# The Impact of Low-Carbon Pilot Provincial and Municipal Construction Policy on Agricultural Carbon Emission Efficiency——Based on SBM-DEA Model and SCM Model

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**Abstract.** Under the current trend of global warming, the issue of agricultural carbon emissions has become one of the key challenges to global sustainable development. Improving agricultural carbon emissions is regarded as an important way to reduce the carbon intensity of agriculture and help achieve the goal of "double carbon". Based on the panel data of 31 provinces in China from 2000 to 2020, this study measures the agricultural carbon emissions of each region, and then analyzes the regional differences in the efficiency of agricultural carbon emissions by using the SBM-DEA model. Finally, the actual impacts of low-carbon pilot policies on the efficiency of agricultural carbon emissions were systematically evaluated through the synthetic control method. The results of the study show that the implementation of the low-carbon pilot provinces and cities construction policy significantly improves the agricultural carbon emission efficiency in most of the pilot provinces, which verifies the positive promotion effect of the policy on agricultural carbon emission efficiency.

**Keywords:** Low Carbon Pilot, SBM-DEA model, Synthetic Control Method, Agricultural Carbon Emission Efficiency.

## 1. Introduction

In recent years, the Chinese government hopes to synergize carbon emission reduction, pollution reduction and green growth through the development of green and low-carbon industries, the improvement of the carbon market mechanism and other important initiatives, so as to provide support for the modernization of beautiful China [1]. Against the backdrop of accelerating global climate change, the knock-on effects of greenhouse gas emissions are profoundly affecting human life. Agriculture presents a significant two-way action mechanism in the process of climate change: on the one hand, droughts, floods and other climate disasters directly food security and rural economy; on the other hand, agriculture itself has become an important source of greenhouse gas emissions such as methane [2].

Existing studies have made progress in agricultural carbon emission research. Huang et al [3] revealed significant geographic heterogeneity in agricultural carbon emissions in different provinces of the province from 1997 to 2016.Wen et al [4] identified effective pathways consistent with China's current efforts to achieve carbon neutrality through the STIRPAT model. Wei et al [5] analyzed carbon neutrality potential and urban agricultural efficiency across 268 Chinese provinces, revealing multidimensional complexity in emission patterns. Zhang et al. [6] applied SBM-DEA models to measure national agricultural carbon emission efficiency, finding widespread inefficiency except in ecological protection zones, with notable north-south clustering. Xi et al. [7] combined dual machine learning with a DID model to assess the impact of the policy on high-quality agricultural development and confirmed the effectiveness of the policy. However, there are limited existing studies focusing on the impacts of low-carbon pilot policies on agricultural emissions, the traditional DID model is difficult to cope with the small sample of pilot policies and regional heterogeneity, and the measurement ignores the dynamics of policy effects. To address these limitations, this study innovatively adopts the synthetic control method (SCM) to assess the impacts of low-carbon pilot policies by constructing optimized counterfactual scenarios, which overcomes the traditional methodological limitations of policy effect assessment. The specific process is shown in Figure 1.

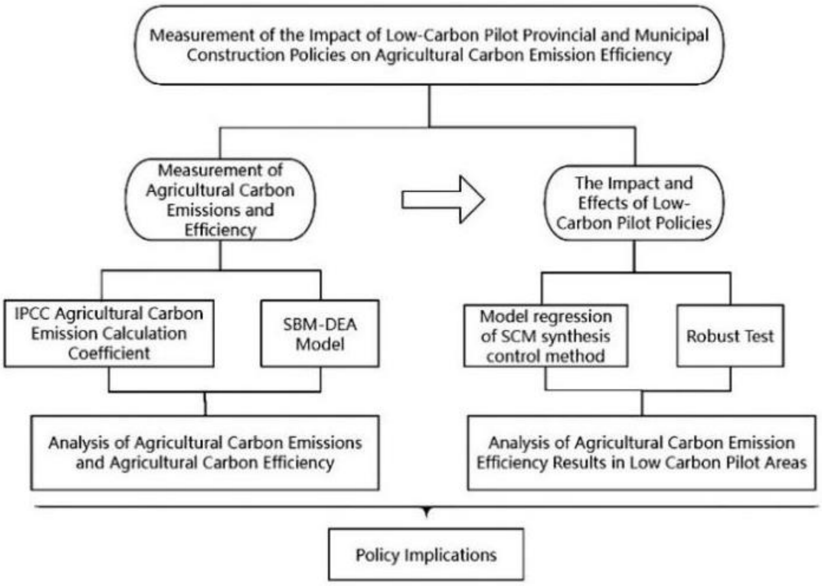

**Figure 1.** Process Framework Diagram

# 2. Model Construction

## 2.1. Measurement of Agricultural Carbon Emissions and Efficiency

This paper adopts the method of carbon emission accounting for farmland utilization, based on the carbon emission coefficient system of the United Nations Intergovernmental Panel on Climate Change (IPCC) [8], and combines the characteristics of the agricultural industry in China's 31 provincial-level administrative districts and the results of the existing research, to construct a model for measuring the total amount of agricultural carbon emissions:

$$C = \sum_{j=1}^{6} C_j = \sum_{j=1}^{6} E_j * F_j, \tag{1}$$

Where $j$ is the type of carbon emission source; $C$ represents the total amount of agricultural carbon emission; $C_j$ represents the agricultural carbon emission of the $j^{th}$ carbon source; $E_j$ is the consumption of the corresponding carbon source; and $F_j$ is the carbon emission factor of the corresponding carbon source. The specific carbon source types, emission coefficients and data sources are shown as Table 1.

**Table 1.** Agricultural Carbon Emission Sources, Factors and Reference Sources

| Classification of Carbon Sources | Emission Factor | Origins |
|---|---|---|
| Farming Inputs | Fertilizer | 0.8956kg(C)/kg |
| | Pesticides | 4.9341kg(C)/kg |
| | Agricultural Film | 5.18kg(C)/kg |
| Farm Machinery Use | Diesel | 0.5927kg(C)/kg |
| Farmland Management | Irrigation | 19.8575kg(C)/hm$^2$ |
| | Plowing | 3.126kg(C)/hm$^2$ |

## 2.2. Measurement of Agricultural Carbon Emission Efficiency in SBM-DEA Modeling

The carbon emission efficiency assessment model adopts the improved SBM-DEA model with reference to the method of scholar Tone, which effectively deals with the problem of multiple inputs and multiple outputs in agricultural production. The model sets 31 provinces in China as independent decision-making units (DMUs). The input indicators are set as fertilizer application, pesticide use, diesel consumption, irrigated area, film use, sown area, desired output indicator is set as gross agricultural output value, and non-desired output indicator is set as agricultural carbon emission. In each decision unit, the elements of input index, desired output index and undesired output index are denoted as $a \in R_m, b^e \in R_{S1}, b^u \in R_{S2}$. Define matrix $X = (x_{ij}) \in R_{m\times n}, Y^e = (y_{ij}^e) \in R_{S1\times n}, Y^u = (y_{ij}^u) \in R_{S2\times n}$. According to the real situation $X > 0, Y^e > 0, Y^u > 0$. The set of production possibilities $P = \{(x, y^e, y^u) | x \geq X\lambda, y^e \geq Y^e\lambda, y^u \geq Y^u\lambda, \lambda \geq 0\}$ is all the combinations of desired and non-desired outputs produced by M factor inputs and λ is the weight vector. The SBM model for evaluating DMU efficiency when considering non-desired output is as follow.

$$\rho^* = min \frac{1-\frac{1}{m}\Sigma_{i=1}^{m} S_i^- / x_{i0}}{1+\frac{1}{S_1+S_2}\left(\Sigma_{r=1}^{S_1} S_r^e / y_{r0}^e + \Sigma_{r=1}^{S_2} S_r^u / y_{r0}^u\right)}, \tag{2}$$

$$s.t. \begin{cases} x = X\lambda + S^-, \\ y_0^e = Y^e\lambda + S^e, \\ y_0^u = Y^u\lambda + S^u, \\ S^- \geq 0, S^e \geq 0, S^u \geq 0, \lambda \geq 0, \end{cases} \tag{3}$$

Where $S_i^-, S_r^e, S_r^u$ are the input redundancy, positive output deficit and compound output overrun of the $i_0{}^{th}$ DMU, and $S^-, S^e, S^u$ are their corresponding vectors. When $\rho^* = 1$, the decision unit reaches the effective state of DEA($S^- = 0, S^e = 0, S^u = 0, \lambda = 0$); when $\rho^* < 1$, ($S^-, S^e, S^u$ are not zero at the same time), there exists the input redundancy or output insufficiency, and the optimization of the production factor allocation is needed. The method overcomes the radial limitation of the traditional DEA model by introducing the relaxation variables $S^-, S^e, S^u$, which can more accurately measure the carbon emission efficiency considering the non-desired outputs, and provides a scientific decision-making basis for the green and low-carbon development of agriculture.

### 2.3. Impact study of the Pilot Policy Based on SCM Model

If regional policy implementation is viewed as a quasi-natural experiment, the observed districts can be divided into two parts, experimental and control, based on whether the districts are subject to policy intervention or not. Assuming that a total of n regions is actually observed, a dichotomous variable D is introduced to indicate whether each region is subject to policy intervention or not, with $D_i$=1 when the region is subject to policy intervention, and $D_i$=0 otherwise. Expressed as a function of:

$$Y_i = \begin{cases} Y_{1i}, D_i = 1, \\ Y_{0i,} D_i = 0, \end{cases} \tag{4}$$

Where Y1i indicates that region $i$ is subject to policy intervention and $\mathrm{Y_{0i}}$ indicates that it is not subject to policy intervention, then $\mathrm{Y_{1i}} - \mathrm{Y_{0i}}$ represents the treatment effect in region $i$. Since it is not possible to observe $\mathrm{Y_{1i}}$ and $\mathrm{Y_{0i}}$ at the same time in the same area, the individual treatment effect is transferred to the group level and assessed with average effect of $Y$. Assuming that there are $\mathrm{n_1}$ experimental group areas and $\mathrm{n_0}$ control group areas, the output of the experimental group that received the intervention is denoted as $\mathrm{Y_{1i}}$, and the output of the control group that did not receive the intervention is denoted as $\mathrm{Y_{0i}}$. The treatment effect for the experimental group is:

$$T_i = Y_{1i} - Y_{0i} (i = 1,2,3, \dots, n_1), \tag{5}$$

If multiple estimators exist, matrix $\mathrm{V_i}$ is introduced to derive average treatment effect:

$$\tau = \frac{1}{n_1}\sum_{i=1}^{n} Y_i D_i - \frac{1}{n_0}\sum_{i=1}^{n} Y_i (1 - D_i) V_i, \tag{6}$$

The weights of the control group areas are related to the degree of similarity of the experimental groups, and in order to make the predicted values of the outcome variables in the synthesized areas close to the predicted values of the corresponding experimental groups, the weights of each experimental group are determined by the method of “synthetic control”.

For the experimental group area, the weight matrix is calculated as follows:

$$W_i^* = \left(W_{i,n_1+1}^*, \dots, W_{i,n}^*\right), \tag{7}$$

$$\min_{w_i \epsilon R^{n_0}} \left|\left| X_i - \sum_{j=n_1+1}^{n} W_{i,j} X_j \right|\right|^2, \tag{8}$$

$$st, W_{i,n_1+1} \geq 0, \dots, W_{i,n} \geq 0, \tag{9}$$

$$\sum_{j=n_1+1}^{n} W_{i,j} = 1. \tag{10}$$

In the equation, $W_{i,j}^*$ is the weight matrix that makes experimental area $i$ closest to control area $j$. Matrix X is the matrix that contains information about the area predictor variables, i.e., it contains the covariates and explanatory variables in the regression equation. The synthetic control method's estimate of the treatment effect for experimental area $i$ is:

$$\hat{\tau}_i = Y_i - \sum_{i=n_1+1}^{n} W_{i,j}^* Y_j, \tag{11}$$

Its average treatment effect was:

$$\hat{\tau} = \frac{1}{n_1} \sum_{i=1}^{n_1} \left(Y_i - \sum_{i=n_1+1}^{n} W_{i,j}^* Y_j\right). \tag{12}$$

# 3. Empirical Analysis

## 3.1. Results of Carbon Emission Efficiency Measurements in Agriculture

Based on the carbon emission accounting model of farmland utilization and the SBM-DEA efficiency evaluation model, this study systematically carries out the measurement and efficiency analysis of agricultural carbon emission by combining the perspectives of policy intervention and regional difference. From 2000 to 2015, the national agricultural carbon emissions showed a continuous upward trend, and the growth rate of the curve slowed down after 2010 and reached the maximum value in 2015. Regional efficiency has been improved as a whole, and the efficiency of agricultural carbon emissions in most of the provinces in China has been steadily improving, with Guangdong, Guizhou and other provinces showing particularly significant growth rates; there is a gradient difference between the east and the west, with the efficiency level of the east being significantly higher than that of the central and western parts of the country, and the typical high-efficiency provinces include Guangdong, Fujian, Beijing and other places; the central part of the country has an outstanding catching-up effect, with the provincial efficiency having a larger annual average increase In central China, the catching-up effect is prominent, and the annual average increase of provincial efficiency is larger, and the intra-regional differences are narrowing, showing obvious efficiency convergence; in western China, the efficiency is relatively stable, with smaller changes, and the overall efficiency is at a lower level and the speed of improvement is relatively lagging.

The results reveal the mechanism of the interaction between policy orientation and regional development level on carbon emission efficiency. The following model regression using the SCM synthetic control method is used to further investigate the impact of low-carbon pilot policies on agricultural carbon emission efficiency.

## 3.2. Solution Results of the SCM Model

The low-carbon pilot provincial and municipal construction policy was first implemented in 2010 in five provinces and eight regions, including Liaoning, Hubei, Guangdong, Yunnan and Shaanxi. The five provinces were selected as the experimental group to measure the corresponding agricultural carbon emission efficiency, and set up before and after controls as well as other provinces that did not implement the policy as the control group. The control group consists of 15 provinces in the east, center, and west of China: Shanxi, Inner Mongolia, Jilin, Heilongjiang, Jiangsu, Anhui, Shandong, Henan, Hunan, Guangxi, Sichuan, Gansu, Qinghai, Ningxia and so on. (Excluding the provinces that are gradually joining the pilot policy). If the selected time series is too long, too many other policy or event shocks may be introduced during the period when the policy occurred. Due to the impact of the epidemic, the data change too much after 2000, and some data are missing, therefore, this paper selects the data from 2000-2020 for the study.

This paper stipulates that the sum of the coefficients of the control group of provinces is 1, and the coefficients are all positive. The provinces in synthetic Liaoning are mainly including Inner Mongolia, Jilin, Heilongjiang, Jiangsu, Shandong and Gansu, and the coefficient of Inner Mongolia in synthetic Liaoning is 0.3336, which accounts for the largest proportion. Synthetic Hubei provinces are mainly Shanxi, Inner Mongolia, Jiangsu, Shandong, Hunan, Sichuan and other seven provinces, of which Sichuan coefficient is 0.2158; synthetic Guangdong provinces are mainly Anhui, Shandong, Hunan and Sichuan and other four provinces, of which 0.6139 is the weight occupied by Hunan, the largest proportion; synthetic Yunnan provinces are Heilongjiang, Sichuan, Gansu and Qinghai and other four provinces, of which Sichuan is The largest proportion of weight is 0.4423; the provinces that synthesize Shaanxi are three provinces, including Heilongjiang, Guangxi and Qinghai, with the coefficients of 0.2676, 0.5329 and 0.1995, respectively. The results of the weight distribution are shown in Table 2.

**Table 2.** Control Group Weighting Coefficients

| Control Group | Synthetic Liaoning | Synthesized Hubei | Synthesize Guangdong | Synthesize Yunnan | Synthesize Shaanxi |
|---|---|---|---|---|---|
| Shanxi | | 0.1155 | | | |
| Inner Mongolia | 0.3336 | 0.197 | | | |
| Jilin | 0.2266 | | | | |
| Heilongjiang | 0.0359 | | | 0.0111 | 0.2676 |
| Jiangsu | 0.1418 | 0.1819 | | | |
| Anhui | | | 0.1439 | | |
| Shandong | 0.0272 | 0.0143 | 0.0685 | | |
| Hunan | | 0.1551 | 0.6139 | | |
| Guangxi | | | | | 0.5329 |
| Sichuan | | 0.2158 | 0.1683 | 0.4423 | |
| Gansu | 0.2349 | | | 0.3161 | |
| Qinghai | | | | 0.2305 | 0.1995 |
| XJ | | 0.1204 | | | |

Figures 2-3 show the changes in policy treatment effects in five provinces, including Liaoning, Hubei, Guangdong, Yunnan and Shaanxi, estimated by the synthetic control method with penalty terms, respectively. As can be seen from Figure 5, the low-carbon pilot policy was implemented in 2010, and the Liaoning policy effect began to appear after 2011, with a certain policy lag characteristic, and the Liaoning policy effect was most significant in 2015. Hubei policy effects began to appear before 2010, with certain antecedent characteristics, and Hubei policy effects were most significant in 2011, making the average agricultural carbon emission efficiency in Hubei increase by about 0.05 units.

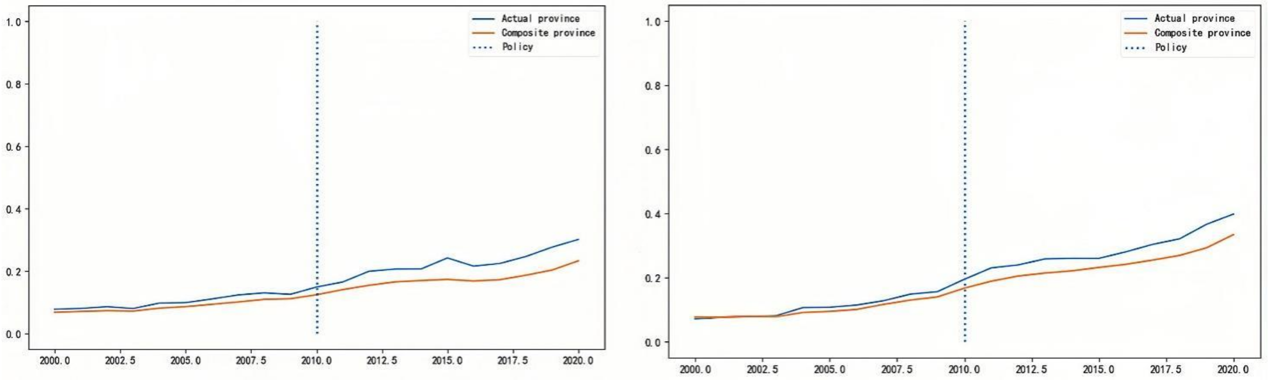

**Figure 2.** Time Trend of Policy Effects in Liaoning and Hubei Provinces

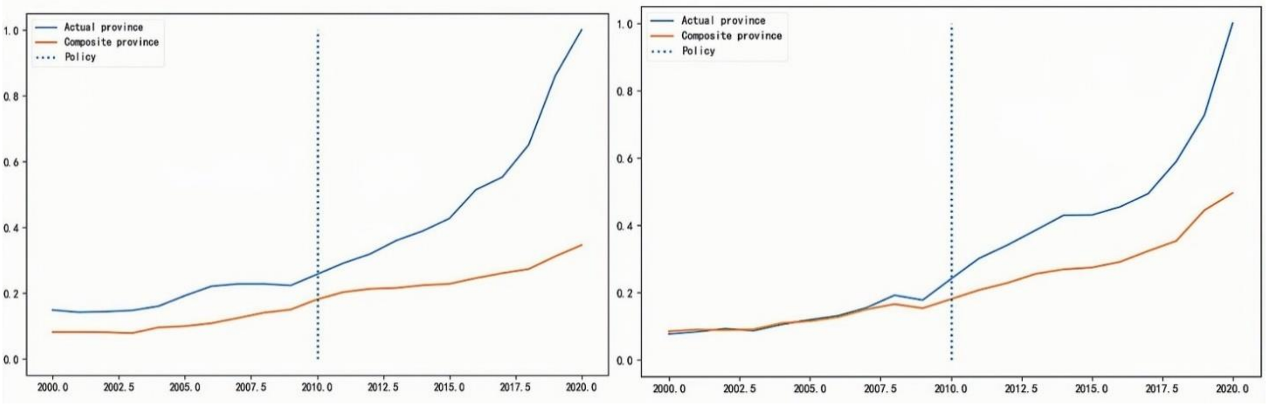

**Figure 3.** Time Trend of Policy Effects in Guangdong, Shaanxi and Yunnan

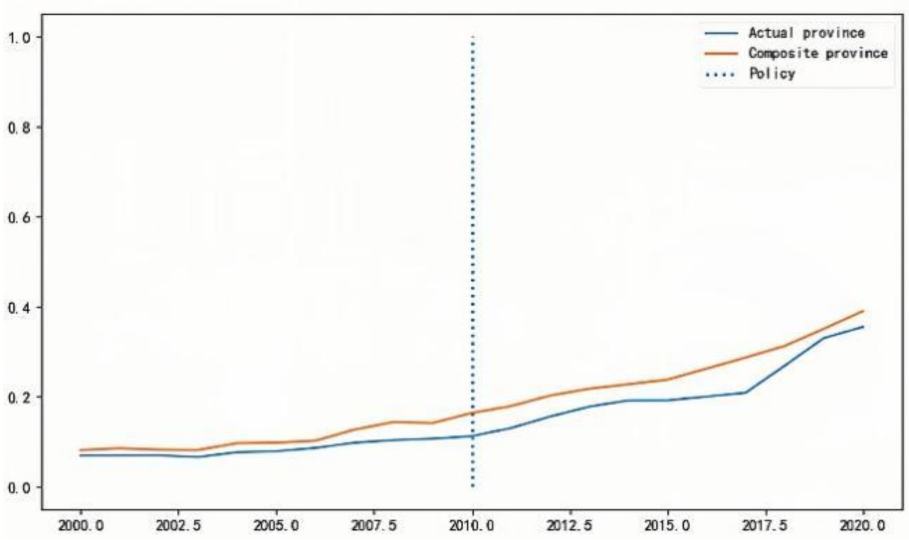

**Figure 4.** Time Trend of Policy Effects in Yunnan

The policy treatment effects in Guangdong, Shaanxi and Yunnan are shown as figure 3 and figure 4. It can be seen from the figure that before 2010, the difference between the average energy efficiency and emission efficiency in Guangdong was slightly greater than 0. However, after the implementation of the policy, the average agricultural carbon emission efficiency in Guangdong increased significantly, and the policy effect was very significant. The average agricultural carbon emission efficiency in Shaanxi increased significantly after the policy was implemented, and the policy effect was very significant. After the implementation of the policy, the difference in the average agricultural carbon emission efficiency in Yunnan fluctuates around 0, and the policy effect is weak.

### 3.3. Robustness Tests

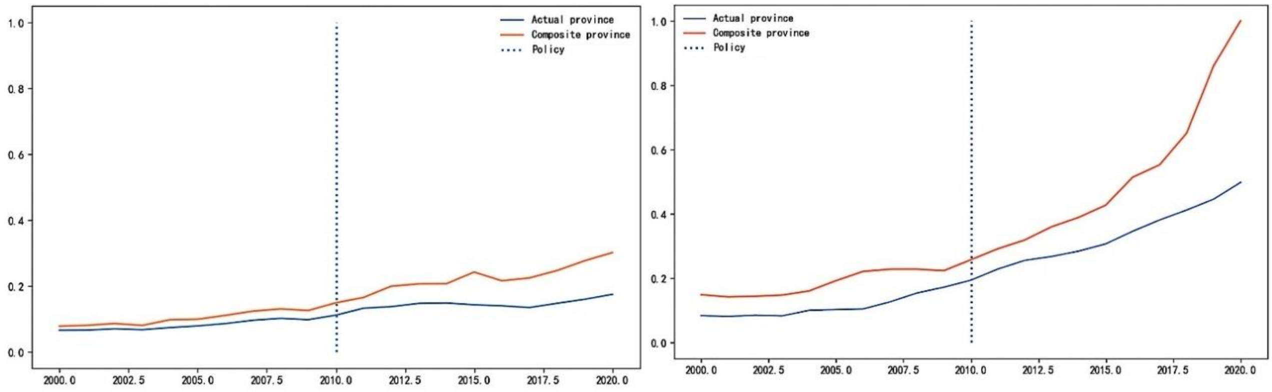

**Figure 5.** Placebo Test in Liaoning and Guangdong Provinces

In order to exclude the influence of other factors, this paper examines the regions with the largest coefficients in the control group. This paper performs the same synthetic control analysis on the provinces with the largest share of coefficients in the control group areas in the experimental group, which theoretically will not have the same policy effect as the experimental group because the control group areas are not affected by the low-carbon pilot policy. Therefore, this paper chooses the province with the largest impact on the experimental group for the placebo test. Figures 5 shows the results of the placebo test for two provinces respectively. From the figures, it can be concluded that none of the regions where the placebo test was conducted produced the same policy effects as the regions in the provinces where the policy was implemented, suggesting that the conclusions of this paper are somewhat robust.

### 3.4. Analysis of Policy Effects in Low-Carbon Pilot Regions

According to the results, the effect of Guangdong Province is obvious after the policy, and the efficiency of agricultural carbon emissions has increased significantly, which may be related to the agricultural science and technology innovation in Guangdong. It was found that the local government of Guangdong Province increased its investment in low-carbon green scientific research according to the policy [9]. In 2010, research funding reached 106,554,000 yuan, an increase of 40.35 percent. The average funding for scientific researchers was 350,500 yuan, an increase of 109,400 yuan from 2000. It can be seen that adequate scientific research funding in Guangdong Province provides strong scientific and technological support for low-carbon agriculture, which improves the efficiency of agricultural carbon emissions. In addition, the development of agricultural mechanization also promotes the development of low-carbon agriculture. In 2000, the total power of agricultural machinery in Guangdong was 1,763,900 watts, and in 2010 it grew to 2,345,300 watts, a year-on-year increase of 32.96%. Shaanxi Province has actively taken some agricultural low-carbon measures since the implementation of the policy, taking the green economy, low-carbon economy and circular economy as the new development concept. Shaanxi has taken a series of measures in the reform and innovation of agricultural production technology, strengthened the input of various agricultural factors [10], strengthened agricultural technology training and so on to help modernize agriculture and high-quality development. Among the pilot provinces, only Yunnan Province has a poor policy effect, which may be due to the fact that Yunnan has mountainous plateaus and sloping arable land, hinders the promotion of agricultural machinery in Yunnan Province and the agricultural mechanization in Yunnan Province still fails to play a role after the implementation of policy, which hinders the development of low-carbon agriculture.

## 4. Conclusion

By summarizing the panel data of the pilot and non-pilot provinces of the provinces and cities that implemented low-carbon pilot projects from 2000 to 2020, this paper finds that there are obvious regional differences in agricultural carbon emissions in China, and there are large differences in agricultural carbon emissions and carbon emission efficiency among provinces. There are gradient differences in carbon emission efficiency between the east and the west, with the highest agricultural carbon emission efficiency in the east, the second highest in the central region, and the lowest in the west, indicating that the level of economic development and agricultural technology have a significant impact on the carbon emission efficiency.

Secondly, the emission reduction effect of agricultural carbon emissions is closely related to the degree of policy implementation, and has little to do with the division of regional scope. The construction of low-carbon pilot provincial and municipal policies has a significant positive effect on the improvement of agricultural carbon emission efficiency, and different provinces have different sensitivities to low-carbon pilot policies, Guangdong, Shaanxi and other provinces have significantly improved carbon emission efficiency driven by policies, while Yunnan Province has limited effect, therefore, for provinces with similar economic development levels to Guangdong, Shaanxi and other provinces, they can learn from their experience to improve agricultural carbon emission efficiency.

However, there are still shortcomings in the current research, such as the differences in the implementation intensity and effect of low-carbon pilot policies at different stages, and future research needs to consider the impact of policy dynamics on the results. In future research, we will further explore the optimization path of low-carbon pilot policies, consider the impact of policy dynamics, and how to improve the overall agricultural carbon emission efficiency through regional coordination mechanisms.

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