

Article

Carbon Emissions Trading System, Health Human Capital and Green Development Efficiency: Evidence from China

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Abstract

The carbon emissions trading system functions as a essential policy tool for coordinating greenhouse gas reduction alongside pollution abatement as well as improving energy and environmental quality. It carries great significance in advancing the shift toward a green and low carbon economy and society, and in accelerating the implementation of the Healthy China Initiative. This article draws on panel data covering 30 Chinese provinces from 2010 to 2023, and employs a staggered DID model. From a public health perspective, it systematically investigates how the carbon emissions trading system shapes green development efficiency across China, while further dissecting the mechanism of health human capital. The research reveals that the carbon emissions trading system boosts health human capital accumulation and green development efficiency within China's pilot areas, with health human capital functioning as the mediating channel through which the carbon emissions trading system affects green development efficiency. Additionally, in regions with high levels of green technological innovation and high levels of financial growth, as well as strong governmental environmental attention, the carbon emissions trading system's beneficial impact on increasing green development efficiency is more noticeable. Spatial effect analysis shows that the carbon emissions trading system generates a positive spatial spillover effect on regional green development efficiency. The adoption of the carbon emissions trading system in a local region can enhance green development efficiency in its adjacent areas. This article proposes to refine the carbon emissions trading system institutional framework and operational mechanisms, optimize the distribution of health human capital, implement differentiated and dynamic regulation strategies, and elevate green development efficiency across regions in line with local realities.

Keywords: carbon emissions trading system; environmental health risks; health human capital; green development efficiency

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1. Introduction

Global warming and ecological and environmental risks caused by high carbon emissions have made climate governance a critical subject of widespread global attention [1,2]. To advance emission reduction in a more cost-effective manner, the carbon emissions trading system (ETS) has gradually emerged as a pivotal policy instrument for

global climate governance. Since the launch of the EU Emissions Trading System (EU ETS) in 2005, the Regional Greenhouse Gas Initiative (RGGI) in the United States, New Zealand ETS, and Korea ETS have been implemented. Together, they constitute global practices of carbon markets covering diverse industries, institutional contexts, and development stages. China is among the world's primary carbon release nations, producing roughly a third of the global total carbon output [3]. For a long time, China's coal-dominated fossil fuel energy mix has driven up greenhouse gas emissions. This energy structure has also spawned air pollution, climate hazards and ecological environmental damage, alongside measurable detrimental outcomes for public health. China's proposed "dual carbon" targets not only align with the inherent requirements of transforming the energy mix, mitigating environmental health risks, and achieving green and low carbon development [4,5], but also offer China solutions for global climate governance and green economic growth. To promote carbon emissions reductions and lower the marginal cost of pollution control, China has launched a regional local ETS pilot covering Beijing, Tianjin, and other regions since 2013 [6]. ETS pilot programs focus on carbon intensive industries like power generation, steel manufacturing, cement production, and aluminum smelting. The determination of total carbon allowances and the allocation of allowances follow a dual control mechanism that prioritizes intensity control, supplemented by total volume control [7]. The programs optimize the baseline for allowance allocation, gradually implement a combination of free and paid carbon allowance allocation methods, and systematically increase the proportion of paid allocations. The EU ETS centers on an absolute emissions cap, progressively expands the share of allowance auctioning, and has introduced the Market Stability Reserve and the Carbon Border Adjustment Mechanism. It features a set of mature institutional arrangements for carbon market regulation. China's ETS in its initial stage, by contrast, places greater emphasis on emission intensity control, free allowance allocation, and gradual reform. This design is closely related to China's stage of development, energy endowment, industrial competitiveness, and regional disparities. As local pilot programs gradually accumulated experience, China's ETS market was officially launched in 2021, with more than 2000 key emitting entities included in the first batch. On its launch day, the trading volume reached 4.104 million tonnes, with a trading turnover of approximately 210 million yuan. By 2025, the carbon emissions covered by this market had accounted for more than 60% of the nationwide total. Together with the National Voluntary Greenhouse Gas Emission Reduction Trading Market, they will jointly form an integrated carbon market framework. With the continuous refinement of China's ETS institutional framework and market operating mechanisms, the policy effects and functional value of this system extend far beyond driving corporate emission cuts and restructuring energy mixes. They also exert a profound influence on health human capital, as well as on the all-round ecological transition of the socioeconomic system through measures such as improving environmental quality and reducing exposure to environmental pollution.

Since the official rollout of the *Healthy China 2030 Planning Outline*, this national strategy has centered on the theme of "joint contribution, shared benefits, and health for all". It delivers systematic policy arrangements across five core dimensions, including advancing wholesome lifestyles, optimizing healthcare services, strengthening health protection systems, building environments conducive to health, and growing the healthcare industry. The initiative aims to comprehensively boost residents' health and achieve coordinated, sustainable development between public health and socioeconomic progress. The environmental stress theory indicates that sustained exposure of an individual to environmental hazards including atmospheric pollution, degraded water quality and severe weather events imposes dual physiological and psychological stress. This accelerates the depreciation of health capital and raises the marginal investment cost

required to maintain a given stock of health. By contrast, improvements in environmental quality slow the rate of health depreciation and free up resources that can be allocated to other human capital investments. Therefore, improving ecological environment quality is a crucial pathway to safeguarding public health. Given the strong homology between carbon emissions and air pollutant discharges across energy consumption, industrial production, transportation and other sectors, the ETS raises carbon emission costs to incentivize enterprises to cut energy use, perhaps optimize energy mix, and upgrade production techniques. This synergetically curbs emissions of pollutants such as SO₂ and NO_x [8], thereby, through the improvement of environmental quality, reducing residents' risk of exposure to pollutants and the incidence rate of related diseases. Existing research has shown that improving health human capital strengthens workers' physical and mental functioning, boosts their capacity for learning and innovation, and facilitates more effective participation of laborers in corporate low-carbon technological innovation [9]. Furthermore, elevated health human capital guarantees an ample supply of health labor, accelerating the flow of labor resources from high-pollution traditional sectors with low marginal output to modern service industries and clean production sectors. This elevates the efficiency of cross-sector factor allocation, cuts pollution emission intensity per unit of output, and drives enterprises toward low-emission transformation and upgrading.

Green development efficiency (GDE) is a key gauge of the economy's high-quality development level, fundamentally assessing an economy's holistic performance in achieving output growth while reducing pollution under resource and environmental constraints [10]. Unlike traditional economic efficiency, which primarily focuses on the nexus between factor inputs like capital and workforce, and desirable outputs, green development efficiency integrates resource and environmental factors including energy consumption and pollutant emissions into a unified analytical framework. It can more comprehensively reflect the resource allocation efficiency of economic growth and environmental governance performance. Improving green development efficiency facilitates the transformation of economic growth modes from a pattern featuring substantial input, high energy use and heavy emissions to one characterized by strong efficiency, minimal resource depletion and reduced pollution, and fosters positive interactions between ecological conservation and economic value creation. Currently, China's green and low-emission transition is steadily advancing, with notable progress achieved in industrial structure upgrading, improved resource utilization efficiency, enhanced pollution abatement outcomes, and green technological innovation. International experience shows that the European Union have established a stable carbon pricing via the EU ETS to guide the optimal allocation of emission reduction resources. By emphasising policy coordination across energy, climate, finance and tariffs, the bloc has improved the operational efficiency of its carbon market while advancing environmental equity and green transition. The RGGI in the United States adopts open auctions as the primary allowance allocation method, and channels auction proceeds into energy efficiency retrofits, clean energy development and public welfare programmes to redistribute gains from carbon emission reductions. These international examples demonstrate that whether a carbon market can enhance the efficiency of green development depends on its institutional design, the use of revenues, and factor endowment. In China, due to disparities in regional economic foundations, industrial structure and layout, and technological innovation capabilities, there are marked differences across regions in terms of energy efficiency, pollution control standards and the progress of the low-carbon transition; as a result, improvements in the efficiency of green development continue to face challenges of unevenness and inadequacy. Regions reliant on resources or with a large share of traditional industries tend to be trapped in "carbon lock-in" and resource path dependence. They face multiple constraints including

inefficient factor allocation, insufficient commercialization of green technologies, and high marginal cost of pollution control, resulting in relatively weak endogenous driving forces for transformation. In contrast, regions boasting solid industrial foundations, favorable resource endowments and sound institutional environments can more readily boost green development efficiency by leveraging green technological progress and energy structure transition.

Accordingly, this marginal contributions of this article are as follows. Firstly, innovation in research perspective: this article departs from the existing analytical framework of energy and environmental policies and green development. It introduces a public health perspective to examine the relationship between the ETS and health human capital. By incorporating health human capital as a transmission channel into the research framework of the mechanisms and effects of the ETS on green development efficiency, this article achieves interdisciplinary integration of environmental economics, health human capital theory and health economics. Secondly, this article expands the scope of research on ETS policy effects from a public health perspective. Taking China's ETS as the research setting, it focuses on how the carbon market affects green development efficiency and health human capital through carbon price signal transmission and resource reallocation effects. Meanwhile, it introduces an international comparative perspective to situate China's ETS within the global practice of carbon markets. Thirdly, this article conducts comparative analyses of factors including green technology innovation level, financial development levels, and governmental environmental attention. It provides conceptual underpinnings and policy suggestions for designing differentiated emissions trading mechanisms, strengthening the health human capital transmission function, and establishing a dynamic regulation system.

2. Theoretical Model and Hypotheses

In Grossman's (1972) model of health demand, environmental quality is regarded as a key exogenous variable influencing the stock of health human capital [11]. By clarifying the property rights of carbon emission allowances, the ETS generates carbon price signals. This imposes explicit costs on firms' carbon emission behaviors, prompting them to weigh costs and benefits across allowance purchasing, energy conservation retrofitting, and technological upgrading, and ultimately reducing energy consumption and emission levels per unit of output [12]. Under China's coal-dominated energy mix, atmospheric pollutants such as CO₂ and PM_{2.5} share a common origin. Given this, the ETS will generate synergistic effects in reducing pollution whilst curbing carbon emissions, thereby driving improvements in air quality [13]. Improved environmental quality reduces residents' pollution exposure and lowers the incidence of pollution-related illnesses such as respiratory illnesses [14]. It also mitigates the loss of working hours caused by illness-induced absenteeism or premature mortality [15]. In addition, Liu (2022) further demonstrates that air pollution exerts a depreciation effect on residents' physical health, mental health, and social adaptability [16]. Lei et al. (2026) further noted that health depreciation induced by environmental pollution is not only reflected in short-term disease burden, but also squeezes out investment in health [17]. Previous studies based on Chinese micro-survey data have also found that the ETS significantly reduces the incidence of pollution-related diseases and healthcare expenditure [18]. Consequently, the ETS improves environmental quality to reduce the rate of health depreciation. This implies that residents can maintain a higher stock of health capital at a given level of health investment and achieve greater marginal returns to health investment, thereby fostering the accumulation of health human capital. Based on the above analysis, the following hypothesis is proposed:

H1. *The ETS can enhance the level of health human capital.*

ETS improves environmental quality through the synergy between carbon pricing and pollution reduction [19,20], and this improvement in environmental quality enhances health human capital, which ultimately contributes to the GDE. Improvements in health human capital can enhance workers' physical stamina, cognitive ability, and job stability, thereby expanding effective labor supply and boosting labor productivity. This enables the economic system to achieve higher output under given energy consumption and environmental constraints [21]. From the perspective of efficiency wage theory, improved worker health helps raise labor effort and reduce absenteeism and job turnover rates, and thus boosts factor utilization efficiency. Furthermore, improved population health alleviates medical burdens on households and society [22], freeing up more resources for human capital investments for example education, and facilitating the improvement and upgrading of human capital composition. Within the measurement framework of green development efficiency, health human capital can be treated as a quality correction term for labor input. Its improvement helps raise the effective economic output generated per unit of energy consumption and pollutant emissions [23]. Furthermore, workers with superior health generally exhibit stronger learning capacity and technological adaptability. This helps cut learning and organizational costs incurred during adoption and diffusion along with application in green technologies, and facilitates popularization in clean production technologies as well as improvements in technical efficiency. To sum up, the ETS can not only directly drive emission abatement, but also elevate health human capital by improving environmental quality. Consequently, it enhances green development efficiency through multiple channels, including upgraded labor quality, optimized resource allocation and enhanced technology absorption capacity. Based on these, this research puts forward the following hypotheses:

H2. *The ETS promotes green development efficiency by elevating the level of health human capital.*

The promoting effect of the ETS on green development efficiency is not universally consistent. Instead, it is jointly shaped by factors including Green technology innovation level, financial development, and government environmental attention, presenting obvious conditional dependence. Firstly, regions with high levels of green technological innovation typically possess stronger capabilities for knowledge absorption and the research, development and commercialization of low-carbon technologies. They are able to transform the cost pressures arising from carbon trading into a driving force for green technological upgrading [24], thereby more fully realizing the "innovation compensation effect" of the ETS. At the same time, green technological innovation also helps to enhance the precision of carbon emissions monitoring, improve the efficiency of carbon market incentive mechanisms, and strengthen the positive guidance provided by the ETS towards green development [25]. By contrast, in regions with low levels of green technological innovation, which are constrained by their technological base and human capital, it is difficult to translate carbon price signals into incentives for innovation. In such cases, an ETS is more likely to act as a cost constraint rather than a driver of efficiency gains. Secondly, research and development of low-carbon technologies is generally marked by substantial capital, lengthy payback periods and high uncertainty. Areas with more developed financial systems have greater ability to spread risks and allocate capital [26], which can effectively cut external financing costs for green projects and raise firms' responsiveness to carbon price signals, thereby strengthening the impact of the ETS upon green development efficiency. By contrast, firms located in areas with backward financial systems generally encounter severe funding constraints. Even if carbon price signals

deliver incentives for emission abatement, enterprises often lack external funds to conduct green technology R&D and equipment upgrading, making it difficult to unlock innovation compensation effects. Furthermore, according to signaling theory, governments' attention to the environment serves as a critical institutional signal guiding the decisions of market participants [27,28]. In regions with substantial government environmental attention, governments' strong emphasis on the environment sends clear expectations to firms that environmental regulations will keep tightening and the shift toward green development is irreversible. Accordingly, enterprises no longer treat the ETS as a short-term, avoidable cost shock, but instead internalize it as a long-term structural constraint, which drives them to scale up investments in green technology R&D and clean production retrofits [29]. Moreover, strong environmental signals raise corporate executives' sensitivity to environmental risks and low-carbon development opportunities, motivating them to respond to carbon constraints through proactive emission abatement rather than passive allowance purchases [30]. By contrast, policy signals remain ambiguous in regions with low government environmental attention. Firms are inclined to adopt an observant stance and passive compliance strategies, so the incentive function of the carbon market can hardly translate into tangible enhancements in green efficiency. The diagram illustrating the theoretical mechanism is shown in Figure 1. Based on this, the present research puts forward the following hypothesis:

H3. *The positive effect of the ETS on green development efficiency is more pronounced in areas with higher levels of green technological innovation, higher levels of financial development, and stronger government environmental attention.*

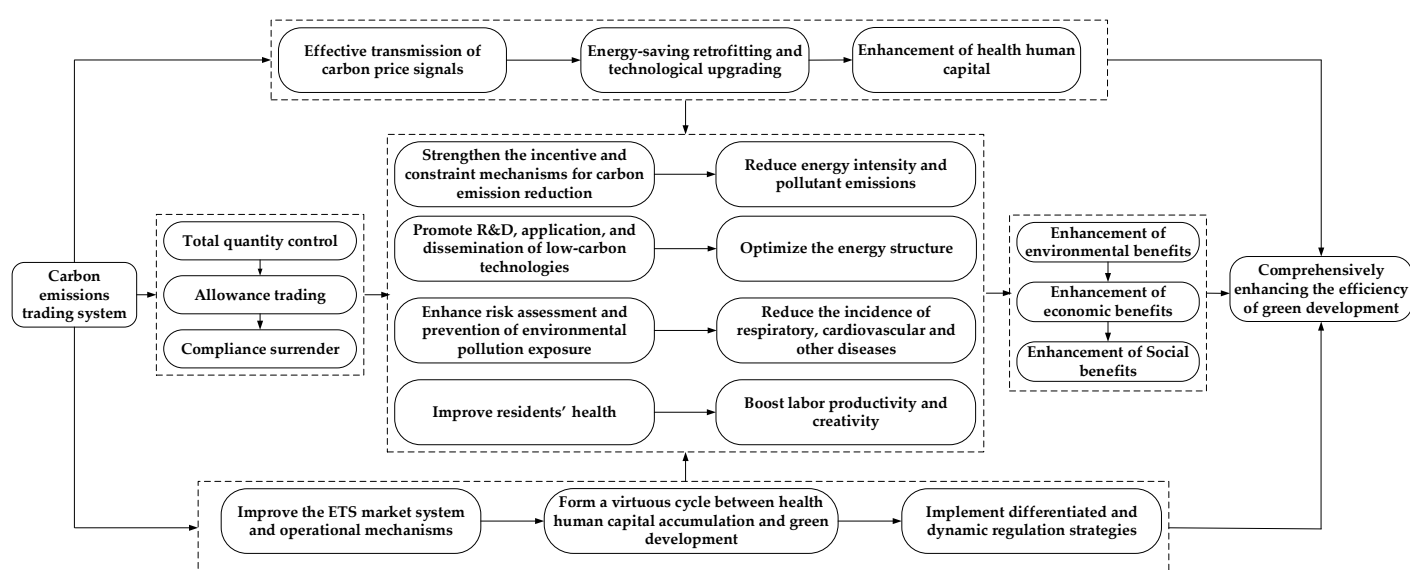


Figure 1. Theoretical mechanism analysis framework.

3. Model Construction and Indicator Selection

3.1. Econometric Regression Model

To assess the effect of the ETS on GDE, this research selects 30 Chinese provinces spanning 2010 through 2023 as the article sample. Treating the official initiation of the carbon market as a quasi-natural experiment, this article designates pilot regions as the treatment group, while the other non-pilot regions form the control group. We employ a fixed-effects DID model to identify the differential GDE trends for the treatment and comparison groups before and after the policy intervention. The specific model specification is presented as follows:

$$Gde_{it} = \alpha_0 + \alpha_1 DID_{it} + \alpha_j Controls_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (1)$$

where i denotes provinces, t denotes years, and Gde_{it} is the dependent variable, representing green development efficiency; DID_{it} serves as the independent variable, standing for the carbon emission trading policy. The value takes 1 if province i has implemented the ETS in year t , and 0 otherwise. α_1 captures the net effect of the policy on GDE; $Controls$ denotes the set of control variables; μ_i stands for province fixed effects; and θ_t represents year fixed effects.

In order to further examine whether the ETS affects GDE by fostering health human capital accumulation, this article follows the three-step mediation effect approach used by Cronley et al. (2017) [31] and conducts stepwise regression to examine the mediating role of health human capital. First, Model (1) serves to estimate ETS policy's total effect on GDE. If the coefficient estimate for the policy variable attains statistical significance, we proceed to the next stage of the test. Second, building upon Model (1), we specify Model (2) by taking the mediating variable as the dependent variable and ETS policy as the independent variable. If the coefficient estimate for the policy variable attains statistical significance, it indicates that the ETS policy significantly influences the mediating variable, allowing us to move on to the subsequent test. Finally, Model (3) is constructed by adding the mediating variable as an independent variable into Model (1). A significant coefficient γ_2 confirms the existence of a mediating effect. The specific model settings are as follows:

$$Hea_{it} = \beta_0 + \beta_1 DID_{it} + \beta_j Controls_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

$$Gde_{it} = \gamma_0 + \gamma_1 DID_{it} + \gamma_2 Hea_{it} + \gamma_j Controls_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (3)$$

where i denotes provinces, t denotes years, and Gde_{it} is the dependent variable, representing the green development efficiency; Hea_{it} denotes the mediating variable, which represents the level of health human capital in each province; and DID_{it} serves as the independent variable, standing for the carbon emissions trading policy.

3.2. Variable Definitions

3.2.1. Dependent Variable: Green Development Efficiency (Gde)

This article employs the super-efficiency SBM model incorporating undesirable outputs proposed by Tone (2002) [32], integrated with the GML (Global Malmquist–Luenberger) index, to compute GDE for 30 provinces in China spanning 2010–2023. This model addresses the drawbacks of traditional Data Envelopment Analysis (DEA), including slack variable bias and difficulties in evaluating undesirable outputs [33]. Additionally, it captures dynamic changes in GDE across different time periods. The model formula is specified as follows:

$$\rho^* = \min \frac{1 - \frac{1}{M} \sum_{i=1}^M \frac{S_i^c}{a_{ik}}}{1 + \frac{1}{S_1 + S_2} \left(\sum_{r=1}^{S_1} \frac{S_r^g}{e_{rk}^g} + \sum_{r=1}^{S_2} \frac{S_r^b}{e_{rk}^b} \right)} \quad (4)$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^n \lambda_j a_{ij} + S_i^c = a_{ik}, i=1, 2, \dots, M \\ \sum_{j=1}^n \lambda_j e_{rk}^g - S_r^g = e_{rk}^g, r=1, 2, \dots, S_1 \\ \sum_{j=1}^n \lambda_j e_{rk}^b + S_r^b = e_{rk}^b, r=1, 2, \dots, S_2 \\ \lambda_j \geq 0, S_i^c \geq 0, S_r^g \geq 0, S_r^b \geq 0, j=1, 2, \dots, n \end{cases}$$

The definitions of the variables in Equation (4) are as follows: ρ^* stands for the efficiency score; S^c , S^g , and S^b represent excess input slacks, shortfalls in desired outputs, and undesired output surpluses, respectively. M , S_1 , and S_2 denote input

factors, the quantity of desirable outputs and the quantity of undesirable outputs, respectively. λ_k represents the weights of each decision unit when constructing the green efficiency structure, and the sum of these weights equals 1.

To better capture the dynamic evolution of GDE, this article constructs the GML index based on the SBM directional distance function following the work of Oh (2010) [34]. The specific expression is presented in Equation (5):

$$GML^{t,t+1}(d^{t+1}, f^{t+1}, h^{t+1}, d^t, f^t, h^t) = \frac{1+D^G(d^t, f^t, h^t)}{1+D^G(d^{t+1}, f^{t+1}, h^{t+1})} \quad (5)$$

The definitions of the variables in Equation (5) are as follows: $GML^{t,t+1}$ reflects the dynamic changes in the GDE across provinces compared to the previous period, while d , f , and h represent input factors, expected output, and unanticipated output, respectively. A GML index value greater than 1 signals rising green production efficiency, whereas a value below 1 indicates declining efficiency. Since the GML index only captures period-by-period dynamic changes in green total factor productivity, we follow the framework of Lyu et al. (2023) [35]. We set the base year (2010) GML index to unity and compute the annual level of GDE via the cumulative multiplication of year-on-year GML indices.

The specific indicators of GDE selected in this article include indicators for inputs, desired outputs, and undesired outputs. Specifically, for capital input, following Wu et al. (2014), we measure urban fixed capital stock estimated via the perpetual inventory approach [36]. Labor input is measured by the total number of urban employees [37]. Energy input is represented by total energy consumption expressed in coal equivalent [38]. Regarding desirable outputs, this article draws on the methodology of Yuan et al. (2023) [39], using real GDP deflated to the base year of 2010, adopted to measure economic output; and per capita disposable income serves as the proxy for social output. Undesirable outputs, following Ye et al. (2024) and Cui et al. (2025) [40,41], are measured by industrial sulfur dioxide emissions, industrial soot (dust) emissions, carbon dioxide emissions, and the generation of general industrial solid waste (Table 1).

Table 1. Green development efficiency indicator system.

Primary Indicator	Secondary Indicator	Tertiary Indicator	Unit	Attribute
Input indicators	Capital input	Capital stock estimated using the perpetual inventory method	10,000 yuan	+
	Workforce input	Number of employees in urban work units at year-end	10,000 persons	+
	Energy input	Total energy consumption (Standard coal equivalent)	10,000 tons	+
Desirable output indicators	Economic output	GDP	100 million yuan	+
	Social output	Per capita disposable income	Yuan	+
Undesirable output indicators	Environmental pollution	Emissions of industrial sulfur dioxide	10,000 tons	−
		Emissions of industrial smoke (dust)	10,000 tons	−
		Emissions of carbon dioxide	10,000 tons	−
		Generation of general industrial solid waste	10,000 tons	−

3.2.2. Independent Variable: Carbon Emissions Trading System (DID)

The core explanatory variable in this article is the carbon emissions trading policy; this variable has been constructed in accordance with the basic logic of the staggered DID method, which is used to identify the net effect of the ETS. Based on the phased list of carbon emission trading pilots released by China's National Development and Reform Commission, seven provincial-level administrative regions, namely Beijing, Shanghai,

Tianjin, Guangdong, Hubei, Chongqing and Fujian, are defined as the treatment group. Given that Shenzhen is a prefecture-level city under the jurisdiction of Guangdong Province, this article does not treat Shenzhen as a separate unit to maintain consistency in the spatial scale of samples. Instead, Guangdong Province is identified as the pilot region for carbon emission trading. The remaining provinces that had not launched the pilot program during the sample period constitute the control group. Specifically, the policy pilots were rolled out in three batches. The first batch, launched in 2013, covered Shanghai, Beijing, Tianjin, Shenzhen and Guangdong; the second batch extended to Hubei and Chongqing in 2014; and Fujian started its pilot in 2016. This article employs a time-varying DID_{it} for identification: the dummy variable equals 1 if province i has been included in the pilot program in year t , and 0 otherwise.

3.2.3. Mediating Variable: Health Human Capital (Hea)

Health human capital refers to the sound physical, mental and social well-being of individuals or groups, a state that can unlock individual potential and advance the economic and social prosperity of families, communities and even the whole country [11]. To scientifically evaluate the level of health human capital in China, this article employs the entropy weighting approach to systematically process panel data covering 30 provinces across China during 2010–2023, as well as to calculate each key indicator's weight. The entropy weighting technique offers an objective means of assigning weights that is grounded in information entropy. The larger the dispersion degree of an indicator (i.e., the lower its information entropy), the more information it contains and the larger its associated weight. Unlike subjective weighting approaches such as the AHP, this method determines weights purely according to the inherent dispersion of raw data, which effectively eliminates interference and bias caused by human subjective judgment. Featuring transparent and replicable calculation procedures, it can impartially capture each indicator's information contribution within the evaluation system, making it especially suitable for comprehensive evaluation research based on panel data. The detailed computation steps are presented below.

Suppose there are a total of N samples (here $N = 420$) and m evaluation indicators ($m = 12$). Let x_{ij} denote the raw value of the j -th indicator for the i -th sample ($i = 1, 2, \dots, N; j = 1, 2, \dots, m$). To remove the effects of units and positive/negative signs, we employ the range normalization technique. To eliminate the influence of measurement scales and indicator directions, the min–max normalization method was applied.

$$\text{Positive indicators: } z_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (6)$$

$$\text{Negative indicators: } z_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (7)$$

where $\max(x_j)$ and $\min(x_j)$ represent the maximum and minimum values, respectively, of the j -th indicator across all N samples. After standardization, $z_{ij} \in [0, 1]$.

Since logarithm transformation of matrix z_{ij} is required in subsequent calculations and standardized values may equal zero, we perform an overall translation on standardized data to avoid undefined logarithmic values. To minimize disturbances to the structure of the original data, the translation constant is set as $\alpha = 0.0001$.

$$z'_{ij} = z_{ij} + \alpha \quad (8)$$

Compute the feature weight for the i -th observation under the j -th indicator.

$$p_{ij} = \frac{z'_{ij}}{\sum_{i=1}^N z'_{ij}}, \quad j = 1, 2, \dots, m \quad (9)$$

The entropy value for indicator j is then computed.

$$e_j = -\frac{1}{\ln N} \sum_{i=1}^N p_{ij} \ln(p_{ij}) \quad (10)$$

In particular, it is stipulated that when $p_{ij} = 0$, $p_{ij} \ln(p_{ij}) = 0$, $0 \leq e_j \leq 1$ can be easily determined.

The variation coefficient of indicator j is then computed.

$$d_j = 1 - e_j \quad (11)$$

(11)

Next, we determine the weight for indicator j .

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (12)$$

Calculate the comprehensive score of health human capital for the i -th sample.

$$S_i = \sum_{j=1}^m w_j \cdot z_{ij} \quad (13)$$

On this basis, this article constructs an indicator system for health human capital based on the measurement of health status in Grossman's health demand curve model, whilst taking into account the actual circumstances in China regarding residents' lifestyle habits, the allocation of healthcare resources and health awareness. The composition of specific indicators is detailed in Table 2. Meanwhile, drawing on the five-dimensional framework of health education, lifestyle, preventive healthcare, medical and health services, and living environment outlined in the *Healthy China Planning Initiative (2019–2030)*, this article narrows the scope and selects indicators from four core dimensions: medical and health conditions, health status, preventive healthcare, and lifestyles. Specifically, following Liu et al. (2024) and Jiang et al. (2023) [42,43], we select indicators including the number of health technicians per 1000 people, the number of primary medical and health institutions, patient visits, population mortality rate, average life expectancy, per capita medical and health expenditure, and the number of people receiving health check-ups. Drawing on Yuan et al. (2025), Grossman (1972), and Dittrich (2011) [11,44,45], we adopt the number of participants in basic medical insurance for employees and per capita expenditure on daily necessities and services.

Table 2. Evaluation indicator system of health human capital.

Primary Indicator	Secondary Indicator	Unit	Attribute
Healthcare services	Health technical personnel per 1000 people	Persons	+
	Primary healthcare institutions	Count	+
	Number of medical consultation visits	10,000 person-times	+
Health status	Population mortality rate	‰	–
	Life expectancy at birth	Year	+
Preventive care	Per capita healthcare expenditure	%	+
	Number of physical examinations	10,000 persons	+
	Number of participants in basic employee medical insurance	10,000 persons	+
Lifestyle	Per capita expenditures on daily necessities and services	Yuan	+

3.2.4. Control Variables

Drawing on existing literature regarding research findings on the influencing factors of GDE and incorporating the practical context of this article, the control variables selected herein include aging level (Old), urbanization rate (Urb), industrial structure (Strc), tax burden level (Tb), and fiscal support (Fs). Detailed measurement methodologies are presented in Table 3.

Table 3. Definitions of variables and calculation methods.

Variable Symbol	Variable Name	Calculation Method
Gde	Green development efficiency	Super-efficiency SBM-GML model with input, desirable output, and undesirable output Indicators
Hea	Health human capital	Constructed as a health human capital index via the entropy weight method, covering four dimensions: medical and healthcare, physical health status, preventive healthcare, and lifestyle.
DID	Carbon emission trading	Province <i>i</i> is assigned a value of 1 if it is included in the pilot program in year <i>t</i> , and 0 otherwise.
Old	Aging level	Population aged 65 and above/Total population
Urb	Urbanization rate	Urban population/Year-end permanent resident population
Strc	Industrial structure	Added value of secondary industry/Regional GDP
Tb	Tax burden level	Tax revenue/Regional GDP
Fs	Fiscal support	General budgetary fiscal expenditure/Regional GDP

3.3. Data Sources

The raw data for relevant indicators are derived from *China Statistical Yearbook*, *China Energy Statistical Yearbook*, *China Environmental Statistical Yearbook*, *China Health Statistical Yearbook*, the CSMAR Database, the EDGAR Database, and statistical bulletins by province. Linear interpolation is adopted to fill partial missing values. In addition, to eliminate the interference of inflation, provincial and municipal GDP figures are deflated at constant 2010 prices. Due to severe data shortages for the Xizang Autonomous Region of China, samples from this region are excluded in this article. Ultimately, panel data covering 30 provinces (excluding Xizang, Hong Kong, Macao and Taiwan) from 2010 to 2023 in China are selected for in-depth analysis. The descriptive statistics for the variables are shown in Table 4.

Table 4. Descriptive statistical results of variables.

Variable	N	Mean	Std. Dev.	Min	Max
Gde	420	1.771	0.589	0.929	4.060
DID	420	0.171	0.377	0.000	1.000
Hea	420	0.269	0.131	0.041	0.754
Old	420	15.801	4.726	7.400	30.600
Urb	420	0.595	0.124	0.338	0.941
Strc	420	0.407	0.082	0.149	0.619
Tb	420	0.080	0.027	0.035	0.181
Fs	420	0.250	0.108	0.104	0.748

4. Empirical Results and Analysis

4.1. Baseline Regression Results

Building on the staggered DID model constructed above, Table 5 presents the baseline estimation outcomes of the ETS on GDE and health human capital. The regression outcomes in columns (1) and (2) demonstrate that coefficients on DID are significantly positive at the 1% level, which indicates that the ETS helps boost GDE. As shown in column (3), the interaction term DID yields a positive coefficient significant at the 1% level, indicating that the ETS policy effectively elevates the level of health human capital. Accordingly, Hypothesis H1 is supported.

Table 5. Benchmark regression results.

Variable	(1)	(2)	(3)
	Gde	Gde	Hea
DID	0.185 *** (3.46)	0.177 *** (3.65)	0.012 ** (2.15)
Controls	No	Yes	Yes
Constant	1.740 *** (136.20)	3.118 *** (4.80)	0.306 *** (11.36)
N	420	420	420
R-squared	0.881	0.892	0.977
Provincial effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes

Notes: ** and *** indicate significance at the 5% and 1% levels, respectively, with t-statistics reported in parentheses. The same notation applies to all subsequent tables.

4.2. Robustness Tests

4.2.1. Parallel Trend Test

To verify the parallel-trends assumption of the staggered DID model, this article adopts an event study approach to identify the dynamic effects of the ETS on GDE. Figure 2 presents the estimation results, with the pre-policy period one year before implementation set as the reference period. Before the policy pilot, all pre-period coefficients fluctuate around zero and are statistically insignificant, indicating no systematic difference in pre-trends between the treatment and control groups and validating the parallel trends assumption. In the current period and the early years after policy implementation, the estimated coefficients remain statistically insignificant, implying that the impact of the ETS on GDE exhibits a certain transmission lag. From the third period after policy implementation onward, the differences between the treatment and control groups become significantly different from zero, and the coefficients show an expanding trend. This indicates that the ETS exhibits sustained and cumulative positive effects on green development efficiency, with its long term positive policy effects emerging gradually. To mitigate the estimation bias of conventional TWFE under staggered DID, this article adopts the Sun and Abraham (2021) estimator for robustness checks [46]. This method drops 2×2 DID components that contain “bad controls.” Figure 2 plots the estimation results from both TWFE and the Sun and Abraham estimator. The dynamic trends of the two sets of estimates are largely consistent, verifying the robustness of our conclusions regarding dynamic effects. In addition, we conduct a joint significance test on the pre-period coefficients, whose results further support the parallel trends assumption (see notes of Figure 2). Consistent with the baseline regression, this article conducts a parallel trends test for the mechanism variable health human capital. The results also validate the parallel trends assumption, as shown in Figure A1 in Appendix A.

4.2.2. Placebo Test

Although the DID approach can alleviate endogeneity concerns to some degree, selecting pilot regions for the ETS is likely non-random. To address this concern, we perform a placebo test via random construction of fictitious treatment groups. In particular, we choose several at random as fake treated units and repeat this random sampling procedure 1000 times, after which we examine whether the coefficients of the “pseudo-policy dummy variables” are significant. If the estimated parameter for this placebo term retains statistical significance, it suggests that baseline regression results

may suffer from estimation bias, and changes in GDE could be driven by confounding omitted factors rather than the ETS. As shown in Figure 3, the kernel density of the coefficient estimates on “pseudo-policy dummy variables” clusters around zero, with corresponding p -values all well above 0.1. The coefficient estimate from the actual treated group alone attains statistical significance. Such evidence confirms that the ETS policy’s promoting effect on GDE does not stem from random shocks or omitted variables, which validates the robustness of our baseline regression estimates. In addition, we conduct an identical placebo test for health human capital. The results indicate that the positive effect of the ETS on health human capital is not driven by random shocks or omitted variables, confirming the robustness of our findings. Detailed results are presented in Figure A2 in Appendix A.

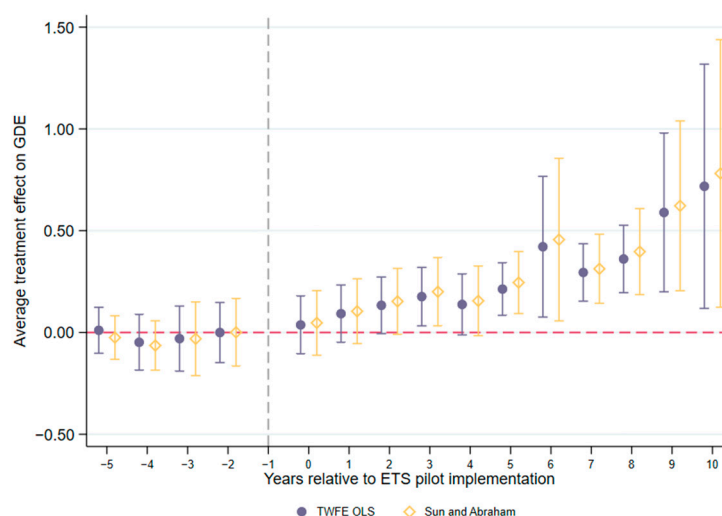


Figure 2. Parallel trend test graph. Note: This article conducts a joint significance test on the three pre-implementation coefficients prior to the policy’s introduction. The F-test statistic for the TWFE model is 0.23, with a p -value of 0.919, whilst the Wald statistic for the Sun and Abraham model is 0.879, with a p -value of 0.928; the results support the parallel trends hypothesis.

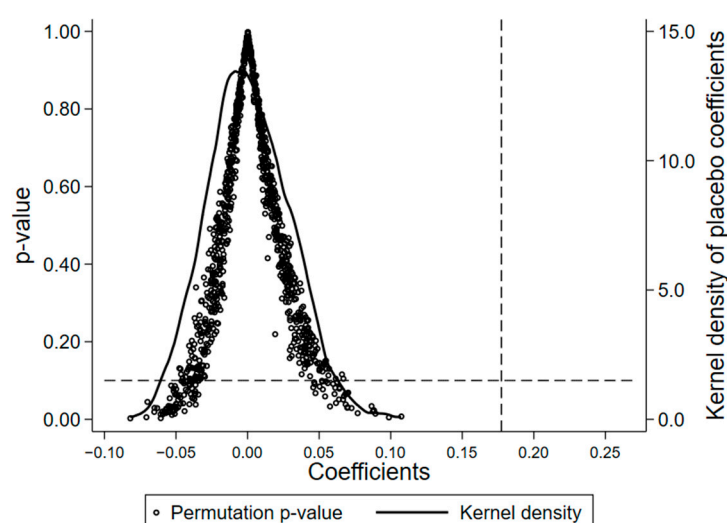


Figure 3. Placebo test graph.

4.2.3. PSM-DID

To mitigate selection bias between treated and comparison units, this article adopts a PSM-DID approach for evaluating the effects from ETS policy. Specifically, this article

selects control variables such as the level of population aging, the urbanization rate, industrial structure, tax burden and fiscal support as covariates, and constructs a Logit model to estimate the propensity scores for each province's participation in the ETS. On this basis, drawing on the study by Fei et al. (2025) [47], the 1:4 nearest-neighbor matching method was employed to match provinces in the treatment group with provinces in the control group that had similar propensity scores. Figure 4 shows that the standardized bias of each covariate is substantially reduced after matching, and all t-tests are insignificant. This indicates that matching effectively balances the covariate distribution between the treatment and control groups. The common support test in Figure 5 suggests that the vast majority of samples lie within the common support region; only a tiny fraction of treated samples fall outside the support, implying good matching quality. Column (1) of Table 6 shows that the DID coefficient is 0.176 and is significant at the 1% level. This suggests that after mitigating sample selection bias, the ETS still exerts a significantly positive promoting effect on green development efficiency, confirming the robustness of the baseline regression results.

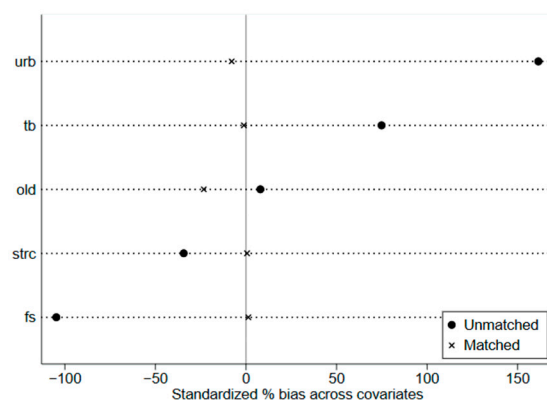


Figure 4. Standardized bias of covariates before and after matching.

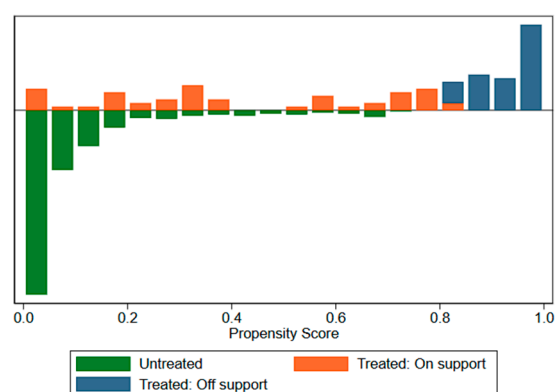


Figure 5. Joint support domain test.

Table 6. Results of robustness test regressions.

Variable	(1) PSM-DID	(2) Replace the Interpreted Variable	(3) One-Period Lag	(4) Two-Period Lag	(5) Shorten the Study Window	(6) Eliminate the Interference of Green Finance Policies	(7) Eliminate the Interference of Energy Rights Trading Policies
DID	0.176 *** (3.64)	0.231 *** (2.89)	0.177 *** (3.35)	0.172 *** (2.85)	0.099 *** (4.75)	0.178 *** (3.65)	0.177 *** (3.59)
Green	—	—	—	—	—	0.040	—

	—	—	—	—	—	(0.71)	—
Energy	—	—	—	—	—	—	0.006
	—	—	—	—	—	—	(0.20)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.091 *** (4.93)	2.751 *** (3.69)	3.371 *** (4.51)	3.564 *** (4.29)	0.623 ** (2.44)	3.090 *** (4.60)	3.120 *** (4.82)
N	420	420	390	360	270	420	420
R-squared	0.892	0.824	0.882	0.869	0.958	0.892	0.892
Provincial effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ** and *** indicate significance at the 5% and 1% levels.

4.2.4. Replace the Dependent Variable

To mitigate the interference of the super-efficiency setting in the DEA model on green development efficiency estimates, following Ma et al. (2025) and Zhang et al. (2024) [48,49], we retain the inputs, desirable outputs, undesirable outputs and the global GML index framework. Instead of adopting the super-efficiency specification, we recalculate green development efficiency using the conventional SBM-GML index for a robustness check concerning measurement approaches. The regression results are shown in Column (2) of Table 6. After replacing the dependent variable, the DID coefficient is 0.231 and significantly positive at the 1% statistical level, consistent with the baseline regression findings. This indicates that our core research conclusion is robust.

4.2.5. Lag Period Test

To assess the potential lagged effect from the ETS and alleviate endogeneity arising from reverse causation, we use the first two lags of the core regressor to re-estimate Model (1). Columns (3) and (4) of Table 6 show that the ETS still generates a positive improvement effect on GDE with 1% statistical significance. This confirms that our core findings remain robust after accounting for policy time lags and potential endogenous biases.

4.2.6. Shorten the Study Window

Given that long-term confounding factors may bias the estimates, we carry out a robustness check by adjusting the time window covering the periods around the ETS policy rollout. Specifically, we limit the observation window to the sample spanning 2010–2018 and run regressions for Model (1), whose outcomes are displayed in column (5) of Table 6. After narrowing the sample time frame, the DID interaction term's sign and significance are identical to the prior regression estimates, further corroborating the reliability of our previous findings.

4.2.7. Excluding the Influence of Other Policies

To avoid confounding effects from policies closely related to the carbon emission trading scheme on our baseline results, we conduct robustness checks using the green finance reform and innovation pilot zones and the energy right trading policy as interfering policies. Specifically, we add policy shock variables for green finance reform and innovation pilot zones (Green) and energy-use right trading policy (Energy) to the baseline regression model. The confounding policy variables are constructed as follows. The policy shock variable equals 1 for regions covered by the interfering pilot policy in and after the pilot year, and 0 otherwise. As shown in Columns (6) and (7) of Table 6, the

estimated DID coefficients remain consistent with the baseline regression, further verifying the robustness of our previous findings.

4.3. Mediation Effect Test

To examine whether the ETS affects GDE via the health human capital channel, this article conducts empirical analysis using Model (2) and Model (3), with column (1) in Table 7 presenting the estimated impact from the ETS upon health human capital (Hea). The findings reveal that the coefficient for DID equals 0.012 and is statistically significant at the 5% level. This indicates that the implementation of the ETS significantly boosts the accumulation of health human capital in ETS pilot regions. Column (2) further incorporates health human capital into the regression model for GDE. The coefficient estimate for Hea is positive and statistically significant, which suggests that the advancement in health human capital can effectively promote the enhancement of GDE. In terms of the mechanism, the ETS policy encourages firms to cut carbon emissions and reduce pollution, improves regional environmental quality, lowers residents' health risks, and thereby facilitates the accumulation of health human capital [50]. Improved health human capital, in turn, significantly elevates GDE through channels such as higher labor productivity and green technological innovation. The empirical findings described above are consistent with the expectation that health human capital mediates the impact of the ETS on the efficiency of green development, thereby supporting Hypothesis H2. To further identify the environmental channels through which the ETS affects health human capital, this article presents an extended analysis in Appendix A. The results show that the ETS not only significantly enhances health human capital but also significantly reduces PM_{2.5} concentrations, indicating that the ETS can enhance health human capital by improving air quality. For detailed results, please refer to Figure A3 and Table A1 in Appendix A.

Table 7. Regression results of mediation tests.

Variable	(1) Hea	(2) Gde
DID	0.012 ** (2.15)	0.168 *** (3.65)
Hea	— —	1.117 ** (2.09)
Controls	Yes	Yes
Constant	0.306 *** (11.36)	2.442 *** (4.33)
N	420	420
R-squared	0.976	0.872
Provincial effect	Yes	Yes
Year effect	Yes	Yes

Notes: ** and *** indicate significance at the 5% and 1% levels.

Furthermore, drawing on the research by Sarpong et al. (2020) [51], this article uses per capita health expenditure (PCHE) as a variable that provides a more direct measure of health human capital to test for mediating effects. Per capita health expenditure directly reflects residents' actual investment in and access to health resources, and is an important indicator for measuring the level of health human capital [52]. As shown in Table 8, the DID coefficient in Column (1) is 133.567 and significant at the 5% level, indicating that the ETS significantly increases PCHE. In Column (2), the PCHE is significantly positive at the 1% level, and the DID coefficient remains significantly positive after incorporating PCHE.

These results align with the expectation that PCHE acts as a mediator in the effect of the ETS on green development efficiency, further supporting Hypothesis H2.

Table 8. Results of the mediation analysis for PCHE.

Variable	(1) PCHE	(2) Gde
DID	133.567 ** (2.33)	0.122 *** (2.72)
PCHE	— —	0.0004 *** (3.91)
Controls	Yes	Yes
Constant	3966.290 *** (7.53)	1.471 ** (2.27)
N	420	420
R-squared	0.957	0.904
Provincial effect	Yes	Yes
Year effect	Yes	Yes

Notes: ** and *** indicate significance at the 5% and 1% levels.

4.4. Heterogeneity Analysis

4.4.1. Heterogeneity Based on the Level of Green Technology Innovation

To examine the heterogeneous policy effects across regions with different levels of green technological innovation, we measure regional green technological innovation using the logarithm of one plus the number of green patent applications. The full sample is split into high and low groups based on the median value. We then employ the Fisher permutation test [53] to statistically verify the intergroup difference in the coefficients of the core explanatory variable. Table 9 columns (1) and (2) present the results of grouped regressions. In regions with high levels of green technological innovation, the estimated DID coefficient is 0.373 and significant at the 1% level. By contrast, the coefficient equals only −0.005 and is statistically insignificant for regions with low green technological innovation. The two sets of coefficients exhibit distinctly different signs and significance levels, implying that the promoting effect of the ETS emerges only in regions with high green technological innovation. Furthermore, the Fisher permutation test yields an intergroup coefficient difference of 0.378, which is significant at the 1% level. This confirms that the coefficient gap between the two groups does not arise from sampling error. These results imply that the level of green technological innovation serves as an important prerequisite for ETS policy effects. Stronger green technological innovation capacity helps amplify the positive effect of the ETS on green development efficiency. A plausible explanation is that regions with high-level green technological innovation possess sounder R&D foundations and human capital, enabling them to effectively translate ETS price signals into technological upgrading incentives. Meanwhile, their well-established institutional environment facilitates the smooth transmission of policy incentives. In contrast, low-innovation regions suffer from weak technological absorption capacity and technological path dependence. Policy shocks in these areas may crowd out productive investment and thus fail to generate positive feedback effects.

Table 9. Regression results of the heterogeneity test.

Variable	(1) High Green Technology Innovation Level	(2) Low Green Technology Innovation Level	(3) High Level of Financial Development	(4) Low Level of Financial Development	(5) High Environmental Attention	(6) Low Environmental Attention
DID	0.373 *** (4.26)	−0.005 (−0.12)	0.262 *** (3.49)	0.073 ** (2.19)	0.154 *** (3.34)	−0.037 (−0.65)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.061 (1.13)	2.713 *** (3.40)	3.432 *** (3.24)	1.454 *** (2.69)	3.123 ** (2.45)	3.816 *** (3.98)
N	210	210	210	210	210	207
R-squared	0.916	0.902	0.866	0.946	0.918	0.884
Provincial effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Fisher's Permutation test	0.378 ***		0.189 **		0.191 **	

Notes: ** and *** indicate significance at the 5% and 1% levels.

4.4.2. Heterogeneity Based on the Level of Financial Development

To investigate how different levels of financial development heterogeneously affect the ETS policy effect, we measure financial development using the ratio of regional financial institutions' total loans to regional GDP each year. Using the pre-policy median of this measure across regions, we classify our entire sample into high- and low-financial-development groups, and then estimate the baseline model separately for each subsample. As shown in Columns (3) and (4) of Table 9, the DID coefficient is 0.262 and statistically significant at the 1% level in regions with high financial development, while it stands at 0.073 and is significant at the 5% level in regions with low financial development. Furthermore, the Fisher permutation test presents a significant intergroup coefficient difference of 0.189 at the 5% statistical level, confirming that the discrepancy between the two groups is statistically robust. Accordingly, the promoting effect of the ETS on green development efficiency is stronger in regions with a higher level of financial development. The possible reasons are that areas with greater financial development generally possess more sound standard systems for green finance and supporting mechanisms for transitional finance. Via tools such as green lending, transition loans, environmental information disclosure and risk assessment, such regions can channel capital toward energy saving, emission cuts, and clean production along with low-carbon technological transformation, thus improving firms' responsiveness to the ETS policy. In contrast, regions with low financial development suffer from insufficient supply of green financial instruments and an imperfect standard system for transition finance. Firms in such regions face tighter financing constraints in pursuing green transformation. Consequently, the emission reduction pressure generated by the ETS policy can hardly be fully translated into tangible technological upgrades and low carbon investment activities, leading to a relatively weaker policy promotion effect.

4.4.3. Based on the Heterogeneity of Government Attention to Environmental Issues

The emphasis placed by local governments on ecological concerns can exert policy guidance and public opinion supervision impacts, thus improving the transparency, precision, and effectiveness in environmental governance information and expediting the holistic green transformation of socioeconomic progress. To investigate how the ETS affects GDE under varying levels of governmental environmental attention, this article

measures governmental environmental attention using the ratio of provincial pollution control investment to regional GDP. All provincial samples are split into two subgroups based on the median value of 0.8987. Observations with values below the median are coded as 0 and categorized as the low environmental governance priority group, while those exceeding the median are coded as 1 and classified as the high environmental governance priority group. Based on the estimates displayed in column (5) of Table 9, the DID equals 0.154 and is significantly positive at the 1% significance level for the high environmental governance priority group. This finding indicates that carbon emission trading policies can significantly improve GDE in regions with high environmental governance priorities. In contrast, the estimated coefficient on DID stands at -0.037 for the low environmental governance priority group and fails to pass the significance test. To ensure the statistical reliability of the differences between groups, Fisher's exact test was conducted in this article. The results showed that the difference in coefficients between groups was 0.191, which was statistically significant at the 5% level. This implies that the policy shock of the ETS exerts an insignificant effect in regions with low environmental attention. The above results indicate that high levels of governmental environmental attention serve as a critical institutional foundation for the effective implementation of the ETS. A plausible explanation is that regions with substantial governmental environmental priorities feature strong local government willingness and regulatory capacity for environmental governance. Local authorities can rigorously enforce carbon allowance allocation and compliance supervision rules, while rolling out complementary policies such as low-carbon incentives and industrial rectification, thereby generating synergies between market-based mechanisms and governmental environmental regulation. Effective institutional constraints compel enterprises to pursue green technological innovation and energy-saving retrofits, optimize the regional allocation of carbon emission resources, fully unlock the policy dividends of the ETS, and substantially boost regional GDE. In contrast, in regions where governments attach low priority to environmental protection, local authorities tend to prioritize economic growth over ecological conservation. To sustain regional economic expansion and industrial scale, they impose lax supervision and weak penalties on corporate carbon emissions. This dilutes the regulatory binding force and market-based emission reduction effects of the ETS, resulting in relatively muted policy impacts in such areas. In summary, research hypothesis H3 is supported.

5. Spatial Spillover Effect

Before examining the spatial spillover effects of the ETS on green development efficiency, this article uses the LM, LR and Wald tests to identify the spatial econometric model (Table 10). The results show that LM-Error, LM-Lag and their robust statistics are all significant at the 1% level, and the Moran's I for the residuals is 15.447, indicating that there is significant spatial correlation in green development efficiency. Furthermore, the results of both the Wald test and the LR test reject the null hypothesis that the SDM can be reduced to an SAR or SEM, thereby supporting the use of the spatial Durbin model. The Hausman test statistic is 142.52, with a p -value of 0.000; the random-effects model is rejected, and the fixed-effects model should therefore be selected. In light of the above, this article employs the spatial Durbin model (SDM) with spatiotemporal fixed effects to estimate spatial spillover effects.

Table 10. Spatial econometric model selection test results.

Test	Statistic	p -Value
LM (error) test	209.560	0.000

Robust LM (error) test	31.625	0.000
LM (lag) test	356.864	0.000
Robust LM (lag) test	178.928	0.000
Moran's I	15.447	0.000
Wald test spatial lag	15.70	0.015
LR test spatial lag	28.40	0.000
Wald test spatial error	7.12	0.007
LR test spatial error	24.30	0.000
Hausman test	142.52	0.000

Table 11 presents the results of the spatial Durbin model estimates and effect decomposition based on a geospatial weighting matrix. The regression results show that the $W \times DID$ coefficient for the core explanatory variable in the model is significantly positive, and the indirect effect also passed the significance test, indicating that the ETS has a positive spatial spillover effect on green development efficiency. Furthermore, this article goes on to present the direct, indirect and total effects of the core explanatory variable. The indirect effects reported in Table 11 are significantly positive at the 1% level, further suggesting that the ETS exerts a pronounced positive spatial spillover effect on regional green development efficiency. Specifically, the implementation of the ETS not only improves green development efficiency in pilot regions but also significantly promotes green development in neighboring areas through technology diffusion and demonstration effects. These findings verify the “benefiting neighbors” effect of the ETS policy.

Table 11. Analysis of spatial effects.

Variable	SDM	Direct Effect	Indirect Effect	Total Effect
DID	0.195 *** (3.36)	0.174 *** (2.66)	0.551 *** (2.62)	0.726 *** (3.84)
$W \times DID$	1.008 *** (3.16)	—	—	—
Controls	Yes			
sigma2_e	0.033 *** (3.35)			
Provincial effect	Yes			
Year effect	Yes			
Log-L	112.931			
R-squared	0.780			
N	420			

Note: *** indicates significance at the 1% significance level; the values in parentheses represent the corresponding z-scores.

6. Research Findings and Recommendations

6.1. Research Findings and Policy Recommendations

This article uses the panel data covering 30 provinces in China spanning 2010–2023 as the article sample, measures green development efficiency using the super-efficiency SBM-GML model, and employs the staggered DID method to assess the effect of the ETS on green development efficiency and its mechanisms. The findings indicate that the ETS, through its carbon pricing mechanism, internalizes the externality of emission reduction, thereby generating a price signal that “carbon emissions incur costs while carbon reductions yield benefits.” This signal channels production factors like capital, technological resources, and human capital toward low-carbon sectors, and incentivizes

firms to pursue green technological innovation, while exerting pressure on high-carbon industries to transform and upgrade and to phase out backward production capacity, ultimately improving firms' GDE. Furthermore, by reducing air pollution and improving environmental quality, the ETS helps lower environmental health risks such as respiratory diseases and reduces the depletion of health human capital. This, in turn, enhances production efficiency, strengthens societal capacity to absorb and transform new technologies, and supplies high-quality health human capital for green technology adoption and industrial structure upgrading, thereby elevating green development efficiency. The spatial effect indicates that the implementation of a local ETS can enhance the green development efficiency of neighboring regions. According to heterogeneity analysis, ETS's promoting effect on green development efficiency is particularly evident in regions having a high level of green technology innovation, high level of financial development, and substantial government environmental attention. This indicates that strong support from green technological innovation, efficient allocation of financial resources, and a comprehensive environmental governance system and high governance efficiency are essential conditions for the ETS to achieve a coordinated enhancement in environmental, economic, and social benefits.

Based on the above findings, we propose the following policy recommendations:

Firstly, improve the institutional framework and operational mechanisms of the ETS market. Anchor national greenhouse gas emission control targets, closely align with the requirements for controlling both aggregate carbon emissions and carbon intensity, scientifically set the total quota volume and allocation pathways, explore paid allocation methods and gradually raise the share of paid allowances, and strengthen the forcing effect of total carbon emission constraints on low carbon transition. Steadily expand the industrial coverage of carbon markets, diversify carbon trading products, market participants and transaction modalities, and establish incentive and constraint mechanisms linking carbon pricing with carbon emission reductions. It is necessary to unify national carbon emission management and trading rules, eliminate cross-regional market fragmentation, and establish an operational mechanism featuring horizontal coordination and vertical governance.

Additionally, optimize the allocation of health human capital and promote the synergistic enhancement of health human capital accumulation and green development. Sustained funding for public healthcare undertakings needs to be scaled up to elevate public health service standards and optimize medical resource allocation. Scale up health industry deployment, and channel social capital into sectors including health management. Furthermore, regular publicity and education campaigns on health risk prevention shall be carried out to raise residents' awareness of self-health management and self-protection capabilities. Additionally, the public and media should be encouraged to focus on environmental health issues and exercise supervision through public opinion. Promote low carbon and green production and lifestyles such as green commuting and clean energy adoption.

Furthermore, adopt differentiated and dynamic regulation strategies to boost green development efficiency tailored to local conditions. Innovation indicators, such as the number of green patent applications, should be incorporated into the carbon market performance assessment system; quota incentives or tax concessions should be granted for highly efficient emission-reduction technologies; and mechanisms for the trading of green technologies and the protection of intellectual property rights should be improved. Concurrently, financial institutions need to be encouraged to develop green financial products and services linked to emission allowances. Pursue the orderly innovation of carbon financial products and derivatives, clean technology innovation and green equipment renewal. Accelerate the cultivation of a green financial intermediary service

system and enterprises' carbon asset management capabilities. In addition, local governments should bear greater responsibility for ecological and environmental protection outcomes, and green development performance must be deeply embedded within the government performance assessment framework. A multi-dimensional, differentiated system of evaluation indicators should be established that balances ecological conservation with economic development. Scientifically optimize the environmental governance system, improve and refine environmental policies and regulations, and reasonably allocate responsibilities and authorities to local governments in environmental protection matters.

6.2. Research Limitations and Future Directions

The findings of this article are subject to certain limitations. Firstly, the establishment of carbon emissions trading pilot schemes was not a strictly randomized experiment; the selection of pilot regions may have been influenced by multiple factors, such as the level of economic development, industrial structure and environmental governance capacity, resulting in a degree of self-selection bias. Secondly, due to limitations in the availability of data at the provincial level, linear interpolation was employed to handle some missing values in this article. Health human capital was measured using the entropy method; however, the specific selection of indicators and the calculation methods still require further refinement. At the same time, aggregating data at the provincial level may obscure heterogeneity among prefectures and cities within a province. Furthermore, the identification of spatial spillover effects depends on the specification of the spatial weight matrix. However, there is no uniform standard for selecting different weight matrices. Moreover, in scenarios where spatial spillover exists, the assumption of independence between the treatment and control groups, on which traditional DID relies, faces further challenges. Although the above limitations do not invalidate the core conclusions of this article, they suggest that future research could utilize microdata, refine identification strategies, and employ spatial DID or robust tests with multiple weighting schemes to further enhance the credibility of the findings.

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Conflicts of Interest: The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ETS	Carbon Emissions Trading System
DID	Differences-in-Differences
GDE	Green Development Efficiency
EU ETS	EU Emissions Trading System
RGGI	Regional Greenhouse Gas Initiative
SBM	Slacks-based Measure
GML	Global Malmquist–Luenberger
DEA	Data Envelopment Analysis
GDP	Gross Domestic Product
Hea	Health Human Capital
AHP	Analytic Hierarchy Process
PSM	Propensity Score Matching
PCHE	Per Capita HealthExpenditure
SDM	Spatial Durbin Model

Appendix A

Figure A1 presents the event-study estimates for health human capital. Taking the period immediately before policy implementation as the reference period, the coefficients for all pre-policy periods fluctuate around zero, with their confidence intervals containing zero. This suggests no statistically significant pre-trend difference between the treated and control groups, so the parallel trends assumption holds. Post-policy coefficients rise gradually and become significantly positive from the fourth period onwards, indicating that the ETS exerts a positive effect on health human capital with a certain time lag and persistence.

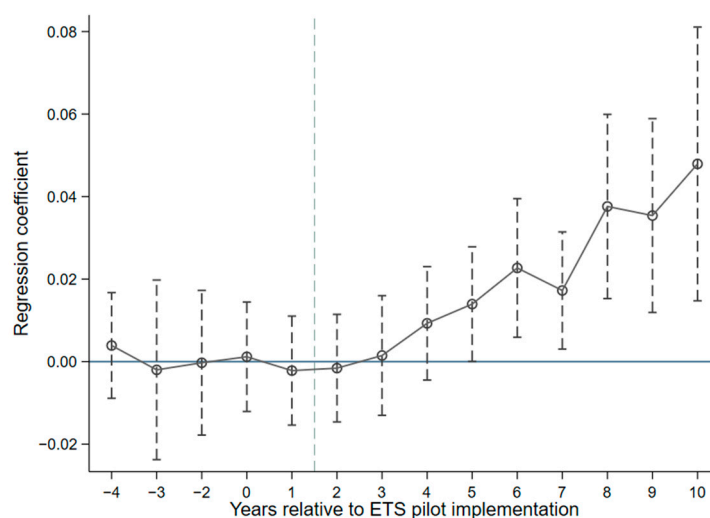


Figure A1. Parallel trends test of the ETS on health human capital.

Figure A2 presents the results of the placebo test for health human capital. By randomly generating a dummy treatment group and repeating the process 1000 times, the kernel density of the pseudo policy variable coefficients was concentrated around 0, whilst the true policy estimate deviated significantly from this random distribution, corresponding to a p -value of less than 0.1. This indicates that the positive effect of the ETS on health human capital is not driven by random shocks or omitted variables. This test

further supports the robustness of the association between the ETS and health human capital.

Figure A3 depicts the trends in China's annual average PM_{2.5} concentration and average life expectancy from 2010 to 2023. In terms of PM_{2.5} concentrations, China experienced persistently high and fluctuating PM_{2.5} levels prior to the launch of the ETS in 2013. After 2013, alongside the gradual rollout of the ETS, PM_{2.5} concentrations exhibited a marked fluctuating downward trend, declining from approximately 54.91 $\mu\text{g}/\text{m}^3$ in 2013 to 28.40 $\mu\text{g}/\text{m}^3$ in 2023. This trend preliminarily suggests a positive association between the ETS and air quality improvement. Regarding the average life expectancy of the population, China's life expectancy maintained a continuous upward trend over the sample period, rising from approximately 75.93 years in 2013 to 79.16 years in 2023. The steady increase in life expectancy and the sustained decline in PM_{2.5} concentrations exhibit a strong negative correlation in their temporal trends, suggesting that the ETS may have a positive effect on health human capital by improving air quality.

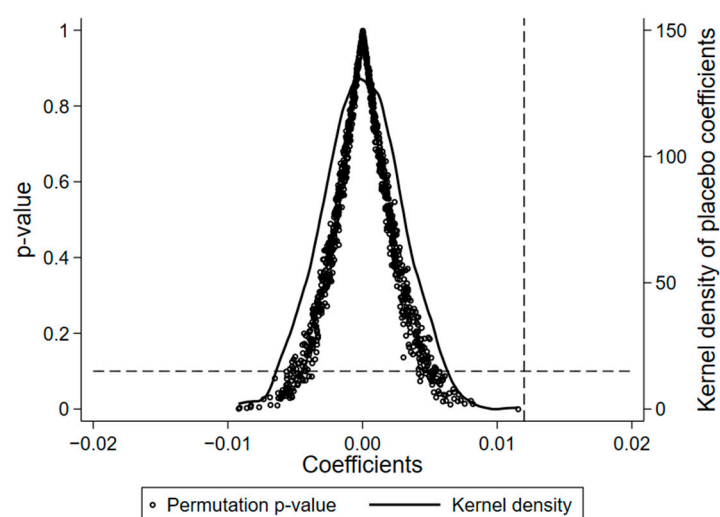


Figure A2. Placebo test of the ETS on health human capital.

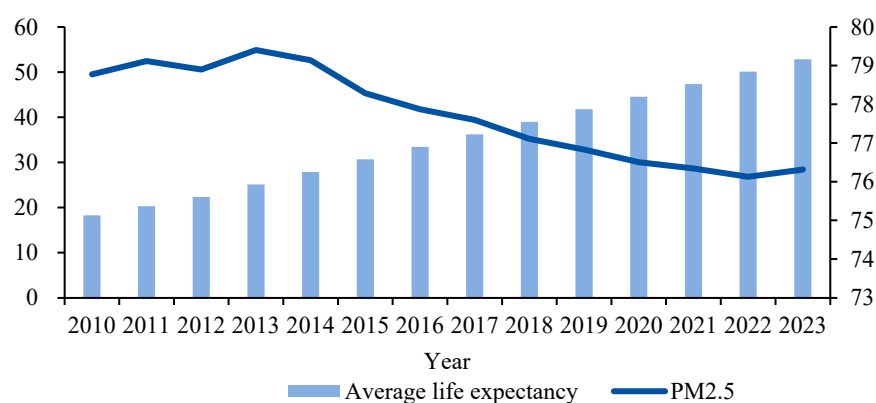


Figure A3. Annual average PM_{2.5} concentration and life expectancy trends in China. Note: The line graph corresponds to the left vertical axis and denotes the annual average PM_{2.5} concentration ($\mu\text{g}/\text{m}^3$); the bar chart corresponds to the right vertical axis and denotes average life expectancy (years).

To examine whether the ETS affects health human capital by improving air quality, this article uses PM_{2.5} concentration as the measure of air quality and applies a logarithmic transformation to this variable. The regression results are reported in Table A1. Column

(1) of Table A1 shows that the DID estimator is significantly positive, implying that the implementation of the ETS substantially promotes the accumulation of regional health human capital. Column (2) of Table A1 reports that the DID coefficient is -0.056 and statistically significant at the 1% level, which suggests that the ETS effectively reduces $PM_{2.5}$ concentration and improves regional environmental quality in China to a certain extent. Graff Zivin et al. (2013) argue that air pollution exerts widespread adverse impacts on health human capital [54]. Using U.S. birth cohort data, Swetschinski et al. (2023) [55] find that childhood $PM_{2.5}$ exposure is significantly negatively associated with adult income percentiles, providing empirical evidence that air pollution undermines the formation of health human capital.

Table A1. Air quality mediated effect test results.

Variable	(1) Hea	(2) ln $PM_{2.5}$
DID	0.012 ** (2.15)	-0.056 *** (-4.26)
Controls	Yes	Yes
Constant	0.306 *** (11.36)	3.434 *** (22.98)
N	420	420
R-squared	0.977	0.976
Provincial effect	Yes	Yes
Year effect	Yes	Yes

Notes: ** and *** indicate significance at the 5% and 1% levels.

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