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Yu Duan and Yutong Ruan *

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How Does Technology Diffusion Affect Carbon Emissions in China's Agricultural Sector?

Yu Duan [1] and Yutong Ruan [2,*]

[1] Shenzhen University, China
[2] University of Hong Kong, Hong Kong
* Correspondence: 1315109609@qq.com

Abstract: This paper employs Principal Component Analysis (PCA) to comprehensively assess technology diffusion by reducing dimensions and examines the influence of technology diffusion on the tripartite carbon emissions of the agricultural sector. Utilizing panel data from 21 cities in Guangdong Province spanning from 2015 to 2020, the paper establishes a Two-way fixed effects model to demonstrate how technology diffusion affect carbon emissions in Chinese cities. The empirical results reveal that: (1) technology diffusion contributes to a reduction in carbon emissions within the agricultural sector in Guangdong Province; (2) technology diffusion can enhance the total carbon absorption in the agricultural sector in Guangdong Province; (3) technology diffusion effectively bolsters the net carbon sequestration effect within the agricultural sector in Guangdong Province, China.

Keywords: technology diffusion; agricultural sector; carbon impact

1. Introduction

Global warming stands as one of the most significant threats to human survival and social development (Xu and Lin, 2017). China, as the world's largest carbon emitter, is responsible for 35.6% of global carbon emissions (Li et al., 2022). In 2020, China set forth ambitious objectives to achieve carbon emission peaking by 2030 and carbon neutrality by 2060. The agricultural sector in China contributes to 17% of carbon emissions, and effective control of agricultural carbon emissions is crucial for China to meet its carbon peaking and carbon neutrality goals and mitigate global warming. Within China, the planting industry serves as the primary source of agricultural carbon emissions (You et al., 2011). This industry exhibits dual characteristics, involving both carbon emission and carbon absorption. Crop growth results in both carbon dioxide emissions and absorption. Consequently, the planting industry produces a dual effect of carbon emission and carbon absorption, giving rise to the concept of the net carbon sink effect. This effect is calculated by subtracting carbon emissions from carbon absorption. Carbon emissions in the planting industry primarily stem from the use of chemicals such as fertilizers, pesticides, and agricultural films, along with the energy consumption of agricultural machinery and equipment. Carbon sequestration in the planting industry arises from crop photosynthesis. Research into the factors influencing carbon emission, carbon absorption, and net carbon sequestration in the planting industry is not only crucial for "emission reduction and sink increase" in this sector but also contributes to the timely attainment of "carbon peaking" and "carbon neutrality" objectives.

Technological innovation serves as one of the four driving forces behind agricultural economic growth and represents a key avenue for advancing the transformation and modernization of traditional agriculture (Wu and Liu, 2021). Specifically, innovation in green science and technology furnishes technical support for achieving environmentally friendly agricultural development, reducing carbon emissions, and accomplishing the "emission reduction and sink increase" goal in the planting industry (Dong et al., 2022; Zeng et al., 2022). However, technological innovation may struggle to achieve its full potential without technology diffusion. Technological innovation relies on technology diffusion to generate more extensive economic, social, and ecological benefits. Research into the influence of technology diffusion on carbon emissions, carbon absorption, and net carbon sequestration in the planting industry can offer fresh insights into carbon emissions reduction and the creation of additional carbon sinks.

Located in the southern region of China, Guangdong Province plays a significant role in Chinese agriculture, boasting a high degree of representativeness and reliable data sources due to its strong statistical foundations. Consequently, this paper selects data from 21 cities in Guangdong Province spanning from 2015 to 2020 and conducts an empirical study on the impact of technology diffusion on the triple carbon effects of the planting industry by constructing an econometric model. Compared to previous studies, this research deepens and broadens the subject matter in three key ways. Firstly, it enhances the precision of carbon emission measurements. Many existing studies fail to provide sufficient detail in measuring carbon emissions. For example, they often overlook the internal composition of fertilizer use when calculating fertilizer-related carbon emissions from the planting industry. To achieve more accurate measurements of carbon emissions in the planting industry, this study dissects chemical fertilizers into phosphate fertilizer, nitrogenous fertilizer, potash fertilizer, and compound fertilizer. Moreover, it also accounts for direct carbon emissions from potash fertilizer, equivalent to the carbon emissions arising from nitrous oxide application. Secondly, it introduces a novel approach to carbon emission reduction within the planting industry, emphasizing the role of technology diffusion. Lastly, it conducts a comprehensive examination of the influence of technology diffusion on the carbon emission effect, carbon absorption effect, and net carbon sink effect of the planting industry, taking into account its dual carbon emission and absorption characteristics.

2. Literature Review

Currently, research on carbon emissions in the planting industry predominantly centers on two key aspects: the measurement of carbon emissions and the factors influencing these emissions. Regarding the measurement of carbon emissions, most scholars employ the coefficient method, which entails estimating carbon emissions for various agricultural subdivisions based on established carbon emission coefficients and then aggregating the results (Zhang et al., 2014; Guan et al., 2018; Wang et al., 2017). More specifically, carbon emissions within the planting industry are primarily assessed based on the inputs of chemicals and the energy consumption associated with planting. Typically, these coefficients are derived from sources such as the Intergovernmental Panel on Climate Change (IPCC) and the Oak Ridge National Laboratory in the United States. When estimating carbon sinks in the planting industry, calculations often rely on the carbon emission coefficients, crop water content, economic coefficients, and crop yields (Cui et al., 2021; Van, 2007) . Net carbon sinks in the planting industry are determined by subtracting carbon emissions from carbon absorption.

Regarding the factors influencing agricultural carbon emissions, Wu et al. (2019) discovered that improved levels of agricultural economic development could reduce net carbon emissions within the agricultural sector, based on data from 30 provinces in China spanning from 2007 to 2016. Xiong Chuanghe et al. Xiong et al. (2020) found that agricultural mechanization and urbanization impact agricultural carbon emissions through a thorough analysis of driving factors. Utilizing an endogenous technological growth model, Papyrakis and Reyer (2007) examined the influence of technological progress on carbon emission reduction and found that technological advancement significantly reduced the cost of carbon emission reduction through the learning effect while enhancing the social returns of carbon emission reduction.

In summary, current research predominantly emphasizes the measurement of carbon emissions in agriculture as a whole and the factors influencing these emissions, with relatively fewer studies focusing specifically on the planting industry. Research into the factors affecting agricultural carbon emissions primarily centers on the levels of agricultural mechanization, the urbanization process, per capita income, industrial structure, and technological innovation. Rarely are efforts directed towards exploring the perspective of technology diffusion. Moreover, many studies primarily concentrate on carbon emissions, neglecting the analysis of the carbon absorption effect within the planting industry.

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Consequently, this paper takes Guangdong Province as a case study to investigate the impact of technology diffusion on the triple carbon effects within the planting industry, encompassing carbon emissions, carbon absorption, and net carbon sequestration. The aim is to offer a novel approach for the planting industry to "reduce emissions and increase sequestration" and contribute to the attainment of "carbon peaking and carbon neutrality" objectives.

3. Research Hypotheses

There are two contrasting viewpoints regarding the impact of agricultural technological progress on agricultural carbon emissions. One perspective argues that agricultural technological progress can facilitate a reduction in agricultural carbon emissions (Fan and Wei, 2016; Fei and Lin, 2017). The other contends that it may lead to an increase in agricultural carbon emissions (Liu and Yang, 2021). These opposing views can be attributed to the diversity of technological innovations and the complexity of the external environment.

In terms of agricultural technological innovations, they encompass biotechnological advancements such as improving existing crop varieties and cultivating new ones, as well as mechanical and chemical technology innovations like enhancing agricultural production equipment and pesticides. Notably, these two types of technological innovations have different effects on carbon emissions in the planting industry. Generally, biotechnological innovations, such as developing new crop varieties, tend to reduce carbon emissions in the planting industry. Conversely, innovations in mechanical and chemical technology can increase carbon emissions in the planting industry due to heightened chemical and energy inputs. The external environment for technological innovation and progress can be categorized as either positive or adverse. A positive external environment is characterized by high levels of economic development, significant social human capital, and relatively advanced technology, making it more likely for agricultural technological progress to reduce carbon emissions in the planting industry. Conversely, an adverse external environment is marked by low economic development, limited social human capital, and underdeveloped technology, which increases the likelihood of agricultural technological progress leading to increased carbon emissions in the planting industry.

In reality, technological progress in China's planting industry primarily involves biotechnological advancements, especially in southern China. In this region, disseminating and implementing mechanical technological innovations is challenging due to natural geographic factors like hilly terrain and social factors such as traditional farming practices. Given these practical considerations, agricultural technology progress in southern China primarily takes the form of biotechnological advancement. Furthermore, Guangdong Province exhibits a relatively high level of economic development and urbanization, providing a favorable positive external environment where agricultural technological innovation is likely to reduce carbon emissions in the planting industry. Regarding technological progress, technology diffusion serves as both an "amplifier" and a "booster". On one hand, technology diffusion allows new technologies to be applied more extensively, strengthening the ecological impact of green agricultural technology progress. On the other hand, technology diffusion accumulates human capital and technological expertise, fostering further technological innovation and progress. Additionally, the Chinese government's emphasis on food security has curbed practices among grain growers that result in high carbon emissions, such as excessive pesticide and fertilizer use (Dumortier and Elobeid, 2021). Consequently, several hypotheses are proposed.

Hypothesis 1: Technology diffusion contributes to the reduction of carbon emissions in the planting industry in Guangdong Province.

Crop carbon absorption is primarily influenced by economic coefficients, water content, carbon absorption coefficients, and crop yields. Economic coefficients, water content, and carbon absorption coefficients remain stable over extended periods. Therefore, crop yield has a significant impact on carbon absorption in crops, and crop yield is largely influenced by technological innovation and

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technology diffusion. Technological innovations directly lead to increased crop yields, and technology diffusion facilitates the broader application of these innovations, maximizing their positive effects on crop yield. As a result, the overall carbon sequestration of the planting industry increases due to the enhanced crop yield across the region.

Hypothesis 2: Technology diffusion plays a positive role in increasing the carbon sequestration in the planting industry in Guangdong Province.

Based on the aforementioned assumptions, it can be inferred that technology diffusion, when promoting the reduction of carbon emissions in the planting industry and significantly contributing to increased carbon absorption in the planting industry, is conducive to an overall increase in the net carbon sequestration of the planting industry in Guangdong Province. Therefore, Hypothesis 3 is proposed.

Hypothesis 3: Technology diffusion enhances the net carbon sequestration effect of the planting industry in Guangdong Province.

4. Research Design

4.1. Introduction to the Research Region

Guangdong Province is situated in the southern region of China, spanning between 20°13′-25°31′ north latitude and 109°39′-109°1′ east longitude. The province comprises 21 prefecture-level cities. As of 2021, the permanent population of Guangdong Province was 126.84 million. Guangdong Province is located in the East Asian monsoon (EAM) region, exhibiting mid-subtropical, south subtropical, and tropical climates from north to south. It is endowed with abundant sunlight, warmth, and water resources, making it one of the cradles of agricultural civilization. In terms of its economy, Guangdong has held the top position in terms of GDP among all Chinese provinces since 1989. It ranks as a leading economic powerhouse in China, contributing to 1/8 of the country's total economic output.

4.2. Introduction to the Data Sources

The data required for this study primarily originate from the Guangdong Statistical Yearbook on Agriculture, Guangdong Statistical Yearbook, and Guangdong Social Statistical Yearbook spanning from 2016 to 2021. Specifically, agricultural data for each city, including crop yields, the added value of the planting industry, and membership in rural professional and technical associations, are sourced from the Guangdong Statistical Yearbook on Agriculture. Non-agricultural data for each city, such as the proportion of the urban population to the permanent population, the per capita disposable income (PCDI) of residents, industrial output value, and import and export volumes, are drawn from the Guangdong Statistical Yearbook and Guangdong Social Statistical Yearbook. It's important to note that data for potash fertilizer, phosphate fertilizer, pesticides, and agricultural film for prefecture-level cities in Guangdong Province for the year 2017 are missing. Therefore, the average values from 2016 and 2018 are used as substitutes. The few remaining missing data points are estimated based on the average development rate.

4.3. Dependent Variables

4.3.1. Measurement of Carbon Emission Effect in the Planting Industry

The carbon emission effect in the planting industry refers to the total amount of carbon dioxide generated by chemical inputs and energy consumption during the production processes of the planting industry. The primary sources of carbon emissions in the planting industry include chemical fertilizers, pesticides, agricultural films, and carbon emissions resulting from energy inputs in farming machinery and irrigation. It's noteworthy that many studies do not consider the internal composition of fertilizer usage, thereby overlooking variations in carbon emission coefficients among different types of fertilizers. To achieve a more accurate assessment of carbon emissions in the planting industry, this paper categorizes chemical fertilizers into nitrogenous fertilizer, phosphate fertilizer, potash fertilizer, and compound fertilizer, with calculations based on the carbon emission coefficients of each type of chemical fertilizer. Additionally, direct emissions from nitrogenous fertilizer, specifically the carbon emissions equivalent to the application of nitrous oxide, are also taken into account. Eq.1 is the formula for calculating carbon emissions in the planting industry.

$$\text{carbem} = \sum \text{carbem}_i \times c_i \quad (1)$$

In Formula (1), "carbem" signifies the overall carbon emissions of the entire planting industry, "carbemi" represents the yield of the crop "i", and "Ci" denotes the carbon emission coefficient of the crop "i". The carbon emission coefficients for each carbon source are sourced from research findings by the Intergovernmental Panel on Climate Change (IPCC) and Dubey and Lal (2009)(refer to Table 1).

Table 1. Carbon emission coefficients.

Carbon Source Category	Carbon Source	Carbon Emission Coefficient	Unit
Chemical input	Indirect emissions of nitrogenous fertilizer	1.74	tCO2/t
	Direct emissions of nitrogenous fertilizer	0.0056	tCO2/t
	Phosphate fertilizer carbon emissions	0.2	tCO2/t
	Potash fertilizer carbon emissions	0.15	tCO2/t
	Carbon emissions of compound fertilizer	0.3810	tCO2/t
	Pesticide carbon emissions	13.8	tCO2/t
	Carbon emission of agricultural film	9.44	tCO2/t
Energy consumption	Carbon emissions from farmland irrigation	266.48	Kg/hm2
	Carbon emissions from electricity	0.18	Kg/KW

Carbon emissions from nitrogenous fertilizers consist of two components. The first component is direct carbon emissions, which are equivalent to the carbon emissions generated when nitrous oxide is applied. The second component is indirect carbon emissions, which are produced during the manufacturing process. To calculate indirect carbon emissions, the result can be obtained by multiplying the quantity of nitrogenous fertilizer (converted to its purity) by the corresponding carbon emission coefficient. Further explanation of the calculation of direct carbon emissions from nitrogenous fertilizers will be provided, and the calculation formula can be seen in Eq.2:

$$\text{carbx} = q \times k \times 127.71 \quad (2)$$

In Eq.2, "carbx" signifies the direct carbon emissions from nitrogenous fertilizer. "q" represents the quantity of nitrogenous fertilizer applied, "K" denotes the direct carbon emission coefficient of nitrogenous fertilizer, and "127.71" represents the carbon dioxide equivalent generated per unit of nitrogenous fertilizer used.

4.3.2. Measurement of the Carbon Sink Effect in the Planting Industry

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The carbon sink effect in the planting industry refers to the total quantity of carbon dioxide absorbed by all crops through photosynthesis during their growth. The calculation formula for carbon absorption in the planting industry is as follows:

$$\text{carbab} = \sum \frac{\text{carbab}_i \cdot E_i (1 - r_i)}{H_i} \quad (3)$$

In Eq.3, "carab" denotes the total carbon sequestration in the planting industry, "carbab_i" represents the yield of crop "i", "E_i" signifies the economic coefficient of crop "i", "r_i" represents the water content of crop "i", and "H_i" represents the carbon absorption coefficient of crop "i". For crops such as rice, tobacco, and vegetables, their economic coefficient, water content, and carbon absorption coefficient are derived from existing research findings (Cui et al., 2021; Guo et al., 2021). The economic coefficient, water content, and carbon absorption data for other crops, classified as food crops and cash crops, are based on the average values within each category. Please refer to Table 2 for the economic coefficients, water content, and carbon absorption values of the primary crops considered in this study.

Table 2. Calculation coefficient of carbon absorption of main crops.

Category	Food crops			Cash crops					
Species	Rice	Soybean	Other food crops	Sugar cane	Peanut	Tobacco	Cassava	Vegetable	Other cash crops
Water content (%)	12	13	12.5	50	10	85	70	90	61
Economic coefficient	0.45	0.34	0.395	0.5	0.43	0.55	0.7	0.6	0.556
Carbon absorption coefficient	0.414	0.45	0.432	0.45	0.45	0.45	0.423	0.45	0.45

4.3.3. Measurement of the Net Carbon Sink Effect in the Planting Industry

The net carbon sink effect in the planting industry signifies the net quantity of carbon dioxide absorbed by crops during their growth, which is determined by subtracting the total carbon dioxide emissions from the planting industry from the total carbon dioxide absorption by the planting industry. The formula for calculating the net carbon sequestration in the planting industry is as follows:

$$\text{ncarbsin} = \text{carbab} - \text{carbem} \quad (4)$$

In Eq.4, "ncarbsin" represents the net carbon sequestration of the planting industry, "carbab" is the carbon absorption of the planting industry, and "carbem" refers to the carbon emissions of the planting industry.

4.4. Core Explanatory Variable

The central explanatory variable in this study is agricultural technology diffusion. To measure technology diffusion more precisely, this paper comprehensively assesses agricultural technology diffusion based on the mode of technology dissemination. Specifically, it constructs an agricultural technology diffusion index by considering the demonstration effect of technology diffusion and the

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flow of human capital. The flow of human capital encompasses both tangible and intangible aspects. Here, we primarily focus on the intangible flow, which involves technology diffusion facilitated by information exchange without the physical movement of individuals.

Considering the availability and representativeness of data, six indicators are selected for comprehensive measurement, including rural professional technology associations, membership in rural professional technology associations, rural science popularization demonstration bases, rural science popularization demonstration townships, rural science popularization demonstration villages, and rural science popularization demonstration households (refer to Table 3). To construct the agricultural technology diffusion index from multiple dimensions, this study employs principal component analysis (PCA) to reduce the dimensionality of the six selected indicators. PCA is a widely used statistical tool, initially introduced by Pearson and further developed by Horelling.

Table 3. Descriptive statistics of index construction of agricultural technology diffusion.

Indicators (number)	Minimum value	Maximum value	Mean value	Standard deviation
Rural professional technology associations	0.00	337.00	53.95	62.26
Membership of rural professional and technology associations	0.00	24490.00	5392.74	5874.91
Rural science popularization demonstration bases	0.00	280.00	42.52	44.37
Rural science popularization demonstration townships	0.00	211.75	12.1	25.86
Rural science popularization demonstration village	0.00	213.00	54.20	51.457
Rural Science popularization demonstration households	0.00	6219.00	516.41	1053.40

Calculating the KMO value and operating the Bartlett test is to verify whether the above indicators were suitable to reduce dimensions through PCA. The calculation results are shown in Table 4. According to Table 4, the KMO value is greater than 0.6, and the significance of Bartlett's test of sphericity is less than 0.05, which shows the selected indicators are suitable for dimension reduction using principal component analysis.

Table 4. KMO and Bartlett's test.

KMO		0.654
Bartlett's test of sphericity	Approximate chi-square	198.849
	Degrees of freedom	15
	Significance	0.000

The contribution rate of each component was calculated according to PCA, and the principal components with eigenvalues greater than 0.9 were extracted. The calculation results are presented in Table 5.

Table 5. Interpretation of total variance of the technology diffusion index.

Component	Initial eigenvalue			Extraction sums of squared loadings		
	Total	Percentage of variance	Cumulative%	Total	Percentage of variance	Cumulative%
1	2.646	44.092	44.092	2.646	44.092	44.092
2	1.322	22.037	66.129	1.322	22.037	66.129

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3	0.903	15.048	81.177	0.903	15.048	81.177
4	0.538	8.962	90.139			
5	0.387	6.443	96.582			
6	0.205	3.418	100.000			

It can be seen from Table 5 that the cumulative contribution rates of the first three components are 44.092%, 66.129% and 81.177% respectively. According to the criterion of a cumulative contribution rate of 80%, the first three principal components are extracted, and the agricultural technology diffusion index is calculated according to Formula (5).

$$\text{Index} = 0.54 \times C1 - 0.27 \times C2 - 0.19 \times C3 \quad (5)$$

In addition, because the agricultural technology diffusion index obtained by the PCA has a negative number, in order to eliminate the influence of the negative number on the logarithm, the method of coordinate translation is used to eliminate the influence of the negative number (the agricultural technology diffusion index of each sample + the absolute value of the minimum value of the agricultural diffusion index + 0.01). The natural logarithm of the agricultural spread index is taken after eliminating the negative effects.

4.5. Control Variables

Academics have studied and empirically tested the impact of agricultural mechanization level, urbanization level, industrialization, planting development level, technological innovation and per capita income on carbon emissions of the planting industry. Therefore, these factors are set as control variables. See Table 6 for the calculation of control variables.

Table 6. Calculation of control variables.

Variable name	Variable meaning	Variable calculation	Unit
Mech	Agricultural mechanization level	The logarithm of the total power of agricultural machinery	Kilowatt
Uba	Urbanization level	The proportion of the urban population to the permanent resident population	%
Ind	Industrialization level	Industrial output value/gross regional output value	%
Crstr	The development level of the planting industry	The added value of the planting industry/output value of the planting industry	%
Tec	Technological innovation	The logarithm of government expenditure on sci-tech	yuan
Income	Per capita income	The logarithm of per capita income of all residents	yuan

4.6. Model Design

In order to verify H1, H2 and H3, the following measurement models are designed:

$$\text{Carbem}_{it} = \alpha_0 + \alpha_1 \text{Index}_{it} + \alpha_{jt} \text{Control}_{ijt} + \mu_i + \delta_{it} \quad (6)$$

$$\text{Carbab}_{it} = \beta_0 + \beta_1 \text{Index}_{it} + \beta_{jt} \text{Control}_{ijt} + \rho_i + \varepsilon_{it} \quad (7)$$

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$$\mathrm{Ncarbsin}_{it} = \gamma_0 + \gamma_1 \mathrm{Index}_{it} + \gamma_{jt}\mathrm{Control}_{ijt} + \sigma_i + \theta_{it} \quad (8)$$

For the above formulas, the subscript "i" represents prefecture-level city "i"; the subscript "j" represents control variable "j"; "t" means a particular year. "Carbemit" refers to the carbon emissions of the planting industry of the prefecture-level city "i" in the year "t". "Carbabit" represents the carbon absorption of the planting industry of the prefecture-level city "i" in the year "t". "Ncarbsinit" represents the total net carbon sinks of the planting industry of the prefecture-level city "i" in the year "t". "Carbem" represents the carbon emissions of the planting industry; "Carbab" represents the carbon absorption of the planting industry; "Ncarbsin" represents the net carbon sinks of the planting industry. "Index" stands for the index of agricultural technology diffusion which is obtained by applying PCA to reduce the dimensions of referred six indicators like rural professional association technology. "Control" stands for control variables, including agricultural mechanization level, urbanization level, industrialization level, the development level of the planting industry, technological innovation and per capita income of residents.

Table 7. Variable description statistics.

Variable category	Variable name	Variable meaning	Mean value	Standard deviation	Minimum value	Maximum value
Explained variables	Carbem	Carbon emissions of the planting industry	12.636	1.033	8.124	14.285
	Carab	Carbon absorption of the planting industry	13.236	1.425	9.252	15.975
	Ncarbsin	Net carbon sinks of the planting industry	12.839	1.885	-0.443	15.782
Core explanatory variable	Index	Technology diffusion index	-0.683	0.910	-4.605	1.102
Control variables	Mech	Agricultural mechanization level	6.417	3.748	3.300	15.249
	Uba	Urbanization level	63.708	19.369	37.51	99.85
	Ind	Industrialization level	1.364	0.520	0.540	2.844
	Crstr	The development level of the planting industry	0.0517	0.131	-0.564	0.579
	Income	Residents income	10.258	0.403	9.685	11.080
	Tec	Sci-tech input	11.568	1.500	9.179	15.529

5. Empirical Analysis

5.1. The Influence of Technology Diffusion on the Carbon Effect of the Planting Industry

The regression results are presented in Table 8. Column (1) of Table 8 indicates, with a 1% statistical significance level, that the agricultural technology diffusion index has a substantial inhibitory effect on the carbon emissions of the planting industry. When the agricultural technology diffusion index increases by 1%, the carbon emissions of the planting industry decrease by 0.147%. This validates Hypothesis 1, affirming that agricultural technology diffusion indeed contributes to

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the reduction of total carbon emissions in the planting industry. Column (2) in Table 8 reveals, at a 5% statistical significance level, that the agricultural technology diffusion index plays a noteworthy role in enhancing the carbon sinks within the planting industry. A 1% increase in the agricultural technology diffusion index leads to a 0.031% rise in carbon absorption within the planting industry, thus confirming Hypothesis 2. Column (3) in Table 8 demonstrates that, at a 10% statistical significance level, agricultural technology diffusion significantly increases the net carbon sinks of the planting industry. A 1% increase in the agricultural technology diffusion index results in a 0.266% increase in the net carbon sinks of the planting industry.

The impact of technology diffusion on the carbon emissions, carbon absorption, and net carbon sinks of the planting industry is assessed. In terms of statistical significance levels, technology diffusion exerts a significant impact on these aspects at 1%, 5%, and 10%, respectively. Moreover, technology diffusion appears to have a more pronounced effect on reducing carbon emissions compared to increasing carbon absorption or net carbon sinks. This could be attributed to two factors: (1) the innovation and diffusion of agricultural technology often involve strong externalities, typically led by governmental and public sector initiatives. As government awareness of environmental protection deepens and central government requirements regarding carbon emissions increase for local authorities, public sectors and agencies become more dedicated to reducing carbon dioxide emissions through technological innovation and diffusion. (2) Carbon dioxide emissions receive more public attention compared to carbon dioxide absorption, making the introduction of new machinery and chemical products specialized in carbon dioxide emission reduction a priority.

Concerning the influence of technology diffusion on the carbon effects of the planting industry, its impact is estimated at -0.147% for carbon emissions, 0.031% for carbon absorption, and 0.266% for net carbon sinks. The effect of technology diffusion on the reduction of carbon emissions in the planting industry is nearly five times stronger than its impact on carbon absorption. Notably, technology diffusion has the most significant effect on the net carbon sinks of the planting industry, highlighting the robust net carbon sink effect of technology diffusion. In practice, greater attention should be directed toward assessing the net carbon sink effect in the evaluation of carbon emission reduction within the planting industry, as this index encompasses both carbon emission reduction and carbon absorption effects. In conclusion, technology diffusion can significantly enhance the net carbon sink effect of the planting industry, emphasizing the importance of promoting technology diffusion to achieve "carbon peaking and carbon neutrality" goals, considering the carbon absorption function of the planting industry.

Table 8. Regression results.

Variables	**Carbem (1)**	**Carbab (2)**	**Ncarbsin (3)**
Index	-0.147***	0.031**	0.266*
	(-3.48)	(2.07)	（1.89）
Uba	-0.056***	0.047***	0.189*
	(-9.69)	(3.86)	（1.66）
Crstr	-0.421	0.095	6.103***
	(-1.28)	(0.86)	（5.98）
Mech	0.031**	0.145**	-0.118**
	(2.48)	(2.57)	（-2.26）
Tec	0.116	-0.339	-0.704**
	(1.49)	(-0.89)	（-2.00）
Ind	-0.091	0.309	0.850*
	(-1.04)	（0.61）	（1.81）
Income	1.232***	-0.439*	-4.303*
	(3.26)	（-1.64）	（-1.73）
(Constant)	15.439	15.216***	52.696**
	(0.79)	（6.93）	（2.59）

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Number of samples	126	126	126
Within-R2	0.47	0.66	0.16
F(p)	0.00	0.00	0.00

Note: the superscripts "*", "**" and "***" of the coefficients in the table represent "p < 0.10", "p < 0.05" and "p < 0.01" respectively; the numbers in parentheses are "t " values; F(P) is the "p-value" of the "F-test".

5.2. Robustness Test

The robustness test is performed by adding control variables and replacing the core explanatory variable. The foregoing analysis is based on a closed economy without the consideration of an open economy. The degree of opening to the outside world also affects the carbon emissions and carbon absorption of the planting industry. The main effective ways include the spread of ideas, the introduction of advanced technology and the inflow of foreign capital. Therefore, it is necessary to incorporate the degree of openness into the measurement model. The ratio of total imports and exports to GDP is used to measure the degree of opening up. See Table 9 for the regression results of the econometric model.

Table 9. Robustness test for adding control variables.

Variables	**Carbem (1)**	**Carbab (2)**	**Ncarbsin (3)**
Index	-0.144***	0.031**	0.254*
	(-3.83)	(2.05)	(1.83)
Open	-0.776***	-0.04	-3.373*
	(-5.06)	(0.969)	(-1.65)
The remaining control variables	Control	Control	Control
The number of samples	126	126	126
Within-R2	0.57	0.65	0.16
F(p)	0.00	0.00	0.00

Column (1) of Table 9 demonstrates that even after controlling for the degree of openness, technology diffusion continues to have a favorable impact on reducing carbon emissions in the planting industry, affirming the validity of Hypothesis 1. Column (2) of Table 9 reveals that technology diffusion contributes to an increase in carbon absorption within the planting industry, confirming the validity of Hypothesis 2. Column (3) of Table 9 illustrates that technology diffusion positively influences the expansion of net carbon sinks within the planting industry, thus confirming the validity of Hypothesis 3. In summary, the primary conclusions discussed earlier remain valid even when accounting for the degree of openness.

Public broadcasting revenue is used as a replacement for the aforementioned technology diffusion index, which was constructed using PCA dimension reduction. Two primary reasons support this choice. First, while the technology diffusion index generated through PCA provides a comprehensive assessment of technology diffusion, it inevitably loses some information. Thus, a single indicator is selected as an alternative. Second, the technology diffusion index constructed previously is based on the concept of tangible flow, focusing solely on material entities such as the number of rural professional associations and their membership, lacking information on monetary flow. Public broadcasting revenue effectively reflects the scale of public broadcasting and the extent of information dissemination within a region. Consequently, public broadcasting revenue is examined from the perspective of monetary flow. Key information from the model regression results is presented in Table 10. It is evident from Table 10 that, at a 10% statistical significance level, technology diffusion exhibits a significantly negative influence on the carbon emissions of the planting industry. Furthermore, technology diffusion has a notably positive impact on both carbon absorption and the net carbon sink effect within the planting industry. In summary, even with a

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different method for measuring technology diffusion variables, Hypothesis 1, Hypothesis 2, and Hypothesis 3 all remain valid, emphasizing the robustness of the primary conclusions.

Table 10. Robustness test of substitution variables.

Variables	Carbem (1)	Carbab (2)	Ncarbsin (3)
Index	-0.119*	0.044*	0.45*
	(-2.17)	(1.53)	(1.74)
Control variable	Control	Control	Control
The number of samples	126	126	126
Within-R^2	0.52	0.69	0.10
F(p)	0.00	0.00	0.00

6. Conclusion

Agriculture is an important source of carbon, and planting is the main component of agriculture. Planting has the dual characteristics of carbon source and carbon sink, resulting in the triple effects of carbon emission, carbon absorption and net carbon sink. Technology diffusion is the amplifier and booster of technology progress. Technology diffusion can expand the scope of application of new technologies, which help technology progress improve social, economic and ecological benefits to a greater extent. At present, there are few academic suggestions on the “emission reduction and sink increase” of the planting industry from the perspective of technology diffusion. Therefore, based on the panel data of 21 cities in Guangdong Province, this paper uses the fixed effect model to analyze the influence of technology diffusion on the three carbon effects of the planting industry, including carbon emission, carbon absorption and net carbon sink. The main conclusions are as follows: Firstly, technology diffusion plays a positive role in reducing carbon emissions of the planting industry in Guangdong Province. Secondly, technology diffusion will increase the total carbon sinks of the planting industry in Guangdong Province. Thirdly, technology diffusion will significantly increase the net carbon sink effect of the planting industry in Guangdong Province. After adding the control variable and replacing the core explanatory variable, the above conclusions are still valid and robust. The above conclusions also possibly apply to the economically developed provinces in southern China.

Based on the above analysis, the following four suggestions are put forward. Firstly, technology diffusion is necessary for technological innovation and technological progress to have a better performance. In the process of promoting the “emission reduction and sink increase” of the planting industry, it is necessary to strengthen the guidance and support of technology diffusion. Secondly, technology diffusion has a significant role in reducing carbon emissions and increasing the carbon absorption of the planting industry. Therefore, the focus of policy and financial input shouldn’t be placed just on technological innovation, and it’s necessary to take increasing support for technology diffusion into consideration. Thirdly, the technology diffusion of agriculture bears strong externalities. So the government needs to screen the relevant agricultural technologies and select the agricultural technologies that have significantly positive influence on ecological, social and economic benefits, and takes the lead of the technology diffusion concerning its content and direction, so as to better influence of technological innovation and technology diffusion on “reducing emissions and increasing sinks” of planting industry, contributing to achieving “carbon peaking and carbon neutrality” goals. Fourthly, agricultural technology associations, universities, governments and public welfare organizations should take the initiative to carry out technology popularization activities for a wide spread of green technology and emission reduction technology. At the same time, R&D departments of agricultural technology should strengthen their contacts with farmers, which will enhance new agricultural technologies to meet the needs of farmers better. To achieve the goal

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of reducing carbon sources and increasing carbon sinks in the planting industry, the cost of technology diffusion needs to be reduced and green agricultural technologies need to be promoted more easily.

Currently, research on carbon emissions in the planting industry predominantly centers on two key aspects: the measurement of carbon emissions and the factors influencing these emissions. Regarding the measurement of carbon emissions, most scholars employ the coefficient method, which entails estimating carbon emissions for various agricultural subdivisions based on established carbon emission coefficients and then aggregating the results (Guan et al., 2018; Wang et al., 2017; Cui et al., 2021). More specifically, carbon emissions within the planting industry are primarily assessed based on the inputs of chemicals and the energy consumption associated with planting. Typically, these coefficients are derived from sources such as the Intergovernmental Panel on Climate Change (IPCC) and the Oak Ridge National Laboratory in the United States. When estimating carbon sinks in the planting industry, calculations often rely on the carbon emission coefficients, crop water content, economic coefficients, and crop yields (Van, 2007; Wu et al., 2019). Net carbon sinks in the planting industry are determined by subtracting carbon emissions from carbon absorption.

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