


## Article

# The Low-Carbon City Pilot Policy and Urban Land Use Efficiency: A Policy Assessment from China

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**Abstract:** Against the backdrop of severe global warming, the low-carbon city pilot policy, with carbon emission reduction as its main objective, is an important initiative for China to fulfil its international commitment to carbon emission reduction and promote a green and low-carbon development strategy. However, none of the literature has yet evaluated whether the pilot low-carbon city policy promotes urban land use efficiency as a policy effect. In view of this, this paper measures urban land use efficiency from a low-carbon perspective using a global reference super-efficiency SBM model based on data from 186 prefecture-level cities in China from 2005–2017, and subsequently constructs a difference-in-differences method to test the true impact of low-carbon city pilot policies on urban land use efficiency and carbon emissions, and uses a propensity score matching method to test its robustness. It is found that: (1) the average level of urban land use efficiency in China is low and on a downward trend; (2) overall, cities are predominantly low-efficiency cities, with only the high-efficiency cities in Guangdong Province showing spatial agglomeration; and (3) the low-carbon city pilot policy reduces carbon emissions while also negatively affecting urban land use efficiency. Accordingly, this paper puts forward corresponding policy recommendations.

**Keywords:** low-carbon city pilot policy; urban land use efficiency; carbon emissions; difference-in-differences method



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## 1. Introduction

Since its reform and opening up, China's urbanization process has been in a rapid development stage, and the rapid expansion of urban land and large-scale population migration have become important features of China's urban development process [1]. From 1990 to 2014, China's urban construction land has grown from 13,148 square kilometers to 49,882.7 square kilometers [2]. The urbanization rate reached 58.52% in 2017, and this trend has not seen any significant change, with the rate expected to reach 70% by 2030 [3,4]. While the rapid urbanization process has made great contributions to economic development, it has also posed challenges to food security [5]. Urban expansion has encroached on a large amount of fertile farmland, resulting in a decline in the area of arable land per capita from 0.16 hectares in 1961 to 0.09 hectares in 2017, which is far below the world average [6]. In response to this situation, the central government has gradually strengthened the management of land use, mainly by setting a "red line for arable land" to limit the excessive growth of built-up areas [7]. As urbanization progresses, urban construction land, a basic element of urban development, will continue to increase [8]. The contradiction between the supply of urban construction land and the demand for urban development is becoming increasingly prominent, and the low efficiency of land use has seriously restricted the sustainable development of cities [9]. Therefore, how to improve the efficiency of urban

land use is a major problem that needs to be solved in China's urbanization process and regional economic development.

The rapid growth of CO<sub>2</sub> emissions is considered to be the main driver of global warming [10,11]. The warming has led to a nonlinear and rapid increase in the intensity and frequency of extreme weather and climate events such as heat waves, floods, and droughts [12], which not only adversely affects the ecological environment and agricultural production, but also poses a threat to economic development and human survival [13–15]. Reducing greenhouse gas emissions has become an important task for all governments, especially for the Chinese government. According to a report by the International Energy Agency (IEA), in 2007 China became the world's largest emitter of carbon dioxide, surpassing the United States [16]. As a responsible power, China has pledged to reduce its carbon dioxide emissions per unit of GDP by 60–65% by 2030 relative to 2005 and to achieve carbon peaking [17]. To achieve this goal, the Chinese government has made many efforts, the most important of which is the “low-carbon city pilot policy”.

Due to the high concentration of human activities and energy use, urban areas have become the main areas of CO<sub>2</sub> emissions [18,19]. According to statistics, urban areas, which account for only 2% of the global land area, account for as much as 78% of CO<sub>2</sub> emissions [20]. As urban land continues to expand, it further contributes to the increase of CO<sub>2</sub> emissions [21,22], while the reduction of ecological land weakens its carbon sequestration function, making the situation even more critical [23,24]. In response to this, the Chinese government launched and implemented the “Low-Carbon City Pilot Policy” in 2010, with the aim of reducing urban carbon emissions to ensure that China's greenhouse gas emission control targets are met. The scope of the pilot was then further expanded in 2012 and 2017. Considering the link between carbon emissions, urbanization, and land use [25], an important question to ponder is: What is the effect of the pilot low-carbon city policy on urban land use efficiency while achieving the goal of reducing carbon emissions? Is it positive or negative? Or is there no impact? The answer to this question will help to provide a more comprehensive understanding of the impact of the pilot low-carbon city policies.

To answer the above questions scientifically, the biggest challenge in this study was the endogeneity issue that is prevalent in the literature. In the case of this study, the selection of low-carbon city pilots was not random: the pilot cities and non-pilot cities themselves differ in terms of geographic location and level of economic development, and these unobservable characteristics may have an impact on urban land use efficiency, resulting in biased results from direct regressions that cannot properly assess the policy effects of low-carbon city pilots [26]. Therefore, this study treats the pilot low-carbon city policy as a quasi-natural experiment by using the difference-in-differences method to control for area fixed effects and time fixed effects, to mitigate the influence of unobservable factors on the empirical results and to obtain correct policy evaluation results. In addition, later in the study, the data are pre-processed using propensity matching scores to keep the characteristics of the pilot cities and non-pilot cities as similar as possible, so as to weaken the influence of selection bias on the policy evaluation, and then regressed using the difference-in-differences method as a robustness check.

Unlike previous studies, the marginal contributions of this study are mainly in the following aspects: first, from the perspective of research, low-carbon city construction is an important tool for low-carbon governance by the government, but its impact on urban land use efficiency has not received much attention. This study also assesses the impact of the policy on urban carbon emissions, which to a certain extent enriches and expands the evaluation of the effect of the pilot policy on low-carbon cities. Second, from the perspective of index measurement, this study uses the global reference super-efficiency SBM model to measure urban land use efficiency based on a low-carbon perspective and CO<sub>2</sub> emissions as a non-desired output, which provides a new idea for measuring urban land use efficiency and solves the problem of incomparability of traditional urban land use efficiency indicators across time. Thirdly, from the perspective of research methodology,

this study treats the pilot low-carbon city policy as a quasi-natural experiment and adopts the difference-in-differences method to examine the effect of low-carbon urban governance on urban land use efficiency, which solves the endogeneity problem commonly found in the previous literature and allows for more rigorous research findings.

The remainder of the study is structured as follows: Section 2 review of the previous literature; Section 3 is an introduction to the background of low-carbon city pilot policy development and implementation; Section 4 is a theoretical analysis of the policy effects of low-carbon city pilots; Section 5 is the construction of an econometric regression model and a description of the variable measures and data; Section 6 provides empirical results and analysis; and Section 7 draws conclusions and makes policy recommendations.

## 2. Literature Review

At present, relevant research on low-carbon city construction and urban land use efficiency are mainly focused on the following aspects.

The first is the evaluation of the policy implementation effect of the low-carbon city pilot. In terms of methods, there are mainly two types of methods. The first type is to evaluate the policy from the low-carbon pilot areas themselves, based on the changes in their carbon emission performance before and after the pilot [27]; the second one is using the difference-in-differences method to compare the pilot and non-pilot areas to evaluate the effect of low-carbon pilot policies [28,29], so that the net effect of low-carbon pilot policies can be obtained, which is also the most popular method for policy evaluation at present. In terms of the effect on carbon emissions, the results are inconsistent. The research results of Huo et al. show that the low-carbon city policy can reduce the annual carbon emissions of pilot cities by about 2.72% [29]. Feng came to the opposite conclusion after evaluating the effect of low-carbon pilot policies in East China, finding that the implementation of low-carbon city pilot policies instead increased carbon emissions in the pilot cities [30]. There are also studies showing that low-carbon city pilot policies have no significant effect on the carbon emissions of pilot cities [31]. In addition, some studies have focused on other effects of low-carbon city policies, such as the effects on air quality, health of residents and green growth [32–34].

The second is the measurement of urban land use efficiency and the analysis of its influencing factors, which vary greatly depending on the method and purpose of the study. System efficiency evaluation has gradually developed from the initial single factor input and single output to multiple factors input and multiple output input–output [35–37], and some studies have measured urban land use efficiency by constructing a comprehensive index evaluation system [38–40], but it is difficult for this to be widely recognized because of its different focus and strong subjectivity. From the perspective of models for evaluating the efficiency of input–output systems, there are mainly two commonly used models, namely stochastic frontier analysis [41] and data envelopment analysis [36,37]. Data envelopment analysis has been more widely used by virtue of its ability to measure multi-input and multi-output models without setting the production function, which is also the measurement model used in this study. Finally, urban land use efficiency is influenced by many factors, including the level of economic development, economic structure, government regulation and control, technological progress, and foreign economic ties [5,36,42,43], which directly or indirectly affect urban land use efficiency.

In summary, there has been extensive research in the literature on the efficiency effects of low-carbon city policies, but no studies have examined the effects of low-carbon city policies on urban land use efficiency. At the same time, the connotation and measurement of urban land use efficiency has been more fully discussed, which will help us to carry out the next step. Therefore, this paper uses the low-carbon city pilot policy as a quasi-natural experiment and adopts the difference-in-differences method to assess the impact of the low-carbon city pilot policy on urban land use efficiency, hoping to provide new ideas for improving urban land use efficiency.

### 3. Policy Background

The rapid development of urban economy is accompanied by a large amount of energy consumption and greenhouse gas emissions increase year by year. In 2017, China’s urban areas accounted for 70% of the country’s total carbon emissions [44]. To reduce greenhouse gas emissions, the state has launched a series of policies and guidelines one after another. The “Notice on Launching Pilot Work in Low-Carbon Provinces and Low-Carbon Cities” (the “Notice”) identified five provinces (Guangdong, Liaoning, Hubei, Shaanxi, and Yunnan) and eight cities (Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, and Baoding) as pilot low-carbon cities. The “Notice” identifies five tasks, including the preparation of a low-carbon development plan, the formulation of supporting policies to support low-carbon green development, the establishment of an industrial system characterized by low-carbon emissions, the establishment of a carbon emissions statistics and management system, and the promotion of a low-carbon ‘green’ lifestyle, requiring each pilot city to actively explore a low-carbon green development model that matched the local situation. Subsequently, in April 2012, the second batch of low-carbon city pilots was organized and in November of the same year, the “Notice on the Second Batch of National Low-Carbon Provinces and Low-Carbon Cities Pilots” was issued, adding Hainan Province and the other 28 cities as low-carbon pilot cities. In 2017, the National Development and Reform Commission continued to add 45 cities (districts and counties), including Wuhai City, Inner Mongolia Autonomous Region, to carry out the third batch of low-carbon city pilot projects. The distribution of the first and second batch of pilot cities is shown in Figure 1.

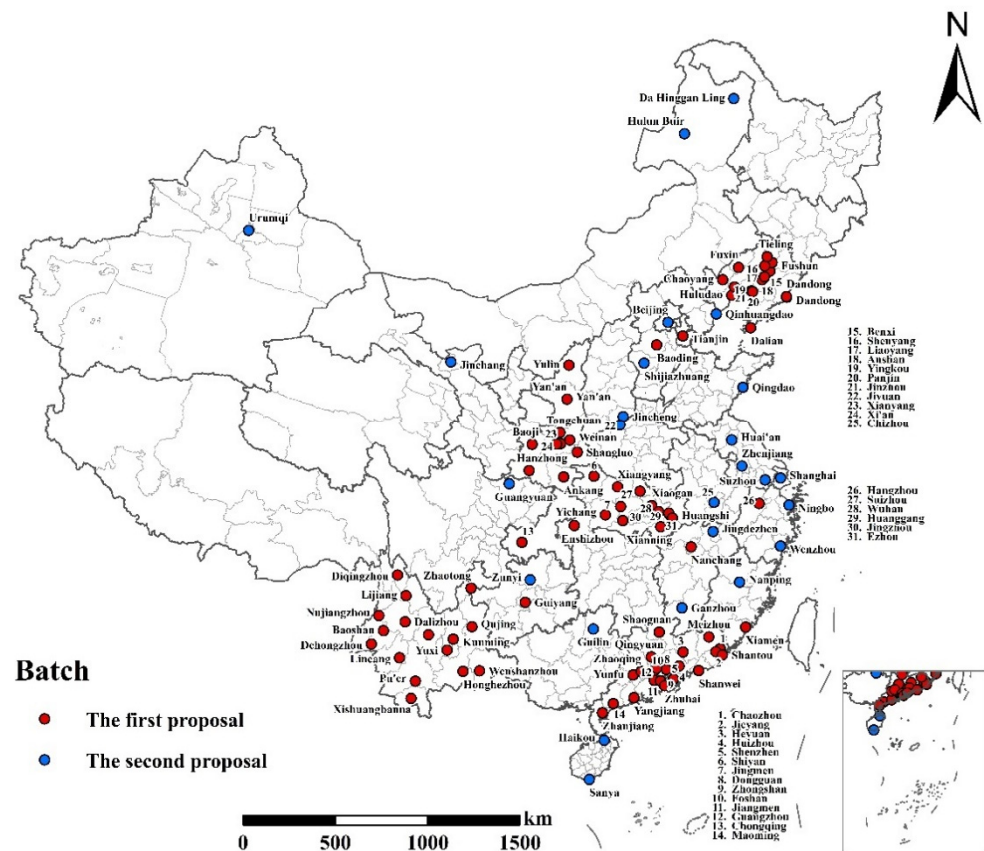


Figure 1. The distribution of the first and second batch of pilot cities.

Throughout the three batches of pilot projects, the provinces were the main pilots in the early days, and projects then gradually spread to districts and counties. From the perspective of the selection mechanism, the initial batch of pilots was established from the top down, while the second and third batches of regions and cities had additional

bottom-up declaration and expert assessment sessions, which were more fair and equitable in terms of procedures. From the perspective of each pilot region itself, it contains both first-tier cities and regions with lower levels of economic development, with a wide variation in geographical location, resource endowment, and stage of economic development in each region, which are well represented. Considering that the second batch was declared from the bottom up, this may have caused self-selection bias and prevented an accurate assessment of the policy effect. For the third batch of pilots, the impact is smaller, and the data are incomplete due to the late implementation of the policy and the short impact period. Accordingly, we mainly assess the policy effects for the first batch of low-carbon pilot cities.

#### 4. Theoretical Analysis

The temperature increases and environmental pollution caused by excessive carbon emissions are considered to have the characteristics of negative externalities. Pigou believes that when negative externalities occur in economic activities, the government can internalize the externalities by imposing taxes on the enterprises causing the negative externalities [45]. Coase put forward a different point of view; he believes that when property rights are clear, the negative externalities can be solved through market transactions, which is also the theoretical basis of the emissions trading mechanism [46]. Based on Coase's theory, Dales proposed that the emission of pollutants is the property right granted by the government to the pollutant-discharging enterprises, and the emission rights can be transferred through market transactions, so as to use the market mechanism to improve the efficiency of environmental pollution control [47].

Based on the above theories, low-carbon city pilot policies use a combination of environmental regulation tools to reduce carbon emissions, such as command and control, market incentives, and public participation [48]. On the one hand, facing the assessment pressure of low-carbon policies, local governments have introduced stricter low-carbon environmental regulation policies and improved the policy system to match the low-carbon policies [49]. For example, the actions of manufacturers are regulated through more stringent emission permits and tax controls. Specifically, levying carbon emission taxes and energy taxes on manufacturers and users of energy with high carbon emissions, etc., increases the production costs of enterprises in industries with high energy consumption and high pollution emissions, and reduces the usage of highly polluting energy sources such as coal, improving energy efficiency and thereby reducing carbon emissions [50,51]. On the other hand, the local government can build a carbon emission trading market to trade carbon dioxide emission rights as a special commodity, using the market mechanism to achieve a reasonable allocation of carbon emission rights, and at the same time, the market revenue also promotes enterprises to carry out energy saving and emission reduction, innovation, upgrading, and other production activities [52]. In addition, the government also encourages residents to participate in the supervision of environmental regulation policies to strengthen public recognition of the concept of low-carbon 'green' energy, to develop a low-carbon green lifestyle, increase green consumption demand and guide enterprises to low-carbon green production [53].

While low-carbon cities use a combination of environmental regulation tools to reduce carbon emissions, they can also have other impacts. The Porter hypothesis suggests that strict and appropriate environmental regulations could stimulate firms to develop new technologies, thereby offsetting environmental costs and increasing their productivity and market competitiveness, achieving a win–win situation for both profitability and environmental protection [54]. However, Deng and Zhan found that the low-carbon city pilot policy did not significantly increase the level of investment in innovation [55], and the effect of the Porter hypothesis did not emerge. In fact, under the pressure of environmental regulations, enterprises are more inclined to reduce their productive inputs to reduce pollution emissions, resulting in low productivity [56–58] and lower land use efficiency. For industrial enterprises in particular, the rapid expansion of industrial land is considered

to be one of the main sources of growth in CO<sub>2</sub> emissions [59,60]. Low-carbon city pilot policies with the primary objective of reducing carbon emissions inevitably have a knock-on effect on industrial enterprises, prompting them to reduce production to achieve carbon emission reductions, thereby reducing the efficiency of industrial land use. Yao and Shen assessed the policy effects of the pilot low-carbon city policy on air quality and economic development and showed that while the pilot low-carbon city policy improved air quality, it reduced labor productivity [61], indirectly supporting the above argument. Moreover, according to the 'pollution sanctuary' hypothesis, strict environmental regulations also have a crowding-out effect on foreign direct investment (FDI), reducing local investment by multinational firms [62]. At the same time, government intervention can also affect the global flow of resources, which in turn has a negative impact on corporate exports [63]. These not only limit local economic development, but also create distortions in factor allocation, thereby reducing the efficiency of local land use.

Based on the above analysis, this study proposes the following two hypotheses.

**Hypothesis 1.** *Low-carbon city pilot policies will reduce urban carbon emissions.*

**Hypothesis 2.** *Low-carbon city pilot policies will have a negative impact on urban land use efficiency.*

## 5. Methodology and Data

### 5.1. The DID Model

The traditional approach to policy evaluation is to set up a dummy variable for the occurrence or otherwise of a policy and then run a regression, which often yields biased estimates. Compared to traditional methods, the difference-in-differences models are more scientific, easier to understand and apply, and largely reduce the effects of endogeneity [64], so that the policy effect can be more accurately estimated, and it is widely used in the field of policy effect evaluation [65]. In this study, a quasi-natural experiment was conducted to test the impact of a pilot low-carbon city policy on urban land use efficiency using the difference-in-differences models. The specific model is shown in Equation (1).

$$Y_{it} = \beta_0 + \beta_1 \times treat_i \times post_t + \beta X_{it} + \theta_i + \rho_t + u_{it}, \quad (1)$$

where  $i$ ,  $t$  denote city and year respectively,  $Y$  denotes urban land use efficiency (ULUE);  $treat$  denotes the dummy variable for the treatment group. In this study we mainly assessed the policy effect of the first batch of low-carbon pilot cities, so we gave a value of 1 to the cities is the first batch of pilot cities and 0 for other years;  $post$  denotes the policy dummy variable, as the pilot policy was released in the second half of 2010. Since the pilot policy was released in the second half of 2010, we set 2011 as the time of policy implementation, so it was marked as 1 when the year was greater than 2010 and 0 for other years;  $X$  represents a set of control variables;  $\theta$  represents the individual control effect, and  $\rho$  represents the year control variable, so that this constitutes a double fixed effect and  $u$  is the random error term.

Selection of control variables: In order to avoid missing variables and drawing on relevant studies, we selected the following control variables.

- (1) Economic level: economic development, and land use efficiency are closely linked, and usually areas with high levels of economic development have higher land use efficiency, so we used GDP per capita to measure economic level [36].
- (2) Population density: Population density has a two-way effect on urban land use efficiency, both positively through resource aggregation and by increasing congestion costs and environmental pressures, which inhibit the improvement of urban land use efficiency, so we used the number of people per unit area [2].

- (3) Industrial structure: The optimization of industrial structure can promote the intensive use of urban land and thus affect urban land use efficiency, which we have expressed as the ratio of secondary industry to GDP [36].
- (4) Financial level: Financial capital can have an impact on land use patterns, structure and efficiency, which we have expressed using the ratio of year-end financial institution deposit and loan balances to GDP [66].
- (5) Government intervention: Government intervention can distort the role of the market in the rational allocation of resources and thus affect the efficiency of urban land use, which we have expressed using the ratio of general budget expenditure to GDP.
- (6) Transportation levels: These increase both accessibility and urban sprawl [67], so we used the actual urban road area per capita at the end of the year.

To reduce the effect of heteroscedasticity, we calculated a natural logarithm of economic level, population density, and traffic level. The specific information of each variable is shown in Table 1.

**Table 1.** Description of variables.

Variable	Symbol	Index
Treatment group dummy variable	treat	1 for the first batch of pilot cities, 0 for the rest
Policy dummy variable	Post	1 for years > 2010, 0 for all others
Economic level	ln_rgdp	GDP per capita
Population density	ln_den	Number of people per unit area
Industrial structure	stru	Ratio of secondary sector to GDP
Financial development	fina	Balance of deposits and loans of financial institutions at the end of the year as a percentage of GDP
Government intervention	gover	General public budget expenditure as a percentage of GDP
Transport level	ln_road	Real urban road area per capita at the end of the year

## 5.2. Measuring Urban Land Use Efficiency

### 5.2.1. Global Super-SBM Model

The data envelopment analysis (DEA) model was first introduced in 1978 by Charnes et al. It evaluates the relative effectiveness of comparable objects by using a linear programming approach based on multiple input and multiple output indicators [68]. DEA models have the advantage that when using them it is not necessary to use a validated production function, but only real data, especially for multi-indicator input and multi-indicator output, so DEA models and their derivatives are widely used for efficiency evaluation in various fields [69]. After decades of development, the initial DEA models have been continuously refined. Among them, Huang et al. proposed a super-efficient SBM model that takes into account the global covariance of non-expected output [70]. This model integrates slack variables, and non-expected outputs, and allows further differentiation of the efficiency of decision units for situations with multiple effective decision units at the same time. Furthermore, the efficiency values can be compared across time, which is a relatively perfect remedy to the shortcomings of traditional DEA models. Therefore, this study uses the global super-SBM model to measure urban land use efficiency, which is constructed as follows.

Assuming that there are  $N$  decision-making units (DUMs) with a total of  $T$  observation periods, each decision-making unit has three types of elements: input, desired output, and non-desired output. The input–output variables of the  $i$  ( $i = 1 \dots, N$ ) DUMs in period  $t$  ( $t = 1 \dots, T$ ) can be expressed as:  $x_{it} \in R^m$ ,  $y_{it}^g \in R^{s_1}$  and  $y_{it}^b \in R^{s_2}$ , where  $m$ ,  $s_1$ , and  $s_2$ , respectively, represent the number of the three types of elements. Then the efficiency value

of the  $i$ th decision unit in period  $t$  can be obtained by solving the following plan as shown in Equation (2) [70].

$$\begin{aligned}
 \rho_{it}^* &= \min \frac{1 + \frac{1}{m} \sum_{k=1}^m \frac{s_{kit}^-}{x_{kit}}}{1 - \frac{1}{s_1 + s_2} \left( \sum_{r=1}^{s_1} \frac{s_{rit}^g}{y_{rit}^g} + \sum_{r=1}^{s_2} \frac{s_{rit}^b}{y_{rit}^b} \right)} \\
 x_{it} - \sum_{j=1(j \neq i, \text{if } \tau=t)}^N \sum_{\tau=1}^T \lambda_{j\tau} x_{j\tau} + s_{it}^- &\geq 0 \\
 \sum_{j=1(j \neq i, \text{if } \tau=t)}^N \sum_{\tau=1}^T \lambda_{j\tau} y_{j\tau}^g - y_{it}^g + s_{it}^g &\geq 0 \\
 y_{it}^b - \sum_{j=1(j \neq i, \text{if } \tau=t)}^N \sum_{\tau=1}^T \lambda_{j\tau} y_{j\tau}^b + s_{it}^b &\geq 0 \\
 1 - \frac{1}{s_1 + s_2} \left( \sum_{r=1}^{s_1} \frac{s_{rit}^g}{y_{rit}^g} + \sum_{r=1}^{s_2} \frac{s_{rit}^b}{y_{rit}^b} \right) &\geq \varepsilon \\
 \lambda_{it}, s_{it}^-, s_{it}^g, s_{it}^b &\geq 0
 \end{aligned} \tag{2}$$

where  $s_{it}^-$ ,  $s_{it}^g$ ,  $s_{it}^b$ , respectively represent the slack variables corresponding to inputs, desired outputs, and non-desired outputs;  $\varepsilon$  is non-Archimedean infinitesimal. This equation can be transformed into a linear program by using Charnes–Cooper, and then solved to obtain the value of  $\rho_{it}^*$  for each decision unit in each period, which is the urban land use efficiency of each city in each year [71]. The larger the efficiency value, the more efficient the city’s land use is, and when  $\rho_{it}^* \geq 1$ , the city has reached the efficiency frontier in that year. In addition, this equation assumes a constant payoff to scale; if it is necessary to assume a variable payoff to scale, it is sufficient to add Equation (3) to the constraints.

$$\sum_{j=1(j \neq i, \text{if } \tau=t)}^N \sum_{\tau=1}^T \lambda_{j\tau} = 1 \tag{3}$$

### 5.2.2. Selection of Indicators

**Input indicators:** Classical economic growth theories consider capital and labor to be the basic elements of economic development, thus ignoring the role of the land element, which is included in the factor inputs in order to meet the basic connotation of urban land use efficiency [72]. Therefore, there are three types of factor inputs: land, labor, and capital. In this study, the urban built-up area reflects the land input status of the city; the number of people employed in secondary and tertiary industries in the city reflects the labor input status, because the city is the place where the non-farm economy is concentrated and people in the city are mainly engaged in secondary and tertiary industries. The capital stock is selected to reflect the capital input, as there is no data on the capital stock; it is measured by the perpetual inventory method based on Tang et al. [37].

**Output indicators:** Output is divided into desired and undesired outputs. Economic development is the goal of both productive and service activities; therefore, this study uses economic output as the desired output, measured by the gross value of secondary and tertiary industries within the municipal area. As shown above, the city has a predominantly non-farm economy concentration. We assumed that there are no primary industries in built-up areas, rather than no secondary or tertiary industries in unbuilt-up areas. As shown above, the city has a predominantly non-farm economy concentration.

We assumed that there are no primary industries in built-up areas, rather than no secondary or tertiary industries in unbuilt-up areas. Generally, this error is acceptable [9].  $CO_2$  is inevitably produced during human activities and land development, which is the most direct manifestation of the environmental impact of urban economic activities. Therefore,  $CO_2$  emissions were selected as the non-desired output in this study. For the measurement of  $CO_2$ , refer to Shan et al. [73]; it will not be repeated here.

The specific information of each indicator variable is shown in Table 2.



**Table 2.** Input-output index table.

Variable Type		Index
Input	Land	The urban built-up area
	Capital	The capital stock
	Labor	The number of people employed in secondary and tertiary industries in the city
Output	Economic	The gross value of secondary and tertiary industries within the municipal area
	Undesired	CO <sub>2</sub> emissions

### 5.3. Data Source

All indicator data used in this study are from the China Urban Statistical Yearbook 2006–2017, except for CO<sub>2</sub>, which is sourced from scientific data, with some missing data supplemented by local statistical yearbooks, government gazettes, or interpolation. In order to avoid the effects of price changes, we have used price indices to convert to constant prices for the base period 2005. It is interesting to note that due to the effect of merging districts and counties, the data for some municipal districts are not comparable before and after the merger. Therefore, this study removed cities that have changed their municipal administrative areas during the study period. At the same time, as this study focuses on the policy effects of the first batch of pilot cities, we also removed the second and third batches of pilot cities. In the end, a panel dataset of 186 cities over 12 years was constructed, with descriptive statistics for the variables shown in Table 3.

**Table 3.** Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
ULUE	2232	0.227	0.138	0.034	1.126
treat	2232	0.253	0.435	0	1
Post	2232	0.5	0.5	0	1
gover	2232	0.161	0.095	0.032	1.428
fin	2232	2.651	1.224	0.213	10.187
ln_den	2232	7.944	0.848	3.296	9.908
ln_rgd	2232	10.202	0.67	7.887	13.87
stru	2232	0.503	0.126	0.08	0.91
ln_road	2232	2.178	0.624	−1.177	4.685

## 6. Results

### 6.1. Trends in Urban Land Use Efficiency

This study used MaxDEA software to calculate the urban land use efficiency values for each city and make a time series plot of the average value of urban land use efficiency over the years, as shown in Figure 2. From an overall perspective, the average value of urban land use efficiency for all years from 2005 to 2016 ranged from 0.19 to 0.31, which is much less than 1. The average level was lower, the overall DEA was not achieved effectively, and there is still great potential. From the perspective of time progression, before the implementation of the policy, urban land use efficiency was in a state of long-term decrease, but the decreasing trend gradually eased, which is in line with China's early economic development model, where the economic development model of high inputs, high consumption and high emissions resulted in low urban land use efficiency [74]; after the implementation of the policy, urban land use efficiency experienced a short period of decrease and then gradually stabilized and had an upward trend, which may be related to China's gradual change of development model.



**Figure 2.** The time trend of the mean urban land use efficiency.

The “parallel trend hypothesis” is one of the important prerequisites for the use of difference-in-differences [75]. For this study, satisfying the parallel trend hypothesis meant that the time trend changes in urban land use efficiency for the treatment and control groups should be consistent as far as possible before the implementation of the pilot low-carbon city policy; this similar time trend change would break down after the policy is implemented. Therefore, we plotted the time trend of the mean urban land use efficiency for the treatment and control groups, as shown in Figure 3. It can be seen that the urban land use efficiency of the treatment group was higher than that of the control group, and both were on a decreasing trend. It can be seen that the urban land use efficiency of the treatment group was higher than that of the control group, and both were on a decreasing trend. Before the implementation of the policy, the time trend of urban land use efficiency of the treatment group and the control group was basically the same, which satisfies the “parallel trend hypothesis”; after the implementation of the policy, the urban land use efficiency of the treatment group decreased faster than that of the control group, which also provides preliminary evidence for this paper to predict that the low-carbon city pilot policy reduces urban land use efficiency.

### 6.2. Characteristics of the Spatial Distribution of Urban Land Use Efficiency

To further study the spatial distribution of urban land use efficiency of cities in China, limited by space, this study selects four years, 2005, 2009, 2012, and 2016, to draw a spatial distribution map of urban land use efficiency, as shown in Figure 4. As can be seen from the images, the early urban types were mainly medium-low efficiency and low efficiency, accounting for 62% and 32% of the total, respectively, while there were only six high-efficiency cities, and their distribution is relatively scattered. In the later period, most cities with low efficiency were 86%. The reason is local governments are excessively pursuing economic interests, blindly increasing the input of urban land elements, and enthusiastically pursuing high energy consumption and high emission production methods. This crude development model has resulted in the inefficient use of urban land, which has been declining year by year.

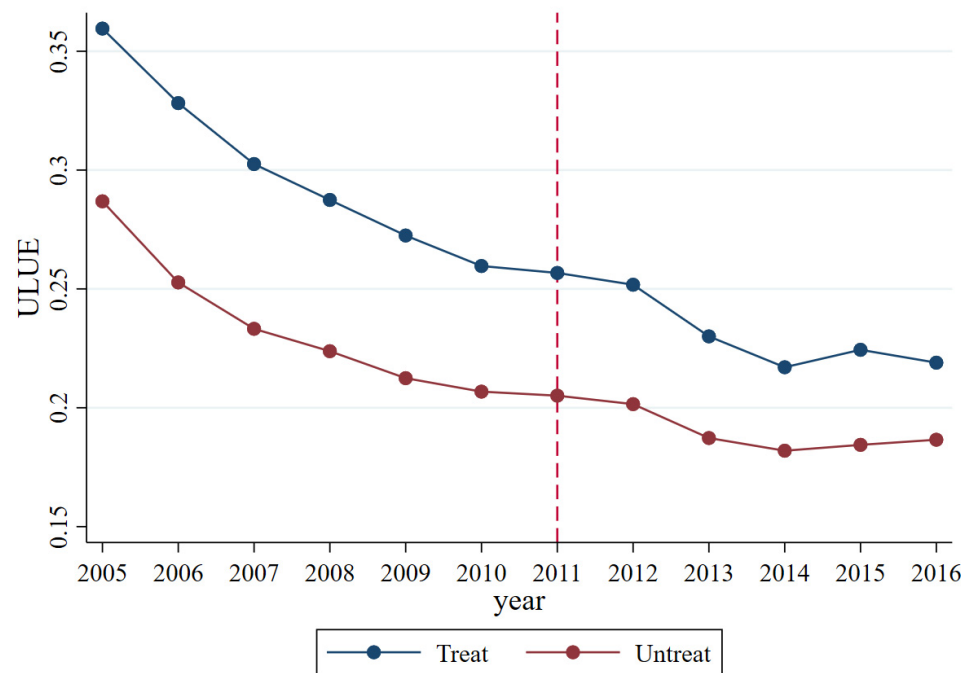


Figure 3. The time trend of the mean urban land use efficiency for the treatment and control groups.

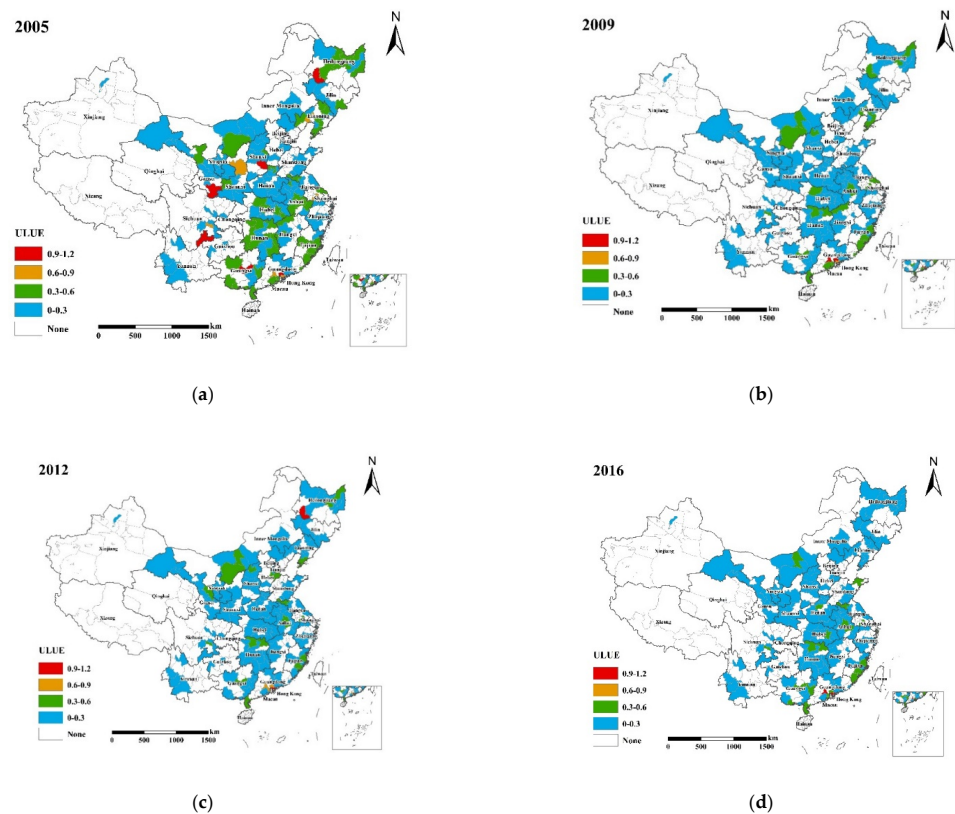


Figure 4. The spatial distribution diagram of urban land use efficiency. (a) The spatial distribution diagram of urban land use efficiency in 2005. (b) The spatial distribution diagram of urban land use efficiency in 2009. (c) The spatial distribution diagram of urban land use efficiency in 2012. (d) The spatial distribution diagram of urban land use efficiency in 2016.

In terms of distribution characteristics, the urban land use efficiency of southern cities was higher than that of northern cities, with coastal cities in Guangdong performing the best, consistently at a higher level of urban land use efficiency and showing an obvious

spatial agglomeration. Their land use experience should be adopted by other cities. The low land use efficiency in northern cities is partly due to the fact that northern cities are dominated by heavy industry and are limited by climatic conditions. Northern cities have a need for heating in winter, which makes their carbon emissions much higher than those of southern cities [76], and the increase in undesired outputs results in low land use efficiency; on the other hand, there is a gap between the economic development level of northern cities and southern cities, which also results in low land use efficiency in southern cities. In the case of Guangdong, its proximity to Hong Kong and Macau has provided good conditions for the development of its trade and service sectors. In addition, land use efficiency is generally low in central and western cities, which may be related to the fact that the central government has given more construction land targets to the central and western regions. More construction land targets have prompted local governments to overdevelop and further exacerbate the inefficient use of local construction land.

### 6.3. Baseline Regress

The effect of China's policy has been questioned for a long time. For this reason, this study assessed the impact of the pilot low-carbon city policy on carbon emissions and urban land use efficiency using the difference-in-differences method, and the results are shown in Table 4, where (1) is the regression result on carbon emissions and (2) is the regression result on urban land use efficiency. It can be seen that the coefficient of the interaction term is significantly negative regardless of whether the explanatory variable is carbon emissions or urban land use efficiency. The result indicates that the implementation of the low-carbon city pilot policy has had a negative impact on urban land use efficiency while reducing carbon emissions. From the perspective of economic significance, the implementation of the policy reduced carbon emissions by an average of 4.57% and reduced urban land use efficiency by an average of 0.0283. Considering that the mean urban land use efficiency of the treatment group before the implementation of the policy was 0.3016, the implementation of the policy reduced the urban land use efficiency by an average of 9.38%, which is a very significant reduction and confirms our previous hypothesis.

**Table 4.** Results of the two estimations for the effects on CO<sub>2</sub> and ULUE.

Variable	(1) ln_C	(2) ULUE
Treat × post	−0.0457 ** (0.0185)	−0.0283 * (0.0155)
ln_rgd	0.0778 *** (0.0241)	0.0385 ** (0.0159)
stru	0.177 * (0.0947)	0.0643 (0.0615)
ln_road	0.0292 (0.0185)	−0.0186 ** (0.0088)
fina	0.0114 * (0.00656)	−0.0129 ** (0.0052)
gover	0.0443 (0.0799)	−0.0838 ** (0.0327)
ln_den	0.00407 (0.00834)	0.0028 (0.004)
Constant	0.496 * (0.272)	−0.0467 (0.161)
Year fixed	Yes	Yes
City fixed	Yes	Yes
Observations	2232	2232
R-squared	0.848	0.295

Note: Robust standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

From the perspective of the control variables, it is intuitive that the level of economic development, industrial structure, and financial development all have a positive effect on carbon emissions. The higher the level of economic development, the more productive activities there are, and the energy use grows, which promotes CO<sub>2</sub> emissions. The secondary sector is characterized by high energy consumption and high emissions. The larger the share of the secondary sector, the more prominent the carbon emissions. In the case of financial development, financial institutions are motivated by profits to invest in enterprises with high capital and energy consumption, thus stimulating carbon emissions. Economic development has a positive impact on urban land use efficiency, while transport levels, financial development, and government intervention all significantly reduce urban land use efficiency. The increase in the level of economic development has a positive effect on the rational use of factors; for the degree of transport development, on the one hand, the increase in transport development promotes the accessibility of markets, effectively reduces the cost of factor circulation, and improves the efficiency of factor resource allocation, while on the other hand, it expands the urban area, increases the input of land factors and promotes the emission of polluting gases from transport. Obviously, its negative effects are greater than the positive ones. The financial and governmental actions are both a way of allocating resources, and to pursue economic efficiency, they tend to allocate resources to industries with high short-term profitability but high pollution, resulting in factors not being allocated in a reasonable and rational manner.

#### 6.4. Robustness Tests

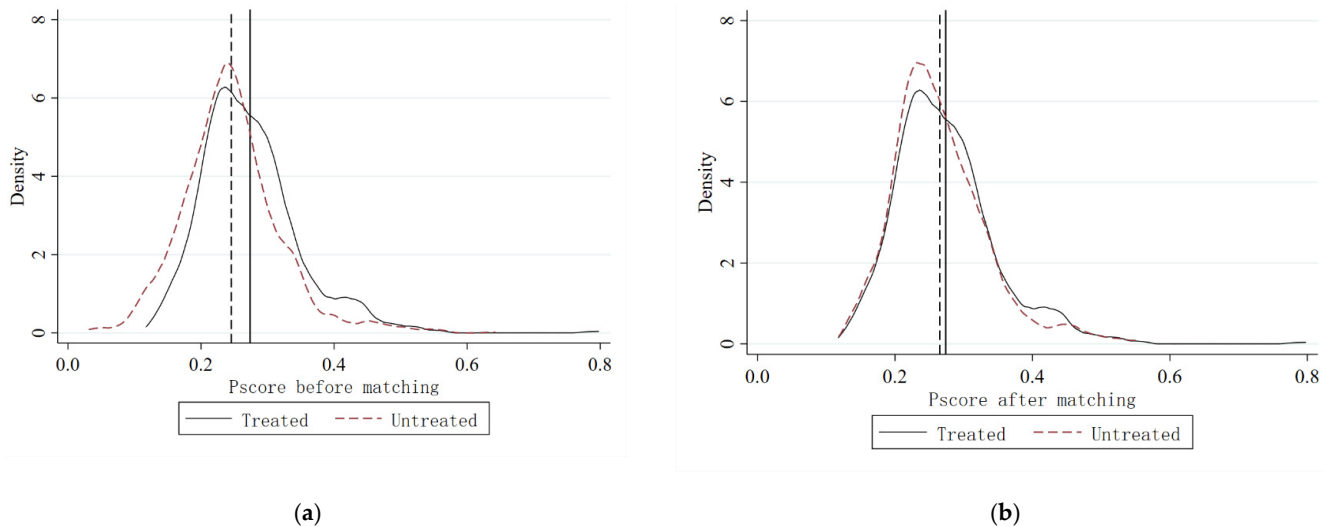
Although the difference-in-differences method can identify the net effect of the low-carbon city pilot policy and reduce the endogenous effects well, there may still be some unobservable factors that affect both the establishment of pilot cities and urban land use efficiency, resulting in a selection bias that biases the estimation results. For this reason, this study used the propensity score matching method (PSM) to match the data so that the treatment and control group of cities were as similar as possible in all aspects of their characteristics, eliminating the selection bias. Table 5 shows the equilibrium tests for the variables. It can be seen that the post-match deviations for all variables in the treatment and control groups were much smaller than the pre-match deviations, with the absolute values of the deviations falling by 79.7–95.5%. After matching, the *p*-values of all variables were more than 10%, and the original hypothesis of “no systematic bias in the values of the covariates between the two groups” was not rejected.

**Table 5.** Balance test results.

Variable	Matching	Mean		Bias (%)	Reduction of Bias (%)	<i>t</i> -Test	
		Treated	Control			<i>t</i>	<i>P</i> >   <i>t</i>
ln_rgd	Before	10.273	10.178	14.2		2.92	0.004
	After	10.272	10.259	1.9	86.4	0.33	0.741
stru	Before	0.513	0.500	11.1		2.13	0.033
	After	0.513	0.512	0.5	95.5	0.09	0.931
ln_road	Before	2.162	2.1829	−3.3		−0.70	0.487
	After	2.162	2.1858	−3.7	−10.6	−0.63	0.526
fina	Before	2.784	2.6058	14.6		3.00	0.003
	After	2.771	2.8021	−2.5	82.8	−0.39	0.699
gover	Before	0.148	0.16537	−19.8		−3.69	0.000
	After	0.1484	0.14495	4.0	79.7	0.90	0.371
ln_den	Before	8.010	7.922	10.5		2.12	0.034
	After	8.008	7.997	1.3	87.4	0.23	0.821

Further, the kernel density plots of the propensity score (P-score) values of the two groups before and after matching are shown in Figure 5. Figure 5a shows that the probability density distribution of the P-score of the treatment group and the control group were

significantly different before matching, while the probability density distributions of the retained samples converged after matching. This indicates that the urban characteristics of the two groups were very similar after matching. In general, the matching results are relatively satisfactory.



**Figure 5.** The P-score kernel density. (a) P-score before matching. (b) P-score after matching.

After matching the samples, we re-evaluated the policy effects of the low-carbon city pilot and the results are shown in Table 6. It can be seen that the low-carbon city pilot policy reduced CO<sub>2</sub> emissions and urban land use efficiency, and the coefficients did not change from the pre-matching period. The changes in values were small, indicating that the empirical results are robust and reliable.

**Table 6.** Robustness tests.

Variable	(1) ln_C	(2) ULUE
Treat × post	−0.0382 ** (0.0188)	−0.0291 * (0.0160)
Control variable	Yes	Yes
Year fixed	Yes	Yes
City fixed	Yes	Yes
Observations	1278	1278
R-squared	0.869	0.317

Note. Robust standard errors in parentheses. \*\*  $p < 0.05$ , \*  $p < 0.1$ .

### 7. Conclusions and Policy Recommendations

An accurate grasp of the policy effects of low-carbon city construction on urban land use efficiency is of great theoretical and practical significance for further deepening the efficient use of urban land and promoting green and high-quality economic development.

This study considers the “low-carbon city pilot policy” as a quasi-natural experiment. Based on the panel data of 186 cities in China from 2005 to 2016, the urban land use efficiency of each city was measured using the global reference super-efficiency SBM model, and its trend in time and spatial analysis characteristics were analyzed. The difference-in-differences method was used to assess the policy effects of urban low-carbon governance on carbon emissions and urban land use efficiency, and finally the results were tested for robustness using PSM-DID. The conclusions are as follows:

- (1) The overall level of urban land use efficiency in China is low and declining, but the downward trend is slowing down over time.

- (2) The spatial distribution is relatively scattered and does not show a large-scale spatial agglomeration of highly efficient cities; only Guangdong Province shows a small-scale agglomeration of highly efficient cities.
- (3) On average, the low-carbon city pilot policy reduced carbon emissions by 4.57%, but at the cost of a 9.38% reduction in urban land use efficiency.

The above conclusions indicate that the intended policy objectives of China's low-carbon city pilot policy for carbon emission reduction have been achieved, but its incentive capacity for rational factor allocation is weak. Based on the above conclusions, this study puts forward the following policy recommendations. First, the government should use a more reasonable land use evaluation index system when planning urban land use and should focus on its environmental impact while pursuing economic development. Second, in low-carbon construction, enterprises should adopt more "market-incentive" environmental regulation tools, build a market-oriented green technology innovation system, and increase their enthusiasm for innovation and upgrading, energy saving and emission reduction. Thirdly, we should increase support for low-carbon transformation of enterprises and guide them to make clean and low-carbon transformations, such as through tax breaks and government subsidies, to help them get through the "painful period" of low-carbon upgrading and eventually achieve transformation and upgrading of their production mode, to avoid loss of efficiency. Fourthly, we should continue to invest in green technology innovation, continue to promote the development of environmental protection technology, and introduce relevant policies to help the development of new energy industries, energy conservation and environmental protection industries, and other strategic new industries, so as to promote the optimization and upgrading of cities' industrial structure.

In addition, there are some shortcomings in this study that can be addressed in future research. Firstly, due to the influence of sample self-selection, this study only assessed the policy effects of the first batch of low-carbon city pilots; secondly, due to the influence of merging districts and counties, this study excluded cities with changes in the administrative areas of municipal districts, which resulted in the loss of sample data; finally, due to the limitations of data and space, this study did not conduct a more in-depth analysis of the transmission mechanism of the impact of low-carbon city pilot policies on urban land use efficiency, which will be the focus of our next phase of research.

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