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The Impact Mechanism of New Quality Productive Forces in Agriculture on Agricultural Carbon Emissions

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Abstract: Agricultural carbon emissions are a key issue in global climate governance. New quality productive forces in agriculture, an advanced productivity form driven by scientific and technological innovation, significantly directly inhibit agricultural carbon emissions by promoting the green and low-carbon transformation of agricultural production methods. Employing panel data spanning from 2010 to 2023 across 31 provincial - level administrative units in China (including autonomous regions and municipalities directly under the central government), this research paper systematically assesses the influence, transmission processes, and spatial attributes of the new - quality productive forces in the agricultural sector on agricultural carbon emissions. It achieves this by utilizing two - way fixed - effects models, mediation - effects models, and spatial Durbin models. The conclusions are as follows: (1) The emergence of novel, high - quality productive forces in the agricultural sector exerts a substantial direct suppressive impact on agricultural carbon emissions. This effect remains stable even after addressing endogeneity issues and conducting multiple robustness verifications. (2) The enhancement of agricultural total factor productivity and the optimization of agricultural industrial agglomeration are two parallel mediating transmission pathways; (3) The carbon reduction effect of new quality productive forces in agriculture has significant regional heterogeneity, with a stronger inhibitory effect in northern China than in southern China; (4) It has a significant spatial spillover effect, which can not only suppress local carbon emissions, but also play a radiating driving role in adjacent regions. This paper provides systematic theoretical framework and empirical evidence for understanding the carbon reduction effect of new quality productive forces in agriculture.

Keywords: New Quality Productive Forces in Agriculture; Agricultural Carbon Emissions; Agricultural Total Factor Productivity; Agricultural Industrial Agglomeration Level.

1. Introduction

Global climate change brings severe threats to global agricultural production via extreme weather. Meanwhile, the existing agricultural system, which serves as a significant contributor to greenhouse gas emissions, exacerbates the adverse interplay between climate change and agricultural output. The IPCC Sixth Assessment Report warns that if global warming exceeds the 1.5°C critical threshold, the collapse risk of the global food system will rise exponentially. Against this background, the international community has reached broad consensus on agricultural green and low-carbon transformation. Driven by scientific and technological progress and characterized by digitization and greening, new quality productive forces in agriculture have become the core driving force for sustainable agricultural carbon reduction. However, the impact of new quality productive forces in agriculture on agricultural carbon emissions is non-linear. It acts through multiple transmission channels including total factor productivity improvement and industrial agglomeration optimization. Scientifically identifying these influence mechanisms is of great theoretical and practical significance for formulating targeted agricultural carbon reduction policies.

In recent times, the connection between advancements in agricultural technology and agricultural carbon emissions has emerged as a crucial subject of academic research. Existing studies focus on three dimensions: The quantification and determinants of agricultural carbon emissions, the environmental impacts of agricultural technological advancement, and the spatial spill - over consequences are being addressed. Specifically, we focus on the quantification and determinants of agricultural carbon emissions. Burney et al. (2010)[1] prove that agricultural productivity improvement has significant carbon reduction synergies. Gebbers and Gebbers and Adamchuk (2010) [2]pointed out that precision agriculture technologies reduce carbon emission intensity per unit output and increase yield. Bahmutsky et al. (2024)[3] found that precision agriculture can significantly reduce pesticide and fertilizer input. Liu et al. (2021)[4] found that agricultural carbon emissions show an inverted U-shaped trend. Rada and Fuglie (2019)[5] found that technological inspire research on technology-driven carbon reduction paths. Cheng et al. (2022)[6] found that expanding farm size provides micro evidence for the synergistic effect of scale advantage and technological progress on carbon reduction. In environmental effects of agricultural technological progress: Porter and Linde (1995) [7] proposed the "Porter Hypothesis", laying a theoretical foundation for the win-win relationship between technological progress and carbon reduction. Adamopoulos and Restuccia (2014)[8] confirmed that land misallocation has a significant impact on agricultural efficiency and environmental performance. Gollin et al. (2014)[9] emphasized the important role of agricultural technological progress in promoting green structural transformation. Yang et al. (2024)[10] found that fertilizer and pesticide application shows economies of scale, while mechanization and irrigation show diseconomies of scale. Fu and Zhang (2022)[11] presented empirical proof indicating that the process of digitalization has the potential to substantially enhance the overall factor productivity in agriculture and foster the green transformation of the agricultural sector. Tunio et al. (2025)[12] discovered that organizational integration presents a novel viewpoint for comprehending the function of industrial organization in the process of low - carbon transformation. In spatial spillover effects: Conley and Udry (2010)[13] verified that information spillovers lay a micro theoretical foundation for analyzing the spatial diffusion mechanism of agricultural new quality productive forces. Rong et al. (2023)[14] found that green technological innovation directly inhibits local agricultural carbon emission intensity. Bai et al. (2023)[15] found that agricultural productive services can significantly reduce local agricultural carbon emissions. Ma et al. (2023)[16] verified that human capital and agricultural mechanization have effects on local agricultural carbon emission intensity. Romer (1990)[17] 's endogenous technological change theory provided a basic theoretical framework for analyzing the spatial spillover of agricultural new quality productive forces. Liu et al. (2022)[18] found that there is an inverted U-shaped relationship between agricultural industrial agglomeration and total factor carbon productivity. In summary, although existing studies have explored carbon emission measurement, technological effect, spatial spillover and other dimensions in depth, few have systematically analyzed the impact mechanism of agricultural new quality productive forces on agricultural carbon emissions from an integrated perspective, and the empirical identification of the dual transmission path of "total factor productivity improvement—industrial agglomeration optimization" is still insufficient. This study aims to fill this research gap.

This paper's marginal contributions are mainly three aspects: First, it introduces "new quality productive forces in agriculture" into agricultural carbon emissions research, builds an evaluation index system covering workers, means of work and labor objects, and provides a new theoretical analysis framework. Second, it verifies the direct impact of new quality productive forces in agriculture on agricultural carbon emissions, identifies two indirect channels: "total factor productivity enhancement" and "organizational industrial agglomeration optimization", and clarifies the internal logical chain of "productive forces leapfrogging driving green transformation of production methods". Thirdly, it employs the mediation effect model and the spatial Durbin model to investigate the regional disparities and spatial spill - over impacts of new agricultural productive forces on agricultural carbon emissions. Moreover, it offers empirical backing for the formulation of well - targeted and coordinated agricultural carbon emission policies.

2. Theoretical Analysis and Research Hypotheses

2.1. Direct Effects of New Quality Productive Forces in Agriculture on Agricultural Carbon Emissions

Productivity theory holds that productivity core categories are three major elements—laborers, means of labor, and subjects of labor—which jointly determine labor productivity level [19]. First, at the level of agricultural laborers, Agricultural scientific and technological personnel lead low-carbon technology R&D and innovation, reconstruct traditional agricultural material circulation and energy flow, promote large-scale application of innovative achievements, and curb agricultural carbon emissions. Second, at the level of agricultural subjects of labor, Modern biotechnology has produced new high-yield, stress-resistant, low-carbon crop and livestock breeds, cutting the biological basis of agricultural carbon emissions at the source. Third, at the level of agricultural means of labor, Introduction of new agricultural production tools represented by intelligent agricultural machinery and UAV plant protection replaces traditional tools, restructuring traditional agricultural input-output system and reducing unit output energy consumption and carbon emission intensity. In summary, new quality productive forces in agriculture directly inhibit agricultural carbon emissions through three pathways: laborer quality enhancement, labor subject greening, and means of labor intelligentization.

H1: New quality productive forces in agriculture can significantly suppress agricultural carbon emissions.

2.2. Indirect Effects of New Quality Productive Forces in Agriculture on Agricultural Carbon Emissions

New quality productive forces in agriculture can produce indirect inhibitory effects by enhancing agricultural total factor productivity and raising the degree of agglomeration in the agricultural industry. First, novel high - quality productive forces within agriculture suppresses agricultural carbon emissions by enhancing agricultural total factor productivity. New quality productive forces in agriculture cultivate new agricultural operators such as family farms and specialized cooperatives, which tend to adopt advanced green production technologies. Green production technologies optimize production factor allocation and facilitate the growth of overall productivity in the agricultural sector. Elevated overall productivity means equivalent or greater output with lower resource consumption, which ultimately effectively suppresses agricultural carbon emissions[20]. Second, new quality productive forces in agriculture suppresses agricultural carbon emissions by raising agricultural industrial agglomeration levels. It drives production factors to concentrate in advantageous regions and improves agricultural industrial agglomeration levels. Geographically adjacent agricultural operators can form a synergistic development pattern, which facilitates the exchange, promotion and large-scale application of cleaner production technologies [21]. Thus, new quality productive forces in agriculture effectively suppresses agricultural carbon emissions through agricultural industrial agglomeration. Accordingly, this paper proposes the following hypotheses:

H2: New quality productive forces in agriculture significantly inhibit agricultural carbon emissions by enhancing agricultural total factor productivity.

H3: New quality productive forces in agriculture significantly inhibit agricultural carbon emissions by raising agricultural industrial agglomeration level.

3. Research Design

3.1. Variable Selection

3.1.1. Dependent Variable

The dependent variable in this paper is agricultural carbon emissions (NLT), measured by total carbon emissions generated during agricultural production. Drawing on existing research, this study identifies six carbon sources: chemical fertilizers, agricultural film, pesticides, agricultural diesel, irrigation and tillage, uses their corresponding carbon emission coefficients, and estimates total carbon emissions from crop production with the following carbon accounting formula:

$$NLT = \sum ZY_i = \sum \eta_i \times \delta_i \tag{1}$$

where NLT denotes the total amount of agricultural carbon emissions, ZY_i denotes the carbon emissions from the i-th agricultural carbon source, η_i denotes the input quantity of each carbon source, and δ_i denotes the carbon emission coefficient of each carbon source.

3.1.2. Explanatory Variable

The explanatory variable in this paper is new quality productive forces in agriculture(NXZ). An indicator system for new quality productive forces in agriculture is constructed from three dimensions, namely agricultural laborers, agricultural subjects of labor, and agricultural means of labor. The entropy technique is utilized to compute the weights of indicators at every level. Subsequently, the weighted summation approach is applied to obtain the development degrees of the new high - quality productive forces in the agricultural sector across 31 provinces, autonomous regions, and municipalities directly under the central government in China from 2010 to 2023.

Table 1. Indicator System for Agricultural New Quality Productive Forces

Primary Indicator	Secondary Indicator	Measurement Indicator	Attribute	Unit	Weight
Agricultural Laborers	Laborer Skills	Average years of schooling in rural areas	+	Year	0.0041
	Laborer Quantity	Number of agricultural science and technology activity personnel	+	Person	0.1247
	Laborer Income	Per capita disposable income of rural residents	+	Yuan	0.0760
Agricultural Labor Objects	Ecological Environment	Forest coverage rate	+	%	0.0475
	New Quality Industry	Value added of agriculture, forestry, animal husbandry, and fishery	+	100 Million Yuan	0.0885
	Digital Business	Per capita transportation and communication consumption of rural residents	+	Yuan	0.1062
Agricultural Labor Means	Material Production Means	Number of rural broadband access subscribers	+	10,000 Households	0.1771
		Mobile telephone ownership per 100 rural households	+	Units	0.0189
	Intangible Production Means	Number of R&D projects	+	Items	0.2168
		Digital inclusive finance level	+	Index	0.1402

3.1.3. Mediating Variables

This paper selects agricultural total factor productivity (NQS) and the degree of agricultural industrial agglomeration (NJD) as mediating variables. Among them, agricultural total factor productivity (NQS) is measured following existing research, employing the super-efficiency SBM model for estimation. This approach effectively avoids estimation biases arising from radial and angular choices, and enables effective discrimination and further evaluation among multiple efficient decision-making units. In terms of specific indicator construction, input factors encompass traditional agricultural production factors including labor, land, agricultural machinery, chemical fertilizers, pesticides, and agricultural film, while the desired output is represented by the gross output value of agriculture, forestry, animal husbandry, and fishery. The specific model specification is as follows:

Where ρ_{SE} denotes the efficiency value; x and y represent the input and output variables, respectively; m and q denote the numbers of input and output indicators, respectively; k denotes the production period; i and r denote the decision-making units for inputs and outputs, respectively; s^+ an s^- denote the slack variables for inputs and outputs, respectively; and γ is the weight vector. If ρ_{SE} ≥1, the decision-making unit is considered relatively efficient; conversely, if ρ_{SE} <1, the decision-making unit is considered relatively inefficient, indicating efficiency losses.

$$\begin{aligned}
&\min \rho_{SE} = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1+\frac{1}{q}\sum_{r=1}^{q} s_r^+ / y_{rk}} \\
&s.t. \\
&\sum_{j=1, j\neq k}^{n} x_{ij}\gamma_j + s_i^- \leq x_{ik} \\
&\sum_{j=1, j\neq k}^{n} y_{rj}\gamma_j - s_i^+ \leq y_{rk} \\
&y, s^-, s^+ \geq 0 \\
&i = 1,2\cdots,m; r = 1,2\cdots,q; j = 1,2\cdots n(j \neq k)
\end{aligned} \tag{2}$$

The degree of agricultural industrial agglomeration (NJD), following common practices in existing studies and with comprehensive consideration of data availability, is defined by the proportion of the total production value of agriculture, forestry, livestock breeding, and fisheries in each province relative to the overall national production value of this sector. divided by the ratio of the gross domestic product of that province to the national gross domestic product. The specific calculation formula is as follows:

Table 2. Indicator System for Agricultural Total Factor Productivity

Indicator	Variable	Variable Description
Input Factors	Labor Input Land Input Agricultural Machinery Input Fertilizer Input Pesticide Input Agricultural Film Input Irrigation Input	Number of employees in the crop farming sector (10,000 persons) Total sown area of crops (1,000 hectares) Total power of agricultural machinery (10,000 kW) Agricultural chemical fertilizer input (10,000 tons) Pesticide usage (10,000 tons) Agricultural plastic film usage (tons) Effective irrigated area (1,000 hectares)
Desirable Output	Agricultural Gross Output Value	Gross output value of the crop farming sector (100 million yuan)

$$LQ_{it} = \frac{Q_{it} / \sum_{i=1}^{31} Q_{it}}{G_{it} / \sum_{i=1}^{31} G_{it}} \tag{3}$$

where LQ_{it} denotes the location quotient of province ii, Q_{it} denotes the gross output value of agriculture, forestry, animal husbandry, and fishery in province i ; $\sum_{i=1}^{31} Q_{it}$ denotes the national gross output value of agriculture, forestry, animal husbandry, and fishery; G_{it} denotes the gross domestic product of province i ; and $\sum_{i=1}^{31} G_{it}$ denotes the national gross domestic product.

3.1.4. Control Variables

To mitigate measurement bias from omitted variables, this paper selects the following control variables that affect agricultural carbon emissions: Urbanization level(UL), measured by the proportion of year-end urban permanent population in total population; Agricultural mechanization level(MH), measured by the logarithm of total agricultural machinery power; Agricultural fiscal expenditure level(AP), measured by the proportion of agriculture-related expenditure in local general public budget expenditures; Infrastructure level(JC), measured by the ratio of highway mileage to year-end population; Rural residents' disposable income(NZ), measured by the logarithm of per capita disposable income of rural residents; Economic development level(DL), measured by the logarithm of per capita gross domestic product.

3.2. Data Sources

This research paper conducts an analysis of the panel data spanning from 2010 to 2023, which is derived from 31 provincial - level administrative units in China, including provinces, autonomous regions, and municipalities directly under the central government. The data primarily originate from a variety of national and provincial year - books, such as the Statistical Yearbook of Rural China and the China Statistical Yearbook.

3.3. Model Specification

3.3.1. Baseline Regression Model

To examine the impact of agricultural new quality productive forces on agricultural carbon emissions, this paper constructs the following baseline regression model:

$$NLT_{it} = a_0 + a_1 NXZ_{it} + a_2 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{4}$$

where NLT denotes agricultural carbon emissions, NXZ denotes agricultural new quality productive forces, Z denotes the control variables, a_0 denotes the constant term, a_1 denotes the regression coefficient of agricultural new quality productive forces, a_2 denotes the regression coefficients of the control variables, μ_i denotes individual fixed effects, δ_t denotes time fixed effects, ε_{it} denotes the random error term, the subscript i denotes the region, and t denotes the time period.

3.3.2. Mechanism Testing Model

To examine the influence mechanism of agricultural new quality productive forces and agricultural total factor productivity on agricultural carbon emissions, this paper constructs a mediation effect model as follows:

$$NQS_{it} = b_0 + b_1 NXZ_{it} + b_2 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{5}$$

$$NLT_{it} = d_0 + d_1 NQS_{it} + d_2 NXZ_{it} + d_3 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{6}$$

where NQS denotes agricultural total factor productivity, b_0 and d_0 denote the constant terms, b_1 and d_2 denote the regression coefficients of agricultural new quality productive forces, d_1 denotes the regression coefficient of agricultural total factor productivity, and b_2 and d_3 denote the regression coefficients of the control variables.

To examine the influence mechanism of agricultural new quality productive forces and agricultural industrial agglomeration level on agricultural carbon emissions, the present paper devises a mediation effect model in the following manner:

$$NJD_{it} = f_0 + f_1 NXZ_{it} + f_2 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{7}$$

$$NLT_{it} = y_0 + y_1 NJD_{it} + y_2 NXZ_{it} + y_3 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{8}$$

where NJD denotes agricultural industrial agglomeration level, f_0 and y_0 denote the constant terms, f_1 denotes the regression coefficient of agricultural new quality productive forces, y_1 denotes the regression coefficient of agricultural industrial agglomeration level, y_2 denotes the regression coefficient of agricultural new quality productive forces, and

f_2 and y_3 denote the regression coefficients of the control variables.

4. Empirical Results and Analysis

4.1. Baseline Regression Results

As shown in Table 3, Column (1) reports the regression coefficient of agricultural new quality productive forces is -152.750, significant at the 1% level. In Column (2), after adding control variables on the basis of Column (1), the regression coefficient of agricultural new quality productive forces is -363.871, still significant at the 1% level with an increased absolute coefficient value. Therefore, Hypothesis 1 is supported.

Table 3. Benchmark Regression Test Results

Variable	(1)*NLT*	(2)*NLT*	Variable	(1)*NLT*	(2)*NLT*
NXZ	-152.750***	-363.871***	*lnNZ*		105.379***
	(11.463)	(27.370)			(10.863)
UL		-298.255***	*lnDL*		50.712***
		(62.563)			(12.815)
lnMH		48.624***	Constant	312.432***	-1326.001***
		(6.921)			
AP		5.461***		(3.304)	(151.201)
		(0.896)			
JC		-0.626***	Observations	434	434
		(0.137)	adj. R^2	0.253	0.517
Time & Region FE	Yes	Yes	Time & Region FE	Yes	Yes

4.2. Endogeneity Test and Robustness Checks

Table 4. Results of Endogeneity Tests and Robustness Tests

	Endogeneity Test		Robustness Test		
Variable	First Stage	Second Stage	*NLT*(Excluding municipalities)	*NLT*(Excluding municipalities,)	*NLT* (Winsorized)
	-0.005*** (0.001)				
NXZ		-748.926*** (288.800)	-382.262*** (29.141)	-288.364*** (30.641)	-363.871*** (27.370)
				-119.927*** (30.130)	
				3207.281*** (425.774)	
Controls					
_cons	-2.847*** (0.157)	-5,123.797*** (851.007)	-1732.063*** (184.264)	-1684.894*** (170.529)	-1326.001*** (151.201)
Stock-Yogo 10% CV	16.380				
Cragg-Donald Wald F	21.833				
Kleibergen-Paap rk LM	26.053***				
Kleibergen-Paap rk Wald F	34.623				
Hansen p-value	0.000				
N	434		378	378	434
adj.R^2		0.793	0.548	0.615	0.517

To avoid endogeneity between variables, in this research paper, the two - stage least squares (2SLS) method is employed for conducting tests. As shown in Table 4, the first-stage regression results in Column (1) show the instrumental variable coefficient is -0.005, significant at the 1% level. The Cragg-Donald Wald F statistic is 21.833, larger than the Stock-Yogo 10% critical value 16.380, and the Kleibergen-Paap rk LM statistic is 26.053, passing the 1% significance test. Column (2) second-stage regression results show the regression coefficient of agricultural new quality productive forces(NXZ is -748.926, significant at the 1% level, with coefficient direction consistent with the baseline regression. Column (3) shows regression results after deleting Beijing, Shanghai, Tianjin and Chongqing. The coefficient of agricultural new quality productive forces is -382.262, significant at the 1% level. Column (4) adds control variables on the basis of Column (3), the coefficient is -288.364, still significant at the 1% level with consistent coefficient direction. Column (5) presents regression results after 1% two-sided winsorization for all continuous variables to eliminate extreme observation interference. The coefficient is -363.871, significant at the 1% level, with no obvious changes in coefficient direction and significance.

4.3. Mechanism Testing

As shown in Table 5, Columns (1) and (2) take agricultural total factor productivity (NQS) as the dependent variable. The regression coefficients of agricultural new quality productive forces are 1.238 and 0.607, both significant at the 1% level. In Columns (3) and (4), after adding agricultural total factor productivity to the baseline regression model, its regression coefficients are -53.153 and -54.903, both significant at the 1% level. Meanwhile, the absolute values of the regression coefficients of agricultural new quality productive forces (-86.935 and -330.548) are lower than those of the baseline regression, and still significant at the 1% level. Thus, Hypothesis 2 is confirmed.

Table 5. Mechanism Test Results

Variable	NQS	NQS	NLT	NLT
NZX	1.238*** (0.040)	0.607*** (0.111)	-86.935*** (20.777)	-330.548*** (27.710)
NQS			-53.153*** (14.092)	-54.903*** (12.107)
Controls	No	Yes	No	Yes
_cons	0.228*** (0.012)	0.716 (0.613)	324.534*** (4.568)	-1286.709*** (147.853)
N	434	434	434	434
adj.R^2	0.683	0.722	0.277	0.540
Time & Region FE	Y e s	Y e s	Y e s	Y e s

As shown in Table 6, in Column (1), the regression coefficient of agricultural new quality productive forces on agricultural industrial agglomeration level is 0.242, passing the 1% significance level test. In Column (2), after adding control variables, the regression coefficient of agricultural new quality productive forces becomes -0.514, still passing the 1% significance level test. In Columns (3) and (4), the regression coefficient of agricultural industrial agglomeration level is 28.367 in Column (3), and becomes -14.848 in Column (4) after adding control variables, passing the 1% and 10% significance level tests, respectively. Meanwhile, the regression coefficients of agricultural new quality productive forces are -159.612 and -371.507, both remaining significantly negative. Therefore, Hypothesis 3 is supported.

Table 6. Mechanism Test Results

Variable	NJD	NJD	NLT	NLT
NXZ	0.242*** (0.062)	-0.514*** (0.159)	-159.612*** (11.550)	-371.507*** (27.660)
NJD			28.367*** (9.067)	-14.848* (8.621)
Controls	No	Yes	No	Yes
_cons	1.150*** (0.018)	-0.030 (0.879)	279.801*** (10.930)	-1326.442*** (150.827)
N	434	434	434	434
adj.R^2	-0.038	0.234	0.269	0.520
Time & Region FE	Y e s	Y e s	Y e s	Y e s

5. Conclusion and Policy Recommendations

5.1. Conclusion

Drawing upon panel data from 31 provincial - level administrative divisions (including autonomous regions and municipalities directly under the Central Government) in China covering the years from 2010 to 2023, this paper systematically examines the impact mechanism of agricultural new quality productive forces on agricultural carbon emissions and draws the following conclusions. Agricultural new productive forces for quality improvement show a substantial direct inhibitive influence on agricultural carbon emissions, and this conclusion is still valid after adjusting for endogeneity bias and undergoing multiple robustness tests, suggesting that the comprehensive transformation of agricultural productivity including digitization, intellect and sustainable development can efficiently promote the transition of agricultural production methods towards low - carbon practices. In regard to the working principles, the new high-quality productive forces in agriculture show indirect effects on emission reduction through two ways: improving the total factor productivity of agriculture and adjusting the pattern of agricultural industrial concentration. Among them, the enhancement in total factor productivity decreases the carbon emission intensity per unit of output by improving the factor allocation efficiency, while the emission reduction effect of industrial clustering shows conditional dependence, being affected simultaneously by the quality of agglomeration and regional characteristics.

5.2. Policy Recommendations

According to the above empirical results, this paper puts forward the following policy suggestions. Firstly, the basic regression outcomes show that the new quality productive forces in agriculture have a significant direct inhibitive impact on agricultural carbon emissions. It remains valid even after taking endogeneity into account and going through numerous robustness checks. Therefore, we should hasten the cultivation and development of new agricultural productive forces, particularly in promoting the widespread use of low-carbon technologies like smart irrigation, precision fertilization and digital crop condition monitoring. A mechanism for adjusting agricultural subsidies according to the carbon reduction performance should be set up, and pilot initiatives ought to be launched in the primary grain - producing areas to incorporate agricultural carbon sinks within the scope of green financial support, thus establishing a cycle promoted by technology, regulated by policy and motivated by the market. Second, the mechanism tests indicate that the enhancement of agricultural total factor productivity and the optimization of agricultural industrial agglomeration are the dual transmission channels by which agricultural new quality productive forces can lead to carbon reduction. Efforts should be made to vigorously cultivate new agricultural business entities such as family farms and specialized cooperatives to accelerate the adoption and diffusion of green production technologies. Finally, simultaneous measures should be taken to improve the capacity at the local level, include intelligent monitoring devices in the agricultural machinery subsidy list, carry out a digital capacity enhancement plan for agricultural technicians, and establish a green technology extension system by adopting the cooperation model of "institute + new enterprises," guaranteeing that all the policies are put into effect and bring about noticeable effects.

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