Carbon Disclosure Effect, Corporate Fundamentals, and Net-zero Emission Target: Evidence from China

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ABSTRACT

Chinese companies are facing stricter policies to undergo green transformation towards national carbon neutrality. Effective management of green transformation and adaptability to climate change can impact the financial performance of companies, influencing their carbon mitigation pathways. Voluntary carbon accounting and disclosure have been adopted as effective digitization tools for green transformation. These mechanisms allow companies to communicate their environmental information to investors, who evaluate their climate risks. This study evaluates how company-level carbon emission disclosure behavior can influence financial performance. By leveraging artificial intelligence tools, including open-source intelligence and natural language processing, we have established a database containing emission disclosure information for 4,336 A-share listed Chinese companies from 2017 to 2022. Our findings indicate that carbon disclosure behavior has a positive impact on corporate financial performance. In particular, carbon disclosure increases company stock returns, return on equity, and Tobin's Q, while reducing stock price volatility. Robustness tests, including placebo tests, propensity matching scores, and two-stage least squares models support these conclusions. Furthermore, we examine the determinants of corporate carbon disclosure and find that environmental policies play a significant role in promoting disclosure. Our research emphasizes the importance of corporate carbon disclosure in enhancing adaptability to climate change, and highlights that the financial market favors companies that actively disclose their carbon emissions as a response to environmental policies. Through the application of AI-based techniques, we enhance the efficiency of collecting and analyzing enterprise-level environmental information.

1. Introduction

Corporate carbon disclosure refers to reporting a company's greenhouse gas emissions and efforts to reduce emissions. It is becoming increasingly crucial for informing stakeholder decisions on environmental impact, incentivizing sustainable practices, promoting accountability, and enhancing financial performance. The disclosure of accurate and comprehensive information on a company's carbon footprint plays a crucial role in supporting informed investment decisions and green transformation management. However, despite its importance, the level of corporate carbon disclosure remains relatively low in many countries including China.

This study aims to examine the impact of corporate carbon disclosure on financial performance, as well as the determinants of carbon disclosure in China's environmental context, while accounting for climate change resilience, green transition management, and industry-specific characteristics. Our research is motivated by the growing public concern surrounding corporate carbon emissions, and the need for companies to adapt to climate change and promote sustainable development.

Climate change is a pressing global challenge, and in response, many countries, including China, have implemented strict environmental policies to reduce carbon emissions and achieve carbon neutrality. As the world's largest carbon emitter, China has been actively addressing climate change in recent years. In 2020, China announced its "dual carbon" policy to peak carbon emissions before 2030 and achieve carbon neutrality by 2060 (Liu and Zhang, 2022). To achieve these goals, China launched a nationwide carbon market in 2021, providing a market mechanism for corporate-level carbon emissions and quotas. These policies have prompted companies to incorporate their ability to adapt to climate change and implement green transformation management into their strategic considerations.

Public concern about corporate carbon emissions has increased interest in climate-related financial risks. In this context, accurate and comprehensive information on a company's carbon footprint is crucial in supporting informed investment decisions (Alsaifi et al., 2020). Carbon footprint is a measure of the carbon dioxide or equivalent greenhouse gas emissions associated with a product, service, or area (Onat et al., 2014). In 2022, the Stock Exchange of Hong Kong (HKEX) and the US Security & Exchange Commission (SEC) (Securities, US and Exchange Commission, 2022) proposed to enhance and standardize climate-related disclosures for investors, which require the disclosure of company-level scope 1, scope 2, and scope 3 emissions. Scope 1 and scope 2 emissions refer to direct emissions and indirect emissions generated by the company's operations, respectively. Scope 3 emissions are indirect emissions that

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are not owned or controlled by the company but are related to the company's activities. More and more countries have become aware of the importance of standardizing carbon disclosure for climate risk analysis. Federal Council in Switzerland has required mandatory climate disclosures for large companies since 1 January, 2024 (Federal Council). Accurate carbon measurement at the company level is essential for reducing emissions, supporting carbon market trading, and analyzing future climate risks businesses face.

The absence of corporate carbon disclosure data creates a conflict with the demand for carbon disclosure data from government scientific research institutions. To address this problem, this study uses advanced artificial intelligence technologies such as natural language processing (NLP) and open-source intelligence to collect and analyze ESG reports. We have established the emission disclosure information of 4336 Chinese A-share listed companies from 2017 to 2022, which enabled us to acquire carbon emission data from public reports at a company level. To our knowledge, we are the first to obtain corporate carbon emissions data by parsing public reports.

Currently, global carbon information databases mainly focus on countries and regions, with few enterprises included. Most of these databases collect carbon emission data through questionnaire collection or simulation modeling based on carbon satellite data. As one of the few organizations with enterprise-level carbon data, Carbon Disclosure Project (CDP) was also collected through questionnaires. However, their coverage rate for Chinese enterprises is low. In contrast, our database provides a rich source of data that allows us to examine the relationship between carbon disclosure behavior, climate change resilience, green transition management, industry characteristics (high-carbon vs. low-carbon), and financial performance at a granular level.

Previous studies have examined the relationship between carbon disclosure and financial performance in developed countries such as the United States and Europe, there is a research gap in the understanding of this relationship in China's unique institutional environment (Alsaifi et al., 2020; Siddique et al., 2021; Downar et al., 2021). China's institutional environment is characterized by a complex regulatory framework, the fact that many companies are state-owned, the coexistence of regional and national carbon markets, and a rapidly developing market economy. Such factors may affect the relationship between carbon disclosure and financial performance in ways different from those observed in other countries.

Therefore, this study aims to bridge this research gap by examining the impact of corporate carbon disclosure on financial performance in the Chinese unique context. Specifically, we analyze the relationship between carbon disclosure behavior and financial performance. Our study provides empirical evidence for the impact of China's carbon disclosure on financial performance. The findings have important implications for policymakers, investors, and business managers seeking to promote sustainable development while maintaining competitiveness in financial markets.

The contributions of this study are as follows. Firstly, we have established a carbon-finance database of 4336 Chinese A-share listed companies from 2017/01/01 to 2022/07/01. To the best of our knowledge, this is the first Chinese A-share company database to include carbon disclosure data after the implementation of the "Dual Carbon" target. Secondly, taking 19 different industries as our subjects, we analyze the effects of carbon disclosure on four main financial variables of Chinese A-share listed companies, including the stock return, volatility of stock price, return on equity, and Tobin's Q. We demonstrate that investors respond positively to policy breakthroughs such as the "Dual Carbon" target and the emission trading system, and reward companies with better disclosure performance. Thirdly, our research sheds light on the determinants of corporate carbon disclosure in China, and finds that environmental policies play a significant role in promoting disclosure.

The remainder of this paper proceeds as follows. Section 2 reviews literature and presents hypothesis development. Section 3 describes the data. Section 4, we present the main empirical results and interpretation. Section 5 concludes and proposes policy implications.

2. Relevant Literature Review and Hypothesis

2.1. The Indicator of Carbon Disclosure

In general, two main methodologies are utilized to assemble the carbon disclosure information: keyword searching and Carbon Disclosure Project (CDP) directory data. Regarding CDP directory data, corporate carbon disclosure is measured according to whether a company responded to the CDP survey, or how well their answers to the survey based on the CDP Leadership Index (CDLI) (Luo et al., 2014; Lu et al., 2021; Luo et al., 2012). CDP is a not-for-profit charity that runs the global disclosure system and pressures companies to report their efforts and performance of GHG emissions. Luo et al. (2014) showed that firms' voluntary carbon disclosure in the CDP indicates their underlying actual carbon performance. CDP annually scores companies to evaluate their environmental disclosure. Scores are calculated using a standardized method that measures whether and how well a company responds to each question, such as disclosure of its current position, awareness of its environmental impact, management, and leadership. However, a company is awarded points if it reports its greenhouse gas emissions, but the actual amount of emissions do not affect its score. Meanwhile, the coverage rate of Chinese enterprises is relatively low. About 100 Chinese companies or organizations in the CDP data set disclosed data through CDP. CDP directory data only covers the voluntary carbon disclosure of companies with large asset scales and represents the insufficient range of industries worldwide.

Keyword searching is the other methodology to measure the carbon disclosure information, which utilizes words and phrases such as *carbon disclosure*, *carbon reporting* and *greenhouse gas emissions disclosure* in public reports, including sustainability or environmental reports, annual reports, and corporate homepages (Borghei, 2021). It takes a lot of work to search thousands of companies for keywords related to carbon disclosure. This method requires summarizing all relevant keywords as completely as possible so it may be prone to subjective bias. Considering the substantial human workload of collecting textual information, Karim et al. (2021) used computerized textual analysis to score the carbon emission disclosure level in the annual reports covering UK FTSE All-share non-financial firms from 2013 to 2019. However, their data is not comprehensive enough. The CFIE, the scoring software used in their research, only captures the textual information in the text but not in tabular or images. It is unsuitable for analyzing Hong Kong and A-share listed companies. They are more likely to organize such emission information in tables according to Global Reporting Initiative (GRI) framework or other ESG reporting standards.

2.2. The Impact of Carbon Disclosure on Corporate Performance

Carbon accounting and disclosure play a crucial role in corporate environmental performance management and information transparency. Studies have found a positive relationship between carbon disclosure and environmental performance, suggesting that voluntary carbon disclosure is reflective of a firm's actual carbon performance (Luo and Tang, 2014). The relationship between corporate environmental performance (CEP) and corporate financial performance (CFP) has also been studied, with a number of researchers finding a positive correlation between the two (Dixon-Fowler et al., 2013; Endrikat et al., 2014; Endrikat, 2016; Fujii et al., 2013; Alsaifi et al., 2020). Carbon disclosure can also improve the allocation of resources in the capital market by reducing the information asymmetry between external investors and corporate insiders (Bae et al., 2018).

Proactive climate measures, carbon disclosures, and the development of climate-friendly products can enhance a company's image and reduce risks related to climate change (Sullivan and Gouldson, 2012; McLaughlin, 2011). However, the impact of carbon disclosure on companies is not always positive. Some studies suggest that negative environmental performance is met with a stronger market response compared to positive performance (Endrikat, 2016; Lee et al., 2015). In such cases, companies may choose not to disclose negative emissions information (Healy and Palepu, 2001). Additionally, disclosure costs can violate the principle of capital maximization as companies may be required to increase their environmental spending and invest limited resources in environmental protection (Reverte, 2009; Karpoff et al., 2005; Eccles et al., 2014). Therefore, we hypothesize:

H1. With the implementation of the dual carbon policy, our hypothesis is that carbon disclosure can positively impact a company's financial performance.

2.3. Determinants of Carbon Disclosure

Previous literature has discussed several determinants of corporate carbon disclosure, including the legitimacy theory, stakeholder theory, and economics-based theories of voluntary carbon disclosures. Carbon disclosure can be divided into two categories: mandatory and voluntary.

From the legitimacy theory perspective, carbon disclosure is a reaction to external pressure, such as legislation implemented by governments or rule makers (Pattern, 2002). Companies are determined to disclose carbon information to prove that their behavior conforms to social values. At this time, the company tends to disclose relevant information, which is self-interested behavior in which enterprises defend their legitimacy (Tang et al., 2020). Li et al. (2018) explored the influence of environmental legitimacy on corporate carbon disclosure and investigated the role of green innovation as a mediator. Deegan et al. (2002) illustrate how environmental disclosure can be used to maintain the implicit social contract between a company and society. Therefore, firm participation in carbon disclosure strongly depends on the national context (Grauel and Gotthardt, 2016). Luo et al. (2022) investigated the negative relationship between the intensity of product market competition and carbon disclosure and explored the moderating effect of earnings pressure and environmental legitimacy pressure on this relationship.

According to stakeholder theory, carbon disclosure can also be explained as a response to stakeholder demand for information on climate change as a pressing societal issue (Roberts, 1992). Companies establish a good corporate image by disclosing carbon information, responding to public pressure, and avoiding conflict with stakeholders. Luo et al. (2012) found that corporate carbon disclosure was correlated with social, economic, and legal/institutional pressures, and the attitude of the general public and government appeared to be the decisive determinants. In China, the Ministry of Ecology and Environment has issued regulations to encourage environmental disclosure by companies, but these regulations only apply to firms and institutions listed as key pollutant emission units (Li et al., 2019). The launch of the national/regional carbon market has made it necessary for emission-controlling companies to report their carbon emissions, although the data is not required to be made public. Nevertheless, the carbon market plays a significant role in regulating carbon emissions for companies participating in the trading system. The dual carbon target set by the Chinese government signals the country's intention to turn its focus on emission reduction into a national strategy, potentially increasing the pressure on enterprises to reduce their carbon emission. Despite mandatory environmental disclosure regulations, only a small proportion of Chinese companies are required to disclose their carbon information. The majority of Chinese companies engage in voluntary carbon disclosure and corporate social responsibility initiatives. He and Shen (2019) explored the impact of external pressure and internal governance on carbon information disclosure for listed companies from 2009 to 2015 in China.

In terms of voluntary disclosure, economics-based theories suggest that companies voluntarily disclose information to interested actors based on evaluating costs and benefits (Verrecchina et al., 2001; Clarkson et al., 2008). The capital markets transactions hypothesis assumes that managers have incentives to provide voluntary disclosure to reduce the information asymmetry problem, thereby reducing the firm's external financing cost and attracting investment funds (Deegan, 2002; Healy and Palepu, 2001). Li et al. (2019) enriched the motivation research of carbon disclosure with four new incentives: proprietary cost motivation, financing motivation, sense-making motivation and self-interested motivation. This means that a company's willingness to disclose carbon emission data will increase if it is confident in its data and believes it will be beneficial. Yu et al. (2020) explored the drivers of voluntary carbon disclosure among Chinese firms, including firm size, and profitability. Besides, results showed that SOE block holder and high carbon emission industries are significantly more dedicated to carbon disclosure. The results of the research show a positive relationship between capital expenditure and carbon emission disclosure, and internal governance strengthens the relationship (Karpoff et al., 2021). Also, there is a significant positive relationship between internal governance and carbon emission disclosure. Besides, Luo et al. (2014) examined whether voluntary carbon disclosure reflects firms' true carbon performance and showed a significant positive association between carbon disclosure and performance. He et al. (2021) found that female directors have a positive association with carbon information disclosure. Therefore, we hypothesize:

H2. The likelihood of carbon disclosure can be increased by various factors, including research and development costs (R&D), overseas listing status (Overseas), participation in the national/regional carbon market (Carbon market), being a state-owned enterprise (State-owned), and the timing of the dual-carbon targets release (Post^{dual}).

3. Data

3.1. Financial database with carbon disclosure data

In contrast to developed countries, there has been limited research and public data available on the disclosure of carbon emissions data for Chinese companies. The national authoritative department (www.mee.gov.cn) only provides data up to 2014, and the China Carbon Emissions Database (CEADs) developed by Chinese research institutes only includes data up to 2015. In order to address this gap, we created a financial database of Chinese A-share listed companies that contain updated carbon emissions data up to June 2022. For the purposes of this study, "carbon disclosure" is defined as the standardized reporting of specific data on carbon emissions in environmental reports.

3.1.1. Implementation technology

To construct a financial database of Chinese A-share listed companies that include up-to-date carbon emission data, we propose a four-step process as illustrated in Fig. 1. First, we obtained the download links of all environmental reports of A-share companies from January 1, 2018 to June

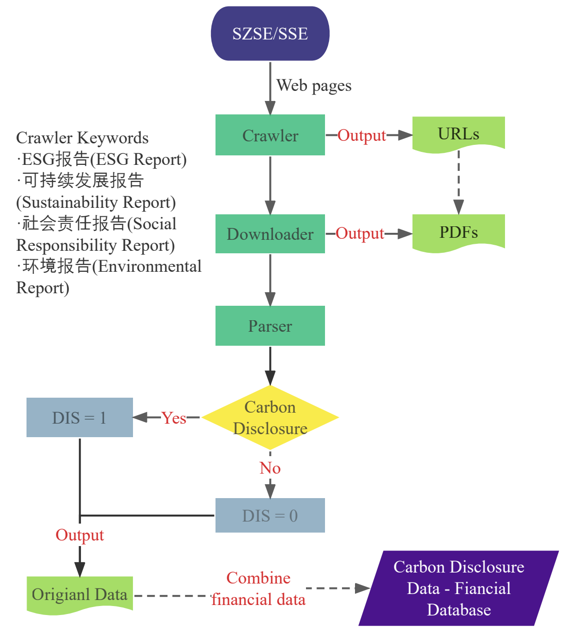


Figure 1: Flow chart of building carbon disclosure data-financial database

1, 2022 from the official websites of the Shenzhen and Shanghai Stock Exchanges using Python crawler scripts. Next, we downloaded the pdf files of these reports to our local hard drive. To extract the carbon disclosure information, we utilized the Python third-party library pdfplumber, which is well-suited for analyzing machine-generated PDFs that utilize wireframe complete forms for carbon information disclosure. The process of parsing the pdf files is inspired by Tabula, and follows a series of steps to detect and group the cells that contain carbon information. We then combined the extracted carbon information with the financial information obtained from China Stock Market & Accounting Research (CSMAR) into a new database.

In order to accurately identify and extract the carbon disclosure information from the pdf files, we designed a rule-based algorithm as outlined in Alg. 1. Our algorithm takes as inputs the paths to pdf files of ESG reports and chosen keywords, which are listed in Table 1. The first row of the table explains the meaning of the corresponding keyword expressions, which can take various forms within the reports. The output of the algorithm is an Excel file containing dummy variables for carbon disclosure information.

To determine whether a page may contain carbon disclosure, we used the *extract_text* method in pdfplumber to obtain the content string of each page of the pdf file, and checked whether the content string contained any of the keywords. If a page object contained keywords, we used the *extract_tables* method to parse the tables on the page into a Python list format. If these tables contained numerical data or numeric information with commas, we identified that carbon disclosure had been performed. Our algorithm enabled us to efficiently and accurately extract the carbon

Table 1
Carbon Disclosure Information Keywords (Mainly)

Meaning	Emission of greenhouse gases	Scope 1 emission	Scope 2 emission
	Total greenhouse gas emissions (Scopes 1, 2, and 3)	Direct greenhouse gas emissions (Scope 1)	Indirect energy-related greenhouse gas emissions (Scope 2)
	Total greenhouse gas emissions (Scopes 1 and 2)	Scope 1 greenhouse gas emissions	Scope 2 location-based greenhouse gas emissions
	Total greenhouse gas emissions (Scopes 1 and 2)	Total greenhouse gas emissions (Scope 1)	Total greenhouse gas emissions (Scope 2)
	Total greenhouse gas emissions	Direct greenhouse gas emissions (Scope 1)	Indirect greenhouse gas emissions (Scope 2)
Keywords	Carbon emissions	Scope 1: Direct greenhouse gas emissions	Scope 2: Indirect greenhouse gas emissions
	Greenhouse gas emissions	Scope 1 greenhouse gas emissions	Scope 2 greenhouse gas emissions
	Total greenhouse gas emissions	Scope 1 CO_2 emissions	Scope 2 CO_2 emissions
	CO_2 emissions	Scope 1 greenhouse gas emissions	Scope 2 greenhouse gas emissions
	Greenhouse gas emissions	Scope 1: Direct greenhouse gas emissions	Scope 2: Indirect greenhouse gas emissions

This paper analyzes the Chinese report, so the keywords are in Chinese. The first row of the table represents the meaning of the corresponding keywords expression. For the same meaning, there may be many different expressions in the reports.

information from a large volume of pdf files, providing the foundation for constructing our financial database of Chinese A-share listed companies.

Algorithm 1 Rule-based Carbon Disclosure Judgment Algorithm

Require: Paths to pdf files P_s; keywords K
Ensure: Dummy variables indicating whether companies have carbon disclosures
Initialization: Initialize an empty list $output$ to store the dummy variables

```
for P in Ps do
    Open the file specified by P
    Set the dummy variable DIS to 0
    for p in the pages of the opened file do
        Use the extract_text method to get the content string cs
        if any keyword of K in cs then
            Use the extract_tables method to get a list Ts indicating the tables in page p
            for T in Ts do
                if the length of T != 1 then
                    if any word in the table is numerical data or numeric information with commas then
                        Set DIS to 1 and abort retrieval of this file
                    end if
                else
                    if any word in the table is numerical data or numeric information with commas then
                        Set DIS to 1 and abort retrieval of this file
                    end if
                end if
            end for
        end if
    end for
    Store DIS in output
end for
```

3.2. Data and variables

3.2.1. Dependent variable

In our study, we investigate the relationship between carbon disclosure and financial performance. We focus on four dependent variables that capture different aspects of financial performance: rate of return, stock volatility, return on equity (ROE), and Tobin's Q.

Return on stock price is a key measure of the change in the value of a stock over a specific period of time. It reflects a company's stock performance and its impact on investor returns. It focuses on the past performance of a business and its impact on investor returns.

Stock volatility is a measure of stock price fluctuations over a given period of time. As a key indicator of stock risk, higher volatility is often associated with greater investment risk. This variable focuses on measuring potential risks involved in investing in a stock and the market's perception of the company's future performance.

Return on equity (ROE) is a widely used ratio that measures a company's net income relative to its total equity. It is an important indicator of a company's profitability and reflects the level of compensation received by owners' equity. This variable focuses on a company's current profitability and its ability to generate returns for shareholders.

Tobin's Q measures a company's market value relative to its replacement cost. It is often used to gauge a company's overall financial performance and its ability to generate returns for shareholders. Generally, the higher Tobin's Q of an enterprise, the greater its development potential. This variable focuses on a company's potential for future growth.

In conclusion, rate of return, stock volatility, ROE, and Tobin's Q are four key dependent variables in finance and economics research that provide valuable insights into various aspects of a company's financial performance.

3.2.2. Control variables

To control for other factors that may influence financial performance, we include four control variables in our analysis: company size, fixed asset turnover (FAT), total assets turnover (TAT), and current ratio (CR).

Size: Company size is often measured by the log of total assets, which is a commonly used control variable in finance and accounting research. According to Hart and Banbury (1994), larger companies may have a different level of resources and economies of scale that can impact their financial performance.

Fixed asset turnover (FAT) measures the efficiency of a company's use of its fixed assets to generate revenue. According to Al-ANI (2013), a high FAT indicates a company is effectively utilizing its fixed assets to generate revenue, while a low FAT may indicate inefficiencies in the use of fixed assets. As such, controlling for FAT helps isolate the effect of carbon disclosure on financial performance by taking into account a company's efficiency in using its fixed assets.

Total assets turnover (TAT) measures a company's ability to generate revenue from its total assets. According to Hapsoro and Husain (2019), a high TAT indicates a company is effectively using all its assets to generate revenue, while a low TAT may indicate inefficiencies in the use of assets. By controlling for TAT, this study aims to isolate the effect of carbon disclosure on financial performance by taking into account a company's overall efficiency in using its assets.

Current ratio (CR) is a measure of a company's ability to pay its short-term obligations with its current assets. According to Saleem and Rehman (2011), a high CR indicates a company has sufficient liquid assets to meet its short-term obligations, while a low CR may indicate financial stress and difficulty in meeting short-term obligations. Therefore, controlling current assets is conducive to studying the impact on the company's financial performance.

In conclusion, controlling for company size, fixed asset turnover, total assets turnover, and current ratio allows this study to isolate the effect of carbon disclosure on financial performance and avoid potential confounding effects from other factors that may impact financial performance.

The detailed variable definitions are provided in the Table 2.

3.2.3. Sample and descriptive statistics

Our sample consists of 2,298 Chinese A-share companies listed from 2018 to 2022, obtained from a combination of sources including CSMAR, the Shanghai and Shenzhen Stock Exchanges, China National Knowledge Infrastructure (CNKI), and Wind Financial Database. In order to ensure data quality, companies that were not listed on the Shanghai and Shenzhen A-shares, underwent special treatment, or lacked necessary data for our analysis, as well as those in the finance and financial services industries, were excluded from the sample.

The industries of the sample companies were classified based on the system established by the China Securities Regulatory Commission (CSRC) and China's eight major industry sectors. This classification divided the sample into high-carbon industries and low-carbon industries, with the latter further divided into non-financial and financial industries. This classification system is considered to be more scientifically sound as it takes into account both industry characteristics and emission intensity.

Table 3 provides the descriptive statistics of the main variables included in our analysis.

4. Empirical results

4.1. Baseline regression result

To assess the impact of carbon disclosure on corporate financial performance, we employ a fixed-effects difference-in-difference (DID) approach. To do so, we categorize firms into two groups based on their level of carbon emissions: high-carbon industries and low-carbon industries. At the same time, with the proposal of the dual carbon target as the boundary, two periods are divided, from January 1, 2018 to June 30, 2020, and from October 1, 2020 to December 31, 2021. Such a grouping allows us to explore the impact of carbon disclosure on companies in different industries before and after the dual carbon targets are proposed.

We use the fixed-effects difference-in-difference (DID) approach to assess the impact of carbon disclosure on financial performance, using *return*, *volatility*, *return on equity (ROE)*, and *Tobin's Q* as the dependent variable, the company's carbon disclosure is used as the independent variable. The model form is as follows:

when $t \in [2018Q1, 2020Q2]$,

$$Y_{i,t} = \alpha_0 + \beta_1 Treat_i^1 \times post_t^{dis} + \gamma Z_{i,t} + \delta_t + \varphi_i + \varepsilon_{i,t} \tag{1}$$

when $t \in [2020Q4, 2021Q4]$,

$$Y_{i,t} = \alpha_0 + \beta_1 Treat_i^2 \times post_t^{dis} + \gamma Z_{i,t} + \delta_t + \varphi_i + \varepsilon_{i,t} \tag{2}$$

where $Treat_i^1$ ($Treat_i^2$) assumes a value of one if a firm has made carbon disclosure between 2018Q1 and 2020Q2 (2020Q4 and 2021Q4); otherwise, its value is zero. $post_t^{dis}$ is a dummy variable equal to 1 after firm i has made carbon disclosure; otherwise, its value is zero. i indexes the firm, and t indexes the quarter. $Y_{i,t}$ represents *Return*, *Vol*, *ROE* and *Tobin's Q*. $Z_{i,t}$ denotes a vector of control variables (*TAT*, *FAT*, *CR*, *ALR*, *Size*). δ_t represents the time fixed effect, φ_i represents the entity fixed effects, and $\varepsilon_{i,t}$ represents the random error item.

Table 2
Variable definition

Variable	Definition	Data Source
$Treat^{National}$	Dummy variable for inclusion in national carbon market. If included in the national carbon market, its value is one; otherwise, its value is zero.	National ecological environment bureau
$Treat^{local}$	Dummy variable for inclusion in local carbon markets. If included in the local carbon market, its value is one; otherwise, its value is zero.	local ecological environment bureau
$Post^{local}$	Dummy variable taking the value of one after being included in the local carbon market, zero otherwise.	local ecological environment bureau
$Treat^{DIS}$	Dummy variable for carbon emission information disclosure. If a disclosure is made, its value is one; otherwise, its value is zero.	Official website of SSE and SZSE
$Post^{dis}$	Dummy variable taking the value of one after after carbon emission information disclosure, zero otherwise.	Official website of SSE and SZSE
$Post^{dual}$	Dummy variable taking the value of one after being included in the local carbon market, zero otherwise.	
High-carbon	Dummy variable for industry classification. If a company is in high-carbon industries, its value is one; otherwise, its value is zero.	Wind
Return	Rate of return; the calculation period is weekly, calculated from the equal weighted average.	Wind
Ln(Price)	Log value of stock price; the calculation period is daily, calculated from the equal weighted average.	Wind
Vol	Volatility; the calculation period is weekly.	Wind
VaR	Value-at-risk; the calculation period is weekly, and the confidence level is 95%.	Wind
ROE	Return on equity	Wind
FAT	Fixed asset turnover	Wind
TAT	Total assets turnover	Wind
CR	Current ratio	Wind
ALR	Asset liability ratio	Wind
Size	Log value of total asset; Total asset is measured in CNY.	Wind
R&D	Log value of R&D expense; R&D expense is measured in CNY.	Wind
Oversea	Dummy variable for overseas listing. If listed overseas, its value is one; otherwise, its value is zero.	Wind
State-owned	Dummy variable for whether it is a state-owned company. If it is a state-owned company, its value is one; otherwise, its value is zero.	Wind
Tobin's Q	Market value divided by assets' replacement cost.	CSMAR

Table 3
Summary statistics

Variable	N	Mean	S.D.	Min	25%	Median	75%	Max
Nation carbon market	90896	0.0054	0.0735	0	0	0	0	1
Local carbon market	90896	0.0178	0.1321	0	0	0	0	1
Post local	90896	0.0137	0.1164	0	0	0	0	1
DIS	90896	0.0353	0.1846	0	0	0	0	1
Post dis	90896	0.0161	0.1259	0	0	0	0	1
Post dual	90896	0.3684	0.4824	0	0	0	1	1
High-carbon	90896	0.7584	0.4281	0	1	1	1	1
Return	71059	0.2262	4.2195	-93.8819	-0.1802	-0.0023	0.2215	635.0785
Vol	71106	6.5956	101.5892	0.0000	3.9222	5.3750	7.3604	27045.2240
VaR	71846	7.5949	4.0044	-61.0903	4.9696	7.1173	9.6755	74.5523
ROE	77588	0.0272	1.8425	-186.5570	0.0124	0.0404	0.0863	281.9892
FAT	82904	14.9880	312.3227	-19.2507	0.9216	2.1136	4.9291	55200.7410
TAT	80258	0.4295	0.4429	-0.1383	0.1527	0.3148	0.5673	11.9755
CR	80255	2.7522	3.6187	0.0055	1.2301	1.7834	2.9840	235.4652
ALR	80295	41.8940	98.3184	0.6171	24.5952	39.7723	55.2340	19173.8860
Size	79821	22.0597	1.4365	15.3766	21.0668	21.9036	22.8694	28.6364
R&D	60027	16.4680	1.6233	-4.6052	15.5880	16.4640	17.4084	23.6736
Oversea	90896	0.0383	0.1918	0	0	0	0	1
State-owned	90896	0.2184	0.4131	0	0	0	0	1
TobinQ	70774	2.0323	2.0864	0.0162	1.2120	1.5570	2.1766	129.9253

This table presents the summary statistics of the variables in our main analysis for the mean, median, standard deviation (STD), minimum (Min), 25% percentile (Q1), 75% percentile (Q3) and maximum (Max) distributions. Variable definitions are detailed in Table ??.

Table 4
Panel A: Effect of disclosure on high-carbon industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Before dual-carbon targets: 2018/01/01 - 2020/06/30				After dual-carbon targets: 2020/10/01 - 2021/12/31			
Variables	Return	Vol	ROE	Tobin's Q	Return	Vol	ROE	Tobin's Q
$post \times treat_1$	-0.0295	-0.0445	-0.0129	0.076				
	(-0.52)	(-0.23)	(-0.73)	(0.70)				
$post \times treat_2$					**0.176***	**-0.650***	**0.0616***	**0.357****
					(1.74)	(-1.95)	(1.91)	(2.35)
FAT	-0.00000139	-0.0000580***	-0.00000979*	0.00000261	-0.0000457**	-0.000261***	-0.0000492	-0.0000637***
	(-0.60)	(-11.74)	(-1.98)	(0.30)	(-3.21)	(-13.28)	(-1.10)	(-7.49)
TAT	0.0813	0.367**	0.187	0.130***	0.0207	0.303	0.332**	0.171***
	(1.75)	(3.23)	(1.05)	(2.78)	(0.12)	(1.57)	(2.84)	(3.51)
CR	-0.0183*	0.0269*	-0.0195**	-0.0149	0.0425	0.0521*	-0.0216	-0.0254**
	(2.13)	(1.96)	(-3.25)	(-0.78)	(1.21)	(2.26)	(-1.08)	(-2.06)
ALR	0.000101	-0.000365	-0.0174***	0.00607*	0.0000413	0.0000360	-0.0160	0.00604***
	(1.26)	(-0.35)	(-3.35)	(1.93)	(0.95)	(0.54)	(-0.66)	(255.69)
Size	-0.0630*	-0.622***	0.295**	-1.952*	0.239	0.699	0.689*	-0.953***
	(-2.55)	(-13.64)	(2.64)	(-1.79)	(0.91)	(1.66)	(2.24)	(-6.52)
Company fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25877	26120	28865	26143	16215	16035	17413	16039

Panel B: Effect of disclosure on low-carbon industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Before dual-carbon targets: 2018/01/01 - 2020/06/30				After dual-carbon targets: 2020/10/01 - 2021/12/31			
Variables	Return	Vol	ROE	Tobin's Q	Return	Vol	ROE	Tobin's Q
$post \times treat_1$	0.0289	-0.737	-0.0603	**1.430****				
	(0.22)	(-1.20)	(-0.83)	(2.56)				
$post \times treat_2$					0.108	-0.00761	0.0150	1.122
					(0.59)	(-0.01)	(0.25)	(1.22)
FAT	0.000173	-0.0000575	-0.000133	-0.000502*	0.000484	-0.000635	-0.0000629	-0.000175*
	(1.85)	(-0.28)	(-1.38)	(-1.81)	(0.88)	(-1.47)	(-1.48)	(-1.84)
TAT	-0.0451	-0.0593	0.0949	0.0032	-0.363	0.0348	0.101*	-0.0523
	(-1.34)	(-0.67)	(1.24)	(0.13)	(-0.60)	(0.19)	(1.98)	(-1.14)
CR	0.0340**	0.0435*	-0.0125	0.00330	-0.0125	0.0278	-0.0338***	-0.0137
	(2.67)	(2.48)	(-0.46)	(0.14)	(-0.31)	(1.19)	(-3.43)	(-1.09)
ALR	-0.000962	-0.000434	-0.0243	0.00668**	-0.000651	0.000491	-0.0267***	0.0138***
	(-1.37)	(-0.17)	(-1.65)	(2.75)	(-0.23)	(0.12)	(-4.36)	(3.78)
Size	-0.146**	-0.627***	0.487	-1.416**	-0.823*	-0.0158	0.554***	-1.671***
	(-3.22)	(-8.81)	(1.91)	(-3.34)	(-2.35)	(-0.04)	(3.86)	(-6.15)
Company fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8635	8684	9451	8684	5189	5137	5547	5137

This table reports the results of the DID analysis designed to test the impact of disclosure on high-carbon and low-carbon industries. Variable definitions are reported in Appendix A. All regressions include company and Quarter fixed effects. The t-statistics reported in parentheses are based on standard errors clustered at the company level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

The results of the regression analysis are presented in Table 4. Columns (1) and (5) use the rate of return to evaluate stock market performance, while columns (2) and (6) use volatility to assess the risk performance of the stock market. Columns (3) and (7) use ROE to gauge the fundamental performance, and Columns (4) and (8) use Tobin's Q to reflect the market's expectations for a company's future profit.

Our findings suggest that carbon disclosure has a significant impact on the financial performance of high-carbon industries after the implementation of the dual carbon targets. Prior to the implementation of the dual carbon targets, there was no significant change in financial performance for high-carbon industries. However, after the implementation of the dual carbon targets, the return rate of companies that disclosed carbon information increased significantly by 0.176, while the risk index (Vol) decreased significantly by 0.650. Additionally, ROE increased significantly by 0.0616, and Tobin's Q increased significantly by 0.357. These positive effects can be attributed to the reduction of the information gap between investors and company management, the enhancement of the company's ability to deal with future climate risks, and the increase in investor confidence resulting from carbon information disclosure.

For low-carbon industries, our results show almost no significant change in financial performance before and after the implementation of the dual carbon targets. The reason for the difference between high-carbon and low-carbon industries may be due to the greater vulnerability of high-carbon industries to climate risks in the context of dual-carbon targets. Overall, our findings highlight the importance of carbon disclosure in improving the financial performance of high-carbon industries. Encourage carbon information disclosure to increase transparency and reduce information asymmetry between companies and investors to increase corporate climate change resilience.

4.2. Dynamic effects model

To alleviate our results are driven by reverse causation and examine the dynamic impact of carbon disclosure on corporate financial performance. We used the dynamic effects model. We included lagged dependent variables in the model as explanatory variables to reflect dynamic effects in our panel data analysis, an approach that has been widely adopted in studies examining the relationship between corporate environmental performance and financial performance (Elsayed and Paton, 2005). Specifically, our dynamic effect test not only compares the difference between groups before the policy event, but also considers the differences between groups after the event. If the cross-items before period 0 (including period 0) are significant, it indicates that our model passes the parallel trend test. If the cross-items after period 0 (including period 0) are significant, it indicates that the policy implementation has a lasting effect. The form of the model is as follows:

$$
\begin{aligned}
Y_{i,t} = {} & \alpha_0 + \beta_1 Treat_i \times Before_{i,t}^{-4} + \beta_2 Treat_i \times Before_{i,t}^{-3} \\
& + \beta_3 Treat_i \times Before_{i,t}^{-2} + \beta_4 Treat_i \times Before_{i,t}^{-1} \\
& + \beta_5 Treat_i \times Current_{i,t}^{0} + \beta_6 Treat_i \times After_{i,t}^{1} \\
& + \beta_7 Treat_i \times After_{i,t}^{2} + \beta_8 Treat_i \times After_{i,t}^{3} \\
& + \beta_9 Treat_i \times After_{i,t}^{4} + \gamma Z_{i,t} + \delta_t + \varphi_i + \varepsilon_{i,t} \qquad (3)
\end{aligned}
$$

where $Before_{i,t}^{-4}$ ($Before_{i,t}^{-3}$, $Before_{i,t}^{-2}$ or $Before_{i,t}^{-1}$) is assigned a value of 1 if the observation is made four quarters (three quarters, two quarters, or one quarter) prior to carbon information disclosure and 0 otherwise. $Current_{i,t}^{0}$ is assigned a value of 1 if the observation is made in the quarter of carbon information disclosure and 0 otherwise. And $After_{i,t}^{-4}$ ($After_{i,t}^{-3}$, $After_{i,t}^{-2}$ or $After_{i,t}^{-1}$) is assigned a value of 1 if the observation is made four quarters (three quarters, two quarters, or one quarter) after carbon information disclosure and 0 otherwise. All other variables are the same as those described in the baseline DID regression.

Fig. 2 and Fig. 3 show the dynamic effects of carbon information disclosure before and after the dual-carbon targets, respectively. To verify the parallel trends assumption, we studied the coefficients β_1, β_2, β_3, and β_4. Our findings indicate that, in most cases, the coefficients are not significant even at a 90% confidence level, particularly after the dual-carbon targets have been implemented, indicating that the parallel assumption of DID holds and alleviates the concern of reverse causation to some extent.

To illustrate the persistent impact of carbon disclosure on corporate financial performance, we focused on coefficients β_5, β_6, β_7, β_8, and β_9. We found that before the dual-carbon targets, companies that disclosed carbon information had a persistent impact on Tobin's Q, but not on other dependent variables. This suggests that even before the dual-carbon targets, the financial market was aware of the better development potential of companies that disclosed carbon information.

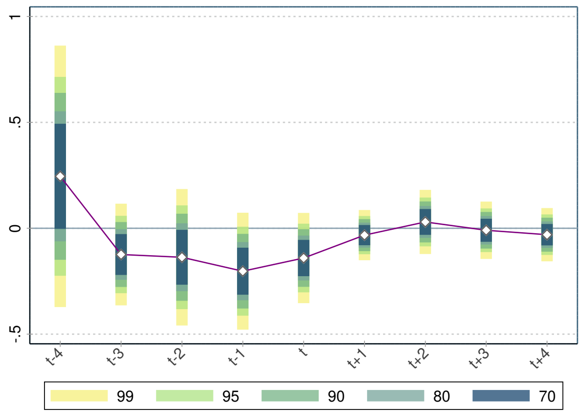
After the dual-carbon targets, we found that both $return$ and ROE had a significant and persistent positive effect, while $Tobin'sQ$ had a short-term positive effect but no obvious persistence. Additionally, Vol showed a significant negative effect after a period of time. These results indicate that after the dual-carbon targets, companies that made carbon disclosure had sustained positive advantages in the stock and financial markets, with increased development potential in the short term and decreased stock market risk.

Overall, our findings suggest that carbon disclosure can give companies a sustainable competitive advantage.

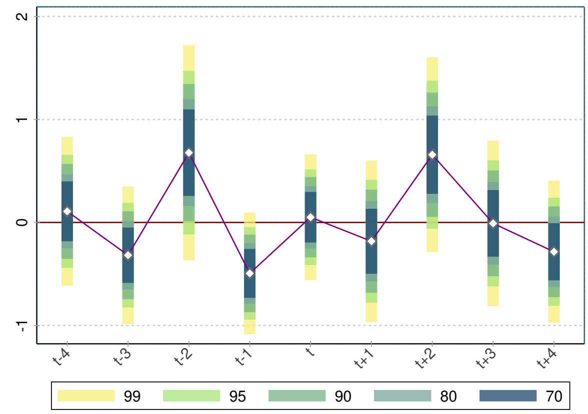
4.3. Identification issues and robustness checks

4.3.1. Placebo tests

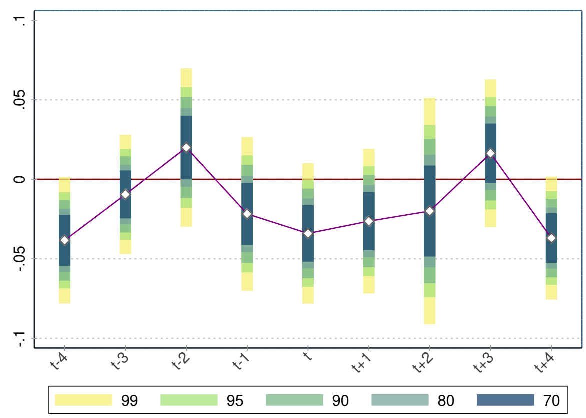
To avoid the possibility of our DID analysis results being accidental, we performed a placebo test. The traditional placebo test randomly selects the same number of companies as the experimental groups as the "pseudo-treatment group" and the remaining companies as the control group, then generates "pseudo-policy dummy variables" for regression. This method is suitable for the classic DID model where policy times are consistent, but it is not applicable in our case



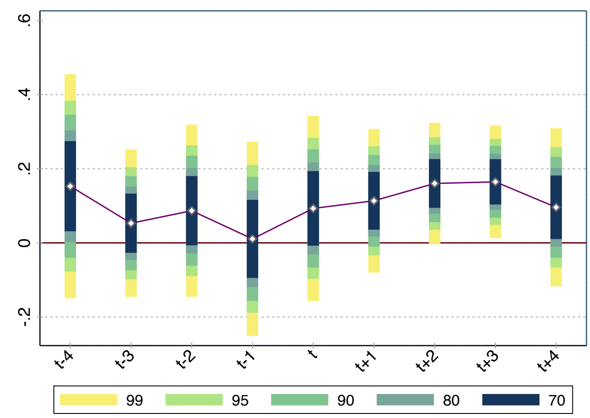
(a) Return



(b) Volatility



(c) ROE



(d) Tobin's Q

Figure 2: The dynamic effect of carbon information disclosure before the dual-carbon targets

of time-varying DID where each unit has a different policy time.

Therefore, we first recorded the disclosure times of all the original experimental group samples and then randomly assigned these disclosure times to other companies. The selected companies became the experimental group, and the disclosure time was their selected time. By randomly assigning the treatment and control groups, we expected the impact of the "pseudo-policy dummy variables" on stock prices to be zero, otherwise, the policy effects we obtained in the previous section would be unreliable (Li et al., 2021). Additionally, if carbon disclosure does indeed have a positive impact on stock prices, we would expect the truly estimated coefficients to be greater than the placebo effect.

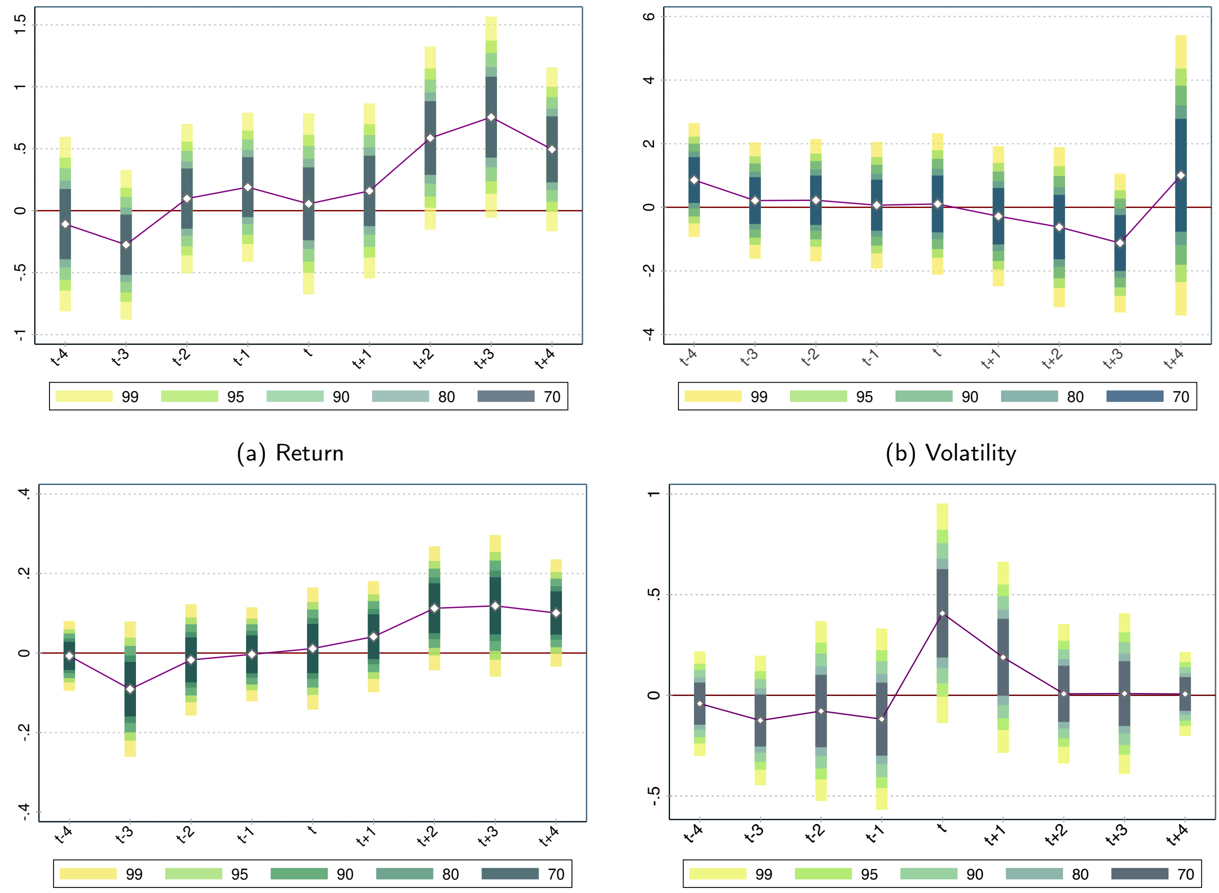
We repeated the process 500 times, and the results are presented in Table 5. The table summarizes the distribution of the coefficients of $Treat \times Post$ from the DID regressions by reporting the mean, 5th percentile, 25th percentile, median, 75th percentile, and 95th percentile. Our findings show that the estimated coefficients are mostly centered around zero, and most p-values are greater than 0.05 (not significant at the 5% level). This suggests that our results are unlikely to have been obtained by chance and are therefore robust, not affected by other policies or random factors.

4.3.2. *Propensity score matching*

To estimate the treatment effect with reduced selection bias and endogeneity, we employ the Propensity Score Matching-Difference-in-Differences (PSM-DID) method. This technique uses observational data to analyze the impact of interventions and is rooted in logistic regression. The propensity score represents the probability of a sample being part of the treatment group, and by matching these scores, PSM helps ensure that the treatment and control groups are similar in terms of observed characteristics.

In this study, we enhance the robustness of our results by applying PSM in conjunction with the Difference-in-Differences (DID) model. The equation used in our analysis is given below. We use the expectation operator (denoted by E(·)), and the parameters $\Delta API^{1}i,t$ and $\Delta API^{0}i,t$ represent the relative financial performance change in the treatment and control groups, respectively. The parameter $E(\Delta API^{0}i,t \mid DISi = 1)$ is a "counterfactual" that indicates the change in financial performance if the company did not make a carbon disclosure.

$$ATT_{i,t} = E(\Delta API^{1}_{i,t} \mid DIS_i = 1) - E(\Delta API^{0}_{i,t} \mid DIS_i = 1) \tag{4}$$



(a) Return (b) Volatility (c) ROE (d) Tobin's Q

Figure 3: The dynamic effect of carbon information disclosure after the dual-carbon targets

Table 5
Placebo test

Variable	Actual	Mean	p5	p10	p25	p50	p75	p90	p95
Return	**0.176***	-0.0206	-1.023	-0.5266	-0.1913	-0.018	0.1461	0.4501	1.0157
Vol	**-0.650***	0.0068	-0.7703*	-0.5691	-0.282	-0.0078	0.2875	0.5803	0.7974*
ROE	**0.0616***	-0.0126	-0.1943	-0.0717	-0.0207	-0.0012	0.0158	0.047	0.0953
Tobin's Q	**0.252***	-0.0017	-0.1606	-0.1174	-0.0600	-0.0047	0.0574	0.1216	0.1594

***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 6
The Pseudo R^2 and Joint Statistical Significance of the Covariate Propensity Score

Type	Pseudo R^2	LR chi2	P>chi2
Unmatched	0.271	1444.96	0.000
Matched	0.000	0.52	0.992

To match the samples, we used the radius matching method (with a radius of 0.001). After matching, we checked the balance of the distribution of covariates between the experimental and control groups, and the results are shown in Table 7. We also report the pseudo R^2 and joint statistical significance of the covariate propensity score in Table 6. As can be seen from Table 7, many variables had significant differences between the treatment and control groups before PSM matching, but they all became insignificant after PSM matching. The pseudo R^2 of the matched samples is close to 0 and its P-value becomes insignificant, as shown in Table 6. This suggests that the difference in economic performance between the treatment and control groups can only be attributed to the carbon disclosure after PSM matching. Hence, the DID model combined with the PSM method effectively estimates the causal effect of a specific policy on relevant outcomes.

We present the PSM-DID results in Table 8. The coefficient significance of the cross term $post \times treat$ does not change, indicating that our estimation results are robust.

Table 7
Balance tests of PSM (high carbon industry)

Covariate	Type	Mean		Bias(%)	Reduct Bias(%)	T-test	
		Treated	Control			t	P >|t|
FAT	Unmatched	3.4732	10.092	-3.3		-0.57	0.566
	Matched	3.3152	3.2258	0.0	98.6	0.30	0.767
TAT	Unmatched	0.5281	0.4649	15.9		4.08	0.000
	Matched	0.5236	0.5225	0.3	98.2	0.04	0.968
CR	Unmatched	1.7103	2.9096	-42.6		-8.02	0.000
	Matched	1.7471	1.7442	0.1	99.8	0.02	0.980
ALR	Unmatched	50.742	39.354	60.9		13.99	0.000
	Matched	50.07	50.576	-2.7	95.6	-0.46	0.643
Size	Unmatched	24.467	22.061	165.0		44.08	0.000
	Matched	24.256	24.256	-0.0	100.0	-0.00	1.000

Table 8
Propensity score matching

Variables	(1) Return	(2) Vol	(3) ROE	(4) Tobin's Q
post × *treat*	**0.179***	**-0.661***	**0.0578***	**0.368****
	(1.71)	(-1.87)	(1.80)	(2.36)
FAT	-0.0000420***	-0.000276***	-0.0000492	-0.0000643***
	(-2.82)	(-12.89)	(-1.10)	(-7.50)
TAT	0.0202	0.288	0.333***	0.160***
	(0.11)	(1.50)	(2.83)	(3.35)
CR	0.0479	0.0319	-0.0216	-0.0264**
	(1.34)	(1.62)	(-1.08)	(-2.06)
ALR	0.00875	-0.0330**	-0.0160	0.00468
	(1.13)	(-2.29)	(-0.66)	(1.58)
Size	0.207	1.160**	0.689**	-0.936***
	(0.85)	(2.17)	(2.24)	(-5.52)
Company fixed effect	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes
Obsevations	16085	15908	17375	15922

4.3.3. Two-stage least-squares model

To alleviate concerns about endogeneity driven by simultaneity and reverse causality, we employ an instrumental variable (IV) approach to examine the impact of carbon information disclosure on corporate financial performance. We carefully selected two instrumental variables – lagged dependent variable and the female director ratio. Based on previous research, the lagged dependent variable is often chosen as an instrumental variable in papers on information disclosure (Buallay et al., 2020; Cui et al., 2018). The female director ratio refers to the percentage of women on a company's board of directors. Previous research has found that female directors in China have a positive impact on corporate carbon disclosure (He et al., 2021). However, there is no direct influence of this ratio on firm financial performance (Rose, 2007). Based on the above, we employ a two-stage least-squares analysis (2SLS) as follows.

First-stage:

$$CID_{i,t} = \beta_0 + \beta_1 CID_{i,t-1} + \beta_2 FEMALE\_RATIO_{i,t} + \sum_{j=3}^{n} \beta_j Z_{i,t} + \delta_t + \varphi_i + \varepsilon_{i,t} \tag{5}$$

Second-stage:

$$Y_{i,t} = \gamma_0 + \gamma_1 \widehat{CID_{i,t}} + \sum_{j=2}^{n} \gamma_j Z_{i,t} + \delta_t + \varphi_i + \varepsilon_{i,t} \tag{6}$$

where $CID_{i,t}$ is carbon information disclosure, which is *post* × *treat* in baseline regression. $CID_{i,t-1}$ is the one-period lagged $CID_{i,t}$. $FEMALE\_RATIO_{i,t}$ is female director ratio. All other variables are the same as those described in the baseline DID regression.

The results of this analysis, which can be seen in Table 9, are consistent with the baseline results and provide further evidence to mitigate concerns about reverse causality. The coefficient significance of the cross term $CID_{i,t}$ (*post* × *treat*) remains unchanged, providing further confidence in the robustness of our results.

4.4. Determinants of carbon disclosure

4.4.1. Logistic regression

In this section, we use logistic regression analysis to examine the determinants of corporate carbon disclosure.

Table 9
Two-stage least-squares (2SLS) model

Variables	(1) Return	(2) Vol	(3) ROE	(4) Tobin's Q
post × treat	**0.176***	**-0.650****	**0.0616****	**0.357*****
	(1.78)	(-2.29)	(2.18)	(2.92)
FAT	-0.0000457**	-0.000261***	-0.0000492	-0.0000637*
	(-2.44)	(-3.70)	(-1.05)	(-1.83)
TAT	0.0207	0.303	0.332***	0.171***
	(0.12)	(1.50)	(2.65)	(3.79)
CR	0.0425	0.0521***	-0.0216	-0.0254***
	(1.41)	(2.61)	(-1.33)	(-2.74)
ALR	0.0000413	0.0000360	-0.0160	0.00604***
	(0.90)	(0.16)	(-0.80)	(17.93)
Size	0.239	0.699*	0.689**	-0.953***
	(0.96)	(1.91)	(2.49)	(-7.99)
Company fixed effect	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes
Observations	16132	15942	17394	15955

To this end, we use the logistic regression model described in Eq. (7) to estimate the impact of the six factors – R&D costs, whether listed overseas, inclusion in a carbon market, whether it is a state-owned enterprise, whether it belongs to the high-carbon industry, and whether the time is after the double carbon target is proposed – on the likelihood of carbon information disclosure. It should be noted that in the literature review section, the existing studies on the determinants of corporate carbon information disclosure were summarized and the gaps in previous studies were identified.

$$Pr(DIS_{i,t} = 1|X, Z) = \frac{exp(\alpha_0 + \beta X_{i,t} + \gamma Z_{i,t} + \delta_t + \varphi_i + \varepsilon_{i,t})}{1 + exp(\alpha_0 + \beta X_{i,t} + \gamma Z_{i,t} + \delta_t + \varphi_i + \varepsilon_{i,t})} \quad (7)$$

where X = [*R&D*, *Oversea*, *Local carbon market*, *State-owned* ,*High-carbon*, $Post^{dual}$]. All other variables are the same as those described in the baseline DID regression.

The results of the logistic regression analysis are reported in Table 10 and show that all six factors (R&D expenditure, overseas listing, carbon market inclusion, state-owned status, high-carbon industry, and dual carbon targets) have a positive and significant effect on carbon information disclosure. These findings indicate that both external pressures and self-competitive advantages play a role in prompting companies to disclose their carbon information.

Table 10
Logit regression model

	$Post^{dis}$
R&D	0.107***
	(4.16)
Oversea	1.164***
	(10.23)
Carbon market	0.599***
	(3.59)
State-owned	0.193*
	(2.36)
High-carbon	0.862*
	(2.09)
$Post^{dual}$	0.469*
	(2.42)
FAT	-0.00377
	(-1.88)
TAT	0.477***
	(5.33)
CR	-0.0481
	(-1.75)
ALR	-0.0106***
	(-3.92)
Size	0.931***
	(26.56)
Industry fixed effect	Yes
Quarter fixed effect	Yes
Observations	44972

4.4.2. Carbon disclosure from an environmental score perspective

In an effort to determine whether companies in high-carbon and low-carbon industries choose to disclose carbon information due to external pressure or self-assurance, we analyzed the distribution of environmental scores among companies with and without carbon disclosure. As a relevant environmental indicator, carbon emissions data is not yet available in China's A-share market, therefore, we used the company's environmental score as a proxy to reflect their carbon score. To uncover the possible motives behind carbon disclosure, we obtained environmental score data from the Wind database. The scores were normalized to ensure comparability across different years and were divided into two groups based on whether or not the companies disclosed carbon information in each year from 2018 to 2021.

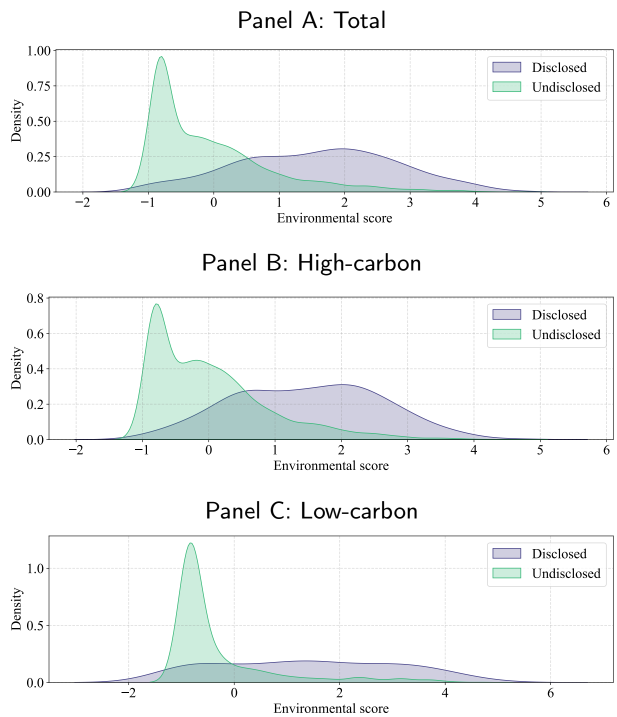


Figure 4: The company's environmental score for whether or not to disclose carbon information

The environmental score distribution is presented in Fig. 4. The results indicate that companies that choose to disclose carbon information have significantly higher environmental scores, with a clear trend observed in low-carbon industries. This may suggest that low-carbon industries have higher levels of self-confidence, as external pressure plays a lesser role in their decision-making. In high-carbon industries, however, external pressure may play a more significant role, leading to a higher number of companies with poor environmental performance still disclosing carbon information.

In conclusion, our findings support the idea that companies' self-assurance in their carbon emissions data can act as a competitive advantage and motivate them to disclose this information.

5. Conclusion

In this study, we investigated the association between corporate carbon disclosure and the financial performance of Chinese A-share listed companies in the context of dual carbon targets. Our results indicate that there is a significant and persistent relationship between carbon disclosure and financial performance in high-carbon industries. Specifically, we found that carbon disclosure has a positive impact on stock price return, ROE, and Tobin's Q, with a significant decrease in stock price volatility. This impact is robust, as evidenced by the results of our dynamic DID, placebo test, PSM test, and 2SLS tests, which all support our findings.

Based on these results, we can conclude that corporate carbon disclosure is an important factor in enhancing the financial performance of high-carbon industries. The important point of this finding is that it highlights the positive effect of companies' carbon disclosure measures on improving their financial performance and sustainable development, which is very meaningful for corporate governance.

Given these findings, we would like to make the following recommendations to corporate and governments:

(1) Encourage carbon disclosure: By promoting transparency and accountability, companies can attract more investors and improve their financial performance.

(2) Enhance the quality of carbon disclosure: Companies should strive to provide accurate and consistent carbon information to stakeholders to maximize the benefits of carbon disclosure.

(3) Implement a standardized carbon reporting system: Standardized carbon reporting can ensure the reliability and comparability of carbon information, which can increase the effectiveness of carbon disclosure.

(4) Foster stakeholder engagement: Companies should engage with stakeholders to understand their concerns and expectations and to ensure that their carbon information meets their needs.

Overall, our study provides new insights into the importance of climate change resilience and green transition management for companies operating in high-carbon industries. We hope our findings will encourage the development of more effective carbon disclosure practices and contribute to the advancement of sustainability practices in China and beyond.

Declaration of competing interest

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

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