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Has China's Carbon Emissions Trading Pilot Policy Improved Agricultural Green Total Factor Productivity?

Zhuohui Yu [1,2], Shiping Mao [1,*] and Qingning Lin [1]

[1] Institute of Agricultural Economics and Development, Chinese Academy of Agricultural Sciences, 12 South Avenue, Zhongguancun, Haidian District, Beijing 100081, China
[2] College of Economics, Northwest Normal University, No. 967 East Road, Anning District, Lanzhou 730071, China
* Correspondence: maoshiping@caas.cn; Tel.: +86-10-8210-8388

Abstract: The carbon trading system affects all aspects of the economy and society profoundly. Agriculture, as a high-carbon-emitting industry, has been hard-hit. China's agricultural activities will emit about 820 million tons of carbon dioxide equivalents, accounting for 7% of the country's total carbon emissions. In order to develop a green and low-carbon economy and control greenhouse gas emissions, China officially launched the pilot carbon emissions trading policy in 2013. The effects and mechanism of this on agricultural carbon emissions are still unclear. Herein, this paper uses China's provincial panel data from 2000 to 2019 to measure agricultural green total factor productivity regarding the implementation of China's carbon emissions trading pilot policy in 2013 as a quasi-natural experiment, and uses PSM-DID robustness analysis to evaluate the effect of China's carbon emission rights trading pilot policy on agricultural green total factor productivity in pilot areas. The propensity score method is a type of statistical method that uses nonexperimental or observational data for intervention-effect analysis, which reduces the effects of bias and allows for more reasonable comparisons between treatment and control groups. "Difference in difference" is an approach to policy-effect evaluation based on a counterfactual framework to assess the change in the observed factors in both cases of policy occurrence and nonoccurrence. PSM-DID is a combination of PSM and DID using the PSM method to match each treatment group sample to a specific control group sample, which can solve the problem of self-selection bias in the DID method and assess the policy implementation effect more accurately. This study found that China's carbon emissions trading pilot policy has significantly improved China's agricultural green total factor productivity. Further impact mechanism tests show that China's carbon emissions trading pilot policy will improve agricultural green total factor productivity through environmental protection policies and technological innovation. Finally, this paper puts forward corresponding countermeasures and suggestions based on the research results.

Keywords: carbon emission trading pilot; agricultural green total factor productivity (AGTFP); PSM-DID model

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1. Introduction

Since the country's reform and opening up, China's agriculture has been developing continually and rapidly. With production methods pursuing only quantity results with inefficient use of water and soil resources, excessive input of chemical fertilizers and pesticides, and massive discharge of livestock and poultry manure [1–3], multiple negative impacts have caused severe damage to the ecosystem and rural environment, restricting the sustainable development of agriculture. Currently, the global climate problem is serious and urgent. Climate warming threatens global food safety by affecting agricultural production. Climate change, as a common challenge faced by people all over the world, has changed from a future to a current crisis. At the same time, the frequent occurrence of extreme weather has aggravated the fluctuation in agricultural production and sometimes even turned into serious agricultural disasters, causing farmers to work in vain. The search for strategies to mitigate climate change has become an integral part of ensuring food safety and the bottom line of farmer income. The United Nations Framework Convention on Climate Change in 1992, the Kyoto Protocol in 1997, and the Paris Agreement in 2016 all showed that reduction in CO_2 has always been a key topic of global concern. In reality, carbon emissions in developing countries are gradually becoming the main source of global carbon emissions [4]. Among them, China has become the world's largest carbon emitter, with carbon emissions reaching 9.899 billion tons in 2020, accounting for 30.7% of global carbon emissions. Agriculture, as a contributor to climate change, is one of the largest anthropogenic sources of greenhouse gas emissions [5]. According to statistics from the FAO's official website, the greenhouse gas released from agricultural land exceeds 30% of the total global anthropogenic greenhouse gas emissions. Equivalent to 15 billion tons of CO_2 will be generated every year. Therefore, the development of agriculture must also join the action to deal with the global climate crisis. In response to this situation, it is an inevitable trend for agriculture to change from traditional production methods to green production methods [6,7]. Sustainable agriculture, total factor productivity (TFP), and ecological resilience have high synergistic potential [8]. A vital factor for sustainable and healthy development is green total factor productivity (GTFP) [9–13]. Therefore, the Chinese government has shifted its focus from simply pursuing GDP growth to GTFP growth when pursuing development goals [14]. GTFP is a new definition under environmental and energy constraints [15], referring to adding environmental factors when measuring TFP.

Similarly, as a large agricultural country, improving agriculture total factor productivity (AGTFP) is imperative to solving the dilemma of crude production methods dominating Chinese agriculture [13]. AGTFP is an objective indicator reflecting the sustainable development of agriculture. It refers to maximizing agricultural output productivity while minimizing agricultural pollution emissions on the premise of determining the factors of agricultural input [16]. AGTFP can reveal a sustainable growth component beyond input factors under environmental stress and has been applied in many studies [17,18]. The research on AGTFP focuses on the following three parts. First is to study the input and output factors of AGTFP [19]. With the increasing emphasis on ecology, agricultural carbon emissions as well as nonpoint source pollution are included in the framework of calculating AGTFP. Scholars such as Liu et al. (2021) [20] and Wang et al. (2021) [21] measured and analyzed agricultural carbon emissions, and included them in the measurement of AGTFP, and found that China's AGTFP has a fluctuating growth trend in general. Chen et al. (2021) [22] and Yang et al. (2022) [23] added agricultural nonpoint source pollution in addition to carbon emission factors to the AGTFP measure, and the results of the study found that AGTFP has been constrained by the external environment, although there is an increasing trend. However, agriculture as a complete cycle system contains not only carbon emissions but also carbon sinks, but few studies have addressed this point, so we took carbon sinks into account when calculating agricultural carbon emissions. Second is to study the measurement method of AGTFP, which is based on the GTFP calculation method, and based on input–output data using stochastic frontier analysis (SFA), data-envelopment analysis (DEA) and other methods. For example, Coelli (2005) [24] used DEA to derive the Malmquist productivity index to study agricultural productivity levels in 93 developed and developing countries. Yang et al. (2022) [23] constructed a Malmquist productivity index based on a nonradial and nonangular SBM directional distance function to calculate China's AGTFP. Third is to study the factors affecting AGTFP. Some scholars have found that agricultural FDI has a significant positive effect on AGTFP [25]. There is a significant double-threshold effect between rural human capital and AGTFP [26]. Increased agricultural insurance or reduced air pollution could increase AGTFP [27]. Technological progress is the main force influencing green total factor productivity changes in Chinese agriculture innovation [28]. Environmental regulation has a significant positive effect on AGTFP [29], but some studies have shown that the direct effect of environmental regulation on AGTFP has a significant U shape [30]. Despite the carbon emission rights trading pilot being a significant tool of environmental regulation, there has been no study addressing the effect on AGTFP.

As a core means of environmental regulation, China has implemented carbon trading and it has had a significant impact on industries [31], which provides a reference for studying the impact of carbon trading on the agricultural sector. According to current statistics, there are about 32 carbon trading systems operating or about to operate in the world, and carbon trading has become one of the core policy means to reduce carbon emissions. China officially launched carbon emission rights trading pilots in seven regions—Beijing, Tianjin, Shanghai, Chongqing, Guangdong, Hubei, and Shenzhen—in 2013. Carbon trading has been implemented as a key means of environmental regulation in China. However, there are few studies on the effect and mechanism of the carbon emissions trading system and AGTFP. The reason is that the carbon emissions trading system mainly involves power generation, petrochemical, chemical, building materials, steel, nonferrous metals, and other industries, research on carbon emissions trading systems has focused on cities and industries [32,33]. Agriculture, as the primary industry, is closely related to the above industries. From the feedback effect between industries, other industries have a significant impact on the agricultural economy [34]. For example, there are strong volatility spillovers between crude oil and agricultural markets [35], and spillovers between metals, energy, and agriculture [36]. In addition, agriculture is closely related to climate change, and as a carbon emission source of greenhouse gas, the emission is huge. Therefore, it is meaningful to study the impact of the operation of China's carbon trading system on the AGTFP from the perspective of the carbon emissions rights trading pilot policy, which is significant for the sustainable development of agriculture in the direction of green efficiency.

The existing research on AGTFP and carbon emissions trading pilot policies provides the research basis for this paper, but research about carbon trading and AGTFP are still lacking, and the influence effect and influence mechanisms between the carbon emissions rights trading pilot policy and AGTFP are still unclear. The marginal contributions of this paper are as follows. First, agricultural ecosystems are important atmospheric carbon sources and carbon sinks, agricultural soils have great carbon sequestration potential, and carbon sinks have a large impact on mitigating climate change. However, few scholars have taken carbon sinks into account when studying agricultural production. We included agricultural carbon sinks in the calculation framework of AGTFP, which enriches the factors of AGTFP measurement. Second, although agriculture is currently not a major industry in China's carbon trading market, agriculture is closely related to petrochemical, metal and other industries and has spillover effects, and as a carbon emission source of greenhouse gas, the emission is huge. Therefore, we built a theoretical framework for the impact of carbon emissions rights trading pilot policy on China's AGTFP and studied the effect and mechanism of the carbon emissions trading pilot policy on AGTFP. To a certain extent, this paper is a supplement to the current research that focuses on chemical, petrochemical, and other industrial fields. We fill a gap in the impact of carbon trading policies on agriculture. Third, this paper provides more ideas to study the impact of carbon emissions trading system on economy and society. Are the pilot areas of carbon emissions trading significantly affected by the policy? How will the implementation of the pilot carbon trading policy affect the green and sustainable development of agriculture?

2. Analysis of Policy Evolution and Influence Mechanism

2.1. Evolutionary Logic of China's Carbon Emission Policy

In response to the climate crisis, China has formulated a series of policies related to emission reduction, which has made great contributions to controlling greenhouse gas emissions. As early as 1992, China signed the United Nations Framework Convention on Climate Change. Subsequently, China established a special "National Climate Change Response Coordination Agency" by introducing a series of policies and measures to deal with the continuous warming of the global climate. In 2007, 14 departments, including the National Development and Reform Commission, jointly issued "China's Special Action on Climate Change Science and Technology." In 2011, China officially approved carbon emissions trading to be piloted in seven regions. On 1 February 2021, the implementation of the Measures for the Administration of Carbon Emissions Trading (for Trial Implementation) indicated that China's unified carbon market was launched. Table 1 shows the policies that related to China's carbon emission from 1992 to 2021.

Table 1. China's carbon emission related policies from 1992 to 2021.

Policy	Background	Objectives	Measures
Signed the United Nations Framework Convention on Climate Change (1992)	Became one of the first parties to sign the Convention	Dealt with the continuous warming of the global climate.	Established a special "National Climate Change Countermeasure Coordination Agency"
China's Special Action on Climate Change Science and Technology (2007)	The issue of climate change was becoming more and more prominent. Properly addressed the issue of climate change was related to the realization of economic and social development goals.	By 2020, the independent innovation capability in the field of climate change was greatly improved; a batch of key technologies for controlling greenhouse gas emissions and mitigating climate change with independent intellectual property rights made breakthroughs etc.	Increased investment in science and technology through multiple channels. Increased financial support for climate change scientific research. Strengthen international scientific and technological cooperation. Promoted international technology transfer
Carbon Emission Rights Trading Pilot Work (2011) (From June 2013 to June 2014, the 7 provinces and cities in the pilot program formally established carbon markets)	Implemented the requirements of the "Twelfth Five-Year Plan" for gradually. Established a domestic carbon emissions trading market	Promoted the use of market mechanisms to achieve the goal of controlling greenhouse gas emissions in 2020 at a lower cost. Accelerated the transformation of economic development patterns and the upgrading of industrial structures	Identified Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen as pilot areas for carbon emissions trading. Established a carbon emission rights trading supervision system and registration system in the region
Measures for the Administration of Carbon Emissions Trading (for Trial Implementation) (2021)	Given full play to market mechanisms in addressing climate change and promoting green and low-carbon development,	Promoted greenhouse gas emission reduction. Regulated national carbon emissions trading and related activities	Formulated policies applicable to national carbon emissions trading and related activities, including carbon emission allowance allocation and settlement; carbon emission registration; trading, settlement, etc.

(1) United Nations Framework Convention on Climate Change (UNFCCC) established basic principles for international cooperation in addressing climate change. After signing the treaty, China established a "National Climate Change Response Coordination Agency" in accordance with the requirements of the national sustainable development strategy, and a series of policies and measures related to addressing climate change have been adopted, all of which have made an active contribution to climate change mitigation and adaptation.

(2) China's Special Action on Climate Change Science and Technology put forward China's goals, tasks, and specific safeguard measures in addressing climate change by 2020. For example, by 2020, China will make breakthroughs in key technologies for mitigating climate change and enhance the public's scientific understanding of climate change.

(3) Carbon Emission Rights Trading Pilot Work, compared with other carbon emission policies that only have macro-goals, is the first time that China has proposed a specific

policy that has been implemented in pilot provinces, and has established a carbon emissions trading platform. This pilot work shows that the carbon emission mechanism is officially established in China, so this policy is very valuable for research. Therefore, we chose this policy to study the effect of its implementation.

(4) Determination of Measures for the Administration of Carbon Emissions Trading establishes a unified national carbon trading market. From regional pilot carbon emissions trading to national unified carbon emissions trading, the local carbon trading market should gradually transition to the national carbon trading market.

2.2. Influence Mechanism and Policy Effects

In essence, carbon trading is the market trade of greenhouse gas emission rights. This type of asset, part of public goods, can be traded and allocated through the market, thereby eliminating externalities and improving social welfare. Agricultural carbon emissions are huge. In the context of green agriculture development, it is the general trend to include agriculture in the carbon trading market. As of 2016, the National Development and Reform Commission has approved 5074 Clean Development Mechanism Project (CDM) projects. Hubei Province also piloted agricultural carbon trading in 2019, developed the province's rural resource emission reduction project, and implemented greenhouse gas emission control from rural biogas delivery. Under the influence of the carbon emissions trading rights policy, a large amount of funds will flow into the construction of green and low-carbon agricultural development. At the same time, greenhouse gas emissions in agricultural production have also been controlled, which will improve China's AGTFP and promotes green agriculture development.

The implementation of the carbon emissions trading pilot policy is to allocate a fixed share of emissions to enterprises, which will take a series of measures to reduce production costs, such as reducing carbon emissions, introducing green technologies and thus increasing AGTFP. At the same time, the carbon emissions trading rights pilot policy, as an environmental regulation policy, will also exert its environmental regulation impact effect. Specifically, the carbon trading pilot policy will have an impact on AGTFP through two mechanisms: environmental regulation and technological innovation (Figure 1).

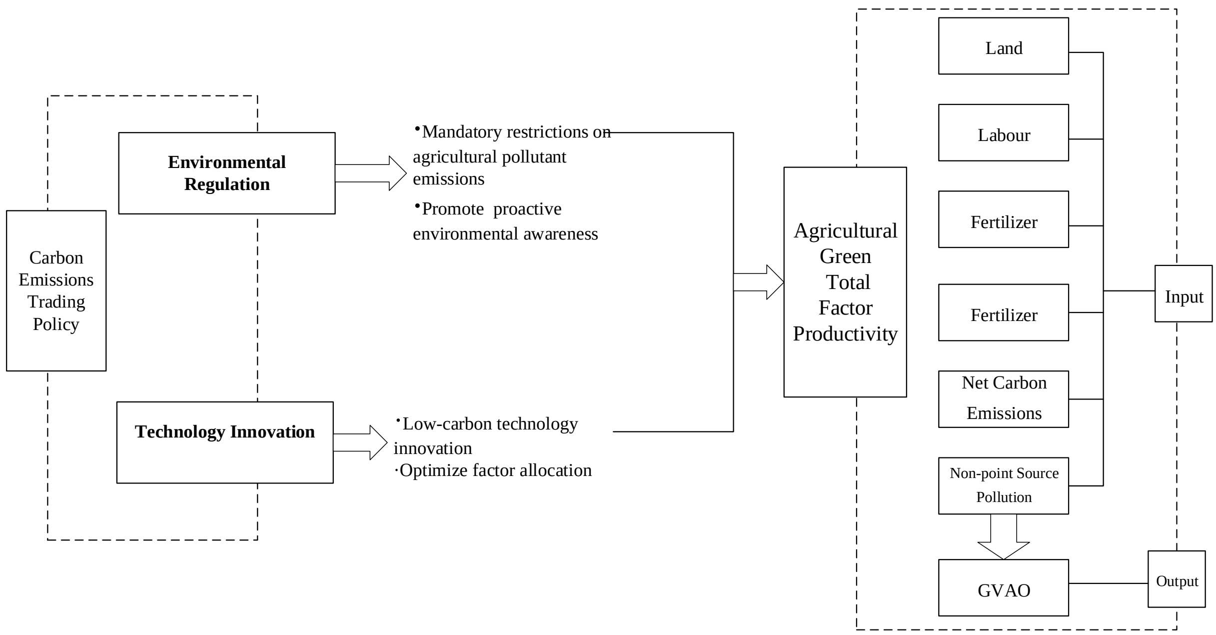

Figure 1. Schematic diagram of the impact of carbon emissions trading rights pilot policy on AGTFP.

(1) Environmental regulation has always been an effective means to improve green production [37]. First, the implementation of the carbon emissions trading rights pilot policy

will stimulate the government's awareness of energy conservation and emission reduction, so as to formulate relevant environmental regulation policies. After the implementation of the carbon emissions rights trading pilot policy, environmental protection policies in the agricultural sector have increased significantly. In 2012, the Ministry of Agriculture and the Ministry of Environmental Protection issued the "Twelfth Five-Year Plan for the Prevention and Control of Pollution from Livestock and Poultry Breeding." In 2015, the Ministry of Agriculture of China successively issued the "Action Plan for Zero Growth of Chemical Fertilizer Application by 2020" and the "Action Plan for Zero Growth of Pesticide Use by 2020," and made detailed arrangements for the reduction of chemical fertilizers and pesticides. In 2017, the General Office of the CPC Central Committee and the General Office of the State Council issued the "Opinions on Innovating Systems and Mechanisms to Promote the Green Development of Agriculture." First of all, the environmental protection policies have forced restrictions on the wanton emissions of agricultural pollutants, which can improve the original heavy pollution, inefficient production technology, and production methods. Second, the carbon emissions rights trading pilot policy is an environmental regulation policy is a nonmarket intervention to address the externality of pollution, and the "emission reduction" effect of the policy is conducive to the "economic growth" effect. It can optimize the ecological environment and comprehensively improve the environmental protection awareness of the public and agricultural producers, then encourage agricultural producers to take the initiative to reduce environmental pollution [38,39], which can promote green production in the whole society and make China's AGTFP improve.

(2) According to the Porter hypothesis, the implementation of environmental policies, such as the carbon emissions right trading pilot policy, will prompt firms to innovate in science and technology and strengthen technological progress [40]. Specifically, the carbon trading pilot policy gives emission allowances to petrochemical and power industries, then companies and industries will take the following two options to reduce their own emissions and reduce high-carbon factors. First, low-carbon technology innovation is a major driver of green production efficiency [41]. Companies can choose to conduct their own R&D and introduce green technologies and advanced equipment to promote a higher level of innovation in low-carbon technologies [42]. After the introduction of carbon trading, the promotion of green production efficiency in agriculture is more evident from the mandatory reforms brought about by the rising costs of agricultural production [13]. Second, optimizing factor allocation is also an important factor affecting the efficiency of green production. Companies and industries can choose to reduce resource investment in production processes accompanied by high carbon emission products and instead invest in the development of cleaner energy sources [43], such as solar energy, wind energy, water energy, and other clean energy, to achieve clean energy supply in agricultural production and ecological environment management and enhance China's AGTFP.

3. Materials and Methods

3.1. Transcend Logarithmic Production Function

The parametric method and the nonparametric method are the two main methods for measuring AGTFP, but the nonparametric method does not have a specific functional form, so cannot reflect the interaction between input factors. Therefore, we chose the parametric method to calculate AGTFP, specifically, referring to the methods of Ramanathan (2005) [44] and Song et al. (2020) [45] to deal with environmental factors, incorporate environmental factors into the production function together with production factors, such as labor and land. This method expands the calculation structure of production efficiency from the input side while adding the net agricultural carbon dioxide emissions and agricultural nonpoint source pollution to calculate AGTFP. In order to investigate the interactions between material materials and environmental factor, this paper determined the specific form of the production function as the translog production function. Transcend logarithmic production function, as one of production functions, has good inclusiveness. It also can study interactions between input factors. In addition, the time-varying factor enhancement factor is added to the model to calculate AGTFP. The specific setting form of the function is as follows:

$$lnY_{it} = \beta_0 + \beta_t t + \frac{1}{2}\beta_{tt}t^2 + \sum_{k=1}^{6}(\beta_k + \beta_{tK})lnX_{it} + \frac{1}{2}\sum_{k=1}^{6}\sum_{j=1}^{6} lnX_{kit}lnX_{jit} + v_{it} \quad (1)$$

where Y_{it} represents the output of the i-th decision endmember in the t-thperiod. X_{it} represents the input of the i-th decision endmember in the t-th period, includes land input, labor input, machinery input, fertilizer conversion, net carbon emissions, agricultural nonpoint source pollution. And t = 2000, 2001, . . . , 2019. The β represents the parameter vector to be estimated; v_{it} represents a random error term, and $v_{it} \sim N\left(0,\ \sigma_v^2\right)$. Taking the derivation of the time trend term on both sides of formula (1), the expression of the rate of scientific and technological progress is as follows.

$$\mathrm{TP} = \frac{\partial lnY_{it}}{\partial t} = \beta_t + \beta_{tt} + \sum_{k=1}^{6} \beta_{tk} lnX_{it} \quad (2)$$

Transcend logarithmic production function contains interaction terms of input elements, so it is inevitable that there will be serious collinearity problems. Only discarding variables that cause multicollinearity is not advisable in this study. Conventional regression methods will cause overfitting. This paper chose penalized regression to estimate formula (1). It can not only solve multicollinearity but also estimates more realistic parameters.

3.2. Penalized Regression

Penalized regression is divided into ridge regression, lasso regression, and elastic net-based regression. The elastic net estimator, proposed by Zou and Hastie (2005) [46], has the advantages of both ridge regression and lasso. And it will not arbitrarily filter highly correlated variables and has the shrinking function. the loss function of elastic net includes both 1-norm and 2-norm penalty terms.

$$\min_{\beta}(y - X\beta)'(y - X\beta) + \lambda_1\|\beta\|_1 + \lambda_2\|\beta\|_2^2 \quad (3)$$

where $\lambda_1 \geq 0$, $\lambda_2 \geq 0$ represents the adjustment parameter. Since the value ranges of λ_1 and λ_2 are infinite, it is inconvenient to use the cross-validation method to select the optimal value. Therefore, after defining $\lambda \equiv \lambda_1 + \lambda_2$, $\alpha \equiv \lambda_1/\lambda$, formula (3) can be equivalently transformed into the following formula.

$$\min_{\beta}(y - X\beta)'(y - X\beta) + \lambda\left[\alpha\|\beta\|_1 + (1-\alpha)\|\beta\|_2^2\right] \quad (4)$$

where $\lambda \geq 0$ and $0 \leq \alpha \leq 1$ represent the adjustment parameter. The value interval of the adjustment parameter α is [0, 1], which can facilitate the selection of its optimal value through cross-validation. Ridge regression and lasso are both special cases based on elastic net regression. If α = 0, the elastic net degenerates to ridge regression; if α = 1, the elastic net degenerates to lasso; if 0 < α < 1, the elastic net is a compromise between ridge regression and lasso.

In general, penalized regression weighs the impact of bias and variance on the estimated results by adding penalty terms, and will get a smaller mean square error (MSE) than the general regression method. It has a stronger ability to adapt to the multidimensional data environment and accurately fit the model data, and the regression coefficients are more shrunk toward the origin, which is a more realistic and reliable regression method.

3.3. PSM-DID

DID is an effective method to test the effect of a policy implementation. It is based on a counterfactual framework to assess the change in the observed factors in both cases of policy occurrence and nonoccurrence. The sample subjected to an exogenous policy impact is divided into two groups: the treatment group and the control group. The treatment group is subjected to policy intervention and the control group not subjected to policy intervention. By comparing the change in observations in the treatment group (D1) and the change in observations in the control group (D2), we can obtain the actual effect of the policy impact (D = D1−D2). The advantage is that the established model can not only avoid the trouble of endogeneity problems to a large extent but can also isolate the "policy disposition effect," and the net effect of the assessed policy can be accurately derived. In reality, the development level, population size, resource endowment, etc. of each province in China are different, so there is a large heterogeneity between regions. It is very important to ensure that there are no systematic differences between the treatment group and the control group. Sample matching can solve the problem of sample selection bias [47]. This paper uses the propensity score matching (PSM) method to generate matching samples and combines the double-difference model to estimate the impact of the carbon emissions trading pilot policy on AGTFP to ensure the accuracy of the estimation results.

This paper set up the PSM-DID model based on the implementation time and the provinces of China's carbon emissions rights trading pilot policy. The treatment group and the control group were distinguished from the two aspects of region and time, so as to study the effect of the implementation of carbon emissions rights trading pilot policy on China's AGTFP.

First, matching samples are generated using the PSM method. It selects a sample with a similar distribution of observable variables to the treatment group from a large number of potential control groups. Specifically, the samples are divided into two groups: one group is the treatment group, representing the pilot areas of carbon emissions trading; the other group is the control group, representing the areas that are not pilot areas during the investigation period. Logit regression was used to estimate the conditional probability of a province becoming a pilot area based on a series of observable variables. Suppose the probability of a province becoming a pilot area is $\mathrm{P} = P_r\{treated_{it} = 1\} = \Phi\{X_{it}\}$, where P represents the probability of the i-th province becoming a pilot area for carbon emission rights trading, and $\Phi\{\cdot\}$ represents the normal cumulative distribution function. X_{it} represents the matching variable. Then this method uses the propensity score to construct a distance function for matching, so the matched treatment group and control group have the same distribution on the observable variables. DID was used method to estimate policy effects based on matching samples, and introduce two dummy variables. One of the dummy variable is $PROVINCE_{it}$, which represents the province where the carbon emissions trading pilot is set up, and the other is $PERIOD_{it}$, that represents the period when the carbon emissions trading pilot policy was implemented. The model is as follows.

$$AGTFP_{it} = \alpha_0 + \alpha_1 PERIOD_{it} \times PROVINCE_{it} + \sum_{i=1}^{4} \alpha_j Control_{it} + u_i + u_t + \xi_{it} \quad (5)$$

where $AGTFP_{it}$ represents the AGTFP of the i-th province in the t-th period. $PERIOD_{it}$ is a dummy variable of year, and the treatment group implemented the carbon emissions trading pilot policy in 2013, so $PERIOD_{it}$ = 0 from 2008 to 2015 and $PERIOD_{it}$ = 1 from 2014 to 2019; $PROVINCE_{it}$ is the dummy variable of the treatment group, if province I belongs to the policy area, $PROVINCE_{it}$ = 1, otherwise $PROVINCE_{it}$ = 0. $PERIOD_{it} \times PROVINCE_{it}$ is the interaction item: $Control_{it}$ represents the control variable; u_i represents the individual effect; u_t represents the time effect; ξ_{it} represents the random interference item.

In order to further clarify the impact mechanism of carbon emission rights trading pilot policy on China's AGTFP, this paper studies whether the pilot policy of carbon emissions rights trading has an impact on China's AGTFP through environmental protection policies and technological innovation. The mediation effect test adopts the stepwise regression method. Since the impact of the pilot carbon emissions trading policy on the regional AGTFP has been tested, the following will mainly focus on the second and third steps of the mediation effect test. The mediation effect test equation is as follows:

$$M_{it} = \alpha_0 + \alpha_1 PERIOD_{it} \times PROVINCE_{it} + \sum_{i=1}^{4} \alpha_j Control_{it} + \lambda_i + \varepsilon_{it} \quad (6)$$

$$AGTFP_{it} = \beta_0 + \beta_1 PERIOD_{it} \times PROVINCE_{it} + \beta_2 M_{it} + \beta_j \sum_{i=1}^{4} Control_{it} + \sigma_i + \gamma_{it} \quad (7)$$

where, M_{it} represents the mediating variable: technological innovation and environmental protection policies; $PERIOD_{it} \times PROVINCE_{it}$ is still an interaction item; $Control_{it}$ is a control variable, λ_i and σ_i both represent individual effects; ε_{it} and γ_{it} represent random interference items.

3.4. Variable Selection and Data Source

(1) The data used in the calculation of AGTFP in this paper are the provincial agricultural output and input data of 30 provinces in mainland China (except Tibet) from 2000 to 2019.

Input indicators include land, labor, agricultural machinery, fertilizers, and environmental variables. ① Land is represented by the total sown area of crops. The data come from "China Agricultural Statistics" and "China Rural Statistical Yearbook." ② The labor is represented by employees in the primary industry. Since the statistical caliber of labor indicators has changed during 2000–2019, the data for 2000–2010 were sourced from the "China Statistical Yearbook," the data for 2011–2019 sourced from the statistical yearbooks of various provinces, and data with inconsistent statistical calibers have been adjusted. ③ The agricultural machinery is represented by the total power of agricultural machinery, and the data come from "China Agricultural Statistics" and "China Rural Statistical Yearbook." ④ The amount of chemical fertilizer applied is represented by the amount of chemical fertilizer actually used in agricultural production calculated by the pure method, and the data come from "China Agricultural Statistics" and "China Rural Statistical Yearbook." ⑤ The environmental variable has two parts: agricultural net carbon emissions and agricultural nonpoint source pollution (NP). Net carbon emissions (NCE) specifically refer to the value that uses agricultural carbon emissions minus agricultural carbon sinks. Agricultural carbon emissions are represented by greenhouse gases such as CO_2, N_2O, CH_4, etc. emitted into the atmosphere by agriculture product process; agricultural carbon sinks refer to the processes or activities that reduce greenhouse gases in the atmosphere in agricultural systems. Then, convert the greenhouse gases contained in the two into standard carbon (C) equivalents in a unified measurement unit. NP is manifested in the pollution of chemical oxygen demand (CODCr), total nitrogen (TN), and total phosphorus (TP) caused by pollutants entering the water body through surface runoff and farmland drainage. Then, convert the three types of agricultural NP discharges into agricultural nonpoint source pollution and other pollution loads according to the Class III standard of the surface water environment quality standard (GB3838-2002), which is convenient for subsequent analysis in this paper.

The agricultural output (GVAO) indicator is represented by the total output value of agriculture, forestry, animal husbandry and fishery at constant prices in 2000. The data come from "China Agricultural Statistics" and "China Rural Statistical Yearbook."

(2) The influencing mechanisms are environmental protection policy (EP) and technological innovation (TI), where, the EP is represented by the environmental protection policies promulgated by the provinces [48], and the data come from the "China Environmental Yearbook." TI is represented by the patent index [49], which is the total number of patents granted for invention, utility model and design at the end of the year, and the logarithm is used to measure. The data come from the "China Science and Technology Statistical Yearbook."

(3) $PERIOD_{it} \times PROVINCE_{it}$ is an interaction term in the PSM-DID model, which reflects the net effect of the implementation of the carbon emissions rights trading pilot policy. The data come from Carbon Emission Rights Trading Pilot Work (2011).

(4) Based on the influence mechanism of AGTFP and the policy effects of carbon emission rights trading pilots, this paper selects agricultural industrial structure adjustment (AISA) [50], intensity of environmental regulation (IOER) [51], effective irrigation rate (EIR), disaster incidence (DI) [52] as control variables, where AISA is calculated from the total output value of planting industry/total agricultural output value, and the data come from

"China Agricultural Statistics" and "China Rural Statistical Yearbook." IOER is calculated from total agricultural output value/carbon dioxide emissions, and the data come from "China Agricultural Statistics." EIR is calculated from the effective irrigated area/total sown area of crops. The data come from "China Agricultural Statistics" and "China Rural Statistical Yearbook." DI is represented by the area of agricultural disaster areas/total sown area of crops, and the data come from "China Agricultural Statistics" and "China Rural Statistical Yearbook."

Table 2 summarizes the output, four input variables, four control variables, and two mediator variables in the agricultural sector in 30 provinces in China from 2000 to 2019, Annual growth rates used the country-level data from 2000 to 2019. GVAO is growing at a rate of 3.92% per year (at 2000 constant prices). The total sown area between regions is quite different, the maximum value is 166.939 million hectares, which is 116 times the minimum value, and the average annual growth rate is 0.3%. In China's labor market, the number of employees in the primary industry decreases by 0.60% per year. The annual growth rate of fertilizer use is 1.33%. The annual growth rate of total agricultural machinery volume is relatively high, reaching 17.41%. The NCE showed a downward trend, declining at a rate of 0.09% per year, and NP still increased at a rate of 0.46, but the growth rate was declining year by year. The AISA is negative growth, the proportion of planting in agriculture, forestry, animal husbandry and fishery has declined, and the IOER has increased at an annual rate of 3.38%. The average annual growth rate of EPR is 3.83%, and the number of granted patents has increased significantly, reaching 18.29%. The annual growth rate of the EIR was 0.01%; the DI showed a negative growth, with an annual growth rate of −0.05%.

Table 2. Summary statistics.

Category	Variables	Unit	Mean	S.D.	Min	Max	Annual Growth Rate (%)
Output	GVAO	108 CNY	2615.86	7292.78	56.98	53,831.0	3.92
Input	Land	104 hectares	1030.36	2756.70	8.86	16,693.9	0.30
	Labor	104 People	3522.81	9905.53	37.09	50,784.2	−0.60
	Fertilizer	104 Tons	339.11	915.94	6.2	6022.6	1.33
	Machinery	104 Kilowatts	5449.80	15,105.65	94	111,728.1	17.41
	NCE	104 Tons	1255.12	3382.17	16.04	22,735.0	−0.09
	NP	104 Tons	254.65	706.97	3.74	4375.12	0.46
interactive term	$PERIOD_{it} \times PROVINCE_{it}$	-	0.07	0.26	0	1	-
Control Variable	AISA	-	0.56	0.09	0.381	0.76	−0.14
	IOER	-	1.46	0.99	0.175	13.269	3.38
	EIR	-	0.42	0.38	0.03	2.46	0.01
	DI	-	0.23	0.16	0	0.94	−0.05
Mediating Variable	EP	Unit	1.063	1.791	0	18	3.83
	TI	Unit	8.917	1.731	4.248	13.176	18.29

4. Results and Analysis

4.1. China's AGTFP

This paper uses penalized regression to regress formula (1), and the agricultural technology progress rate (TP) is calculated by the formula (2). Then, the AGTFP is calculated by TP and the average agricultural output value growth rate within 5 years to overcome the interference of short-term random factors on the AGTFP calculation.

Figure 2 presents the changes in China's AGTFP and TP from 2000 to 2019. ① China's AGTFP showed an overall upward trend during the inspection period, from 0.214 in 2000 to 0.548 in 2019, a cumulative increase of 0.334, and the average annual AGTFP growth rate was 4.81%. China's TP has also shown a steady upward trend, from 1.665% in 2000 to 3.219% in 2019, a cumulative increase of 1.554 percentage points, and the average annual agricultural technology progress rate is about 14.1%. From 2000 to 2012, AGTFP rose slowly. After the implementation of the carbon emissions rights trading pilot policy in 2013, AGTFP rose sharply from 2014 to 2015, from 0.374 in 2014 to 0.548 in 2019, with an average annual growth rate of 7.96%.

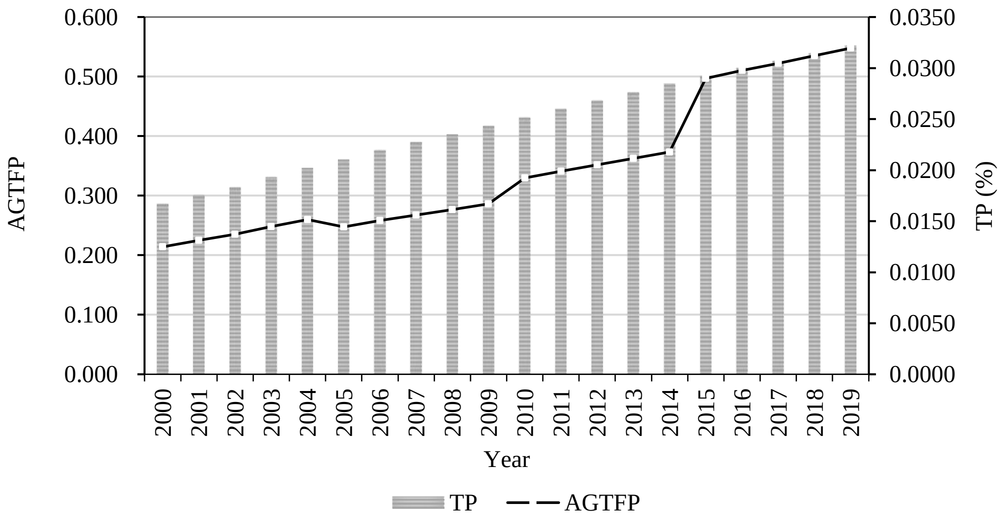

Figure 2. China's agricultural green total factor productivity and technology progress rate in 2000–2019.

4.2. Empirical Results and Analysis of PSM-DID

Table 3 lists the estimation results of the DID and PSM-DID models, and studies the impact of China's carbon emission right trading pilot policy on China's AGTFP. The $PERIOD_{it} \times PROVINCE_{it}$ coefficient is the most critical result of the regression process. Model 1 uses the DID model to calculate formula (6) without adding control variables and without controlling individual fixed effects and year fixed effects, and the coefficient of $PERIOD_{it} \times PROVINCE_{it}$ is significantly positive at the 1% significance level. Model 2 uses the DID model to calculate formula (6) without adding control variables and without controlling the year fixed effect, but controlling the individual fixed effects, and the coefficient of $PERIOD_{it} \times PROVINCE_{it}$ is significantly positive at the 1% significant level. Model 3 uses the DID model to calculate formula (6) with the addition of control variables and controlling the individual fixed effects, but without controlling the year fixed effect, and the coefficient of $PERIOD_{it} \times PROVINCE_{it}$ is significantly positive at the 5% significance level. Model 4 uses the PSM-DID model to calculate formula (6) by adding control variables and controlling individual fixed effects and year fixed effects, and the coefficient of $PERIOD_{it} \times PROVINCE_{it}$ is significantly positive at the 1% significant level. The results of the four models show that the pilot policies of carbon emission rights trading have a positive impact on AGTFP, this is consistent with the results of existing studies [13,32]. The goodness of fit R^2 of Model 4 is the highest among the four models, indicating that the PSM-DID model is reasonably set and has strong explanatory power.

Table 3. DID and PSM-DID regression results.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
$PERIOD_{it} \times PROVINCE_{it}$	0.117 *** (0.0253)	0.116 *** (0.0126)	0.0541 *** (0.0161)	0.029 *** (0.0061)
AISA	-	-	0.130 (0.132)	0.005 (0.8045)
IOER	-	-	0.0239 (0.0155)	0.006 (0.9362)
EIR	-	-	0.0173 (0.0553)	0.036 * (0.0562)
DI	-	-	−0.274 *** (0.0295)	−0.01 (0.7001)
Constant	0.254 *** (0.0103)	0.254 *** (0.00381)	0.186 ** (0.0868)	1.199 *** (0.0490)
Individual fixed effects	N	Y	Y	Y
Year fixed effects	N	N	N	Y
Observations	600	600	600	600
R^2	0.77	0.34	0.51	0.79

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. N/Y represents for No and Yes

4.3. Empirical Results and Analysis of Influence Mechanism

In order to further explore the impact mechanism of the carbon emission rights trading pilot policy on China's AGTFP, formulas (6) and (7) are gradually returned to study whether the carbon emission rights trading pilot policy affects China's AGTFP through the two paths of environmental protection policy and technological innovation. Table 4 lists the impact mechanism of China's carbon emissions rights trading policy on AGTFP. Model 5 uses EP as an intermediary variable to study its impact on the interaction term $PERIOD_{it} \times PROVINCE_{it}$ in the carbon emission rights trading pilot policy, which reflects the indirect impact of EP on AGTFP. Model 6 reflects the effect of environmental protection policy on AGTFP direct effect. Model 5 uses TI as an intermediary variable to study its impact on the interaction term $PERIOD_{it} \times PROVINCE_{it}$ in the carbon emission rights trading pilot policy, which reflects the indirect impact of EP on AGTFP. Model 6 reflects the effect of TI on AGTFP direct effect.

Table 4. The impact mechanism of China's carbon emissions rights trading policy on AGTFP.

Variables	Model 5	Model 6	Model 7	Model 8
	Regulation	AGTFP	Innovate	AGTFP
$PERIOD_{it} \times PROVINCE_{it}$	1.484 *** (0.497)	0.0287 * (0.0162)	0.608 *** (0.207)	0.0185 * (0.0112)
Regulation	-	0.00714 *** (0.00190))	-	-
Innovate	-	-	-	0.0604 *** (0.00367)
Control	Y	Y	Y	Y
Regional effect	Y	Y	Y	Y
Constant	2.379 ** (1.113)	0.192 ** (0.0795)	4.359 *** (0.567)	−0.0971 * (0.0536)
Observations	600	600	600	600
R^2	0.22	0.52	0.85	0.69

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$%.Y represents for Yes

The coefficient of $PERIOD_{it} \times PROVINCE_{it}$ in Model 5 is significant at the 1% level, indicating that the implementation of China's carbon emission rights trading pilot policy has a significant positive effect on regional environmental protection policies. In Model 6,$PERIOD_{it} \times PROVINCE_{it}$ coefficient is significant at the 1% significant level, indicating that the implementation of China's carbon emission rights trading pilot policy has a significant positive effect on the improvement of the level of scientific and technological innovation, and both effect mechanisms have significant indirect effects on AGTFP. The coefficients of EP and $PERIOD_{it} \times PROVINCE_{it}$ in Model 7 are significant at the significant levels of 1% and 10%, indicating that the combined effect of the environmental protection policy and the carbon emission rights trading pilot policy has a positive impact on the regional AGTFP. In Model 8, the coefficients of TI and $PERIOD_{it} \times PROVINCE_{it}$ are significant at the 1% and 5% significance levels, indicating that the combined effect of technological innovation and carbon emissions rights trading pilot policies has a positive impact on regional AGTFP.

In order to further verify the robustness of the conclusion of the mediation effect test, the bootstrap test was used to conduct random sampling 1000 times to test whether the mediation effect of formulas (6) and (7) existed. Table 5 shows the results of the bootstrap test of the mediation effect. The confidence intervals in the indirect effect do not contain 0, indicating that the indirect effect of environmental protection policy and technological innovation on AGTFP is significant. Although 0 is included in the direct effect, the coefficients of the interaction terms in Model 6 and Model 8 of Table 4 are significant, and the coefficients of $PERIOD_{it} \times PROVINCE_{it}$ in Model 5 and Model 7 are the same as those in Model 6 and Model 8, showing positive signs for the coefficients of EP and TI, indicating that there is a partial intermediary effect. The direct effect contains 0, indicating that there were other intermediate mechanisms in the impact of the implementation of the carbon emission rights trading rights policy on China's AGTFP.

Table 5. Bootstrap test results.

Mediating Variable	Inspection	Bias Corrected 95% Confidence Interval		Percentile 95% Confidence Interval	
		Lower Limit	Upper Limit	Lower Limit	Upper Limit
Regulations	Indirect Effect	0.0011	0.0246	0.0006	0.0217
	Direct Effect	−0.0011	0.0451	−0.0138	0.0423
Innovate	Indirect Effect	0.0859	0.1131	0.0850	0.1122
	Direct Effect	−0.0012	0.0563	−0.0020	0.0541

4.4. Statistical Tests

The PSM-DID model largely eliminates the possibility of bias caused by unobservable heterogeneity and omitted variables [53,54]. To further test the soundness of the data and model settings, we used the variance inflation factor (VIF), White and Hausman methods to test for multicollinearity, heteroskedasticity, and endogeneity, respectively.

Table 6 shows that the VIF of each variable is less than 5, indicating that there is no multicollinearity. Table 7 shows that the p-value in the White test results is greater than 0.1, indicating that there is no heteroscedasticity, and the p-value in the same Hausman test results is greater than 0.1, indicating that there is no endogeneity problem.

Table 6. VIF test results.

Variables	VIF	Variables	VIF
$PERIOD_{it} \times PROVINCE_{it}$	1.36	AISA	1.26
IOER	1.96	DI	1.47
EIR	1.26	Regulation	1.10
Innovate	2.20	-	-

Table 7. White and Hausman test results.

	χ^2	p Value
Heteroscedasticity	41.44	0.1779
Endogeneity	5.12	0.401

4.5. Robustness Tests

In the calculation of AGTPF, we chose penalized regression to deal with Equation (1). In order to test the accuracy of the model calculation results, we first used the superefficient SEM model to estimate the Malmquist index to calculate China's AGTFP and observe its trend change. Then, we used the Malmquist index to verify whether there is a significant effect of carbon emissions trading pilot policies on AGTFP. Finally, we used the Malmquist index to test whether the carbon emissions trading pilot policies affect AGTFP through two mechanisms: regulation and innovation.

Figure 3 is similar to the calculation results in Section 4.1. China's AGTFP shows a fluctuating upward trend in general, increasing from 1.1020 in 2001 to 1.1215, with a cumulative increase of 0.0195. And after the implementation of the carbon emission right trading pilot policy in 2013, the AGTFP has increased significantly, from 0.9938 in 2013 to 1.1215 in 2019.

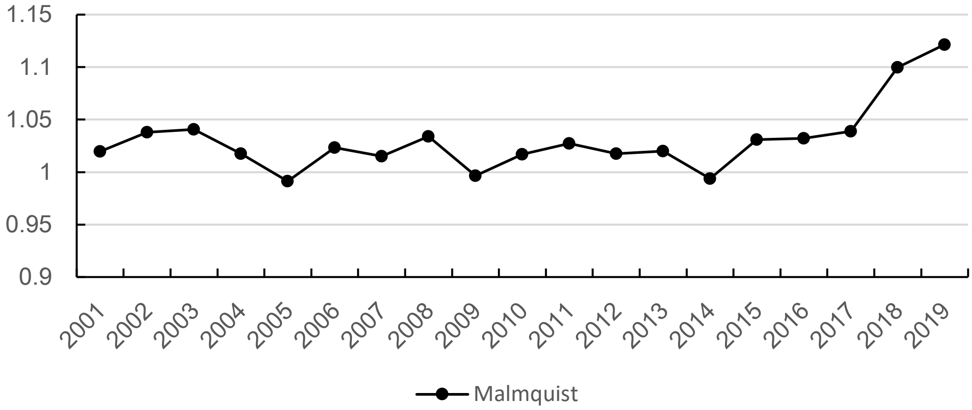

Figure 3. Trends in agriculture green total factor productivity in China.

We used the PSM-DID model to examine the impact of the carbon trading pilot policy on AGTFP. The settings of models 9 and 10 are the same as those of models 1 and 4. The results in Table 8 show that the carbon emission rights trading pilot policy has a positive impact on AGTFP. This is consistent with the calculation results in 4.2, where the carbon trading pilot policy having a significant positive effect on AGTFP is verified.

Table 8. DID and PSM-DID regression results based on Malmquist index.

Variables	Model 9	Model 10	Model 1	Model 2
$PERIOD_{it} \times PROVINCE_{it}$	0.0255 *** (0.00973)	0.0294 * (0.0172)	0.0295 * (0.0167)	0.0315 * (0.0168)
AISA	-	-	0.0431 * (0.0245)	0.236 ** (0.112)
IOER	-	-	0.0139 (0.0171)	0.0297 (0.0192)
EIR	-	-	0.0541 (0.157)	0.169 (0.118)
DI	-	-	0.0179 *** (0.00658)	0.411 (0.309)
Constant	1.018 *** (0.00264)	0.988 *** (0.00727)	0.950 *** (0.0205)	0.738 *** (0.115)
Individual fixed effects	N	Y	Y	Y
Year fixed effects	N	N	N	Y
Observations	600	600	600	600
R^2	0.36	0.24	0.31	0.52

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1\%$. N/Y represents for No and Yes.

Then, we ran a stepwise regression of Equations (6) and (7) based on the Malmquist index, and the settings of models 13–16 are consistent with those of models 5–8. The results in Table 9 show that the implementation of China's carbon emissions rights trading pilot policy has a significant positive effect on the regional environmental protection policy and innovation level improvement; the joint effect of carbon trading pilot policy with regulation and innovation on AGTFP is positive. This verifies the conclusion in 4.3 that regulation and innovation as carbon emissions trading pilot policy are two ways to promote the improvement of AGTFP. The results also support the robustness of our study.

Table 9. Channels of the effect of Chinese carbon trading rights policy on AGTFP based on the Malmquist index.

Variables	Model 3	Model 4	Model 5	Model 6
	Regulation	**AGTFP**	**Innovate**	**AGTFP**
$PERIOD_{it} \times PROVINCE_{it}$	1.473 *** (0.497)	0.0313 * (0.0168)	0.930 *** (0.131)	0.0304 * (0.0164)
Regulation	-	0.237 ** (0.111)	-	-
Innovate	-	-	-	0.245 ** (0.113)
Control	Y	Y	Y	Y
Regional effect	Y	Y	Y	Y
Constant	3.307 *** (0.616)	0.783 *** (0.107)	4.359 *** (0.567)	0.866 *** (0.109)
Observations	600	600	600	600
R^2	0.23	0.31	0.84	0.32

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Y represents for Yes

4.6. Discussion

Although there were intrastage fluctuations in China's AGTFP, the overall trend showed an upward trend from 2000 to 2019, which is similar to that of Chen et al. (2021) [22] and Hua et al. (2022) [55] and Yu et al. (2022) [13] and other scholars using DEA to measure the growth trend. However, the specific magnitude of fluctuations differs from these studies because we put agricultural carbon sinks in the measurement framework of AGTFP, which is slightly different from the measurement results without considering carbon sinks. The change of AGTFP was flat from 2000 to 2014t, with an annual growth rate of only 2.62%, but since 2014 AGTFP has achieved substantial growth. Since the formulation of the pilot carbon emission rights trading policy in 2011, the green development of China's agriculture has entered an accelerated stage, and the action plan for zero growth of pesticides and fertilizers has been steadily promoted. The Ministry of Agriculture of China has successively issued the "Implementation Opinions on Fighting the Battle of Agricultural Nonpoint Source Pollution," "Action Plan for Zero Growth of Fertilizer Application by 2020," and "Action Plan for Zero Growth of Pesticide Use by 2020," which made detailed arrangements for the reduction of chemical fertilizers and pesticides. A series of long-term reductions in material inputs and various comprehensive management measures have gradually taken effect, and the green transformation of China's agricultural development has also achieved initial results. By 2017, the General Office of the CPC Central Committee and the General Office of the State Council issued the "Opinions on Innovative Systems and Mechanisms to Promote the Green Development of Agriculture." In the same year, the Ministry of Agriculture launched the "Five Actions for Agricultural Development" (the action of resource utilization of livestock and poultry manure; the action of replacing chemical fertilizers with organic fertilizers for fruit, tea and vegetables; the action of straw disposal in northeast China; the action of recycling agricultural film; and the action of protecting aquatic organisms with emphasis on the Yangtze River, etc.), so China's AGTFP increased steadily from 2017 to 2019, which is consistent with the findings of Yang et al. (2022) [23].

The implementation of the carbon emission rights trading pilot policy has already been verified to enhance the GTFP of industries and cities [52,56,57]. However, few studies have dealt with the impact effect and impact mechanism between carbon emissions trading system and AGTFP. The reason is that the carbon emissions trading system mainly involves power generation, petrochemical and other industries; however, agriculture, as the primary industry, has a feedback effect with other industries, and other industries have a significant impact on the agricultural economy. As a carbon emission source of greenhouse gas, the emission is huge. Therefore, through the PSM-DID model, this paper verifies that the implementation of China's carbon emissions trading rights pilot policy has a positive effect on the significant improvement of China's AGTFP, Yu et al., (2022) [13] and Hua et al. (2022) [55] had similar findings, while Yu et al. (2022) [13] find that the implementation of a carbon trading pilot policy has a significant contribution to AGTFP, and the policy has an increasingly stronger contribution to AGTFP under the constraint of reduced carbon allowances. Hua et al. (2022) [55] concluded that carbon trading rights significantly increased the TFP of agricultural enterprises. At the same time, this paper also found that environmental regulation and technological innovation are the two influencing mechanisms for the policy effect to be exerted, and both of them have a significant positive effect on AGTFP, which is consistent with the findings of Fan et al. (2022) [29] and Wang et al. (2021) [58], where Fan et al. (2022) [29] found that environmental regulation and technological innovation have a significant contribution to productivity, and Wang et al. (2021) [58] found that green technological innovation has a significant positive effect on productivity. However, whether it is the PSM-DID or the mediation effect test, the coefficient value of $PERIOD_{it} \times PROVINCE_{it}$ is relatively small. Yu et al. (2022) [13] and Hua et al. (2022) [55] also reached the same conclusion. The main reason is that the carbon emissions trading system was in the pilot stage from 2011 to 2021, and there are still imperfections, which are manifested in the poor liquidity of the carbon emissions trading market [59]; the certain defects exist in the system design.; the pricing mechanism is distorted; and the transaction system lacks legal guarantees.

(1) The liquidity of the carbon emissions trading market is poor. China's pollution emissions and greenhouse gas emissions trading cases are scattered in various cities, and the transparency of trading information is not enough. At the regional level, the seven pilots are independent and closed to each other. However, China is already in the process of establishing a unified national carbon trading market, though during the inspection period, it was a closed market and lack liquidity.

(2) There are certain flaws in the institutional design related to the carbon emissions trading policy. From an industry point of view, only large enterprises that produce and discharge pollutants can trade in the carbon emission exchange, and many competitive "small farmers" do not really participate in it. From the characteristics of China's "big country and small farmers," such settings are unreasonable. In terms of carbon sources and carbon sinks, it only includes carbon sources and basically does not involve carbon sinks. Agricultural carbon emission reduction and carbon sequestration are not included in the carbon trading market, resulting in the inability to effectively allocate the element of carbon sinks.

(3) The pricing mechanism of the emissions trading system is distorted. On one hand, the lag in the construction of China's carbon trading market has lost its pricing power and initiative in the global carbon trading market. It has not formed a reasonable pricing mechanism, and the price of carbon emissions trading rights fails to reflect the true value of carbon emission rights. On the other hand, as a public resource, emission rights are easily influenced by the management department, which interferes with the price of carbon emissions trading, causing the trading price to deviate from the real price.

(4) The carbon emissions trading system lacks legal protection. A legal system is an institutional guarantee for the effective implementation of the carbon emissions trading rights policy. Currently, China still lacks laws and regulations on carbon emissions trading, resulting in unclear legal responsibilities and lack of legal supervision mechanism for carbon emission reduction during the implementation of the system, which affects the policy implementation effect of the carbon emissions trading system.

5. Conclusions and Recommendations

5.1. Conclusions

Improvements and developments in carbon trading systems gradually increase the impact on AGTFP [13]. Although agriculture is not dominant in the carbon trading market, it is closely related to petrochemical, metal and other industries and has spillover effects. Besides, agriculture, as an important carbon emission source of greenhouse gases, emits huge amounts of energy. It is crucial to study the impact of carbon emissions right trading pilot policy on agriculture. Therefore, we deeply explored the effect and mechanism of carbon emissions rights trading pilot policies on AGTFP. First, we incorporated the agricultural carbon sink into the calculation framework of AGTFP, and build a translog production function including environmental factors, used the provincial panel data of 30 provinces in China from 2000 to 2019 and the elastic network-based ridge regression to calculate China's AGTFP. Second, we used the construction of PSM-DID to study the impact of the implementation of China's carbon emissions right trading pilot policy on China's AGTFP, chose environmental protection policies and technological innovation as the intermediary mechanism for carbon emissions rights trading policy to affect AGTFP. The research results are as follows.

(1) China's agricultural total factor productivity changed slowly from 2000 to 2013, with an annual growth rate of only 2.62%. After the implementation of the pilot carbon emissions trading policy in 2013, AGTFP achieved substantial growth.

(2) The impact of China's carbon emissions trading pilot policy on China's AGTFP is significantly positive, and the implementation of the policy has improved AGTFP.

(3) Further impact mechanism testing shows that China's carbon emission rights trading pilot policy will enhance AGTFP through environmental protection policies and technological innovation.

5.2. Recommendations

According to the empirical results of this paper, the implementation of carbon emission rights trading pilot policy in China can significantly increase AGTFP, and it will affect AGTFP through two paths: technological innovation and environmental regulation. Therefore, the government should further transform China's agricultural production methods, develop and improve the carbon trading system, enhance the level of scientific and technological innovation of enterprises and farmers as well as improve the strength and rationality of environmental regulation, so that the AGTFP can be effectively improved, which will break through the dilemma that China's agricultural development relying on the rough production methods and promote green and sustainable agricultural development.

(1) China's previous high pollution and emission production methods are unsustainable. Agricultural production should be driven by traditional factors to technological innovation. The government should increase the support for agricultural technology research and development, and realize the organic connection between industry, university and research, and improve the conversion rate of agricultural science and technology achievements, gradually improve the green and low-carbon agricultural production technology and factor inputs. The government should consider reducing the factor inputs of pesticides and chemical fertilizers to achieve a reasonable allocation of agricultural production factors and to tap the production potential of each production factor. At the same time, the government can transform the agricultural production mode, realize the moderate-scale operation of agriculture, improve the agricultural AGTFP, break through the dilemma that Chinese agriculture relies on the rough production mode, and promote the green and sustainable development of Chinese agriculture.

(2) The empirical results of this paper showed that the carbon emission rights trading pilot policy has significantly increased AGTFP. With the improvement and development of the carbon trading system, the impact on AGTFP will gradually increase [13]. Therefore, consideration should be given to gradually increase the number of pilot provinces for carbon trading nationwide, expand the influence of the carbon trading policy, and

narrow the development gap between the pilot provinces and nonpilot provinces in the development of the carbon trading market. The government should improve the legal construction and supervision system of carbon emissions trading market. Using carbon markets effectively to improve AGTFP. Enterprises and farmers should actively cooperate with the implementation of the pilot policy to avoid the "unethical behavior" of stealing and releasing emissions, and make joint efforts to contribute to global climate governance.

(3) The carbon emissions rights trading pilot policy will affect China's AGTFP through two paths: environmental regulation and scientific and technological innovation. Therefore, the government should strengthen green innovation compensation, encourage enterprises and farmers to introduce green technologies and advanced equipment, improve their capacity for independent research and cooperative innovation, and effectively increase AGTFP. On the other hand, based on the different resource endowments of each province, the government should steadily improve the strength and rationality of environmental regulations, improve the constraint and incentive mechanism for energy conservation and emission reduction, to make the policy effect of environmental regulation effectively exercised and further enhance AGTFP, and promote the green and sustainable development of China's agriculture.

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