Journal of Environmental Management 353 (2024) 120134

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Does environmental regulation affect analyst forecast bias? Evidence from China's Low-Carbon Pilot Policy[☆]

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ARTICLE INFO

JEL classification:
G14
G38
G41

Keywords:
Low-Carbon Pilot Policy
Analyst forecast
Accounting information quality
Environmental regulation
Financial market

ABSTRACT

This study investigates the impact of China's Low-Carbon Pilot Policy on analyst forecast behaviors. Using a staggered difference-in-difference approach, we find that the program reduced analyst forecast errors and divergence, as mandatory sustainability disclosures enable analysts to incorporate new information to improve forecast quality. The effect is concentrated in state-owned firms and manufacturing-oriented cities. Additional tests explore accounting information quality and investor attention as plausible channels. Overall, exploiting a major Chinese environmental regulation, we provide novel evidence that green policies can enhance transparency and capital market efficiency. The findings offer implications for regulators, investors, and managers as countries pursue climate change mitigation strategies.

1. Introduction

With growing awareness of climate change and sustainability issues, environmental policies and regulations are coming under increased scrutiny from policymakers, investors, and the public. Climate change with its mitigation were not effective enough that encouraged to make additional efforts (Avagyan, 2018; Avagyan and Singh, 2019; Avagyan, 2021). Financial analysts serve as key information intermediaries between firms and capital market participants, evaluating how environmental initiatives may impact firm performance and value. Prior studies like Bushee and Noe (2000) and Healy and Palepu (2001) examined the role of disclosure practices in reducing analyst forecast errors without isolating environmental disclosures. Plumlee et al. (2015) found that voluntary sustainability disclosures can inform analyst predictions but did not analyze mandatory policies.

This study investigates how a major sustainability initiative – China's national Low-Carbon Pilot Policy (LCPP) – affects analyst earnings forecasts for affected firms. We aim to address the research question: Do environmental regulations such as emissions standards and disclosure rules reduce forecast bias and divergence among analysts? Answering this question matters for several reasons.

First, analyst forecast accuracy is an important indicator of efficient capital allocation and reduced information asymmetry in financial markets (Hong and Kubik, 2003). Biased or divergent forecasts can misprice assets, increasing the cost of capital for firms and creating uncertainty that hampers investment (Diether et al., 2002; Barron et al., 1998). If ecological policies improve forecast precision, it suggests environmental oversight can enhance informational efficiency. Second, analyst forecasts influence stock prices and investor decisions, so changes in forecast attributes may shape asset values and risk perceptions (Stickel, 1992). Determining how green regulations affect predictive qualities helps reveal their financial market impacts. Finally, forecast performance depends partly on disclosure policy (Hope, 2003; Lang and Lundholm, 1996). Mandatory sustainability disclosures may provide analysts with non-financial data to incorporate into earnings models (Dhaliwal et al., 2012). This study sheds light on how ecological

☆ We are grateful for the valuable comments and suggestions from the participants at the 2022 China Econometrics Scholar Conference and 2023 Green Low-Carbon Industry Development Forum. Kai Wu acknowledges financial support from the National Natural Science Foundation of China, China (No. 72103217). Sun was supported by National Natural Science Foundation of China (Nos. 72322016, 72073126, 71973116 and 72091212) and Young Elite Scientists Sponsorship Program by CAST. Hong was supported by National Natural Science Foundation of China Basic Science Center Project (No. 71988101) entitled as Econometric Modeling and Economic Policy Studies. All remaining errors are our own.
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https://doi.org/10.1016/j.jenvman.2024.120134
Received 14 November 2023; Received in revised form 11 January 2024; Accepted 17 January 2024
Available online 27 January 2024

reporting rules within broader environmental reforms shape financial transparency.

While existing research explores the stock market effects of environmental regulations (Ramiah et al., 2013; Guo et al., 2020) and the use of environmental, social, and governance (ESG) metrics in analyst decisions (Plumlee et al., 2015), no study has examined forecast attributes under sustainability policies. Our work helps fill this gap and leverages China's unique state-directed approach to green reforms versus decentralized policies in Western economies (Chen et al., 2022). Overall, investigating how ecological regulations shape analyst forecast bias and divergence provides novel evidence on the financial market consequences of sustainability initiatives. The findings offer implications for academics, investors, managers, and policymakers as countries pursue climate change mitigation strategies.

China provides a unique opportunity to examine how environmental regulations shape analyst forecasting for several reasons. First, China has undertaken major national sustainability initiatives like the Low-Carbon Pilot Policy, allowing us to isolate the impacts of sizable eco-reforms (Chen et al., 2022). Such ambitious state-led programs are rarer in other large economies. Second, China has a much greater prevalence of state-owned enterprises (SOEs), which facilitates exploring how firm ownership mediates policy effects (Cuervo-Cazurra et al., 2014). Finally, China exhibits significant variation in local enforcement of central directives (Lo and Fryxell, 2003). We leverage this regional heterogeneity in the stringency of Low-Carbon Project implementation. Overall, China's distinctive institutional features – sweeping top-down environmental policies, pervasive SOEs, and decentralized execution – offer an ideal setting to illuminate how ecological regulations shape analyst behavior and forecast performance.

As Lang and Lundholm (1996) show, enhanced disclosure from regulations can converge analysts' views and improve accuracy. The LCPP strengthened environmental reporting and transparency, providing analysts with more high-quality data to incorporate into forecasts. We then conducted several heterogeneity tests to determine if the LCPP impact varied by firm and city characteristics. First, we split the sample into state-owned enterprises (SOEs) and non-SOEs based on the ultimate ownership structure. The forecast improvements concentrated in SOEs. This aligns with prior research that SOEs face greater pressure for social responsibility (Dhaliwal et al., 2011) and have closer government ties to comply with top-down environmental reforms. Next, we grouped firms by the share of secondary industry in their home city GDP. Those in high secondary industry cities showed significant forecast gains. Higher industrial pollution likely compelled stricter local enforcement of the LCPP, enhancing corporate transparency. Finally, dividing by subsidy level revealed greater forecast changes for high-subsidy firms. Green subsidies can directly fund eco-investments and compliance, improving forecast quality. The parallel trends and placebo tests help validate the difference-in-difference model. We include leads and lags for the LCPP indicator, finding minimal pre-trends but large post-adoption forecast improvements. Randomly assigning placebo treatment fails to replicate the significant LCPP coefficient. Instrumental variables using localized air pollution further mitigate endogeneity concerns related to pilot city selection.

2. Institutional background and hypothesis development

2.1. Low-carbon pilot policy in China

The Chinese government has implemented the Low-Carbon Pilot Policy, a significant environmental protection plan, to improve environmental governance and achieve emissions reduction goals. This directive, top-down policy led by the National Development and Reform Commission (NDRC) aims to reduce emissions by optimizing industrial structures, modernizing traditional industries, promoting a circular economy, improving energy efficiency, and advocating for energy efficiency in buildings. The policy requires pilot areas to explore suitable low-carbon development models based on local conditions. They must set carbon emission limits and encourage industries to reduce emissions.

The Low-Carbon Pilot Policy introduced new corporate environmental disclosure requirements for firms in pilot cities, including formulating low-carbon development plans, establishing emissions management systems, and disclosing greenhouse gas emissions data. Multiple provinces and cities now mandate enhanced environmental information disclosure from local firms, meaning the quality of corporate environmental reporting will improve.

In addition, China's state capitalist system shapes how firms respond to sustainability policies. The country's reliance on top-down, command-and-control environmental regulation could make firms more responsive to eco-policies from central authorities compared to market-based incentives. Also, state-owned enterprises are motivated to serve government objectives beyond profit so that they may show greater commitment to new green policies than private firms. However, analysts face political constraints that could limit their ability to incorporate new sustainability information into forecasts candidly. Still, China's approach means firms likely have a strong incentive to comply with low-carbon city disclosure rules, though forecast responses may be muted.

2.2. Hypothesis development

As a macro-level environmental protection policy, the Low-Carbon Pilot Policy likely influences analyst forecast behavior primarily through impacts on analyst attention and accounting information quality. From the corporate perspective, environmental policies often compel stricter reporting standards, improving accounting information quality and reducing analysts' information-gathering costs, thereby improving forecast reliability. Externally, policy implementation significantly increases investor attention to environmental issues in the research process. Consequently, the quantity and quality of information available to analysts improves, reducing forecast divergence and bias.

A growing body of research explores environmental policies' effects on corporate behavior and financial markets (Huang et al., 2022; Guo et al., 2020). Initial Porter Hypothesis studies suggested stricter regulations can stimulate innovation and improve firm productivity and competitiveness (Berman and Bui, 2001; Jaffe and Palmer, 1997). Evidence from China supports this view, finding environmental policies significantly promote corporate low-carbon innovation (Pan et al., 2022). Regulations also encourage allocating more resources toward environmental compliance (Leiter et al., 2011). Analyses of stock market reactions to new eco-regulations further indicate significant impacts on asset prices and risks (Ramiah et al., 2013; Dietz et al., 2016). Additionally, research shows environmental policies influence market expectations and uncertainty (Monasterolo and Raberto, 2018; Huang et al., 2022). In summary, existing literature provides robust evidence that environmental regulations meaningfully impact corporate disclosure, innovation, stock market responses, and analyst expectations.

Research shows environmental policies influence listed firms' financial performance at both the market and corporate levels. For instance, firms with better environmental performance tend to have lower capital costs, indicating a correlation between voluntary non-financial disclosure and cost of equity (Dhaliwal et al., 2011). Other studies have analyzed mandatory environmental disclosure's impacts on financial performance in depth (Matsumura et al., 2014). Environmental policies also enhance corporate disclosure practices. Regulations enforcing reporting requirements have increased disclosure quality (Plumlee et al., 2015), while accounting standardization improves information reliability (Georgakopoulos et al., 2022). However, disclosure ambiguity may increase forecast errors (Li, 2018).

As capital market participants, analysts are impacted by environmental policies (Li et al., 2021). Analysts face bounded rationality, introducing systematic biases (Ramnath et al., 2008). Transparent regulations can reduce ambiguity and bias. Institutional theory suggests pollution industries face imitation pressures to focus on new environmental data (DiMaggio and Powell, 1983). From an accounting perspective, stricter policies may increase compliance costs, affecting reported profitability and forecasts (Christensen et al., 2019). The political economy theory views policies as reflecting interest group competition (Paterson and P-Laberge, 2018); analysts may assess differential policy impacts based on industries' political influence and exemptions secured.

From an information disclosure perspective, ecological policies often mandate more stringent ESG reporting requirements (Hahn et al., 2015), providing analysts with expanded sustainability data to inform predictions and evaluations. For example, research shows analysts incorporate ESG information into forecasts, improving accuracy (Plumlee et al., 2015). Similar to Heinkel et al. (2001), analysts may factor corporate social responsibility into valuations, influencing predictions. Firms performing well on material sustainability issues also tend to have more accurate analyst forecasts (Eccles et al., 2014). Under stricter supervision, managers may rely more on real versus accruals-based earnings management, which is less detectable (Graham et al., 2005; Li et al., 2016). Furthermore, accounting information comparability and accruals-based earnings management are negatively correlated in strict regulatory environments; the opposite is true for real earnings management (Xu and Liu, 2014).

Information is a key analyst forecasting tool, and disclosure significantly impacts behavior (Lang and Lundholm, 1993). Firms with high transparency attract analyst attention, reducing errors and dispersion (Bai, 2009). Listed firms' disclosure status also affects forecast characteristics; more frequent, timely, and accurate disclosures reduce divergence (Fang, 2007). By mandating greater social responsibility and disclosure, the Low-Carbon Pilot Policy will likely improve firms' information transparency and disclosure quality. This should further reduce analyst prediction bias and improve consistency. Based on the above discussion, we propose hypothesis 1 as follows[1]:

H1: Low-carbon pilot policies reduce the analyst forecast dispersion and forecast bias of listed firms.

Public Choice Theory holds that policymakers act based on self-interest, responding to political incentives and pressures (Stigler, 1971; Peltzman, 1976). Environmental regulations ostensibly aim to maximize social welfare but also allow politicians and bureaucrats to increase economic oversight and control to serve their interests. Meanwhile, regulated entities like businesses seek to influence policymaking through lobbying, revolving doors, and strategic actions that benefit themselves (Hillman and Hitt, 1999; Holburn and Vanden Bergh, 2014). This recursive relationship between regulators and regulated entities impacts policy formulation and implementation (Mitnick, 1980).

In this context, China's centralized Low-Carbon Pilot Policy is expected to garner greater compliance from local governments and state-owned enterprises (SOEs) than a voluntary, decentralized approach (Cuervo-Cazurra et al., 2014; Wang et al., 2012). As state-owned entities, SOEs balance political tasks and profit goals (Tian and Estrin, 2008; Lin et al., 1998). With local governments as controlling shareholders, Chinese SOEs also pursue political aims like social responsibility and environmental protection alongside profit maximization (Bo et al., 2009). Pursuing diverse political objectives can misallocate resources and weaken SOEs' focus on financial performance.

Local governments, as environmental governance executors, can leverage their state shareholder status to intervene in SOEs and compel environmental management actions (Tang et al., 2013). Additionally, SOE manager promotions and salaries depend on financial, social, and political performance, incentivizing national policy implementation locally over profit maximization (Wang et al., 2022). SOEs also benefit from implicit local government backing and state-owned bank shareholders, easing financing constraints for low-carbon investments.

Conversely, private Chinese firms have limited public obligations so regulation adherence costs may outweigh benefits. Research shows increased government ownership positively correlates with more corporate social responsibility disclosure (Eng and Mak, 2003; Ghazali, 2007). SOEs face greater stakeholder pressures and disclosure requirements than non-SOEs (Cormier et al., 2011; Bansal and Clelland, 2004). The Low-Carbon Pilot Policy's disclosure impacts appear stronger for SOEs versus non-SOEs (Chen et al., 2022), likely further improving environmental disclosure (Bansal and Clelland, 2004; Cormier et al., 2011). Thus, the policy's influence on listed firms' environmental disclosures may relate to ownership structure, in turn affecting analyst forecast quality. This suggests the policy's impacts on forecast dispersion and bias will be more pronounced for state-owned firms. Consequently, hypothesis 2 is proposed as follows:

H2: The impact of the Low-Carbon Pilot Policy on the analyst forecast dispersion and forecast bias is stronger for SOEs.

Government officials in China can formulate economic policies within their jurisdictions following government regulations and national laws, and local officials play a vital role in local economic development. Their different preferences, policy understanding, and enforcement levels can significantly affect the behavior of local firms (Chen et al., 2016, 2018a). For a long time, the central government assessment mechanisms of local officials were driven by economic indicators. In the superior government promotional evaluation of multiple local officials, key economic indicators include gross domestic product, fiscal revenue, industrial added value, fixed asset investment, imports and exports (Li and Zhou, 2005). As a major driving force for local economic growth and tax revenue, secondary industry production is particularly key to the performance assessment of local governments; however, the secondary industry is a significant source of environmental pollution. According to the 2016–2019 National Ecological Environment Statistical Bulletin, the sulfur dioxide emission from industrial sources decreased from 7.705 million tons in 2016 to 3.954 million tons in 2019, accounting for 6.5 times that from living sources.[2] When a city has a higher proportion of secondary industry than other cities, the pollution emission problem will be more severe to some extent.

Furthermore, the difference in the pressure to reduce pollution can affect the effect of environmental regulations implementation (Han et al., 2021). To achieve economic performance in cities with a low share of manufacturing industries, local governments will, to some extent, ignore the pollution problem and relax environmental controls. However, when the share of the manufacturing industries is high, environmental pollution becomes an issue that is difficult to ignore; therefore, local governments will adopt stricter environmental governance strategies (Huang et al., 2016), strengthen the implementation and enforcement of the Low-Carbon Pilot Policy, and enable analysts to obtain more information on listed firms, thus influencing the quality of analyst predictions. Therefore, hypothesis 3 is proposed as follows:

H3: The impact of the Low-Carbon Pilot Policy on analyst forecast dispersion and forecast bias is stronger for listed firms in cities with a higher proportion of manufacturing industries.

Government subsidies are essentially a reallocation of social resources by the government; that is, the government distributes funds to micro-firms, such as small businesses or individuals, through subsidies to achieve certain policy objectives (Pigou, 1924). In the process of economic transition, subsidies are the most direct way for the government to act as a "helping hand" (Frye and Shleifer, 1997). At a critical moment in China's economic transition and upgrading, government subsidies are an important component of fiscal and industrial policies.

[1] Fig. A.1 presents the theoretical framework of the main research hypothesis.

[2] For further details, please refer to National Ecological and Environmental Statistics Bulletin 2016–2019, https://big5.mee.gov.cn/gate/big5/www.mee.gov.cn/hjzl/sthjzk/sthjtjnb/202012/P020201214580320276493.pdf.

They are one of the main forces driving economic restructuring. They are also the most direct and effective tool among government incentive policies (Wang et al., 2014). Policy subsidies can guide local firms to increase their investments in environmental protection through direct funding, effectively incentivizing them to reduce pollution. For example, local governments can use financial subsidies such as special technology subsidies to encourage firms to invest in green R&D innovation and equipment transformation, thus promoting the green transformation of firms.

They can also directly provide special funds to support investment projects for environmental protection facilities or pollution control activities, solving the problem of insufficient environmental protection funds for firms and enhancing their environmental protection investment capabilities. This proactive approach addresses the environmental pollution issues from the source (Lu et al., 2019). Undeniably, firms that have received high government subsidies may already have a high environmental responsibility, which can generate potential endogeneity issues and influence the allocation of subsidies and the prediction of outcomes. Listed firms with high government subsidies can implement the requirements of the Low-Carbon Pilot Policy, helping to increase environmental disclosure from listed firms. Analysts are more strongly affected by the policy when predicting the behavior of listed firms with high government subsidies. Therefore, we propose hypothesis 4 as follows:

H4: The impact of the Low-Carbon Pilot Policy on analyst forecast dispersion and forecast bias is stronger for listed firms that receive high government subsidies.

3. Data and empirical design

3.1. Data and sample

This study used data from multiple sources, including financial information, analyst forecasts, research and survey responses, provincial-level characteristics, and data from the China Stock Market and Accounting Research Database (CSMAR). Information on pilot regions was sourced from the Notice on Pilot Work on Low-Carbon Provinces and Cities issued by the NDRC. Environmental regulation data were obtained from provincial government work reports. The detailed data sources are presented in Table A.2.

The sample includes all listed Chinese A-share firms from 2008 to 2019. First, we exclude financial firms from the sample following the 2012 Industry Classification Guide issued by the China Securities Regulatory Commission, which is subject to special capital structure policies and regulations. After matching and eliminating relevant missing values from the financial data of the listed firms, we obtained 2863 firms and 19,637 firm-year observations. We then matched the registered location information of the listed firms with the low-carbon pilot areas to obtain the treatment group sample. At the same time, the remaining firms registered outside the pilot areas were used to eliminate the control group.[3] We winsorized all continuous variables at the 1st and 99th percentiles to eliminate extreme values.

3.2. Empirical model and variable definition

To test the proposed research hypothesis, we constructed the following difference-in-difference model exploring the staggered introduction of the low-carbon pilot cities in China:

$$FDISP_{it}/FERROR_{it} = \beta_0 + \beta_1 LCC + \beta_2 X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}, \qquad (1)$$

[3] There is a concern that firms registered in the pilot regions might differ from those registered outside the region. Note that the selection of the low-carbon pilot city does not depend solely on city-level carbon emissions, and firms cannot anticipate the announcement of the pilot policy. Furthermore, propensity matching was performed to alleviate sample selection issues.

Table 1
Summary statistics.

	Mean	S.D.	Q5	Q25	Median	Q75	Q95	N
FDISP1	1.553	3.221	0.094	0.256	0.564	1.308	6.341	19,947
FERROR1	2.155	4.844	0.036	0.220	0.672	1.817	9.083	19,947
LCC	0.415	0.493	0.000	0.000	0.000	1.000	1.000	19,947
Lev	0.437	0.205	0.111	0.274	0.434	0.593	0.773	19,947
Size	22.343	1.303	20.521	21.400	22.169	23.109	24.866	19,947
ROA	0.046	0.057	−0.018	0.020	0.042	0.072	0.133	19,947
MepsVol	0.239	0.246	0.026	0.084	0.162	0.304	0.721	19,947
Surprise	0.252	0.341	0.010	0.050	0.133	0.302	0.920	19,947
Loss	0.065	0.246	0.000	0.000	0.000	0.000	1.000	19,947
Follow	2.052	0.887	0.693	1.386	2.079	2.773	3.466	19,947
Horizon	5.611	0.283	5.094	5.442	5.624	5.849	5.985	19,947

This table reports the descriptive statistics for a sample of Chinese-listed firms from 2008 to 2019. The detailed variable definitions are presented in Table A.2.

where the primary dependent variables are analyst forecast dispersion FDISP, calculated as the standard deviation of earnings forecasts scaled by the absolute value of the actual EPS. For each analyst, we retain the last forecast of the year. A larger FDISP indicates a greater divergence of analyst opinions on the corporate surplus. The other measure, analyst forecast bias, FERROR, denotes the analyst forecast error for each listed firm, calculated as the absolute value of the difference between the firm's mean forecasted EPS and the actual EPS scaled by the absolute value of the actual EPS. Similarly, for each analyst, we only retain the last forecast of the year. It measures the absolute level of analyst forecast bias without considering its direction.

The key independent variable, a dummy variable for the low-carbon pilot city LCC, equals one if the registered city of the listed firm implements the Low-Carbon Pilot Policy and zero otherwise. China has conducted three rounds of low-carbon city pilot studies with crossovers between different batches of pilot areas. For example, Shenyang, located in Liaoning Province, was included in the first group of pilot areas. To address this issue, we followed the methods of Zhang (2020) and Ma et al. (2021) and handled the situation as follows. If a province and its cities were included in different batches of pilot areas, the pilot time of the cities was set to the earliest batch. Because the Low-Carbon Pilot Policy implementation plan for the first batch of pilots was officially approved by NDRC in January 2012, and the approval of the implementation plan meant that the pilot project had entered the full-scale organization and implementation stage, we set the policy implementation year for the first and second rounds as 2013, and the third round as 2017.

Research has shown that analyst forecast divergence and bias are closely related to the firm and the analyst characteristics (Liang and Riedl, 2014; Lys and Soo, 1995). This study follows Hope (2003) to reflect on the influence of capital structure and the overall information environment of listed firms in controlling for the asset-to-liability ratio (Lev) and firm size (Size). The operating performance of listed firms affects analyst forecast behavior, and financial performance is also related to corporate ownership. We considered EPS volatility (MepsVol) and the dummy variable for loss (Loss) to reflect the difficulty of analyst forecasts (Hope, 2003). Based on Liang and Riedl (2014), we also include the surprise earnings (Surprise). Competition among analysts, as tracked by Lys and Soo (1995), is believed to produce higher-quality reports. Additionally, analysts can acquire more information as predictions are made later (Dhaliwal et al., 2012). Finally, this study controls for the number of analysts tracked (Follow) and the prediction interval (Horizon). We also include firm-specific fixed effects (α_i) to account for features that do not vary over time and year-fixed effects (λ_t) to control for macroeconomic factors that do not vary between firms.

3.3. Descriptive statistics

Table 1 presents the descriptive statistics of the main variables. The mean values of analyst forecast dispersion (DISP1) and analyst forecast error (FERROR1) are 1.553 and 2.155, respectively, with standard deviations of 3.221 and 4.844, indicating significant variations in analyst forecast dispersion and error between firms. The mean leverage (Lev) is 0.437, which is slightly higher than the 0.434 reported by Deng et al. (2021), which implies that the sample mean of the debt-to-asset ratio of listed firms is approximately 43.7%. The average total asset return on assets (ROA) of listed firms was approximately 0.046, indicating that each unit of the asset can generate 0.046 units of net profit on average for this sample. The average EPS volatility (MepsVol) is 0.239, indicating that the average EPS volatility is approximately 23.9%. The average value of Loss is 0.065, suggesting that 6.5% of the firms have a negative net income. The logarithmic mean of analysts following (Follow) is 2.052, indicating that approximately seven analysts follow each listed firm on average.

4. Empirical results

4.1. Baseline regression

Table 2 reports the regression results of the Low-Carbon Pilot Policy and analyst forecast behavior. Columns (1) and (2) show the baseline regression results. The findings indicate that the LCC coefficients are significantly negative at the 1% and 5% levels. This suggests that the Low-Carbon Pilot Policy significantly reduces analyst forecast divergence for listed firms, resulting in more consistent and accurate predictions. This result supports Hypothesis 1. Specifically, the Low-Carbon Pilot Policy achieves carbon neutralization and carbon peak reduction targets through improvements in industry structure, technological innovation, and production modes.

In addition, it strengthens regulation and encourages firms to improve environmental information disclosure and environmental impact accounting. The increase in corporate information transparency and the decrease in analyst information asymmetry enable analysts to access more and higher quality environmental information for their predictive behavior. Therefore, analyst forecast bias significantly reduced after the policy was implemented. In other words, the policy effect of environmental disclosure improved the accuracy of analyst predictions, reduced the divergence of their predictions, and enhanced the consistency of the prediction results.

This discovery has profound economic implications. The policy helps financial markets price more accurately by reducing predictive bias and divergence. Investors who rely on predictions to make informed decisions tend to eliminate bias and lead to more efficient capital allocation. Thus, resources can flow to the most productive places, which may spur innovation in low-carbon technologies, which is crucial for sustainable economic growth. Predictive divergences often indicate differing opinions on market outcomes, reflecting potential uncertainty. By minimizing this discrepancy, the Low-Carbon Pilot Policy can help standardize expectations. This consistency is crucial for reducing systemic risk as markets become less susceptible to perceptible and emotional fluctuations. As such, it stabilizes economic conditions and encourages long-term investments rather than speculative short-term trading.

The regression coefficient of MepsVol is significantly positive in the control variables, indicating that the higher the volatility of the EPS, the more difficult it is for analysts to make predictions. This increases forecast divergence and bias (Dichev and Tang, 2009; Zúñiga et al., 2020). Follow negatively correlates with the explained variables, and the regression coefficient is significant at the 1% level. This is due to increased competition among analysts following the same listed firm, which incentivizes them to improve report quality, reduce divergence, and minimize bias in their predictions (Zúñiga et al., 2020; Dhaliwal et al., 2012). The regression coefficient of Horizon is significantly positive, indicating that the longer the forecast period, the less information analysts have. Consequently, this increases their forecast divergence and bias (Muslu et al., 2019).

Columns (3)–(8) present the results of the cross-sectional heterogeneity, with Columns (3) and (4) dividing the sample into state-owned enterprises (SOEs) and non-state-owned enterprises (Non-SOEs). The results demonstrate that the regression coefficient of LCC is significantly negative in the SOEs but insignificant in non-SOEs. This suggests that for SOEs, the impact of the Low-Carbon Pilot Policy can reduce analyst forecast dispersion, whereas the policy effect is not apparent for non-SOEs, aligning with Hypothesis 2. One possible explanation is that a higher government ownership ratio is associated with increased disclosure of corporate social responsibility (Eng and Mak, 2003; Ghazali, 2007), which can influence analyst forecast behavior (Dhaliwal et al., 2012; Muslu et al., 2019). Hence, when implementing the Low-Carbon Pilot Policy, SOEs' environmental disclosure level is higher than non-SOEs, reducing analyst forecast dispersion and bias.

We divide the sample into two groups based on the share of the manufacturing industries in regional GDP in Columns (5) and (6). The regression results indicate that the coefficient of LCC is insignificant in the low-share group and was significantly negative at the 5% level in the high-share group. This reflects the heterogeneity of the influence of the Low-Carbon Pilot Policy due to industrial structure differences, supporting Hypothesis 3. When the share of manufacturing industries is higher, local governments face more serious environmental pollution, prompting them to implement environmental regulations (Huang et al., 2016). As a result, the Low-Carbon Pilot Policy is more widely enforced, and the level of environmental disclosure of firms in related industries improves, making the effects of the policy on divergence and bias more pronounced.

Columns (7) and (8) divide the sample into high and low groups based on government subsidy levels. The regression results show that the coefficient of LCC is insignificant in the low-subsidy group and significantly negative at the 1% level in the high-subsidy group. This suggests that the effects of the Low-Carbon Pilot Policy on analyst forecast behavior are more pronounced in firms that receive high government subsidies, supporting Hypothesis 4. Government subsidies are effective incentive policies for environmental management (Shi et al., 2016). Firms with higher government subsidies demonstrate greater commitment to environmental management and can respond quickly and implement the environmental disclosure requirements of the pilot policy. This helps analysts obtain a greater quantity and higher quality of information, thus improving the accuracy of their predictions and reducing the divergence of predictions.

4.2. Dynamic treatment effect

To ensure the validity of the model results, we performed parallel trend tests by decomposing the LCC variable in Eq. (1) into separate period dummy variables. We examined the coefficient changes of LCC between the periods before and after the implementation of the policy. In Fig. 1, the coefficient of LCC differs insignificantly from zero at the 90% level before the policy launch, while it significantly differs from zero in most periods after the launch of the policy, suggesting that analysts' predictions in the treatment group and the control group had a parallel trend before implementing the Low-Carbon Pilot Policy. The policy had a significant effect on analyst behavior after implementation.

4.3. Addressing endogeneity concerns

4.3.1. Instrumental variable regression

Given that the selection of Low-Carbon Pilot Policy may be affected non-randomly, certain city-level factors, such as the local political environment, may be overlooked. In addition, local governments with stronger group forces in environmental publicity and sustainable development advocacy are more likely to be selected as pilot cities through lobbying. Thus, this study uses the instrumental variable method to solve the potential endogeneity problem. The instrument is defined as the city-level annual wind speed in year *t* scaled by the annual

Table 2
Low carbon pilot city policy and analyst forecast bias.

	(1) FDISP1	(2) FERROR1	(3) SOE = 0	(4) SOE = 1	(5) LowSecInd	(6) HighSecInd	(7) LowSubsidy	(8) HighSubsidy
LCC	−0.475***	−0.475**	−0.103	−0.511**	−0.300	−0.707**	−0.103	−0.765***
	(−3.10)	(−2.17)	(−0.54)	(−2.46)	(−1.39)	(−2.17)	(−0.44)	(−2.82)
Lev	−0.860***	−2.073***	−0.284	−2.322***	−0.652	−0.152	−1.097*	−0.369
	(−2.79)	(−4.46)	(−0.80)	(−4.12)	(−1.36)	(−0.27)	(−1.87)	(−0.73)
Size	0.215**	0.402***	0.075	0.242*	0.230**	0.040	0.374***	0.004
	(2.57)	(2.90)	(0.72)	(1.83)	(1.99)	(0.26)	(2.81)	(0.02)
ROA	−14.449***	−20.153***	−12.903***	−17.493***	−11.345***	−17.013***	−14.258***	−17.324***
	(−14.05)	(−13.27)	(−10.41)	(−9.42)	(−7.57)	(−9.34)	(−8.28)	(−9.02)
MepsVol	1.998***	2.093***	2.479***	1.835***	2.311***	2.065***	1.422***	2.688***
	(7.98)	(5.77)	(7.62)	(4.90)	(5.49)	(5.02)	(4.09)	(5.79)
Surprise	−1.282***	−1.116***	−1.359***	−1.168***	−1.339***	−1.277***	−1.164***	−1.514***
	(−8.97)	(−5.49)	(−7.59)	(−5.31)	(−5.88)	(−5.57)	(−6.23)	(−5.75)
Loss	−2.309***	−1.995***	−2.521***	−2.308***	−2.053***	−2.688***	−1.716***	−3.147***
	(−9.27)	(−5.50)	(−7.70)	(−6.16)	(−5.50)	(−6.19)	(−4.04)	(−8.35)
Follow	−0.519***	−0.966***	−0.544***	−0.466***	−0.487***	−0.566***	−0.459***	−0.610***
	(−11.67)	(−14.47)	(−10.20)	(−6.50)	(−6.89)	(−7.94)	(−6.28)	(−8.28)
Horizon	0.238***	1.140***	0.226**	0.193	0.223*	0.210	0.223	0.268*
	(2.69)	(8.81)	(2.14)	(1.28)	(1.71)	(1.49)	(1.58)	(1.94)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	19,637	20,037	11,140	8487	8187	8512	8067	8562
Number of firms	2863	2910	1834	1054	1528	1530	1829	1794
Adjusted R^2	0.19	0.17	0.20	0.20	0.23	0.19	0.16	0.24

This table presents the effect of low-carbon pilot policy on analyst forecast bias for a sample of Chinese-listed firms from 2008 to 2019. The dependent variables are *FDISP1* and *FERROR1*. *FDISP1* calculates the dispersion variable for analysts' forecasts by retaining the last forecast value of each analyst for the earnings per share of each listed firm i in year t and then dividing the standard deviation of the forecast earnings per share by the absolute value of the actual earnings per share. *FERROR1* calculates analyst prediction errors for each listed firm by retaining the last forecasted value of each analyst for the firm's earnings per share for the year and then taking the absolute value of the difference between the firm-level forecasted mean of earnings per share and the actual earnings per share, divided by the absolute value of the actual earnings per share. *LCC* is a dummy variable that equals one if the firm is located in a city selected as a low-carbon pilot city and zero otherwise. Other control variables include *Lev* (total liabilities over total assets), *Size* (natural logarithm of total assets), *ROA* (net income over total assets), *MepsVol* (volatility of earnings per share), *Loss* (a dummy variable that equals one if net profit is negative and zero otherwise), *Surprise* (the absolute value of the difference between the current year's EPS and the previous year's EPS), *Follow* (number of analysts following the firm), and *Horizon* (the natural logarithm of the median difference between the analysts' forecast time and the next year's earnings announcement date). All regressions include firm and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

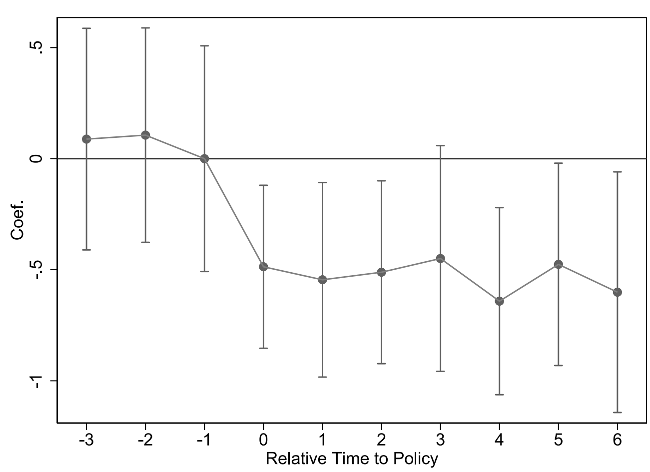

Fig. 1. Dynamic effect of low-carbon pilot policy.

average PM 2.5 in 2011. The information on PM 2.5 is collected from the Atmospheric Composition Analysis Group (ACAG), while the city-level average wind speed is obtained from the National Oceanic and Atmospheric Administration (NOAA). Previous literature has indicated that air pollution influences policymaking and implementation (Chen et al., 2018b; Greenstone, 2004). Cities with poor air quality face greater pressure to implement environmental regulations. At the same time, higher wind speeds help to disperse local air pollutants, lessening the burden of environmental policy. Thus, the interaction between air pollution and wind speed provides a localized exogenous shock to the possibility of a city being chosen as part of the Low-Carbon Pilot Policy.

The regression results for the instrumental variable are shown in Table 3. First, the Anderson-Rubin test p-value supports the validity of the instrument. Secondly, after including the instrumental variables in the regression, LCC is significantly negative at the 5% and 10% level for analyst dispersion and bias, respectively, consistent with our baseline regression conclusion. This suggests that even after controlling for endogeneity, implementing the Low-Carbon Pilot Policy still affects analyst forecast behaviors, significantly reducing their dispersion and bias.

4.3.2. Placebo test

This study uses random number generation methods to select listed firms as the treatment group to construct a random sample and regress according to Eq. (1) to exclude the potential effects of omitted variables and random factors. This random sampling and regression process was repeated 500 times, and a regression coefficient distribution chart of LCC was drawn based on the regression results. This allows us to judge whether analyst predictions are significantly affected by factors other than the Low-Carbon Pilot Policy. If the regression coefficients of LCC are distributed around zero under random sampling, Eq. (1) does not omit the key factors that affect analyst forecast divergence and bias. In other words, the impact on analyst forecast behavior comes from the Low-Carbon Pilot Policy studied in this study. Fig. 2 shows the distribution of the regression coefficients. The results show that when randomly selecting listed firms as the treatment group, the distribution of LCC regression coefficients corresponds to a normal distribution with zero means, indicating that the primary results are unaffected by the omitted variables and random factors.

4.4. Robustness checks

Additional robustness tests were performed. First, we use propensity score matching to construct a matched sample to ensure the robustness of our research conclusions, as there may be systematic differences between listed firms influenced by the Low-Carbon Pilot Policy and

Table 3
Instrumental variable regression.

	First stage	Second stage	
	(1)	(2)	(3)
	LLC	FDISP1	FERROR1
IV	−0.055***		
	(−3.48)		
LCC		−0.335**	−0.436*
		(−2.08)	(−1.68)
Lev	−0.060**	−0.607*	−1.854***
	(−2.00)	(−1.76)	(−3.57)
Size	−0.035***	0.355***	0.564***
	(−4.02)	(3.15)	(3.17)
ROA	0.176***	−14.996***	−21.069***
	(2.84)	(−13.46)	(−12.86)
MepsVol	0.039*	1.924***	1.992***
	(1.90)	(6.94)	(5.00)
Surprise	0.001	−1.298***	−1.135***
	(0.08)	(−8.84)	(−5.47)
Loss	−0.008	−2.269***	−1.927***
	(−0.88)	(−8.68)	(−5.10)
Follow	−0.004	−0.492***	−0.937***
	(−1.19)	(−10.23)	(−13.08)
Horizon	0.013***	0.182*	1.080***
	(2.60)	(1.91)	(7.77)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	19,141	18,747	19,130
Number of firms	2764	2719	2763
F-Statistics		10.98	10.91
p-value of Anderson-Rubin F-test		0.01	0.03

This table presents the results of instrumental variable regression for the effect of low-carbon pilot city policy on analyst forecast bias for a sample of Chinese-listed firms from 2008 to 2019. The dependent variables are *FDISP1* and *FERROR1*. *FDISP1* calculates the dispersion variable for analysts' forecasts by retaining the last forecast value of each analyst for the earnings per share of each listed firm i in year t and then dividing the standard deviation of the forecast earnings per share by the absolute value of the actual earnings per share. *FERROR1* calculates analyst prediction errors for each listed firm by retaining the last forecasted value of each analyst for the firm's earnings per share for the year and then taking the absolute value of the difference between the firm-level forecasted mean of earnings per share and the actual earnings per share, divided by the absolute value of the actual earnings per share. The instrument is defined as the city-level annual wind speed in year t scaled by the annual average PM 2.5 in 2011. *LCC* is a dummy variable that equals one if the firm is located in a city selected as a low-carbon pilot city and zero otherwise. Other control variables include *Lev* (total liabilities over total assets), *Size* (natural logarithm of total assets), *ROA* (net income over total assets), *MepsVol* (volatility of earnings per share), *Loss* (a dummy variable that equals one if net profit is negative and zero otherwise), *Surprise* (the absolute value of the difference between the current year's EPS and the previous year's EPS), *Follow* (number of analysts following the firm), and *Horizon* (the natural logarithm of the median difference between the analysts' forecast time and the next year's earnings announcement date). All regressions include firm and year-fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

other listed firms. Specifically, we used the virtual variable of policy impact (the value equals one if the firm is registered in a city selected as a low-carbon pilot city and zero otherwise) as the dependent variable and all control variables as matching covariates to estimate a logit model and calculate propensity scores for the sample firms. We then constructed a matched sample through 1:1 without replacement nearest-neighbor matching. The results in the first column of Table 4 show that the negative coefficient of LCC is significant at the 10% level, indicating that our results remain robust after mitigating the systematic differences between the experimental and control groups.

Second, we estimate the baseline regression using alternatively constructed explanatory and explained variables. Table 4, Columns (2) and (3), reported the regression results for the analyst forecast dispersion index (FDISP2) and analyst forecast bias (FERROR2). The results showed that the coefficients of LCC were significantly negative at the 1% and 5% levels, consistent with the baseline regression results. Columns (4) and (5) of Table 4 report the regression results after substituting LCC2 and LCC3 for LCC in the baseline regression. The

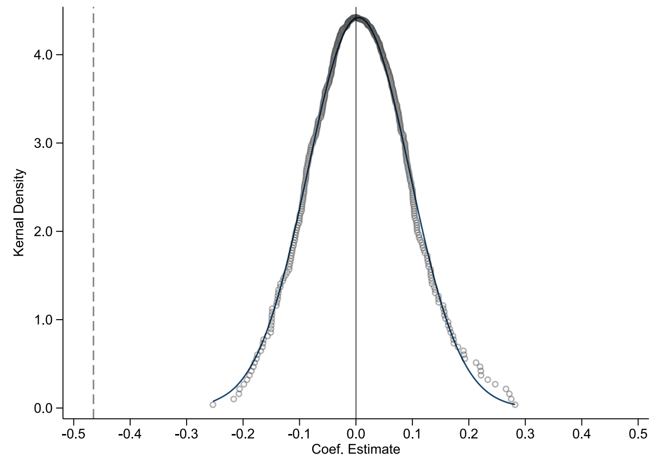

Fig. 2. Placebo test.

implementation year of LCC2 was set as the year the Notice was issued, whereas the implementation year of LCC3 was set as the second year the Notice was issued. The results showed that the coefficients of LCC2 and LCC3 were both significant and negative at the 5% levels.

Finally, we add control variables such as cash holdings, book-to-market ratio, fixed asset ratio, and ownership concentration to the regression Eq. (1). In this case, Column (6) results indicate that the regression coefficient of LCC remains significantly negative even after controlling for other possible factors.

4.5. Plausible channels

4.5.1. Analyst attention

We further explore the effect of the Low-Carbon Pilot Policy on analyst forecast behavior from the perspective of external attention of listed firms. Griffin et al. (2020) pointed out that corporate environmental performance increases analysts' information processing costs, and an empirical study based on the 2006 California Global Warming Solutions Act supports this conclusion. Similarly, implementing Low-Carbon Pilot Policy can increase the amount of information received by analysts and increase information processing costs, thus influencing the number of reports issued by analysts and the degree of attention to listed firms.

To investigate whether Low-Carbon Pilot Policy can increase researchers' concern for environmental protection and low-carbon-related issues, thereby affecting their acquisition of relevant information during the research process, we first match the questions in the research questionnaire with keywords related to low-carbon and environmental protection and count the number of relevant questions.[4] We then take the natural logarithm of the number of questions plus one to obtain investor attention to environmental protection QRecord.

Second, to examine whether the Low-Carbon Pilot Policy affects the level of analyst recommendation of stocks, we assign ratings of Buy, Hold, Neutral, Reduce, and Sell a value of one to five and calculate the mean at the firm-year level for the stock rating Rating. Finally, to investigate whether the Low-Carbon Pilot Policy will increase information processing costs when predicting polluting industries and consequently increase the time spent predicting the profits of polluting industries, we calculate the average proportion of polluting industries in research

[4] The following keywords were relevant to the application: low carbon, dual carbon, carbon peak, carbon neutralization, environmental protection, environmental governance, environmental protection, emission reduction, pollution, emissions, carbon dioxide, GHG, circular economy, ecology, and green.

Table 4
Robustness checks.

	(1) PSM-DID	(2) FDISP2	(3) FERROR2	(4) FDISP1	(5) FDISP1	(6) Control
LCC	−1.024*	−0.419***	−0.498**			−0.420***
	(−1.83)	(−2.90)	(−2.20)			(−2.77)
LCC2				−0.406**		
				(−2.09)		
LCC3					−0.403**	
					(−2.32)	
Cash						−1.595***
						(−5.74)
BM						0.504**
						(2.08)
FA						1.257***
						(2.85)
OwnCon						−3.265***
						(−8.20)
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	2194	19,776	20,037	19,637	19,637	19,252
Number of firms	560	2879	2910	2863	2863	2851
Adjusted R^2	0.22	0.19	0.17	0.19	0.19	0.20

This table presents the robustness checks for the effect of low-carbon pilot policy on analyst forecast bias for a sample of Chinese-listed firms from 2008 to 2019. The dependent variables are *FDISP1*, *FERROR1*, *FDISP2*, and *FERROR2*. *FDISP1* calculates the dispersion variable for analysts' forecasts by retaining the last forecast value of each analyst for the earnings per share of each listed firm i in year t and then dividing the standard deviation of the forecast earnings per share by the absolute value of the actual earnings per share. *FERROR1* calculates analyst prediction errors for each listed firm by retaining the last forecasted value of each analyst for the firm's earnings per share for the year and then taking the absolute value of the difference between the firm-level forecasted mean of earnings per share and the actual earnings per share, divided by the absolute value of the actual earnings per share. *FDISP2* is calculated by retaining the last two analyst forecasts of the firm's earnings per share for each listed firm, then divide the standard deviation of the predictions by the absolute value of the actual earnings per share. *FERROR2* is calculated by retaining the last two analyst forecasts of the firm's earnings per share for each listed firm, and then taking the absolute difference between the firm's mean forecast of earnings per share and the actual earnings per share, divided by the absolute value of the actual earnings per share. Other control variables include *Lev* (total liabilities over total assets), *Size* (natural logarithm of total assets), *ROA* (net income over total assets), *MepsVol* (volatility of earnings per share), *Loss* (a dummy variable that equals one if net profit is negative and zero otherwise), *Surprise* (the absolute value of the difference between the current year's EPS and the previous year's EPS), *Follow* (number of analysts following the firm), and *Horizon* (the natural logarithm of the median difference between the analysts' forecast time and the next year's earnings announcement date). All regressions include firm and year-fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

reports issued by analysts each year at the firm level, obtaining the attention of polluting firms PolluProp, and use the three variables as dependent variables in Eq. (1) for regression.

Table 5 reports the corresponding regression results. The coefficients of LCC in Columns (1) and (2) are significantly positive at the 10% and 5% levels, respectively, whereas the coefficient of LCC in Column (3) is significantly negative at the 1% level. The regression results show that the Low-Carbon Pilot Policy significantly increases investors' attention to the environmental performance of listed firms while reducing the proportion of analyst recommendations and research reports on heavily polluting industry firms. This indicates that under the requirement of Low-Carbon Pilot Policy for environmental disclosure, the improvement of corporate environmental performance increases the cost of information processing for analysts, thus making analysts spend more time and effort analyzing information and publishing reports, resulting in a decrease in the proportion of heavily polluting industry listed firms in research reports. In addition, implementing environmental regulations is a risk factor for listed firms. When investors increase their environmental awareness, analysts' recommendations and the stock rating of listed firms decrease significantly.

Table 5
The impact of low carbon pilot policy on analyst attention.

	(1) QRecord	(2) Rating	(3) PolluProp
LCC	0.024*	0.057**	−0.036***
	(1.72)	(2.57)	(−4.24)
Lev	0.030	−0.140***	−0.030*
	(1.13)	(−3.45)	(−1.79)
Size	0.006	−0.008	−0.006
	(0.83)	(−0.69)	(−1.26)
ROA	0.034	−1.112***	−0.014
	(0.55)	(−9.77)	(−0.40)
MepsVol	0.029*	0.034	0.002
	(1.86)	(1.44)	(0.23)
Surprise	−0.025***	−0.046***	−0.005
	(−2.90)	(−3.37)	(−1.20)
Loss	−0.014	−0.017	0.001
	(−1.52)	(−0.89)	(0.22)
Follow	0.021***	−0.206***	−0.007***
	(5.47)	(−32.12)	(−3.13)
Horizon	−0.011*	0.060***	0.001
	(−1.93)	(5.09)	(0.24)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	20,048	19,870	19,552
Number of firms	2911	2891	2876
Adjusted R^2	0.38	0.45	0.84

This table presents the effect of the low-carbon pilot policy on analyst attention for a sample of Chinese-listed firms from 2008 to 2019. The dependent variables are *QRecord*, *Rating*, and *PolluProp*. *QRecord* first matches the questions in the survey questionnaire with keywords related to low carbon and environmental protection. Then, calculate the number of relevant questions and add 1 to the firm-year level of questions before taking the natural logarithm. *Rating* is the average of ratings at the firm-year level, which analysts assign of 1 to 5 for stock ratings of "Buy", "Hold", "Neutral", "Sell", and "Strong Sell". *PolluProp* is the average calculated across the firm level of the proportion of research reports on heavily polluting firms issued by analysts each year. Other control variables include *Lev* (total liabilities over total assets), *Size* (natural logarithm of total assets), *ROA* (net income over total assets), *MepsVol* (volatility of earnings per share), *Loss* (a dummy variable that equals one if net profit is negative and zero otherwise), *Surprise* (the absolute value of the difference between the current year's EPS and the previous year's EPS), *Follow* (number of analysts following the firm), and *Horizon* (the natural logarithm of the median difference between the analysts' forecast time and the next year's earnings announcement date). All regressions include firm and year-fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.5.2. Accounting information quality

Environmental policies significantly impact corporate disclosure practices, often resulting in improved quality of accounting information due to stringent reporting requirements (Hughes, 2000). For example, De Villiers et al. (2011) found that such eco-centric initiatives increased the transparency and accuracy of financial reporting since firms participating in the programs had to adhere to higher ethical and reporting standards. Building on this, due to the increasing market sensitivity to environmental factors, it is necessary to pivot corporate reporting mechanisms, thereby indirectly improving the quality of accounting information (Richardson and Welker, 2001), i.e., the Low-Carbon Pilot Policy can act as a catalyst to increase the credibility of financial reporting (Cho et al., 2012). At the same time, high-quality disclosure of information improves the accuracy of analyst forecasts, reducing their optimism and forecast dispersion (Hu et al., 2021). For instance, Georgakopoulos et al. (2022) found that standardization of accounting practices helps improve information quality, thus increasing forecast reliability. Therefore, we speculate that the Low-Carbon Pilot Policy may further influence analysts' forecast behavior by improving the quality of corporate accounting information.

We examine the mechanism of the effect of the Low-Carbon Pilot Policy on analyst forecast behaviors. Two variables are introduced based on Bhattacharya et al. (2003) and Dhaliwal et al. (2012): relative earnings aggressiveness REA, which equals one if the quality of accounting information disclosure is lower than the industry average level and zero otherwise; earnings smoothing ES, with higher values, indicating lower quality of accounting information disclosure; and a dummy variable called DownGrade based on the assessment results of accounting information disclosure quality, which equals one if the assessment results are lower or the same as the previous year and zero otherwise.

As shown in Table 6, Panel A examines how pilot policies affect the disclosure of accounting information from listed firms. The LCC coefficients in Columns (1)–(3) are all significantly negative. This suggests that accounting information quality is of great help for analysts in making more accurate predictions of listed firms and reducing the internal prediction divergence of analysts, showing that the improvement of accounting information quality is a crucial mechanism for improving the accuracy of analyst forecasts and reducing prediction divergence under the Low-Carbon Pilot Policy.

We calculate the accrual profit according to the revised Jones model and sum its absolute values over the past three years to obtain the degree of accrual-based earnings management JEM. Accrual-based earnings management is common when this variable is high. Furthermore, we construct the degree of real earnings management REM based on Dechow et al. (1998) and Roychowdhury (2006). Finally, based on De Franco et al. (2011) and Tang et al. (2019), we construct the accounting comparability AccCom to gauge the degree to which annual accounting information from a firm can be compared with other firms in its industry.

Panel B of Table 6 reports the impact of the pilot policy on the earnings management of listed firms. Columns (1) and (2) show significant negative and positive regression coefficients, respectively. This suggests that discretionary accrual-based earnings management is significantly reduced under the Low-Carbon Pilot Policy while real earnings management is encouraged. This confirms the influence of the Low-Carbon Pilot Policy on the earnings management of listed firms. After policy implementation, managers reduce their discretionary accrual-based earnings management and switch to more flexible and less transparent real earnings management (Li et al., 2016; Graham et al., 2005).

Table 6
The impact of low carbon pilot policies on the quality of accounting information.

Panel A. Disclosure quality			
	(1) REA	(2) ES	(3) DownGrade
LCC	−0.056**	−0.756**	−0.036**
	(−2.52)	(−2.24)	(−1.97)
Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	17,924	12,460	12,273
Number of firms	2626	2062	1794
Adjusted R^2	0.05	0.36	−0.00

Panel B. Earnings management			
	(1) JEM	(2) REM	(3) AccCom
LCC	−0.128***	0.018**	0.000
	(−2.98)	(2.14)	(0.60)
Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	19,064	17,579	10,486
Number of firms	2841	2630	1761
Adjusted R^2	0.54	0.31	0.65

This table reports the impact of the low-carbon pilot policy on the quality of accounting disclosure and earnings management for a sample of Chinese-listed firms from 2008 to 2019. The dependent variables are *REA*, *ES*, *DownGrade*, *JEM*, *REM*, and *AccCom*. *REA* equals one if the quality of accounting information disclosure is lower than the industry average, and zero otherwise. *ES* is the surplus smoothing calculated in accordance with Bhattacharya et al. (2003). *DownGrade* equals one if the quality assessment results of accounting information disclosure are lower or unchanged compared to the previous year, and zero otherwise. *JEM* calculates the controllable profit according to the revised Jones model first, then calculate the sum of its absolute values for the preceding three periods. *REM* is the level of true surplus management calculated in accordance with Dechow et al. (1998) and Roychowdhury (2006). *AccCom* is the accounting comparability calculated in accordance with De Franco et al. (2011) and Tang et al. (2019). Other control variables include *Lev* (total liabilities over total assets), *Size* (natural logarithm of total assets), *ROA* (net income over total assets), *MepsVol* (volatility of earnings per share), *Loss* (a dummy variable that equals one if net profit is negative and zero otherwise), *Surprise* (the absolute value of the difference between the current year's EPS and the previous year's EPS), *Follow* (number of analysts following the firm), and *Horizon* (the natural logarithm of the median difference between the analysts' forecast time and the next year's earnings announcement date). All regressions include firm and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.6. Environmental disclosure patterns

The Low-Carbon Pilot Policy proposes that the environmental disclosure mode is also an essential factor for analyst forecasts. Lang and Lundholm (1996) found that the divergence and volatility of analyst forecasts for listed firms that disclose more information are smaller. In addition to conventional financial information, disclosure of nonfinancial information can achieve a similar effect, such as the independent social responsibility disclosure report issued by listed firms, which can significantly reduce analyst forecast bias (Dhaliwal et al., 2012) and increase environmental disclosure to make analyst forecasts more accurate (Aerts et al., 2008; Cormier and Magnan, 2015). The environmental disclosure mode is also an essential factor influencing analyst forecasts. For example, Li (2018) found that a cheap talk environmental disclosure mode significantly increases analyst forecast divergence and reduces forecast precision. Consequently, we expect that implementing the Low-Carbon Pilot Policy can influence the amount and quality of the environmental data information that analysts acquire.

This study explores the relationship between Low-Carbon Pilot Policy and environmental disclosure patterns by constructing four virtual variables based on the environmental disclosures of listed firms. The virtual variable EPtConcept equals one if the listed firm discloses its environmental philosophy, policies, management organization structure, circular economy development model, etc., and zero otherwise. The virtual variable EnvEmerge equals one if it reveals the establishment of an emergency event response mechanism of major environmental impact, emergency measures, and the treatment of pollutants, and zero otherwise. The virtual variable EnvReport equals one if they disclose the environmental report separately and zero otherwise. Finally, the virtual variable WordyNonFeasance equals one if the listed firm's environmental information disclosure mode is the cheap talk mode and zero otherwise. The cheap talk pattern refers to environmental strategy information disclosure items higher than the industry median level for the same year, while environmental action information disclosure items were below the industry median in the current year.

Table 7 reports the regression results of environmental disclosure and pattern analysis. LCC regression coefficients of Columns (1)–(3) are significantly positive, while that of Column (4) is significantly negative, which is in line with the expected results. The results show that under the impact of the Low-Carbon Pilot Policy, listed firms respond to policy requirements by strengthening environmental information disclosure, including environmental concepts, policies, and emergency mechanisms for environmental-related emergencies. In addition to financial and social responsibility reports, they added independent environmental reports as a disclosure vehicle, reducing the cheap talk of environmental disclosure. This environmental disclosure behavior supplements the information sources and the scope of analyst collection, which helps analysts dig deeper into environmental information. Additionally, the cheap talk disclosure essentially reflects the asymmetric disclosure structure of corporate environmental strategy and environmental action information, and the behavioral ambiguity caused by this asymmetry will negatively affect the accuracy and consistency of analyst forecasts (Li, 2018).

Table 7
Low-carbon pilot city policy and environmental disclosure.

	(1) EPtConcept	(2) EnvEmerge	(3) EnvReport	(4) WordyNonFeasance
LCC	0.051**	0.096***	0.021***	−0.016***
	(2.16)	(4.40)	(2.58)	(−2.65)
Lev	−0.027	−0.035	0.013	0.004
	(−0.66)	(−1.06)	(1.29)	(0.32)
Size	0.052***	−0.035***	−0.006***	−0.002
	(4.66)	(−3.81)	(−2.58)	(−0.53)
ROA	0.151	0.183**	−0.003	0.048
	(1.63)	(2.18)	(−0.21)	(1.56)
MepsVol	−0.000	−0.010	−0.008	0.022**
	(−0.01)	(−0.45)	(−0.80)	(2.11)
Surprise	0.008	−0.007	−0.001	−0.007
	(0.64)	(−0.62)	(−0.19)	(−1.15)
Loss	−0.005	0.027*	−0.000	0.003
	(−0.32)	(1.88)	(−0.13)	(0.58)
Follow	0.010*	0.007	0.001	0.002
	(1.80)	(1.39)	(0.62)	(0.92)
Horizon	0.005	0.003	−0.001	0.005
	(0.50)	(0.33)	(−0.66)	(1.41)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	17,128	17,128	20,048	20,048
Number of firms	2843	2843	2911	2911
Adjusted R^2	0.50	0.42	0.45	0.11

This table reports the effect of the low-carbon pilot policy and environmental disclosure for a sample of Chinese-listed firms from 2008 to 2019. The dependent variables are *EPtConcept*, *EnvEmerge*, *EnvReport*, and *WordyNonFeasance*. *EPtConcept* equals one if a listed firm discloses its environmental protection concept, environmental policy, environmental management organizational structure, circular economy development model, and green development, and zero otherwise. *EnvEmerge* equals one if a listed firm discloses its emergency mechanisms, emergency measures, and treatment of pollutants related to environmental emergencies, and zero otherwise. *EnvReport* equals one if a listed firm discloses an environmental report separately and zero otherwise. *WordyNonFeasance* equals one if the environmental strategy disclosure items of a listed firm (environmental concepts, environmental goals, environmental management system, environmental education, and training, environmental emergency response mechanism, and "three simultaneous" system) exceed the industry median level of the same year, and the environmental action disclosure items (environmental special actions, environmental honors or awards, sudden environmental accidents, environmental violations, environmental petitions, whether passed ISO14001 certification, whether passed ISO9001 certification) are lower than the industry median level of the same year, and zero otherwise. Other control variables include *Lev* (total liabilities over total assets), *Size* (natural logarithm of total assets), *ROA* (net income over total assets), *MepsVol* (volatility of earnings per share), *Loss* (a dummy variable that equals one if net profit is negative and zero otherwise), *Surprise* (the absolute value of the difference between the current year's EPS and the previous year's EPS), *Follow* (number of analysts following the firm), and *Horizon* (the natural logarithm of the median difference between the analysts' forecast time and the next year's earnings announcement date). All regressions include firm and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The Low-Carbon Pilot Policy, which establishes clear carbon-peak targets, establishes an assessment system, and assigns tasks to firms in policy coverage areas, has strict requirements for the disclosure of relevant listed firms' actions. This has unified the planning and action in environmental disclosure of firms, curbed the cheap talk disclosure, and weakened its negative impact. The above empirical outcomes are of great help to demonstrate that the Low-Carbon Pilot Policy affects the enhancement of environmental disclosure and the transformation of the information disclosure mode.

5. Further discussion

5.1. Investor expectation

Finally, by increasing the accuracy of predictions, the Low-Carbon Pilot Policy has improved the informational efficiency of the capital market, with fewer forecast biases implying smaller systemic errors among analysts. Meanwhile, investors often rely on analyst forecasts to make investment decisions, so an increase in analyst prediction accuracy could further align investor views (Liao et al., 2015; Downar et al., 2021). The market perceives firms participating in the Low-Carbon Pilot Policy to be more resilient to future environmental regulations and market changes related to climate change (Trinks et al., 2018). Additionally, under the stimulus of the Low-Carbon Pilot Policy, corporate-related low-carbon measures can be seen as a response to the increasing investment demand for environmental responsibility in the market, reflecting a broad expectation shift in the market towards sustainable business practices (Gaviria-Marin et al., 2018). Analyst predictions may bring economic value to investors by improving the informational efficiency of capital markets, encouraging them to raise their expectations of the market. However, the extent to which the Low-Carbon Pilot Policy affects investor expectations depends on the credibility and effectiveness of such initiatives, as superficial or ineffective plans may not shake investor sentiments.

To analyze investor expectations about the Low-Carbon Pilot Policy, this study selected Tobin's Q, the price-earnings ratio, and the annual stock return rate as dependent variables. Tobin's Q and price-earnings ratio reflect investor expectations for firm valuation, while the annual stock return directly reflects its performance as measured by its price change. There is a significant negative correlation between LCC and Columns (1) and (2) in Table 8. This may be because the policy's emission limits and environmental protection requirements have released negative information, reducing investor expectations of corporate profitability and growth potential. In Column (3), LCC has a significant negative regression coefficient at the Low-Carbon Pilot Policy, significantly reducing annual stock return rates. There is a consistent trend in Table 8 with the existing literature regarding the economic effects of other environmental policies (Ramiah et al., 2013; Dietz et al., 2016; Battiston et al., 2017). In summary, the Low-Carbon Pilot Policy reduces investor expectations of firm valuation and future performance.

5.2. Additional impact on corporate performance

To further investigate the wider impacts of the Low-Carbon Pilot Policy on capital allocation and information efficiency, this study selects capital expenditure (CAPX), illiquidity (ILLIQ), and implied cost of equity (COE) as the explanatory variables, where CAPX denotes the capital expenditures scaled by lagged assets, ILLIQ is Amihud illiquidity measure, which reflects the liquidity of the firm's stocks, and COE is the implied cost of capital estimated following Easton (2004), which reflects the market's expectation of future returns from the stocks.

In Column (1) of Table 9, the regression coefficient for LCC is significantly negative. On the one hand, this may be due to emission restrictions and investment requirements imposed by the Low-Carbon Pilot Policy, leading to a decrease in corporate capital expenditures. On the other hand, it may be because excessive optimism can lead to an expansion of investment outlays, and the lower analyst forecast bias caused by the Low-Carbon Pilot Policy reduces uncertainty and information asymmetry, restricting excessive optimism and thus lowering the firm's capital costs (Easley and O'hara, 2004). The LCC regression coefficient in Column (2) is significantly negative at the 1% level, indicating that the Low-Carbon Pilot Policy mitigates liquidity shortage to some degree. This might be because lower information asymmetry reduces the bid–ask spread, a component of Amihud liquidity shortage (Kim and Verrecchia, 1994). The implementation of the Low-Carbon Pilot Policy reduces information asymmetry and adverse selection after reducing analyst forecast bias and divergence (Amihud, 2002; Diamond and Verrecchia, 1991), thus improving pricing efficiency to some extent, reducing the bid–ask spread and transaction friction, and ultimately alleviating Amihud liquidity shortage. Results from the third column indicate that the LCC regression coefficient is still significantly negative at the 1% level, suggesting that implementing the Low-Carbon Pilot Policy will reduce a firm's implicit capital cost. This

Table 8
Low-carbon pilot city policy and firm valuation.

	(1) TobinQ	(2) P/E	(3) AnnualReturn
LCC	−0.229***	−11.114**	−0.048***
	(−4.98)	(−2.30)	(−3.08)
Lev	1.148***	−10.311	0.440***
	(10.94)	(−0.81)	(11.67)
Size	−0.740***	−22.964***	−0.144***
	(−23.62)	(−7.22)	(−14.38)
ROA	3.372***	−725.606***	1.569***
	(11.26)	(−21.11)	(15.86)
MepsVol	0.075	2.316	0.007
	(1.42)	(0.35)	(0.30)
Surprise	0.007	−10.785***	0.030**
	(0.29)	(−2.95)	(2.02)
Loss	0.304***	−192.815***	−0.003
	(8.27)	(−30.06)	(−0.19)
Follow	0.253***	−5.594***	0.064***
	(19.42)	(−3.85)	(11.89)
Horizon	−0.192***	−1.255	−0.282***
	(−9.05)	(−0.40)	(−23.07)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	19,654	20,048	19,699
Number of firms	2899	2911	2878
Adjusted R^2	0.64	0.31	0.55

This table reports the effect of the low-carbon pilot policy on firm valuations for a sample of Chinese-listed firms from 2008 to 2019. The dependent variables are *TobinQ*, *PE* and *AnnualReturn*. *TobinQ* is the Tobin's Q. *PE* is price earnings ratio. *AnnualReturn* is the annual individual stock return considering reinvestment of cash dividends. Other control variables include *Lev* (total liabilities over total assets), *Size* (natural logarithm of total assets), *ROA* (net income over total assets), *MepsVol* (volatility of earnings per share), *Loss* (a dummy variable that equals one if net profit is negative and zero otherwise), *Surprise* (the absolute value of the difference between the current year's EPS and the previous year's EPS), *Follow* (number of analysts following the firm), and *Horizon* (the natural logarithm of the median difference between the analysts' forecast time and the next year's earnings announcement date). All regressions include firm and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Additional test on the impact of low-carbon pilot policy.

	(1) CAPX	(2) ILLIQ	(3) COE
LCC	−0.006**	−0.018***	−0.006***
	(−2.12)	(−3.90)	(−3.38)
Lev	−0.006	0.038	0.018***
	(−1.15)	(1.05)	(4.94)
Size	0.001	−0.044***	0.006***
	(0.62)	(−6.30)	(5.83)
ROA	0.021**	0.049	−0.002
	(1.98)	(0.55)	(−0.18)
MepsVol	−0.004	−0.016**	0.002
	(−1.38)	(−2.34)	(0.76)
Surprise	0.003**	0.015	0.007***
	(1.97)	(1.62)	(5.27)
Loss	−0.004**	0.002	0.001
	(−2.55)	(0.27)	(0.42)
Follow	0.007***	−0.007**	0.004***
	(11.50)	(−2.04)	(6.65)
Horizon	0.002*	0.005	0.007***
	(1.80)	(0.67)	(6.65)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	20,047	20,045	17,614
Number of firms	2911	2911	2754
Adjusted R^2	0.48	0.31	0.39

This table presents the effect of low-carbon pilot city policy on capital expenditure, stock liquidity and implied cost of capital for a sample of Chinese-listed firms from 2008 to 2019. The dependent variables are *CAPX*, *ILLIQ* and *COE*. *CAPX* is capital expenditures scaled by total assets. *ILLIQ* is the Amihud illiquidity measure. *COE* is the implied cost of capital estimated following Easton (2004). *LCC* is a dummy variable that equals one if the firm is located in a city selected as a low-carbon pilot city and zero otherwise. Other control variables include *Lev* (total liabilities over total assets), *Size* (natural logarithm of total assets), *ROA* (net income over total assets), *MepsVol* (volatility of earnings per share), *Loss* (a dummy variable that equals one if net profit is negative and zero otherwise), *Surprise* (the absolute value of the difference between the current year's EPS and the previous year's EPS), *Follow* (number of analysts following the firm), and *Horizon* (the natural logarithm of the median difference between the analyst forecast time and earnings announcement date in the next year). All regressions include firm and year-fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

may be due to the policy-induced reduction in analyst forecast bias and dispersion, which reduces the investors' information risk and, in turn, the risk premium, resulting in a lower expected return on stocks and ultimately a lower implicit capital cost (Lambert et al., 2012). In conclusion, implementing a Low-Carbon Pilot Policy significantly affects corporate capital allocation and information efficiency by reducing analyst forecast bias and dispersion.

6. Implications

Our results provide several important policies and practical implications regarding the implementation of environmental regulations like China's Low-Carbon Pilot Policy.

For policymakers, our findings highlight the effectiveness of well-designed sustainability policies in improving corporate transparency and capital market efficiency. By mandating emissions disclosures and targets, the Low-Carbon Pilot Policy enhanced the breadth and depth of sustainability information available to analysts. In turn, this improved forecast accuracy and convergence, reducing information asymmetry in the stock market. Thus, the research supports the use of disclosure-based environmental regulations to meet ecological goals while also promoting financial stability. Policymakers should consider transparency and reporting rules as critical components of green policy packages.

For investors and analysts, the study reveals how major environmental reforms can shape the quantity and quality of ESG data for stock analysis. Analysts should be aware that sustainability policies may provide valuable new information to incorporate into forecasts and valuation models. Emerging non-financial disclosures related to emissions, energy use, and other indicators can help analysts derive more precise earnings estimates. Investors can also benefit from improved forecast quality when making investment decisions.

For managers, our findings show firms face greater pressure for comprehensive ESG reporting following sustainability regulations. This includes emissions statistics, low-carbon strategies, and other non-financial disclosures. Managers should prepare to meet expanded reporting requirements under environmental policies and view transparency as an opportunity to signal commitment to shareholders. Proactive sustainability disclosure can potentially boost reputation.

Overall, the paper demonstrates that well-designed green policies like China's Low-Carbon Pilot Policy can serve multiple objectives, from meeting environmental goals to strengthening market efficiency, corporate transparency, and data quality for analysts and investors. The implications point to the wide-ranging financial market impacts of sustainability regulations.

7. Conclusion

This study examines an important and timely research question: how do major environmental regulations like China's Low-Carbon Pilot Policy impact analyst earnings forecast attributes? While prior research explores the stock price effects of green policies (Derwall et al., 2005; Ramiah et al., 2013) and the use of ESG metrics in forecasts (Plumlee et al., 2015), no study has isolated the impact of sustainability initiatives on forecast quality. Our work helps fill this gap and leverages

China's top-down approach to eco-reforms. Investigating how ecological regulations shape analyst forecast bias and divergence provides novel evidence on the financial market consequences of sustainability policies. The findings offer implications for regulators, investors, managers, and policymakers as countries pursue climate change mitigation strategies. Overall, this study makes an important contribution by being the first to analyze how a major national environmental regulation affects the accuracy and consistency of analyst earnings predictions. The research sheds light on an under-explored dimension of green policy impacts and the role of enhanced transparency in improving forecast performance.

Using a staggered difference-in-difference method to explore the impact of China's Low-Carbon Pilot Policy on analyst forecast behaviors, we find it reduces both analyst forecast dispersion and forecast error. The forecast improvements were concentrated in state-owned enterprises, cities with a high share of manufacturing and firms receiving high government subsidies, where compliance pressure was greater. Further analysis suggests the policy increased analysts' attention to sustainability issues but made stock recommendations more costly. It also curbed aggressive earnings management and improved accounting information quality. Overall, the mandatory emissions disclosures and targets enabled analysts to incorporate more high-quality data into forecasts, reducing bias by over 20% and lowering divergence by nearly 50%. The results are robust to propensity score matching, placebo tests, and instrumental variables using localized pollution levels. Additional tests reveal the Low-Carbon Pilot Policy dampened investor expectations but improved firms' capital expenditure, liquidity, and cost of equity. In summary, this study provides novel evidence that major environmental regulations can enhance transparency and capital market efficiency through their impact on analyst forecast attributes.

Our study makes several contributions to the literature. First, we provide evidence that China's Low-Carbon Pilot Policy significantly improved analyst forecast accuracy and convergence, while prior research explores the stock price effects of green regulations (Derwall et al., 2005; Ramiah et al., 2013). Our analysis indicates mandatory emissions disclosures and targets reduced forecast errors and divergence for affected firms. This contributes to research on determinants of analyst forecast quality, as Hong and Kubik (2003) shows career incentives can bias predictions, and Hope (2003) documents the benefits of strong accounting standards. We demonstrate sustainability requirements enhanced forecast precision by expanding non-financial transparency. Second, our results reveal forecast improvements concentrated in state-owned enterprises and areas with high secondary industry, underscoring how China's institutional context shaped the policy impact compared to decentralized green initiatives in Western economies. SOEs face greater compliance pressure due to government control (Dhaliwal et al., 2011; Lee et al., 2017). Our study contributes to research on sustainability policies interacting with institutions (Delmas et al., 2010). Finally, we provide evidence on how regulations alter corporate transparency and disclosure quality. The Project strengthened accounting information and reduced aggressive earnings management, facilitating analyst forecasting. This builds on literature examining disclosure responses to regulations (Bushman et al., 2004; Plumlee et al., 2015). Analysts also paid greater attention to sustainability issues. We show mandatory policies can improve the information available to capital market participants.

This study has some limitations that provide opportunities for future research. While lowering analyst forecast bias through the Low-Carbon Pilot Policy can improve information efficiency and market stability, it may also reduce opinion diversity. Analysts could overreact to the decreased bias and become overly pessimistic, potentially dampening capital growth. Thus, maintaining some degree of bias may be reasonable as analysts balance objectivity and incentives. Additionally, this study only examines individual firm forecast behaviors. However, heavily polluting firms likely face greater policy impacts. Comparing effects across industries, especially high-pollution sectors, could provide further insights. Overall, this study makes a valuable contribution despite limitations. Avenues exist to extend the analysis to other contexts and incorporate industry-level heterogeneity.

CRediT authorship contribution statement

Yuying Sun: Writing – review & editing. **Kai Wu:** Formal analysis, Supervision, Writing – original draft, Writing – review & editing. **Sihui Liu:** Investigation, Writing – original draft. **Yongmiao Hong:** Conceptualization.

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.

Data availability

Data will be made available on request.

Appendix. Environmental regulation intensity

According to the notice, local governments in the pilot regions should incorporate the Low-Carbon Pilot Policy into their five-year implementation plans, thus affecting local government environmental governance programs. Analysts examine corporate financial information and market performance when analyzing and predicting securities and consider policy orientation and the industry environment. Macroeconomic and industry research is an important task for analysts, and

Table A.1
Low-carbon pilot city policy and government environmental regulation intensity.

	(1) EnvFrenq	(2) LowCarbon	(3) EnvProtection
LCC	0.210***	0.174***	0.035**
	(5.65)	(5.50)	(2.34)
GDP	0.057*	0.017	0.038***
	(1.76)	(0.61)	(2.95)
IndStru	0.293	0.292	0.005
	(0.83)	(1.02)	(0.04)
EduYear	0.285	0.320	−0.041
	(0.81)	(1.09)	(−0.36)
HigherEdu	−0.591	−0.481	−0.106
	(−1.07)	(−0.99)	(−0.56)
EnvProExpense	0.002*	0.002*	0.000
	(1.94)	(1.69)	(0.83)
STExpense	0.001	0.001	0.000
	(0.63)	(0.56)	(0.32)
EduExpense	0.000	0.000	0.000
	(0.39)	(0.25)	(0.43)
FDI	−0.000	−0.000	−0.000
	(−0.08)	(−0.02)	(−0.33)
Observations	332	332	332
Number of provinces	31	31	31
Pseudo R^2	0.12	0.17	0.11

This table reports the effect of the low-carbon pilot policy on the intensity of government environmental regulations. The dependent variables are *EnvFreq*, *LowCarbon*, and *EnvProtection*. *EnvFreq* is the ratio of environmental vocabulary (carbon dioxide, low-carbon, emissions reduction, energy consumption, green, air, ecology, PM10, PM2.5, sulfur dioxide, chemical oxygen demand, pollution, contamination, environmental protection, environmental protection) to the total number of words in the government's work report is analyzed. *LowCarbon* is the frequency of low-carbon words (carbon dioxide, low-carbon, emission reduction, energy consumption, green, air, ecosystem) in relation to the total number of words in the government's work report. *EnvProtection* is the ratio of environmental vocabulary (PM10, PM2.5, sulfur dioxide, chemical oxygen demand, effluent, pollution, environmental protection, environmental protection) to the total number of words in the government's work report. Control variables include *GDP* (Gross Domestic Product), *IndStru* (Ratio of the secondary sector to GDP), *EduYear* (Average years of schooling), *HigherEdu* (Ratio of higher education), *EnvProExpense* (Ratio of environmental protection expenditures to GDP), *STExpense* (Ratio of science and technology expenditure to GDP), *EduExpense* (Ratio of education expenditure to GDP), and *FDI* (Ratio of foreign direct investment to GDP). The robust *t*-statistics clustered by the province are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

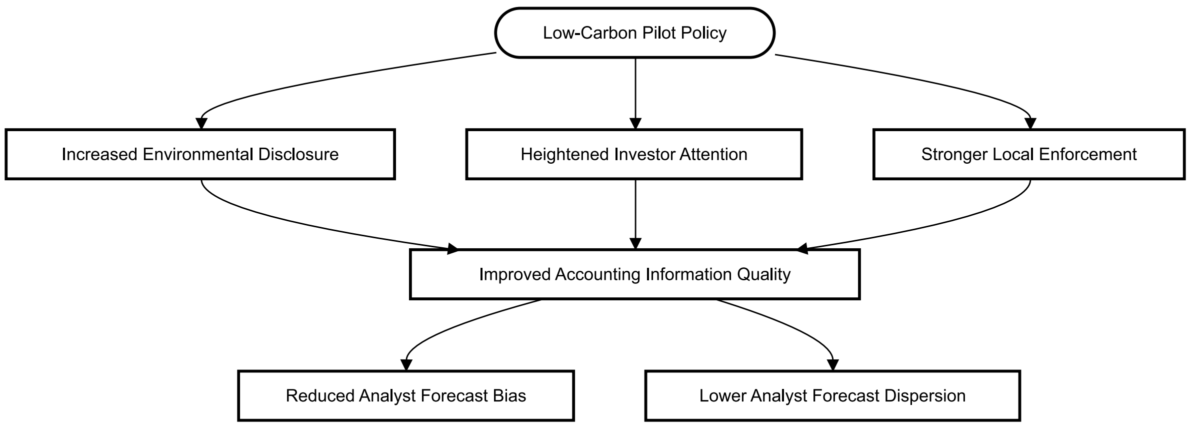

Fig. A.1. Theoretical framework.

government departments are one of their main sources of information (Hu et al., 2003). At the same time, political trends in the government also affect analyst forecast behaviors, such as the inspection activities of the Central Inspection Group, which can increase analyst optimistic bias in forecasts (Li et al., 2021). Therefore, as an important carrier of macro-level information and a reflection channel of political trends, the environmental regulatory strength of local governments is also an important factor influencing analyst forecast behavior.

$$EnvFreq_{pt} = \gamma_0 + \gamma_1 LCC + \gamma_2 X_{it} + \varepsilon_{it} \tag{2}$$

Eq. (2) represents the relationship between the frequency of environmental regulations by the government EnvFreq and other variables. To measure the strength of environmental regulations, we calculated the variable EnvFreq using web crawling to obtain the text of government work reports from 2009 to 2019 in all 31 provinces (including municipalities) in China. We selected words related to environmental science and engineering, such as carbon dioxide, low carbon, emission reduction, energy consumption, green, air, ecology, PM10, PM2.5, sulfur dioxide, chemical oxygen, pollution, and environmental protection as representative words, according to the Environmental Science and Engineering Dictionary (Song and Yang, 2019; Pan and Fu, 2022).

Besides, based on the government work reports for each province, we calculated the frequency of environmental words and the total number of words in each report (Chen et al., 2018b). For the explanatory variable, the dummy variable LCC equals one if the city of registration of the listed firm becomes a low-carbon pilot city and zero otherwise. Following previous studies (Song et al., 2013), we include the following control variables: Gross Domestic Product (GDP), industrial structure (IndStru), average educational years (EduYear), higher education rate (HigherEdu), environmental protection expenditures (EnvProExpense), spending on science and technology (STExpense), educational expenditure (EduExpense), and foreign direct investment (FDI).

To further explore the relationship between the Low-Carbon Pilot Policy and environmental concerns in government reports, we divided the environmental terms involved in the explained variable EnvFreq into two groups: low-carbon and environmental protection. We obtained two explained variables for the Tobit regression using the same calculation method. The low-carbon group includes carbon dioxide, low-carbon, reduction, energy consumption, green, air, and ecology. In contrast, the environmental protection group includes terms such as PM10, PM2.5, sulfur dioxide, chemical oxygen demand, sewage discharge, pollution, and environmental protection.

Table A.1 presents the result of the intensity of government environmental regulation. LCC showed a significant positive regression coefficient for the frequency of environmental-related words in government reports EnvFreq at the 1% level. After decomposing the words related to the environment, the regression coefficient of LCC for the frequency of the word related to low carbon and the frequency of words related to the environmental protection EnvProtection were both significantly positive, the former being five times the latter at 0.174. The regression results show that after implementing the Low-Carbon Pilot Policy, the frequency of environmental words mentioned in the work reports of the provincial governments increased significantly, thus enhancing the intensity of environmental regulation of the provincial governments and local governments, giving greater attention to the issue of low-carbon.

Table A.2
Variable definitions.

Variable	Definitions	Data sources
Dependent variables		
FDISP1	For each publicly traded firm, retain the final analyst prediction of the firm's earnings per share for the year, then divide the standard deviation of the predictions by the absolute value of the actual.	CSMAR
FDISP2	For each publicly traded firm, we retain the last two analyst predictions of the firm's Earnings Per Share for the year, then divide the standard deviation of the predicted by the absolute value of the actual.	CSMAR
FERROR1	For each publicly traded firm, we retain the final forecast of the analysts for the firm's earnings per share for the year and calculate the absolute difference between the forecasted mean earnings per share at the firm level and the actual earnings per share. This difference is then divided by the absolute value of the actual earnings per share.	CSMAR
FERROR2	For each publicly traded firm, we retain the last two analyst predictions of the firm's earnings per share for the year and calculate the absolute difference between the average of these predictions and the actual earnings per share, divided by the absolute value of the actual earnings per share.	CSMAR

(continued on next page)

Table A.2 (*continued*).

Variable	Definitions	Data sources
Other variables		
LCC	A dummy variable that equals one if the city where the firm is located in a city selected as a low-carbon pilot city and zero otherwise.	NDRC
Lev	Total liabilities over total assets.	CSMAR
Size	Natural logarithm of total assets.	CSMAR
ROA	Net income over total assets.	CSMAR
MepsVol	Earnings per share forward five-period standard deviation.	CSMAR
Surprise	The absolute value of the difference between the current year's earnings per share and the previous year's earnings per share.	CSMAR
Loss	A dummy variable that equals one if the firm has a negative net income for the year and zero otherwise.	CSMAR
Follow	The natural logarithm of one plus the total number of analysts following the firm.	CSMAR
Horizon	The natural logarithm of the median difference between the analysts' forecast time and the next year's earnings announcement date.	CSMAR
Cash	Cash over total assets.	CSMAR
BM	Total assets over market capitalization.	CSMAR
FA	Fixed assets over total assets.	CSMAR
OwnCon	The sum of the top 10 shareholders' shareholdings of the firm.	CSMAR
EPtConcept	A dummy variable that equals one if a listed firm discloses its environmental protection concept, environmental policy, environmental management organizational structure, circular economy development model, and green development, and zero otherwise.	Corporate Social Responsibility Reporting
EnvEmerge	A dummy variable that equals one if a listed firm discloses its emergency mechanisms, emergency measures, and treatment of pollutants related to environmental emergencies, and zero otherwise.	Corporate Social Responsibility Reporting
EnvReport	A dummy variable that equals one if a listed firm discloses an environmental report separately and zero otherwise.	Corporate Social Responsibility Reporting
WordyNonFeasance	A dummy variable that equals one if the environmental strategy disclosure items of a listed firm (environmental concepts, environmental goals, environmental management system, environmental education, and training, environmental emergency response mechanism, and "three simultaneous" system) exceed the industry median level of the same year, and the environmental action disclosure items (environmental special actions, environmental honors or awards, sudden environmental accidents, environmental violations, environmental petitions, whether passed ISO14001 certification, whether passed ISO9001 certification) are lower than the industry median level of the same year, and zero otherwise.	Corporate Social Responsibility Reporting
QRecord	The natural logarithm of firm-year level questions number. The number of questions was calculated by matching the text of questions in the research questionnaire with keywords related to low carbon and environmental protection.	CSMAR
Rating	The average of analysts' ratings on stocks at the firm-year level. Analysts rated the stock "Buy", "Hold", "Neutral", "Hold", and "Sell" on a scale of one to five, respectively.	CSMAR
PolluProp	The firm-level average of the proportion of research reports on heavily polluting firms issued by analysts each year.	CSMAR
EnvFreq	The frequency of environmental vocabulary (carbon dioxide, low-carbon, emissions reduction, energy consumption, green, air, ecology, PM10, PM2.5, sulfur dioxide, chemical oxygen demand, pollution, contamination, environmental protection, environmental protection) scaled by the total number of words in the government's work report.	Provincial Government Work Reports
LowCarbon	The frequency of low-carbon words (carbon dioxide, low-carbon, emission reduction, energy consumption, green, air, ecosystem) scaled by the total number of words in the government work report.	Provincial Government Work Reports
EnvProtection	The frequency of environmental vocabulary (PM10, PM2.5, sulfur dioxide, chemical oxygen demand, effluent, pollution, environmental protection, environmental protection) scaled by the total number of words in the government work report.	Provincial Government Work Reports
GDP	Gross Domestic Product.	National Bureau of Statistics
IndStru	The proportion of the manufacturing sector GDP.	National Bureau of Statistics
EduYear	Average years of schooling.	National Bureau of Statistics
HigherEdu	Higher education rate.	National Bureau of Statistics
EnvProExpense	Environmental protection expenditures over GDP.	National Bureau of Statistics
STExpense	Science and technology expenditure over GDP.	National Bureau of Statistics
EduExpense	Education expenditure over GDP.	National Bureau of Statistics
FDI	Foreign direct investment over GDP.	National Bureau of Statistics
REA	As calculated by Bhattacharya et al. (2003) and Dhaliwal et al. (2012), REA is a dummy variable that equals one if the quality of accounting information disclosure is lower than the industry average and zero otherwise.	CSMAR
ES	The earnings smoothing is calculated following Bhattacharya et al. (2003).	CSMAR
DownGrade	A dummy variable that equals one if the quality assessment results of accounting information disclosure are lower or unchanged compared to the previous year and zero otherwise.	Annual report of listed firm
JEM	Calculate the controllable profit according to the modified Jones model first, then calculate the sum of its absolute values for the preceding three periods.	CSMAR

(*continued on next page*)

Table A.2 (*continued*).

Variable	Definitions	Data sources
REM	The estimated value of the real earnings management is calculated following Dechow et al. (1998) and Roychowdhury (2006).	CSMAR
AccCom	The accounting comparability calculated following De Franco et al. (2011) and Tang et al. (2019).	CSMAR
Tobin'Q	Market value over total assets.	CSMAR
P/E	The year-end closing price of the stock scaled by net income.	CSMAR
AnnaulReturn	Annual stock return considering reinvestment of cash dividends.	CSMAR
IV	The city-level annual wind speed in year t scaled by the annual average PM 2.5 in 2011.	ACAG and NOAA
Capx	Capital expenditures scaled by lagged assets.	CSMAR
Illquid	Amihud illiquidity measure.	CSMAR
COE	Implied cost of capital estimated following Easton (2004).	CSMAR

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