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Article

Does Mechanization Improve the Green Total Factor Productivity of China's Planting Industry?

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Abstract: Mechanization is an important factor to improve the green total factor productivity of planting industry, which is the key way to realize the sustainable development and high-quality development of agriculture. Using the panel data of 30 provinces in China from 2001 to 2019, this paper uses the stochastic frontier analysis method of output oriented distance function to measure the green total factor productivity of planting industry based on net carbon sink, and empirically studies the impact of mechanization on the planting green total factor productivity. The empirical analysis finds that mechanization can significantly promote the planting green total factor productivity, and this basic conclusion is still robust after using instrumental variables, sub sample regression. Further research found that the path of mechanization on planting green total factor productivity is mainly reflected in technology progress and spatial spillover. The mechanism of operation scale expansion, factor allocation optimization and technical efficiency change is not significant. Given these findings, the paper adds considerable value to the empirical literature and also provides various policy- and practical implications.

Keywords: Mechanization; Planting industry; Net carbon sink; Green total factor productivity; Technology progress; Operation scale; Factor allocation; Technical efficiency; Spatial spillover

1. Introduction

The improvement of planting total factor productivity means that the production of planting industry changes from factor input to efficiency improvement, which is the effective promoter of the healthy and sustainable growth of China's rural economy and high-quality agricultural development at this stage. However, with the increasing use of agricultural machinery, chemical fertilizers, pesticides, agricultural film and other modern factors, increasing energy consumption and the consequential environmental pollution on planting production are becoming more and more prominent. Therefore, using green total factor productivity (GTFP) to incorporate environmental performance variables into the calculation of planting TFP [1], analyzing its influencing factors and clarifying its promotion mechanism deeply can better fit the concept of agricultural sustainable development and green development, to realize high-quality agricultural development.

The undesirable output in the GTFP research of planting industry can be considered from two dimensions: non-point source pollution and greenhouse gas emission. Under the vision of carbon peak and carbon neutralization, the measurement of undesirable output based on carbon emission is more practical and meaningful. The existing literature to measure carbon emissions of planting industry mainly has the following perspectives. First, considering carbon emissions purely [2] or taking carbon emissions as undesirable output to calculate GTFP [3]. However, only considering carbon emissions overemphasizes the negative side of planting production and ignores the positive yield and carbon sink of crops. Second, using the net carbon sink [4] based on the dual attributes of both carbon sink and carbon source in agriculture, which ignores the ties between input and output. Third, using the ratio of carbon emissions to agricultural output to measure carbon emission intensity. Although the relation between carbon emissions and agricultural output is considered, the correlation between various agricultural inputs is ignored. Based on the analysis above, this paper considers net carbon sink as environmental factors, and adopts the stochastic frontier analysis method to obtain the GTFP from the perspective of input-output.

Another important aspect of planting GTFP research is its influencing factors, mainly including natural environment, regional economic development level, urbanization level, financial support for agriculture, human capital, production risk, planting structure, land management scale and mechanization level[5]. As one of the most important factors to improve planting GTFP, since the cross regional service of agricultural machinery started in 1996 and the large-scale policy subsidy of agricultural machinery started in 2004, the process of agricultural mechanization has been significantly accelerated and the degree of agricultural production mechanization has been continuously improved. On the one hand, the popularization of mechanization, accompanied by energy consumption, emits a large number of greenhouse gases. By 2018, the carbon emissions from energy consumption of agricultural machinery had become the main source of agricultural carbon emissions [6]. On the other hand, the improvement of operation accuracy and technology spillover effect brought by mechanization reduce the unreasonable use of chemical agricultural materials, and then reduce carbon emissions. In addition, mechanization has improved agricultural productivity and added net carbon sink through technology progress and diffusion [7], allocation efficiency optimization [8], planting structure adjustment [9]. That is, the impact of mechanization on GTFP depends on the increasing emission effect brought by its energy consumption, the emission reduction effect brought by the optimization of chemical agricultural inputs and the increasing sink effect brought by the increase of output. However, the mechanism of the impact of mechanization on GTFP has not been fully discussed and analyzed in the academic community. Similar to Balk's decomposition of TFP change [10], this paper attempts to explore the impact of mechanization on GTFP from four aspects: technology progress, operation scale, factor allocation and technical efficiency change. Moreover, mechanization has significant spatial spillover effect, so we also further discusses the impact of mechanization on planting GTFP from the perspective of spatial spillover.

Compared with the existing research, the innovative work of this research is mainly manifested in the following two aspects. Firstly, based on the characteristics of net carbon sink in planting industry, this paper uses the multi output stochastic frontier analysis method based on output oriented distance function to measure planting GTFP, which better corresponds to low-carbon and high-quality agricultural development. Secondly, this paper sorts out and verifies the impact mechanism of mechanization on GTFP from five aspects: technology progress, operation scale, factor allocation, technical efficiency change and space spillover.

The remainder of this article is structured as follows: the "Literature review and mechanism analysis" section reviews the related literature and analyzes the mechanism of mechanization affecting planting GTFP. The "Method and data" section describes the methods and the nature of data. Empirical results are presented and analyzed in the "Results and discussion" section, and the "Conclusion" section concludes the article.

2. Literature Review and Mechanism Analysis

2.1. Decomposition of Planting GTFP

Consider the stochastic frontier model proposed by Battese and Coelli (1992)[11],

$$Y_{it} = f\left(X_{it}, \beta\right) e^{v_{it} - u_{it}} \tag{1}$$

where Y_{it} and X_{it} represent actual outputs and inputs respectively; $f\left(X_{it}, \beta\right)$ refers to production frontier; v_{it} and u_{it} account for stochastic errors term and non-efficiency term respectively.

Take the logarithm and take the derivative of time t, the equation (1) can be transformed as follows:

$$\frac{\partial \ln Y_{it}}{\partial t}=\frac{\partial \ln f\left(X_{it},\beta\right)}{\partial t}+\sum_{j=1}^{n}\frac{\partial \ln f\left(X_{it},\beta\right)}{\partial \ln X_{itj}}\times\frac{\partial \ln X_{itj}}{\partial t}+\frac{\partial \ln e^{-u_{it}}}{\partial t} \tag{2}$$

The change of GTFP refers to the remaining part after the output change minus the change of factor input considering environmental factors, which is as follows:

$$\frac{\partial \ln GTFP_{it}}{\partial t}=\frac{\partial \ln Y_{it}}{\partial t}-\sum_{j=1}^{n}s_{itj}\times\frac{\partial \ln X_{itj}}{\partial t} \tag{3}$$

Bring equation (2) into equation (3), the equation can be converted as follows:

$$\frac{\partial \ln GTFP_{it}}{\partial t}=\frac{\partial \ln f\left(X_{it},\beta\right)}{\partial t}+\left(RTS_{it}-1\right)\sum_{j=1}^{n}\lambda_{itj}\times\frac{\partial \ln X_{itj}}{\partial t}+\sum_{j=1}^{n}\left(\lambda_{itj}-s_{itj}\right)\times\frac{\partial \ln X_{itj}}{\partial t}+\frac{\partial \ln e^{-u_{it}}}{\partial t} \tag{4}$$

where $\partial \ln GTFP_{it}/\partial t, \partial \ln f\left(X_{it},\beta\right)/\partial t, \partial \ln X_{itj}/\partial t$ represent the change rate of lnGTFP, output and factor j with time t respectively; $a_{itj}=\partial \ln f\left(X_{it},\beta\right)/\partial \ln X_{itj}$, $s_{itj}=P_{itj}\times X_{itj}\Big/\sum_{j=1}^{n}P_{itj}\times X_{itj}$, $\lambda_{itj}=a_{itj}/RTS_{it}$ represent the output elasticity, the input cost share and the output elasticity share of input j respectively; $RTS_{it}=\sum_{j=1}^{n}a_{itj}$ represents the return to scale coefficient.

The four items on the right of equation (4) respectively represent the frontier technology progress, the change of return to scale, the improvement of factor allocation efficiency and technical efficiency change, viz. the change of planting GTFP can be divided into frontier technology progress, the change of return to scale, the improvement of factor allocation efficiency and the improvement of technical efficiency relative to the frontier.

2.2. Planting GTFP is Influenced by Mechanization through Technology Progress

The degree of mechanization which represents the quantity of planting machinery and the level of planting technology, can improve the production technology of planting industry, which is an important way to improve planting output, control planting energy growth and realize carbon emission reduction [12]. First, technology progress directly reduces carbon emissions per unit of energy consumption by improving the efficiency of traditional energy use. Second, technology progress reduces carbon emissions by changing the traditional factor input structure [13]. Third, technology progress will indirectly optimize the energy consumption structure in planting industry, increase the utilization of new renewable energy, and reduce the proportion of high energy consumption technologies. Finally, mechanization optimizes the application level and management measures of chemical agricultural materials through experience spillover and information transmission. The optimization of management measures has a positive effect of emission reduction [12]. In short, technology progress can effectively reduce carbon dioxide emissions and improve the GTFP of planting industry.

2.3. Planting GTFP is Influenced by Mechanization through Changing Operation Scale

On the one hand, mechanization promotes land circulation, and then changes the scale of farming land, which reduces the level of agricultural land fragmentation and changes the scale of agricultural land management [14], to reduce the technology adoption cost and improve the grain production efficiency. On the other hand, mechanization improve the standardization degree of operation in the process of agricultural production, to bring the specialized division of labor and production agglomeration of agricultural production, which realize the economies of scale of agricultural production. There is a significant negative correlation between the scale of farming land and the amount of agricultural chemical inputs [15]. The change of chemical agricultural materials intensity will inevitably lead to the change of carbon emission intensity. In addition, the development of mechanization makes it possible for farmers to purchase agricultural machinery

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services. Under the situation of rising labor costs, farmers participate in external division of labor through machinery outsourcing services, which realizes service economies of scale. In particular, for staple food crops, due to the difference in maturity between North and South crops, along with the regional specialization of continuous planting and the marketization of outsourcing services, the spatial layout structure along the latitude further strengthens the cross regional service of agricultural machinery, which is more suitable for the service economies of scale and then transforms the land scale economy into agricultural machinery service scale economy. In short, mechanization leads to the change of planting GTFP by expanding the scale of planting operation and realizing service economies of scale.

2.4. Planting GTFP is Influenced by Mechanization through Optimizing Resource Allocation

The use of planting machinery can change the combination of rural labor force, land and other factors, to optimize the allocation of agricultural production factors. First, the promotion of mechanization will inevitably lead to the adjustment of the input structure of planting factors [16], including the continuous reduction of the relative price of machinery to labor, the decrease of labor input intensity in planting production, and the increase of other capital inputs such as chemical agricultural materials [17]. The change of the input structure of production factors will affect the change of carbon emission of planting industry, resulting in the change of GTFP of planting industry [18]. Second, the promotion of mechanization will change the planting structure. With the improvement of mechanization, the marginal labor input and management cost increase, resulting in the decline of the planting proportion of non-grain crops, while the planting proportion of grain crops with lower labor requirements increases significantly. Compared with non-grain crops, grain crops generally have less demand for chemical agricultural materials. With the increase of the planting proportion of grain crops, the total input of chemical agricultural materials may decrease, the carbon emission will decrease, and the GTFP of planting industry will also change.

2.5. Planting GTFP is Influenced by Mechanization through Improving Technical Efficiency

In the process of mechanization, the internal differentiation caused by farmers' heterogeneity is aggravated, resulting in the widening gap of the technology utilization. In China, the main form of mechanization in planting industry is mainly reflected in the cross regional operation of agricultural machinery and the purchase of agricultural machinery services, in which the diffusion of advanced farming and harvesting technology and the overflow of planting experience is accompanied. For high-efficiency agricultural operators who have strong resource endowment, they are easier to adopt new technologies and have stronger learning ability. Therefore, their marginal output capacity is improved more than that of low-efficiency farmers, which leads to the continuous expansion of production frontier and the depression of technical efficiency. In addition, with the continuous outflow of labor force in the process of mechanization, the quantity and quality of rural labor force have decreased. The decline of labor quality leads to the decline of agricultural management level and technical efficiency [19].

2.6. Planting GTFP is Influenced by Mechanization through Spatial Spillover Effect

The impact of mechanization on planting GTFP is carried out under the background of spatial interaction, which has a strong spatial spillover effect [20]. Agricultural machinery containing agricultural technology has obvious diffusion and spillover, which depends on good technological innovation and technology diffusion, specialized division of labor and cooperation. In terms of geographical status of planting industry, the endowment conditions of agricultural production in adjacent areas are similar, which is easy to form agricultural agglomeration effect and enhance the agricultural industrial network

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connection. The improvement of mechanization will not only lead to the change of planting GTFP in the region, but also influence the competition and cooperation interaction with neighboring areas [21], and the planting GTFP of neighboring areas will also change.

Based on the above analysis, this article establishes the analysis framework shown in Figure 1 and puts forward research hypothesis: Mechanization can improve planting GTFP, and the promotion mechanism mainly includes five aspects: technology progress, expansion of operation scale, optimization of factor allocation, improvement of technical efficiency and spatial spillover.

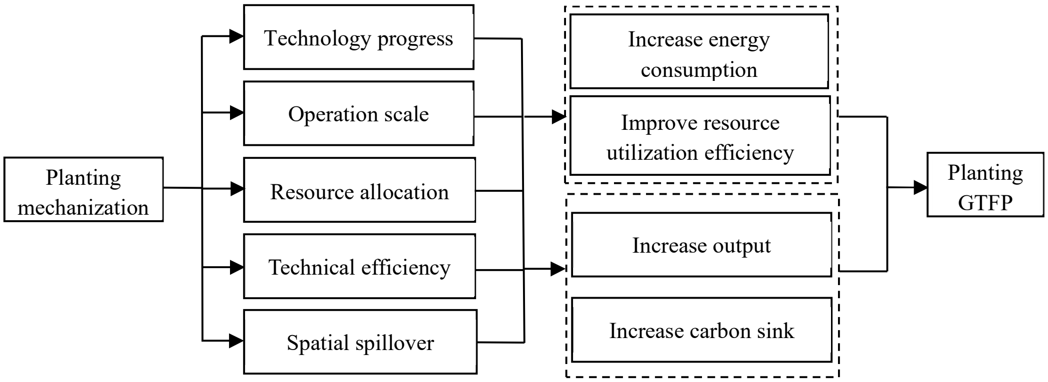

Figure 1. Influence mechanism of mechanization on planting GTFP

3. Method and Data

3.1. Method

3.1.1. The Basic Econometric Model

To test the relationship between mechanization and planting GTFP, the basic regression model is set as follows:

$$\ln GTFP_{it} = \alpha_0 + \alpha_1 X_{it} + \sum_j \lambda_j Z_{itj} + \mu_i + \eta_t + \xi_{it} \tag{5}$$

where $GTFP_{it}$ represents the planting GTFP of province i at year t, X_{it} denotes the degree of mechanization, Z_{itj} refers to control variables; α_0 is the intercept term, α_1、λ_j are the estimation coefficient of each explanatory variable; μ_i and η_t represent the fixed effect of province and year , ξ_{it} is a stochastic error term.

3.1.2. Recursive Model for Mediating Effect Test

To explore the mechanism of mechanization affecting planting GTFP, based on the research methods of Hayes and Andrew (2009)[22], the recursive model for mediating effect test is set as follows:

$$med_{it} = \beta_0 + \beta_1 X_{it} + \sum_j \lambda_j Z_{itj} + \mu_i + \eta_t + \xi_{it} \tag{6}$$

$$\ln GTFP_{it} = \gamma_0 + \gamma_1 X_{it} + \gamma_2 med_{it} + \sum_j \lambda_j Z_{itj} + \mu_i + \eta_t + \xi_{it} \tag{7}$$

where med_{it} represents the intermediary variables, β_0, γ_0 are the intercept terms, and β_1、γ_1、γ_2 are the estimation coefficient of each variable. Equation (6) is used to test the effect of the independent variable on the intermediary variables, and equation (7) is used to test the effect of the independent variable on the dependent variable after the introduction of intermediary variables.

3.1.3. Spatial Econometric Model

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Based on goodness of fit, log likelihood, likelihood ratio and Wald test, the Spatial Dubin Model is selected to verify the spatial spillover effect of mechanization on planting GTFP.

$$\ln GTFP_{it} = \alpha_0 + \tau \ln GTFP_{i,t-1} + \rho W \cdot \ln GTFP_{it} + \alpha_1 X_{it} + \alpha_2 WX_{it} + \sum_j \phi_j Z_{itj} + \mu_i + \eta_t + \xi_{it} \quad (8)$$

where W represents the spatial weight matrix, including adjacent space matrix, geographical distance matrix and economic distance matrix, τ is the first-order lag coefficient of the dependent variable, ρ is the spatial correlation coefficient, α_1、α_2、ϕ_j are the estimated coefficient of each explanatory variable.

3.2. Data

3.2.1. Dependent Variable

Both net carbon sink and planting output belong to desirable output, so this paper adopts the multi production stochastic frontier analysis method based on the output oriented distance function [23] to estimate planting GTFP based on its significant characteristics of net carbon sink. In terms of the production function form, the adjustment ability of planting for input factors such as land and capital is weak, and the adjustment speed is relatively slow, so it is suitable to adopt C-D production function, although the transcendental logarithmic production function has the advantages of flexible form and good inclusiveness. The core of estimation is to alleviate the endogenous problem which mainly comes from the changes of macro external factors rather than capital and labor input [24-26]. Therefore, we use the fixed effect model to estimate and alleviate the endogenous problem by controlling the fixed effect at the provincial year level.

This paper follows the traditional literature in selecting inputs and outputs for the production function[27-29]. The output variables include gross value of planting output (in thousand CNY) and planting net carbon sink (in thousand tons of CO2-equivalent). The calculation formula, coefficient of agricultural carbon sink and carbon emission are based on the research of Tian et al. (2014) [30]and Chen et al. (2019)[31]. The main input variables of agricultural production are labor, land, machinery and fertilizer. Labor (in thousands) is measured as the number of employees in the primary industry multiplied by the proportion of the total output value of planting industry in the total output value of f primary industry. Land (in thousand hectares) refers to the sown area reflecting the actual utilization of the cultivated land. Machinery (in thousand kilowatts) is measured by the total power of agricultural machinery multiplied by the proportion of the total output value of planting industry in the total output value of primary industry. Fertilizer (in thousand tons) refers to the sum of the gross weight of nitrogen, phosphate, potash, and complex fertilizers.

3.2.2. Independent Variable

This paper adopts the comprehensive mechanization rate of crop cultivation and harvest as the core explanatory variable, which is measured by the weighted average value of machine tillage rate, machine sowing rate and machine yield rate(the weights are 0.4, 0.3 and 0.3 respectively).

3.2.3. Instrument Variable

There may be some endogenous problems in mechanization and planting GTFP for two reasons: first, there may be missing variables which affect planting GTFP. Although this paper tries to control a series of characteristic variables related to planting environment in the empirical model, such as agricultural planting structure and rural human capital, it is still unable to completely control the omitted variables in theory. Second, mechanization and planting GTFP may be simultaneous. Provinces with high planting GTFP level usually are areas with high level of factor endowment. Due to the high level of regional development and high relative labor price, these areas will adapt to the requirements of local agricultural development through large-scale application of mechanized operation, to improve mechanization level in their region. Therefore, this paper uses the

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transportation infrastructure, viz. the proportion of grade road mileage and cultivated land area in the region, as the instrument variable to alleviate the estimation error caused by the possible endogenous problems. Transportation infrastructure will not have a direct impact on planting output and net carbon sink, but it can improve the level of planting mechanization by improving the road conditions of agricultural machinery operation and reducing traffic costs. That is, transportation infrastructure variable meets the requirements that are highly related to explanatory variables but not related to error terms.

3.2.4. Intermediary Variables

This paper studies the transmission mechanism of mechanization to GTFP from the perspectives of technology progress (tp), operation scale (os), resource allocation (ra) and technical efficiency change (tec). Technology progress is represented by the total power of machinery per unit area, operation scale is measured as the ratio of cultivated land area to planting population, resource allocation is characterized by the ratio of fertilizer application per unit area to labor input, and technical efficiency is expressed by the reciprocal of the distance between actual output and frontier output.

3.2.5. Control Variables

The main control variables include: agricultural land management scale, agricultural planting structure, rural human capital, regional economic development level, part-time employment of labor force, production risk and urban-rural income gap. Agricultural land management scale (in hectare per household) is represented by the ratio of cultivated land area to rural households and its square term is introduced to examine the possible threshold of agricultural land scale. Agricultural planting structure is characterized by the ratio of grain sowing area to crop sowing area. Rural human capital (in years) is measured as the average number of years of education of rural population. Regional economic development level (in CNY per person) is represented by per capita GDP. The proportion of wage income of rural residents is selected to represent the part-time employment of labor force. Production risk refers to the ratio of affected area to total sown area of crops. The urban-rural income gap is measured as the ratio of disposable income of urban residents to rural residents.

3.3. Data Description

Since the impact of mechanization on planting production is persistent and spillover, the long-term panel data is indispensable for the study of planting GTFP. To ensure that the research samples change as much as possible, the data used in this study is provincial-level planting outputs and inputs of 30 provinces in mainland China from 2001 to 2019 due to the lack of some statistical data of Hong Kong, Macao, Taiwan and Tibet. The data comes from China rural statistical yearbook and China agricultural machinery yearbook. Taking into account the price factor, the variables related to price are deflated according to the price level in 2001. The descriptive statistics of variables are shown in Table 1.

Table 1. Descriptive statistics

Variable type	Variable	Abbreviation	Mean	Std. Dev.	Min	Max
Dependent Variable	Log(planting GTFP)	lnGTFPit	4.850	0.388	3.931	6.007
Independent Variable	mechanization	mac	0.441	0.231	0.014	1
Instrument Variable	transportation infrastructure	inf	32.707	22.153	4.568	121.937
Intermediary Variables	technology progress	tp	0.558	0.266	0.139	1.416
	operation scale	os	9.766	6.716	2.236	44.132
	resource allocation	ra	0.385	0.172	0.062	1.173
	technical efficiency	tec	0.678	0.153	0.438	0.986
	agricultural land management scale	sca	6.843	6.026	0.929	30.643

Control Variables	agricultural planting structure	pst	0.651	0.129	0.328	0.971
	rural human capital	hum	7.372	0.727	4.811	9.731
	regional economic development level	agdp	0.011	0.006	0.003	0.033
	part-time employment of labor force	ccj	15.327	21.269	0.062	76.300
	production risk	ris	0.227	0.155	0.000	0.936
	urban-rural income gap	inc	2.874	0.572	1.850	5.120

4. Results and Discussion

4.1. The Basic Regression Results

The basic regression results are shown in Table 2. The OLS regression results show that mechanization plays an obvious role in promoting planting GTFP. The second stage regression results of 2SLS using instrument variable shows that mechanization and planting GTFP still show the same positive relationship and the coefficient is significant at the level of 1%. The regression results of the first stage show that there is an obvious positive correlation between instrument variable and independent variable, which passes the significance test of 1%, whether adding control variables or not, which means that there is a positive correlation between a regional transportation infrastructure level and mechanization. The regression results of the first stage meet the correlation hypothesis of instrumental variable. Among the control variables, agricultural land scale and rural human capital play an obvious role in promoting planting GTFP, and there is a negative relationship between production risk and planting GTFP. The results provide empirical evidence for hypothesis, viz. the degree of mechanization and planting GTFP show a positive relationship.

Table 2. Results of the relation between mechanization and planting GTFP

Method	**OLS**		**2SLS**	
Model	(1)	(2)	(3)	(4)
mac	1.356***	0.512***	1.611***	1.386***
	(0.130)	(0.161)	(0.068)	(0.308)
sca		0.011***		0.007**
		(0.003)		(0.003)
pst		0.396*		-0.068
		(0.225)		(0.214)
hum		0.077***		0.002
		(0.023)		(0.029)
gdp		32.690***		12.205
		(5.990)		(9.733)
ccj		0.002***		0.001
		(0.001)		(0.000)
ris		-0.182***		-0.099*
		(0.053)		(0.053)
inc		-0.076**		0.017
		(0.035)		(0.043)
R-squared	0.706	0.812	0.681	0.735
Coefficient of IV in the first stage			0.007***	0.002***
			(0.000)	(0.000)
Value F in the first stage			231.970	18.700
Fixed province		Yes		
Fixed year		Yes		

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Observations	570
Provinces	30

Note: *, **, ***: statistically significant at 10%, 5%, and1%, respectively; Standard error in parentheses.

4.2. Mechanism Test

According to the previous analysis of the transmission mechanism of mechanization on planting GTFP, this paper uses the recursive model for mediating effect test from the perspectives of technology progress, operation scale, resource allocation and technical efficiency, and uses Spatial Dubin Model to study the transmission mechanism from the perspective of spatial spillover.

Table 3 reports the results of the mechanism test. Model (1), (2), (3) and (4) show the regression results of the first step. The regression coefficients in model (1), (2) and (3) are positive and all pass the significance test of 1%, indicating that the popularization of mechanization has significantly improved the level of planting technology, expanded the scale of planting operation and improved the factor allocation structure. The coefficient in model (4) is negative, which shows that technical efficiency declines with the improvement of mechanization. The other models show the regression results of the second step. Model (5) shows that the impact coefficient of mechanization is 0.512 when no intermediary variable is added. Model (6), (7), (8) and (9) show that after adding the variables of technological progress, operation scale, factor allocation and technical efficiency respectively, the impact coefficient of mechanization on planting GTFP decreases, but the significance of the coefficient does not change significantly. After adding all intermediary variables to model (10), the coefficient and significance of mechanization have decreased, while the technology progress are still significant at the 1% level, indicating that the intermediary variable of technology progress selected in this paper plays a partial mediating role. The coefficient of operation scale is positive, but fails to pass the significance test at the 10% level, indicating the mechanism of operation scale is not established. This is mainly because the planting industry shows the characteristics of constant returns to scale [32, 33]. The coefficient of factor allocation is positive but also fails to pass the significance test at the 10% level, indicating that the mechanism of factor allocation is not established. The main reason is that the farmers are rational economic people, who have realized the optimization of factor resource allocation through the learning effect and experience accumulation of long-term production practice. The coefficient of technical efficiency is negative, indicating that the mechanism of technical efficiency change is not established, which illustrates that the contribution of technical efficiency to planting GTFP is negative.

Table 3. Results of the transmission mechanism of mechanization to planting GTFP

Dependent variable	**tp**	**os**	**ra**	**tec**	**lnGTFP**					
Model	（1）	（2）	（3）	（4）	（5）	（6）	（7）	（8）	（9）	（10）
mac	0.453*** (0.056)	4.268*** (3.338)	0.431*** (0.138)	-0.016** (0.007)	0.512*** (0.161)	0.167*** (0.063)	0.301*** (0.058)	0.217*** (0.063)	0.505*** (0.161)	0.131** (0.066)
tp						0.184*** (0.033)				0.176*** (0.030)
os							0.016*** (0.004)			0.007 (0.004)
ra								0.522*** (0.100)		0.063 (0.057)
tec									-0.449 (0.477)	-0.467 (0.069)
R-squared	0.683	0.747	0.562	0.181	0.812	0.752	0.750	0.760	0.813	0.930
Control variable	Controlled									

Fixed province	Yes
Fixed year	Yes
Observations	570
Provinces	30

Note: *, **, ***: statistically significant at 10%, 5%, and1%, respectively; Standard error in parentheses.

There are spillover and re feedback effects in spatial panel regression, so direct parameter estimation is easy to cause result error. Only through calculating the direct effect and spatial spillover effect in spatial econometric model and summing up to obtain the total effect, can we comprehensively describe the interactive relationship between dependent variables and independent variables. Table 4 reports the results of the spatial regression model under different spatial weight matrices such as adjacency space matrix, geographical distance matrix and economic distance matrix. From the results of spatial coefficient and spatial spillover effect, mechanization has a significant spatial spillover effect on planting GTFP, viz. the level of mechanization in adjacent areas will have a positive impact on planting GTFP in this region. It reflects that mechanization is not limited to serve a single region, but may also expand the market space of mechanized operation with the help of differences in crop maturity. Therefore, mechanized operation not only has a promoting relationship with local planting GTFP, but also has a positive impact on the planting GTFP in surrounding regions due to the spatial spillover of its cross regional operation.

Table 4. Results of the spatial effect of mechanization on planting GTFP

	Adjacency matrix	**geographical distance matrix**	**Economic distance matrix**
Model	(1)	(2)	(3)
spatial coefficient	0.213***	0.354***	0.419***
	(0.054)	(0.087)	(0.063)
LR_Direct	0.178***	0.125*	0.200***
	(0.066)	(0.074)	(0.069)
LR_Indirect	0.823***	1.182***	0.648***
	(0.114)	(0.277)	(0.209)
LR_Total	1.000***	1.307***	0.848***
	(0.119)	(0.275)	(0.222)
R-squared	0.565	0.549	0.607

Note: *, **, ***: statistically significant at 10%, 5%, and1%, respectively; Standard error in parentheses.

4.3. Heterogeneity Analysis

To verify the relationship between mechanization and planting GTFP in different regions, the samples are divided into two groups: main grain producing areas and non-grain producing areas. The main grain producing areas include 13 provinces such as Liaoning and Jilin. Model (1) and (2) in Table 5 show that there are differences in the effect of mechanization on the planting GTFP in different regions. In the main grain producing areas, the coefficient of the impact of mechanization on planting GTFP is 0.704, and the corresponding elasticity is 0.138, that is, for each percentage point increase of mechanization level, the planting GTFP increases by 0.138%; while the coefficient and elasticity of non-grain producing areas are 0.335 and 0.128 respectively. This may be caused by the high level of planting machinery in the main grain producing area.

To verify the correctness of our inference, according to the agricultural industry standard in China, this paper further divides the development stage of agricultural mechanization into three stages: primary (mechanization rate less than 40%), intermediate (40% to 70%) and advanced (more than 70%), to investigate whether there are differences in the impact of mechanization on planting GTFP at different development levels. The results in model (3), (4) and (5) verify the above speculation. With the improvement of mechanization level, the regression coefficient continues to increase, viz. the effect of different levels of mechanization on the improvement of planting GTFP will be different. When the degree of mechanization is low, the use of machinery in planting production is relatively small, and farmers will give priority to those that can greatly reduce factor input, mechanization is mainly manifested in the effect of technological progress. With the improvement of mechanization level, its contribution to the improvement of planting GTFP through the path of technology progress has a decreasing trend of marginal utility. However, at this stage, the substitution effect of machinery on labor is increasing, a large number of labor force is liberated from the planting industry sector, and the improvement of the standardization of mechanical operation leads to the professional division of labor and industrial agglomeration of planting production, which makes the factor allocation effect and economies of scale effect of mechanization begin to appear. Meanwhile, the application and popularization of mechanization are generally carried out in the form of cross regional operation. With the diffusion of production technology and experience spillover, the improvement effect of technical efficiency and spatial spillover effect begin to play an important role. Therefore, with the improvement of mechanization level, its role in improving planting GTFP is increasing.

Table 5. Results of heterogeneity analysis

	non-grain producing area	main grain producing area	primary mechanization	intermediate mechanization	advanced mechanization
Model	（1）	（2）	（3）	（4）	（5）
mac	0.335***	0.704***	0.826***	0.929***	1.139***
	(0.091)	(0.082)	(0.132)	(0.121)	(0.356)
sca	0.013***	-0.006	-0.002	-0.021*	0.013***
	(0.002)	(0.007)	(0.007)	(0.011)	(0.003)
pst	0.925***	0.342**	0.326	0.291*	-0.427
	(0.182)	(0.145)	(0.216)	(0.161)	(0.416)
hum	0.116***	0.047***	0.009	0.066***	0.063
	(0.025)	(0.017)	(0.022)	(0.020)	(0.052)
agdp	17.849***	40.117***	50.180***	11.986	-5.040
	(6.709)	(5.786)	(11.338)	(7.946)	(9.779)
ccj	0.003***	0.002***	0.002***	0.001***	0.002**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
ris	-0.224***	-0.172***	-0.110**	-0.192***	-0.223*
	(0.052)	(0.046)	(0.050)	(0.049)	(0.114)
inc	-0.045	-0.051**	-0.032	-0.061**	-0.074
	(0.036)	(0.023)	(0.026)	(0.031)	(0.112)
R-squared	0.867	0.789	0.744	0.755	0.763
Fixed province			Yes		
Fixed year			Yes		
Observations	323	247	251	241	78
Provinces	17	13	23	25	11

Note: *, **, ***: statistically significant at 10%, 5%, and1%, respectively; Standard error in parentheses.

5. Conclusions

This paper selects the panel data of 30 provinces in China from 2001 to 2019, uses the stochastic frontier analysis method of output oriented distance function to measure the planting GTFP based on net carbon sink, and further discusses the influence and mechanism of mechanization on planting GTFP using instrumental variable method, recursive model and spatial econometric method. The main conclusions drawn from this paper are as follows: (1) No matter from the analysis of different regions or different degrees of mechanization, mechanization can significantly promote the planting GTFP. (2) The relationship between mechanization and planting GTFP depends on the input effect, output effect and environmental effect caused by mechanization. The action path is mainly reflected in technology progress, improvement of technical efficiency and spatial spillover, while the path of operation scale expansion and factor allocation optimization is not significant. (3) When the level of mechanization is high, the impact of mechanization on planting GTFP is more significant. The reason is that with the improvement of mechanization level, the superposition of factor allocation effect, economies of scale effect, technical efficiency improvement effect and spatial spillover effect to technology progress effect makes the impact of mechanization on planting GTFP increasing.

Given the above evidence and arguments, some policy implications can be drawn as follows. The first is to accelerate the improvement of the mechanization in planting industry and realize the leap of mechanization development. The second is to strengthen inter regional coordination and cooperation, realize the rational flow and scientific allocation of agricultural machinery resources, and give full play to the positive spatial spillover effect of mechanization. The third is to increase investment in transportation infrastructure appropriately, improve the traffic and operation conditions of agricultural machinery effectively to lay a solid foundation for the all-round promotion of mechanization.

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