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The Policy Impact of Carbon Emission Trading on Building Enterprises' Total Factor Productivity in China

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Abstract: Nearly 40 percent of worldwide energy and process-related CO_2 emissions are produced by the construction sector. China's construction industry is the largest in the world, with Chinese construction enterprises completing a total output value of RMB 26.39 trillion in 2020; these buildings contribute to about 20 percent of China's overall carbon emissions and 20 percent of the global total emissions. There is an urgent need to prove whether construction enterprises are benefiting from the carbon trading policy. Compared to the traditional method, a double difference model can be used to highlight the consequences of different states of construction enterprises' responses to carbon trading regimes. In this study, we examine the following results based on cross-sectional data collected from 2006 to 2021, from listed construction enterprises: (1) Existing carbon emission policies have had a significant impact on the improvement of construction enterprises' total factor productivity. This improvement is more pronounced in large state-owned enterprises in particular. (2) Construction enterprises' greater involvement in carbon trading income is most strongly influenced by their green innovation level. (3) Construction enterprises located in eastern and central China benefit significantly from carbon trading, but construction enterprises based in the west do not. The research result indicates that future incentive initiatives should pay more attention to western regions and privately owned building enterprises. The leading role of large state-owned building enterprises should be reinforced.

Keywords: total factor productivity; building enterprise; carbon emission trading policy; double difference

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1. Introduction

In January 2020, global land and ocean surface temperatures were 1.14 degrees Celsius warmer than the 20th century average January temperature (12 degrees Celsius), surpassing the record set in January 2016. For the 44th consecutive January, temperatures were above the 20th century average January temperature, with the 10 hottest Januarys, since meteorological records, all occurring since 2002 [1]. Arctic sea ice cover is 5.3% below the 1981–2010 average and Antarctic sea ice cover is 9.8% below the 1981–2010 average [2]. Rapid human economic development and urbanization are accelerating global carbon emissions and, consequently, the global greenhouse effect. China, as the world's largest emitter of carbon, is under pressure to make a low-carbon transition [3]. Several studies have shown that fine particulate matter (PM2.5) over urban built-up land has increased with urbanization, and land use patterns may be the second key driver after fossil fuel combustion [4–6].

Nowadays, worldwide sustainable development is advancing two significant processes simultaneously. One is to promote the United Nations Sustainable Development Agenda 2030, which aims to achieve coordination and balance between global economic development, social progress, and environmental protection; the other is the implementation of the Paris Agreement, which aims to promote energy development and to achieve low-carbonization transformation. These two documents are consistent and trigger an extensive synergy. To realize the goal of controlling global warming and solving the energy shortage, more and more individuals support establishing a low-carbon energy system by forming a green, cyclical economic system, and through collaborative management, address oversize carbon dioxide emissions [7]. Therefore, many governments worldwide have strengthened carbon emission regulations [8,9]. These regulations include mandatory regulations, market-oriented regulations, and voluntary actions [10]. Carbon emission trading, as one of the exemplary implementations to reach emission reduction goals, has a significant advantage in cost [11]. Consequently, such market-oriented implementations have now been widespread in the United States, Europe, Japan, China, and other countries with noticeable effects [9]. Especially by promotion of the Kyoto Protocol in 1997, there are also a variety of countries that have announced their aim to establish carbon trading markets [12–15].

China's 14th Five-Year Plan period is currently in progress and involves maintaining its determination and adherence to goals aimed at energy conservation and carbon reduction. Figure 1 shows the milestones of China's carbon trading policy. In 2011, China established Beijing, Shanghai, Tianjin, Chongqing, Shenzhen, and other regions as pilot areas [16]. Five years later, in 2017, the national carbon emission trading system started operating, which represented the start of the era of carbon emission trading in China. Carbon emission trading is a flexible and efficient environmental regulatory method [8] and its core mechanism is officially allocated quotas of carbon emissions. The fewer quotas an industry or an enterprise receives, the more stringent the control is, and as a consequence, the more influence it has on shaping enterprise green behavior [17]. Through fluctuations in carbon prices, the carbon emission trading system aims to achieve the optimal allocation of emission reduction resources [18]. Environmental protection does not mean giving up economic development. To address the decrease in capital returns and disappearance of demographic dividends, the Fifth Plenary Session of the 19th Central Committee of the Communist Party of China states the importance of promoting total factor productivity to shift the current mode of economic growth in China. Total factor productivity can be defined as a measure of a company's production ability, and it is widely applied in enterprise performance assessments in competitiveness and growth investigation situations [19]. By analyzing the literature, previous studies have reported that total factor productivity can comprehensively reflect the development of an enterprise compared with other indicators [20]. To some extent, total factor productivity could be a critical indicator for assessing the environmental performance of the Chinese society [21]. As a consequence, many scholars have used total factor productivity to evaluate green policy effects and the relationship between policy implementation and TFP fluctuation [22–24]. For instance, some scholars have redefined the total factor productivity theory and extended the theory into total factor energy productivity for green action evaluation [25,26]. In addition, China's total factor energy productivity has been tested and its fluctuations decomposed into technical factors and efficiency changes [22]. Alternatively, research has classified Chinese industry according to geographical locations such as the Qinling-Huaihe River and cities to analyze the regional differences in green total factor productivity [27–29]. Moreover, with the maturation of information technology, studies have also investigated the relationship between digital economy and total factor productivity under environmental regulation [30–34]. Interestingly, since the pilot of China's carbon emission trading policy in 2012, a growing number of scholars have used various methods to assess the impact of carbon trading policies on business conditions and sustainable development [35,36]. Among these studies, the development of agricultural enterprises has received the most attention [37,38]. In terms of research methodology, some studies have used multi-agent simulation to analyze the operations of 100 companies under a carbon trading system, revealing the operational mechanisms and dynamic evolution of the carbon trading market [39].

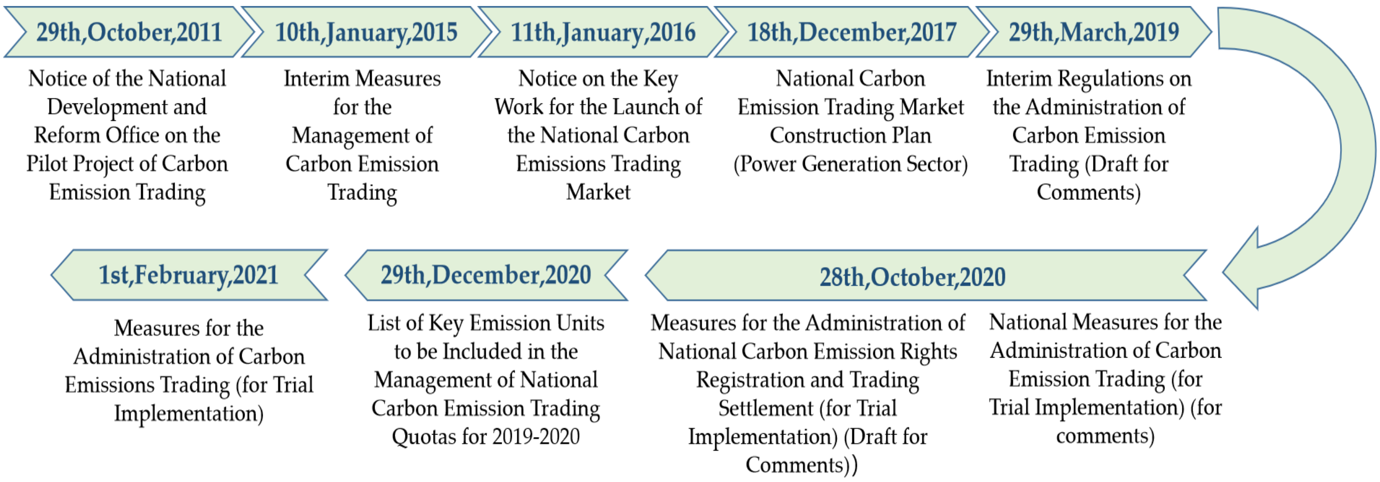


Figure 1. The milestones of China's carbon trading policy.

The current research methods have mostly involved simulations and analyses to establish a CGE model, but have lacked the support of empirical data [40]. In addition, most research has involved listed enterprises, with a focus on the entire industry, but lacked micro investigations into engineering enterprises. Moreover, previous studies also reflect a shortage in testing the heterogeneity of the economic effect of carbon emission trading in different enterprises, and there is a relatively small number of studies in the literature that have been concerned with the green invention development of engineering enterprises, especially through independent green patent application and publication perspectives.

To advance the research, by considering listed construction enterprises from 2006 to 2021, in this paper, we apply endogenous growth theory, innovation compensation theory, and a dual path of a logical reasoning approach as well as mathematical derivation, to deeply analyze the relationships among carbon emission trading and engineering enterprises' total factor productivity. Then, an empirical test is carried out, and its heterogeneity is deeply analyzed. The contributions of this study are as follows:

Firstly, this study offers direct empirical evidence for an accurate assessment of the pilot carbon emission trading policy from the perspectives of the environment and economics, which fills the shortage of empirical evidence in China's carbon trading.

Secondly, by combining with the industry traits, this study evaluates the impact of emission trading policies on the total factor productivity of listed construction enterprises and expands the research perspective of carbon trading fields.

Thirdly, in order to analyze the heterogeneity of the economic effect of carbon emission trading in different types of enterprises, this research, through multiple tests, ensures the research's conservativeness and develops the existing studies from a micro perspective. To sum up, the scientific problem of this study is to determine if carbon trading policies have had favorable effects on the total factor productivity of construction enterprises, and to investigate the elements via which these benefits are mediated, and to determine if the effects of carbon trading programs varied for different features of construction enterprises and what future policy changes should be made to promote better results.

The objectives of this study are to assess whether trading policies have contributed to the improvement of total factor productivity of listed construction enterprises, and to reveal those factors that played a key role in the process. On this basis, this study also aims to conduct a flexible carbon trading policy according to the different characteristics of construction enterprises.

The remainder of this paper is structured as follows: Section 2 describes the materials and methods; Section 3 demonstrates the research process and methodology; Section 4 outlines the empirical analysis; the final section states conclusions based on all the research results and implications.

2. Materials and Methods

2.1. Theoretical Analysis and Hypotheses

In 2011, China launched a pilot scheme for carbon emission trading in seven provinces and cities, including Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen. Under the scheme, enterprises acquired the right to emit greenhouse gases into the atmosphere in accordance with the law. In the pilot cities, a carbon emission trading policy was implemented, whereby enterprises obtained quotas for greenhouse gas emissions for a certain period of time, as approved by the local development and reform commission (now under the responsibility of the environmental protection department). When an enterprise's actual emissions exceeded the quota, the excess had to be purchased at a cost; when the enterprise's actual emissions were less than the quota, the balance could be carried forward, to be used or sold to the public. Therefore, the aim of this research, at the provincial scale, was to study the policy impact of carbon emission trading policy on building enterprises' total factor productivity in China.

The price mechanism of carbon emission trading achieves control over carbon emissions during the production and operation of enterprises by internalizing the external costs of the carbon emissions of construction enterprises. Cost-push and revenue incentives are the two main approaches to enable the above process. Cost-push means that commercialized carbon emission rights are strictly regulated by government departments [41]. Under governmental regulations, construction enterprises whose carbon emissions exceed their allowances are required to buy more allowances from the government or the market, resulting in higher operating costs. In such a context, the total factor productivity (TFP) of enterprises decreases to some extent. Enterprises that do not comply with the regulations are fined, which undoubtedly increases the costs of enterprises, pushing them to use their carbon emission allowances more efficiently. The revenue incentive effect is mainly manifested in the fact that carbon emission rights can be traded under a certain market mechanism, which creates space and opportunities for the participants to reap profits. On this basis, construction enterprises can reduce their carbon emissions by improving their technological innovation abilities, and the remaining allowances can be traded to generate income. Specifically, when the cost of emission reduction is lower than the market price of carbon, carbon emission allowances can be sold in carbon exchanges, and the profit generated is the difference between the cost and the selling price. Motivated by this effect, enterprises have become more efficient in technological innovation, resulting in lower emission reduction costs and higher carbon trading profits [41]. The market trading mechanism facilitates an effective allocation of carbon emission allowances, and thus reduces carbon emissions and the costs of emission reduction of different stakeholders as much as possible. Therefore, in terms of the effect of the implementation of policies on carbon emission trading, in this paper, we proposed the following hypothesis:

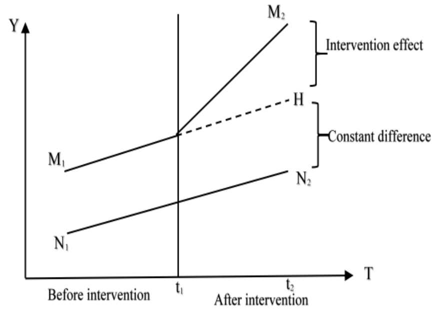
H_1. *The carbon emission trading pilot project promotes TFP development of construction enterprises.*

Developing scientific and technological innovation is also a major way to enhance the TFP of construction enterprises. On the one hand, with the given carbon allowances, construction enterprises in the pilot areas pay more attention to research related to emission reduction technology to reduce the cost of emission reduction and to improve the efficiency of emission reduction. On the other hand, these enterprises save some carbon allowances by developing their green emission reduction technologies and generate profits by trading the surplus allowance in the carbon trading market. In the long run, the optimal choice for profit-oriented construction enterprises is to develop and use green emission reduction technologies to solve the problem of carbon emission constraints and emission reduction costs. Therefore, the formulation and implementation of carbon trading policy urge construction enterprises to conduct research and development on green innovations. This phenomenon not only enables the total carbon emissions of the construction industry to meet the goal of carbon emission constraints set by the government but also stimulates green innovations across the industry, thus increasing the TFP of the whole industry. For this reason, in this paper, we selected green patents, and then tested the transmission mechanism of the conducted policy. To confirm that the pilot project increases the TFP of building enterprises in pilot areas through increasing the green creation ability of construction enterprises, we proposed the following hypothesis:

H_2. *The carbon emission trading pilot project increases the TFP of construction enterprises through promoting innovation.*

2.2. Methods

The difference-in-differences (DID) technique is widely applied in the field of econometrics and quantitative research. The rationale for choosing regression analysis is that this method is suitable for large sample regressions and, in particular, it better reflects trends in large samples of data. Data on 1040 listed construction enterprises were obtained for this study, which met the research requirements for a large sample regression. The logic underlying this method was applied as early as the 1850s by John Snow and is named a "controlled before-and-after study" [42]. Especially in social sciences, it tries to mimic experimental research through observational data by analyzing the differential performance of a treatment on a "treatment group" versus a "control group" in a natural experiment [43]. This method evaluates the performance of a treatment on an outcome by comparing and contrasting typical traits or changes over time in the outcome variable for the treatment group to that for the control group. Before conducting DID experimental research, the time-series data of treatment and control groups require two or more different ranges, particularly, at least one before the treatment point and at least one after that point. This method has been widely applied to assess the performance of certain treatments or interventions, such as the passage of laws, or enactment of a certain policy, as well as mega project implementation. Figure 2 explains the primary mechanism of a DID model for inspecting a particular treatment or policy [44]. In the sub figure a of Figure 2, the performance of the treatment group is represented by line M, and the performance in the control group is represented by line N. The outcome variable for both groups is assessed at time t_1 before either group has received the policy treatment, which refers to points M_1 and N_1. The treatment group then acquires the policy intervention, and two groups are tested a second time at time t_2. The gap between the two groups at time t_2 (that is, the difference in M_2 and N_2) is not precisely tested as the performance of the treatment or a specific policy, because the treatment group and the control group may not initially be the same at time t_1. As a consequence, DID evaluates the ordinary difference in the outcome elements between treatment and control groups, which is represented by the dotted line H. Notably, the slope from M_1 to H is the same as that of N_1 to N_2. Consequently, the treatment or policy intervention effect can be tested based on the difference between the observed outcome (M_2) and the normal outcome H (the difference between M_2 and H). In Figure 2b, the performance of the treated group before and after the therapy is represented by the letters Y_{M1} and Y_{M2} respectively. ΔY_{treat}, which is determined by deducting the value of Y_{M1} from the value of Y_{M2}, represents the variation in the treatment group's performance between before and after the treatment. Y_{N1} and Y_{N2}, by analogy, represent, respectively, the performance of the control group prior to and following the treatment. By deducting the value of Y_{N1} from the value of Y_{N2}, which is the value of $\Delta Y_{control}$, it was possible to determine the difference in the performance of the control group before and after receiving treatment. Contrarily, the difference between the treated and control groups is shown in the figure as ΔY_{treat} minus $\Delta Y_{control}$.



(**a**)

	Before Change	After Change	Difference
Treat Group	Y_{M1}	Y_{M2}	$\triangle Y_{treat} = Y_{M2} - Y_{M1}$
Control Group	Y_{N1}	Y_{N2}	$\triangle Y_{control} = Y_{N2} - Y_{N1}$
Difference			$\triangle Y_{treat} - \triangle Y_{control}$

(**b**)

Figure 2. Double difference model visualization [44].

A constant difference can be observed between the normal outcome H and the normal outcome of line N, which refers to N_2.

In order to ensure that the estimation of the intervention effect is critical, there are several assumptions that should be made, i.e., exchangeability, positivity, and stable unit treatment value assumptions, as follows:

- There is no relationship between intervention and baseline outcome, which means the intervention allocation is not attributed to the outcome.
- A parallel trend can be seen between the treatment group and control groups (see line M and line N).
- Performance of intervention and comparison results is consistent for repeated research design.
- No spillover phenomenon exists.

3. Research Design

3.1. Theoretical Framework

The research framework and experimental findings of this study not only reveal the changes in the total factor productivity of construction enterprises after participating in carbon trading policies but also provide a theoretical framework for evaluating the effectiveness of carbon trading policies and for guiding practice. In terms of generalizability, as shown in Figure 3, the industry sector should be identified before the carbon trading policy evaluation is conducted, for example, the research area of this paper is listed construction enterprises. This is followed by the collection and screening of data on the listed construction enterprises, from which experimental data are identified. Before constructing the benchmark double difference regression model, the research variables should be determined with include the dependent variable, independent variable, intermediary variable, and control variable. Subsequently, the benchmark double difference regression model is determined based on each research variable, and the benchmark regression model is tested for multicollinearity to ascertain that there is no serious multicollinearity between the variables before conducting the research results and a series of robustness tests. In conducting the study, different business entities will have different characteristics and will respond differently to the effects of the policy. Therefore, robustness checks are added to the Figure 3 research framework to explore the effects of different characteristics of firms' responses to carbon trading. This research framework enriches the theoretical framework of carbon trading policy evaluation, and has strong generalizability and scientific significance.

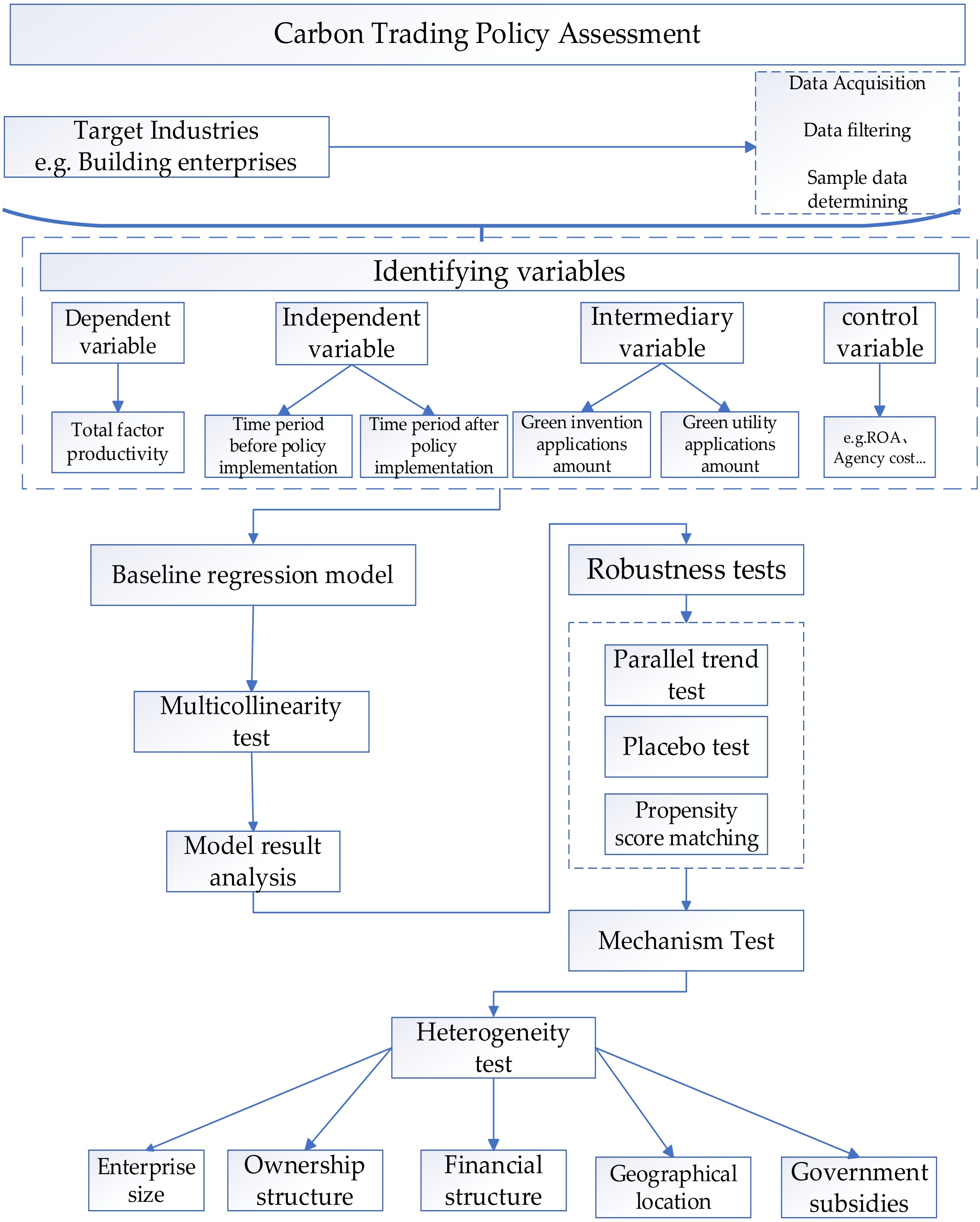


Figure 3. Carbon trading policy assessment framework.

3.2. Model Setting

3.2.1. Data Description

In this study, for the explained variable, similar to a study by J. Hua [41], we took into account the endogenous problems faced by sample selection and statistical methods.

Afterward, semiparametric methods (the Olley_Pakes method and the Levinsonh and Petrin method) were adopted to calculate the TFP. The results of the Levinsonh and Petrin (LP) method were applied for baseline regression, and then the output of the Olley–Pakes (OP) method was applied for robustness testing. The method for calculating total factor productivity and the indicators selected are as follows (the base period for the above variables is 2006):

$$TFP_{ijt} = \alpha_{jt} + \beta_{jt} L_{ijt} + \delta_{jt} C_{ijt} + \omega_{jt} M_{ijt} \varepsilon_{ijt} \quad (1)$$

TFP_{ijt}—the logarithm of the TFP of private enterprise i in industry j in year t
L_{ijt}—the logarithm of the labor input intensity of enterprise i in industry j in year t
C_{ijt}—the logarithm of enterprise i capital input in industry j in year t M_{ijt}—the logarithm of enterprise i intermediate capital input in industry j in year t ε_{ijt}—the random error terms

In the above model, in this study, we regress Model (1) to test the effect of carbon emission trading policy on the total factor productivity of construction enterprises. If the coefficient is significantly positive, it indicates that there is a positive linear relationship between the implementation of carbon emission trading policy and the total factor productivity of construction enterprises. If the coefficient is significantly negative, it means that there is a negative linear relationship between the implementation of carbon emission trading policy and the total factor productivity of construction enterprises.

To avoid estimation bias, in this study, we drew on the elements that could possibly influence the TFP of construction enterprises, determined by existing studies, and selected the following variables as control variables: enterprise size (Size), return on assets (Roa), asset-liability ratio (Lev), agency cost (Cost), cash flow from operations (CF), factor intensity (Capital), and the shareholding ratio of the largest shareholder (Top1). The specific definition of each variable is listed in Table 1.

Table 1. Definitions of variables.

Variable Symbol	Variable Name	Description
TFP	Total factor productivity of enterprises	Calculated by the C-D production function approach, the OP method, and the LP method
DID	Difference-in-differences interaction term	Treat * Post
Size	Enterprise size	Ln (total assets at the end of the period)
ROA	Return on assets	Net profit/total assets
Lev	Asset-liability ratio	Total liabilities at the end of the period/total assets at the end of the period
Cost	Agency cost	Administrative expenses/income from main businesses
CF	Cash flow from operations	Cash flow from operations/total assets at the end of the period
Capital	Factor intensity	Ln (actual net fixed assets per capita)
Top1	The shareholding ratio of the largest shareholder	The proportion of shares of the largest shareholder
GreInvia	The enterprise's innovation of green inventions	The number of green invention applications
GreUmia	The enterprise's innovation of green utility models	The number of utility applications

* Treat denotes the dummy variable of policy treatment (1 for provinces located in pilot areas and 0 for provinces located in non-pilot areas) and Post denotes the dummy variable of time (1 for the post-policy period and 0 for the pre-policy period).

3.2.2. Model Construction and Theories

To explore the effects of carbon emission rights on the TFP of construction enterprises, in this study, we constructed the following model:

$$\begin{aligned} TFP_{i,t} = \alpha_0 + \beta_1 DID_{i,t} + \beta_2 Size_{i,t} + \beta_3 ROA_{i,t} + \beta_4 Lev_{i,t} + \beta_5 Cost_{i,t} \\ +\beta_6 CF_{i,t} + \beta_7 Capital_{i,t} + \beta_8 Top1_{i,t} + \delta_t + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{2}$$

The following model was constructed to test the existence of the mechanism effect:

$$\begin{aligned} TFP_{i,t} = \alpha_0 + \beta_1 DID_{i,t} \times Patent_{i,t} + \beta_2 DID_{i,t} + \beta_3 Patent_{i,t} + \beta_4 Size_{i,t} + \beta_5 ROA_{i,t} + \beta_6 Lev_{i,t} \\ +\beta_7 Cost_{i,t} + \beta_8 CF_{i,t} + \beta_9 Capital_{i,t} + \beta_{10} Top1_{i,t} + \delta_t + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{3}$$

TFP_{it} reflects the TFP of building enterprises of sample enterprise i in the observation period t, α_0 represents the constant term (constant), and β represents the regression coefficient of each variable. If $\beta_1 > 0$, the TFP of building enterprises that are affected by carbon emission trading is significantly higher than that of those not affected by carbon emission trading. In other words, policies on carbon emission rights increase the TFP of construction enterprises. DID refers to $Treat_i * Time_t$, the interaction term of the treatment effect (Table 1), which reflects the average difference between the TFP of building enterprises affected by carbon emission trading and that of those not affected by carbon emission trading. Specifically, Treat denotes the dummy variable of policy treatment. Locations of pilot areas are assigned the value 1, and provinces located in non-pilot areas are assigned the value 0. Time is the dummy variable of time. The period before policy implementation is assigned the value zero, and the period after policy implementation is assigned the value one. $Patent_{i,t}$ is a variable related to the levels of green innovation of enterprises, which refers to the number of green inventions or the number of green utility models of construction enterprises in this study; δ_t is used to measure the time effect in the temporal dimension; μ_i is used to measure the fixed effect in the individual dimension; $\varepsilon_{i,t}$ is the random disturbance term that varies with the individual and time.

4. Empirical Analysis

4.1. Descriptive Statistics and Data Sources

As we all know, the data of listed enterprises have better accessibility and accuracy. At the same time, the data of listed construction enterprises are usually derived from the annual reports of the enterprises, which are highly standardized. Such data are very convenient for scientific research. For this reason, in this study, we selected all listed construction enterprises on the Shanghai and Shenzhen Stock Exchanges that belong to the building industry, and the data used were in line with the industry classification standard issued by the China Securities Regulatory Commission (CSRC). It included construction materials; real estate; construction of municipal roads; construction of municipal public utilities; water distribution projects; centralized heating, water supply and gas supply projects; construction of public welfare facilities such as cultural, educational, health, sports and music facilities; construction of monumental architectural facilities; and various construction enterprises. The annual data of the enterprises during the sample period (2006–2021) were selected, and the relationship between the rights to carbon emissions and trading, green innovation of construction enterprises, and the TFP of the civil engineering and construction industry. The data were preprocessed and cleaned before being used. The study obtained data from a sample of 1728 construction enterprises, from which 688 sample data did not qualify for the study and were removed. Therefore, 1040 observed values were obtained. The financial data of the listed construction enterprises involved were obtained from the Chinese Research Data Services (CNRDS) (http://www.cnrds.com) (accessed on 10 October 2022), and the data of green technology patents of enterprises were obtained from the national patent database. The data of the TFP of building enterprises were obtained by using the opreg command program in Stata17.0, the China Stock Market & Accounting Research Database (CSMAR) (https://www.gtarsc.com/) (accessed on 10 October 2022) and the RESSET Database were also data sources, supported by Tonghuashun (stock software) and Sina Finance.

This research used the level of green innovation of construction enterprises as the mechanism variable. There are three categories of patents in China, i.e., invention, utility model, and appearance, among which invention and utility model are technology-related patents. This study used the number of green invention applications and green utility applications to measure the green innovation of enterprises. The data of the listed construction enterprises' green innovation were obtained from the China National Intellectual Property Administration (http://english.cnipa.gov.cn/) (accessed on 15 October 2022), and the data were selected applying the green technology patent classification defined by the World Intellectual Property Organization (WIPO) (https://www.wipo.int/portal/en/index.html) (accessed on 15 October 2022) to obtain the amount of green invention applications and green utility applications. Greater numbers mean higher levels of green innovation in enterprises. Then, 16,083 green invention applications and 21,354 green utility applications were acquired.

Table 2 shows the results of descriptive statistics of the main variables. As shown in Table 2, the mean value, the minimum value, and the maximum value of the TFP of construction enterprises are 9.532, 6.685, and 12.959, respectively, and the standard deviation is 1.125, indicating significant fluctuations in the TFP of private enterprises and a wide dispersion of data. The mean values of the number of green invention applications and that of the number of green utility model applications of enterprises are 9.307 and 11.753, respectively, and the standard deviations are 34.535 and 40.437, respectively, suggesting huge gaps exist between construction enterprises' levels of green innovation during the sample period.

Table 2. Descriptive statistics of the main variables.

	N	Mean	SD	Min	Median	Max
TFP	1040	9.532	1.125	6.685	9.562	12.959
DID	1040	0.409	0.492	0	0	1
Size	1040	22.858	1.802	16.185	22.507	28.502
ROA	1040	0.015	0.076	−0.986	0.022	0.502
Lev	1040	0.643	0.188	0.028	0.675	1.89
Cost	1040	0.064	0.098	0.001	0.044	1.404
CF	1040	−0.001	0.365	−11.056	0.013	0.43
Capital	1040	12.03	1.137	4.431	12.06	15.386
Top1	1040	0.375	0.151	0.044	0.36	0.786
GreInvia	1040	9.307	34.535	0	0	534
GreUmia	1040	11.735	40.437	0	1	396

In the descriptive statistics of the data (see Table 2), Mean is the sample mean; SD is the sample standard deviation, representing the degree of dispersion of the data; Min is the sample minimum; Max is the sample maximum; and Median denotes the median value.

4.2. Multicollinearity Test

Multicollinearity refers to precise or high correlations between the explanatory variables in a regression model, which leads to skewed results or makes the results hard to estimate [45]. To remove multicollinearity, in this study, we adopted the variance inflation factor (VIF) method to perform a multicollinearity test on the model. When the maximum value of VIF is greater than 10, there might be serious multicollinearity [46]. When all VIF values are less than 10, there is no multicollinearity problem in the model [46]. Multicollinearity affects the results of model estimation and causes the results to be unreliable. In this study, Table 3 shows that there is no multicollinearity problem because all VIF values are less than 10.

Table 3. Multicollinearity test.

Variable	VIF	1/VIF
Size	1.850	0.540
Lev	1.540	0.649
Top1	1.170	0.852
Cost	1.170	0.853
ROA	1.160	0.862
DID	1.150	0.872
Capital	1.060	0.946
CF	1.030	0.971
Mean VIF	1.270	

4.3. Analysis of Regression Results

The regression results of regression model are shown in Table 4. Column (3) shows the regression results of the DID model, and Columns (1) and (2) show the regression results of the DID model after the individual and time fixed effects were controlled. As can be seen from the experimental results in Table 4 below, the coefficients of the regression model underlying this study are positive, demonstrating that there is a positive linear relationship between the introduction of a carbon emission trading policy and the total factor productivity of construction enterprises. Therefore, the positive linear relationship in Equations (2) and (3) derived from the base regression model also holds.

Table 4. Model results.

	(1)	(2)	(3)
VARIABLES	TFP	TFP	TFP
DID	0.1483 **	0.4338 ***	0.2451 ***
	(0.0737)	(0.0391)	(0.0607)
Size		0.3826 ***	0.3878 ***
		(0.0136)	(0.0277)
ROA		1.2609 ***	1.2183 ***
		(0.2553)	(0.1944)
Lev		1.1627 ***	0.7200 ***
		(0.1183)	(0.1228)
Cost		−1.8069 ***	−0.7403 ***
		(0.1989)	(0.1641)
CF		−0.1110 **	−0.1399 ***
		(0.0500)	(0.0391)
Capital		−0.1478 ***	−0.1220 ***
		(0.0162)	(0.0165)
Top1		0.3749 ***	0.3497 *
		(0.1284)	(0.2044)
Constant	8.2875 ***	1.5953 ***	1.0127 *
	(0.0916)	(0.3079)	(0.5789)
Observations	1040	1040	1040
R-squared	0.5301	0.7374	0.7741
Number of id	96	96	96
Firm	Yes	no	yes
Year	yes	no	yes
F value	65.44 ***	361.8 ***	95.30 ***

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In Table 4, “standard errors in parentheses” under the table indicates that the robust standard errors in parentheses are White’s standard errors. The * symbol indicates the significance level of the model. Specifically, * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Yes, in the row of the Firm variable means that individual fixed effects are controlled, and

Yes in the row of Year variable means that time fixed effects are controlled. F-test is the significance test of the model, and *** indicates that the model is significant at the 1% level, which suggests a good fit and the ability to fully reflect the interactions among variables in the model.

In Column (1) of Table 4, control variables are not included, and two-way fixed effects are included. The coefficient is 0.1483, showing significance at the 1% level. In Column (2), control variables are included, and fixed effects are not. The coefficient is 0.4338, still significantly positive at the 1% level. Meanwhile, a significant increase in R^2 suggests a better fit after the addition of control variables, and the results are still robust. In Column (3), both control variables and two-way fixed effects are included, and the coefficient is 0.2451, significantly positive at the 5% level. The regression results show that the pilot policy of carbon emission trading affects the TFP of construction enterprises, and thus verifies the reasonable addition of individual and time fixed effects to the baseline regression. According to the above consequence, the coefficients of the interaction terms of explanatory variables are significantly positive, indicating that the pilot project of carbon emission trading improves the TFP levels of building enterprises to some extent, preliminarily verifying H_1. In order to confirm this conclusion, in this study, we performed a range of robustness tests.

5. Robustness Test

5.1. Parallel Trend Test

The parallel trend assumption is one of the basic preconditions for applying the DID method. Based on this, the data of the experimental group and the indicators of the control group should be largely consistent with each other, with a parallel trend, before 2013 when the government issued the pilot policy of carbon emission trading; otherwise, the conditions of using the DID model are not satisfied and the results may be skewed. In this study, the regression equation for constructing the parallel trend test using dummy variables is as follows: As Equation (4) evolves from the underlying Equation (1), and the results in Table 4 demonstrate a positive linear relationship between the implementation of a carbon emission trading policy and the total factor productivity of construction enterprises. Therefore, the positive linear relationship in Model 4 also holds.

$$\begin{aligned} TFP_{i,t} = \alpha_0 + \beta_1 Pre3_{i,t} + \beta_2 Pre2_{i,t} + \beta_3 Pre1_{i,t} + \beta_4 Current_{i,t} + \beta_5 Post1_{i,t} + \beta_6 Post2_{i,t} + \beta_7 Post3_{i,t} \\ +\beta_8 Size_{i,t} + \beta_9 ROA_{i,t} + \beta_{10} Lev_{i,t} + \beta_{11} Cost_{i,t} + \beta_{12} CF_{i,t} + \beta_{13} Capital_{i,t} + \beta_{14} Top1_{i,t} + \delta_t + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{4}$$

In Equation (4), $Pre3_{i,t}$ denotes the third year before enterprise i is affected by a carbon emission trading pilot area in period t. The value of this variable is one when the enterprise is in the third year before being affected; otherwise, its value is zero. $Post1_{i,t}$ denotes the first year after enterprise i is affected by a carbon emission trading pilot area in period t. The value of this variable is one when the enterprise is in the first year after being affected; otherwise, its value is zero. $Current_{i,t}$ denotes the current period of enterprise i being affected by a carbon emission trading pilot area in period t. The value of this variable is one when the enterprise is in the current period of being affected; otherwise, its value is zero. The rest of the variables are defined in the same way as in the regression results. According to the test results shown in Column (1) of Table 5 below, the regression coefficients from Pre_3 to Current are not significant, and the regression coefficients from Post_1 to Post_3 are significantly positive. These results indicate that, before the implementation of the pilot policy, there were no significant differences between the experimental group and the control group, meeting the parallel trend assumption. In the pilot areas, carbon emission trading is effective in promoting the TFP of construction enterprises, but the implementation of this policy has a certain lag. At the same time, Figure 4 also shows the parallel trend test results which were acquired from the results of Table 5. In summary, the design of this study meets the assumption of using the DID method. Before Current (i.e., the implementation of the policy), there are no significant differences between the experimental group and the control group (the confidence interval covers zero) when the covariates Size, ROA, Lev, Cost, CF, Capital, and Top1 are controlled, indicating that the parallel trend assumption is satisfied. The confidence intervals of the first, second, and third periods after the implementation of the policy do not cover zero (the lower limit is greater than zero), suggesting that the policy significantly promotes TFP.

Table 5. Parallel trend test results.

	(1)
VARIABLES	**TFP**
Pre_3	−0.1974
	(0.1228)
Pre_2	−0.1915
	(0.1300)
Pre_1	−0.1428
	(0.1119)
Current	0.0318
	(0.1145)
Post_1	0.2402 **
	(0.1089)
Post_2	0.2130 **
	(0.1031)
Post_3	0.2287 **
	(0.0912)
Size	0.3753 ***
	(0.0667)
ROA	1.2287 *
	(0.6330)
Lev	0.7529 **
	(0.3070)
Cost	−0.7536 **
	(0.3071)
CF	−0.1245 ***
	(0.0273)
Capital	−0.1222 **
	(0.0482)
Top1	0.2106
	(0.4509)
Constant	1.3276
	(1.0568)
Observations	1040
Number of id	96
R-squared	0.7064
Firm	yes
Year	yes
F value	35.30 ***

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2. Placebo Test

To achieve robustness of the experimental results, in this study, we drew on Topaova's study [47] to perform a placebo test using a counterfactual test. Specifically, the policy time of the sample data was adjusted to 2011 and 2012, before the implementation of the policy, for the regression analysis. If the pilot policy of carbon emission trading implemented in 2013 could indeed increase the TFP of construction enterprises, the coefficient of the interaction term should be insignificant in the regression results of the year of a dummy carbon emission trading pilot area. In Columns (1) and (2) of Table 6 below, Test2011 refers to an assumption that the policy came into force in 2011, and Test2012 refers to an assumption that the policy came into force in 2012. The coefficients of interaction terms DID2011 and DID2012 are not significant, verifying that the increase in the TFP of construction enterprises results from the pilot policy implemented in 2013. It is indicated that the pilot policy of carbon emission trading significantly increases the TFP of construction enterprises in the pilot area.

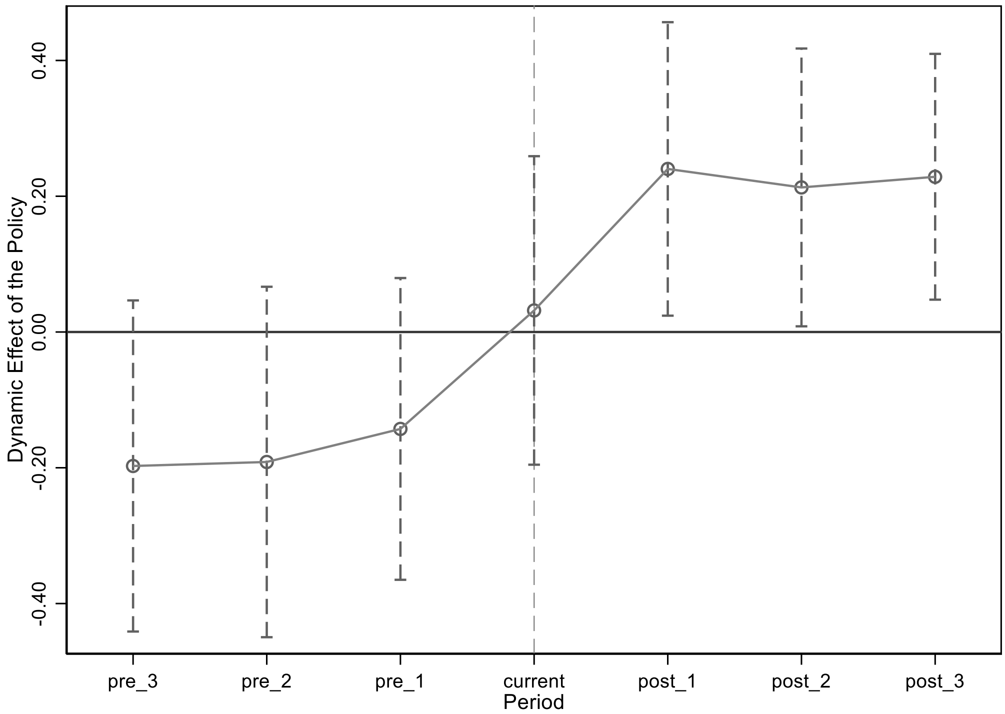


Figure 4. Parallel trend test results visualization.

Table 6. Placebo test results.

	(1)	(2)
VARIABLES	**TFP (Test2011)**	**TFP (Test2012)**
DID2011	−0.1679	
	(0.1962)	
DID2012		0.2166
		(0.1752)
Size	0.3813 ***	0.3860 ***
	(0.0697)	(0.0708)
ROA	1.2303 *	1.2200 *
	(0.6464)	(0.6457)
Lev	0.7400 **	0.7307 **
	(0.3228)	(0.3234)
Cost	−0.7644 **	−0.7545 **
	(0.3120)	(0.3129)
CF	−0.1388 ***	−0.1380 ***
	(0.0282)	(0.0281)
Capital	−0.1215 **	−0.1222 **
	(0.0488)	(0.0492)
Top1	0.2754	0.3195
	(0.4414)	(0.4470)
Constant	1.1672	1.0616
	(1.1330)	(1.1336)
Observations	1040	1040
R-squared	0.7007	0.7025
Number of id	96	96
Firm	yes	yes
Year	yes	yes
F value	26.85 ***	26.84 ***

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3. Propensity Score Matching

The above results can only prove that, on average, the pilot policy of carbon emission trading can increase the TFP of construction enterprises. However, the exact causal relationship between the policy and the TFP of construction enterprises cannot be precisely revealed. In addition, enterprise size and investments in research and development (R&D investments) are closely related to the increase in the TFP of construction enterprises, and the influences of related variables such as enterprise size and R&D investments should be removed to confirm that the increase in the TFP of construction enterprises is not a random or accidental event. Therefore, in this study, we used the propensity score matching method to correct the selective biases of the sample to reduce the disturbance in the experimental results, and thus, strengthen the robustness of this study. In Table 7 below, kernel, neighbor, and radius refer to kernel matching, neighbor matching, and radius matching, respectively. Table 7 shows that the coefficient signs and significance levels of the interaction term DID are consistent with the previous analysis, indicating that the regression results are robust. This also verifies the results of the basic regression that the pilot policy of carbon emission trading promotes the improvement of the TFP of construction enterprises.

Table 7. Propensity score matching results.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
VARIABLES	**TFP (Kernel)**	**TFP (Neighbor)**	**TFP (Radius)**	**tfp_op**	**TFP**
DID	0.2346 ***	0.2383 ***	0.2451 ***	0.1156 ***	
	(0.0578)	(0.0836)	(0.0607)	(0.0410)	
L.DID					0.2257 ***
					(0.0595)
Size	0.4034 ***	0.4332 ***	0.3878 ***	−0.4844 ***	0.4091 ***
	(0.0282)	(0.0411)	(0.0277)	(0.0187)	(0.0274)
ROA	1.8580 ***	1.2500 ***	1.2183 ***	0.0645	1.0474 ***
	(0.2350)	(0.3783)	(0.1944)	(0.1311)	(0.1883)
Lev	1.0121 ***	1.0727 ***	0.7200 ***	0.2337 ***	0.5797 ***
	(0.1354)	(0.2195)	(0.1228)	(0.0828)	(0.1251)
Cost	−0.8097 ***	−2.3120 ***	−0.7403 ***	−0.1277	−0.8029 ***
	(0.1936)	(0.4180)	(0.1641)	(0.1107)	(0.1591)
CF	0.1263	−0.0240	−0.1399 ***	−0.1534 ***	−0.1376 ***
	(0.1905)	(0.2633)	(0.0391)	(0.0264)	(0.0377)
Capital	−0.1161 ***	−0.1163 ***	−0.1220 ***	0.7978 ***	−0.1432 ***
	(0.0157)	(0.0215)	(0.0165)	(0.0111)	(0.0169)
Top1	0.3332 *	0.4270	0.3497 *	0.0963	0.3902 *
	(0.2021)	(0.3012)	(0.2044)	(0.1379)	(0.2063)
Constant	0.4066	−0.2459	1.0127 *	5.1146 ***	1.5324 **
	(0.5879)	(0.8263)	(0.5789)	(0.3906)	(0.6306)
Observations	1032	469	1040	1040	944
R-squared	0.7278	0.7855	0.7041	0.9374	0.7095
Number of id	96	88	96	96	96
Firm	yes	yes	yes	yes	yes
Year	yes	yes	yes	yes	yes
F value	106.2 ***	57.01 ***	95.30 ***	599.3 ***	91.69 ***

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.4. Substitution of Explained Variables

Column (4) of Table 7 shows the TFP calculated using the OP method. The results show that the regression coefficients of pilot carbon emission trading and the TFP of construction enterprises are still significantly positive, thus, indicating that the regression results are robust.

5.5. One-Period Lag of Explanatory Variables

Given the possible lag effect of the policy implementation, the core explanatory variables were regressed in the following period (the coefficient L. DID in the table), as shown in

Column (5) of Table 7. The results show that the regression coefficients are still significantly positive, indicating that the regression results are robust.

6. Mechanism Test

The above results show that the TFP of construction enterprises can be significantly increased by the implementation of the pilot strategy of carbon emission trading. In terms of its mechanism of action, however, some scholars have suggested that green technological innovations related to carbon emission reduction technologies can significantly affect the fluctuation of TFP. Based on this, in this study, we attempted to use a mediating effect model, with green technological innovation as the mediating variable, to test the mechanism of the effect of carbon emission trading on the TFP of construction enterprises. In Table 8 below, the interaction term DID_Inv in Column (1) is the interaction term with the number of green invention applications (GreInvia) of construction enterprises. The coefficient is 0.0031, and this significantly positive value indicates that GreInvia positively moderates (accelerating effect) the positive relationship between DID and TPF. The interaction term DID_Um in Column (2) is the interaction term between DID and the number of green utility model applications (GreUmia). The coefficient is 0.0027, and this significantly positive value indicates that GreUmia positively moderates (accelerating effect) the positive relationship between DID and TPF. The above tests prove that construction enterprises can increase their TFP by strengthening research on green innovation technology.

Table 8. Mechanism test results.

	(1)	**(2)**
VARIABLES	**TFP**	**TFP**
DID_Inv	0.0031 ***	
	(0.0011)	
GreInvia	−0.0004	
	(0.0010)	
DID_Um		0.0027 **
		(0.0013)
GreUmia		−0.0008
		(0.0014)
DID	0.1901 ***	0.1892 ***
	(0.0617)	(0.0628)
Size	0.3917 ***	0.3914 ***
	(0.0275)	(0.0277)
ROA	1.1927 ***	1.2026 ***
	(0.1923)	(0.1929)
Lev	0.7674 ***	0.7525 ***
	(0.1218)	(0.1221)
Cost	−0.7453 ***	−0.7486 ***
	(0.1623)	(0.1629)
CF	−0.1450 ***	−0.1419 ***
	(0.0387)	(0.0388)
Capital	−0.1264 ***	−0.1274 ***
	(0.0163)	(0.0164)
Top1	0.4324 **	0.3509 *
	(0.2031)	(0.2031)
Constant	0.9202	0.9767 *
	(0.5731)	(0.5767)
Observations	1040	1040
R-squared	0.7112	0.7093
Number of id	96	96
Firm	yes	yes
Year	yes	yes
F value	90.54 ***	89.71 ***

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7. Further Discussion

7.1. Analyzing by Enterprise Size

The size of a construction enterprise largely determines the amount of carbon emissions it needs to reduce and the costs of the reduction process. For this reason, to examine whether the role of carbon emission trading in promoting the TFP of construction enterprises is different for enterprises of different sizes, in this study, the median asset size of construction enterprises was selected for the sample data. Firms above the median are considered to be large scale firms, and those below the median are considered to be small scale firms. Basic regressions were conducted on large and small enterprises separately. The regression results in Columns (1) and (2) of Table 9 below show that implementation of the policy has a greater impact on larger construction enterprises than on smaller enterprises. The phenomenon might be related to the stronger anti-risk capabilities of larger enterprises. When a new policy is implemented in the market, larger construction enterprises have relatively stable industrial chains, which, coupled with the effects of economies of scale, their long-accumulated market shares, and reputations, make it easier for these enterprises to avoid the risk of the new policy. It is worth noting that larger construction enterprises are more likely to receive subsidies from the government due to their greater social influence, and therefore, embark on the road to independent transformation.

Table 9. The first part of heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**TFP (BigSize)**	**TFP (SmallSize)**	**TFP (State)**	**TFP (Private)**	**TFP (HighLev)**	**TFP (LowLev)**
DID	0.4524 ***	0.2544 **	0.1471 **	0.0986	0.2987 ***	0.1696 *
	(0.0643)	(0.1104)	(0.0645)	(0.1038)	(0.0847)	(0.0902)
Size	0.3256 ***	−0.0351	0.4180 ***	0.0316	0.4339 ***	0.2107 ***
	(0.0349)	(0.0595)	(0.0368)	(0.0581)	(0.0459)	(0.0562)
ROA	2.2481 ***	0.9156 ***	2.0884 ***	1.5757 ***	2.1470 ***	0.5898 **
	(0.4484)	(0.2210)	(0.3413)	(0.2824)	(0.3275)	(0.2839)
Lev	0.5320 **	1.2783 ***	0.8098 ***	1.3571 ***	0.5554 **	1.2261 ***
	(0.2463)	(0.1684)	(0.1888)	(0.1846)	(0.2570)	(0.2292)
Cost	−3.9732 ***	−0.6114 ***	−0.9457 ***	−1.0357 ***	−1.0736 ***	−0.3362
	(0.3984)	(0.1912)	(0.2284)	(0.2499)	(0.2788)	(0.2501)
CF	0.2313	−0.0973 **	0.4235 **	−0.0501	−0.1126 ***	0.0141
	(0.2232)	(0.0481)	(0.2056)	(0.0553)	(0.0408)	(0.2441)
Capital	−0.1547 ***	−0.0612 ***	−0.1776 ***	−0.0896 ***	−0.1210 ***	−0.0953 ***
	(0.0242)	(0.0211)	(0.0274)	(0.0208)	(0.0356)	(0.0204)
Top1	0.3878 **	0.2697	0.0101	−1.5812 ***	0.3917	0.2090
	(0.1897)	(0.4037)	(0.2027)	(0.5084)	(0.2619)	(0.3825)
Constant	3.3091 ***	8.8143 ***	1.0599	8.7615 ***	0.4494	4.0085 ***
	(0.7428)	(1.1965)	(0.8546)	(1.2311)	(1.0743)	(1.1679)
Observations	520	520	550	490	520	520
R-squared	0.7818	0.4340	0.8211	0.5193	0.7175	0.6223
Number of id	64	79	52	61	71	77
Firm	yes	yes	yes	yes	yes	yes
Year	yes	yes	yes	yes	yes	yes
F value	67.45 ***	13.93 ***	94.80 ***	19.07 ***	47.04 ***	30.09 ***

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7.2. Analyzing by Enterprise Ownership

The functions of construction enterprises in society vary according to their ownership, which is especially true for state-owned enterprises and private enterprises. Therefore, in this study, we constructed a dummy variable for enterprise ownership and divided the sample enterprises into two groups of data, i.e., state-owned enterprises and private enterprises. The DID method was applied to the two groups of data, and the results are shown in Columns (3) and (4) of Table 9. The TFP of state-owned enterprises shows significantly positive effects, and the coefficient of the interaction term is 0.1471, while the coefficient of the interaction term of private enterprises is not significant. The results suggest that the national policy of carbon emission trading has a greater impact on state-owned enterprises than on private enterprises, possibly because China's state-owned enterprises in the construction industry, whose business operations are under state control, shareholder more responsibilities and undertake more missions than private enterprises. The increase in TFP of state-owned enterprises is usually in line with the development of macro policies issued by the national government, and these enterprises are likely to be industry leaders.

7.3. Analyzing by Financial Structure

According to the principles of financial leverage, borrowing can somewhat lower a company's cost of capital to conduct business activities, thus helping the company to reap profits. For management, the higher the debt ratio, the greater the equity concentration [41]. In such a context, a shareholder can earn more profits from each project. In construction enterprises with risk preferences, in particular, the increase in the debt ratio will push up investments in more risky projects. The median debt ratio of construction enterprises for the sample data was selected for this study. Construction enterprises above the median are considered to have a high debt level and those below the median are considered to have a low debt level. Consequently, this study classified the sample enterprises into two groups with high and low debt levels, respectively, and regressions were conducted on the two groups separately to try to explore whether the policy of carbon emission trading has different effects on enterprises with different debt levels. Columns (5) and (6) of Table 9 show the results of construction enterprises with high debt levels and those with low debt levels, respectively. The coefficient of the interaction term for enterprises with high debt levels is significantly positive at the 1% statistical level, and that for enterprises with low debt levels is significantly positive at the 5% statistical level, suggesting that the policy of carbon emission trading has a greater impact on construction enterprises with high debt levels than those with low debt levels. This phenomenon may be because a high debt ratio reflects an enterprise's confidence in making profits in the future.

7.4. Analyzing by Geographical Location

China is a vast country, and the eastern and western regions have significantly different development levels. In his study, we categorized the pilot regions based on the division of the eastern, central, and western regions by using the National Bureau of Statistics of China (www.stats.gov.cn/ztjc/zthd/sjtjr/dejtjkfr/tjkp/201106/t20110613_71947.htm) (accessed on 20 October 2022). The eastern regions are Beijing, Tianjin, Shanghai, and Guangdong; the central region is Hubei; and the western region includes Chongqing. In the construction industry, similarly, different regions are affected by the pilot policy of carbon emissions to different extents. Therefore, in this study, we divided the sample enterprises into three groups according to their locations. The results are shown in Table 10 below. Columns (1), (2), and (3) present the regression results for the eastern, central, and western groups, respectively. The coefficients of the interaction item are 0.2397 for the eastern group and 0.8990 for the central group, and they are significant at the 1% statistical level. The difference between these two regions shows that the same policy has a greater impact on construction enterprises in central China than in eastern China. The coefficient of the interaction item for the western group is not significant, indicating that the policy does not have a significant impact on this region. It is said that carbon emission trading, as a new policy tool, is more effective in economically developed regions [41]. The current situation of the inactive market in western China relies mainly on traditional high-energy-consuming construction technologies, which are not enough to give full play to this new policy.

Table 10. The second part of heterogeneity.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**TFP (East)**	**TFP (Middle)**	**TFP (West)**	**TFP (YES)**	**TFP (NO)**
DID	0.2397 ***	0.8990 ***	0.2284	0.2374 ***	1.2236 ***
	(0.0736)	(0.1906)	(0.1687)	(0.0643)	(0.3908)
Size	0.3514 ***	0.5789 ***	0.6616 ***	0.3934 ***	0.1149
	(0.0303)	(0.0870)	(0.0598)	(0.0280)	(0.1924)
ROA	1.0911 ***	2.7451 ***	7.2857 ***	0.9582 ***	0.1656
	(0.2009)	(0.6982)	(2.2270)	(0.2354)	(0.5468)
Lev	0.6578 ***	1.0717 **	0.9739 **	0.7315 ***	−0.0454
	(0.1291)	(0.4688)	(0.4606)	(0.1288)	(0.4862)
Cost	−1.0754 ***	0.0390	4.4635 ***	−1.2561 ***	0.1870
	(0.1980)	(0.3158)	(1.3190)	(0.2292)	(0.4155)
CF	−0.1379 ***	−0.0783	0.6572	−0.1234 ***	0.6723
	(0.0399)	(0.4911)	(0.8775)	(0.0382)	(0.5413)
Capital	−0.0942 ***	−0.3218 ***	−0.2861 ***	−0.1414 ***	−0.1453 **
	(0.0173)	(0.0603)	(0.0744)	(0.0193)	(0.0589)
Top1	0.8081 ***	−1.7837 ***	0.2846	0.3370	−0.8615
	(0.2434)	(0.5863)	(0.3243)	(0.2066)	(1.0601)
Constant	1.4196 **	−0.6186	−3.5124 ***	1.8078 ***	7.7415 *
	(0.6325)	(1.9576)	(1.2185)	(0.6592)	(4.2954)
Observations	817	129	94	944	96
R-squared	0.6929	0.9039	0.8831	0.6967	0.6789
Number of id	75	11	10	96	36
Firm	yes	yes	yes	yes	yes
Year	yes	yes	yes	yes	yes
F value	70.53 ***	38.83 ***	21.71 ***	86.24 ***	4.563 ***

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7.5. Analyzing by Official Subsidies

Government subsidies affect the business activities of enterprises to some extent. To further examine whether the policy of carbon emission trading affects enterprises with and without government subsidies in different ways, in this study, we constructed a dummy variable for government subsidies and divided the sample data into enterprises with and without government subsidies. Basic regressions were conducted on the two groups, and the results are shown in Table 10. According to Columns (4) and (5), the TFP of enterprises in both groups significantly increases, regardless of government subsidies. The coefficient of the interaction item for the group with government subsidies (0.2374) is lower than that for the other group (1.2236). To explain this phenomenon, it is said that construction enterprises not subsidized by the government constantly improve their innovation and managerial abilities in order to survive in the changing market, which drives up their TFP and improves their performance [41].

8. Conclusions and Policy Recommendations

8.1. Conclusions

The policy of carbon emission trading is the policy tool for reducing emissions that China has initially used at the market level to tackle global climate change and the energy crisis. In addition, it is an important strategy to promote the green and low-carbon development of the country and a crucial measure to peak CO_2 emissions before 2030 and achieve carbon neutrality before 2060.

Subsequently, in this study, we used the data of A-share and the ChiNext board listed construction enterprises from 2006 to 2021, and adopted a DID model and a mediating effect model to empirically test the effects of the policy of carbon emission trading implemented in China on the TFP of construction enterprises in the country, and conducted an in-depth analysis of the mechanism.

Based on the study results, the following conclusions have been drawn: The policy of carbon emission trading significantly promotes the TFP of construction enterprises; green technological innovation has a mechanism effect on the TFP of China's construction enterprises during the policy implementation; the heterogeneity analysis of sample data shows that the policy has greater effects on large construction enterprises, state-owned construction enterprises, and construction enterprises with high debt levels. Meanwhile, the TFP of construction enterprises located in eastern and central regions increases more significantly than that of enterprises located in western regions.

Ultimately, this study also has its own limitations. Since the data for this study were sourced from listed construction enterprises, non-listed micro enterprises in the construction industry were not included in the scope of this study. Therefore, the findings of this study do not apply to unlisted construction enterprises. The double difference model in this study, based on data from China, can only be used to draw conclusions for the national context of China. Other scholars, internationally, can draw on Equation (1) in this study and select relevant data from other countries or regions for their research.

In future studies, the impact of carbon emission policies on enterprises in other industries could be assessed and data from unlisted enterprises should be included in the study for a more accurate judgement of such studies.

8.2. Policy Recommendations

The construction of a national carbon market is a complex and systematic project. According to the results of this study, efforts need to be made in various aspects of the construction work, such as the top-level design, market system, and subsidy mechanism. Based on this, we propose the following recommendations:

First, various regulations and supporting systems need to be established and improved for the carbon market to ensure that carbon allowances can be traded in a lawful manner in China's carbon trading market, to give full play to the role of the policy of carbon trading in promoting enterprises' TFP, and to facilitate the transformation and upgrading of construction enterprises. At the same time, the government should strengthen the promotion of the policy, call on market participants to consciously abide by the market order, create an excellent atmosphere in the carbon trading market, and further improve the TFP of the construction industry. From the experiments on firm size and firm ownership groupings, larger construction enterprises have a greater social effect due to their huge market share and well-established industrial chain. In the construction industry, due to the huge initial capital requirements and long investment cycles, the larger enterprises are generally state-owned enterprises. Therefore, it is suggested that government departments can appropriately strengthen the performance incentives for large state-owned construction enterprises to participate in carbon emission trading policies, so that these enterprises can form a leading role in the industry.

Second, from the experiments with different liability groupings, it is recommended that banks or financial institutions appropriately expand green financial loans, issue green bonds, and avoid discrimination against the construction industry for its slow capital turnover. This will encourage construction enterprises to actively participate in the market for carbon emission trading. The carbon financial market system should be gradually improved to strengthen the incentive effect of market mechanisms on innovative enterprises. China's market of carbon financial products is still in a nascent stage; the pilot trading and use of carbon financial products are not active and not accepted by the general public. Therefore, the construction of the carbon market in China should extend further into the derivatives market, and incentive-based financial instruments should be developed for green innovation technologies, as an attempt to reinforce the role of green innovation in increasing the TFP of construction enterprises.

Third, from the experiments on whether or not to receive government subsidies, the government should avoid excessive subsidies to enterprises and use the market mechanism to urge enterprises to forge ahead independently on the road of "peaking carbon emission and carbon neutrality". Meanwhile, carbon emission transfers across regions due to different regional subsidy policies should be avoided, and the subsidy mechanism should serve as a booster for carbon emission reduction. As a consequence, subsidies could encourage building enterprises to enter carbon emission trading to earn profits from it and to develop financing channels. The government should then set a benchmark for subsidies; provinces and municipalities could adjust the benchmark subsidies according to the actual situation, and their adjustments should not exceed a certain range, so as to co-ordinate the carbon emission situation of construction enterprises nationwide and make the subsidy mechanism a booster for carbon emission reduction.

Fourth, from the experiments of the different regional economic groupings, the western region did not benefit from the carbon pilot policy because of its economic backwardness. It is recommended that the state strengthen its policy of encouraging participation in carbon emission trading in the western region, and keep up with the green transformation and upgrading of western construction enterprises, abandoning overly traditional and backward construction techniques. Under this case, it is suggested that the state should set different policies on carbon emission trading according to the industrial and economic development characteristics of different regions. For the eastern region, tough policies should be adopted to abandon traditional and dated technologies; construction enterprises in the western region should adopt flexible policies to release some space for development in order to keep pace with the green transformation and upgrading. In addition, a favorable competitive environment should be established to maximize the policy effect of environmental regulations, so that high production capacity can be decoupled from high carbon emissions as soon as possible.

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