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Original Research

Promotion Path of Agricultural Eco-Efficiency Under the Background of Low Carbon Pilot Policy

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Abstract

The balance between agricultural development and maintenance of agro-ecological environment becomes a huge challenge because of global climate changes. Existing literature on the low-carbon pilot policy proposed by the government of China and whether the problems of agricultural development and agricultural environmental protection can be solved or not have not been reviewed. This paper analyzes the impact of low-carbon pilot policies on agricultural eco-efficiency by using SARAR model based on the data of 281 cities in China. Results show the spatial spillover effects between low-carbon pilot policies and agricultural eco-efficiency. The implementation of low-carbon pilot policy can improve agricultural eco-efficiency. Although restrained by agricultural economic development, this policy has disequilibrium effect on agricultural eco-efficiency, has a relatively large impact on agricultural eco-efficiency in western China and other poor areas, and promotes the reduction of agricultural carbon emission. The effect of the implementation of low-carbon pilot policy is affected by the initial agricultural economic development and urban economic conditions. This research aims to improve the agricultural eco-efficiency and enforce the green development of the agricultural economy via the perspective of the low-carbon pilot policy.

Keywords: low-carbon pilot policies, eco-efficiency, agricultural, disequilibrium effect, China

Introduction

Background

Agriculture is not only related to national food security, but also related to ecological security. With the progress of agricultural science and technology, the world agriculture has also made a series of achievements. In 2000, the world grain output reached 1.9 billion tons, and in 2021, the world grain output reached 2.8 billion tons. With the growth of world grain production, agricultural development has also brought a series of ecological and environmental problems, especially the sustainable development of agriculture in developing countries is facing great challenges.

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There are two common phenomena in the transformation of traditional agriculture to modern agriculture in developing countries: One is that farmers try to increase the unit yield of agricultural products by adding chemical fertilizers, pesticides and other chemicals [1], however, the agricultural ecological efficiency is not promoted as hoped due to the marginal contribution rate of chemical products is also decreasing; Second, developing countries pay more and more attention to the input of agricultural machinery, although the input of agricultural machinery improves the efficiency of agricultural production, but the agricultural ecological efficiency is affected because the increasing of the agricultural carbon emissions.

Under the background that green agricultural development has become a global consensus, developing countries have taken a series of measures to reduce agricultural carbon emissions and promote green agricultural development. China had also done so in order to maintain the ecological environment and establish a benign and sustainable ecological system. In 2010, China identified five provinces and eight cities as low-carbon pilot areas, and those pilot areas have reduced carbon intensity and pollutant emissions, promoted green economic development and improved economic and ecological efficiency by advocating low-carbon production and green production. On the basis of previous experience accumulation, China identified the second and third batch of low-carbon pilot areas in 2012 and 2017. With the implementation of the low-carbon pilot policy, scholars have also studied the low-carbon pilot policy and found that it has reduced the carbon emissions of industry and service industries [2] and improved the eco-efficiency of the economy [3] by improving the low-carbon development system and optimizing the regional economic structure. However, the real puzzle is: the low-carbon pilot policy can improve the eco-efficiency of the economy,but the effect on agricultural eco-efficiency is still unknown even though the agricultural eco-efficiency as an important symbol of high-quality agricultural development.

Based on the above background, this paper attempts to comprehensively and accurately evaluate the implementation effect of low-carbon pilot policies on agriculture in China from the perspective of agricultural ecological efficiency. Exploring the impact of the low-carbon pilot policy on agricultural ecological efficiency will help clarify the implementation effect of the low-carbon pilot policy and understand how to implement the low-carbon pilot policy in the context of high-quality development of agricultural economy in the future. It can provide policy implications for China to achieve the goals of "carbon peak" in 2030 and "carbon neutrality" in 2060, and also provides Chinese experience for other countries and regions in the world to actively respond to climate change and improve ecological efficiency.

Literature Review

This paper studies the impact of low-carbon pilot policies on agricultural eco-efficiency. The literature related to this paper mainly focuses on two parts: one is the literature on agricultural eco-efficiency; the second one is on low-carbon pilot policies.

Literature on Agricultural Eco-Efficiency

Scholars gradually pay attention to agricultural eco-efficiency with the enhancement of residents' awareness of environmental protection. Agricultural eco-efficiency refers to the relationship between various factor inputs and total output in agricultural economy in a certain period of time, it not only reflects the level of agricultural technology and the allocation of factors, but also reflects the unexpected output of agriculture [4]. The research on agricultural ecological efficiency by scholars mainly focuses on the measurement of agricultural eco-efficiency [5] and the factors affecting agricultural eco-efficiency [6]. Scholars have studied the promotion path of agricultural efficiency and the time-space difference of agricultural efficiency [7] from the perspectives of land productivity [8], agricultural factor input [9] and agricultural policy [10]. Existing literature studies have found that agricultural eco-efficiency has a certain convergence trend [11], and this convergence trend will be affected by agricultural policies [10], and meanwhile, the financial support is the main factor compared with other factors[12]. However, some scholars have reached different conclusions what found that agricultural policies also have an inhibitory effect on agricultural eco-efficiency [13], that means agricultural eco-efficiency depends on different agricultural functions. In other words,when the agriculture bears more functions, the agricultural eco-efficiency will be lower [14].

Literature on Low Carbon Pilot Policies

In the context of the implementation of the low-carbon pilot policy, scholars have gradually begun to pay attention to the low-carbon pilot policy [15]. Some scholars have discussed the reasons for the implementation of the low-carbon pilot policy in China [16], and how the low-carbon pilot policy can achieve carbon emission reduction [17] and improve eco-efficiency [18]. Some scholars also studied the impact of low-carbon pilot policies on total factor productivity [2], urban carbon emissions [19] and household carbon emissions [20] from an empirical perspective. It is found that the low-carbon pilot policy can significantly reduce carbon emissions and improve total factor productivity [21]. With the implementation of the low-carbon pilot policy, a realistic question naturally arises: can the low-carbon pilot policy really achieve green development? The existing literature gives a positive answer from the perspectives of cities [22] and enterprises [23]. However, it should be noted that some scholars have also denied this conclusion [24], believing that the current low-carbon pilot policy will reduce carbon emissions and also generate additional costs due to making up for environmental regulations [25], and scholars have found that the low-carbon pilot policy may weaken the market competitiveness of enterprises [26].

The existing literature has studied the low-carbon pilot policy and agricultural eco-efficiency from different perspectives, but the existing literature also has the following aspects to be expanded: first, the path to improve agricultural eco-efficiency from the perspective of low-carbon pilot policy. The existing literature found that there are differences in the impact of policies on agricultural eco-efficiency. At the same time, there is no literature to study the impact factors of agricultural eco-efficiency from the perspective of low-carbon pilot policies. Therefore, this paper attempts to analyze the impact factors of low-carbon pilot policies on agricultural eco-efficiency. Second, provide the implementation effect of low-carbon pilot policies from the perspective of agriculture. The existing literature has studied the impact factors of low-carbon pilot policies on carbon emissions and ecological efficiency, but it has not seen the relevant literature analyze the implementation effect of low-carbon pilot policies from the perspective of agriculture. Therefore, this paper attempts to analyze the impact of low-carbon pilot policies on agricultural eco-efficiency from the perspective of agriculture. Third, the impact of low-carbon pilot policies on agricultural eco-efficiency from the perspective of disequilibrium. The impact of low-carbon pilot policies on agricultural eco-efficiency may be different due to the different levels of agricultural economic development in different regions. This paper put the initial level of agricultural economic development into the model to study the unbalanced effect of low-carbon pilot policies on agricultural eco-efficiency.

Material and Methods

Model Setting

SARAR Model

The low-carbon pilot policy has spatial correlation [20], and the agricultural eco-efficiency between cities also has a real correlation, therefore, the spatial correlation between the low-carbon pilot policy and the agricultural eco-efficiency needs to be considered when analyzing the impact of the low-carbon pilot policy on the agricultural eco-efficiency. Referring to the existing literature research on spatial related econometric models, this paper attempts to analyze the impact of low-carbon pilot policies on agricultural eco-efficiency by using Spatial Autoregressive Model with Spatial Autoregressive Disburbances (SARAR model). The mathematical expression of SARAR model is:

$$Y = \rho WY + X\beta + \mu \tag{1}$$

$$\mu = \lambda W\mu + \varepsilon \tag{2}$$

where Y represents the urban agricultural eco-efficiency, X represents the explained variable, W represents $n \times n$ order spatial weight matrix, ε represents the independent and identical random disturbance term and $\varepsilon \sim N(0, \sigma^2 I_n)$, λ represents the residual autoregressive coefficient, ρ represents the spatial autoregressive coefficient, and ρ significant (or not significant) means that there is (or not) spatial spillover effect between urban agricultural eco-efficiency. Considering that Formulas (1) and (2) involve weight matrix, the empirical analysis of this paper uses the geographical distance weight matrix, and the weight matrix constructed is $W_{ij} = 1/d(i,j)$, where $d(i,j)$ represents the spatial distance between two cities, and the diagonal of the weight matrix is set as 0.

Meta-RDM Model

When the output is negative, the RDM model will have no solution in the process of solving the direction distance function, and the traditional DEA model cannot recognize the negative data [27]. In order to solve this problem, Portela et al. [28] introduced the common frontier on the basis of RDM model and proposed Meta-RDM model that evaluates the output as negative. The Meta-RDM model with common frontier can not only deal with the negative value that DEA model can not deal with, but also deal with the problem that RDM model cannot solved. The direct distance function under the common frontier surface can be expressed as: $\overline{DR}^{mf} = (x_k^t, y_k^t, 0, R_{y_k^t}^{mf})$, where DR superscript mf indicates that the direct distance function is based on the common frontier, and R superscript mf indicates the maximum product output of the agricultural sector under the definition of the direct distance function under the common frontier. The target value of the direct distance function under the common front surface can be expressed as: $I_r = max_i max_j \{y_{rj}^t\}$, and the relative Meta-RDM model can be expressed as:

$$\overline{RDM}^{mf}(x_k^t, y_k^t, 0, R_{y_k^t}^{mf}) = 1 - \overline{DR}^{mf}(x_k^t, y_k^t, 0, R_{y_k^t}^{mf}) \tag{3}$$

When the direction distance of the agricultural department k from the period t to the global front to the current front is on the same straight line, $\overline{RDM}^{mf}$ can be decomposed into:

$$\overline{RDM}^{mf}(x_k^t, y_k^t, 0, R_{y_k^t}^{mf}) = 1 - \overline{DR}^{mf}(x_k^t, y_k^t, 0, R_{y_k^t}^{mf}) \times TG_k^t \tag{4}$$

According to Equation (4), TG_k^t can be expressed as:

$$TG_k^t = \frac{\overline{RDM}^{mf}(x_j^t, y_j^t, 0, R_{y_j^t}^{mf})}{\overline{RDM}^{t}(x_j^t, y_j^t, 0, R_{y_j^t}^{mf})} \tag{5}$$

Based on the above definitions, the Meta-Malmquist index under the condition of negative data is obtained:

$$MM_r^{t,\,t+1} = \frac{\overline{RDM}^{mf}(x_k^{t+1}, y_k^{t+1}, 0, R_{y_k^{t+1}}^{mf})}{\overline{RDM}^{mf}(x_k^{t}, y_k^{t}, 0, R_{y_k^{t}}^{mf})} \tag{6}$$

where the agricultural eco-efficiency index measures the catch-up degree of agricultural eco-efficiency from t period to $t+1$ period. If the agricultural eco-efficiency index is larger (or smaller) than 1, then the agricultural eco-efficiency in this region is improved (or decreased). If the agricultural eco-efficiency is equal to 1, then no changes occurred in the agricultural eco-efficiency of the region.

Data Specification

The data in this paper were obtained from two aspects. One is the statistical data proposed in the China Urban Statistical Yearbook, China Urban Construction Statistical Yearbook, and China Statistical Yearbook from 2011 to 2020. The missing indicators in the statistical yearbook are supplemented by using the interpolation method. Given that relevant data indicators involve price variables, this paper uses the consumer price index to reduce the added value of the primary industry, investment in agricultural fixed assets, and fiscal expenditure to the constant price based on 2010. The other one is the low-carbon pilot city announcements proposed by the China government in 2010, 2012, and 2017.

Calculation of Agricultural Eco-Efficiency

In this paper the agricultural eco-efficiency is the explained variable. The agricultural eco-efficiency reflects the relationship between the input elements of agriculture and the output products of agriculture. Thus, a clear definition of input factors and output products must be provided. According to the Cobb-Douglas production function and consideration of the availability and consistency of data of urban agricultural sector, the agricultural input factors should include labor, capital, and land factors.

The input indicators of agricultural eco-efficiency are as shown as follows: (1) the Labor factor, which it can be measured by the number of employees in the primary industry. (2) the Capital factor, the existing literature mainly uses the capital stock to measure the Capital factor. However, considering the particularity of the agricultural sector, the agricultural Capital factor should be measured combined with agricultural capital stock and agricultural machinery. The fixed asset investment of the agricultural sector can be calculated according to the fixed asset investment of the whole city and the non-agricultural sector, and then the capital stock of the agricultural sector is calculated by the perpetual inventory method. The depreciation rate of the capital stock in the agricultural sector is set as 9.6%, meanwhile, the research method of Perkins [29] is used to calculate the urban agricultural capital factor stock in 2009 by using the urban agricultural production value in 2010, and the capital output ratio is selected as 3; the agricultural machinery is measured by the total power of agricultural machinery. (3) Land elements, this paper uses the research method of Zhao [30] for reference and selects cultivated land area as the index of land elements.

According to the output index of agricultural eco-efficiency, the output of the agricultural sector not only has the expected output but also has the unexpected output. To accurately measure the output of agricultural sector, the expected output of the agricultural eco-efficiency is measured by the output of the primary industry. The undesired output of the agricultural sector is measured by the total carbon emission of the agricultural sector. Referring to the research method of Liu et al. [31], the total carbon emission of the agricultural sector is calculated as follows:

$$\mathrm{E} = \sum_{i=1}^{n} E_i = \sum_{i=1}^{n} T_i \times \delta_i \tag{7}$$

where E represents the total agricultural carbon emissions; E_i represents the carbon emissions of chemical fertilizers, pesticides, agricultural plastic film, diesel oil, and agricultural effective irrigation area in the agricultural sector; T_i represents the input amount of the above-mentioned carbon emission sources in the urban agricultural sector; and δ_i represents the coefficient of the above-mentioned carbon emission sources. According to the research results obtained by the Oak Ridge National Laboratory, the carbon emission coefficients of chemical fertilizers and pesticides are set at 0.8956 kg/kg and 4.9341 kg/kg, respectively. According to the research results obtained by the Nanjing Agricultural University, the carbon emission coefficient of the agricultural film was set at 5.18kg/kg; According to the research results obtained by the Intergovernmental Panel on Climate Change, the carbon emission coefficient of diesel was set at 0.5927 kg/kg. According to the research results obtained by the College of Biology and Technology of China Agricultural University, the carbon emission coefficient of the agricultural effective irrigated area was set at 25 kg/cha. Data on fertilizers, pesticides, plastic film for agriculture, diesel oil, and agricultural irrigated acreage in the agricultural sector are derived from provincial statistical yearbooks. The quantitative and descriptive statistics of factor input and product

Table 1. Quantification and descriptive statistics of input and output indicators of agricultural sector.

Indicators	Index selection	Index construction and units	Mean value	Standard deviation	Maximum	Minimum
Input	Labor variable	Employees in the primary industry (ten thousand)	12.5713	1.9557	2.3026	18.5311
	Capital variables	The natural logarithm of the capital stock (100 million yuan)	6.3939	1.4073	1.9653	10.1922
		The natural logarithm of the total power (kilowatts) of agricultural machinery	2.6395	2.9370	1.5659	21.0645
	Land variables	The natural logarithm of the area of cultivated land (1000 ha)	5.5850	0.9786	1.0438	7.7831
Output	Expect output	The natural logarithm of the gross product of agricultural industry (100 million yuan)	4.1595	0.9268	-0.8535	6.7830
	Undesired output	The natural logarithm of the total carbon emissions of the agricultural sector is taken	12.7494	3.5661	1.6723	17.3077

Table 2. Analysis of temporal and spatial differences of agricultural ecological efficiency.

Year	National agricultural ecological efficiency	Eastern region	Central region	Western region
2010-2011	0.9939	0.9917	0.9967	0.9930
2011-2012	0.9966	0.9975	0.9990	0.9927
2012-2013	0.9963	0.9959	0.9968	0.9962
2013-2014	1.0046	1.0101	1.0041	0.9989
2014-2015	1.0061	1.0051	1.0102	1.0023
2015-2016	1.0108	1.0042	1.0198	1.0077
2016-2017	1.0307	1.0353	1.0432	1.0158
2017-2018	0.9975	1.0017	1.0105	0.9769
2018-2019	1.0031	1.0043	1.0007	1.0048

The results are output by MAXDEA6.9 software

output indicators in the agricultural sector are shown in Table 1.

Labor and capital factors are set as non-radial indicators in this paper because of the substitution relationship between labor and capital factors in the agricultural sector, and the total power of agricultural machinery in the agricultural sector may be affected by the capital stock in the agricultural sector. To emphasize the importance of land elements in the process of agricultural production and consider on the particularity of urban land elements, the land elements are set as radial indicators in this paper. The measurement results of agricultural eco-efficiency are shown in Table 2.

The spatial and temporal differences of agricultural eco-efficiency in Table 2 show that the agricultural eco-efficiency in China is relatively low. The agricultural eco-efficiency in the central region is relatively high compared with the agricultural eco-efficiency in the eastern and western regions because the eastern region in China is dominated by industry and service industry, and the proportion of agriculture in the eastern region is relatively low, thereby causing the transfer of a large number of young and middle-aged labor force to non-agricultural sectors in the eastern region and leads to the low agricultural eco-efficiency in the eastern region. The western region is mainly mountainous, which also limits the improvement of agricultural eco-efficiency in the western region. The central region is dominated by plains, and the central region also undertakes the task of food production. Although a phenomenon of rural labor force shifting to non-agricultural sectors in the central region occurs, the local governments will continue to invest in agriculture under the guidance of policies to ensure China's food security, thereby improving agricultural eco-efficiency.

Low-Carbon Pilot Policies

This paper studies the impact of low-carbon pilot policy on agricultural production efficiency, so the low-carbon pilot policy is the core explanatory variable. The low-carbon pilot policy is in order to reduce greenhouse gas emissions, build a low-energy production system and explore a high-quality economic development mode which the economic growth and carbon emissions are decoupled. China implemented low-carbon pilot policies in relevant cities in three batches in 2010, 2012 and 2017, and these areas have realized regional industrial restructuring and innovated low-carbon technologies by advocating low-carbon production, relying on technology to reduce carbon intensity and establishing carbon emission trading markets.

If the low-carbon pilot policy is implemented in year I in City X, then year I and subsequent years in City X will be set as 1, and the other years will be set as 0. The above shows the scope of the first batch of pilot policies in 2010 includes five provinces and eight cities. The cities under the jurisdiction of the five provinces in the first batch of pilot policies are all identified as low-carbon pilot cities because cities are the research object of this paper. Given that the first batch of low-carbon pilot areas includes part of the second batch of pilot cities, this paper refers to the research method of Song et al. [21]. If City X is in the second batch of pilot cities and the provinces of City X are also in the first batch of pilot cities, then they will be identified as the earlier one to implement low-carbon pilot policies. The implementation plan of the second batch of low-carbon pilot policies was reported on December 31, 2012. Considering that the time was close to the end of the year, the implementation time of the second batch of pilot policies was defined as 2013 by referring to the research method of Zhang [19] in this paper.

Control Variables

This paper draws on the studies of Zhang [15] and other scholars to introduce nine control variables, including industrial structure, urbanization level, and information level. The quantification method of industrial structure (Structure) is expanded as $\text{structure} = \sum_{i=1}^{3} i\theta_i$ where θ_i represents the proportion of i industrial output value in the gross urban product. Urbanization level (Urbanization) is expressed by the proportion of the non-agricultural employed population in the urban employed population. Industrial concentration (Concentration) is expanded as $\text{Industrial} = \left[\theta_{ji} / \sum_{i}^{i=3} \theta_{ji}\right] / \left[\sum_{j=1}^{281} \theta_{ji} / \sum_{j=1}^{281} \sum_{i}^{i=3} \theta_{ji}\right]$, where θ_{ij} represents the added value of the i industry of city j. Foreign investment is measured by the ratio of the summation of foreign investment and investment from Hong Kong, Macao, and Taiwan to the total industrial output value. Considering that foreign investment (Foreign) is calculated in US dollars, the average exchange rate of foreign investment in the current year is first converted into RMB price, and then the actual value based on 2010 is converted by the consumer price index of each city. Information (Information) is measured by the logarithm of Internet users. Human capital (Human) is measured by the number of college students per 10,000 people in a city. Traffic (Traffic) is measured by the per capita traffic volume of a city's railways and roads. Government (Government) intervention is measured by using the proportion of urban financial revenue in GDP. Social consumption (Consumption) is measured by the ratio of total retail sales of social consumer goods to the total population at the end of the year. The descriptive statistics of control variables are shown in Table 3.

Results and Discussion

Spatial Correlation Test

To test the spatial correlation between the low-carbon pilot policies and the agricultural eco-efficiency before constructing the econometric model, when the spatial correlation between low-carbon pilot policies or agricultural eco-efficiency is existing, the

Table 3. Descriptive statistics.

Variable	Full Sample		Experimental Group		Control group	
	Mean	Standard error	Mean	Standard error	Mean	Standard error
Structure	2.2466	0.1358	2.2878	0.1306	2.2285	0.1341
Urbanization	0.5306	0.1364	0.5160	0.1323	0.5370	0.1377
Concentration	1.0215	0.2093	1.2476	0.1117	0.9220	0.1587
Foreign	0.1310	0.1465	0.1249	0.1369	0.1336	0.1504
Information	0.7873	1.5797	1.8277	2.5608	0.3295	0.1601
Human	0.1807	0.2446	0.1937	0.2500	0.1750	0.2421
Traffic	0.3117	0.7696	0.3241	0.2945	0.3063	0.9026
Government	0.0762	0.0267	0.0799	0.0257	0.0747	0.0270
Consumption	1.7171	1.5874	2.2380	1.7613	1.4880	1.4470

Table 4. Spatial correlation test results.

Year	LCPP			Agro-eco-efficiency		
	Moran's I	sd (I)	Z-Value	Moran's I	E (I)	Z-Value
2010	0.034***	0.011	3.560	0.012**	0.011	1.517
2011	0.034***	0.011	3.560	0.020***	0.011	2.319
2012	0.013*	0.011	1.578	0.036***	0.011	3.709
2013	0.013*	0.011	1.578	0.021***	0.011	2.322
2014	0.013*	0.011	1.578	0.031***	0.011	2.617
2015	0.013*	0.011	1.578	0.055***	0.011	5.601
2016	0.013*	0.011	1.578	0.015**	0.010	1.808
2017	0.007*	0.011	1.517	0.047***	0.010	4.978
2018	0.007*	0.011	1.517	0.018**	0.010	2.067
2019	0.007*	0.011	1.517	0.120***	0.010	12.582

Statistics are shown in parenthesis; ***, **, and * represent significance at the 1, 5, and 10% levels, respectively.

spatial econometric model can be used to analyze the relationship between low-carbon pilot policies and agricultural eco-efficiency. Otherwise, the relationship between low-carbon pilot policies and agricultural eco-efficiency is only analyzed by using traditional econometric models. In this part, Moran's I index is used to analyze the relationship between low-carbon pilot policies and agricultural production efficiency, and the spatial correlation test results are shown in Table 4.

Table 4 shows the spatial correlation test results of the low-carbon pilot policies and agricultural eco-efficiency. The result shows that the Moran's I index of low-carbon pilot policies and agricultural production efficiency is significant, indicating a significant spatial correlation between the low-carbon pilot policies and the agricultural eco-efficiency, which shows that the low-carbon pilot policies (agricultural eco-efficiency) not only have impacts on the low-carbon pilot policies (agricultural eco-efficiency) of the city but also in neighboring areas. As shown as in Table 4, Moran's I index is positive. These results indicate a significant spatial correlation between low-carbon pilot policies (agro-eco-efficiency) in Chinese cities, which is manifested as spatial aggregation in regions with (not yet) the implementation of low-carbon pilot policies and spatial aggregation in the regions with high (low) agro-eco-efficiency. The Z value of Moran's I index in Table 4 shows that the spatial correlation of low-carbon pilot policies is decreasing with the promotion of low-carbon pilot policies. Therefore, the low-carbon pilot policies are becoming increasingly popular in China.

Average Relative Effect of LCPP

Since there is spatial correlation between the low-carbon pilot policy and agricultural eco-efficiency, it is necessary to consider the spatial correlation in the analysis of the impact of the low-carbon pilot policy on agricultural eco-efficiency. Since the spatial autoregressive effect and spatial error term of the low-carbon pilot policy and agricultural eco-efficiency may exist at the same time, this paper analyzes the impact of the low-carbon pilot policy on agricultural ecological efficiency by using the SARAR model that can solve the problem. It is also necessary to determine which of mixed effect, random effect and fixed effect is more suitable for analyzing the impact of low-carbon pilot policies on agricultural eco-efficiency due to the data in this paper are panel data,. BP test shows that mixed effect is more suitable than the random effect to analyze the impact of low-carbon pilot policies on agricultural eco-efficiency. Husman's test found that the fixed effect is more suitable than random effect in analyzing the impact of low-carbon pilot policies on agricultural eco-efficiency. Therefore, the SARAR model is adopted in this paper to analyze the impact of low-carbon pilot policies on agricultural eco-efficiency. The estimated results of the impact of low-carbon pilot policies on agricultural eco-efficiency are shown in Table 5.

The average effect of the low-carbon pilot policy on agricultural eco-efficiency is reported in Table 5. The model in Table 5 estimates 281 cities and be divided into three regions due to the different climate conditions between the Eastern region, Central region, and Western region in China. The model gives three estimated results of the central region and four estimated results of the western region. It can be seen from the estimated results of Model 1 to Model 4 in Table 5 that the spatial autoregressive coefficients ρ are all significantly negative. Therefore, the use of a spatial econometric model is necessary when analyzing the impact of low-carbon pilot policies on agricultural eco-efficiency. The specific analysis on the impacts of the low-carbon pilot policies on the agricultural eco-efficiency is shown as follows:

Table 5. Average relative effect of LCPP.

Variable	Model(1)	Model(2)	Model(3)	Model(4)
Policy	0.2442***	0.1305***	0.1845***	0.4106***
	(0.0156)	(0.0079)	(0.0155)	(0.0454)
Structure	0.1965	−0.1027	−0.1101	0.9242*
	(0.1415)	(0.1191)	(0.1038)	(0.4937)
Urbanization	−0.0930	−0.1100***	−0.0026	0.1834
	(0.0907)	(0.0394)	(0.0988)	(0.2832)
Concentration	2.5091***	2.1877***	2.5587***	2.9734***
	(0.0421)	(0.0403)	(0.0466)	(0.1018)
Foreign	−0.0454	−0.0189	−0.0675	0.7769
	(0.0817)	(0.0255)	(0.1633)	(0.6513)
Information	0.2632***	0.2018***	0.1755***	0.2757***
	(0.0035)	(0.0040)	(0.0079)	(0.0059)
Human	−0.0520	−0.2000***	−0.0871	−0.0899
	(0.1391)	(0.0707)	(0.1522)	(0.3665)
Traffic	−0.0037	0.0071	−0.0012	−0.0042
	(0.0058)	(0.0313)	(0.0103)	(0.0098)
Government	2.4628***	0.4742*	0.5316	1.8261*
	(0.4028)	(0.2574)	(0.4113)	(1.0897)
Consumption	0.0662***	−0.0006	0.0121	0.1434**
	(0.0146)	(0.0057)	(0.0205)	(0.0593)
rho	−0.1725***	−0.0047	−0.0411*	−0.1803***
	(0.0225)	(0.0180)	(0.0216)	(0.0399)
lambda	0.5857***	0.7025***	0.4251***	0.3643***
	(0.0532)	(0.0643)	(0.1000)	(0.0907)
sigma2_e	0.0367***	0.0030***	0.0131***	0.0882***
	(0.0010)	(0.0001)	(0.0006)	(0.0045)
r2	0.9088	0.9698	0.9633	0.8780
Log-likelihood	594.4982	1060.8775	574.2780	−78.9187
N	2810	980	1000	830

Statistics are shown in parenthesis; Standard error in brackets, ***, **, and * represent significance at the 1, 5, and 10% levels, respectively.

The first one refers to the analysis on the impacts of the low-carbon pilot policies on the agricultural eco-efficiency. Model 1 in Table 5 shows that the impacts of the low-carbon pilot policies on the agricultural eco-efficiency are positive and have passed the significance level test. In other words, the implementation of the low-carbon pilot policies can improve agricultural eco-efficiency. The possible explanation is that the low-carbon pilot policy affects the supply and demand sides of agriculture. On the supply side, the implementation of the low-carbon pilot forces the department of agriculture to transform the mode of agricultural production and apply environmental protection technology during the agricultural production process to improve the efficiency of agricultural ecology. The high energy consumption and high pollution of agricultural structure during the process of agricultural production will be eliminated. On the demand side, the implementation of the low-carbon pilot policies have changed the residents' consumption patterns. The agricultural structure is forced to change to match the situation of the residents when they gradually reduce their demands for high-energy and high-pollution agricultural products. Subsequently, the agricultural production efficiency will be improved.

The second one refers to the analysis on the differences of the impacts of the low-carbon pilot policies on the agricultural eco-efficiency. Models 2 to 4 in Table 5 shows that the impacts of the low-carbon pilot policies on the agricultural eco-efficiency in the eastern region, the central region, and the western region are all positive and have passed the significance level test. Comparison of the low-carbon pilot policy estimated coefficients in different regions shows that that in the western region is greater than that in the central region, and that of the central region is greater than that in the eastern region. Therefore, the space difference of the impact of the low-carbon pilot policy exists. The possible explanation is that the economy in the eastern region prioritizes the industry and services. Thus, the eastern region focuses on industry and services but not on the reduction of carbon emissions in agriculture. Cities implement low-carbon pilot policies to improve agricultural eco-efficiency by reducing the carbon emissions of the agricultural sector in western China.

The third one refers to the analysis on the spatial spillover effects of the low-carbon pilot policies. According to the spatial autoregressive coefficients ρ of Models 1 to 4 in Table 5, the spatial autoregressive coefficients of low-carbon pilot policies are nearly all significantly negative, except for the spatial autoregressive coefficients of Model 2, which did not pass the significance level test. It shows that the impact of low-carbon pilot policies on agricultural eco-efficiency has a significant negative spatial spillover effect, which means that while the low-carbon pilot policies affect the agricultural eco-efficiency in the local area, they will inhibit the agricultural eco-efficiency in the neighboring areas. The possible explanation is that the regional agricultural economy is not a closed but an open economy system that promotes the efficiency of agricultural ecological in area A may cause the advanced agricultural technology gathering in area A from area B. Therefore, the agricultural eco-efficiency in area A would not drive the adjacent area to promote the efficiency of agricultural ecology but may have an inhibitory effect on adjacent area B.

The fourth one refers to the analysis on the influences of control variables on the agricultural eco-efficiency. Models 1 to 4 in Table 5 show that not only the low-carbon pilot policies have a significant impact on the agricultural eco-efficiency but also the government intervention and urban industrial agglomeration in the econometric model. The influences of control variables on agricultural eco-efficiency is no longer analyzed because of the secondary position of control variables in the process of empirical analysis and the word limitation of this paper.

Heterogeneous Relative Effects of LCPP

For the purpose of discussion of the low-carbon pilot influences on the efficiency of the agricultural ecological policy in different initial states of the economy, this paper makes reference to He et al. [32], attempts to urban agricultural economy development level considering the initial measurement model, analyzes the heterogeneity of the initial level of economic development condition and the different influences of the low-carbon pilot policy on agricultural eco-efficiency. In the process of empirical analysis, the initial level of agricultural economic development is represented by the added value of the primary industry in 2010, and the estimated results of the disequilibrium effect of the low-carbon pilot policies on the agricultural eco-efficiency are shown in Table 6.

Table 6 shows the disequilibrium effect of the low-carbon pilot policies on agricultural eco-efficiency. According to the pseudo R2 in Table 6, the low-carbon pilot policies and control variables can explain the path of improvement of agricultural eco-efficiency. The disequilibrium effect of the low-carbon pilot policies on agricultural eco-efficiency is analyzed as follows:

First, the impact of the low-carbon pilot policies on the agricultural eco-efficiency is analyzed. The part of disequilibrium effect in Table 6 shows that the impact of the low-carbon pilot policies on the agricultural eco-efficiency is positive and passed the significance level test. The low-carbon pilot policies still improve agricultural eco-efficiency when the level of urban agricultural economic development is considered, thereby further verifying the conclusion of the balanced effect of the low-carbon pilot policies. The comparison of the estimated coefficients of the low-carbon pilot policies in Table 6 with the data in Table 5 shows that the estimated coefficients of the low-carbon pilot policies become larger when the initial level of the agricultural economic development is considered. That is, the level of initial agricultural economic development can affect the implementation effect of the low-carbon pilot policies. In other words, the impact of the low-carbon pilot policies on the agricultural eco-efficiency might be underestimated during the process of studying without the consideration of the initial level of agricultural economic development.

Second, the disequilibrium effect of the low-carbon pilot policies is analyzed. The part of disequilibrium effect in Table 6 shows that the interaction term between the low-carbon pilot policies and the initial level of agricultural economic development has a positive impact on the agricultural eco-efficiency and has passed the significance level test. The finding shows that the impact of the low-carbon pilot policies on agricultural eco-efficiency has a significant disequilibrium effect, which means that the low-carbon pilot policies improve the agricultural eco-efficiency in poor areas much better than in rich areas. The possible explanation for the low-carbon pilot policy on the agricultural eco-efficiency is where has a non-equilibrium effect of different areas in the implementation of the low-carbon pilot policy. In other words, poor areas might be reducing agricultural carbon emission to carry out the policies of the low-carbon pilot to maintain the growth of their regional economy, but it might be a good choice for rich regions to adjust their industrial structure to reduce carbon emission due to the particularity of agriculture, which is difficult when adjusting the industrial structure. Therefore, the low-carbon pilot policies have relatively

Table 6. Heterogeneous relative effects of LCPP.

Variable	Full Sample	Differences between rich and poor		
		Poor areas	Middle areas	Rich regions
Policy	2.5313***	4.4997***	1.3824***	1.6224***
	(0.2205)	(0.6298)	(0.1667)	(0.1234)
Policy*GDP2010	−0.1824***	−0.3170***	−0.1023***	−0.1157***
	(0.0145)	(0.0413)	(0.0111)	(0.0082)
Structure	0.2301*	0.4852	−0.2763**	−0.0338
	(0.1391)	(0.4241)	(0.1228)	(0.0547)
Urbanization	−0.0517	−0.2719	−0.0707	0.0562
	(0.0870)	(0.2373)	(0.0502)	(0.0499)
Concentration	2.7155***	2.6866***	2.5888***	2.0241***
	(0.0438)	(0.1008)	(0.0325)	(0.0451)
Foreign	−0.0301	−0.0731	−0.0275	−0.0849
	(0.0784)	(0.1348)	(0.0966)	(0.0682)
Information	0.2781***	0.3608***	0.2026***	0.2798***
	(0.0035)	(0.0164)	(0.0051)	(0.0013)
Human	−0.0554	−0.2986	−0.0361	0.0114
	(0.1335)	(0.5505)	(0.0874)	(0.0532)
Traffic	−0.0033	−0.0044	0.0084	−0.0030
	(0.0056)	(0.0089)	(0.0079)	(0.0125)
Government	1.9074***	2.9542***	0.6254***	−0.0833
	(0.3893)	(0.9150)	(0.2282)	(0.2806)
Consumption	0.0521***	0.2121***	0.0019	−0.0106*
	(0.0141)	(0.0645)	(0.0107)	(0.0054)
rho	−0.2109***	−0.2723***	−0.0513***	−0.0282**
	(0.0216)	(0.0388)	(0.0136)	(0.0111)
lambda	0.6378***	0.5802***	0.4469***	0.7566***
	(0.0480)	(0.0631)	(0.0813)	(0.0384)
sigma2_e	0.0338***	0.0799***	0.0041***	0.0030***
	(0.0009)	(0.0039)	(0.0002)	(0.0001)
r2	0.9349	0.8964	0.9862	0.9902
Log-likelihood	671.2520	−69.3616	908.4682	1004.0308
N	2810	940	930	940

Statistics are shown in parenthesis; Standard error in brackets ,***, **, and * represent significance at the 1, 5, and 10% levels, respectively.

minimal impact on the agricultural eco-efficiency in rich regions.

Third, the heterogeneity of the impacts of the low-carbon pilot policies on the agricultural eco-efficiency is analyzed. To further analyze the differences in the impacts of the low-carbon pilot policies on the agricultural eco-efficiency, this part attempts to divide 281 cities into three, namely, rich, medium, and poor cities, and then further discusses the heterogeneity of the impacts of the low-carbon pilot policies on agricultural eco-efficiency. Table 6 shows that the impacts of the low-carbon pilot policies on the agricultural eco-efficiency in poor, medium, and rich areas are all positive and have passed the significance level test. The result shows that the low-carbon pilot policy has a steady impact on agricultural eco-efficiency. The comparative analysis of the impacts of the low-carbon pilot policies on the agricultural eco-efficiency in different regions shows that the impact of the low-carbon pilot policies on the agricultural eco-efficiency in poor areas is greater than those in rich areas. The low-carbon pilot policies can improve the agricultural eco-efficiency in poor areas.

Table 7. Explore the heterogeneity patterns.

Variable	Agricultural working population	Agricultural carbon emissions	Agriculture as a share of GDP	Manufacturing as a share of GDP
Policy	0.0788**	−0.5521***	−0.0292***	0.0133
	(0.0400)	(0.0855)	(0.0051)	(0.0058)
Policy*GDP2010	−0.0050*	−0.0369***	0.0019***	−0.0006*
	(0.0026)	(0.0057)	(0.0003)	(0.0004)
Structure	0.0205	0.0932*	−0.0103***	0.0237***
	(0.0235)	(0.0493)	(0.0030)	(0.0035)
Urbanization	−0.0023	−0.3664***	0.0216***	−0.0185***
	(0.0170)	(0.0382)	(0.0023)	(0.0026)
Concentration	−0.0054	−0.0142	0.0015	−0.0010
	(0.0074)	(0.0156)	(0.0009)	(0.0011)
Foreign	−0.0197	−0.0624*	0.0032	−0.0064***
	(0.0163)	(0.0363)	(0.0022)	(0.0024)
Information	−0.0009	−0.0025	0.0001	−0.0003**
	(0.0007)	(0.0016)	(0.0001)	(0.0001)
Human	−0.2231***	0.1512**	−0.0077**	−0.0012
	(0.0270)	(0.0587)	(0.0035)	(0.0040)
Traffic	−0.0004	−0.0021	0.0001	0.0001
	(0.0012)	(0.0026)	(0.0002)	(0.0002)
Government	0.1955***	0.4190***	−0.0156	−0.0075
	(0.0748)	(0.1610)	(0.0095)	(0.0110)
Consumption	0.0091***	0.0143***	0.0004	−0.0017***
	(0.0024)	(0.0049)	(0.0003)	(0.0003)
rho	0.6514***	−0.6977***	−0.6662***	−0.8136***
	(0.0599)	(0.0334)	(0.0407)	(0.0321)
lambda	−0.3744***	0.7367***	0.6885***	0.4711***
	(0.1185)	(0.0601)	(0.0712)	(0.0974)
sigma2_e	0.0015***	0.0073***	0.0000***	0.0000***
	(0.0000)	(0.0002)	(0.0000)	(0.0000)
r2	0.1121	0.5373	0.3991	0.2310
Log-likelihood	3762.7684	2160.0132	7713.7190	7481.6842
N	2810	2810	2810	2810

Statistics are shown in parenthesis; Standard error in brackets, ***, **, and * represent significance at the 1, 5, and 10% levels, respectively.

Understanding the Heterogeneity

Based on the analysis of the heterogeneity of the impacts of the low-carbon pilot policies on the theory of increasing returns to scale and comparative advantage, this paper attempts to analyze the causes. The first one refers to the theory of increasing returns to scale. Because of this effect, the low carbon pilot policy will not only bring in the agricultural economy of low-carbon production technology but also bring in the low carbon production technology from adjacent regions, thus promoting the agricultural eco-efficiency in adjacent areas becomes unfavorable [33]. The second one is the theory of comparative advantage. Under the framework of the theory of comparative advantage, lower trade costs encourage advantages to specialize in particular business sectors in the regions. The theory of comparative advantage does not have a clear impact on agriculture although it can change the relative structure of the economy. In other words, regions with different levels of economic development may have different advantages. According to the theory of pollution transfer, regions with a higher level of manufacturing development have more advantages in terms of the prevention and control of the pollution, but the regions with a higher level of agricultural development. Based on the above analysis, this paper attempts to analyze the causes of the heterogeneity of the impacts of the low-carbon pilot policies on the agricultural eco-efficiency from four dimensions of the agricultural eco-efficiency. The estimated results are shown in Table 7.

Table 7 shows the results of the exploration of heterogeneity patterns. The estimated results in Table 7 shows that the low-carbon pilot policies have negative impacts on the agricultural carbon emissions and have passed the significance level test. The low-carbon pilot policies reduce the agricultural carbon emissions. An interesting finding is that the low-carbon pilot policies have positive impacts on the manufacturing share but did not pass the significance level test. The low-carbon pilot policies have negative impacts on the agricultural share, and passed the significance level test. That is, the implementation of the low-carbon pilot policies inhibit the development of agriculture but it does not have impacts on non-agricultural sectors. The possible explanation is that the local governments selectively implement the low-carbon pilot policy in the process of policy execution because of the high portion of the local tax revenue sources from the non-agricultural sector. Furthermore, the implementation of low-carbon pilot policies will inhibit agriculture, but will not affect non-agricultural sectors.

The interaction term between the low-carbon pilot policies and the initial agricultural economic development is also included in the empirical analysis in Table 7. Both of them have negative impacts on agricultural carbon emissions and manufacturing and have passed the significance level test. However, its effect on agriculture is positive and has passed the significance level test, indicating that the implementation of the low-carbon pilot policies have significant differences in the impact on different regions. In other words, the low-carbon pilot policies reduce the agricultural carbon emissions in rich regions but promote the development of the agricultural economy in poor regions. The possible explanation is a choice between the protection of the agricultural ecological environment and the development of the agricultural economy is provided, and achieving the goals of ecological environment protection or economic development at the same time is difficult.

Estimation Results Based on PSM-DID Method

To improve the persuasive power of empirical analysis, this part attempts to use the PSM-DID model to analyze the impacts of the low-carbon pilot policies on agricultural eco-efficiency. Models 1 to 5 use data for two years, whereas Model 6 uses the data starting from 2010 to 2019.

The estimated results of different years in Table 8 show that the impacts of the low-carbon pilot policies on the agricultural eco-efficiency are positive and have passed the significance level test. In particular, the low-carbon pilot policies in column (6) have positive impacts on agricultural eco-efficiency and passed the significance level test. It is consistent with the estimated results in Table 5, which verifies once again that the low-carbon pilot policies can improve agricultural eco-efficiency.

Non-Randomness of Low-Carbon Pilot Cities

The random selection of the low-carbon pilot cities is the premise of accurately identifying the impacts of the low-carbon pilot policies on agricultural eco-efficiency. However, according to the document proposed by the Chinese National Development and Reform Commission, the selection of low-carbon pilot policy is based on the "declaration of current situation, demonstration, and pilot city layout of the representative of," which means that the establishment of the low-carbon pilot cities is not random but is considered with the city's economic development level, geographic location, and environmental conditions. These factors will have different impacts on the eco-efficiency of urban agriculture with the changes in time and which will result in differences in estimation. To control the influences of the aforementioned factors, this paper refers to the research methods of scholars, such as Chen et al. [34], and adds the interaction term of urban attribute and time trend item into the econometric model. The econometric model constructed is shown as follows:

$$Y_{it} = \alpha + \beta_1 CLPP_{it} + \beta_2 X_{it} + S_C \times F(t) + \mu_i + \lambda_t \tag{8}$$

where the Sc within Formula (8) represents the city properties. Four variables are selected as antecedent factors of urban property. The four types of variables include the city for the 1998 Liang Kong District, the city's deputy provincial city, the cities in northern cities, and the cities on right side of the Hu Huanyong line[1]. $F(t)$ represents the expression of time trend term. Formula (8) includes the first-, second-, and third-order

[1] In 1998, in order to control acid rain and sulfur dioxide pollution, acid rain and sulfur dioxide pollution sites were designated as acid rain and sulfur dioxide pollution, that is, the dual control area; The northern cities refer to the cities north of the Qinling Mountains and Huaihe River line. Hu Huanyong Line refers to the Heihe-Tengchong Line proposed by Hu Huanyong in 1935. This line divides China into two parts of equal size, with densely populated areas on the right is de of Hu Huanyong Line and sparsely populated areas on the left.

Table 8. Estimation results based on PSM-DID model.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	2010–2011	2012–2013	2014–2015	2016–2017	2018–2019	2010–2019
Policy	0.1332***	0.0957***	0.1966***	0.1754***	0.0518***	0.2893***
	(0.0301)	(0.0121)	(0.0109)	(0.0088)	(0.0132)	(0.0140)
Structure	−0.0695	0.0140	0.0278	−0.0235	0.0125	−0.0087
	(0.1175)	(0.1003)	(0.0287)	(0.0349)	(0.0524)	(0.0516)
Urbanization	0.1476**	0.2422***	0.0071	−0.0238	−0.1055***	−0.0321
	(0.0749)	(0.0722)	(0.0219)	(0.0242)	(0.0362)	(0.0359)
Concentration	3.4584***	3.5026***	2.7874***	2.5748***	1.0269***	2.5208***
	(0.0990)	(0.0815)	(0.0266)	(0.0346)	(0.0502)	(0.0343)
Foreign	0.0069	0.0294	0.0338	0.0401	0.0174	0.0538
	(0.0642)	(0.0619)	(0.0238)	(0.0277)	(0.0453)	(0.0367)
Information	−0.3667***	−0.1650**	0.1348***	0.1778***	0.2860***	0.2555***
	(0.1342)	(0.0673)	(0.0077)	(0.0049)	(0.0017)	(0.0034)
Human	−0.0155	−0.0264	−0.0105	0.0231	0.0434*	0.0336
	(0.0558)	(0.0515)	(0.0143)	(0.0154)	(0.0233)	(0.0244)
Traffic	−0.1318**	−0.0117	−0.0145***	−0.0065	−0.0314***	−0.0117**
	(0.0519)	(0.0072)	(0.0020)	(0.0053)	(0.0085)	(0.0058)
Government	0.9377**	−0.0712	-0.0267	0.0564	0.3286	0.4971***
	(0.4606)	(0.4051)	(0.1078)	(0.1183)	(0.2040)	(0.1893)
Consumption	0.0028	−0.0020	0.0014	0.0020	−0.0004	0.0004
	(0.0121)	(0.0100)	(0.0028)	(0.0030)	(0.0039)	(0.0045)
_cons	0.9605***	0.9575***	0.9639***	0.9668***	0.9818***	0.9664***
	(0.0025)	(0.0022)	(0.0007)	(0.0008)	(0.0012)	(0.0011)
r2	0.8316	0.8846	0.9824	0.9809	0.9957	0.9359
N	562	562	562	562	562	2810

Statistics are shown in parenthesis; Standard error in brackets , ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively. The matching method is the second-order nearest neighbor matching in caliper.

terms of time trend term. Therefore, the interaction term between S_c and $F(t)$ controls the impacts of urban attribute differences on low-carbon pilot policies, which mitigates the estimation bias between low-carbon and non-low-carbon pilot cities to a certain extent. Other variables in Equation (8) are set in the same way as in Equations (1) and (2). The non-random estimation results of low-carbon pilot cities are shown in Table 9.

Table 9 presents the estimated results of the non-random selection of the low-carbon pilot policies. The city attribute of Columns (1), (2), (3), and (4) suggest whether the city is the dual-control area in 1998, a sub-provincial city, a northern city, or the city is on the right side of the Hu Huanyong Line, respectively. The estimated results in Table 9 shows that the impacts of the low-carbon pilot policies on the agricultural eco-efficiency are all positive and significant at the statistical level of 1%. This result proves once again that the low-carbon pilot policy is conducive to improving the agricultural eco-efficiency whether the natural and socio-economic conditions of the city are considered or not. An interesting finding is that the time trend item of Columns (2) and (4) has significant positive impacts on agricultural eco-efficiency. However, the influence of the time trend item of Columns (1) and (3) on agricultural eco-efficiency did not pass the significance level test. This finding shows that the impacts of the low-carbon pilot policies on agricultural eco-efficiency are affected by social and economic conditions but not the natural environment. That is, the low-carbon pilot policies are economic activities and hence should not be constrained by the natural environment.

Impact Difference of Low-Carbon Pilot Policies on Agricultural Ecological Efficiency under Terrain Difference

The difference in the impact of low-carbon pilot policies on agricultural eco-efficiency is mainly

Table 9. Estimation of non-random selection of low-carbon pilot policies.

Variable	(1)	(2)	(3)	(4)
Policy	0.2453***	0.2452***	0.2445***	0.2515***
	(0.0158)	(0.0158)	(0.0156)	(0.0158)
Year1	−0.0176	−0.0990*	−0.0780	−0.0965*
	(0.0584)	(0.0595)	(0.1375)	(0.0568)
Year2	0.0054	−0.0330**	0.0201	−0.0271*
	(0.0165)	(0.0168)	(0.0386)	(0.0160)
Year3	−0.0006	−0.0031**	−0.0016	−0.0025*
	(0.0014)	(0.0014)	(0.0032)	(0.0013)
Structure	0.1866	0.2357	0.1966	0.2428*
	(0.1412)	(0.1448)	(0.1417)	(0.1420)
Urbanization	−0.0800	−0.0775	−0.0909	−0.0836
	(0.0910)	(0.0911)	(0.0912)	(0.0917)
Concentration	2.5085***	2.5071***	2.5087***	2.5350***
	(0.0421)	(0.0422)	(0.0422)	(0.0432)
Foreign	−0.0392	−0.0321	−0.0460	−0.0490
	(0.0819)	(0.0819)	(0.0817)	(0.0821)
Information	0.2638***	0.2634***	0.2633***	0.2647***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
Human	−0.0653	−0.0428	−0.0562	−0.0577
	(0.1393)	(0.1394)	(0.1396)	(0.1391)
Traffic	−0.0035	−0.0038	−0.0037	−0.0033
	(0.0059)	(0.0059)	(0.0058)	(0.0059)
Government	2.4692***	2.4302***	2.4683***	2.4393***
	(0.4027)	(0.4026)	(0.4030)	(0.4055)
Consumption	0.0743***	0.0629***	0.0681***	0.0677***
	(0.0157)	(0.0148)	(0.0163)	(0.0146)
rho	−0.1646***	−0.1642***	−0.1730***	−0.1259***
	(0.0230)	(0.0231)	(0.0226)	(0.0288)
lambda	0.5667***	0.5518***	0.5867***	0.4574***
	(0.0566)	(0.0590)	(0.0534)	(0.0760)
sigma2_e	0.0367***	0.0367***	0.0367***	0.0368***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
r2	0.9310	0.9314	0.9306	0.9325
Log	595.9349	598.5145	594.6843	599.5088
N	1967	1967	1967	1967

Note: Output by Stata 14.0, Standard error in brackets ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

analyzed from the economic and social perspective. However, the biggest difference between agriculture and other departments is that agriculture is greatly affected by the terrain, so the terrain difference needs to be considered when analyzing the impact of low-carbon pilot policies on agricultural eco-efficiency. Based on the difference of topographic conditions between the East, the Middle and the West in China, this part attempts to divide the city into plain areas, hilly areas and mountainous areas[2]. Table 10 shows

2 The specific criteria for the division of plain areas, hilly areas and mountainous areas are as follows: the largest propor-

Table 10. Impact difference of low carbon pilot policies on agricultural eco-efficiency under different terrain.

Variable	Plain areas	Hilly areas	Mountainous areas
Policy	0.4102***	0.1703***	0.1535***
	(0.0413)	(0.0126)	(0.0120)
Gis	0.3837***	0.3290**	0.2603
	(0.1264)	(0.1556)	(0.2558)
Urb	0.0002	0.0708	0.0887
	(0.0679)	(0.0849)	(0.2687)
Agg	2.6551***	2.4503***	2.8798***
	(0.0386)	(0.0415)	(0.0963)
Foreign	0.0221	-0.1369	0.5839
	(0.0495)	(0.1498)	(0.5365)
Information	0.1373***	0.1934***	0.2753***
	(0.0075)	(0.0058)	(0.0056)
Human	0.0110	-0.0167	-0.0938
	(0.1179)	(0.1077)	(0.3870)
Traffic	0.0009	-0.0009	-0.0051
	(0.0131)	(0.0072)	(0.0099)
Government	0.4320	1.8538***	3.3251***
	(0.3408)	(0.4262)	(0.9122)
Consum	-0.0131	-0.0365**	0.0985**
	(0.0086)	(0.0156)	(0.0497)
rho	0.1751***	0.1294***	-0.1477***
	(0.0108)	(0.0063)	(0.0352)
lambda	0.1039	0.0118	0.2987***
	(0.0884)	(0.0131)	(0.0854)
sigma2_e	0.0974***	0.0055***	0.0832***
	(0.0004)	(0.0003)	(0.0040)
r2	0.9617	0.9695	0.9122
Log-likelihood	348.6502	509.7311	109.9001
N	1310	580	920

Note:Output by Stata 14.0, Standard error in brackets ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

the estimated results of the impact of low-carbon pilot policies on agricultural eco-efficiency under different terrain conditions.

Table 10 shows the topographic difference of the impact of low-carbon pilot policies on agricultural eco-efficiency. From the estimation in table 10 can be seen that the impact of low-carbon pilot policies on agricultural eco-efficiency under different topographic conditions is positive and has passed the significance level test. It can be seen that low-carbon pilot policy has the greatest impact on agricultural eco-efficiency in plain areas, followed by hilly areas, and has the smallest impact on agricultural eco-efficiency in mountainous areas by comparing the impact of low-carbon pilot policy on agricultural eco-efficiency under different terrain conditions. The possible explanation is that the agricultural development level in the plain area is relatively high, and the low-carbon pilot policy can significantly improve the agricultural eco-efficiency

tion of plain areas, hilly areas and mountainous areas is used as the benchmark to determine the county type. For example, Shuozhou City, Shanxi Province, has a mountainous area accounting for 26.5% of the total area; The hilly area accounted for 34.3% of the total area; The plain area accounts for 39.2% of the total area. So Shuozhou City is determined as a plain area in this paper.

by promoting low-carbon production; the most need of mountainous areas is to increase the agricultural output due to the relatively low level of agricultural development. Therefore, the impact of the low-carbon pilot policy on mountainous areas is limited even though the low-carbon pilot policy can improve agricultural eco-efficiency.

Conclusions

To achieve the goal of “the carbon peak” in 2030 and “the carbon-neutral” in 2060, the Chinese government has implemented three batches of the low-carbon pilot policies in 2010, 2012, and 2017. To reduce agricultural carbon emissions, the agricultural sector has been actively developing green planting and recycling agriculture with the financial support given by the government. In general, the implementation of the low-carbon pilot policies has promoted the reduction of chemical fertilizers, improved the quality of arable land, and reduced agricultural carbon emissions. Furthermore, the agricultural economy has achieved high-quality development. On this basis, this paper takes the implementation of low-carbon pilot policies as the research object and uses the spatial SARAR model to analyze the equilibrium and disequilibrium effects of the low-carbon pilot policies on agricultural eco-efficiency based on the data of 281 cities in China from 2010 to 2019. The results show a significant spatial correlation between low-carbon pilot policies and agricultural eco-efficiency. The implementation of low-carbon pilot policies can improve agricultural eco-efficiency. These policies have the greatest impact on the agricultural eco-efficiency in western China. Their impacts on the agricultural eco-efficiency are affected by the level of agricultural economic development, and their impacts on the agricultural eco-efficiency have disequilibrium effect, which can improve the agricultural eco-efficiency better in poor areas than in rich areas. Although the implementation of the low-carbon pilot policies reduces agricultural carbon emissions, it also inhibits agriculture. The impacts of the low-carbon pilot policies on the agricultural eco-efficiency are affected by social and economic conditions, and the natural environment does not play a significant role in this process.

The accurate and objective evaluation of the implementation effects of the low-carbon pilot policies not only help China to reduce carbon emissions better but also provide experiences and references for other countries in the world to reduce carbon emissions and improve agricultural eco-efficiency. In view of the reality of climate change, the requirements of the Agriculture Green Transition, and based on the research conclusions, this paper presents two policy suggestions to promote agricultural productivity. The first one refers to the expansion of the scope of the low-carbon pilot policies. Empirical analysis shows that the low carbon pilot policy is helpful in promoting agricultural eco-efficiency. Therefore, China’s low-carbon pilot policy should be referenced by other countries to propose their own policies to maintain the balance between agricultural development and agricultural ecological environment and to respond to global climate changes. In the second suggestion, the level of agricultural development should be considered seriously during the implementation of low-carbon pilot policies. The empirical analysis shows that the impacts of low-carbon pilot policies on agricultural eco-efficiency are unbalanced. However, the level of agricultural development should be considered when the low-carbon pilot policies are introduced in different regions. The regions with low levels of agricultural development can take the lead in introducing low-carbon pilot policies. Meanwhile, the regions with higher agricultural development levels need to cooperate with other policies in the future to avoid the inhibiting effects of low-carbon pilot policies on agricultural economic development.

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Conflict of Interest

The authors declare no conflict of interest.

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