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Can Carbon Finance Optimize Land Use Efficiency? The Example of China's Carbon Emissions Trading Policy

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Abstract: Land resources have become one of the major factors limiting urban development in China. In the context of sustainable development, how to improve land use efficiency (LUE) has become a major challenge on the road to sustainable development in China. Carbon finance provides a new idea for sustainable development. With the help of carbon emissions trading policy (CETP), this paper aims to investigate whether carbon finance can optimize LUE in terms of economic effects and environmental effects. Based on the data of 158 prefectural-level cities in China from 2010 to 2017, this paper uses a combination of qualitative and quantitative analysis to investigate these issues. Specifically, this paper measures the land use efficiency from economic effects (LUE_Eco) and environmental effects (LUE_Env) using the entropy method, and visualizes the data to obtain information on their spatio-temporal evolution patterns. Furthermore, this paper verifies the causal relationship between policy implementation and LUE_Eco and LUE_Env by using the difference in differences (DID) method. The conclusions show that: (1) the levels of LUE_Eco and LUE_Env in the pilot regions generally increase after the implementation of the CETP, but only the increase of LUE_Env is due to the policy implementation; (2) the CETP not only effectively reduces CO_2 emissions, but also promotes the reduction of industrial 'three wastes' emissions. Accordingly, this paper has gained insights on how to improve LUE in China.

Keywords: carbon finance; land use efficiency; carbon emissions trading policy; economic effects; environmental effects

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1. Introduction

United Nations statistics indicate that the global urban population is expected to reach 70% in 2050. The deepening of global urbanization implies the increasing prominence of cities as the main carriers of human life [1]. Obviously, cities have become an important driver of national economic development, which in turn feeds the urbanization process [2,3]. Not only that, the quality of cities is also related to the degree of ecosystem health and human well-being of future generations [4]. In China, the urbanization rate has increased from 17.90% at the beginning of reform and opening-up to 58.52% in 2017, and the upward trend is still obvious [5,6]. However, rapid urbanization has brought many problems to China. One of the basic elements of urban development is land for urban construction [7], which is mainly derived from agricultural and environmental land [8–10]. Zhou [11] and You et al. [12] found that some local officials would develop the economy at the cost of the environment to improve their own political performance. Wang et al. [13] also found that the level of land revenue in some Chinese cities is gradually declining. Land resources are important spatial carriers for urban production, living, and ecological activities as well as important input factors for socio-economic development [14]. At the same time, the scarcity of land resources limits the sustainable development of cities [15]. Therefore, land use efficiency (LUE) is a representative concept in sustainable development [16]. Exploring how to optimize urban LUE is important for building sustainable cities and promoting sustainable development.

LUE is a direct representation of land value realization during urban economic development [17] and it covers various elements within the urban system [18]. Therefore, scholars have measured LUE from different perspectives depending on the purpose of the study. Hasse and Lathrop [14] measured LUE from the perspective of population and resource growth. van Zanten [19] measured LUE from the perspective of livestock systems. Kytzia et al. [20] measured LUE from the perspective of tourism facilities. Pu et al. [21] measured LUE from the perspective of industrial land. Yu et al. [15] measured LUE from the perspective of urban agglomeration and economic development. Liu et al. [22] measured LUE from the perspective of environmental pollution. In addition, scholars have different methods for measuring LUE. The parametric method is based on the production function, adding a random error term to the production equation and estimating the efficiency value through regression, but it is difficult to determine the specific form of the distribution of the error [23]. The data envelopment analysis (DEA) method overcomes the problem that estimation requires specific form of inputs and outputs [24] and has become the mainstream LUE measure [25]. However, DEA is inferior to the entropy method in terms of objectivity of the assignment and interpretability of the weights [26]. In addition, principal component analysis [27] and slacks-based measure (SBM) method [28] have also been used to measure LUE. In short, scholars will choose the most appropriate estimation method according to the needs of the study.

The rise of 'carbon finance' originates from the change of international climate policy and two significant international conventions—the United Nations Framework Convention on Climate Change and the Kyoto Protocol. Carbon finance refers to direct investment and financing, carbon trading and bank lending for technologies and projects that limit greenhouse gas emissions. Carbon finance is an innovative attempt by countries around the world to seek sustainable development. The carbon emissions Trading Pilot Policy (hereinafter referred to as the carbon emissions trading policy, CETP), implemented in June 2013, approved seven provinces and cities—including Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen—to carry out carbon trading pilot work. This is an important milestone in the history of carbon finance in China and is of representative significance. Environmental regulation policy instruments produce both economic and environmental effects. The economic effect emphasizes the green economy [29], accompanied by economic efficiency improvement and industrial structure upgrading [30]. Environmental effects emphasize environmental quality and effectiveness of governance, such as pollution emissions, air quality, and greenness [31–34]. As a part of environmental regulation tools, carbon finance also has economic and environmental effects. Can the China's CETP optimize LUE in terms of economic and environmental effects? This question has not been fully investigated. Based on this, two hypotheses are proposed in this paper.

Hypothesis 1 (H1). *carbon emission trading policy can optimize land use efficiency through economic effect.*

Hypothesis 2 (H2). *carbon emissions trading policy can optimize land use efficiency through environmental effects.*

The possible contributions of this paper are as follows: (1) few studies have been conducted on CETP in China, and no study has yet fully discussed its effects on land use efficiency; (2) the economic effects and environmental effects of CETP, and the correlation between the two are examined simultaneously; (3) most of the previous studies emphasize qualitative analysis (measuring LUE and analyzing it), but ignore the causal argumentation process. In this paper, based on the qualitative analysis, the quantitative analysis (difference in differences, DID) is further used to strengthen the convincing power of the conclusions.

The remainder of this paper is organized as follows: Section 2 describes the various methods used in this study, the empirical path and illustrates the variables and data.

Section 3 presents the results of the qualitative and quantitative analyses. Section 4 discusses the results of the study and provides relevant policy recommendations.

2. Material and Method

2.1. Main Study Areas

According to the CETP, China gradually opened seven policy pilot areas in mid-2013, which are the main study areas and the "treatment group" in the DID model later on. The following is the basic information of these pilot regions.

Beijing, located in northern China, is bordered by Tianjin and Hebei. As of 2020, Beijing has a total area of 16,410.54 km^2, a resident population of 21,893.1 thousand, and a GDP of 3610.26 billion RMB.

Tianjin, located in northern China, is adjacent to Beijing and Hebei Province. By 2020, Tianjin will have a total area of 11,966.45 km^2, a resident population of 13,866 thousand, and a GDP of 1408.373 billion RMB.

Hubei Province, located in central China, is bordered by Anhui, Chongqing, Shaanxi, Jiangxi, Hunan, and Henan. Currently, Hubei province has 12 prefecture-level cities: Wuhan, Huangshi, Shiyan, Yichang, Xiangyang, Ezhou, Jingmen, Xiaogan, Jingzhou, Huanggang, Xianning, and Suizhou. As of 2020, the total area of Hubei province reaches a total of 185,900 km^2, with a resident population of 57.75 million people and a GDP of 4344.346 billion RMB.

Shanghai, located in the east of China, is bordered by Jiangsu and Zhejiang provinces. By 2020, Shanghai will have a total area of 6340.5 km^2, a resident population of 24,870.9 thousand, and a GDP of 3870.58 billion RMB.

Guangdong Province, located in the southernmost part of China, shares borders with Hong Kong, Macau, Guangxi, Hunan, Jiangxi, and Fujian. Currently, there are 21 prefecture-level cities in Guangdong Province: Guangzhou, Shenzhen, Foshan, Dongguan, Zhongshan, Zhuhai, Jiangmen, Zhaoqing, Huizhou, Shantou, Chaozhou, Jieyang, Shanwei, Zhanjiang, Maoming, Yangjiang, Yunfu, Shaoguan, Qingyuan, Meizhou, and Heyuan. Among them, the data of Shanwei is missing more seriously and is excluded from this paper. As of 2020, Guangdong Province has a total area of 179,725 km^2, a resident population of 126,012.5 thousand, and a GDP of 11,076.094 billion yuan, ranking first in China.

Chongqing, located in western China, is bordered by Sichuan, Shaanxi, Hubei, Hunan, and Guizhou. By 2020, Chongqing have a total area of 82,402 km^2, a resident population of 32,054.2 thousand, and a GDP of 25,027.279 billion yuan.

For the sake of space and focus, only the pilot areas of CETP—i.e., the "treatment group" in Section 3.2—are described above. Considering that this study focuses on economic, land, and environmental factors, this paper selects control group areas in terms of both geographic location and economic level. First, geographic location contains many unknown influencing factors [35] that need to be controlled. Therefore, the prefecture-level cities in the provinces adjacent to the experimental group are used as an alternative to the control group areas. Second, considering that the number of the control group should not exceed the experimental group by too much, this paper takes the economic level (GDP) as the basis and excludes Guizhou, Guangxi, and Hainan provinces, which are three regions with relatively weaker economic levels. Finally, based on the two steps, the control group areas of this study are obtained, as shown in Figure 1. In addition, the reasons for not introducing more "control groups" in this section are as follows: first, the number of control regions is large, which makes it lengthy; second, the role of control groups is to reflect the policy effects of the treatment group, which is not unique. However, it is possible to determine whether they are eligible control groups by methods such as parallel trend tests [36].

Figure 1. Study areas.

2.2. *Research Method and Ideas*

2.2.1. Entropy Method

In Section 2.3.1, this paper uses the entropy method to measure the LUE scores. Entropy method assigns weights based on the degree of variation between variables, the greater the variation, the greater the weight. Compared with other indicator reduction methods, the entropy method can determine the "degree of difference" between secondary indicators by the size of the weight, which indirectly reflects the "priority" of the optimized indicator content. Entropy method is calculated as follows [37].

Step 1. Calculate a standardised matrix of indicators ($E_{it,k}$). i indicates the region i, t indicates the year t, k indicates the kth indicator, total K indicators. $e_{it,k}$ is the matrix of unprocessed.

$$E_{it,k} = \frac{e_{it,k} - \min\limits_{K}|e_{it,k}|}{\max\limits_{K}|e_{it,k}| - \min\limits_{K}|e_{it,k}|} \tag{1}$$

Step 2. Obtain the information entropy ($I_{t,\,k}$) by Equation (2). Whree, $E'_{it,k}$ is calculated by Equation (3). n is the total number of regions.

$$I_{t,k} = -ln(n)^{-1} \sum\nolimits_{i=1}^{n} E'_{it,k} * ln\left(E'_{it,k}\right) \tag{2}$$

$$E'_{it,k} = \frac{E_{it,k}}{\sum_{i=1}^{n} E_{it,k}} \tag{3}$$

Step 3. Calculate the weight matrix ($W_{t,\,k}$) by Equation (4).

$$W_{t,k} = \frac{1 - I_{t,k}}{K - \sum I_{t,k}} \tag{4}$$

2.2.2. Map Visualization of Data

Although the data can adequately reflect the relevant information, the purely numerical form is not easy to form a deep impression. The map visualization of data method presents the data information in the form of geographic maps, which can visually reflect and analyze the spatio-temporal evolution patterns of the two type of LUE before and after the implementation of CETP, and then test the hypotheses. Specifically, in this paper, the aggregated values of LUE scores from 2010–2012 are selected for comparison with those from 2015–2017, and if the latter is greater than the former, it is considered that the LUE scores of the corresponding cities have improved with the implementation of the CETP, indicating that the policy is effective. The above qualitative analysis discarded the data from 2013 and 2014 in order to highlight the difference in LUE before-and-after the policy. This is because the CETP was centrally implemented from June 2013 to the first half of 2014, and the policy starting point is set to 2014 in this paper, so the data from these two years tend to interfere with the trends in LUE before-and-after the policy. Section 3.1 will analyze and discuss the spatio-temporal evolution patterns of LUE_Eco and LUE_Env one by one.

2.2.3. DID Estimation Method

In Section 3.2, this paper conducts an empirical analysis using the difference in differences (DID) model, which is described in relation to the DID model as follows.

When evaluating the treatment effect of a policy or event, economists often use a counterfactual framework in which the difference between data (actually observable) that are treated (the treatment group) and data that would have been treated if they had not been treated (the counterfactual) is referred to as the "treatment effect". Since the untreated data are counterfactuals and not actually observable, the difference between the before-and-after change in the treated group and the before-and-after change in the control group is the "treatment effect". DID is the most widely used measure for estimating treatment effects. The idea of this method was originally proposed by the medical scientist John Snow [38] in his study of the cholera epidemic in London, and was introduced into economics by Obenauer and von der Nienburg [39] in their study of the effect of the minimum wage method. To estimate the treatment effect, the difference between post-treatment and pre-treatment is compared by subtracting the pre-post change in the control group from the pre-post change in the treatment group, which is the treatment effect, hence the name "double difference". The prerequisite assumption for DID is that the treatment group and the control group must have the same trend before being treated, which is the 'parallel trend' assumption.

2.2.4. Empirical Path

With the help of CETP, this paper aims to investigate whether carbon financial behavior can optimize LUE. After constructing a LUE evaluation system and measuring the overall LUE score, this paper verifies the purpose of the study through the following two steps in turn (Figure 2). In the first step, the LUE score is visualized through maps with 2014 as the cut-off point, and these are used to analyze the spatio-temporal evolution pattern of LUE before-and-after the policy, and then to verify the hypothesis. In the second step, with the initial judgment of the first step, the change in LUE is further tested by quantitative analysis through the DID model to see if it is due to the CETP. Through the above two steps, this paper combines qualitative analysis with quantitative analysis in order to prove the research hypothesis more clearly.

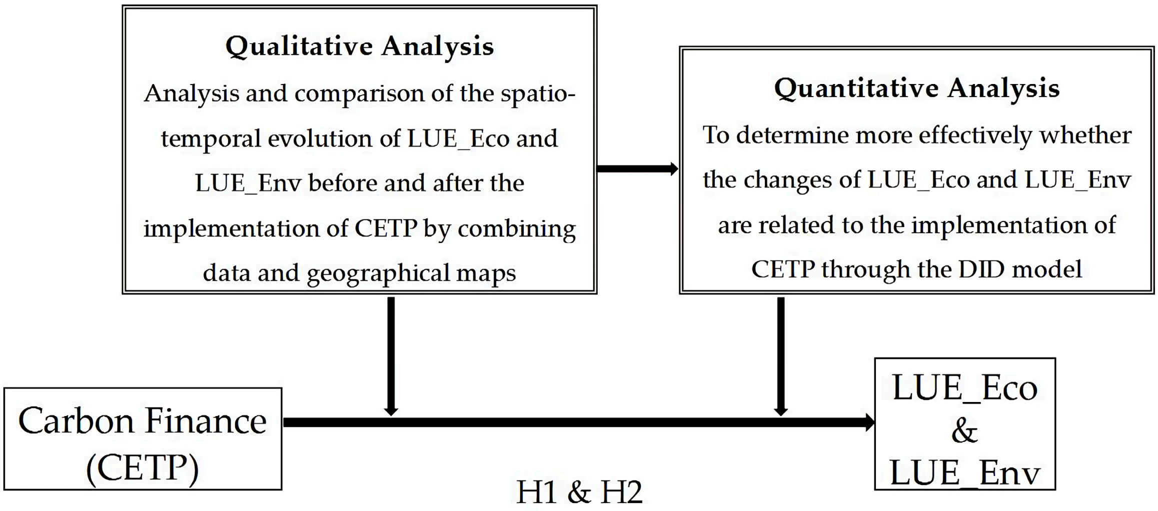


Figure 2. Empirical path.

2.3. Variables and Data

2.3.1. Explained Variables

The explained variable in this paper is land use efficiency (LUE). According to the previous research objectives and hypotheses, LUE is subdivided into two levels—the economic effect level and the environmental effect level.

The economic effect of land use efficiency (LUE_Eco) focuses on uncovering the influencing factors of LUE from the economic perspective. In this paper, the evaluation system of LUE_Eco index will be constructed from two dimensions—economic level and development potential (Table 1).

Table 1. Land use efficiency evolution system in economic and environmental effects.

Explained Variable	Dimension	Secondary Indicator	Unit	Average Weight (2010–2017)	Attribute
Economic Effects of Land Use Efficiency (LUE_Eco)	Economic level	Output intensity	10,000 Yuan/km^2	29.98% (2nd)	+
		GDP per capita	Yuan	11.60% (4th)	+
	Development potential	Industrial structure	%	6.89% (5th)	+
		Innovation level	Items/10,000 people	32.24% (1st)	+
		R&D intensity	%	19.29% (3rd)	+
Environmental Effects of Land Use Efficiency (LUE_Env)	Pollution level	Industrial wastewater emission density	10,000 tons/km^2	27.01% (1st)	-
		Industrial dust emission density	Tons/km^2	22.97% (2nd)	-
		SO_2 emission density	Tons/km^2	21.55% (3rd)	-
		CO_2 emission density	10,000 tons/km^2	13.68% (5th)	-
	Recovery ability	Green space density	%	14.78% (4th)	+

The economic level aspect reflects the economic transformation capacity of urban land. The more output obtained from the same amount of land area, the higher its economic conversion capacity. In this paper, we use the following two secondary indicators to measure the economic level of LUE_Eco. (1) Output intensity, which is the quotient of the city's GDP and urban land area. GDP can directly reflect the economic level of a region [40], but is easily disturbed by the city size. Therefore, the output intensity indicator is used to exclude the influence of city size on economic volume. (2) The level of GDP per capita, i.e., the ratio of the city's GDP to total population of the city at the end of the year. The total population is also an important factor influencing GDP [41], so this paper uses the GDP per capita variable to exclude the influence of population size.

The development potential aspect reflects the space for improvement of the economic transformation capacity of the urban land. If two regions have the same economic level, the one with higher development potential will surpass the region with lower development potential in the future. Therefore, economic development potential is an important part of LUE. In this paper, we use the following three secondary indicators to measure the development potential of LUE_Eco. (1) Industrial structure, i.e., the proportion of value added of tertiary industry to GDP. The higher the share of tertiary industry, the lower the industrial dependence of the region's economy and the lower the demand for land to purchase factories [42], thus contributing to the LUE. (2) Innovation capacity, i.e., the ratio of patents granted for utility models and inventions to the total population at the end of the year. Patents can better reflect the level of innovation in a region [43], where the number of patents granted is often used [44]. However, there is a significant interference of population size. Therefore, in this paper, it is divided by the total population at the end of the year to remove this interference. (3) R&D intensity, i.e., the proportion of general public budget expenditures for science and technology. R&D intensity measures the local government's support for R&D in science and technology. The research and development of innovative results requires a large amount of physical capital [45], and government support is important for innovative subjects, especially small and micro enterprises.

The environmental effect of land use efficiency (LUE_Env) emphasizes the environmental factors that affect LUE. In this paper, the evaluation system of LUE_Env index will be constructed from the pollution level dimension and the recovery capacity dimension (Table 1).

The pollution level dimension reflects the environmental carrying level of urban land. This paper uses pollution emission density, i.e., pollution emissions divided by urban land area, to reflect the environmental carrying level of the area and exclude the interference of urban scale [46]. The specific pollutants are the three waste pollutants (SO_2, industrial wastewater, industrial dust) and CO_2. Three waste pollutants are the main pollution products of traditional industrial production and can better reflect the industrial pollution in the region, while CO_2 emissions are currently a global concern and the most important pollutant that needs to be addressed in China at present [47]. At the same time, another reason for using CO_2 pollutants is that this paper was developed by using the CETP as an example, and although this policy does not only have an impact on CO_2 emissions, there is no doubt that we should include CO_2 in the pollutant options.

The restoration capacity dimension, which reflects the level of environmental restoration of urban land, is an important influencing factor of LUE [48]. Green vegetation is better able to clean air pollution [49] and is one of the excellent pollution remediation tools. Urban green space is the sum of natural and artificial vegetation in the city, which reflects the total amount of green vegetation in the city. Therefore, this paper uses green space density, which is the ratio of green space area to urban land area, to measure the level of environmental remediation.

2.3.2. Core Explanatory Variable

The core explanatory variable in this paper is applied in the study in Section 3.2, which measures whether region i in year t is a region that has implemented CETP. First, the region dummy variable $Treat_i$ is constructed to determine whether region i is a carbon trading pilot region. If region i is a carbon trading pilot region, $Treat_i = 1$, and otherwise, $Treat_i = 0$. Second, the year dummy variable $Post_t$ is constructed to determine whether the CETP has been implemented in year t. If the CETP has been implemented in year t and before, $Post_t = 1$, and otherwise, $Post_t = 0$. Considering that the CETP was fully launched in all pilot regions from June 2013 to the first half of 2014, and because it takes some time for enterprises to change their production behavior and development strategies, the starting point of the CETP is set to 2014 in this paper [50]. Therefore, in 2014 and after, $Post_{2014} = 1$, otherwise, $Post_{2014} = 0$. Finally, the region dummy variable is multiplied with the year dummy variable, and its interaction term is the core explanatory variable $Treat_i \times Post_{2014}$ in this paper.

2.3.3. Control Variable

Since LUE is a composite variable, it covers a larger number of secondary indicators. Therefore, the correlation between control variables and explanatory variables (LUE_Eco and LUE_Env) is easy to exist, thus creating the problem of endogeneity. To avoid this problem, this paper will reduce the number of control variables as much as possible while ensuring the effect of control variables. In this paper, only the effects from foreign countries are controlled [41–53]. The actual utilization of foreign capital measures the domestic absorption of foreign investment in China, which can effectively control the interference of foreign investors on domestic LUE.

2.3.4. Data

Three data sets are involved in this study: the China Urban Statistical Yearbook, the China Research Database Service (CNRDS), and the China Carbon Accounting Database (CEADs). In this study, the data on granted patents and pollutant emissions of 'three wastes' are obtained from CNRDS, and the measurement method of CO_2 emissions is based on Shan et al. [54,55], and the specific data are obtained from CEADs. This paper limits the study sample interval to 2010–2017, mainly based on the following considerations: first, the data of pollutant emissions are only updated to 2017. Second, since 2014 is the start point of the CETP set in this paper, and DID requires that the time intervals before-and-after the policy implementation are as equal as possible. Therefore, we use 2010 as the starting point of the sample interval, to ensure that the years before the policy implementation (2010, 2011, 2012, and 2013) and the years after the policy implementation (2014, 2015, 2016, and 2017) are the same. Third, in order to ensure the air quality during the 2008 Beijing Olympics, a strict environmental regulation strategy was implemented in Beijing and its surrounding areas (Hebei Province and Tianjin City) during 2008–2009. Failure to exclude these factors will inevitably reduce the persuasiveness of the DID findings. In this paper, the study sample is set in the carbon trading pilot regions (Beijing, Hebei, Tianjin, Shanghai, Zhejiang, Guangdong, and Chongqing) and their surrounding areas, for the detailed reasons given in Section 2.1.

Table 2 reports the descriptive statistics of the main variables in this paper.

Table 2. Variable description.

Variable Type	Variable	Unit	Obs	Mean	Std.	Min	Max	Label
Explained variable	Economic effects of land use efficiency	%	1264	0.6151	0.5179	0.0489	4.3689	LUE_Eco
	Environmental effects of land use efficiency	%	1264	0.5994	0.7868	0.1363	9.4610	LUE_Env
Core explanatory variable	Carbon trading policy pilot	-	1264	0.0741	0.2620	0	1	Treat × Post
Control variables	Actual utilization of foreign capital	Items/10,000 people	1264	91,927.87	245,328.7	19	3,082,563	AUFC

3. Results

3.1. Results of Qualitative Analysis

3.1.1. Spatio-Temporal Evolution Analysis of the LUE_Eco

Figure 3 shows the spatio-temporal evolution pattern of the economic effects of land use efficiency (LUE_Eco) in Beijing, Shanghai, Chongqing and Tianjin, respectively. Figure 4 shows Guangdong Province and Hubei Province, respectively.

Figure 3. Spatio-temporal evolution pattern of LUE_Eco in Beijing, Shanghai, Chongqing, and Tianjin.

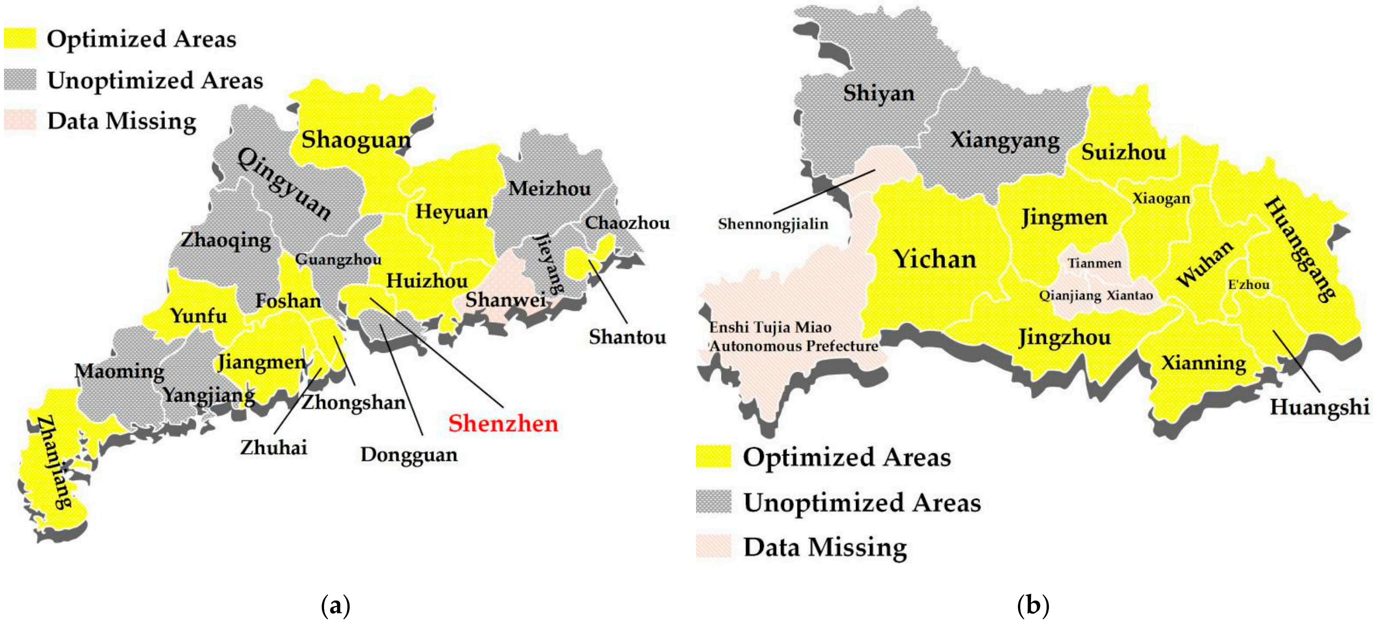


Figure 4. Spatio-temporal Evolution Pattern of LUE_Env. (**a**) Guangdong Province. (**b**) Hubei Province.

Figure 3 shows that among the four municipalities, only Chongqing's LUE_Eco has been optimized after the implementation of the CETP. It is reasonable to tentatively infer that the CETP did not improve the LUE_Eco in the pilot areas, and the optimization in Chongqing may be due to other factors.

Figure 4a,b show the spatio-temporal evolution pattern of LUE_Eco in each prefecture-level city in Guangdong Province and Hubei Province, respectively. From Figure 4a, it can be found that 11 cities in Guangdong Province have optimized LUE_Eco and 9 have not been optimized after the policy implementation, with an optimization rate of 55%. Optimized areas are mostly concentrated in the central region and the southern coastal region. From Figure 4b, it can be found that there are 10 optimized cities and 2 unoptimized cities in Hubei province after the policy implementation, with an optimization rate of 83.33%. Optimized areas are mostly concentrated in the eastern region.

Combining the findings in Figures 3 and 4, we can find that among the 36 pilot cities of carbon trading, there are 22 optimized areas and 14 unoptimized areas, with a total optimization rate of 61.11%. Therefore, this paper tentatively judges that the implementation of CETP helps pilot areas to improve LUE_Eco.

3.1.2. Spatio-Temporal Evolution Analysis of the LUE_Env

Figure 5 shows the spatio-temporal evolution pattern of the environmental effects of land use efficiency (LUE_Eco) in Beijing, Shanghai, Chongqing, and Tianjin, respectively. Figure 6 shows Guangdong Province and Hubei Province, respectively.

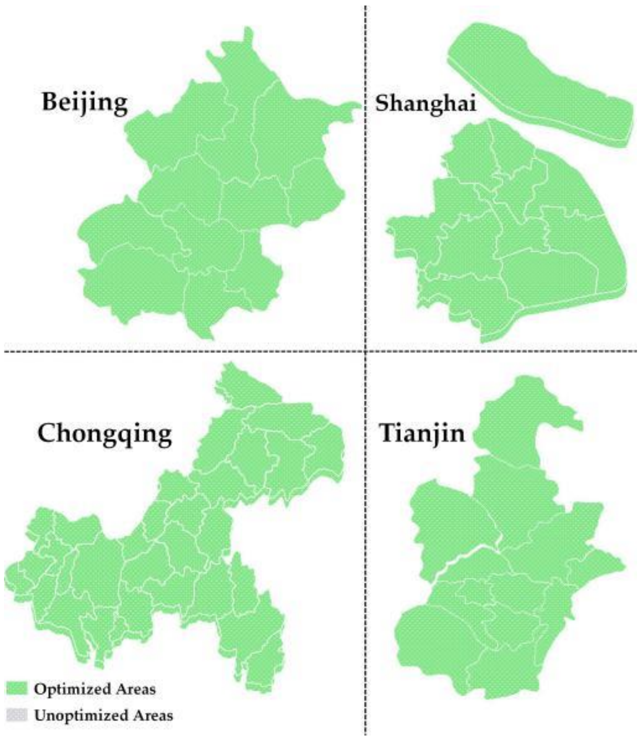
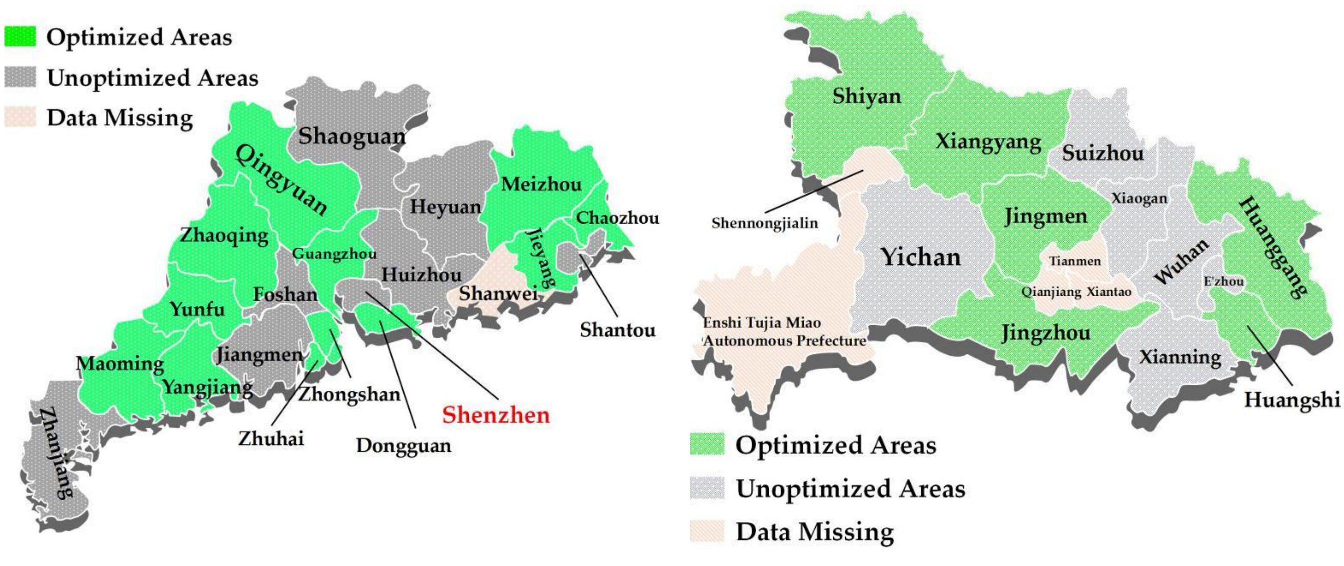


Figure 5. Spatio-temporal evolution pattern of LUE_Env in Beijing, Shanghai, Chongqing, and Tianjin.



(**a**) (**b**)

Figure 6. Spatio-temporal Evolution Pattern of LUE_Env. (**a**) Guangdong Province. (**b**) Hubei Province.

From Figure 5, we can see that the LUE_Env of all four municipalities has been optimized after the implementation of the CETP. We have reason to tentatively infer that the CETP has enhanced the LUE_Env levels in the pilot regions.

Figure 6a,b show the spatio-temporal evolution pattern of LUE_Env in each prefecture-level city of Guangdong Province and Hubei Province, respectively. From Figure 6a, we can find that there are 11 optimized areas and 9 unoptimized areas in Guangdong Province after the policy implementation, with an optimization rate of 55%. Optimized areas are mostly concentrated in the eastern and western regions. From Figure 6b, it can be found that there are 6 prefecture-level cities in Hubei Province with LUE_Env improved after the policy implementation, and the remaining six areas with LUE_Env not improved, with an optimization rate of 50%. Optimized areas are mostly concentrated in the eastern and central regions.

Combining the findings in Figures 5 and 6, it can be found that among the 36 carbon trading pilot municipalities, there are 21 optimized areas and 15 unoptimized areas, with a total optimization rate of 58.33%, which is slightly less than the 61.11% of LUE_Eco. Therefore, this paper tentatively judges that the implementation of CETP helps pilot areas to improve LUE_Env levels.

3.2. Results of Quantitative Analysis

In Section 3.1, this paper has preliminarily analyzed and discussed the spatio-temporal evolution patterns of LUE_Eco and LUE_Env during the period of 2010–2017. The conclusions show that CETP is beneficial to enhance LUE_Eco and LUE_Env levels. However, the conclusions drawn from the qualitative analysis are relatively less convincing, and it is not possible to determine whether there is a necessary link between these changes and CETP. Therefore, further analysis will be done in this section of the paper to argue for a causal relationship between the changes in LUE and CETP.

3.2.1. Identification Strategy and Results

The difference in differences (DID) model can effectively mitigate the endogeneity problem arising from the causality between variables and assess the policy effects. In this paper, a DID model is constructed to identify the causal relationship between the two effects of LUE and CETP. The model is shown in Equation (5).

$$LUE_{it} = \alpha + \beta Treat_i \times Post_{2014} + \ln Control_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (5)$$

In Equation (5), i represents the region and t represents the year. LUE_{it} is the collective name of LUE_Eco and LUE_Env. The coefficient β is the main coefficient examined in this study, and the significance of β can argue the causal relationship between the core explanatory variables and the explained variables. μ_i reflects city fixed effects, γ_t reflects year fixed effects, and ε_{it} is the error term.

Table 3 reports the regression results for LUE_Eco and LUE_Env, respectively. Columns 1 to 3 of Table 3 show the regression results for the control variables with the stepwise inclusion of fixed effects (year fixed effects and urban fixed effects). Among them, column 3 shows the results of the basic regression. The results in Table 3 show that the regression coefficients of $Treat_i \times Post_{2014}$ terms in LUE_Eco and LUE_Env do not change significantly under different types of fixed effects, control variables, indicating that the conclusions are more robust.

It can be found that the regression coefficients of $Treat_i \times Post_{2014}$ in the regression results of LUE_Eco, although negative, do not pass the significance test at the significance level of 10%, which indicates that there is no significant causal relationship between the change of LUE_Eco and the CETP, suggesting that the decline of LUE_Eco is not due to the implementation of CETP.

Table 3. Regression results of DID.

LUE_Eco			
Explanatory Variables	**(1)**	**(2)**	**(3)**
$\text{Treat}_\text{i} \times \text{Post}_{2014}$	−0.0035 (1.80)	0.0036 (−0.21)	−0.0099 (−0.67)
Control	-	YES	YES
Year fixed effects	-	-	YES
Urban fixed effects	-	-	YES
R-sq	0.3515	0.4312	0.4451
Obs	1264	1264	1264
LUE_Env			
Explanatory Variables	**(1)**	**(2)**	**(3)**
$\text{Treat}_\text{i} \times \text{Post}_{2014}$	0.0970 * (1.80)	0.0981 * (1.84)	0.1229 * (1.86)
Control	-	YES	YES
Year fixed effects	-	-	YES
Urban fixed effects	-	YES	YES
R-sq	0.2321	0.0627	0.2341
Obs	1264	1264	1264

* indicate statistical significance at the 10% levels.

In the regression result of LUE_Env, regression coefficient of $Treat_i \times Post_{2014}$ is significantly positive, which indicates that there is a positive causal relationship between the change of LUE_Env and the CETP, that is, the CETP has improved the environmental effects of land use efficiency in the pilot areas.

3.2.2. Parallel Trend Test

Satisfying the parallel trend assumption is a necessary condition for the validity of the DID model. Therefore, this study sets the parallel trend hypothesis: if China does not implement the CETP, the trends of LUE_Eco and LUE_Env in different pilot regions are basically similar. In this paper, the event analysis method framework is used to test this hypothesis. The regression equation is given in Equation (6).

$$LUE_{it} = \sum_{\tau=2011}^{2017} \beta_\tau Treat_i \times Dummy_\tau + \ln Control_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (6)$$

where $Dummy_\tau$ is the year dummy variable and β_τ is the examination coefficient of the parallel trend test. In Equation (5), this paper sets the initial year of the sample, 2010, as the base year. If the model satisfies the parallel trend hypothesis, β_{2011} to β_{2013} are insignificant, while β_{2014} to β_{2017} are significant. Figure 7 plots the β_τ estimates and the 90% confidence intervals. Among them, the explained variable in Figure 7a is LUE_Eco, while the explained variable in Figure 7b is LUE_Env. From Figure 7a, it can be found that β_τ is significantly negative only in 2014, while none of the years after 2014 is significant, which indicates that this DID model fails the parallel trend hypothesis test, i.e., there is no significant change in LUE_Eco with the implementation of CETP. The results in Figure 7b show that β_τ is significantly positive in 2014, 2015, and 2016, and its regression coefficients are not significant in 2010–2013, indicating that the DID model passes the parallel trend hypothesis test, i.e., there is a positive causal relationship between LUE_Env and the CETP. However, β_τ fails the significance test at the 10% significance level in 2017, indicating that, at least for 2017, this causal relationship disappears temporarily. As to how it changes after 2017, we cannot infer. What is certain, however, is that the environmental effect of the CETP on LUE works for three consecutive years.

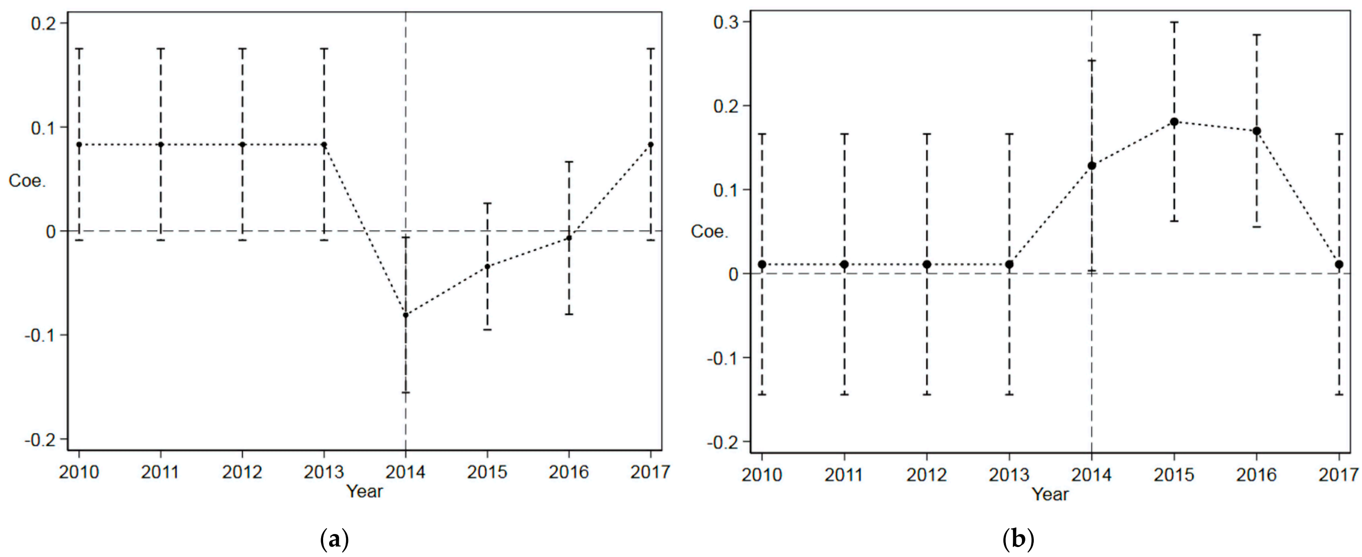


Figure 7. Parallel trend test. (**a**) Explained variable is LUE_Eco. (**b**) Explained variable is LUE_Env.

4. Discussion

4.1. Discussion of the Results

In Section 3.1, the changes of LUE_Eco and LUE_Env before-and-after the CETP are analyzed qualitatively by using map visualization method. It can be found that: first, the optimization rate of LUE_Eco reaches 61.11% among the 36 pilot regions after the implementation of the CETP. Among them, Hubei province has the highest optimization rate (83.33%). Second, the optimization rate of LUE_Env is 58.33% after the implementation of the policy. The optimization rate of Hubei Province is only 50%, which is lower than that of Guangdong Province (55%). This paper tentatively concludes that the implementation of the policy has optimized LUE_Env. Third, combined with the findings in Figures 3–6, it is found that the optimized areas of LUE_Eco and LUE_Env overlap to a lesser extent, indicating that the enhancement of economic effects and environmental effects are difficult to be achieved at the same time, and also reflecting the environmental pollution dependence of economic development in the pilot areas.

The above conclusions, combined with the information on the average weights of the secondary indicators presented in Table 1, lead to a more detailed conclusion:

(1) For LUE_Eco, the top two highest average weights—innovation level (32.24%) and output intensity (29.95%)—contribute to the LUE_Eco variables contribute more than 60%. This on the one hand reflects that the pilot areas have the greatest variability in innovation level and output intensity, and on the other hand reminds us that we can obtain higher gains from improving LUE_Eco in these areas. Therefore, for the optimized areas, we can assume that their innovation level and output intensity improve significantly after the policy implementation. In addition, the average weight of the first three indicators contribute more than 80% to LUE_Eco, and two of them are related to R&D in scientific and technology, so this paper also argues that the CETP promotes the R&D and innovation behavior of actors within the region.

(2) For LUE_Env, the top three with the highest average weight are industrial wastewater emission density (27.01%), industrial dust emission density (22.97%) and SO_2 emission density (21.55%), which contribute more than 70% to the LUE_Env variable. These three types of pollutant emissions are classified as 'three waste' pollutants, which are mainly produced by the production activities of industrial enterprises. Therefore, for the optimized areas, we can infer that the implementation of the CETP has a greater impact on the industrial enterprises in the area, resulting in a significant reduction of their pollution emissions.

(3) The main purpose of CETP is to control and reduce carbon emissions. However, the average contribution of CO_2 emission density to LUE_Env in Table 1 is only 13.68%, which seems to indicate that the policy does not have much effect on CO_2 emission reduction. In fact, the contribution rate referred to above is the average value from 2010 to 2017, and Figure 8 shows the contribution rate of CO_2 emission density over the years. It can be found that the contribution rate of CO_2 emission density is changing in a decreasing trend, which indicates that the difference in values of CO_2 emission density among pilot regions is gradually decreasing, indirectly reflecting that the policy has an emission reduction effect on CO_2. It is worth mentioning that the weights of the other nine secondary indicators do not show an increasing or decreasing trend over the years, and the magnitude does not change as much as CO_2 emission density. Therefore, the above conclusions are robust.

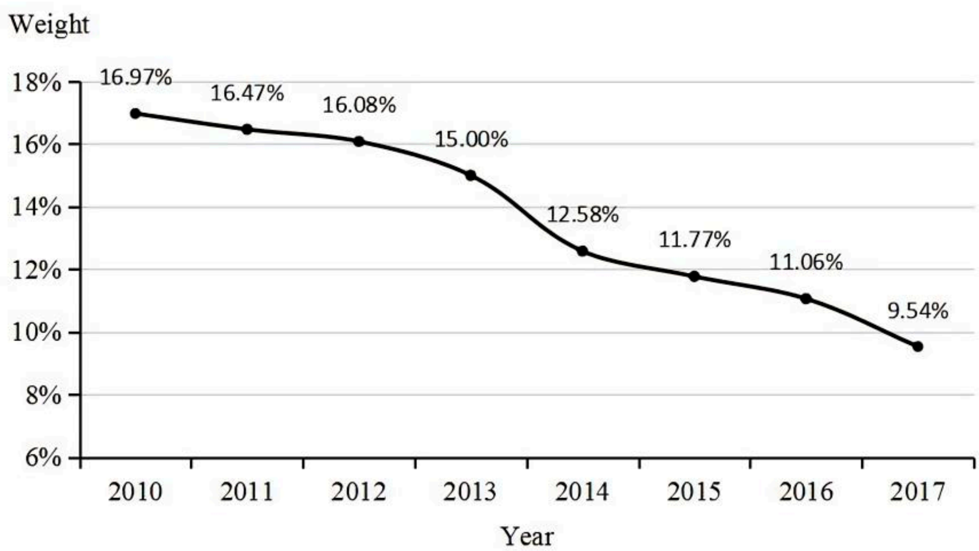


Figure 8. Trend of weight of CO_2 emission density.

On this basis, the results of the DID model were used in this paper to refine the causality of the above findings. The conclusion shows that there is no significant causal relationship between CETP and LUE_Eco. Therefore, the enhancement of LUE_Eco after the policy implementation may be due to other factors. Meanwhile, there is a significant causal relationship between CETP and LUE_Env, indicating that the carbon trading pilot policy has a significant environmental effect and optimizes LUE_Env.

4.2. Policy Recommendations

Based on the above discussions, this study has obtained some inspiration on policy making:

(1) The CETP has effectively improved the LUE_Env level, which verifies the effectiveness of the policy. However, the policy also makes it difficult to improve the LUE_Eco level in the pilot areas, which indicates that the CETP is a 'double-edged sword', which produces environmental effects while hindering the economic effects. Therefore, the pilot regions should encourage the development of tertiary industries while not inhibiting the development of secondary industries, so as to upgrade the industrial structure and promote economic development. At the same time, the government of the pilot region can increase innovation support, encourage and promote enterprises' independent R&D to enhance product competitiveness and alleviate the problem of production reduction brought by environmental regulation policies.

(2) There are seven optimized areas where both LUE_Eco and LUE_Env are improved, and Hubei Province accounts for four of them, indicating that the development model of Hubei Province during 2010–2017 is excellent. Further exploration of the

development model in Hubei province may be beneficial to find ways to optimize LUE in terms of both environmental and economic effects, and thus improve the CETP.

(3) From a national macro perspective, China must transform itself into an innovative power and follow a sustainable development path if it is to reach its 'carbon peak' and 'carbon neutral' goals without hindering economic development. Improving LUE is an important part of sustainable development. However, the study findings of the carbon emissions pilot regions indicate that China is unable to optimize LUE in terms of both economic and environmental effects. This also reflects that China's innovation-driven development model and sustainable development path still have a long way to go.

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References

1. The United Nations. *China's Urban Population Will Increase by 255 Million in 2050*; The United Nations: New York, NY, USA, 2018.
2. Wang, H.J.; He, Q.Q.; Liu, X.J.; Zhuang, Y.H.; Hong, S. Global urbanization research from 1991 to 2009: A systematic research review. *Landsc. Urban. Plan.* **2012**, *104*, 299–309. [CrossRef]
3. Michael, F.L.; Noor, Z.Z.; Figueroa, M.J. Review of urban sustainability indicators assessment—Case study between Asian countries. *Habitat. Int.* **2014**, *44*, 491–500. [CrossRef]
4. Paulsen, K. Geography, policy or market? New evidence on the measurement and causes of sprawl (and infill) in US metropolitan regions. *Urban. Stud.* **2014**, *51*, 2629–2645. [CrossRef]
5. Wang, Z.B.; Liang, L.W.; Sun, Z.; Wang, X.M. Spatiotemporal differentiation and the factors influencing urbanization and ecological environment synergistic effects within the Beijing-Tianjin-Hebei urban agglomeration. *J. Environ. Manag.* **2019**, *243*, 227–239. [CrossRef]
6. Liu, Y.S.; Li, J.T.; Yang, Y.Y. Strategic adjustment of land use policy under the economic transformation. *Land Use Policy* **2018**, *74*, 5–14. [CrossRef]
7. Wang, J.; Lin, Y.F.; Glendinning, A.; Xu, Y.Q. Land-use changes and land policies evolution in China's urbanization processes. *Land Use Policy* **2018**, *75*, 375–387. [CrossRef]
8. Lian, H.P.; Li, H.; Ko, K. Market-led transactions and illegal land use: Evidence from China. *Land Use Policy* **2019**, *84*, 12–20. [CrossRef]
9. Qian, Z. Land acquisition compensation in post-reform China: Evolution, structure and challenges in Hangzhou. *Land Use Policy* **2015**, *46*, 250–257. [CrossRef]
10. Wang, J.L.; Li, H.; Shi, C. Urban Land-ues Efficiency, Spatial Spillover, and Determinants in China. *Acta Geogr. Sin.* **2015**, *11*, 1788–1799.
11. Zhou, L.A. Governing China's Local Officials: An Analysis of Promotion Tournament Model. *Econ. Res. J.* **2007**, *7*, 36–50.
12. You, M.D.; Zhang, Y.; Yuan, B.L. Research about influence of environmental regulation and central-local decentralization policy on environmental pollution in the championship mechanism of official promotion. *J. Cent. South Univ. Soc. Sci.* **2018**, *24*, 66–77.
13. Wang, K.; Tang, Y.; Chen, Y.; Shang, L.; Wang, P. The Coupling and Coordinated Development from Urban Land Using Benefits and Urbanization Level: Case Study from Fujian Province (China). *Int. J. Environ. Res. Public Health* **2020**, *17*, 5647. [CrossRef] [PubMed]
14. Hasse, J.E.; Lathrop, R.G. Land resource impact indicators of urban sprawl. *Appl. Geogr.* **2003**, *23*, 159–175. [CrossRef]
15. Yu, J.; Zhou, K.; Yang, S. Land use efficiency and influencing factors of urban agglomerations in China. *Land Use Policy* **2019**, *88*, 104143. [CrossRef]
16. Jaeger, J.A.; Bertiller, R.; Schwick, C.; Cavens, D.; Kienast, F. Urban permeation of landscapes and sprawl per capita: New measures of urban sprawl. *Ecol. Indic.* **2010**, *10*, 427–441. [CrossRef]
17. Ji, Z.H.; Zhang, P. Spatial Difference and Driving Mechanism of Urban Land Use Efficiency Under the Environmental Constraints: Based on 285 Cities in China. *China Land Sci.* **2020**, *34*, 72–79.
18. Zhang, Z. Study of Chinese Urban Land Use Efficiency. *J. Quant. Tech. Econ.* **2014**, *31*, 134–149.
19. Van Zanten, H.H.; Mollenhorst, H.; Klootwijk, C.W.; van Middelaar, C.E.; de Boer, I.J. Global food supply: Land use efficiency of livestock systems. *Int. J. Life Cycle Assess.* **2016**, *21*, 747–758. [CrossRef]

20. Kytzia, S.; Walz, A.; Wegmann, M. How can tourism use land more efficiently? A model-based approach to land-use efficiency for tourist destinations. *Tour. Manag.* **2011**, *32*, 629–640. [CrossRef]
21. Pu, W.; Zhang, A.; Wen, L. Can China's Resource-Saving and Environmentally Friendly Society Really Improve the Efficiency of Industrial Land Use? *Land* **2021**, *10*, 751. [CrossRef]
22. Liu, S.; Xiao, W.; Li, L.; Ye, Y.; Song, X. Urban land use efficiency and improvement potential in China: A stochastic frontier analysis. *Land Use Policy* **2020**, *99*, 105046. [CrossRef]
23. Huang, Z.; He, C.; Wei, Y.H.D. A comparative study of land efficiency of electronics firms located within and outside development zones in Shanghai. *Habitat Int.* **2016**, *56*, 63–73. [CrossRef]
24. Charnes, A.; Cooper, W.W.; Li, S. Using data envelopment analysis to evaluate efficiency in the economic performance of Chinese cities. *Socio-Econ. Plan. Sci.* **1989**, *23*, 325–344. [CrossRef]
25. Gao, X.; Zhang, A.; Sun, Z. How regional economic integration influence on urban land use efficiency? A case study of Wuhan metropolitan area, China. *Land Use Policy* **2020**, *90*, 104329. [CrossRef]
26. Meng, Y.; Wang, K.; Lin, Y. The Role of Land Use Transition on Industrial Pollution Reduction in the Context of Innovation-Driven: The Case of 30 Provinces in China. *Land* **2021**, *10*, 353. [CrossRef]
27. Zitti, M.; Ferrara, C.; Perini, L.; Carlucci, M.; Salvati, L. Long-term urban growth and land use efficiency in Southern Europe: Implications for sustainable land management. *Sustainability* **2015**, *7*, 3359–3385. [CrossRef]
28. Yao, M.; Zhang, Y. Evaluation and Optimization of Urban Land-Use Efficiency: A Case Study in Sichuan Province of China. *Sustainability* **2021**, *13*, 1771. [CrossRef]
29. Du, J.; Thill, J.C.; Peiser, R.B. Land pricing and its impact on land use efficiency in post-land-reform China: A case study of Beijing. *Cities* **2016**, *50*, 68–74. [CrossRef]
30. Wang, Z.; Chen, J.; Zheng, W.; Deng, X. Dynamics of land use efficiency with ecological intercorrelation in regional development. *Landsc. Urban Plan.* **2018**, *177*, 303–316. [CrossRef]
31. Panayotou, T. Demystifying the environmental Kuznets curve: Turning a black box into a policy tool. *Environ. Dev. Econ.* **1997**, *2*, 465–484. [CrossRef]
32. Coria, J. Taxes, permits, and the diffusion of a new technology. *Resour. Energy Econ.* **2009**, *31*, 249–271. [CrossRef]
33. Hwang, J.A.; Kim, Y. Effects of environmental regulations on trade flow in manufacturing sectors: Comparison of static and dynamic effects of environmental regulations. *Bus. Strat. Environ.* **2017**, *26*, 688–706. [CrossRef]
34. Yang, Z.; Wang, S.; Guo, M.; Tian, J.; Zhang, Y. Spatiotemporal Differentiation of Territorial Space Development Intensity and Its Habitat Quality Response in Northeast China. *Land* **2021**, *10*, 573. [CrossRef]
35. Zeng, Y.; Feng, Z.B.; Zhang, Q. Geographical Location, Environmental Regulation and Enterprise Innovation Transformation. *J. Financ. Econ.* **2016**, *9*, 87–98. [CrossRef]
36. Chen, L.; Wu, H.J. Research Status and Potential Problems of Differences-in-differences Method in China. *J. Quant. Tech. Econ.* **2015**, *7*, 133–148. [CrossRef]
37. Qiyue, C. Structure entropy weight method to confirm the weight of evaluating index. *Syst. Eng. Theory Pract.* **2010**, *30*, 1225–1228.
38. Snow, J. On the comparative mortality of large towns and rural districts, and the causes by which it is influenced. *J. Public Health Sanit. Rev.* **1855**, *1*, T16. [PubMed]
39. Obenauer, M.L. *Effect of Minimum-Wage Determinations in Oregon: July 1915*; US Government Printing Office: Washington, DC, USA, 1915.
40. Trinh, T.H. A primer on GDP and economic growth. *Int. J. Econ. Res.* **2017**, *14*, 13–24.
41. Li, D.K.; Liu, L.L.; Wang, H.L. The U Curve of Labor Share in GDP during Economic Development. *Econ. Res. J.* **2009**, *1*, 70–82.
42. Huang, L.X.; Wang, X.B.; Liu, S.L.; Han, Y.H. Regional Interactions in China's Industrial Restructuring—Horizontal Interprovincial Competition and Vertical Local Follow-up. *China Ind. Econ.* **2015**, *8*, 82–97. [CrossRef]
43. Ahn, S.J.; Yoon, H.Y. "Green chasm" in clean-tech for air pollution: Patent evidence of a long innovation cycle and a technological level gap. *J. Clean. Prod.* **2020**, *272*, 122726. [CrossRef]
44. Shi, X.L. A Research on Interregional Knowledge Spillovers—Based on Spatial Econometrics Model. *Econ. Surv.* **2014**, *6*, 1–6. [CrossRef]
45. Shields, M.D.; Young, S.M. Managing innovation costs: A study of cost conscious behavior by R & D professionals. *J. Manag. Account. Res.* **1994**, *6*, 175–196.
46. Glaeser, E.L.; Kahn, M.E. The greenness of cities: Carbon dioxide emissions and urban development. *J. Urban Econ.* **2010**, *67*, 404–418. [CrossRef]
47. Xu, X.; Huo, H.; Liu, J.; Shan, Y.; Li, Y.; Zheng, H.; Ouyang, Z. Patterns of CO_2 emissions in 18 central Chinese cities from 2000 to 2014. *J. Clean. Prod.* **2018**, *172*, 529–540. [CrossRef]
48. Wang, A.; Lin, W.; Liu, B.; Wang, H.; Xu, H. Does Smart City Construction Improve the Green Utilization Efficiency of Urban Land? *Land* **2021**, *10*, 657. [CrossRef]
49. Wu, H.; Tang, J.; Huang, H.; Chen, W.; Meng, Y. Net Carbon Sequestration Performance of Cropland Use in China's Principal Grain-Producing Area: An Evaluation and Spatiotemporal Divergence. *Land* **2021**, *10*, 714. [CrossRef]
50. Hu, J.; Huang, N.; Shen, H.T. Can Market-incentive Environmental Regulation Promote Corporate Innovation? A Natural Experiment Based on China's Carbon Emissions Trading Mechanism. *J. Financ. Res.* **2020**, *1*, 171–189.

51. Chen, D.K. Trade Barrier Reduction and Environmental Pollution Improvement: New Evidence from firm-level Pollution Data in China. *Econ. Res. J.* **2020**, *12*, 98–114.
52. Ouyang, Y.Y.; Huang, X.F.; Zhong, L.M. The Impact of Outward Foreign Direct Investment on Environmental Pollution in Home County: Local and Spatial Spillover Effects. *China Ind. Econ.* **2020**, *2*, 98–121. [CrossRef]
53. Omri, A.; Hadj, T.B. Foreign investment and air pollution: Do good governance and technological innovation matter? *Environ. Res.* **2020**, *185*, 109469. [CrossRef]
54. Shan, Y.; Guan, D.; Zheng, H.; Ou, J.; Li, Y.; Meng, J.; Zhang, Q. China CO_2 emission accounts 1997–2015. *Sci. Data* **2018**, *5*, 1–14. [CrossRef] [PubMed]
55. Shan, Y.; Huang, Q.; Guan, D.; Hubacek, K. China CO_2 emission accounts 2016–2017. *Sci. Data* **2020**, *7*, 1–9. [CrossRef] [PubMed]