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Carbon emission trading system and stock price crash risk of heavily polluting listed companies in China: based on analyst coverage mechanism

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Abstract

This study reveals the inconsistencies between the negative externalities of carbon emissions and the recognition condition of accounting statements. Hence, the study identifies that heavily polluting enterprises in China have severe off-balance sheet carbon reduction risks before implementing the carbon emission trading system (CETS). Through the staggered difference-in-difference (DID) model and the propensity score matching-DID model, the impact of CETS on reducing the risk of stock price crashes is examined using data from China's A-share heavily polluting listed companies from 2007 to 2019. The results of this study are as follows: (1) CETS can significantly reduce the risk of stock price crashes for heavily polluting companies in the pilot areas. Specifically, CETS reduces the skewness (negative conditional skewness) and down-to-up volatility of the firm-specific weekly returns by 8.7% and 7.6%, respectively. (2) Heterogeneity analysis further shows that the impacts of CETS on the risk of stock price crashes are more significant for heavily polluting enterprises with the bear market condition, short-sighted management, and intensive air pollution. (3) Mechanism tests show that CETS can reduce analysts' coverage of heavy polluters, reducing the risk of stock price crashes. This study reveals the role of CETS from the stock price crash risk perspective and helps to clarify the relationship between climatic risk and corporate financial risk.

Keywords: Carbon emission trading system, Stock price crash risk, Off-balance sheet carbon reduction risks, Analyst coverage

Introduction

The *BP Statistical Review of World Energy (1965–2020)*[1] noted that China accounts for 30% of the global annual carbon emissions. At the *Copenhagen Climate Conference* in 2009, China pledged to reduce its carbon intensity by 40–45% by 2020 compared with that in 2005. Then, in 2020, the Chinese government further pledged to peak carbon

[1] BP Statistical Review of World Energy (1965–2020): https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html.

emissions by 2030 and become carbon neutral by 2060 (Yu et al. 2021; Chen and Lin 2021; Fan et al. 2022). To this end, China faces the arduous task of carbon reduction commitment (Liu et al. 2022).

The carbon emission trading system (CETS) is a central institutional innovation that uses market means to control carbon emissions (Fang et al. 2018; Guo et al. 2020). The Chinese government piloted CETS in 2013 to fulfill its carbon emission reduction commitment (Liu and Zhang 2021; Zhang et al. 2021). Numerous studies focused on the effects of CETS in China, including carbon emission reduction (Zhang et al. 2020), pollution control (Liu et al. 2021), green innovation (Yao et al. 2021), and energy efficiency (Tan et al. 2022). Meanwhile, the present study further identifies the effect of CETS on corporate governance and stock pricing efficiency from the perspective of corporate carbon emission risk disclosure to build an analytical framework of "CETS-Carbon Risk Disclosure-Stock Pricing Efficiency."

First, China's heavy polluters faced severe off-balance sheet carbon emission reduction risks[2] before implementing carbon trading, which would increase their stock price crash risk. Since the government makes the emission reduction commitment, heavy polluters bear the massive risk of carbon emission reduction (Zhou et al. 2016b) because of the negative externalities of carbon emissions (Sajid et al. 2021; Li et al. 2014; Hao et al. 2016). However, heavy polluters could not specify legal carbon emission quotas or pay costs for excess carbon emissions when implementing carbon emission reduction policies (Donhauser 2019). The enterprise and investors cannot evaluate the enterprise's carbon emission reduction risk. That is, the off-balance sheet carbon emission reduction risk is created. Based on the negative information hiding hypothesis proposed by Jin and Myers (2006), heavy polluters' stock price crash risk will also increase as the risk of carbon emission reduction increases.

However, CETS has changed the problem by reducing the off-balance sheet carbon emission reduction risks. On the one hand, heavy polluters can legally obtain carbon emission quotas (Lo 2012; Cong and Lo 2017; Zhang and Duan 2020), thereby reducing the threat of their illegal carbon emissions (Zhang et al. 2021). On the other hand, even if excess carbon emissions occur, carbon emission quotas can be purchased and the cost can be recognized in accounting (Yan et al. 2020; Zhang et al. 2021). In the end, both enterprises and external investors can grasp the carbon emission quotas of enterprises and bear the emission cost of excess carbon emissions, thereby avoiding the off-balance sheet carbon emission reduction risk.

In this study, analyst coverage is further discussed as an intermediary mechanism. Analysts are essential information intermediaries in the capital market and are very sensitive to corporate information disclosure. If heavy polluters have off-balance sheet carbon emission reduction risks, Zhang (2022) called this case the "misalignment of environmental responsibility disclosure," which will attract analysts' coverage. Analyst coverage will stimulate management to hide unfavorable information (He and Tian

[2] Off-balance sheet risks are liabilities, contingencies, and potential accounting losses that do not appear on a company's balance sheet or are not fully disclosed. OBSR items may cause unexpected changes in cash flow, liquidity, leverage, earnings, etc. (Morrison 1993).

Table 1 Chinese carbon trading market inclusion criteria

Pilot area	Start-up time	Industries to be included	Inclusion criteria	Number of enterprises
Shenzhen	June 18, 2013	Industries (electricity, water, manufacturing, etc.) and buildings	Industries: over 5000 tons of carbon emissions Public buildings: 20,000 m^2 or more Government buildings: 10,000 m^2 or more	721 (in 2019)
Shanghai	November 26, 2013	Electricity, steel, petrochemical, non-ferrous, aviation, and other industries	Annual energy consumption of 10,000 tons of standard coal or more	323 (in 2021)
Beijing	November 28, 2013	Electricity, heat, petrochemicals, cement, road transport, service industry, and other industries	Over 5000 tons of carbon emissions	843 (in 2019)
Guangdong	December 19, 2013	Six industries: electricity, cement, steel, petrochemicals, paper, civil aviation	Over 20,000 tons of carbon emissions or annual energy consumption of 10,000 tons of standard coal	268 (in 2020)
Tianjin	December 26, 2013	Five industrial sectors: electricity and heat, steel, chemicals, petrochemicals, oil, and gas extraction	Over 26,000 tons of carbon emissions or annual energy consumption of 10,000 tons of standard coal	139 (in 2021)
Hubei	April 2, 2014	Sixteen industrial sectors: electricity and heat, non-ferrous metals, iron and steel, chemicals, cement, petrochemicals, etc	Annual energy consumption of 10,000 tons of standard coal or more	373 (in 2021)
Chongqing	June 19, 2014	Electricity, electrolytic aluminum, ferroalloy, calcium carbide, caustic soda, cement, steel	Over 26,000 tons of carbon emissions or annual energy consumption of 10,000 tons of standard coal	242 (in 2015)
Fujian	December 22, 2016	Nine industries: electricity, petrochemical, chemical, building materials, steel, non-ferrous, paper, aviation, ceramics	Annual energy consumption of 10,000 tons of standard coal or more	269 (in 2020)

2013) and investors' reactions (Yang et al. 2021), ultimately exacerbating the risk of stock price crashes (Xu et al. 2013).

This study takes A-share heavily polluting enterprises from 2007 to 2019 in China as the study samples. The staggered difference-in-difference (DID) model and the propensity score matching (PSM)-DID model will be employed to empirically test the impact of CETS on stock price crash risks. Table 1 shows the statistics of the inclusion criteria for the eight Chinese pilot carbon trading markets. High-carbon industries, such as electricity, iron and steel, cement, chemicals, and petrochemicals, dominate each pilot carbon trading market. These high-carbon industries are also highly polluting because of the strong homology between carbon and pollutant emissions. In addition, listed companies in China are the major source of carbon emissions in the country. The "China Listed Companies Carbon Emissions Ranking (2021)" noted that, in terms of carbon emissions, the top 100 listed companies have a total of 4.424 billion tons of carbon dioxide emissions, accounting for approximately 44.7% of the national total, with the lowest emissions reaching 6.19 million tons.[3] Ultimately, this study argues that carbon trading pilot projects will significantly affect Chinese listed companies in highly polluting industries.

The results show that CETS could help reduce the risk of stock prices crash of heavily polluting companies in pilot areas. The heterogeneity analysis shows that the influence of CETS on the risk of stock price crashes is more significant for heavily polluting enterprises with bear market conditions, short-sighted management, and intensive air pollution. Mechanism tests also show that analyst coverage plays a mediating role in CETS' impact on the stock price crash risks.

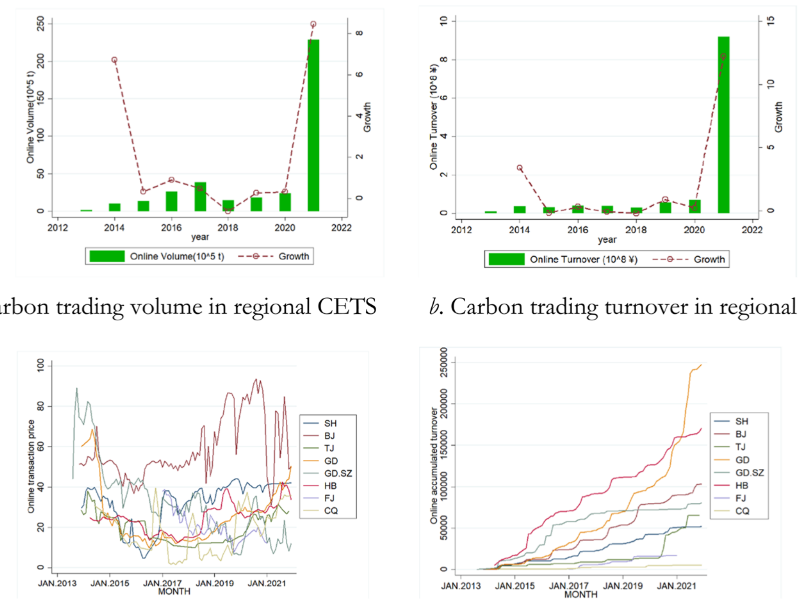
The contributions of this study include the following aspects: first, the study revealed the inconsistency between the negative externalities of carbon emissions and the confirmation requirements of accounting statements, which posed an off-balance sheet carbon emission reduction risk for heavily polluting enterprises exacerbating their financial risks, such as stock price crash risk. Second, although scholars began to discuss the relationships between Environmental, Social Responsibility, and Governance (ESG) and financial risk (Xu et al. 2021a; Bae et al. 2021; Thuy et al. 2021), the relationship between CETS and financial risk is ignored. From the perspective of regulating carbon emission behavior and confirming the cost of carbon emission, this study reveals the mechanism of CETS to reduce the stock price crash risk of heavily polluting enterprises. This study is complementary to ESG and financial risk research.

The rest of this paper is organized as follows: "Background" section presents an introduction to the CETS pilot project in China; "Literature review and hypothesis development" section conducts the theoretical analysis and puts forward the research hypotheses; "Empirical research design" section shows the empirical research design; "Empirical results analysis" section includes the empirical results; and the discussion. Finally, "Conclusion" section concludes the study.

Background

The National Development and Reform Commission of China issued the *Notice on the Pilot Work of Carbon Emission Trading* in 2011 to cope with global climate change and reduce CO_2 emissions, formally approving the pilot work on carbon emissions trading. In 2013, five pilot carbon emission trading markets were set up in Beijing (BJ), Tianjin (TJ), Shanghai (SH), Guangdong Province (GD), and Shenzhen in Guangdong Province (GD.SZ). In 2014, Hubei (HB) and Chongqing (CQ) also launched carbon emission trading. In 2016, Fujian (FJ) opened the last regional carbon emission trading market. The pilot carbon emission trading involved 2837 key emitting units and 11,169 natural persons. As shown in Fig. 1, carbon trading is active in China's regional CETS. Particularly in 2014, China's carbon trading reached more than 3.85 million tons, with a trading

[3] Carbon Emissions Ranking of Listed Companies in China (2021): http://www.eco.gov.cn/news_info/54114.html.



a. Carbon trading volume in regional CETS

b. Carbon trading turnover in regional CETS

c. Sub-market online transaction average price

d. Sub-market online cumulative turnover

Fig. 1 The transaction situation of China's regional CETS

amount of 125.01 million yuan, making China the world's second-largest bond trading market after the EU.[4]

Based on the success of the regional CETS pilot project, the Chinese government launched the *National Carbon Emission Trading System* (NCETS) on July 16, 2021. The NCETS includes 2162 key emitters in the power generation industry, covering approximately 4.5 billion tons of CO_2 emissions. This emission already exceeds the emissions covered by the EU carbon market, making it the world's largest carbon market.[5] By 2021, the cumulative transaction volume of the carbon emission quota in the NCETS was 179 million tons, with a total transaction value of 7.661 billion yuan (Fig. 2).

As the world's largest carbon emitter, China attaches great importance to carbon reduction. The pilot regional CETS in China has been successful, which provides compelling natural experimental evidence for scholars to study the economic consequences of CETS (Zhang and Wang 2021).

Literature review and hypothesis development

Literature review

Since the 1987 stock market crash, scholars have conducted extensive research on the stock market crash and proposed theories such as *Leverage Effect Hypothesis*, *Rational Bubble Hypothesis*, *Volatility Compensation Hypothesis*, and *Heterogeneity Investors Hypothesis*. Among them, Campbell et al. (1992) proposed the *Volatility Compensation Hypothesis*, arguing that both good and bad news would increase stock

[4] China Government Website: http://www.gov.cn/xinwen/2014-06/10/content_2698098.htm.

[5] China Government Website: http://www.gov.cn/zhengce/2021-10/27/content_5646697.htm.

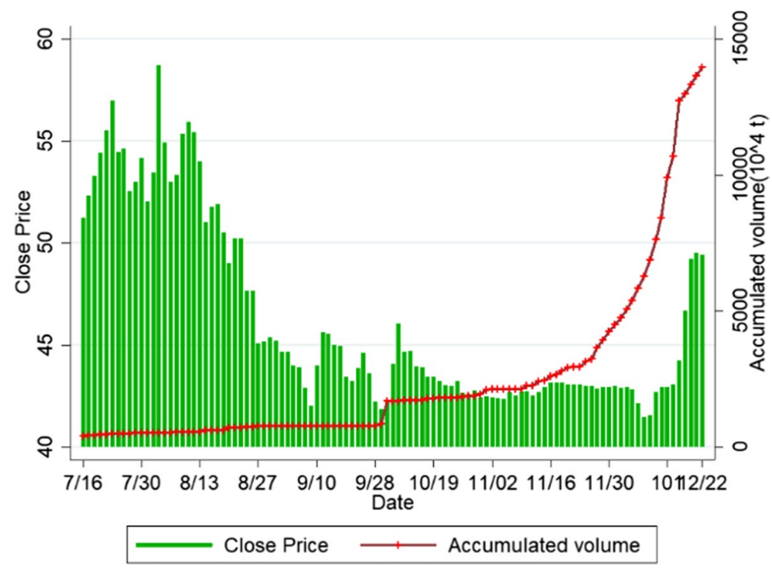


Fig. 2 The transaction situation of China's national CETS

price volatility, increasing investors' risks and returns and thereby reducing the company's stock price. Therefore, Campbell et al. (1992) pointed out that *no news is good news*. According to the *Heterogeneity Investors Hypothesis* proposed by Chen et al. (2000), bearish investors are more likely to get into trouble and their bearish information cannot be fully reflected in stock prices, thereby aggravating the crash risk in subsequent transactions. Meanwhile, the process of a stock price crash can be further divided into three categories: the form of a rising to crash (Zeira 1999), the form of a slight decline to crash (Black 1976), and the form of the sudden crash (Jin and Myers 2006).

Unlike previous studies from the capital market effectiveness perspective, Jin and Myers (2006) looked for the causes of stock price crashes from the company's management level. Jin and Myers (2006) proposed the famous *Negative Information Hiding Hypothesis*. According to this hypothesis, owing to information asymmetry, the management could withhold awful news for various reasons, such as compensation maximization or occupational safety (Cai et al. 2019). When the accumulation of negative information reaches its peak, the company's stock price plummets without warning until it crashes (Xu et al. 2022b).

The Negative Information Hiding Hypothesis is the most crucial theoretical hypothesis in studying stock price crash risk (Hutton et al. 2009; Habib et al. 2018). For instance, Khurana et al. (2018) verified that executives would cover up negative information, such as low-yield projects, resource transfer, and ineffective risk control through earnings smoothing, eventually leading to the stock price crash. Bao et al. (2018) pointed out that companies voluntarily adopting Dodd-Frank would cover up negative information by providing incomprehensible accounting information, ultimately increasing the risk of stock price crashes. Moreover, Chen et al. (2018) proved that with the promotion of senior executives of Chinese state-owned enterprises, their aversion to adverse events would increase, which would ultimately reduce the risk of stock price crashes. Li et al. (2019) verified that the pressure of market competition would prompt the management to hide negative information and that centralized release would lead to a stock price crash. Xu et al. (2021b) found that the stock price crash risk for firms that searched more on Google before its withdrawal subsequently increases by 19%, suggesting that Internet searching facilitates investors' information processing. Zhang et al. (2022a, b) showed that intensive product market advertising would eventually divert investors' attention from negative information, thereby increasing the risk of a stock price crash.

Hypothesis development

As the main body of energy consumption and environmental pollution, the carbon emissions of heavily polluting enterprises have strong negative externalities (Donhauser 2019; Sajid et al. 2021). The government's carbon emission control will inevitably impact its operations and capital market performance (Tian et al. 2019). Heavily polluting enterprises are faced with severe off-balance sheet risks of carbon emission reduction risks before implementing CETS owing to the pressure from the Chinese government to commit to reducing carbon emissions (Yu et al. 2021).

On one hand, the carbon emission reduction task of heavily polluting enterprises is uncertain. Carbon emission reduction is a strategic goal proposed by the Chinese government and this goal needs to be achieved by heavily polluting enterprises (Na et al. 2017). However, before the implementation of CETS, their carbon emission reduction tasks are unclear. In addition, how much carbon emission they can emit, the accurate target of carbon emission reduction, and how to deal with excess carbon emission are unclear. Along with the long-term accumulation of extensive carbon emission behavior, the unclear task constitutes an important negative event for heavily polluting enterprises (Tian et al. 2019). Zhou et al. (2016b) called this case the carbon risk of heavily polluting enterprises in China.

On the other hand, the carbon emission cost of heavily polluting enterprises cannot be recorded. According to the *Accounting Standards for Business Enterprises* in China[6], the activities that affect the capital movement of the company are the accounting objects. However, those that do not affect the capital movement of the company are not accounting objects and should be regarded as off-balance sheet activities (Bauman 2003; Segura and Zeng 2020). The carbon emission behavior does not constitute the accounting object of the reporting entity owing to its solid negative externalities (Donhauser 2019; Sajid et al. 2021). Therefore, the negative externality of carbon emissions is inconsistent with the recognition condition of accounting standards. However, as major environmental polluters, heavily polluting enterprises are directly affected by environmental regulations, including the CETS. This case creates additional compliance costs and profitability uncertainty for heavily polluting enterprises (Costantini et al. 2013).

To sum up, the financial statements of heavily polluting enterprises omitted the cost of carbon emissions before the implementation of CETS, resulting in hidden potential carbon emission reduction risks in the financial statements. According to the *Negative*

[6] China's Ministry of Finance. Accounting Standards for Business Enterprises-Basic Principles: http://www.gov.cn/flfg/2006-04/11/content_250845.htm, 2006–2.

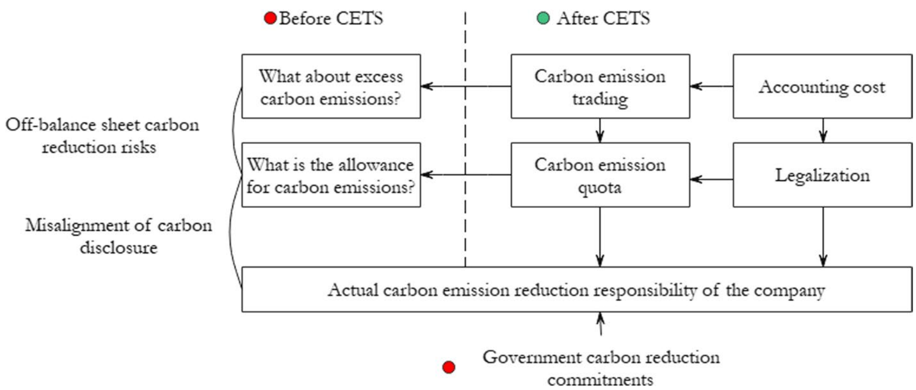


Fig. 3 CETS pilot and carbon risk of heavily polluting companies

Information Hiding Hypothesis proposed by Jin and Myers (2006), their stock prices are more likely to experience abnormal volatility (Tian et al. 2019) or even crash.

The carbon emission cost of heavily polluting enterprises in CETS areas can be measured and reported through the establishment of a greenhouse gas measurement reporting and verification system (Zhang and Duan 2020). This case will transform enterprises' internal carbon emission information into public information (Zhang and Wang 2021) to solve the threat of off-balance sheet carbon emission reduction and alleviate the stock price crash risk caused by it.

First, CETS mitigates the threat of carbon emission reduction caused by policy uncertainty for heavily polluting enterprises. CETS also clarifies the carbon emission quota of enterprises and establishes the carbon emission trading market (Dai et al. 2018; Pollitt 2019). Hence, heavily polluting enterprises in the pilot areas can accurately identify their carbon emission permit and have legal channels to trade carbon emission quotas. Moreover, these enterprises in the pilot areas can reduce carbon emissions under a legal framework (Calel and Dechezlepretre 2012) to reduce the illegal threat of carbon emission (Zhang et al. 2021).

Second, CETS could help enterprises to recognize and record the costs and benefits of carbon emissions in their financial statements. China's CETS has established comprehensive laws on carbon trading, including the greenhouse gas measurement reporting and verification system, the carbon emission quota allocation system, and the carbon trading system and rules (Weng and Xu 2018). These laws allow enterprises to quantify the cost of carbon emissions in real time and convert carbon emissions into actual capital flows (Lo 2012; Cong and Lo 2017; Zhang and Duan 2020). Meanwhile, carbon emission trading internalizes the cost of excessive carbon emissions through trading, making them record their carbon emission costs in financial statements (Yan et al. 2020; Zhang et al. 2021). In this way, the off-balance sheet carbon emission reduction threat caused by the externality of carbon emissions can be avoided.

In summary, implementing CETS promotes enterprises to fulfill the responsibility of carbon emission reduction and creates conditions for recognizing carbon emission costs and benefits in financial statements. Figure 3 depicts the relationship between CETS and enterprise carbon risk of heavily polluting companies proposed in this study. Heavy polluting companies faced large carbon risks before the implementation of CETS, mainly stemming from the carbon reduction commitments proposed by the government (Zhou et al. 2016b). The lack of carbon emission reduction policies proposed by the government brings about the following two major problems: First, what is the allowance of carbon emissions? Second, what about excess carbon emissions? Neither heavy polluters nor investors can answer these two questions. Hence, a misalignment exists between carbon emissions disclosure and carbon reduction responsibility (Liu and Zhang 2021). The implementation of CETS effectively solves these two problems. On the one hand, heavy polluters can legally obtain carbon emission quotas, clarifying the problem of the carbon emission allowance. Second, heavy polluters can legally purchase emission quotas through carbon trading, clarifying the problem of excess carbon emissions. In this way, CETS enables enterprises and investors to obtain timely carbon emission reduction information and reduce the risks of off-balance sheet carbon emission reduction.

Furthermore, similar to Zhang et al. (2022a, b), the transparency of business information, business legitimacy, and corporate reputation of heavily polluting enterprises will weaken the speculative behavior of management and the panic selling of investors with the improvement of the quality of environmental information disclosure. Finally, the risk of a company's stock price crash is reduced. Implementing CETS may also reduce the stock price crash risk for China's heavy polluters by reducing the risks of off-balance sheet carbon emission reduction.

Therefore, this study puts forward the following research hypothesis:

Hypothesis 1 The CETS pilot project will help reduce the risk of stock price crashes in heavily polluting enterprises.

Mechanism discussion

As a capital market information intermediary, analysts are professional and have a wide range of information sources (Yu 2008). They are an important external alternative mechanism for internal corporate governance (Knyazeva 2007; Brown et al. 2014). In addition, analysts are sensitive to corporate information disclosure. If the quality of corporate information disclosure is poor, analysts will pay more attention to corporate non-financial information to make up for the lack of corporate information disclosure (Dhaliwal et al. 2012). Therefore, an alternative relationship exists between analyst coverage and corporate information disclosure (Hinze and Sump 2019), including corporate social responsibility (CSR) information disclosure (Adhikari 2016).

Once a misalignment exists between CSR disclosure and performance, analysts are likely to focus on this misalignment (Zhang 2022). The market will recognize this kind of information content analyst report. In addition, analysts are prone to conflicts of interest because of the potential business opportunities of the covered companies (Zhu et al. 2021). The pursuit of hidden negative information about listed companies could increase commission compensation for analysts, such as facilitating future underwriting of covered companies (Xu et al. 2013). In this way, before the implementation of CETS, the off-balance sheet carbon emission reduction risk of China's heavy polluters may also attract analysts to cover, obtain the bargaining chip with the covered enterprises, or increase the market attractiveness of their report.

The influence of analysts, in turn, will exert enormous pressure on the managers of the companies covered. On the one hand, the management fears that social responsibility misalignment will be identified by external stakeholders and that they will be blamed (Zhang 2022). Under the framework of legitimacy, resource dependence, and principal–agent theory, avoiding the misalignment of CSR disclosure is difficult (Zhang et al. 2022a, b). The misalignment of CSR constitutes a potential risk for enterprises (Kim and Lyon 2015). Hence, management is incentivized to act opportunistically to meet societal expectations to avoid the adverse consequences of analyst coverage (Fuller and Jensen 2010), including aggressive strategies and continuing to hide bad news (He and Tian 2013).

On the other hand, analyst coverage increases investor attention and their panicky behavior. The negative reaction of investors could increase if analysts truthfully reveal the misalignment of CSR disclosure. Even if analysts do not truthfully disclose the decoupling of CSR disclosure, analyst coverage will increase investor focus on companies (Yang et al. 2021), which increases the risk of decoupling of CSR disclosure misalignment. Investors who discover corporate social misconduct may drive down share prices or even panic selling (Zhang et al. 2022a, b). As a result, analyst coverage increases the risk of a company's share price crashing (Xu et al. 2013).

In conclusion, China's heavy polluters' off-balance sheet carbon emission reduction risks may attract analysts to cover them before implementing CETS. Analyst coverage intensifies the management's opportunistic behavior and investor reaction, intensifying the stock price crash risk. However, this phenomenon may be optimized after implementing CETS because it reduces the off-balance sheet carbon emission reduction risk of China's heavy polluters and ultimately reduces analyst coverage and its impact on the stock price crash risk. Therefore, this study puts forward the following further hypotheses:

Hypothesis 2 The CETS pilot project can reduce the stock price crash risk by reducing analyst coverage of heavily polluting companies.

Empirical research design

Benchmark model design

Referring to the studies of Gao et al. (2020) and Liu and Zhang (2021), in the present study, the staggered DID model is applied to estimate the impact of CETS on the risk of stock price crashes of heavily polluting listed companies.

The benchmark model is as follows:

$$NCSKEW_{i,T} \ or \ DUVOL_{i,T} = C + \rho Post_{i,T} \times Treat_{i,T} + \beta CVs_{i,T} + \mu_T + \varphi_i + \varepsilon, \tag{1}$$

In Eq. (1), negative conditional skewness (*NCSKEW*) and down-to-up volatility (*DUVOL*) are the stock price crash risk indicators. The coefficient of *Post* × *Treat*, that is, ρ, captures the impact of CETS on the stock price crash risk of heavily polluting listed companies. If the coefficient is significantly less than 0, then CETS helps reduce the risk of stock price crashes. Otherwise, it implies that CETS has not reduced the risk. *CVs* represent the control variables, including the average abnormal return (*RET*), volatility of abnormal returns (*SIGMA*), total assets (*SIZE*), asset–liability ratio (*LEV*), accrued earnings management (*ABSDA*), total asset turnover (*TURN*), return on equity (*ROE*), male Chief Executive Officer (*GENDER*), highly educated Chief Executive Officer (*DEGREE*), combining the Chief Executive Officer and chairman (*DUAL*), executive compensation incentive (*SALARY*), the proportion of independent directors (*INDEP*), the post-subprime crisis (*FINRISK*), abnormal cash flow (*ABCFO*), and the proportion of fixed assets (*PPE*). Variables μ_T and ϕ_i denote the year trend effect and firm fixed effect, respectively.

Propensity score matching

The robustness of the empirical results in this study may be threatened by the systematic differences of heavily polluting enterprises in pilot areas. A PSM-DID model is also established to guarantee robustness, referring to Zhang and Wang (2021). The propensity score matching steps are as follows:

1. The Logit model estimates the probability that heavily polluting enterprises are located in pilot areas.
2. A 1:3 matching in the 5% radius.[7]
3. Regression tests are conducted based on the PSM-paired samples.

Table 2 reports the differences between the samples before and after matching. In the unpaired samples, significant group differences exist in *SIZE*, *ROE*, *DEGREE*, *DUAL*, *SALARY*, *INDEP*, state-owned (*STATE*), and *PPE*. However, no significant intergroup differences exist in the paired samples.

Figure 4 plots the kernel density distribution of sample firms' p-scores before and after matching. Furthermore, significant systemic differences exist between the treatment and control groups before PSM pairing. However, PSM pairing significantly eliminates the systemic differences between the two groups, verifying the effectiveness of PSM pairing.

Variable measurement

Stock price crash risk

We first estimate the firm-specific weekly returns for each firm and year following Chen et al. (2001), Aman (2013), and Defond et al. (2015) to measure the risk of a stock price crash:

$$R_{i,t} = a + \beta_1 R_{m,t-2} + \beta_2 R_{m,t-1} + \beta_3 R_{m,t} + \beta_4 R_{m,t+1} + \beta_5 R_{m,t+2} + \varepsilon_{i,t}, \tag{2}$$

where $R_{i,t}$ is the company's t-week return; $R_{m,t}$ is the market's t-week return. $\varepsilon_{i,t}$ is the abnormal return of company *i* in t-week. The firm-specific weekly returns ($W_{i,t}$) of company *i* in t-week are calculated as follows:

$$W_{i,t} = \ln\left(1 + \varepsilon_{i,t}\right) \tag{3}$$

Then, the measurement of stock price crash risk is conducted as follows:

[7] Because 1:1 matching cannot solve the group difference, differences between groups after 1:1 matching are shown in Table A1 in the Appendix; this paper chose 1:3 matching to solve the group difference.

Table 2 The differences between samples before and after matching

Variable	Matched	Mean		*t* Value	Sig
		Treat	Control		
SIGMA	N	0.046	0.046	− 0.150	0.878
	Y	0.046	0.046	− 0.320	0.745
RET	N	− 0.001	− 0.001	− 0.230	0.819
	Y	− 0.001	− 0.001	0.160	0.870
SIZE	N	22.386	22.174	5.910***	0.000
	Y	22.382	22.355	0.590	0.556
LEV	N	0.443	0.453	− 1.760*	0.078
	Y	0.443	0.442	0.050	0.958
ROE	N	0.058	0.049	1.880*	0.060
	Y	0.058	0.055	0.550	0.585
ABSDA	N	0.054	0.055	− 0.720	0.472
	Y	0.054	0.055	− 0.720	0.474
TURN	N	0.666	0.671	− 0.360	0.722
	Y	0.667	0.660	0.460	0.648
GENDER	N	0.951	0.948	0.460	0.643
	Y	0.951	0.957	− 0.990	0.322
DEGREE	N	0.917	0.838	8.260***	0.000
	Y	0.916	0.912	0.470	0.640
DUAL	N	0.237	0.214	2.000**	0.045
	Y	0.236	0.255	− 1.370	0.171
SALARY	N	42.017	41.355	2.090**	0.037
	Y	42.040	42.102	− 0.160	0.874
INDEP	N	0.372	0.367	3.850***	0.000
	Y	0.372	0.373	− 0.430	0.666
STATE	N	0.453	0.477	− 1.750*	0.080
	Y	0.454	0.440	0.870	0.386
FINRSIK	N	0.887	0.886	0.080	0.933
	Y	0.887	0.885	0.140	0.891
ABCFO	N	− 0.001	0.002	− 1.370	0.171
	Y	0.000	0.001	− 0.200	0.842
PPE	N	0.282	0.326	− 9.050***	0.000
	Y	0.283	0.281	0.290	0.770

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively

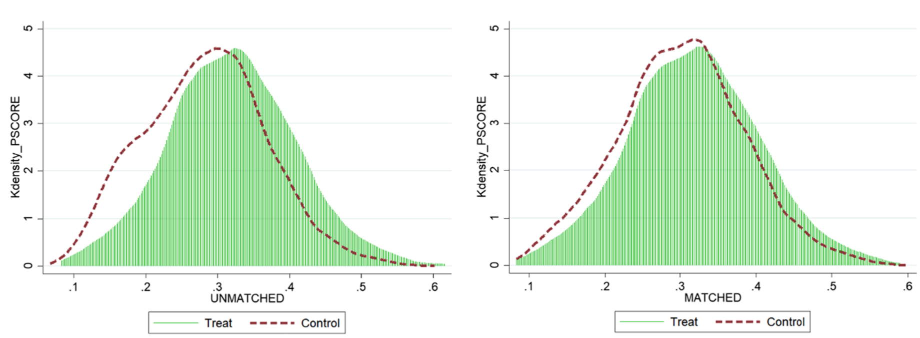


Fig. 4 The kernel density distribution of p-score

Table 3 Measures of other variables

Variable code	Variable name	Variable measure
SIGMA	Volatility of abnormal returns	Standard deviation of firm-specific weekly return
RET	Average abnormal return	Average firm-specific weekly return
SIZE	Total assets	The logarithm of total assets
LEV	Asset–liability ratio	Total liabilities to total assets
ROE	Return on equity	Net income to net assets
ABSDA	Accrued earnings management	The absolute of discretionary accrued earnings
TURN	Total assets turnover rate	Operating income to total assets
GENDER	Male Chief Executive Officer (CEO)	Male CEO are 1 and female CEO are 0
DEGREE	Highly educated CEO	1 for CEO with a bachelor's degree or above, and 0 for others
DUAL	Combining the CEO and Chairman	1 for CEO as chairman, and 0 for others
SALARY	Executive compensation incentive	Percentage of top three executives' compensation
INDEP	Independent directors	Proportion of independent directors in the board
FINRISK	Financial crisis	1 for after the 2008 financial crisis, and 0 otherwise
ABCFO	Abnormal cash flow	Abnormal cash flow of REM (Real Earnings Management) (Roychowdhury 2006)
PPE	The proportion of fixed assets	Ratio of fixed assets

$$NCSKEW_{i,T} = -\left[n_{i,T}\left(n_{i,T}-1\right)^{3/2}\sum W_{i,t}^{3}\right] \Big/ \left[\left(n_{i,T}-1\right)\left(n_{i,T}-2\right)\left(\sum W_{i,t}^{2}\right)^{3/2}\right], \tag{4}$$

$$DUVOL_{i,T} = Ln\left\{\left[\left(n_{i,T,Up}-1\right)\sum R_{i,T,Down}^{2}\right] \Big/ \left[\left(n_{i,T,Down}-1\right)\sum R_{i,T,Up}^{2}\right]\right\}, \tag{5}$$

where $NCSKEW_{i,T}$ is the skewness of the firm-specific weekly returns in T-year, $DUVOL_{i,T}$ is the down-to-up volatility of the firm-specific weekly returns in T-year. The greater the $NCSKEW_{i,T}$ and $DUVOL_{i,T}$, the greater the risk of a stock price crash (Chen et al. 2001). Among them, $n_{i,T}$ is the number of trading weeks of firm *i* in T-year, $n_{i,T,Up}$ is the number of weeks in which the firm-specific weekly returns of firm *i* exceeds the average in T-year, and $n_{i,T,Down}$ is the number of weeks in which the firm-specific weekly returns of firm *i* is below the average in T-year.

CETS pilot project

Since 2013, the Chinese government has been piloting CETS in eight administrative provinces or cities. Among them, BJ, TJ, SH, GD, and GD.SZ began pilot carbon emission trading in 2013, CQ and HB began in 2014, and FJ province began in 2016. By referring to Gao et al. (2020) and Liu and Zhang (2021), the heavily polluting listed companies in the pilot provinces or cities are taken as the experimental group, where *Treat* is recorded as 1. Moreover, heavily polluting listed companies in the non-pilot provinces are taken as the control group, where *Treat* is recorded as 0. Further, if the pilot provinces or cities are in the post-pilot phase, *Post* is recorded as 1; otherwise, *Post* is recorded as 0. The interaction term of *Post* and *Treat* ($Post \times Treat$) identifies the policy effect of the CETS pilot project.

Table 3 shows the measures of other variables.

Table 4 The sample industry distribution statistics

Industry name	Frequency	Percent (%)
Chemical raw materials and chemical products manufacturing	1346	21.14
Chemical fiber manufacturing	210	3.30
Pharmaceutical manufacturing	1106	17.37
The nonferrous metal smelting and rolling processing industry	402	6.31
Nonferrous metal mining and selection industry	68	1.07
Rubber and plastic products	410	6.44
Coal mining and washing	159	2.50
Electric power and heat production and supply	461	7.24
Leather, fur, feather, and their products and footwear	19	0.30
Petroleum processing, coking, and nuclear fuel processing industry	131	2.06
Oil and gas extraction	33	0.52
Textile industry	475	7.46
Textile clothing, apparel industry	152	2.39
Paper and paper products industry	237	3.72
Wine, beverage, and refined tea manufacturing	289	4.54
Non-metallic mineral products industry	620	9.74
Non-metallic mining and selection industry	1	0.02
The ferrous metal smelting and rolling processing industry	232	3.64
Ferrous metal mining and selection industry	15	0.24
Total	6366	100

Description of sample source

Considering China's heavy polluters' low carbon efficiency and high carbon emissions, they face more significant carbon risks (Zhou et al. 2016b). Therefore, China's CETS policy will inevitably directly impact the country's heavily polluting enterprises. We chose the heavily polluting companies in Chinese A-share listed companies from 2007 to 2019 as the research samples. The financial statement and stock price information are collected from the CSMAR database, one of the most authoritative databases of listed companies in China (Chen et al. 2018).

Following Xu et al. (2020), companies in heavily polluting industries are categorized as polluting firms. According to the *Guidelines for Environmental Information Disclosure for Listed Companie*s issued by *China's Ministry of Environmental Protection* in 2010, the heavily polluting industries include electrical power, steel, cement, electrolytic aluminum, coal, metallurgy, building materials, mining, petrochemical, chemicals, pharmaceutical, brewing, paper-making, fermentation, textile, and leather-making.

Table 4 shows the industry distribution statistics.

Empirical results analysis

Descriptive statistics and benchmarking test

Table 5 presents the descriptive statistical results of the main variables in this study. The average skewness of the firm-specific weekly returns (*NCSKEW*) in the sample is − 0.244, and the down-to-up volatility (*DUVOL*) of the firm-specific weekly returns in the sample is − 0.168. Table 5 presents the descriptive statistics for the other variables.

Table 5 Variables descriptive statistics

Variable name	Mean	SD	Min	Max
NCSKEW	− 0.244	0.628	− 2.150	1.366
DUVOL	− 0.168	0.458	− 1.278	0.982
TREAT	0.297	0.457	0.000	1.000
SIGMA	0.046	0.017	0.016	0.105
RET	− 0.001	0.001	− 0.006	0.000
SIZE	22.119	1.374	19.027	26.990
LEV	0.458	0.227	0.050	1.100
ROE	0.051	0.180	− 1.052	0.376
ABSDA	0.056	0.066	0.000	0.352
TURN	0.656	0.428	0.026	2.544
GENDER	0.944	0.230	0.000	1.000
DEGREE	0.851	0.356	0.000	1.000
DUAL	0.244	0.430	0.000	1.000
SALARY	42.240	11.757	21.224	79.177
INDEP	0.368	0.053	0.111	0.750
FINRISK	0.884	0.320	0.000	1.000
ABCFO	0.000	0.101	− 2.598	2.512
PPE	0.302	0.182	0.000	0.995

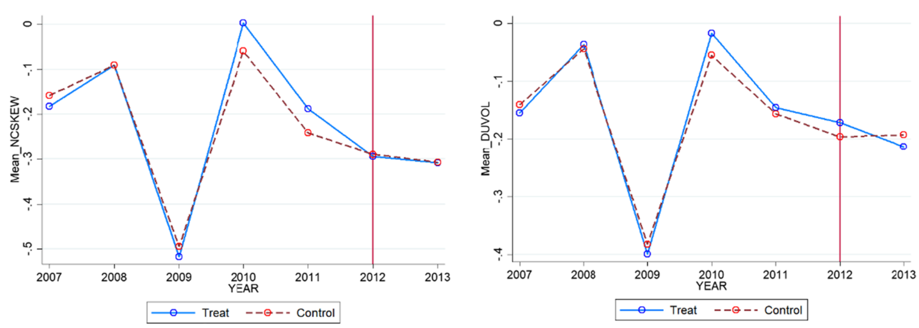


Fig. 5 Stock price crash risk change trend comparison chart

Table 6 CETS impact on the stock price crash risk

	$NCSKEW_{i,T}$		$DUVOL_{i,T}$	
	(1)	**(2)**	**(3)**	**(4)**
$TREAT_{i,T} \times POST_{i,T}$	− 0.094**	− 0.087**	− 0.076***	− 0.076**
	(− 2.348)	(− 2.061)	(− 2.750)	(− 2.580)
C	− 0.403	− 0.243	0.127	0.152
	(− 0.826)	(− 0.387)	(0.353)	(0.355)
Fixed effect	√	√	√	√
Year trend	√	√	√	√
Controls	√	√	√	√
Psm samples	×	√	×	√
N	6366	4683	6366	4683
ADJ. R^2	0.026	0.025	0.029	0.027

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses

Table 7 Control of other policies' impacts

	NON_FTC		*NON_NRC*	
	$NCSKEW_{i,T}$	$DUVOL_{i,T}$	$NCSKEW_{i,T}$	$DUVOL_{i,T}$
	(1)	**(2)**	**(3)**	**(4)**
$TREAT_{i,T} \times POST_{i,T}$	− 0.117**	− 0.105***	− 0.110**	− 0.098***
	(− 2.075)	(− 2.740)	(− 2.301)	(− 2.978)
C	0.704	0.942*	− 0.003	0.468
	(0.918)	(1.932)	(− 0.004)	(1.002)
Fixed effect	√	√	√	√
Year trend	√	√	√	√
Controls	√	√	√	√
Psm samples	×	√	×	√
N	3140	3140	3421	3421
ADJ. R^2	0.022	0.029	0.022	0.028

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses. *NON_FTC* refers to the sample that does not include Free Trade Cities. *NON_NRC* refers to the sample that does not include Northeast Revitalization Cities

Figure 5 shows the volatility trend of the average stock price crash risk of the treatment and control groups before the implementation of CETS. Before the implementation of CETS, the stock price crash risk of the treatment and control groups showed a similar trend.

Table 6 reports the empirical results. A significant negative correlation exists between the CETS pilot project ($TREAT_{i,T} \times POST_{i,T}$) and the stock price crash risk ($NCSKEW_{i,T}$ *or* $DUVOL_{i,T}$) of heavily polluting listed companies. The results indicate that for the heavily polluting listed companies in the pilot areas after the implementation of CETS ($TREAT_{i,T}=1$ and $POST_{i,T}=1$), their skewness of the firm-specific weekly returns (*NCSKEW*) is 8.7% lower than those in pre-CETS regions ($TREAT_{i,T}=1$ and $POST_{i,T}=0$) and non-CETS pilot regions ($TREAT_{i,T}=0$) (Column 2 Table 6). Their DUVOL of the firm-specific weekly returns (*DUVOL*) is 7.6% lower than those in pre-CETS regions ($TREAT_{i,T}=1$ and $POST_{i,T}=0$) and non-CETS pilot regions ($TREAT_{i,T}=0$) (Column 4 Table 6). Based on these results, CETS helps reduce the risk of stock price crashes of heavily polluting listed companies in pilot provinces. The conclusion is consistent with the expectation that CETS can reduce the off-balance sheet carbon emission risk of heavily polluting companies proposed in this study, verifying Hypothesis 1.

Robustness tests

Control other policies' impacts

During the sample period, other significant events in China, such as *Free Trade Cities*[8] and the *Northeast Revitalization Cities*,[9] may affect the reliability of DID results in this study. Therefore, the impacts of these events should be excluded. Table 7 shows the empirical results. The empirical results still show a significant negative correlation

[8] Free Trade Cities: Cities after *The State Council a*pproves the establishment of the free trade zone.

[9] Northeast Revitalization Cities: Cities in Heilongjiang, Jilin, and Liaoning provinces and Inner Mongolia Autonomous Region after 2016.

Table 8 Control the impact of New Environmental Protection Law

	$NCSKEW_{i,T}$ (1)	$DUVOL_{i,T}$ (2)
$TREAT_{i,T} \times POST_{i,T}$	− 0.091*	− 0.084**
	(− 1.721)	(− 2.222)
$NPL_{i,T} \times TREAT_{i,T} \times POST_{i,T}$	0.006	0.013
	(0.123)	(0.359)
C	− 0.239	0.161
	(− 0.382)	(0.377)
Fixed effect	√	√
Year trend	√	√
Controls	√	√
Psm samples	√	√
N	4683	4683
ADJ. R^2	0.024	0.027

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses. The t-value is in parentheses. After the implementation of the *New Environmental Protection Law* in 2015, *NPL* is recorded as 1, otherwise it is 0

between the implementation of the CETS pilot project ($TREAT_{i,T} \times POST_{i,T}$) and the stock price crash risk ($NCSKEW_{i,T}$ or $DUVOL_{i,T}$) of heavily polluted listed companies in China.

Control the impact of New Environmental Protection Law (NPL)

The Chinese government has also introduced strict environmental regulations for heavy pollution (Xu et al. 2022a), particularly the *NPL* enacted in 2014, which has been described as the strictest ever. Based on this consideration, the stock price crash risk of heavy polluters may be affected by NPL rather than CETS. Table 8 reports the results of robustness tests after controlling for the implementation of the *NPL*. The empirical results still show a significant negative correlation between the implementation of the CETS pilot project ($TREAT_{i,T} \times POST_{i,T}$) and the stock price crash risk ($NCSKEW_{i,T}$ or $DUVOL_{i,T}$) of heavily polluted listed companies in China.

Placebo test

A placebo test is carried out in this part to verify the reliability of the conclusions. The samples before the implementation of CETS (i.e., before 2013) are selected as test samples. The treatment and control groups remain unchanged. However, it is assumed that 2010 is the implementation year of the CETS pilot project ($POST^*_{i,T}$). Suppose a fictitious CETS pilot project ($TREAT_{i,T} \times POST^*_{i,T}$) still significantly reduces the risk of stock price crashes of heavily polluting listed companies in China. In that case, this study's test results are unreliable. Table 9 shows no significant negative correlation between the fictitious CETS pilot project ($TREAT_{i,T} \times POST^*_{i,T}$) and the stock price crash risk ($NCSKEW_{i,T}$ or $DUVOL_{i,T}$) of heavily polluted listed companies in China.

Table 9 Placebo robustness test

	$NCSKEW_{i,T}$		$DUVOL_{i,T}$	
	(1)	**(2)**	**(3)**	**(4)**
$TREAT_{i,T} \times POST^*_{i,T}$	0.013	0.056	− 0.008	− 0.058
	(0.245)	(1.475)	(− 0.039)	(− 0.431)
C	− 1.118	− 0.649	1.947	0.541
	(− 1.007)	(− 0.767)	(0.607)	(0.250)
Fixed effect	√	√	√	√
Year trend	√	√	√	√
Controls	√	√	√	√
Psm samples	×	√	×	√
N	2380	2380	527	527
ADJ. R^2	0.045	0.044	0.065	0.081

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses. The t-value is in parentheses

Table 10 Counterfactual tests based on non-heavily polluting industries

	$NCSKEW_{i,T}$		$DUVOL_{i,T}$	
	(1)	**(2)**	**(3)**	**(4)**
$TREAT_{i,T} \times POST_{i,T}$	0.038	− 0.000	0.033*	− 0.031
	(1.456)	(− 0.001)	(1.724)	(− 0.262)
C	0.282	1.582	0.407	1.967
	(0.733)	(0.841)	(1.408)	(1.429)
Fixed effect	√	√	√	√
Year trend	√	√	√	√
Controls	√	√	√	√
Psm samples	×	√	×	√
N	11,514	1613	11,514	1613
ADJ. R^2	0.008	0.018	0.010	0.021

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses. The t-value is in parentheses

Counterfactual test

As the main body of carbon emissions (Tian et al. 2019), CETS affects heavily polluting enterprises' off-balance sheet carbon emission reduction risk (Zhou et al. 2016b). However, for non-heavily polluting enterprises, CETS may not have the impact found in this study. Therefore, similar tests with non-heavily polluting enterprises as study samples are carried out. Table 10 shows the empirical results. The CETS pilot project could not reduce the stock price crash risk of non-heavily polluting enterprises.

Substitution of dependent variables

This part further selects the dummy variable *CRASH* to carry out the robustness test of the replacement variable (Kim et al. 2011, 2019; Bao et al. 2022). We define crash weeks in a given fiscal firm-year, during which the firm experiences firm-specific weekly returns 3.09 standard deviations below the mean firm-specific weekly returns over the entire fiscal year. $CRASH_{i,T}$ is denoted as 1 when company i experienced at least one

Table 11 Counterfactual tests based on non-heavily polluting industries

	$CRASH_{i,T}$	
	(1)	**(2)**
$TREAT_{i,T} \times POST_{i,T}$	− 0.039**	− 0.033*
	(− 2.282)	(− 1.790)
C	− 0.242	− 0.246
	(− 1.172)	(− 0.835)
Fixed effect	√	√
Year trend	√	√
Controls	√	√
Psm samples	×	√
N	6366	3980
ADJ. R^2	0.004	0.003

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses

Table 12 CETS impact on the stock price crash risk

	$NCSKEW_{i,T}$		$DUVOL_{i,T}$	
	(1)	**(2)**	**(3)**	**(4)**
$TREAT^*_{i,T} \times POST_{i,T}$	− 0.306***	− 0.271***	− 0.144**	− 0.130**
	(− 4.466)	(− 3.678)	(− 2.481)	(− 2.123)
C	− 0.328	− 0.546	0.184	− 0.013
	(− 0.674)	(− 0.786)	(0.515)	(− 0.029)
Fixed effect	√	√	√	√
Year trend	√	√	√	√
Controls	√	√	√	√
Psm samples	×	√	×	√
N	6366	3980	6366	3980
ADJ. R^2	0.025	0.025	0.028	0.027

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses

week of a stock price crash in year T, and 0 if otherwise. Table 11 shows the empirical results. These results still show a significant negative correlation between the implementation of the CETS pilot project ($TREAT_{i,T} \times POST_{i,T}$) and the stock price crash risk ($CRASH_{i,T}$) of heavily polluted listed companies in China.

Substitution of independent variables

Considering that different heavily polluting companies may suffer different impacts from CETS, this part further selects *Carbon Trading Concept* (CTC) stocks released by Flush Finance (300033. SZ) as the experimental group.[10] *Flush Finance* is a famous stock trading management software listed on China's Shenzhen Stock Exchange. If the heavily polluting listed company in the pilot province belongs to CTC stock, then *Treat** is recorded as 1. Otherwise, *Treat** is 0. Table 12 shows the empirical results. These results still show

[10] http://q.10jqka.com.cn/gn/detail/code/300931/.

Table 13 Heterogeneity test based on capital market performance

	$NCSKEW_{i,T}$					$DUVOL_{i,T}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$TREAT_{i,T} \times POST_{i,T}$	0.060	− 0.248***	− 0.021	− 0.176***	− 0.227***	0.014	− 0.169***	− 0.069	− 0.128***	− 0.184***
	(1.084)	(− 3.674)	(− 0.325)	(− 2.767)	(− 3.740)	(0.342)	(− 3.849)	(− 1.437)	(− 2.819)	(− 4.451)
$BULL_{i,T} \times TREAT_{i,T} \times POST_{i,T}$					0.207***					0.164***
					(4.033)					(4.683)
$BULL_{i,T}$					− 0.032					− 0.034**
					(− 1.439)					(− 2.077)
$INF_{i,T} \times TREAT_{i,T} \times POST_{i,T}$					0.041					0.016
					(0.742)					(0.402)
$INF_{i,T}$					− 0.109***					− 0.048***
					(− 4.299)					(− 2.704)
C	− 0.866	− 0.094	1.675	− 1.187	− 0.006	− 0.289	0.484	1.406**	− 0.435	0.480
	(− 1.072)	(− 0.091)	(1.593)	(− 1.205)	(− 0.009)	(− 0.479)	(0.717)	(2.068)	(− 0.599)	(1.060)
Fixed effect	√	√	√	√	√	√	√	√	√	√
Year trend	√	√	√	√	√	√	√	√	√	√
Controls	√	√	√	√	√	√	√	√	√	√
Psm samples	√	√	√	√	√	√	√	√	√	√
N	2573	2110	1846	2321	4167	2573	2110	1846	2321	4167
ADJ. R^2	0.029	0.058	0.051	0.023	0.034	0.031	0.063	0.059	0.025	0.036

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses. Columns (1) and (6) are the bull market condition group, columns (2) and (7) are the bear market condition group, columns (3) and (8) are the high informativeness group, columns (4) and (9) are the low informativeness group, and columns (5) and (10) are all samples a significant negative correlation between the implementation of the CETS pilot project ($TREAT^{*}_{i,T} \times POST_{i,T}$) and the stock price crash risk ($NCSKEW_{i,T}$ or $DUVOL_{i,T}$) of heavily polluted listed companies belonging to CTC stocks in China.

Heterogeneity test

Heterogeneity of capital market performance

China's stock market volatility is relatively large compared with developed capital markets, particularly the abnormal rise and fall (Long et al. 2014). If the market is in a bull condition, investors may ignore carbon risk because of the market's optimism. Conversely, if the market is in a bear condition, investors may focus on carbon risk because of market pessimism. Therefore, the market condition may affect the impact of the CETS on the capital market. Table 13 divides the sample into the bull and bear market conditions. The bull market condition refers to the years in which the Shanghai Composite Index rises and BULL is denoted as 1. The bear market condition refers to the years in which the Shanghai Composite Index falls and BULL is denoted as 0.

In addition to market condition, stock price informativeness is another critical factor that affects stock pricing and stock price crash risk (Hutton et al. 2009). For enterprises with lower stock price informativeness, CETS may provide more information about carbon emissions, which is conducive to reducing the risk of stock price crashes. For companies with higher stock price informativeness, the cumulative information supply effect of CETS may be weakened, decreasing its impact on the stock price crash risk. Therefore, based on Morck et al. (2000) and Durnev et al. (2003), Table 13 divides the sample companies into companies with high ($INF=1$) and low ($INF=0$) stock price informativeness according to the synchronization of stock price.

Table 13 reports the results of the heterogeneity test of capital market performance. Among them, market condition heterogeneity tests show that CETS can reduce the stock price crash risk of heavily polluting companies more in bear market conditions. This finding indicates that the market's optimism may ignore the carbon emission risk. When the market is pessimistic, the carbon emission risk is more likely to attract the attention of investors. Stock price informativeness heterogeneity tests show that CETS can reduce the stock price crash risk of heavily polluting companies with lower stock price informativeness. This result indicates that the information supply effect of CETS is affected by the informativeness of the company's stock price. The triple difference model further shows that the bull market condition will significantly weaken the impact of CETS on the stock price crash risk, indicating that market conditions significantly impact the consequences of CETS.

Heterogeneity of corporate management characteristics

Managers are the main decision-making body of enterprises, so the implementation effect of CETS is affected by the management style. Considering that carbon emission reduction will directly affect the short-term economic performance of heavily polluting enterprises, it may be excluded by short-sighted management. On the contrary, carbon emission reduction brings long-term value to enterprises and society and may be more popular with long-sighted management (Xu et al. 2020). Referring to Brochet

Table 14 Heterogeneity test based on corporate management characteristics

	$NCSKEW_{i,T}$					$DUVOL_{i,T}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$TREAT_{i,T} \times POST_{i,T}$	− 0.164**	− 0.037	− 0.292**	− 0.051	− 0.030	− 0.129***	− 0.051	− 0.250***	− 0.048	− 0.030
	(− 2.275)	(− 0.660)	(− 2.312)	(− 1.004)	(− 0.576)	(− 2.605)	(− 1.273)	(− 2.704)	(− 1.380)	(− 0.786)
$SHORT_{i,T} \times TREAT_{i,T} \times POST_{i,T}$					− 0.093*					− 0.073*
					(− 1.712)					(− 1.876)
$SHORT_{i,T}$					0.019					0.036**
					(0.797)					(2.001)
$CER_{,T} \times TREAT_{i,T} \times POST_{i,T}$					− 0.052					− 0.046
					(− 0.779)					(− 0.972)
$CER_{i,T}$					0.042					0.003
					(1.244)					(0.128)
C	− 1.381	0.893	1.322	− 0.580	− 0.059	0.132	0.526	1.153	0.019	0.264
	(− 1.182)	(1.129)	(0.539)	(− 0.834)	(− 0.093)	(0.162)	(0.976)	(0.703)	(0.040)	(0.616)
Fixed effect	√	√	√	√	√	√	√	√	√	√
Year trend	√	√	√	√	√	√	√	√	√	√
Controls	√	√	√	√	√	√	√	√	√	√
Psm samples	√	√	√	√	√	√	√	√	√	√
N	2573	2110	1846	2321	4167	2573	2110	1846	2321	4167
ADJ. R^2	0.029	0.058	0.051	0.023	0.034	0.031	0.063	0.059	0.025	0.036

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses. Columns (1) and (6) are the short-sighted management group, columns (2) and (7) are the long-sighted management group, columns (3) and (8) are the actively CSR group, columns (4) and (9) are the passively CSR group, and columns (5) and (10) are all samples

Table 15 Heterogeneity test based on pollutants

	$NCSKEW_{i,T}$				$DUVOL_{i,T}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$TREAT_{i,T} \times POST_{i,T}$	− 0.137**	− 0.220**	− 0.049	− 0.062	− 0.122***	− 0.159**	− 0.035	− 0.048
	(− 2.163)	(− 2.139)	(− 0.595)	(− 1.076)	(− 2.848)	(− 2.334)	(− 0.652)	(− 1.201)
$AIR_{i,T} \times TREAT_{i,T} \times POST_{i,T}$				− 0.156**				− 0.128**
				(− 1.979)				(− 2.444)
$SOLID_{i,T} \times TREAT_{i,T} \times POST_{i,T}$				0.143				0.090
				(1.478)				(1.390)
$WATER_{i,T} \times TREAT_{i,T} \times POST_{i,T}$				0.012				0.025
				(0.142)				(0.444)
C	1.570*	− 0.979	0.249	− 0.419	1.360**	0.092	0.712	0.128
	(1.808)	(− 0.605)	(0.236)	(− 0.854)	(2.269)	(0.088)	(0.957)	(0.357)
Fixed effect	√	√	√	√	√	√	√	√
Year trend	√	√	√	√	√	√	√	√
Controls	√	√	√	√	√	√	√	√
Psm samples	√	√	√	√	√	√	√	√
N	2207	711	1737	6366	2207	711	1737	6366
ADJ. R^2	0.037	0.049	0.032	0.026	0.048	0.060	0.028	0.029

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses. Columns (1) and (5) are the air pollution intensive industries, columns (2) and (6) are the solid waste pollution intensive industries, columns (3) and (7) are the water pollution intensive industries, and columns (4) and (8) are all samples

et al. (2015) and Hu et al. (2021), based on text analysis technology,[11] Table 14 divides the sample companies into short-sighted management (*SHORT* = *1*) and long-sighted management (*SHORT* = *0*).

As a part of corporate environmental responsibility (CER), environmental governance behaviors, including carbon emission reduction, will be affected by the enthusiasm of listed companies for environmental responsibility (Xu et al. 2020). If corporate environmental responsibility is passive, then CETS can become a formality. Enterprises will try their best to avoid carbon emission trading governance, thereby weakening the governing role in the CETS pilot project. Therefore, referring to Chen et al. (2018), Table 14 divides the sample companies into active CSR (*CER* = *1*) and those that do not (*CER* = *0*) according to the information disclosure of corporate environmental performance.

Table 14 reports the results of the heterogeneity test of corporate management styles. Among them, short-sighted management heterogeneity tests show that CETS can reduce the stock price crash risk of heavily polluting companies more in short-sighted management. This finding indicates that CETS may compensate for short-sighted management's neglect of carbon reduction risk. Corporate environmental performance heterogeneity tests show that CETS has a more significant impact on the companies that actively undertake environmental responsibility. This finding indicates that the governance effect of CETS will be affected by the enthusiasm for CER. The triple difference model further shows that short-sighted management will significantly enhance the

[11] Data from WinGO financial text data platform: http://www.wingodata.com.

Table 16 Analyst coverage mechanism test

	PANEL A			PANEL B		
	$ALY_{i,T}$	$NCSKEW_{i,T}$	$DUVOL_{i,T}$	$REP_{i,T}$	$NCSKEW_{i,T}$	$DUVOL_{i,T}$
	(1)	(2)	(3)	(4)	(5)	(6)
$ALY_{i,T}$		0.006***	0.010***			
		(4.841)	(5.640)			
$REP_{i,T}$					0.002***	0.004***
					(4.382)	(5.367)
$TREAT_{i,T} \times POST_{i,T}$	− 1.727**	− 0.081**	− 0.074	− 3.321**	− 0.085**	− 0.078
	(− 2.425)	(− 2.280)	(− 1.497)	(− 2.028)	(− 2.391)	(− 1.586)
C	− 91.912***	0.540	0.322	− 219.275***	0.490	0.249
	(− 8.042)	(0.917)	(0.379)	(− 8.366)	(0.837)	(0.303)
Fixed effect	√	√	√	√	√	√
Year trend	√	√	√	√	√	√
Controls	√	√	√	√	√	√
Psm samples	√	√	√	√	√	√
N	3496	3496	3496	3553	3553	3553
ADJ. R^2	0.146	0.022	0.027	0.134	0.021	0.026

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The t-value is in parentheses

impact of CETS on the stock price crash risk, indicating that management styles have a more significant impact on the consequences of CETS.

Heterogeneity of pollutants

Considering the difference in carbon emissions of different heavily polluting industries, Table 15 further divides the samples into air pollution–intensive industries ($AIR=1$), solid waste pollution–intensive industries ($SOLID=1$), and water pollution–intensive industries ($WATER=1$) by referring to Yang and Tang (2022). Table 15 reports the results of the heterogeneity test of pollutants. The results show that CETS can reduce the stock price crash risk of heavily polluting enterprises with intensive air pollution and solid waste. However, CETS has no significant influence on the stock price crash risk of heavily polluting enterprises with intensive water pollution. The triple difference model further shows that CETS has a more significant impact on the stock price crash risk of heavily polluting enterprises with intensive air pollution. Greenhouse gases represented by CO_2 have apparent homologies with air pollution, such as SO_2 and NO_X. A strong synergy exists between carbon emission and air pollution (Van et al. 2006). Therefore, carbon emission control policies, such as CETS, will also have a synergistic effect on air pollution (Zhou et al. 2016a).

Discussion on mechanism

Referring to Xu et al. (2017), the company's analyst coverage is measured based on the number of analysts' concerns (ALY) and the number of analyst research reports (REP). This study further constructs the following analyst coverage mechanism test model:

$$ALY_{i,T} \text{ or } REP_{i,T} = C + \rho_0 Post_{i,T} \times Treat_{i,T} + \beta CVs_{i,T} + \mu_T + \varphi_i + \varepsilon, \quad (6)$$

$$NCSKEW_{i,T}\ or\ DUVOL_{i,T} = C + \rho_1 ALY_{i,T}\ or\ REP_{i,T} + \rho_2 Post_{i,T} \times Treat_{i,T} + \beta CVs_{i,T} + \mu_T + \varphi_i + \varepsilon. \tag{7}$$

Equation (6) tests the impact of *CETS* on analyst coverage (*ALY* and *REP*), and Eq. (7) tests the impact of analyst coverage (*ALY* and *REP*) on stock price crash risk (*NCSKEW* and *DUVOL*). Coefficients ρ_0 and ρ_1 are concerned.

Table 16 reports the results of the heterogeneity test of corporate management styles. The results of columns (1) and (4) show that a significant negative correlation exists between the CETS pilot project ($TREAT_{i,T} \times POST_{i,T}$) and the analyst coverage ($ALY_{i,T}$ *or* $REP_{i,T}$) of heavily polluting listed companies. This result is consistent with the hypothesis analysis in "Literature review and hypothesis development" section, that is, heavy polluting enterprises have significant off-balance sheet carbon emission reduction risk before the implementation of CETS, which will attract the attention of analysts (Zhang 2022). However, the implementation of CETS has weakened the off-balance sheet carbon emission reduction risk of heavy polluters and reduced the attention of analysts. The results of the other columns further show a significant positive correlation between analyst coverage ($ALY_{i,T}$ *or* $REP_{i,T}$) and the stock price crash risk ($NCSKEW_{i,T}$ *or* $DUVOL_{i,T}$) of heavily polluting listed companies. These results are consistent with Xu et al. (2013), that is, analyst coverage intensifies the management's negative news hiding and investors' reaction, further exacerbating the risk of stock price crashes.

In conclusion, before the implementation of CETS, the off-balance sheet carbon emission reduction risk of heavily polluting enterprises attracted analysts' coverage. Eventually, the risk of stock price crashes aggravated. However, CETS changed that, reducing the exposure of heavy polluters to analysts and thus reducing the risk of stock price crashes. As a result, Hypothesis 2 is verified.

Conclusion

Owing to the enormous pressure of carbon emission reduction, heavily polluting enterprises in China are facing severe carbon emission reduction risks. China's CETS pilot project creates the condition for heavy polluters to mitigate the risks of carbon emission reduction and record the cost. The CETS pilot project could reduce the stock price crash risk of China's heavy polluters caused by the threat of off-balance sheet carbon reduction. Based on the Chinese A-share heavily polluting listed companies from 2007 to 2019, the staggered DID and PSM-DID models are constructed in this study to verify the effect of CETS on reducing the risk of stock price crashes.

The results show that CETS could help reduce the stock price crash risk of heavily polluting companies in the pilot areas. The heterogeneity analysis further shows its influence on heavily polluting enterprises with the bear market condition, short-sighted management, and intensive air pollution. Mechanism tests show that analyst coverage plays a mediating role in CETS' impact on the stock price crash risk. This study helps clarify the relationship between corporate climate risk and financial risk.

As the firm-level carbon emission and carbon trading information is unavailable in China (Zhang et al. 2019), this study chooses listed companies in the heavy pollution industry to examine the effect of CETS. In the future, in-depth research can be conducted around more accurate carbon emission industries and information by implementing the carbon trade information disclosure system.

Appendix

See Table 17.

Table 17 The differences between samples before and after matching (1:1 matching)

Variable	Matched	Mean		t-Value	Sig
		Treat	Control		
SIGMA	N	0.046	0.046	− 0.150	0.878
	Y	0.046	0.045	0.970	0.330
RET	N	− 0.001	− 0.001	− 0.230	0.819
	Y	− 0.001	− 0.001	− 1.400	0.161
SIZE	N	22.386	22.174	5.910***	0.000
	Y	22.382	22.361	0.450	0.655
LEV	N	0.443	0.453	− 1.760*	0.078
	Y	0.443	0.438	0.740	0.460
ROE	N	0.058	0.049	1.880*	0.060
	Y	0.058	0.052	1.110	0.268
ABSDA	N	0.054	0.055	− 0.720	0.472
	Y	0.054	0.054	− 0.340	0.736
TURN	N	0.666	0.671	− 0.360	0.722
	Y	0.667	0.647	1.330	0.184
GENDER	N	0.951	0.948	0.460	0.643
	Y	0.951	0.961	− 1.600	0.110
DEGREE	N	0.917	0.838	8.260***	0.000
	Y	0.916	0.914	0.290	0.769
DUAL	N	0.237	0.214	2.000**	0.045
	Y	0.236	0.262	− 1.820*	0.069
SALARY	N	42.017	41.355	2.090**	0.037
	Y	42.040	42.199	− 0.410	0.680
INDEP	N	0.372	0.367	3.850***	0.000
	Y	0.372	0.372	0.000	0.999
STATE	N	0.453	0.477	− 1.750*	0.080
	Y	0.454	0.439	0.890	0.374
FINRSIK	N	0.887	0.886	0.080	0.933
	Y	0.887	0.892	− 0.520	0.602
ABCFO	N	− 0.001	0.002	− 1.370	0.171
	Y	0.000	− 0.001	0.590	0.558
PPE	N	0.282	0.326	− 9.050***	0.000
	Y	0.283	0.282	0.120	0.907

In this paper, ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively

Abbreviations

CETS	Carbon emission trading system
DID	Difference-in-difference
PSM	Propensity score matching
NCSKEW	Negative conditional skewness
DUVOL	Down-to-up volatility

ESG	Environmental, social responsibility, and governance
BJ	Beijing
TJ	Tianjin
SH	Shanghai
GD	Guangdong province
GD.SZ	Shenzhen in Guangdong province
HB	Hubei
CQ	Chongqing
FJ	Fujian
NCETS	National Carbon Emission Trading System
CSR	Corporate social responsibility
RET	Average abnormal return
SIGMA	Volatility of abnormal returns
SIZE	Total assets
LEV	Asset–liability ratio
ABSDA	Accrued earnings management
TURN	Total asset turnover
ROE	Return on equity
GENDER	Male CEO
DEGREE	Highly educated CEO
DUAL	Combining the CEO and Chairman
SALARY	Executive compensation incentive
INDEP	Proportion of independent directors
FINRISK	Post-subprime crisis
ABCFO	Abnormal cash flow
PPE	Proportion of fixed assets
STATE	State-owned
CEO	Chief Executive Officer
REM	Real earnings management
NPL	New Environmental Protection Law
CRASH	Stock price crash risk
CTC	Carbon trading concept
INF	Stock price informativeness
SHORT	Short-sighted management
CER	Corporate environmental responsibility
AIR	Air pollution–intensive industries
SOLID	Solid waste pollution–intensive industries
WATER	Water pollution–intensive industries
ALY	Number of analysts' concerns
REP	Number of analyst research reports

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Declarations

Competing interests
We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

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