnings per share. To minimize the impact of other factors, we only keep the first forecast of each analyst for each year. When the *Sentiment* is negative, it means that the earnings per share forecast by analysts are less than the actual earnings per share, and there is a negative forecast bias, indicating that analysts have a pessimistic view of the company. Conversely, when *Sentiment* is positive, analysts are optimistic.

3.3. CPU index

The independent variable CPU index of this paper is provided by Ma et al. (2023). They collected news data from six influential Chinese newspapers: People's Daily, Guangming Daily, Economic Daily, Global Times, Science and Technology Daily, and China News Service, and used a deep learning algorithm, the MacBERT model, to construct an index of climate policy uncertainty for China's countries and provinces and cities. Larger CPU values indicate greater policy uncertainty in China's response to climate change.

3.4. Firm and analyst characteristics

Several studies have reported that many factors may influence analysts' forecasts. In this paper, we control for two sets of variables: firm characteristics and analyst characteristics. For example, Lee and So (2017) claim that as a resource constraint, firm characteristics could help predict a company's future earnings. Therefore, following Gong et al. (2023), Wen et al. (2023), and Yang et al. (2023), we control for the size of the company (*Size*), stock return (*Return*), book-to-market value ratio (*Book-to-market*), intangible asset ratio (*Intasset*), analyst coverage (*Attention*), company's profitability (*ROA*), equity concentration (*Largehold*) and leverage rate (*Leverage*). At the same time, we also control for analyst characteristics. According to the extant literature by Kim et al. (2011), analyst forecast is associated with their features, so we control for analyst features, including analyst gender (*Gender*), education (*Master*), experience (*Experience*), number of analyst forecasts (*Number*), and analyst team size (*Groupsize*). Consistent with Dong et al. (2021), we also control for analyst consensus forecasts to exclude the effect of analysts' herding effect (*ConFeps*). The detailed definitions of variables are shown in Appendix A.

3.5. Summary statistics

Table 1 presents the summary statistics of the variables. In Panel A, the descriptive statistics for the analyst forecast level are provided, while Panel B shows the descriptive statistics for the firm level. It is observed that the mean value of Sentiment is 0.57 and the median is 0.14, both of which are positive, thereby corroborating the view that analysts generally exhibit a tendency towards over-optimism. Additionally, its standard deviation amounts to 1.52, indicating a substantial variation in analysts' forecasts. The mean and standard deviation of the CPU are 2.15 and 0.52 respectively, which is in line with the high degree of uncertainty in climate policy. The values of the other variables all fall within a reasonable range and are comparable to those in the existing literature.

To initially explore the relationship between the variables, we calculated Pearson correlation coefficients for the key variables used in our paper.[1] Moreover, according to the results, the correlation coefficient between CPU and Sentiment is −0.045, preliminarily validating our previous hypothesis. Furthermore, the maximum variance inflation factor (VIF) is 2.81, and the mean VIF value is 1.67, which is well below 10,[2] so multicollinearity is not a problem to be a concern.

4. Empirical analysis

4.1. Empirical design

In this section, we use a multiple regression model to examine the impact of CPU on analyst forecasts:

Table 1
Summary statistics.

Variable name	N	Mean	Std. Dev.	P25	P50	P75
Panel A. Summary statistics for forecast-level variables						
Sentiment	51,986	0.57	1.52	−0.55	0.14	10.88
CPU	51,986	2.15	0.52	0.65	2.17	3.51
Size	51,986	23.14	1.54	20.45	22.94	27.47
Book-to-market	51,986	0.64	0.25	0.14	0.64	1.15
Return	51,986	0.26	0.67	−0.72	0.09	2.93
ROA	51,986	0.06	0.05	−0.05	0.06	0.21
Largehold	51,986	38.57	15.71	10.76	37.50	77.32
Intasset	51,986	0.05	0.05	0.00	0.04	0.31
Leverage	51,986	0.46	0.19	0.07	0.47	0.83
Attention	51,986	19.11	13.09	1.00	17.00	75.00
Gender	51,986	0.22	0.39	0.00	0.00	1.00
Master	51,986	0.92	0.25	0.00	1.00	1.00
Experience	51,986	1.62	1.25	0.00	1.76	3.88
Number	51,986	2.22	1.71	0.00	2.64	5.30
Groupsize	51,986	0.20	0.35	0.00	0.00	1.61
ConFeps	51,986	0.83	0.66	0.02	0.67	3.65
EPU	51,986	1.96	1.08	0.92	1.29	3.90
Panel B. Summary statistics for firm-level variables						
Size	7552	22.77	1.47	20.45	22.54	27.47
Book-to-market	7552	0.67	0.24	0.14	0.68	1.15
Return	7552	0.19	0.63	−0.72	0.04	2.93
ROA	7552	0.05	0.04	−0.05	0.04	0.21
Largehold	7552	38.38	15.48	10.76	37.38	77.32
Intasset	7552	0.05	0.05	0.00	0.04	0.31
Leverage	7552	0.46	0.19	0.07	0.47	0.83
Attention	7552	11.78	10.39	1.00	9.00	75.00

Note: This table shows the descriptive statistics for the main variables from 2009 to 2021. Panel A presents summary statistics for forecast-level variables, and Panel B presents summary statistics for firm-level variables. Variable definitions are reported in Appendix A.

$$Sentiment_{ijt} = \beta_0 + \beta_1 CPU_{t-1} + Control\ Variables + FirmFE + Year + \varepsilon_{ijt} \quad (2)$$

where $Sentiment_{ijt}$ is the analyst i's sentiment towards firm j in year t; CPU_{t-1} is the climate policy uncertainty index in year t-1; *Control Variables* denotes the firm-level control variables and analyst-level control variables mentioned above. To ensure the consistency of the results, the control variables are also processed with a one-period lag. To capture the effects of other firm characteristics, we include firm fixed effects *FirmFE*. To control for the effects of time trends and macroeconomic factors, we have included a time trend *Year*. ε_{ijt} is the error term. Referring to Kong et al. (2021), we cluster the standard errors to the analyst level. In Eq. (2), β_1 is the coefficient we are interested in. Based on the analysis in Section 2, we believe that climate policy uncertainty could revise analysts' optimistic expectations, so we predict β_1 should be negative.

4.2. Baseline results

Table 2 presents the estimation outcomes of the baseline regression. In Column (1), the regression coefficients between the main explanatory variable (i.e., CPU) and the explanatory variables are reported. Column (2) incorporates controls for analyst characteristics, firm characteristics, and the other factors aforementioned. The coefficients of the CPU index in both columns are negative and statistically significant at the 1 % level. Based on the result in Column (2), a one standard deviation increase in climate policy uncertainty leads to a decrease in analysts' earnings forecasts by approximately 0.053 (=0.52*0.102), which corresponds to a 9.31 % (=0.52*0.102/0.57) reduction of the sample mean of analyst optimism, These results consistent with prior literature (Zhao et al., 2022), and implicitly imply that climate policy uncertainty can merely partially correct analysts' optimistic expectations and fails to eradicate their optimistic bias. In conclusion, our results furnish statistical evidence that the uncertainty of climate regulation induces less optimistic forecasts by analysts. Hence, Hypothesis 1 is validated.

4.3. Firm performance

The results of our baseline regressions have confirmed that climate policy uncertainty has caused analysts to correct their optimistic forecasts. According to the previous discussion, analysts make forecast corrections because they believe the CPU may bring potentially bad news to the company and hurt its operations. To validate this conjecture, we examine the company's performance. Suppose the CPU weakens the company's profitability. In that case, it is reasonable to believe that climate policy uncertainty has caused analysts to increase their perception of negative information and thus revise their forecasts.

Following Wang et al. (2021), we use the following regression model to explore our question:

$$\Delta Perf_{jt} = \alpha_0 + \alpha_1 CPU_{t-1} + Control\ Variables + FirmFE + Year + \varepsilon_{jt} \quad (3)$$

where the explanatory variables are firm performance, which we measure using *TobinQ* and *P/E* (Price/Earnings) ratios. The *Control Variables* includes firm characteristics as well as *EPU* indicators. Furthermore, we control for firm fixed effects and time trends. We cluster the standard errors at the analyst level. The model measures how the CPU in year t-1 affects the performance of the company in the following year, so we focus primarily on the CPU coefficient.

Table 3 presents the results regarding the impact of CPU on company performance. Specifically, in columns (1)–(2), TobinQ is adopted as the dependent variable, whereas in columns (3)–(4), the P/E ratio serves as the dependent variable. Across all columns, the coefficient related to CPU is significantly negative, which indicates that climate policy uncertainty plays a role in contributing to the poor performance of firms. This finding provides support for the hypothesis of a “correction effect”.

[1] For brevity, we do not report the results.
[2] Scholars generally believe that a VIF value of less than 10 is not an issue for multicollinear.

Table 2
Baseline results.

	(1)	(2)
	Sentiment	Sentiment
CPU	−1.31***	−0.102***
	(−3.45)	(−5.14)
Size		0.372***
		−11.61
Book-to-market		−0.370***
		(−5.99)
Return		−0.144***
		(−11.17)
ROA		−2.182***
		(−7.45)
Largehold		−0.003**
		(−2.34)
Intasset		−1.416***
		(−4.13)
Leverage		−0.593***
		(−6.12)
Attention		−0.001
		(−1.00)
Gender		0.004
		−0.25
Master		−0.018
		(−0.52)
Experience		−0.006
		(−0.67)
Number		0.043***
		−7.32
Groupsize		0.062***
		−2.86
ConFeps		0.224***
		−8.77
EPU		−0.039***
		(−2.59)
_cons	−14.063**	68.82***
	(−2.21)	−4.94
Year	Yes	Yes
Firm	Yes	Yes
Observations	51,986	51,986
R^2	0.233	0.247

Note: This table presents the regression coefficients for the effect of climate policy uncertainty on analysts' projections. The dependent variable in both columns is Sentiment, as defined in the previous section. The explanatory variable CPU, is the climate policy uncertainty index from Gavriilidis (2021), which we divide by 100 to increase the readability of the results. All variable definitions are shown in Appendix A. We control for firm fixed effects, time trends, and standard errors in both regressions are clustered at the analyst level (Kong et al., 2021). Column (1) shows the results including only the main explanatory variables, while column (2) shows the results of adding control variables to the regression. The t-statistic is reported in parentheses. The t-statistic is reported in parentheses. *** represents 1 % significance; ** represents 5 % significance; * 10 % represents significance.

4.4. Cross-sectional tests

As confirmed earlier, analysts make pessimistic forecasts due to the "correction effect". Based on Hypothesis 1, climate policy uncertainty brings additional negative news to analysts because it increases the risk of administrative penalties for companies, which leads to a revision of analysts' optimistic forecasts. If the statement is valid, there is reason to believe that analysts are not pessimistic about all companies, as companies are exposed to climate policy uncertainty to different degrees. The primary purpose of climate policy is to reduce environmental pollution, so it is more likely that climate policy penalizes dirty companies, which in turn leads to more pessimistic forecasts for these companies. To test our conjecture, we compare analysts' predictive behavior across ESG performance and companies with different pollution levels in this section.

The development of ESG scores has provided data to support our study of the heterogeneous role of environmental pollution levels. The

Table 3
The impact of CPU on corporate earnings.

	(1)	(2)	(3)	(4)
	TobinQ	TobinQ	PE	PE
CPU	−3.002**	−2.797**	−5.350**	−5.432**
	(−2.39)	(−2.05)	(−2.58)	(−2.42)
Controls	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
N	7433	7433	7433	7433
R^2	0.938	0.94	0.347	0.351

Note: The table shows the regression coefficients of climate policy uncertainty on firm performance. The main explanatory variable is CPU, the explanatory variable in columns (1)–(2) is TobinQ, and the explanatory variable in columns (3)–(4) is the P/E ratio. To increase the readability of the results, we scaled down the value of TobinQ by a factor of 1,000,000,000 in the same proportion. We control for firm characteristics, EPU indices, firm fixed effects, and time trends. Standard errors are clustered at the firm level. *** represents 1 % significance; ** represents 5 % significance; * 10 % represents significance.

ESG score measures a company's comprehensive performance in environmental, social, and governance (ESG), and a higher ESG rating suggests that companies are performing better environmentally and are less likely to be penalized by climate policies. Therefore, we suspect that the analyst 'correction effect' is at play in the low ESG score grouping. We assign the sample to the High_ESG and Low_ESG groups based on the median ESG score and rerun the baseline regression.[3] Columns (1)–(2) of Table 4 show the results of grouping according to ESG. We find that the CPU Index coefficient is significantly negative in both the Low_ESG and High_ESG groups, but the coefficient is smaller in the Low_ESG group, suggesting that analysts are more pessimistic about companies with lower ESG scores. This result is easy to understand, as ESG is often thought to increase the resilience of firms during crises (Bénabou & Tirole, 2010), for instance, during the financial crisis, high-ESG com-

Table 4
Cross-sectional tests.

	(1)	(2)	(3)	(4)
	High_ESG	Low_ESG	Dirty	Non_Dirty
	Sentiment			
CPU	−0.157***	−0.206***	−0.201***	−0.016
	(−3.31)	(−6.08)	(−6.26)	(−0.69)
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
N	8495	15,276	24,733	27,253
R^2	0.481	0.327	0.221	0.288
P-value for the difference between the CCPU cohort arrays	−0.088***		0.185***	

This table provides the results of cross-sectional tests based on company characteristics. We examine analysts' predictive behavior for companies with high or low ESG scores and contamination levels. Columns (1)–(2) show the results of regressions that divide the sample based on the median ESG score, where our sample size is reduced by missing ESG data. Columns (3)–(4) show the results of the sample are segmented according to whether the industry the firm belongs to is highly polluting. The dependent variable in all columns is Sentiment, and all regressions control for firm fixed effects and time trends. Standard errors are clustered at the analyst level. The t-statistic is reported in parentheses. The p-value for the test of difference between groups of coefficients analysed for heterogeneity was calculated using the Permutation test (1000 samples). *** represents 1 % significance; ** represents 5 % significance; * represents 10 % significance.

[3] ESG data sourced from Bloomberg.

panies had a better performance than low-ESG companies (Lins et al., 2017). In the meantime, Pástor et al. (2021) find that investors tend to hold green assets due to concerns about climate uncertainty, so climate policy uncertainty may rather be an opportunity for companies with high ESG. Therefore, it is reasonable for analysts to be optimistic about companies with high ESG scores.

We further investigate whether the company's pollution level influences analysts' "correction effect" due to climate policy uncertainty. Climate policies are enacted to mitigate climate change, such as global warming, and the government reduces corporate emissions by warning and penalizing companies for their polluting behavior. Therefore, high levels of climate policy uncertainty are connected to a greater likelihood of polluting firms being politically punished and a more pronounced analyst "correction effect". We assign the sample to high and low pollution, based on the list of heavily polluting industries specified by the Ministry of Environmental Protection. The results are presented in columns (3)–(4) of Table 4. We find that the coefficient on CPU is significantly negative in the high pollution group and positive but insignificant in the low pollution group, suggesting that analysts' corrective behavior is only present in high pollution firms, in line with our predictions.

In summary, the "correction effect" of analysts due to climate policy uncertainty is only present in firms with poor ESG performance and high pollution. The results suggest climate policy uncertainty brings analysts terrible news, causing them to revise their optimistic expectations, confirming our Hypothesis 3.

5. Robustness checks and additional test

5.1. Robustness checks

This section presents the results of several robust tests to ensure that the baseline results are robust. A potential concern is that there are noises in the measures of analysts' *Sentiment* and climate policy uncertainty, so we replace critical variables for the regressions. Specifically, referring to most scholars, we excluded concerns about how the dependent variable is measured. Instead of the *Sentiment* calculated by Eq. (1), we use the *logSentiment* as our explanatory variable, which is the logarithm of *Sentiment* plus one. Columns (1)–(2) of Table 5 report the results after replacing the dependent variable, and the coefficients of the *CPU* index are still negative and significant at the 1 % level.

Furthermore, To alleviate concerns that the CPU does not reflect the level of climate policy uncertainty in China, this section uses the Chinese climate policy uncertainty index constructed based on Twitter for robustness testing. Specifically, as the publication of newspaper news in China needs to go through a series of processes such as selecting and rewriting articles, the publication of newspapers in China needs to pass strict censorship before publication (Shao, 2018). Therefore, out of the concern that climate policy uncertainty will be underestimated due to the reporting characteristics of traditional media that report good news but not bad news, Lee and Cho (2023) constructs the TCCPU (Twitter-based China Climate Policy Uncertainty) index by capturing the news on Twitter regarding the uncertainty of China's climate policies. After verification, it can effectively measure the degree of uncertainty in China's climate policies. Specifically, the climate policy uncertainty index is constructed by counting the frequency of tweets that contain the three keywords of "China", "climate change", and "uncertainty". This section uses the TCCPU index instead of the CPU index as our key variable. Columns (3)–(4) of Table 5 present the regression results, and the coefficient of TCCPU is significantly negative at the 1 % or 5 % level.

Moreover, Since the CPU index of the United States constructed by Gavriilidis (2021) has attracted much attention from scholars, and the index is able to reflect global climate policy uncertainty to a certain extent, this paper adopts the UCPU to conduct a robustness test, and the results are shown in columns (5) and (6) of Table 5, and the coefficient of UCPU is significantly negative at the 1 % or 5 % level.

Besides, although in the baseline regression, we controlled for analyst characteristics, one potential concern is that omitted analyst characteristics variables may lead to implausible causal links between CPU and analyst forecasts. To alleviate this concern, we add analyst fixed effects to Eq. (2). Because some characteristics of analysts do not change over time (e.g., gender, education, etc.), we exclude these variables. Columns (1) of Table 6 show the results controlling for analyst fixed effects. The results demonstrate the robustness of the baseline results, as the coefficient on CPU remains significantly negative.

In addition, to exclude this shock of a significant health event, we removed samples from the period of COVID-19. Because the enormous catastrophe caused by COVID-19 may have triggered excessive pessimism. At the end of 2019, the COVID-19 outbreak spread globally, which has had a dramatic impact on both public health and the global economy. Economically, the COVID-19 pandemic caused sales to plummet for most companies (Bloom et al., 2021) and put tremendous operational pressure on firms through demand shortages, supply chain disruptions, financing constraints, and employee health issues (Beck & Keil, 2022; Li, Liu, et al., 2021). More direct evidence suggests that the COVID-19 pandemic also increases stock price volatility (Ding et al., 2021) and reduces stock returns (Hoang et al., 2022). One potential concern is that analyst over-pessimism may be driven by the COVID-19 pandemic rather than the uncertainty of climate regulation. Therefore, we exclude the observations from the COVID-19 pandemic. Specifically,

Table 5
Robustness test I: Substitute variables.

	(1)	(2)	(3)	(4)	(5)	(6)
	logSentiment		Sentiment			
CPU	−0.038***	−0.02***				
	(−8.75)	(−2.86)				
TCCPU			−0.145***	−0.201***		
			(−9.22)	(−5.73)		
UCPU					−0.156***	−0.047**
					(−15.85)	(−2.41)
Controls	No	Yes	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
N	51,986	51,986	47,285	47,285	51,986	51,986
R^2	0.001	0.276	0.002	0.267	0.004	0.247

Note: This table reports a battery of robustness tests by replacing the Key variables. Columns (1)–(2) are the results of replacing the explanatory variables, and columns (3)–(6) are the results of replacing the explanatory variables. Specifically, columns (1) and (2) report the regression results using the alternative variable logSentiment, defined as Sentiment plus one and taken logarithmically. Columns (3)–(6) reports the regression results after substituting independent variables. Columns (3) and (4) show the results of the regression using TCCPU, where TCCPU denotes China's climate policy uncertainty index. Columns (5) and (6) show the results of the regression using UCPU, where UCPU is an index of climate policy uncertainty constructed based on US newspapers. All regressions control for firm fixed effects and time trends. Standard errors are clustered at the analyst level. *** represents 1 % significance; ** represents 5 % significance; * represents 10 % significance.

Table 6
Robustness test II: Excluding the impact of analyst characteristics and COVID-19.

	(1)	(2)
	Sentiment	Sentiment
CPU	−0.097***	−0.073***
	(−4.48)	(−3.07)
Controls	Yes	Yes
Year	Yes	Yes
Firm	Yes	Yes
Analyst	Yes	No
N	51,986	40,843
R^2	0.33	0.261

Note: This table reports the results after excluding the effect of analyst characteristics and the new crown epidemic. In columns (1), we control for analyst fixed effects. In columns (2), we removed samples from the period of the new crown epidemic. Since the new crown pneumonia epidemic was discovered at the end of 2019 and began to break out in early 2020, we removed the sample for 2020–2021, the sample size was reduced to 40,843 analysts' forecast data. *** represents 1 % significance; ** represents 5 % significance; * represents 10 % significance.

we rerun our baseline model to remove the data for 2020 and 2021. Columns (2) of Table 6 report the results, with the coefficient on the CPU index being negatively significant at the 1 % level. Overall, our conclusions rule out speculation that the COVID-19 pandemic is causing analyst pessimism and are consistent with the baseline results.

Although in the main regression analysis we lagged the CPU index and explanatory variables by one period to mitigate reverse causality, in order to further alleviate concerns about endogeneity, this section uses instrumental variables for the analysis. Referring to Ren et al. (2022), this paper uses Global Mean Surface Temperature (GMST) as an instrumental variable in a two-stage least squares regression, and the results are shown in Table 7. In particular, column (1) shows the results of the first-stage regression, from which the results show that GSMT is positively correlated with the CPU index and is significant at the 1 % level, proving the validity of GSMT as an instrumental variable. Column (2) shows the results of the second-stage regression, from which the results show that the coefficient of CPU index is still significantly negative at the 1 % level, confirming the reliability of the main regression results in this paper.

5.2. Additional tests

We believe that the negative causal relationship between CPU and analysts' forecasts is caused by analysts' revisions to optimistic forecasts.

Table 7
Robustness test III: 2SLS regression.

	(1)	(2)
	CPU	Sentiment
GMST	1.326***	
	(−71.97)	
CPU		−0.601***
		(−13.04)
Controls	Yes	Yes
Year	Yes	Yes
Firm	Yes	Yes
N	51,986	51,986
R^2	0.325	0.015

Note: This table reports the results of a two-stage least squares regression using Global Mean Surface Temperature as an instrumental variable. Column (1) shows the results of the first-stage regression and column (2) shows the results of the second-stage regression. All columns control for the control variables in the baseline regression and control for firm fixed effects and time trends. Standard errors are clustered at the analyst level. *** represents 1 % significance; ** represents 5 % significance; * represents 10 % significance.

The statement implies that analysts would only revise forecasts downwards in the sample of optimistic forecasts. To test this statement, based on the sign of the sentiment indicator, we divided the sample into two groups. When *Sentiment* is positive, we consider that there is a positive error in the analyst's prediction and include it in group *Pos_bias*. Conversely, we include it in group *Neg_bias* and rerun our baseline regression. Columns (1)–(2) of Table 8 show that the coefficient of CPU is significantly negative in the *Pos_bias* group, while is positive but insignificant in the *Neg_bias* group. The results suggest that CPU provides negative news for analysts' forecasts, causing analysts to revise their optimistic forecasts.

Our study finds that climate policy uncertainty causes analysts to make forecast revisions that make their optimistic forecasts less optimistic, and if the "correction effect" holds, analysts' forecast accuracy increases. To further improve the robustness of our findings, we examined the impact of CPU on the accuracy of analysts' forecasts. We examine the conjecture by the following regression.

$$Bias_{ijt} = \gamma_0 + \gamma_1 CPU_{t-1} + Control\ Variables + FirmFE + Year + \varepsilon_{ijt} \tag{4}$$

where *Bias* is the analyst's forecast error, which we define as the absolute value of the analyst's *Sentiment*. The larger the value of *Bias*, the greater the difference between the analyst's forecast EPS and the actual value, and the more inaccurate the forecast. Column (3) of Table 8 shows that the coefficient on CPU is significantly negative, indicating that climate policy uncertainty mitigates analysts' forecast errors to some extent. This result further illustrates that climate policy uncertainty acts as a correction to analysts' optimistic forecasts, increasing the accuracy of analysts' forecasts.

6. Conclusion

As an information intermediary, analysts are vital to the development of financial markets. However, there is a consensus among most academics that analysts' forecasts are subject to an optimistic bias. This paper extends the prior literature by investigating how climate policy uncertainty affects analysts' reactions. We focus on the sample of China's energy sectors and access to the CPU index as a proxy variable for uncertainty in climate policy. Our results support a causal relationship between the CPU index and analyst sentiment.

In particular, we have the following findings. We find a negative correlation between climate policy uncertainty and analysts' forecasts, which is consistent with the fact that the company's fundamentals suffer a CPU shock. Our results imply that climate policy uncertainty provides

Table 8
Additional tests.

	(1)	(2)	(3)
	Pos_bias	Neg_bias	
	Sentiment		Bias
CPU	−0.154***	0.0179***	−0.116***
	(−5.94)	(4.89)	(−6.14)
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Firm	Yes	Yes	Yes
N	37,281	14,174	51,986
R^2	0.292	0.432	0.252

Note: This table shows the results of additional tests. Columns (1)–(2) show the results of the subsample regressions based on the positive and negative values of the analysts' prediction errors. Column (1) shows the regression results for the group with positive prediction errors, and column (2) shows the regression results for the group with negative prediction errors. Column (3) shows the regression results on analyst forecast accuracy. All columns control for the control variables in the baseline regression and control for firm fixed effects and time trends. Standard errors are clustered at the analyst level. *** represents 1 % significance; ** represents 5 % significance; * represents 10 % significance.

negative news to analysts, causing them to revise their optimistic forecasts. Heterogeneity analysis validates the ‘correction effect’ conjecture, with empirical results showing that the impact of CPU on analysts' optimistic revisions is only present in companies with poor ESG performance and high pollution levels. We further demonstrate that CPUs merely correct analysts' optimistic forecasts and that analysts' corrective actions can improve the accuracy of forecasts. Our results are robust to alternative measures of the dependent and independent variables, the addition of analyst fixed effects, the exclusion of COVID-19 and the use of instrumental variables.

In summary, our findings suggest that climate policy uncertainty has potential impacts on external stakeholders and economic impacts on firm performance, stock markets, and energy prices. Although the role of climate policy uncertainty in exacerbating market risk has been criticized, this paper provides evidence for its positive externality in the form of a correction for analysts' optimism bias.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Variable definitions

Variable	Description
Sentiment	(analysts' forecast EPS - actual EPS)/actual EPS
LogSentiment	Natural logarithm of 1 plus Sentiment
CCPU	Climate Policy Uncertainty Index for China
Size	company size, defined as the logarithm of total assets
Book-to-market	Book-to-market ratio, defined as the ratio of total assets to market value
Return	Annual stock return
ROA	Profitability, defined as the ratio of net profit to total average assets
Largehold	Shareholding concentration, defined as the shareholding ratio of the largest shareholder
Intasset	The proportion of intangible assets, defined as the ratio of net intangible assets to total assets
Leverage	The stroke ratio, defined as the ratio of total liabilities to total assets
Attention	Analyst Follow, the number of analysts (teams) who follow the company
Gender	Analyst gender is measured as the percentage of female analysts in the analytics team. Equals 1 if there is only one analyst on the team when that analyst is female, otherwise equals 0
Master	Analyst qualifications are measured by the proportion of analysts on the analytics team with master's or doctorate degrees. If there is only one analyst in advance, then the analyst equals 1 if he or she has a master's or doctoral degree, and 0 otherwise.
Experience	Analyst experience, measured by the logarithm of the number of quarters since the first earnings forecast was made in the analyst book
Number	The number of analyst forecasts, measured by the logarithm of the number of analyst reports published
Groupsize	Analyst team size is defined as the logarithm of the number of analyst teams. Groupsize equals 0 if the analyst's forecast is released by a sole analyst.
ConFeps	Consensus forecast, measured by the median of forecast earnings per share issued in the year before the public company forecast
EPU	Arithmetic Average of Monthly EPU Index

Data availability

Data will be made available on request.

References

Abudu, H., Wesseh, P. K., & Lin, B. (2024). Climate bonds toward achieving net zero emissions and carbon neutrality: Evidence from machine learning technique. *Journal of Management Science and Engineering, 9*(1), 1–15.

Atif, M., & Ali, S. (2021). Environmental, social and governance disclosure and default risk. *Business Strategy and the Environment, 30*, 3937–3959.

Azimli, A. (2023). The impact of climate policy uncertainty on firm value: Does corporate social responsibility engagement matter? *Finance Research Letters, 51*, Article 103456.

Beck, T., & Keil, J. (2022). Have banks caught corona? Effects of COVID on lending in the U.S. *Journal of Corporate Finance, 72*, Article 102160.

Bénabou, R., & Tirole, J. (2010). Individual and corporate social responsibility. *Economica, 77*, 1–19.

Beyer, A., & Guttman, I. (2011). The effect of trading volume on analysts’ forecast bias. *The Accounting Review, 86*, 451–481.

Bloom, N., Fletcher, R. S., & Yeh, E. (2021). *The impact of COVID-19 on US firms. Working Paper*. https://doi.org/10.3386/w28314

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics, 142*, 517–549.

Bradley, D., Gokkaya, S., & Liu, X. (2017). Before an analyst becomes an analyst: Does industry experience matter? *The Journal of Finance, 72*, 751–792.

Bradley, D., Gokkaya, S., Liu, X., & Xie, F. (2017). Are all analysts created equal? Industry expertise and monitoring effectiveness of financial analysts. *Journal of Accounting and Economics, 63*, 179–206.

Byard, D., Li, Y., & Weintrop, J. (2006). Corporate governance and the quality of financial analysts’ information. *Journal of Accounting and Public Policy, 25*, 609–625.

Cao, D., Sun, Y., Chai, J., et al. (2023). An assessment of China's joint prevention and control policy on sulfur dioxide emissions reduction: A spatial econometric analysis. *Journal of Management Science and Engineering, 8*(4), 498–511.

Cao, S., Xue, S., & Zhu, H. J. (2022). Analysts' knowledge structure and performance. *Accounting and Finance, 62*(5), 4727–4753.

Chai, J., Zhang, X., Zhang, X., & Wang, Y. (2023). Effects of scenario-based carbon pricing policies on China’s dual climate change mitigation goals: Does policy design matter? *Journal of Management Science and Engineering, 8*(2), 167–175.

Chen, T., Harford, J., & Lin, C. (2015). Do analysts matter for governance? Evidence from natural experiments. *Journal of Financial Economics, 115*, 383–410.

Chen, T., Xie, L., & Zhang, Y. (2017). How does analysts’ forecast quality relate to corporate investment efficiency? *Journal of Corporate Finance, 43*, 217–240.

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

Cuculiza, C., Antoniou, C., Kumar, A., & Maligkris, A. (2021). Terrorist attacks, analyst sentiment, and earnings forecasts. *Management Science, 67*, 2579–2608.

Delis, M. D., de Greiff, K., & Ongena, S. (2019). *Being stranded with fossil fuel reserves? Climate policy risk and the pricing of Bank loans. Working Paper*. https://doi.org/10.2139/ssrn.3451335

Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics, 141*, 802–830.

Donadelli, M., Grüning, P., & Hitzemann, S. (2020). *Understanding macro and asset Price dynamics during the climate transition. Working Paper*. https://doi.org/10.2139/ssrn.3801562

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

Dutta, A., Bouri, E., Rothovius, T., & Uddin, G. S. (2023). Climate risk and green investments: New evidence. *Energy, 265*, Article 126376.

Easterwood, J. C., & Nutt, S. R. (1999). Inefficiency in analysts’ earnings forecasts: Systematic misreaction or systematic optimism? *The Journal of Finance, 54*, 1777–1797.

Ehlers, T., Packer, F., & de Greiff, K. (2022). The pricing of carbon risk in syndicated loans: Which risks are priced and why? *Journal of Banking & Finance, 136*, Article 106180.

Eliwa, Y., Aboud, A., & Saleh, A. (2021). ESG practices and the cost of debt: Evidence from EU countries. *Critical Perspectives on Accounting, 79*, Article 102097.

Fracassi, C., Petry, S., & Tate, G. (2016). Does rating analyst subjectivity affect corporate debt pricing? *Journal of Financial Economics, 120*, 514–538.

Gavriilidis, K. (2021). *Measuring climate policy uncertainty. Working Paper*. https://doi.org/10.2139/ssrn.3847388

Ginglinger, E., & Moreau, Q. (2019). *Climate risk and capital structure. Working Paper.*. https://doi.org/10.2139/ssrn.3327185

Gong, X., Fu, C., Huang, Q., & Lin, M. (2022). International political uncertainty and climate risk in the stock market. *Journal of International Financial Markets, Institutions & Money, 81*, Article 101683.

Gong, X., & Liao, Q. (2024). Physical climate risk attention and dynamic volatility connectedness among new energy stocks. *Energy Economics, 136*, Article 107711.

Gong, X., Song, Y., Fu, C., & Li, H. (2023). Climate risk and stock performance of fossil fuel companies: An international analysis. *Journal of International Financial Markets, Institutions & Money, 89*, Article 101884.

Griffin, P. A. (2003). A league of their own? Financial analysts' responses to restatements and corrective disclosures. *Journal of Accounting, Auditing and Finance, 18*, 479–517.

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

Hoang, H. V., Nguyen, C., & Nguyen, D. K. (2022). Corporate immunity, national culture and stock returns: Startups amid the COVID-19 pandemic. *International Review of Financial Analysis, 79*, Article 101975.

Hong, H., & Kacperczyk, M. (2010). Competition and bias. *The Quarterly Journal of Economics, 125*, 1683–1725.

Hsu, P.-H., Li, K., & Tsou, C.-Y. (2022). *The pollution premium. Working Paper*. https://doi.org/10.2139/ssrn.3578215

Huang, T., & Sun, Z. Y. (2023). Climate policy uncertainty and firm investment. *International Journal of Finance and Economics, 29*(4), 4358–4371.

Huynh, T. D., & Xia, Y. (2021). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis, 56*, 1985–2009.

Ilhan, E., Sautner, Z., & Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies, 34*, 1540–1571.

Ke, B., & Yu, Y. (2006). The effect of issuing biased earnings forecasts on analysts' access to management and survival. *Journal of Accounting Research, 44*, 965–999.

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

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

Kumar, A. (2009). Hard-to-value stocks, behavioral biases, and informed trading. *Journal of Financial and Quantitative Analysis, 44*, 1375–1401.

Kumar, A., Rantala, V., & Xu, R. (2022). Social learning and analyst behavior. *Journal of Financial Economics, 143*, 434–461.

Lee, C. M. C., & So, E. C. (2017). Uncovering expected returns: Information in analyst coverage proxies. *Journal of Financial Economics, 124*, 331–348.

Lee, K., & Cho, J. (2023). Measuring Chinese climate uncertainty. *International Review of Economics and Finance, 88*, 891–901.

Li, B., Yao, Y., Usman, M., & Han, M. D. (2024). How does climate risk affect corporate innovation? Evidence from China. *Accounting and Finance, 6*(3), 2279–2319.

Li, K., Liu, X., Mai, F., & Zhang, T. (2021). The role of corporate culture in bad times: Evidence from the COVID-19 pandemic. *Journal of Financial and Quantitative Analysis, 56*, 2545–2583.

Li, N., Xu, N., Dong, R., Chan, K. C., & Lin, X. (2021). Does an anti-corruption campaign increase analyst earnings forecast optimism? *Journal of Corporate Finance, 68*, Article 101931.

Li, Z., Wen, F., & Huang, Z. J. (2023). Asymmetric response to earnings news across different sentiment states: The role of cognitive dissonance. *Journal of Corporate Finance, 78*, Article 102343.

Liang, C., Umar, M., Ma, F., & Huynh, T. L. D. (2022). Climate policy uncertainty and world renewable energy index volatility forecasting. *Technological Forecasting and Social Change, 182*, Article 121810.

Lim, T. (2001). Rationality and analysts' forecast bias. *The Journal of Finance, 56*, 369–385.

Lin, B., & Li, X. (2011). The effect of carbon tax on per capita CO2 emissions. *Energy Policy, 39*, 5137–5146.

Lin, Y., Cheung, A., & Wai, K. (2024). Climate policy uncertainty and energy transition: Evidence from prefecture-level cities in China. *Energy Economics, 139*, Article 107938. https://doi.org/10.1016/j.eneco.2024.107938

Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance, 72*, 1785–1824.

Liu, Y., Chen, L., Cao, Z., & Wen, F. (2024). Uncertainty breeds opportunities: Assessing climate policy uncertainty and its impact on corporate innovation. *International Review of Financial Analysis, 96*, Article 103560.

Liu, Y., Wang, J., Wen, F., & Wu, C. (2024). Climate policy uncertainty and bank systemic risk: A creative destruction perspective. *Journal of Financial Stability, 73*, Article 101289.

Ma, Y.-R., Liu, Z., Ma, D., Zhai, P., Guo, K., Zhang, D., & Ji, Q. (2023). A news-based climate policy uncertainty index for China. *Scientific Data, 10*, 881. https://doi.org/10.1038/s41597-023-02817-5

Malmendier, U., & Shanthikumar, D. (2014). Do security analysts speak in two tongues? *The Review of Financial Studies, 27*, 1287–1322.

Mamatzakis, E., & Bagntasarian, A. (2021). The nexus between CEO incentives and analysts' earnings forecasts. *International Journal of Finance and Economics, 26*(4), 6205–6248.

Matousek, R., Panopoulou, E., & Papachristopoulou, A. (2020). Policy uncertainty and the capital shortfall of global financial firms. *Journal of Corporate Finance, 62*, Article 101558.

Miah, M. S., Jiang, H., Rahman, A., & Stent, W. (2023). The impact of IFRS complexity on analyst forecast properties: The moderating role of high quality audit. *International Journal of Finance and Economics, 28*(1), 902–928.

Nguyen, T., Bai, M., Hou, G., & Truong, C. (2022). Drought risk and capital structure dynamics. *Accounting and Finance, 62*(3), 3397–3439.

Nordhaus, W. (2019). Climate change: The ultimate challenge for economics. *American Economic Review, 109*(6), 1991–2014.

O'brien, P. C., Mcnichols, M. F., & Hsiou-Wei, L. (2005). Analyst impartiality and investment banking relationships. *Journal of Accounting Research, 43*, 623–650.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics, 142*, 550–571.

Ren, X., Zhang, X., Yan, C., & Gozgor, G. (2022). Climate policy uncertainty and firm-level total factor productivity: Evidence from China. *Energy Economics, 113*, Article 106209.

Seltzer, L. H., Starks, L., & Zhu, Q. (2022). *Climate regulatory risk and corporate bonds. Working Paper*. https://doi.org/10.3386/w29994

Shao, L. (2018). The dilemma of criticism: Disentangling the determinants of media censorship in China. *Journal of East Asian Studies, 18*, 279–297.

Shen, Y., & Zhang, X. (2024). Cleaner production: Analysis of the role and path of green finance in controlling agricultural nonpoint source pollution. *Economics, 18*(1), Article 20220107.

Song, W. Q., Xu, W. S., Qu, W. Z., & Gong, X. (2024). Climate risk exposure and debt concentration: Evidence from Chinese listed companies. *Accounting and Finance, 64*, 3361–3386.

Syed, Q. R., Apergis, N., & Goh, S. K. (2023). The dynamic relationship between climate policy uncertainty and renewable energy in the US: Applying the novel Fourier augmented autoregressive distributed lags approach. *Energy, 275*, Article 127383.

Treepongkaruna, S., Chan, K. F., & Malik, I. (2023). Climate policy uncertainty and the cross-section of stock returns. *Finance Research Letters, 55*, Article 103837.

Wang, L., Dai, Y., & Kong, D. (2021). Air pollution and employee treatment. *Journal of Corporate Finance, 70*, Article 102067.

Welch, I. (2000). Herding among security analysts. *Journal of Financial Economics, 58*, 369–396.

Wen, F., Chen, M. H., Zhang, Y., & Miao, X. (2023). Oil price uncertainty and audit fees: Evidence from the energy industry. *Energy Economics, 125*, Article 106852.

Wen, F., Shui, A., Cheng, Y., & Gong, X. (2022). Monetary policy uncertainty and stock returns in g7 and brics countries: A quantile-on-quantile approach. *International Review of Economics and Finance, 78*, 457–482.

Yang, X., Wei, L., Deng, R., et al. (2023). Can climate-related risks increase audit fees?-Evidence from China. *Finance Research Letters, 57*, Article 104194.

Zhang, D., Zhao, Z., & Lau, C. K. M. (2022). Sovereign ESG and corporate investment: New insights from the United Kingdom. *Technological Forecasting and Social Change, 183*, Article 121899.

Zhang, G., Wang, J., & Liu, Y. (2024). Energy transition in China: Is there a role for climate policy uncertainty? *Journal of Environmental Management, 370*, Article 122814.

Zhang, J., & Chen, D. (2024). Time-frequency cross-country spillovers of climate policy uncertainty: Does it matter for financial risk? *Energy, 312*, Article 133545. https://doi.org/10.1016/j.energy.2024.133545

Zhao, C., Li, Y., Govindaraj, S., & Zhong, Z. (2022). CDS trading and analyst optimism. *The British Accounting Review, 54*, Article 101109.