land

Article

Impact of Carbon Trading System on Green Economic Growth in China

Xin Nie [1,2,3], Zhoupeng Chen [1], Linfang Yang [1], Qiaoling Wang [1], Jiaxin He [1], Huixian Qin [1] and Han Wang [1,2,3,*]

[1] School of Public Administration, Guangxi University, No 100, Da Xue Road, Nanning 530004, China; toefl678@gxu.edu.cn (X.N.); chenzp@st.gxu.edu.cn (Z.C.); yanglf@st.gxu.edu.cn (L.Y.); wang@st.gxu.edu.cn (Q.W.); hejiaxin@st.gxu.edu.cn (J.H.); qinhuixian@st.gxu.edu.cn (H.Q.)
[2] China Center for Agricultural Policy (CCAP), School of Advanced Agricultural Sciences, Peking University, No 5, Yi He Yuan Road, Beijing 100871, China
[3] Department of City and Regional Planning, University of North Carolina at Chapel Hill, Chapel Hill, NC 27599, USA
* Correspondence: hanwang@gxu.edu.cn

Abstract: Whether China's economy can maintain sustainable growth has been debated both in China and internationally, and the most representative critique has been summarized in the "Krugman Query". Faced with such doubts, how to achieve a "win-win" for economic growth and environmental protection has become one of the central objectives of local government work while striving for the new vision of development. Taking China's carbon trading pilot policy as an example, and based on panel data of 30 provincial administrative regions in China from 2001 to 2018, this paper uses the Data Envelopment Analysis-Malmquist index model and the Propensity Score Matching-Difference in Difference method to measure the level of green economic growth from two aspects: green development mode and economic growth effect, and further explore the impact of China's carbon trading system on green economic growth. The results show that the implementation of the carbon trading system promoted both the green development level and economic growth of pilot cities, and positively affected green total factor productivity, refuting the "Krugman Query". Finally, the study puts forward a series of recommendations in strengthening environmental regulation, improving green technology innovation, and developing low-carbon industries.

Keywords: carbon trading system; green economic growth; data envelopment analysis-Malmquist index model; propensity score matching-difference in differences method

check for updates

Citation: Nie, X.; Chen, Z.; Yang, L.; Wang, Q.; He, J.; Qin, H.; Wang, H. Impact of Carbon Trading System on Green Economic Growth in China. *Land* **2022**, *11*, 1199. https://doi.org/10.3390/land11081199

Academic Editors: Baojie He, Ayyoob Sharifi, Chi Feng and Jun Yang

Received: 13 June 2022
Accepted: 28 July 2022
Published: 30 July 2022

1. Introduction

Is the source of power for China's economic growth rate production efficiency improvement or factor input accumulation? In recent decades, China's economy has achieved rapid growth. Indeed, this has led to increasingly severe challenges associated with environmental pollution and sustainable development [1,2]. In academic circles, the ensuing debate on whether China's economy could maintain sustained growth was fierce. American economist Paul Krugman proposed that the economic recovery effect induced by China's early reform and opening up would be short-lived. He further suggested that in the long run, the growth model of China's economy depended on the "Preparation" of factor accumulation rather than the "Inspiration" productivity improvement yields. Without effective institutional support, China's economic growth mode would be difficult to sustain [3]. Scholars have debated the authenticity and sustainability of China's economic growth trying to answer this "Krugman Query", and achieved certain progress. Their efforts mainly focused on the following two aspects: First, the contribution of factor investment to economic growth was assessed. Wu (2013) empirically tested the average revenue of capital input to economic development by using the Stochastic Frontier Analysis (hereinafter abbreviated as "SFA") and Data Envelopment Analysis (hereinafter abbreviated as "DEA") method and found that the contribution of labor input was highest [4]. Based on the non-parametric analysis framework, Dong and Liang (2013) showed that total factor productivity, labor, and capital contributed about 10.9%, 3.7%, and 85.4% to economic growth, respectively [5]. Cheng et al. (2019) showed that the contribution rates of market potential, capital, and labor force to economic growth were 34.55%, 34.86%, and 8.56%, respectively [6]. Second, it evaluated the contribution of total factor productivity to economic growth. However, these studies did not consider the eco-environmental variables affecting China's economic growth, which might lead to certain deviations in the obtained conclusions.

To achieve sustained economic development and the carbon emission target, China adopted increasingly strict environmental regulation policies. Moreover, environmental protection was vigorously strengthened, green development was realized, and efforts were taken to reverse the negative environmental impacts resulting from economic growth. In 2013, the carbon trading pilot system was implemented in seven provinces and cities, including Beijing, Tianjin, and Shanghai; then, in 2017, the system was gradually implemented nationwide (Figure 1). Clearly, only considering the efficiency of economic development is insufficient. Traditional total factor productivity measurements did not consider the resources and environmental problems associated with economic development, which tended to mislead policymaking. Compared with traditional indicators, Green Total Factor Productivity (hereinafter abbreviated as "GTFP") can directly reflect the quality of economic growth under the constraint of factor input. This became a key factor for promoting the transformation of green development and achieving economic growth. In practice, two questions remain: can the pilot policy lead to the improvement of GTFP and promote the growth of China's green economy? Furthermore, what is the contribution of such a carbon trading system to green economic growth? Answers to these questions will help us to understand objectively China's green economic growth. Furthermore, such knowledge can be used to explore the realization of "win-win" strategies benefitting both ecology and economy.

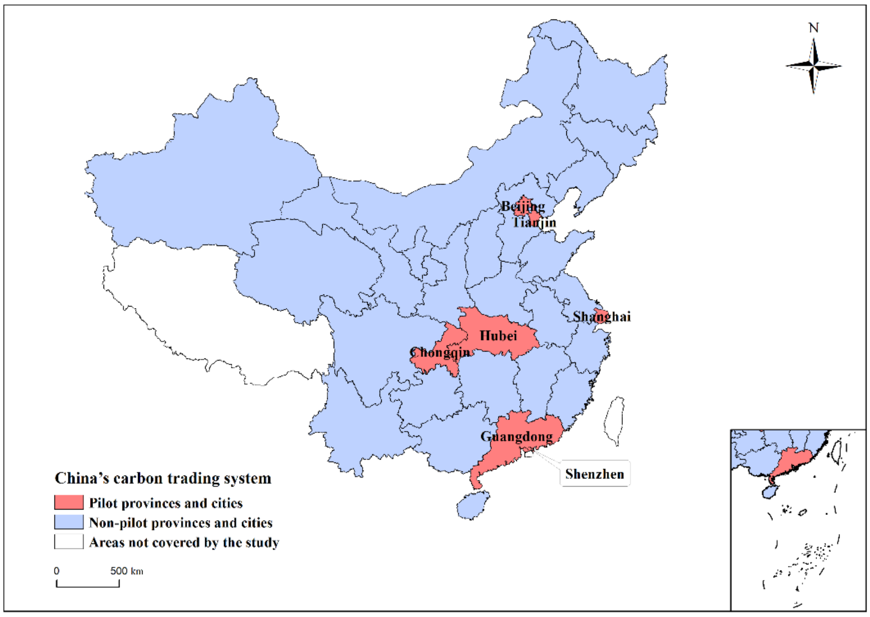

Figure 1. Distribution of pilot and non-pilot provinces and cities of carbon trading system in China.

Previous studies on carbon emissions and economic growth mainly focused on pollution reduction effect, decoupling effect, driving factors, and spatial differentiation. Razzaq et al. (2021) explored the causal relationship between economic growth, carbon emissions and energy efficiency and the emission reduction effect from the perspective of municipal domestic waste recycling [7]. Pei et al. (2021) analyzed the relationship mechanism between carbon footprint and economic growth in the Yangtze River Delta city cluster based on the decoupling model [8]. Saint et al. (2020) analyzed the linkage between carbon emissions, electricity consumption, economic growth and globalization and the driving factors in Turkey [9]. Yan et al. (2014) selected agricultural carbon emission intensity and agricultural economic intensity as the measures to empirically analyze the inflection point changes and spatial and temporal divergence of agricultural carbon emissions in China [10]. However, research on whether carbon trading pilot policies can promote green economic growth is relatively lacking and has not attracted sufficient attention. In addition, the relationship between carbon emissions and green economic growth is complex, comprehensive, and dynamic, and can change due to changes in time and space, so a hybrid approach is needed to systematically and deeply explore the influence path and mechanism of "carbon emissions-green economic growth". It can not only provide theoretical support and policy guidance to promote economic growth, but also promote green and low-carbon transition in a scientific and orderly manner.

Compared to existing studies, the marginal contributions of this paper are mainly in the following areas. First, from a research perspective, this paper aims to provide information on how green development can be achieved and economic growth promoted. For this, the present paper tests whether China's current carbon trading mechanism has enabled a low-carbon economy to achieve a certain degree of transformation. This goal is to offer a decision-making basis for the comprehensive development of China's carbon emission trading mechanism. Second, as far as methods are concerned, different from existing literature methods for calculating total factor energy efficiency, the present article applies the sequential DEA Malmquist productivity index to add pollution emission variables (such as carbon dioxide) to the calculation of total factor productivity. This enables further exploration of the mechanism between carbon emission and GTFP. This indicator can simultaneously consider expected output and unexpected output in periods of economic expansion in the model for calculation, to identify the output of economic development, and help to measure green economic growth more comprehensively. Moreover, the Propensity Score Matching-Difference in Differences (hereinafter abbreviated as "PSM-DID") method is used to explore how the carbon trading pilot policy affects green economic expansion. Third, in terms of the measurement indicators of green economic growth, this paper further examines the influence of carbon trading on efficiency improvement effect and technological progress effect—the two main sources of GTFP improvement. Green development mode and economic growth effect are distinguished, and the growth level of green economy is further comprehensively and systematically measured, to provide theoretical and empirical support for relevant decisions (Figure 2).

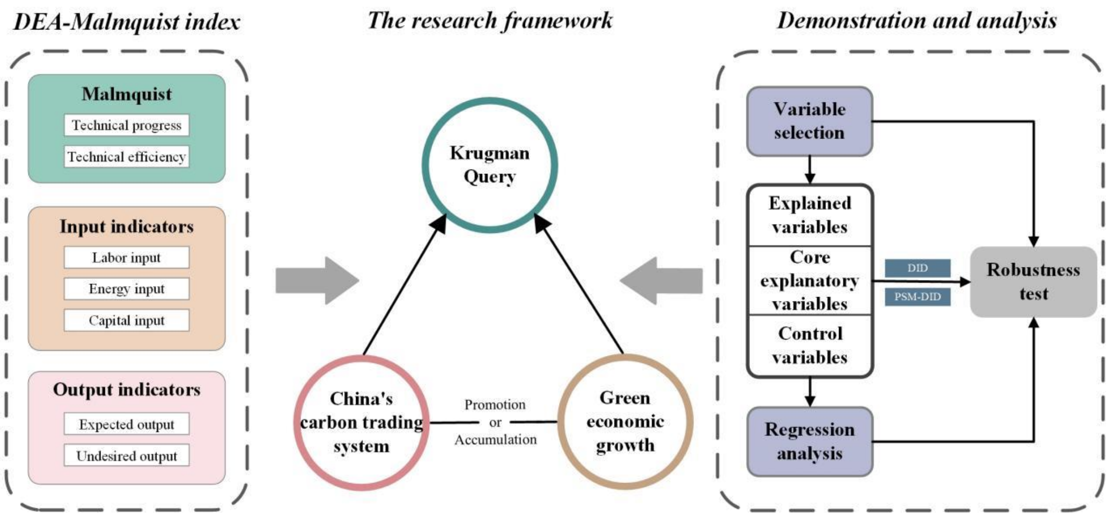

Figure 2. The overall research framework of the paper.

2. Literature Review

In recent decades, China's economic aggregate has expanded rapidly, but this economic growth was mainly driven by investment and factors, which has caused serious resource and environmental problems and resulted in low total factor productivity. With the increasing significant strategic trend of the new normal development, further explorations on the influencing mechanism between environmental regulation and total factor productivity had become an important power source to accelerate the high-quality and green development of the economy, which is of great research value. Scholars mainly focus on the correlation between the two with the following three key focal points.

The first viewpoint namely "Porter hypothesis". Porter suggested that the design of reasonable and proper environmental control could stimulate enterprises to achieve innovative technological development. The advantages of the technological innovation yield could partly counteract or even overcome the costs incurred by environmental regulation. Consequently, resource allocation can be optimized, and total factor productivity can be improved, so as to unify the economic benefits with the ecological benefits. Under the theoretical framework of the Porter Hypothesis, Miyamoto and Takeuchi (2019) proved that rigorous environmental regulations had active effects on enterprise innovation or R&D investment [11]. The second view is summarized in the "cost compliance theory". According to this theory, under the environmental regulation policy, the production cost of enterprises increases with increasing pollution control, which limits the output of profit-maximizing enterprises and leads to a decrease in enterprise productivity. Therefore, at the microcosmic level, environmental regulation exerts a restraining impact on economic growth [12]. Lanoie et al. (2001) [13], Chintrakarn (2008) [14], and Naso (2017) [15] refuted the existence of the Porter hypothesis by empirically testing the correlation between environmental supervision and total factor productivity and competitiveness. The third view is that the influence mechanism between the two is uncertain. Relevant studies showed that there is an "inverted N-type" relationship between the two enterprises [16]. Furthermore, the Porter hypothesis was verified for different regions, and research showed that the middle region cannot verify the Porter effect, but the opposite was found for the eastern region [17].

New institutional economics held that the operation effect of economic policy was closely related to the system. Whether the system applied command-controlled system or a market-driven system, the key to the effect of emission reduction policy lay in suitable system design. At present, many studies have concerned the impact between the two. With specific foci on the micro, meso, and macro levels. Certain research progress has been made. In the carbon trading system (a specific form of environmental regulation), promoting the prosperity and development of the green economy is to achieve carbon emission reduction and economic growth. However, it remains uncertain whether this pilot policy has an impact on China's green total factor productivity growth. If so, what was the underlying mechanism? Analysis of these questions is in favor of further effectively improving green development in China. In the existing relevant literature, most studies on the carbon trading system focused on analyses of its emission reduction impact [18–20], emission reduction targets [21–23], and rationality [24–27]. In measurements of total factor productivity, labor and capital are mostly assumed as the main variables, while related variables such as resources and energy are rarely involved [28,29]. In terms of research methods, empirical methods applied to assess the influence of environmental supervision on green total factor productivity were regression analysis, Generalized Method of Moment, or threshold model [30], while research rarely focused on quantitative assessment such as PSM-DID [31–33]. Using the PSM-DID method to explore the effect of carbon trading on green total factor productivity can effectively avoid deviations between pilot provinces and other provinces and can improve the overall accuracy of policy evaluation results.

A carbon trading policy is a market mechanism innovation aimed at reducing CO_2 emissions and enhancing the combined economic and environmental benefits. Carbon Trading Regarding the effectiveness of carbon trading, as of 31 December 2021, the cumulative volume of carbon emission allowances traded in the pilot carbon market was

483 million tons, with a turnover of 8.622 billion yuan [34]. The pilot carbon market will continue to parallel the national carbon market and gradually transition smoothly to the national carbon market. Guo and Sun (2022) empirically tested that pilot emission trading policies can significantly improve regional economic efficiency [35]. Wang and Wang (2022) argued that carbon emissions trading policies can increase green product innovation among exporters within pilot provinces and cities through the moderating effect of product conversion rates [36]. Regarding the drivers of urban economic development, most of the existing studies analyze the drivers of economic development in terms of natural resources [37], human capital [38], technological innovation [39], data and information [40], and institutional innovation [41], based on the fact that different economic development periods have development rules and development methods. Among them, natural resources, scientific and technological innovation, and institutional innovation are transforming to green development, presenting the characteristics of less input, high output, low pollution, and eliminating the emission of environmental pollutants in the production process as much as possible, which promotes regional development and economic efficiency [42]. In addition, cities act as command and control centers of the world economy [43], with some cities showing a significant increase in command and control functions and a growing position in the global economy [44,45], and Derudder et al. (2018) and Taylor et al. (2010) emphasized the role of world city networks in driving urban economic growth [46,47]. Finally, carbon trading and the realization of high-quality economic development are internally consistent. The carbon trading mechanism can enhance the internal vitality of high-quality economic development through innovation drive.

3. Methods and Data Sources

3.1. DEA Malmquist Exponential Model and Its Decomposition

DEA was proposed by Charnes et al.(1978) based on the relative efficiency principle in reference to the marginal benefit theory and linear programming model [48]. Its principle is to analyze the effective production frontier of sample input-output as reference standard, and then compare the decision-making unit with this reference standard to assess whether the decision-making unit realizes DEA effectiveness. DEA is a non-parametric statistical estimation method. The DEA model effectively avoids the influence of subjective factors on parameters, simplifies the model calculation process, and reduces experimental error.

The Malmquist index was not utilized until Rolf et al. (1997) combined it with DEA in 1994, thus making it widely applicable to various efficiency calculations, which is based on the traditional DEA model and adds a time variable to illustrate the dynamic change value of efficiency from the beginning to the end of a certain observation period [49]. This is an extended application of DEA and can be used to measure the characteristics and trends of the dynamic change of output efficiency in different periods. The Malmquist index reflects the change in investment efficiency between two adjacent periods. If the index is larger than 1, the overall efficiency increased, if the index is equal to 1, the efficiency remained unchanged, and if the index is less than 1, the efficiency decreased. It represents the ratio between the output of a decision-making unit and the input of all factors. Its variation is influenced by the two dimensions of the technological progress change index (hereinafter abbreviated as "TECHCH") and the technical efficiency change index (hereinafter abbreviated as "EFFCH"). In the case of fixed scale, changes in technical efficiency include the pure technical efficiency index (hereinafter abbreviated as "PECH") and the scale efficiency index (hereinafter abbreviated as "SECH"). The Malmquist index can be expressed as: Malmquist index = EFFCH × TECHCH = PECH × SECH × TECHCH. The specific calculation formula is:

$$\begin{aligned} M_i &= \left(x_i^{t+1}, x_i^{t+1}, y_i^t, y_i^t\right) = \left[\left(\frac{D_i^t\left(x_i^{t+1}, y_i^{t+1}\right)}{D_i^t\left(x_i^t, y_i^t\right)}\right)\left(\frac{D_i^{t+1}\left(x_i^{t+1}, y_i^{t+1}\right)}{D_i^{t+1}\left(x_i^t, y_i^t\right)}\right)\right]^{\frac{1}{2}} \\ &= \frac{D_i^{t+1}\left(x_i^{t+1}, y_i^{t+1}\right)}{D_i^t\left(x_i^t, y_i^t\right)} * \left[\frac{D_i^t\left(x_i^{t+1}, y_i^{t+1}\right)}{D_i^{t+1}\left(x_i^{t+1}, y_i^{t+1}\right)} \frac{D_i^t\left(x_i^t, y_i^t\right)}{D_i^{t+1}\left(x_i^t, y_i^t\right)}\right]^{\frac{1}{2}} = Effch_i^{t+1} * Tech_i^{t+1} \end{aligned} \tag{1}$$

In Formula (1), i represents the *ith* decision-making unit, x_i^t, y_i^t and x_i^{t+1}, y_i^{t+1} represents the input and output set of t and $t+1$, respectively; y_i^t is the output vector of the corresponding decision-making unit; $D_i^t(x_i^t,\ y_i^t)$ represents the technical efficiency of phase t; $D_i^{t+1}\left(x_i^{t+1},\ y_i^{t+1}\right)$ represents the technical efficiency of phase $t+1$.

3.2. The PSM-DID Method

The DID method is widely used in the assessment of policy effects by estimating the net effect size of a policy on participating individuals. The data can be divided into treatment and control groups according to whether the carbon trading system is piloted or not, and the differences between the two groups after the carbon trading pilot are studied under the condition of parallel trend assumptions, and the matched samples are generated by the PSM method, and then, the green economic growth effects of the pilot emissions trading policy are estimated by combining the DID method, thus ensuring the accuracy of the estimation results to a greater extent.

3.3. Data Sources

Due to the long service life span, certain data would be missing from each index system, and thus, interpolation was used to supplement the missing data. All data are from statistical yearbooks of relevant fields in China.

4. Results

4.1. Input-Output Index

When constructing the index system, not only the selection of input and output indicators should be considered, but also the output indicators should be divided into expected and unexpected output indicators. The input indicators are labor, energy, and capital.

(1) Regarding labor input, according to most scholars' research on GTFP, the employed personnel in each province over the years was selected as a substitute index.
(2) Regarding energy input, the regional total energy consumption, converted into standard coal, was selected as a substitute index.
(3) Regarding the capital stock index, the method commonly used by most scholars is the perpetual inventory method. The formula is $k_{t+1} = I_t + (1 - \delta_t)\ K_T$, which the depreciation rate of real capital in period t is represented by δt, the total amount of fixed capital formation I_t, and the current capital stock K_T. This includes the determination of base capital stock, current year investment, and economic depreciation rate δ as well as the selection of the investment commodity price index. In this paper, the research results of Shan (2008) are applied and the total fixed capital formation is used to measure I_t [50]. The fixed asset investment price index of each province is used to replace the investment price index. A depreciation rate δ of 10.96% is uniformly applied throughout this paper.
(4) Regarding expected output, the actual GDP of each region is chosen as index.
(5) Regarding undesired output, the CO_2 emission index is selected as the undesired output index of a region.

Currently, no official statistics on China's domestic carbon emission data are available. Therefore, the carbon emission data had to be estimated from existing research. This paper uses IPCC guidelines to calculate carbon emissions and the specific calculation formula is presented in the following: $C_t = \sum E_{it} \times \eta_I$, where C_t represents the total carbon emission in year T, E_{it} represents the consumption of the ith energy in year t, and η_I represents the carbon emission coefficient of the ith energy source.

4.2. Analysis of the Measurement Results of Green Total Factor Productivity

When calculating the Malmquist index, this paper uses three input indexes and two output indexes. The specific input index is labor input L which denotes the employed persons of various provinces and cities over the assessed years. Energy input E is the total energy consumption of the region using converted standard coal. Capital stock k is calculated by the perpetual inventory method. Output indicators are measured by real GDP and carbon dioxide emissions. The specific data used are panel data, calculated by using the data of specific years of specific provinces and cities. Finally, the GFTP of a specific province and city was obtained. The results are shown in Table 1 and a total of 540 GFTP indicators are composed of new panel data.

Table 1. TFP index and decomposition of annual TFP changes in 30 Provinces and cities in China (2001–2018).

Provinces and Cities	PECH	SECH	EFFCH	TECHCH
Anhui	17.992	18.041	18.033	1.0155
Beijing	18.002	18.001	18.006	0.9124
Fujian	18.055	18.007	18.062	0.9617
Gansu	18.176	18.143	18.684	1.1751
Guangdong	18.025	17.997	18.019	1.0097
Guangxi	17.988	18.073	18.063	1.0969
Guizhou	18.009	18.849	18.999	1.1477
Hainan	18.022	18.572	18.591	1.0309
Hebei	18.082	18.001	18.088	0.9151
Henan	18.018	18.005	18.05	1.0267
Heilongjiang	18.009	17.987	18.016	1.0329
Hubei	18.000	17.99	17.987	1.2620
Hunan	17.998	18.002	17.997	1.0502
Jilin	17.951	17.972	17.915	1.0910
Jiangsu	18.07	18.053	18.124	0.9814
Jiangxi	17.987	18.083	18.07	1.0127
Liaoning	18.085	18.483	18.566	0.9483
Inner Mongolia	17.999	18.078	18.077	1.0884
Ningxia	18.298	18.021	18.604	1.2265
Qinghai	18.239	17.817	18.052	1.2121
Shandong	18.017	18.13	18.154	0.9814
Shanxi	17.944	18.17	18.11	1.0232
Shaanxi	18.148	18.252	18.821	1.1560
Shanghai	18.056	18.016	18.072	1.0080
Sichuan	18.01	19.333	19.348	1.1491
Tianjin	18.091	18.004	18.099	0.8966
Xinjiang	18.291	17.925	18.263	1.2449
Yunnan	18.053	18.533	18.961	1.1433
Zhejiang	18.064	18.009	18.071	0.9887
Chongqing	18.002	18.025	18.026	1.1337

According to the results presented in Table 2, overall, China's GTFP was heterogeneous over regions and years, ranging from 0.5 to 1.2. This shows that the GTFP varies among provinces and cities in China and is unevenly developed. It should be noted that if TFPCH > 1, the GTFP of the province in that year was of high quality and showed a significant improvement trend. In contrast, if TFPCH < 1, the GTFP of the province did not develop well in that year. In 2001–2012, TFPCH was low in certain pilot provinces and cities. The reason was that before the implementation of policy pilots, GTFP in China's pilot regions lagged and did not follow a positive development trend. In 2013–2018, most pilot areas had TFPCH < 1. Pilot areas for GTFP in China after pilot development did not yield a positive effect, which was associated with the time lag of policy implementation. The results of policy effectiveness emerge with the further advancement of policy implementation time. The GTFP of all non-pilot provinces and cities improved over this period. Compared with the period from 2001 to 2012, China's GTFP improved, but during the period from 2013 to 2018, in certain provinces and cities, TFPCH was still <1. This indicates that pilot policies did not achieve effectiveness for the time being, indicating that China's GTFP still has development space.

Table 2. Average green total factor productivity from 2001 to 2012 and from 2013 to 2018.

Pilot Areas	2001–2012 TFPCH	Non-Pilot Areas	TFPCH	Pilot Areas	2013–2018 TFPCH	Not-Pilot Areas	TFPCH
Beijing	0.8955	Heilongjiang	1.0569	Beijing	0.8688	Heilongjiang	0.9153
Tianjin	0.9175	Zhejiang	0.9640	Tianjin	0.8733	Zhejiang	0.8788
Shanghai	1.0165	Fujian	0.9976	Shanghai	0.9541	Fujian	0.8863
Chongqing	1.1110	Hebei	0.9376	Chongqing	1.1908	Hebei	0.8706
Hubei	1.0414	Liaoning	0.9563	Hubei	1.0108	Liaoning	0.9071
Guangdong	1.0132	Shandong	1.0058	Guangdong	0.9186	Shandong	0.8850
		Jiangsu	1.0085			Jiangsu	0.5830
		Henan	1.0260			Henan	0.9830
		Anhui	1.0326			Anhui	0.9161
		Hainan	1.0580			Hainan	0.9111
		Hunan	1.0206			Hunan	1.0326
		Jiangxi	1.0107			Jiangxi	0.9646
		Inner Mongolia	1.0693			Inner Mongolia	1.0553
		Guangxi	1.0900			Guangxi	1.1191
		Sichuan	1.1277			Sichuan	1.2806
		Guizhou	1.1166			Guizhou	1.2515
		Yunnan	1.1102			Yunnan	1.2520
		Shaanxi	1.1196			Shaanxi	1.2743
		Gansu	1.1502			Gansu	1.2543
		Qinghai	1.2139			Qinghai	1.1228
		Ningxia	1.2250			Ningxia	1.2251
		Xinjiang	1.2587			Xinjiang	1.1650

4.3. Carbon Trading and Green Economic Growth: An Empirical Test

4.3.1. Variable Selection

(1) Setting of explained variables

① Green development effect. To measure the efficiency of green development, it is necessary to consider not only the allocation efficiency of input-output factors, but also the resource input and environmental costs. In other words, when constructing the index system, the selection of input-output indicators must be considered. Based on the existing research and theory, and according to the core requirements of green development, the green development effect measurement system constructed in this paper mainly examines the level of green production technology. Among them, the output indicators are divided into expected output indicators and non-expected output indicators, and the input indicators are selected as labor, energy, and capital, and the green development efficiency is comprehensively measured by using the DEA model and decomposed by the Malmquist index, in order to fully reflect the concept of green development and comprehensively measure the level of green production technology.

② Economic growth effect. The impact of economic growth is expressed in terms of carbon emission intensity, i.e., CO_2 emissions per unit of GDP. The calculation formula is carbon emission intensity = carbon emission/GDP, denoted as C_i. A decline in carbon emission intensity reflects the coordinated development between the economy and the environment. Specifically, if the pilot policy in China reduces the carbon emission intensity, this represents the economic growth effect, where the stronger the decline, the stronger the economic growth effect. Conversely, it hinders economic growth.

(2) Core explanatory variables

① Implementation of the regional virtual variable *treat* for the pilot policy of the carbon trading system; *Treat* = 1 represents provinces and cities that implemented pilot carbon trading system policies during 2013–2018 (e.g., Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen); *Treat* = 0 represents provinces and cities that did not implement carbon trading system pilot policies during 2013–2018 (excluding Tibet, Hong

Kong, Macao, and Taiwan). ② The time dummy variable before and after the implementation of carbon trading system pilot policies; *Time* = 1 represents the implementation of carbon trading system pilot policies during 2013–2018; *Time* = 0 represents that the pilot policy of carbon trading system was not carried out during 2001–2012. ③ DID estimator *tt*; *tt* is the interaction term between the regional dummy variable and the time dummy variable, which is the core index to verify green development. Through the symbol and significance of *tt*, the effect of carbon trading system pilot policy on green development and economic growth could be assessed.

(3) Control variables

Based on previous research, this paper scientifically selects six control variables that affected the green development level. These are presented in detail in the following:

① Economic development level: Per capita gross national product reflects the per capita GDP, recorded as *pgdp*.

② Industrial structure: The proportion of the added value of the secondary industry in GDP, recorded as *is*;

③ Investment in energy industry, denoted as *eii*; this reflects whether the energy industry investment was moderate or not directly affected by the clean use of energy. Because of the non-renewability of fossil energy, the energy problem has aroused great concern. Coupled with the continuous growth of energy demand, the energy industry had become the key sector of greenhouse gas emission.

④ The technical level: This paper uses domestic patent application acceptance to measure technological progress, recorded as *pi*.

⑤ Population scale, recorded as *pop*; *pop* refers to the number of permanent residents in all provinces and cities.

4.3.2. Double Difference Regression Analysis

This paper establishes the PSM-DID model according to pilot provinces and cities and the implementation time of the pilot policy. Furthermore, GTFP (*gtfp*) is used to measure the level of green production technology; these were assumed as dependent variables. The core variables were the virtual variables of pilot policy, urban virtual variables, and their interaction items. The time selection range of the data was from 2001 to 2018, and the cross-section selection range was all provinces, municipalities directly under the central government, and autonomous regions (except Tibet, Hong Kong, Macao, and Taiwan). Because China's carbon trading system was implemented in 2013, the policy dummy variable *time* = 1 was selected for data from 2013 to 2018, and *time* = 0 was selected for other time periods. The city virtual variable *city* was generated, where the seven pilot cities (i.e., Shanghai, Beijing, Guangdong, Shenzhen, Tianjin, Hubei, and Chongqing) are set as 1, i.e., *city* = 1, while other regions (excluding Xizang, Hong Kong, Macao, and Taiwan) were set as *city* = 0. Therefore, the interaction between policy dummy variable and city dummy variable was defined as their product, namely *jc* = *time* * *city*. The regression model of the benchmark was:

$$gtfp_{it} = \alpha_0 + \alpha_1 * time + \alpha_2 * city + \alpha_3 * jc + u_{it} \tag{2}$$

$$ct_{it} = \beta_0 + \beta_1 * time + \beta_2 * city + \beta_3 * jc + \sigma_{it} \tag{3}$$

Based on the benchmark regression model, the following control variables are added: economic development level (denoted as PGDP), industrial structure (denoted as *is*), energy industry investment (denoted as *eii*), technical level (denoted as *pi*), and the size of the population (denoted as *pop*). Firstly, descriptive analysis was carried out on the variables. The descriptive statistics of each index are shown in Table 3.

Table 3. Descriptive statistics.

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
pgdp	540	34,182.52	25,793.02	3000	140,211
is	540	45.3407	7.9597	19	59
eii	540	631.9064	574.5274	9.35	3382.51
pi	540	47,983.44	92,212.75	124	793,819
pop	540	4417.807	2660.747	523	11,346
ct	540	1.0602	0.7911	0.1015	5.4273
gt	540	1.0545	0.3782	0	2.242

The effect mechanism of carbon trading pilot policy implementation on the level of green production technology and green development effect was tested by the DID method in this paper. Total factor productivity and carbon emission intensity are set as dependent variables and policy dummy variables, urban dummy variables, and interaction terms are set as independent variables. To verify the robustness of variable coefficients, we add control variables to the original model. First, the impact of the pilot policy on the level of green production technology is analyzed (Table 4). Control variables are not added in model 1, and Models 2–6 gradually added control variables.

Table 4. Effect of carbon trading policy implementation on green development—difference in differences method.

Variables	(1) gtfp	(2) gtfp	(3) gtfp	(4) gtfp	(5) gtfp	(6) gtfp
time	0.0535 **	0.0578 **	0.0543 **	0.115 **	0.116 **	0.116 **
	(0.0285)	(0.0274)	(0.0282)	(0.0519)	(0.0520)	(0.0517)
city	0.0718	0.0746	0.0716	0.0457	0.0474	0.0388
	(0.0197)	(0.04288)	(0.0533)	(0.0536)	(0.0538)	(0.0536)
jc	0.0242 ***	0.0268 ***	0.0233 ***	0.0281 ***	0.0309 ***	0.0512 ***
	(0.0060)	(0.0078)	(0.0082)	(0.0093)	(0.0095)	(0.0094)
pgdp		1.45×10^{-07} ***	1.12×10^{-07} ***	6.42×10^{-07} ***	4.24×10^{-07} ***	1.56×10^{-06} ***
		(0.33×10^{-07})	(0.37×10^{-07})	(0.64×10^{-07})	(0.07×10^{-06})	(0.15×10^{-06})
is			−0.000898 ***	−0.00156 ***	−0.00150 ***	−0.000242 ***
			(0.00014)	(0.00028)	(0.00028)	(0.00032)
eii				0.000112 ***	0.000113 ***	0.000139 ***
				(3.75×10^{-05})	(3.76×10^{-05})	(3.87×10^{-05})
pi					1.04×10^{-07} ***	2.68×10^{-07} ***
					(0.22×10^{-07})	(0.63×10^{-07})
pop						-2.04×10^{-05} ***
						(7.84×10^{-06})
Constant	1.088 ***	1.086 ***	1.044 ***	1.122 ***	1.116 ***	1.151 ***
	(0.0222)	(0.0286)	(0.103)	(0.106)	(0.106)	(0.107)
Observations	540	540	540	540	540	540
R-squared	0.013	0.013	0.013	0.029	0.030	0.042

t statistics in parentheses. ** $p < 0.01$, *** $p < 0.001$.

From the results of the DID method, the coefficient coincidence degree and importance of core explanatory variables did not change fundamentally from Model 1 to Model 6. The coefficient significance of other variables changed for the most part, and the decisive coefficient R^2 of the model gradually increased. In Model 6, at a significance level of 5%, the core explanatory variables are positively correlated with the level of green production technology. This indicates that the pilot policy promoted the green development level in pilot cities, but the effect was weak, and merely increased by 5.2%.

Regarding control variables, the level of economic development was positively correlated with the level of green production technology. The industrial structure had a negative correlation with the level of green production technology. Energy industry investment had a significant positive impact on the level of green production technology, i.e., the increased investment would improve the level of production technology. The technology level had a significant positive impact on the technology level of green production, i.e., the improvement of technology yields a "synergistic effect", driving the improvement of green technology. The scale of the population had a significant negative impact on the level of green production technology, and an increase in population constrains the improvement of production technology. This shows that from the perspective of control variables, if spatial factors were not considered, "economic development level", "energy industry investment", and "technology level" would promote green economic growth to a certain extent; however, the "proportion of secondary industry" and "population size" would hinder green economic growth to a certain extent. This proved that the "Krugman Query" was not tenable.

The influence of pilot policy implementation on economic growth effect is analyzed in the following, and control variables are gradually added to the benchmark regression model. The results are shown in Table 5.

Table 5. Effect of carbon trading policy implementation on economic growth—difference in differences method.

Variables	**(1)** **ct**	**(2)** **ct**	**(3)** **ct**	**(4)** **ct**	**(5)** **ct**	**6)** **ct**
time	−0.224 ***	−0.0415 ***	−0.0378 ***	−0.0541 ***	−0.0628 ***	−0.0655 ***
	(0.0768)	(0.0126)	(0.0141)	(0.012)	(0.011)	(0.0040)
city	−0.601 ***	−0.429 ***	−0.432 ***	−0.393 ***	−0.417 ***	−0.363 ***
	(0.0992)	(0.103)	(0.104)	(0.105)	(0.104)	(0.0975)
jc	−0.0844 ***	−0.249 ***	−0.245 ***	−0.323 ***	−0.363 ***	−0.491 ***
	(0.022)	(0.021)	(0.022)	(0.025)	(0.024)	(0.023)
pgdp		-8.96×10^{-06} ***	-8.92×10^{-06} ***	-1.01×10^{-05} ***	-6.90×10^{-06} ***	-1.40×10^{-05} ***
		(1.82×10^{-06})	(1.83×10^{-06})	(1.89×10^{-06})	(2.08×10^{-06})	(2.09×10^{-06})
is			0.000949 ***	0.00467 ***	0.00383 ***	0.00407 ***
			(0.00018)	(0.00046)	(0.00042)	(0.00022)
eii				0.000170 **	0.000191 ***	0.000350 ***
				(7.35×10^{-05})	(7.30×10^{-05})	(7.04×10^{-05})
pi					-1.51×10^{-06} ***	-8.17×10^{-07} *
					(4.31×10^{-07})	(4.79×10^{-07})
pop						−0.000128 ***
						(1.42×10^{-05})
Constant	1.249 ***	1.422 ***	1.466 ***	1.584 ***	1.502 ***	1.720 ***
	(0.0444)	(0.0558)	(0.201)	(0.207)	(0.206)	(0.194)
Observations	540	540	540	540	540	540
R-squared	0.100	0.139	0.139	0.147	0.166	0.276

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In Model 6, at the significance level of 5%, the core explanatory variables had a significant positive impact on the level of green production technology, indicating that the implementation of carbon trading policy exerts a strong effect by reducing the carbon emission intensity of pilot cities by 49.1%.

Regarding control variables, the level of economic development, the technology level, and the population size had a significant negative impact on carbon emission intensity. The industrial structure had a significant negative impact on carbon emission intensity, i.e., the higher the industrial structure, the less the restriction of carbon emissions. Investments in the energy industry had a significant positive impact on carbon emission intensity i.e., increasing investment would improve carbon emission intensity.

4.3.3. PSM-DID Analysis

This paper uses the logit model, where the policy dummy variable time is used as the dependent variable, and variables are used as covariates. The results obtained by using the PSM method are shown in Table 6.

Table 6. Validity test of propensity score matching.

Variable	Experimental Mean	Mean of the Control Group	Difference	t	*p* Values
pgdp	56,398	57,939	−7.1	−0.61	0.542
is	43.056	41.095	25	1.58	0.104
eii	1031.4	749.25	51.1	0.56	0.615
pi	98,471	63,506	35.3	1.05	0.202
pop	4574.1	3467	41.3	1.95	0.429

The data in Table 7 show that at a significance level of 5%, the *p* values of all variables fail to pass significance. The results show that the matching results are effective, and the PSM-DID method is therefore used for estimation, and control variables are added and not added, respectively.

Table 7. PSM-DID estimation.

	Green Production Technology		Green Development Effect	
Variables	**(1)**	**(2)**	**(3)**	**(4)**
time	0.0790 ***	0.000155	0.217 ***	0.134 ***
	(0.0205)	(0.0272)	(0.0145)	(0.0186)
city	0.101 ***	0.0589 **	0.0353 *	0.00379
	(0.0265)	(0.0282)	(0.0187)	(0.0193)
jc	0.176 ***	0.202 ***	−0.0477 ***	−0.0656 ***
	(0.0459)	(0.0469)	(0.0124)	(0.0121)
pgdp		2.89×10^{-06} ***		2.34×10^{-06} ***
		(6.05×10^{-07})		(4.14×10^{-07})
is		0.00113		−0.00368 ***
		(0.00122)		(0.000834)
eii		2.05×10^{-05}		4.09×10^{-05} ***
		(2.03×10^{-05})		(1.39×10^{-05})
pi		-2.79×10^{-07} **		-4.20×10^{-07} ***
		(1.38×10^{-07})		($9.47 \times 10-08$)
pop		2.88×10^{-06}		1.23×10^{-05} ***
		(4.11×10^{-06})		(2.82×10^{-06})
Constant	0.637 ***	0.511 ***	0.945 ***	1.007 ***
	(0.0118)	(0.0560)	(0.00836)	(0.0383)
Observations	540	540	540	540
R-squared	0.043	0.100	0.327	0.404

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Based on the estimation results, in the model that uses green technology level as dependent variable, the interaction terms of core variables in Model 1 and Model 2 pass significance at a level of 1%, and all coefficients are positive. In the model that uses green development effect as dependent variable, the core variable interaction term in Model 3 and Model 4 pass significance at a level of 1%, and all coefficients are positive. This shows that the implementation of the policy promotes green development and reduces carbon emissions, further indicating that the model has good robustness.

4.4. Further Mechanism Testing

The previous analysis shows that after implementing the policy in pilot cities, green development was promoted and carbon emissions were reduced. However, for a better understanding, this paper assessed which factors led to the green development of pilot cities after the implementation of policies (Table 8).

Table 8. Mechanism test of carbon trading policies affecting green economic growth.

Variables	(1) pgdp	(2) is	(3) eii	(4) pi	(5) pop
time	29,650 ***	−2.788 ***	680.4 ***	64266 ***	171.0
	(1782)	(0.781)	(49.13)	(8473)	(271.2)
city	19,211 ***	−2.566 **	−158.3 **	20776 *	−625.8 *
	(2301)	(1.009)	(63.43)	(10,939)	(350.1)
jc	18,362 ***	−3.198 *	−406.3 ***	57,325 ***	317
	(3985)	(1.747)	(109.9)	(18947)	(606.4)
Constant	19,233 ***	47.00 ***	463.8 ***	18,585 ***	4465 ***
	(1029)	(0.451)	(28.37)	(4892)	(156.6)
Observations	540	540	540	540	540
R-squared	0.544	0.080	0.302	0.194	0.008

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The estimation results show that at a significance level of 10%, the core variables are positively related to economic development and technology level, and negatively correlated with the industrial structure and energy investment. This shows that the pilot policy improved the level of economic development and technology, and inhibited the promotion of industrial structure and energy industry investment on green development.

5. Discussion

This review of previous studies shows that certain valuable conclusions have been obtained regarding environmental regulation and economic growth. From the concept of green development, there is a lack of empirical research on carbon trading pilot system and green economic growth. Based on this, this paper specifically focuses on China's carbon trading system, one of China's environmental regulation policies, as the study object, and expands existing knowledge. Although this paper has expanded the innovation in carbon emissions and green economic growth to a certain extent, there are certain shortcomings due to some objective reasons. First, due to the lack of relevant panel data, the accuracy of econometric analysis results could be improved, but this does not affect the main conclusion of this paper. Second, this paper suffers from a lack of targeted comparative analysis with other emission trading mechanisms. Follow-up research could focus on the development goals, compare and analyze the policy evaluation effect of the carbon emission trading pilot system with similar emission trading pilot systems (such as SO_2 emission trading and energy use right trading), and select different indicators to measure the green transformation. Thus, more scientific and reasonable policy suggestions can be put forward.

6. Conclusions and Policy Implications

6.1. Main Conclusions

Based on empirical analyses of the DEA-Malmquist index model using the PSM-DID method, this paper empirically tests the impact and mechanism of the pilot policy on green economic growth. The results show that: (1) "Economic development level", "energy industry investment", and "technology level" promoted green economic growth to a certain extent. However, "proportion of secondary industry" and "population scale" hindered the green economic growth to a certain extent. This proves that the "Krugman Query" is not tenable. (2) The pilot policy has a positive correlation with the growth of GTFP, but a certain time lag emerged. (3) The pilot policy promotes the green development level of pilot cities, but the effect was weak, with increases of only 5.2%, reduces the carbon emission intensity of pilot cities strongly by 49.1%, and promoted economic growth.

6.2. Policy Implications

First, the intensity of environmental regulation should be moderately strengthened. Although China's economy has maintained rapid growth, it still faces severe pressures regarding resources and the environment. In the continuous innovation and reform of environmental regulation, the pilot policy is representative. The assessment of pilot policy only provided empirical and theoretical support for environmental governance and pollution prevention and control measures but is also of great significance for promoting the construction of ecological civilization. Through empirical tests, this paper proves that the pilot policy was conducive to increasing GTFP. The overall goals and stage goals of carbon trading should be defined, and the pilot policy should be promoted in an orderly and step-by-step manner under the overall framework. Furthermore, policy encouragement, financial support, and technical support should be emphasized, the construction of the carbon market should be steadily promoted, and the intensity of environmental regulation should be increased within an appropriate scope. These measures would not only improve the ecological environment but also improve factor productivity and sustainable development. Second, Green technology innovation needs to be further improved. The potential of the carbon market should be fully tapped through technological innovation, the independent innovation and promotion of low-carbon technologies should be improved, and rapid green development should be promoted. Third, the low-carbon energy industry should be further developed. The energy-intensive industries should be reduced in energy consumption, green low-carbon energy should be continuously developed and used, and cleaner production technology should be promoted.

Author Contributions: Conceptualization, X.N. and H.W.; methodology, Z.C.; software, L.Y.; validation, X.N. and H.W.; formal analysis, Q.W.; investigation, J.H.; resources, H.Q.; data curation, L.Y.; writing—original draft preparation, Z.C.; writing—review and editing, X.N.; visualization, Z.C.; supervision, H.Q.; project administration, X.N.; funding acquisition, X.N., H.W. and Z.C. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the National Natural Science Foundation of China (Nos. 71763001 and 71973038); Thousands of Young and Middle-aged Key Teachers Training Program in Guangxi Colleges and Universities (No. 2021QGRW002). Key Topics of Guangxi Science and Technology Think Tank (Gui Science Association-(2022)P-03). Guangxi Social Science Think Tank Topics in 2022 (No. Zkzxkt202202).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available upon request to authors.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Lin, B.; Tan, R. China's economic agglomeration and green economic efficiency. *Econ. Res.* **2019**, *54*, 119–132.
2. Han, C.; Sun, X.; Li, J. Emission reduction effect of vertical management reform of environmental regulation—Evidence from the reform of environmental protection system in prefecture level cities. *Economics* **2021**, *21*, 335–360.
3. Krugman, P. The Myth of Asia's Miracle. *Foreign Aff.* **1994**, *73*, 62–78. [CrossRef]
4. Wu, P. Power transformation of China's economic growth since the reform. *China's Ind. Econ.* **2013**, *2*, 5–17.
5. Dong, M.; Liang, Y. Sources of China's economic growth from 1978 to 2010: A nonparametric decomposition framework. *Econ. Res.* **2013**, *48*, 17–32.
6. Cheng, M.; Jia, X.; Qiu, H. China's economic growth (1978–2015): Inspiration or sweat. *Econ. Res.* **2019**, *54*, 30–46.
7. Razzaq, A.; Sharif, A.; Najmi, A. Dynamic and causality interrelationships from municipal solid waste recycling to economic growth, carbon emissions and energy efficiency using a novel bootstrapping autoregressive distributed lag. *Resour. Conserv. Recycl.* **2021**, *166*, 105372. [CrossRef]
8. Pei, F.; Zhong, R.; Liu, L.A. Decoupling the Relationships between Carbon Footprint and Economic Growth within an Urban Agglomeration—A Case Study of the Yangtze River Delta in China. *Land* **2021**, *10*, 923. [CrossRef]
9. Saint, A.S.; Alola, A.A.; Olasehinde, W.G. The role of electricity consumption, globalization and economic growth in carbon dioxide emissions and its implications for environmental sustainability targets. *Sci. Total Environ.* **2020**, *708*, 134653. [CrossRef] [PubMed]
10. Yan, Y.W.; Tian, Y.; Zhang, J.B.; Wang, Y. Research on Inflection Point Change and Spatial and Temporal Variation of China's Agricultural Carbon Emissions. *China Popul. Resour. Environ.* **2014**, *24*, 1–8.

11. Miyamoto, M.; Takeuchi, K. Climate agreement and technology diffusion: Impact of the Kyoto Protocol on international patent applications for renewable energy technologies. *Energy Policy* **2019**, *129*, 1331–1338. [CrossRef]
12. Jaffe, A.; Palmer, K. Environmental regulation and innovation: A panel data study. *Rev. Econnomics Stat.* **1997**, *79*, 610–619. [CrossRef]
13. Lanoie, P.; Patry, M.; Lajeunesse, R. Environmental regulation and productivity: New findings on the Porter hypothesis. Working paper. 2001. Available online: https://ideas.repec.org/p/iea/carech/0105.html (accessed on 5 May 2022).
14. Chintrakarn, P. Environmental regulation and U.S. states' technical inefficiency. *Econ. Lett.* **2008**, *100*, 363–365. [CrossRef]
15. Naso, P.; Huang., Y.; Swanson., T. The porter hypothesis goes to china: Spatial development, environmental regulation and productivity. CIES Research Paper; 2017. Available online: https://ideas.repec.org/p/gii/ciesrp/cies_rp_53.html (accessed on 12 April 2022).
16. Wang, J.; Liu, B. Environmental regulation and total factor productivity of Enterprises—An Empirical Analysis Based on the data of Chinese industrial enterprises. *China's Ind. Econ.* **2014**, *3*, 44–56.
17. Wang, G.; Wang, D. Porter hypothesis, environmental regulation and enterprise technological innovation—A comparative analysis of central and eastern China. *China Soft Sci.* **2011**, *1*, 100–112.
18. Tang, W.; Wu, L.; Qian, H. From "pollution paradise" to green growth—Research on the regulation mechanism of inter regional transfer of high energy consuming industries. *Econ. Res.* **2016**, *51*, 58–70.
19. Wang, J.; Sun, K.; Ni, J. Evaluation and Factor Analysis of Industrial Carbon Emission Efficiency Based on "Green-Technology Efficiency"—The Case of Yangtze River Basin, China. *Land* **2021**, *10*, 1408. [CrossRef]
20. Wang, H.; Chen, Z.P.; Wu, X.Y.; Nie, X. Can a carbon trading system promote the transformation of a low-carbon economy under the framework of the porter hypothesis? —Empirical analysis based on the PSM-DID method. *Energy Policy* **2019**, *129*, 930–938. [CrossRef]
21. Long, Z.; Zhang, Z.; Liang, S.; Chen, X.; Yang, T. Spatially explicit carbon emissions at the county scale. *Resour. Conserv. Recycl.* **2021**, *173*, 105706. [CrossRef]
22. Fernando, Y.; Hor, W. Impacts of energy management practices on energy efficiency and carbon emissions reduction: A survey of Malaysian manufacturing firms. *Resour. Conserv. Recycl.* **2017**, *126*, 62–73. [CrossRef]
23. Wang, Y.; Yang, H.; Sun, R. Effectiveness of China's provincial industrial carbon emission reduction and optimization of carbon emission reduction paths in "lagging regions": Efficiency-cost analysis. *J. Environ. Manag.* **2020**, *275*, 111221. [CrossRef] [PubMed]
24. Liu, J.; Bai, J.Y.; Deng, Y.; Chen, X.H.; Liu, x. Impact of energy structure on carbon emission and economy of China in the scenario of carbon taxation. *Sci. Total Environ.* **2021**, *762*, 143093. [CrossRef] [PubMed]
25. Chen, H.; Guo, W.; Feng, X.; Wei, W.; Gong, W. The impact of low-carbon city pilot policy on the total factor productivity of listed enterprises in China. *Resour. Conserv. Recycl.* **2021**, *169*, 105457. [CrossRef]
26. Cheng, S.; Fan, W.; Meng, F.; Chen, J.; Cai, B.; Liu, G.; Liang, S.; Song, M.; Zhou, Y.; Yang, Z. Toward low-carbon development: Assessing emissions-reduction pressure among Chinese cities. *J. Environ. Manag.* **2020**, *271*, 111036. [CrossRef] [PubMed]
27. Dong, F.; Li, J.; Zhang, S. Sensitivity analysis and spatial-temporal heterogeneity of CO_2 emission intensity: Evidence from China. *Resour. Conserv. Recycl.* **2019**, *150*, 104398. [CrossRef]
28. Gao, Y.; Zhang, M.; Zheng, J. Accounting and determinants analysis of China's provincial total factor productivity considering carbon emissions. *China Econ. Rev.* **2021**, *65*, 101576. [CrossRef]
29. Su, H.; Liang, B. The impact of regional market integration and economic opening up on environmental total factor energy productivity in Chinese provinces. *Energy Policy* **2021**, *148*, 111943. [CrossRef]
30. Wang, W.; Liu, J. Analysis on the threshold effect between environmental regulation and total factor productivity—Based on HDI zoning and ACF law. *Econ. Issues* **2021**, *2*, 53–60.
31. Fu, Y.; He, C.; Luo, L. Does the low-carbon city policy make a difference? Empirical evidence of the pilot scheme in China with DEA and PSM-DID. *Ecol. Indic.* **2021**, *122*, 107238. [CrossRef]
32. Asdrubali, F.; Baggio, P.; Prada, A.; Grazieschi, G.; Guattari, C. Dynamic life cycle assessment modelling of a NZEB building. *Energy* **2020**, *191*, 1–17. [CrossRef]
33. Miguel, R.; Mario, P.; Pablo, C. Do indicators have politics? A review of the use of energy and carbon intensity indicators in public debates. *J. Clean. Prod.* **2020**, *243*, 118602.
34. Chen, X.X. China's Carbon Emissions Trading Market: Effectiveness, Reality and Strategy. *Southeast Acad. Res.* **2022**, *4*, 167–177.
35. Guo, W.X.; Sun, H. Research on the Relationship between Carbon Emission Trading, Profit and Loss Deviation and Green Economy Efficiency. *Ecol. Econ.* **2022**, *38*, 13–20+76.
36. Wang, X.; Wang, J. Carbon Emission Trading Policy, Product Switching and Green Product Innovation—Experience from Chinese Export Enterprises. *J. Int. Trade* **2022**, *4*, 91–106.
37. Bai, X.J.; Song, P.; Wang, B.L. Energy Saving and Emission reduction Path of Carbon Emission Trading System Efficiency Improvement or Structural Transformation?—Quasi Natural Experiments Based on Provincial Data in China. *J. Bus. Econ.* **2021**, *41*, 70–85.
38. Li, S.D.; Supat, C.; Apichit, M.; Wanich, S.; Cong, P.T.; Quynh, N.N. The moderating role of human capital and renewable energy in promoting economic development in G10 economies: Evidence from CUP-FM and CUP-BC methods. *Renew. Energ* **2022**, *189*, 180–187.

39. Yuan, W.W.; Gao, B. The Development of Digital Economy and the Improvement of High-tech Industry Innovation Efficiency: Empirical Test Based on China's Provincial Panel Data. *Sci. Technol. Prog. Policy* **2022**, *39*, 61–71.
40. Zhang, X.M.; Wei, C. The economic and environmental impacts of information and communication technology: A state-of-the-art review and prospects. *Resour. Conserv. Recycl.* **2022**, *185*, 106477. [CrossRef]
41. Zhang, X.J. An Empirical Study of Regional Economic Development and Institutional Innovation in China. *Econ. Theory Bus. Manag.* **2009**, *1*, 35–38.
42. Zhang, H.W.; Shao, Y.M.; Han, X.P.; Chang, H.L. A road towards ecological development in China: The nexus between green investment, natural resources, green technology innovation, and economic growth. *Resour. Policy* **2022**, *77*, 102746. [CrossRef]
43. Csomós, G. Cities as Command and Control Centres of the World Economy: An Empirical Analysis, 2006–2015. *Bull. Geogr. Socio-Econ. Ser.* **2017**, *38*, 7–26. [CrossRef]
44. Raźniak, P.; Csomós, G.; Dorocki, S.; Winiarczyk-Raźniak, A. Exploring the Shifting Geographical Pattern of the Global Command-and-Control Function of Cities. *Sustainability* **2021**, *13*, 12798. [CrossRef]
45. Raźniak, P.; Dorocki, S.; Winiarczyk-Raźniak, A. Spatial changes in the command and control function of cities based on the corporate centre of gravity model. *Misc. Geogr.* **2020**, *24*, 35–41. [CrossRef]
46. Derudder, B.; Cao, Z.; Liu, X.; Shen, W.; Dai, L.; Zhang, W.; Caset, F.; Witlox, F.; Taylor, P.J. Changing Connectivities of Chinese Cities in the World City Network, 2010–2016. *Chin. Geogr. Sci.* **2018**, *28*, 183–201. [CrossRef]
47. Taylor, P.J.; Ni, P.; Derudder, B.; Hoyler, M.; Huang, J.; Lu, F.; Pain, K.; Witlox, F.; Yang, X.; Bassens, D.; et al. Measuring the world city network: New results and developments. *GaWC Res. Bull.* **2009**, *300*, 1–8.
48. Charnes, A.; Cooper, W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
49. Rolf, F.; Shawna, G.; Mary, N. Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries: Reply. *Am. Econ. Rev.* **1997**, *87*, 1040–1044.
50. Shan, H. Reestimation of China's capital stock k: 1952~2006.Research on Quantitative Economy. *Technol. Econ.* **2008**, *25*, 17–31.