Pol. J. Environ. Stud. Vol. XX, No. X (XXXX), 1-15

DOI: 10.15244/pjoes/208589 ONLINE PUBLICATION DATE: 2025-11-19

Original Research

Study on the Effect of Agricultural New Quality Productivity on Agricultural Carbon Emission Efficiency

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Received: 23 January 2025
Accepted: 23 July 2025

Abstract

Based on the agricultural new quality productivity index and agricultural carbon emission efficiency of provincial administrative regions in China from 2012 to 2021, this study empirically examines the impact of agricultural new quality productivity on agricultural carbon emission efficiency. Furthermore, it examines the mediating role of agricultural industrial structure upgrading, as well as the moderating effect of industrial diversification. The key findings can be summarized as follows: (1) The baseline regression shows that agricultural new quality productivity can significantly improve the development of agricultural carbon emission efficiency. This conclusion remains robust after considering endogeneity and after a series of robustness tests; (2) The mediating effect analysis reveals that agricultural new quality productivity enhances agricultural carbon emission efficiency by facilitating the upgrading of the agricultural industrial structure; (3) The moderating effect analysis demonstrates that industrial diversification significantly and positively amplifies the impact of agricultural new quality productivity on carbon emission efficiency; (4) Heterogeneity analysis indicates that the effect of new quality productivity is more pronounced in eastern provinces and markets with high maturity.

Keywords: agricultural new quality productivity, agricultural carbon emission efficiency, agricultural industrial structure upgrading, industrial diversification

Introduction

Conventional agricultural practices have historically prioritized yield maximization to meet food security and commodity supply demands. However, this paradigm, marked by a reliance on agrochemicals and industrialized animal farming, has inadvertently contributed to a significant increase in greenhouse gas emissions from the agricultural sector. The Food and Agriculture Organization of the United Nations (FAO) and the Intergovernmental Panel on Climate Change (IPCC) have both identified agriculture as the second-largest source of greenhouse gas emissions globally. Furthermore, China's Second National Communication

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on Climate Change indicates that agricultural production activities are among the key contributors to greenhouse gas emissions, underscoring their substantial impact on climate change. As a major agricultural nation, China's transition towards low-carbon agriculture carries profound implications for global carbon mitigation efforts. On an international scale, China articulated its "dual-carbon" goals – aiming for "carbon peak" and "carbon neutrality" – during the 75TH United Nations General Assembly in 2020. This initiative necessitates contributions from all sectors, including agriculture. Domestically, in 2021, the opinions issued by the CPC Central Committee and the State Council regarding the comprehensive implementation of new development concepts emphasized that "agriculture" should be recognized as one of five critical areas for advancing "double carbon" initiatives. This directive provides a policy framework essential for promoting low-carbon development within agricultural production systems.

In the context of the continuous iteration and advancement of digital technology, new quality productivity is transforming our modes of life and production at an unprecedented pace. It serves as a core driving force in promoting the modernization process and has emerged as a hallmark of the deep integration between science, technology, and production. Consequently, it is essential to conduct a thorough analysis to determine whether agricultural new quality productivity consistently contributes to enhancing agricultural carbon emission efficiency. What are the underlying mechanisms? Are there other influencing factors? To address these research questions, this study employs a two-way fixed effects model, mediation analysis, and moderation analysis to empirically assess the impact of agricultural new quality productivity on carbon emission efficiency.

The marginal contributions of this paper are as follows: Firstly, it confirms that the new quality productivity in agriculture positively influences agricultural carbon emission efficiency. This finding enhances our understanding of the relationship between agricultural new quality productivity and carbon emission efficiency, providing valuable insights for promoting both. Secondly, the paper elucidates the mechanism through which upgrading the agricultural industrial structure promotes carbon emission efficiency via improvements in agricultural new quality productivity. This expands and deepens existing research on the factors influencing both agricultural new quality productivity and carbon emission efficiency, thereby facilitating a more accurate comprehension of how agricultural new quality productivity contributes to enhancing carbon emission efficiency. Thirdly, this study discusses the regulatory role of industrial diversification on both agricultural new quality productivity and carbon emission efficiency. The findings derived from examining industrial diversification highlight its positive effects on enhancing both agricultural new quality productivity and carbon emission efficiency.

Literature Review

In the context of the global response to climate change, the issue of agricultural carbon emission efficiency has gained increasing prominence and has emerged as a key focus of academic research. Scholars have conducted extensive studies on this topic, yielding significant results; however, there remains ample opportunity for further exploration and innovation.

West and Post [1] and Johnson et al. [2] have distinctly delineated agricultural carbon sources, encompassing fertilizers, pesticides, rice cultivation, livestock breeding, agricultural waste, and other relevant aspects. This work has established a foundational framework for subsequent research in the field. Concurrently, numerous scholars have dedicated their efforts to calculating agricultural carbon emissions; some focus on specific domains such as livestock farming [3], agricultural inputs [4], and farmland utilization [5], thereby enriching our understanding of agricultural carbon emissions from diverse perspectives. However, previous studies exhibit blind spots regarding the factors influencing the efficiency of agricultural carbon emissions. Despite the depth of their analysis, they often overlook the significant enabling role that new productivity plays in enhancing this efficiency.

In China, the emergence of new agricultural productivity has created unprecedented opportunities for the establishment of a powerful agricultural nation and has become a crucial engine driving the development of high-quality agriculture. Academic research on new agricultural productivity has demonstrated a vigorous trend of development, primarily focusing on four key aspects. First, at the theoretical level, scholars have concentrated on analyzing the "new" and "quality" characteristics inherent in new agricultural productivity. This involves an in-depth examination of its connotation and defining its attributes with precision [6, 7]. Second, from a practical application perspective, researchers are exploring how to cultivate new quality productivity in agriculture through various means such as digital technology [8], emerging industries and future industrial developments [9], as well as scientific and technological innovations [10]. Third, investigations into the impact of new quality productivity on macro-level phenomena are being conducted. These include its effects on rural revitalization [11], high-quality agricultural development [12], and agricultural modernization [13]. Fourth, efforts are underway to construct evaluation systems for new quality productivity in agriculture from multiple dimensions. This includes frameworks based on three dimensions: laborers, labor objects, and labor materials [10], or alternatively, three perspectives: science and technology, green practices, and digital advancements [14].

From the perspective of resource allocation, a reasonable upgrading of the agricultural industrial structure can optimize the distribution of production factors such as land, capital, and labor. This optimization enhances the overall efficiency of agricultural production and subsequently influences the efficiency of agricultural carbon emissions [15]. For instance, developing characteristic agricultural industries that are high in added value yet low in energy consumption can lead to reduced carbon emissions while increasing agricultural output compared to traditional production models. From a technological innovation standpoint, upgrading the agricultural industrial structure is frequently accompanied by the introduction and application of new technologies [16]. Green agricultural technologies – such as intelligent irrigation systems and precision fertilization techniques – not only contribute to reducing carbon emissions during agricultural production but also enhance overall production efficiency [17]. Furthermore, this structural upgrade promotes both the extension and expansion of the agricultural industrial chain, fosters coordinated development among related industries, and creates favorable conditions for establishing and advancing new forms of agricultural productivity [18]. The emergence of new quality productivity will also reciprocally influence the upgrading process within the agricultural industrial structure; thus, these two elements will mutually reinforce each other's development synergistically [19]. For example, advancements in digital agriculture have given rise to innovative formats such as e-commerce for agricultural products and big data services tailored for agriculture. These developments facilitate a transformation towards diversification and higher-end structures within agriculture. Consequently, selecting the upgrading of the agricultural industrial structure as a mediating variable allows for a more comprehensive and in-depth exploration of the intrinsic relationship between the new quality productivity of agriculture and its carbon emission efficiency [20].

In the process of agricultural development, industrial diversification exerts a significant moderating effect on the relationship between new quality productivity in agriculture and agricultural carbon emission efficiency. The selection of industrial diversification as a moderating variable is well-founded from multiple perspectives [21]. Industrial diversification offers extensive opportunities and fertile ground for the cultivation and advancement of new agricultural productivity. Diverse agricultural industry systems can attract a greater array of innovative elements [22]. For instance, advanced production technologies, modern management concepts, and high-caliber talent can be integrated into the development processes of diversified industries such as specialty crop cultivation, deep processing of agricultural products, and agritourism. This integration further stimulates the innovative vitality within agricultural science and technology while promoting enhancements in new quality productivity in agriculture [23]. When industrial diversification is pronounced, the penetration and application of new productivity within agriculture tend to proceed more smoothly, facilitating a more efficient conversion into actual productivity. Conversely, an agricultural production model characterized by a singular focus may restrict the potential for new productivity to manifest fully and impede its beneficial effects on agricultural carbon emission efficiency [24].

Through a systematic literature review, it is evident that since China introduced the concepts of digital villages and new quality productivity, agricultural carbon emission efficiency and new quality productivity have garnered significant academic attention. Scholars have made substantial progress in researching both new quality productivity and agricultural carbon emission efficiency [25]. The conceptual connotations and evaluation metrics for these two areas have been thoroughly discussed, providing valuable references for future studies. However, it is important to note that discussions surrounding new quality productivity within the agricultural sector remain limited, with most existing work focusing primarily on theoretical analysis [26]. While theoretical research on agricultural new quality productivity has yielded certain results, empirical investigations into the impact of agricultural new quality productivity on agricultural carbon emission efficiency are relatively scarce, revealing notable gaps in the current body of research. Integrating agricultural new productivity, upgrading the agricultural industrial structure, and agricultural carbon emission efficiency into a unified research framework can not only address these existing gaps but also offer a more scientific and comprehensive theoretical foundation as well as practical guidance for sustainable development in agriculture. This approach holds significant theoretical and practical implications.

Theoretical Analysis and Hypothesis Research

Effect of Agricultural New Quality Productivity on Agricultural Carbon Emission Efficiency

Agricultural new quality productivity refers to a novel form of productivity that enhances production efficiency, optimizes product quality, and ensures the sustainability of the agricultural production process through the integration of advanced technological methods and innovative management concepts [27]. Its essence lies in facilitating the transformation and upgrading of agricultural production practices via technological innovation and institutional reform, thereby augmenting both the green benefits and competitiveness of agricultural output [28]. With rapid advancements in technology, the agricultural sector is experiencing unprecedented changes. The new quality productivity in agriculture serves as a pivotal force driving this transformation, gradually altering both agricultural production modes and rural economic structures. Fueled by this new paradigm of agricultural productivity, there has been a notable shift from traditional manual labor towards digitalization and intelligence in farming practices. Precision agriculture management – achieved through technologies such as sensors and the Internet of Things – not only conserves resources but also mitigates environmental impacts, thus establishing a robust foundation for sustainable rural economic development. In its operational framework, new quality productivity applies cutting-edge technologies, including IoT, big data analytics, and artificial intelligence within the agricultural production process. This approach not only streamlines various aspects of farming operations but also significantly elevates the level of digitalization within agricultural practices [29]. In the sales process, the emergence of new quality productivity in agriculture has facilitated the development of innovative sales methods. This advancement has significantly strengthened the digital infrastructure in rural areas. Notably, new quality productivity fosters the growth of digital technologies, including cloud computing, big data, and the Internet. As a result, there is an ongoing deepening and materialization of the integration between the digital economy and the daily lives of rural residents. Ultimately, these developments contribute to a substantial enhancement in agricultural carbon emission efficiency [30].

Based on this, we propose Hypothesis 1: the enhancement of agricultural new quality productivity can significantly improve the efficiency of agricultural carbon emissions.

The Intermediary Effect of Agricultural Industrial Structure Upgrading

The upgrading of the agricultural industrial structure refers to the process of promoting high-quality agricultural development through the adjustment and optimization of agriculture's internal structure, as well as enhancing its technological level, added value, and competitiveness [31]. The issues related to labor intensity and resource waste that are prevalent in traditional agricultural production processes have been effectively mitigated. Consequently, agricultural production capacity has significantly improved, while crop planting and breeding management have become more refined. This transformation has led to increased output and quality alongside reduced production costs. Collectively, these advancements have established a solid foundation for the upgrading of the agricultural industrial structure. With modernization in production processes and improvements in industrial chains, both circulation efficiency and market competitiveness for agricultural products have seen significant enhancement [32]. Furthermore, technological progress has introduced information management systems and intelligent agricultural production methods that render the entire process – from production to sales – more transparent and efficient. This advancement effectively reduces information asymmetry and resource waste while fostering healthy development within the agricultural market. Additionally, it supports a transition towards modernization characterized by service orientation and intelligence within the agricultural industrial structure.

The upgrading of the agricultural industrial structure has catalyzed the modernization and development of the rural economy. This transformation has created a broader scope for the introduction and application of digital technologies within agriculture. The enhancement of the agricultural industrial structure has facilitated a shift in agricultural production methods [33]. By integrating advanced agricultural technologies and equipment – such as intelligent planting systems and precision irrigation devices – the automation and precision of agricultural production can be significantly improved. This advancement not only boosts production efficiency while reducing labor costs but also provides essential technical support for enhancing carbon emission efficiency in agriculture.

Based on this, we propose Research Hypothesis 2: The upgrading of the agricultural industrial structure serves as a mediating factor between the new quality productivity of agriculture and the carbon emission efficiency in the agricultural sector.

The Regulating Effect of Industrial Diversification

Industrial diversification refers to the presence of various distinct types of industries within the economic framework of a country or region. These industries differ in terms of their levels of development, technological advancement, market scale, and other factors, thereby creating a diversified economic system [34]. The diversity of industries provides a robust economic foundation for enhancing carbon emission efficiency in agriculture. When rural areas encompass multiple integrated industries – such as agriculture, processing, and services 0 their economic sources become more varied, leading to an increase in fiscal revenue for these regions. This financial growth enables rural areas to allocate more resources towards the construction of digital infrastructure [35]. Moreover, talent is a crucial element in advancing agricultural carbon emission efficiency; industrial diversity plays a significant role in attracting and retaining skilled individuals. Diversified industries mean more job opportunities and career development space, attracting talents from various fields, including information technology, marketing, management, etc., to gather in rural areas [36]. These professionals bring with them advanced knowledge and technologies that can be directly applied across all facets of agricultural carbon emission efficiency. Additionally, they contribute to enhancing the digital literacy and skill levels of residents through training programs and demonstrations.

Based on this, we propose Research Hypothesis 3: Industrial diversity significantly moderates the relationship between agricultural new quality productivity and agricultural carbon emission efficiency.

Research Design

Sample Selection and Data Source

This paper selects panel data from 30 provincial-level administrative regions (except Tibet Autonomous Region and Hong Kong, Macao, and Taiwan) in China from 2012 to 2021. It obtains 300 sample sizes, all of which are from the China Rural Statistical Yearbook, China Statistical Yearbook, China Rural Operation and Management Statistical Annual Report, and Digital Financial Inclusion Index Report.

Variable Setting

In this study, the selection and measurement of variables are critical components for constructing a theoretical model and uncovering relevant internal mechanisms within the agricultural domain.

Explained Variable

The explained variable is agricultural carbon emission efficiency, which holds significant importance for assessing resource utilization and environmental sustainability in agricultural production. The Slacks-Based Measure (SBM) model integrated with the Global Malmquist-Luenberger (GML) index is employed to calculate this efficiency. The SBM model effectively addresses input-output inefficiencies by utilizing slack variables, thereby overcoming limitations associated with traditional Data Envelopment Analysis (DEA). It resolves radial and angular selection issues within the model, allowing for a more precise measurement of decision unit efficiency. The GML index measures changes in total factor productivity (TFP), taking into account undesired outputs such as carbon emissions from agriculture. This methodology enables a comprehensive consideration of various input factors involved in the agricultural production process – including land, labor, capital, and energy – while accurately calculating agricultural carbon emission efficiency in conjunction with both agricultural output and carbon emissions. Consequently, it provides scientific quantitative indicators essential for exploring the relationship between agricultural production and environmental impact.

Explanatory Variable

The explanatory variable is defined as agricultural new quality productivity, which serves as a fundamental element in driving high-quality agricultural development and supporting the establishment of an agricultural power. In accordance with the methodology proposed by Song et al. [14], principal component analysis (PCA) is employed to assess relevant indicators. PCA effectively transforms multiple correlated variables into a limited number of comprehensive variables, known as principal components, through dimensionality reduction. These principal components retain the original variable information to the greatest extent possible. By analyzing and processing a series of indicators that reflect agricultural new quality productivity – such as the intensity of scientific and technological innovation input, the degree of digital technology application in agricultural production, and the scale of emerging agricultural industries – the coefficient value representing agricultural new quality productivity is ultimately derived. This coefficient provides a comprehensive and objective quantification of the level of agricultural new quality productivity, thereby offering a crucial quantitative foundation for subsequent research endeavors.

Mediator Variable

The mediator variable is the upgrading of the agricultural industrial structure, which serves as a crucial bridge in the process of agricultural development. The Theil index is employed to measure the degree of upgrading within the agricultural industrial structure (TL) [27]. This index effectively captures both disparities and equilibrium levels within industrial structures across a given region. In the context of agriculture, it can assess changes in the proportion of each agricultural industry relative to the overall agricultural economy, as well as evaluate the balance of development among various industries by analyzing output values and employment figures for different sectors. The upgrading of the agricultural industrial structure signifies a transition from traditional single-industry models to diversified, efficient, and modern industrial systems. Changes in the Theil index can directly reflect this transformation and provide an effective quantitative approach for examining the mediating role that upgrades in agricultural industrial structure play between new quality productivity in agriculture and other variables.

Moderator Variable

The moderator variable is industrial diversification. According to Frenken et al. [37], industrial diversification (DIV) is assessed by evaluating the balance of sectoral economic activities. This concept reflects the variety of industrial types present within a region or industry, as well as the degree of inter-industry correlation. By analyzing the balance of sectoral economic activities, we can gain deeper insights into the developmental trends of various sub-industries within the agricultural sector. When industrial diversification is pronounced, it facilitates cooperation and leverages complementary advantages among different agricultural sectors, thereby promoting a more rational allocation of resources and enhancing utilization efficiency. For instance, in regions where traditional farming, agro-processing, rural tourism, and other related industries coexist and thrive, these diverse sectors can share resources, technologies, and markets effectively. This synergy serves to moderate the relationship between agricultural new productivity and agricultural carbon emission efficiency, while industrial diversification (DIV) indicators provide quantitative evidence to accurately capture and analyze this moderating effect.

Control Variable

The control variables included six distinct factors: the level of economic development (rjgdp), the urban-rural disparity (cxcj), the degree of industrialization (gyhsp), the extent of openness to external markets (dwkf), agricultural support measures (nyzc), and population density metrics (lnrkmd).

Model Setting

Reference Regression Model

To validate hypothesis 1, this study develops the following bidirectional fixed-effect model:

$$ACEE_{it} = \beta_0 + \beta_1 agr_{it} + jD_{it} + \tau_i + \mu_t + \varepsilon_{it} \tag{1}$$

Among them, $ACEE_{it}$ serves as the explained variable representing agricultural carbon emission efficiency, i denotes the province, and t indicates the year. The core explanatory variable of this study is *agrit*, which reflects the new quality productivity in agriculture for each province, and β_0, β_1, and j are the parameters to be estimated. Additionally, D_{it} comprises a series of control variables, while τi represents the fixed effect associated with each province. μ_t accounts for the time-fixed effect, and ε_{it} signifies the random disturbance term.

Mediating Effect Model

To validate hypothesis 2, a mediating effect model was developed by integrating Model (1), which is presented as follows:

$$TL_{it} = \gamma_0 + \gamma_1 agr_{it} + jD_{it} + \tau_i + \mu_t + \varepsilon_{it} \tag{2}$$

$$ACEE_{it} = \delta_0 + \delta_1 agr_{\mathrm{it}} + \delta_2 TL_{it} + jD_{it} + \tau_i + \mu_t + \varepsilon_{it} \tag{3}$$

Where TL_{it} serves as the mediator variable, indicating the extent of upgrading in the agricultural industrial structure, i denotes the province, t represents the year, and all other variables remain consistent with those presented in model (1).

Moderating Effect Model

To validate hypothesis 3, based on model (1), the interaction terms of agricultural new quality productivity (*agr*) and industrial diversity (*DIV*) are added to build a moderating effect model, which is as follows:

$$ACEE_{it} = \theta_0 + \theta_1 agr_{\mathrm{it}} + \theta_2 DIV_{it} + \theta_3 DIV_{it} \times agr_{\mathrm{it}} + jD_{it} + \tau_i + \mu_t + \varepsilon_{it} \tag{4}$$

Among these variables, DIV_{it} serves as the moderator variable, representing the level of industrial diversity, i denotes the province, and t represents the year, while all other variables remain consistent with those in model (1).

Empirical Result Analysis

Descriptive Statistics

The descriptive statistical analysis of each variable is presented in Table 1. The mean value of agricultural carbon emission efficiency is 1.9000, the variance is 0.5410, the maximum value is 3.6048, and the minimum value is 0.0880. The substantial gap between the maximum and minimum values indicates that the overall development level of agricultural carbon emission efficiency in China remains low at this stage, highlighting a significant imbalance in agricultural carbon emission efficiency across different provinces. The mean value of agricultural new quality productivity is 0.8021, the variance is 0.4537, the maximum value is 0.841, and the minimum value is 0.042. This data suggests that there exists considerable disparity in agricultural new quality productivity among various provinces within China.

Baseline Regression Test

First, an F-test was conducted, yielding a P value of less than 0.001. Consequently, the null hypothesis was rejected, indicating that the mixed effects model is not applicable. Subsequently, a Hausman test was performed on the model, which revealed a P value of less than 0.001; thus, at a 1% significance level, the null hypothesis was also rejected, and the random effects model was deemed inappropriate. Therefore, the fixed effects model was selected for analysis. The regression results incorporating control variables into the model are presented in Table 2.

The regression results showed that when employing the fixed effect model to account for both time and individual effects and subsequently incorporating control variables, the regression coefficients of the core explanatory variable, agricultural new quality productivity (*agr*), were all positive and significant. This finding indicates that agricultural new quality productivity exerts a substantial positive influence on agricultural carbon emission efficiency. Specifically, as control variables were added incrementally, the regression coefficients for agricultural new quality productivity were recorded at 0.307, 0.391, 0.394,

Table 1. Descriptive statistical results of variables.

Variables	Mean	P50	SD	Min	Max
ACEE	1.9000	1.8599	0.5410	0.0880	3.6048
Agr	0.8021	0.6958	0.4537	0.0462	2.4961
TL	0.9841	0.9452	0.6417	0.1475	2.3742
DEI	0.4714	0.4517	0.2479	0.0027	0.9745
DIV	2.3589	2.2146	2.5417	2.1476	2.8947
CALE	0.3249	0.1473	0.0054	-0.0014	0.8472
rjgdp	5.8231	5.0242	2.9173	1.8947	18.7526
cxcj	0.0845	0.0800	0.0373	0.0180	0.1970
gyhsp	0.3163	0.3192	0.0794	0.1008	0.5526
dwkf	0.2590	0.1412	0.2773	0.0076	1.4409
nyzc	0.1149	0.1152	0.0336	0.0411	0.2038
lnrkmd	5.4741	5.6798	1.2913	2.0675	8.2753

Table 2. Baseline regression test results.

Variables	*ACEE*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
agr	0.307^{***} (4.33)	0.391^{***} (4.58)	0.394^{***} (4.72)	0.375^{***} (4.52)	0.380^{***} (4.60)	0.334^{***} (3.97)	0.276^{***} (3.33)
Rjgdp	-	-0.0286 (-1.75)	0.000832 (0.05)	-0.00126 (-0.07)	0.0148 (0.76)	0.0107 (0.55)	-0.0016 (-0.08)
cxcj	-	-	-6.311^{***} (-3.63)	-6.118^{***} (-3.54)	-5.510^{**} (-3.16)	-6.040^{***} (-3.47)	-3.039 (-1.65)
gyhsp	-	-	-	-0.674^{*} (-2.37)	-0.731^{*} (-2.57)	-0.704^{*} (-2.50)	-0.573^{*} (-2.09)
dwkf	-	-	-	-	0.241 (1.24)	0.257 (1.65)	0.381^{*} (2.47)
nyzc	-	-	-	-	-	-1.908^{*} (-2.46)	-1.239 (-1.61)
lnrkmd	-	-	-	-	-	-	1.559^{***} (4.10)
_cons	0.773^{***} (8.63)	1.016^{***} (6.15)	0.988^{***} (6.11)	1.149^{***} (6.60)	0.628^{*} (2.00)	0.927^{**} (2.78)	-10.39^{***} (-3.74)
N	300	300	300	300	300	300	300
STOCK/YEAR	YES	YES	YES	YES	YES	YES	YES
Adj-R^2	0.934	0.935	0.938	0.939	0.939	0.941	0.944

Note: ***, **, and * are significant at 1%, 5%, and 10% significance levels, respectively; the t statistic value in parentheses is the same below.

0.375, 0.380, 0.334, and 0.276, respectively; all values passed the significance level test at the 1% threshold. Furthermore, the adjusted R-squared value increased from 0.934 to 0.944, suggesting an enhancement in the model's explanatory power over successive iterations of adding control variables. Consequently, hypothesis H1 is fully supported by these findings.

Robustness Test

Sample Data of Municipalities Excluded

Regarding Gargiulo [38], a robustness test was conducted by eliminating the sample data of municipalities directly under the Central Government. Specifically, based on the original samples, the four municipalities under direct central government jurisdiction – Beijing, Shanghai, Tianjin, and Chongqing – were omitted from the analysis, and regression was performed anew. The results presented in column (2) of Table 3 indicate that after removing the sample data of these four municipalities, agricultural new quality productivity exerts a positive influence on agricultural carbon emission efficiency. This effect is statistically significant at the 10% level, which aligns with the findings of the baseline regression.

Data Indentation Processing

Regarding the methodology employed by Du and Gupta [39] to mitigate the influence of extreme values arising from significant disparities in agricultural new quality productivity across different regions, a robustness test was conducted utilizing data tailing processing. In this study, the primary explanatory variables were subjected to indentation treatment at the 1% and 99% levels, followed by re-execution of the regression analysis. The results presented in column (2) of Table 3 indicate that following tail reduction treatment, agricultural new quality productivity continues to exert a positive effect on agricultural carbon emission efficiency, with significance maintained at the 1% level. This suggests that the estimation results derived from the initial baseline regression model possess a considerable degree of robustness.

Table 3. Robustness test results.

Variables	*ACEE*	*ACEE*	*ACEE*
	(1)	(2)	(3)
agr	0.236* (2.45)	0.228*** (3.19)	0.245*** (3.87)
rjgdp	0.0434 (1.59)	-0.00527 (-0.31)	-0.00641 (-0.05)
cxcj	-0.918 (-0.44)	-1.631 (-1.02)	-1.846* (-2.24)
gyhsp	-0.542 (-1.81)	-0.942*** (-3.96)	-0.843* (-3.54)
dwkf	0.205 (0.87)	0.429** (3.08)	0.457* (2.49)
nyzc	-0.550 (-0.66)	-2.147** (-3.21)	-3.141 (-4.28)
lnrkmd	1.268*** (3.12)	1.409*** (4.32)	1.539*** (4.89)
_cons	-5.777*** (-2.29)	-9.180*** (-3.85)	-10.170*** (-4.37)
N	260	300	300
Controls	YES	YES	YES
STOCK/ YEAR	YES	YES	YES
Adj-R^2	0.943	0.957	0.958

Change the Measure Mode of the Explanatory Variable

Referring to Freedman et al. [40], this study aims to mitigate the correlation among indicators and reduce the influence of correlated indicators on the measurement results of indicator weights. To achieve this, agricultural new quality productivity is re-evaluated using the CRITIC method, followed by a regression analysis of the results. The results presented in column (3) of Table 3 indicate that agricultural new quality productivity continues to exert a positive impact on agricultural carbon emission efficiency, with significance at the 1% level. This reinforces the enabling effect of agricultural new quality productivity on agricultural carbon emission efficiency, thereby confirming that the previous baseline regression outcomes are robust once again.

Placebo Test

Although the provincial fixed effect was incorporated into the baseline regression to account for its influence, there may still be other random factors affecting the relationship between agricultural new quality productivity and agricultural carbon emission efficiency, potentially leading to estimation bias. If the mean coefficient after random treatment is significantly positive, it indicates that there are other random factors affecting agricultural carbon emission efficiency; conversely, if the mean coefficient after treatment approaches 0 and is not significant, it indicates that these other random factors do not have a substantial impact on agricultural carbon emission efficiency. The results indicate that the coefficients approximately follow a normal distribution. The mean coefficient following random treatment is 0.217 and is not statistically significant, which is closer to 0 than the baseline result. This implies that other random factors do not exert a significant influence on the estimation outcomes, thereby further validating the robustness of the baseline regression results.

Endogeneity Test

The agricultural new quality productivity and agricultural carbon emission efficiency discussed in this paper are derived from a comprehensive index system calculated through PCA. Although controlling for various random factors that influence agricultural carbon emission efficiency, the endogenous issues arising from other potential variables cannot be entirely eliminated. Specifically, there exists a strong correlation between the lagged period of agricultural new quality productivity and its current state, because the development status of agricultural new quality productivity in the early stage, such as the agricultural science and technology innovation resources invested in the early stage and the degree of agricultural digitalization transformation, will directly affect the subsequent development. The better the foundation in the early stage, the more advantageous the current development is, which can effectively reflect the current agricultural quality productivity level. Regarding exogenous factors, it is important to note that the lagged effect of agricultural new quality productivity does not exert a direct influence on current-period agricultural carbon emission efficiency. Instead, it primarily affects this efficiency indirectly by influencing contemporary levels of agricultural new quality productivity while remaining uncorrelated with other random factors that may interfere with current-period carbon emission efficiency. This approach effectively mitigates endogenous problems and ensures the accuracy of research findings. Similarly, Han et al. [41] also employed an instrumental variable approach to address endogeneity in studying the impact of new quality productivity on manufacturing carbon emissions, which further supports the methodological robustness of this study. The utilization of lagged one-period agricultural new quality productivity as an instrumental variable effectively captures the dynamic evolution of agricultural new quality productivity while satisfying the prerequisite for a strong correlation between the instrumental variable and endogenous variables.

Specifically, from a correlational perspective, the technology diffusion and policy effects associated with agricultural new quality productivity are typically characterized by significant time-series dependence. Agricultural technological innovation, the application of mechanization, and the promotion of green production models often necessitate extended adaptation cycles; consequently, their effects may not be fully evident in the current period. Instead, the productivity levels observed during lagging periods more accurately reflect the combined effects of technological accumulation and production inertia. Research has demonstrated that factors such as technological lock-in effects and capital investment stickiness within agricultural production systems contribute to path dependence in productivity enhancement, resulting in statistically significant correlations between lagged variables and current variables. Moreover, agricultural production cycles are generally inter-annual, such as crop rotation systems and soil fertility restoration, all of which rely on inter-annual decision-making. Similarly, Xu and Xu (2022), in their analysis of the coupled and coordinated relationship between ecological protection and high-quality development in Shandong Province, also employed lagged variables to control for inertial effects in regional development. By verifying the stability of the causal chain between long-term policies and economic behaviors, they provided cross-disciplinary empirical support for the validity of using lagged terms as instrumental variables[42].

This further reinforces the causal chain between lagged variables and current new-quality productivity. Consequently, instrumental variables lagged by one period can effectively capture the dynamic evolution of agricultural new quality productivity and fulfill the prerequisite of strong correlation between instrumental variables and endogenous variables.

As far as exogeneity is concerned, the instrumental variables lagged by one period must be strictly independent of the stochastic disturbance term associated with agricultural carbon emission efficiency in the current period. The lagged value of agricultural new quality productivity precedes the carbon emission generation of the current period in a temporal context. This relationship is theoretically insulated from the reverse influence of unobservable factors in the current period (such as sudden climate anomalies or short-term market fluctuations), thereby mitigating endogeneity bias that may arise from bidirectional causation. However, caution is warranted regarding potential confounding time trends, such as sustained long-term regional environmental policies or infrastructure development that may simultaneously drive improvements in productivity and changes in carbon efficiency. Consequently, this study necessitates the incorporation of time-fixed effects or control for covariates like regional development levels within its model to obstruct pathways through which instrumental variables might influence carbon emissions via omitted channels. Moreover, the inertial characteristics of the agricultural production system – such as human capital accumulation and the stock of machinery and equipment 0 are typically fully reflected in the productivity of the preceding period. Their subsequent effects are primarily realized through their influence on current-period productivity rather than exerting a direct impact on carbon emission efficiency. This observation aligns with the exclusivity constraint associated with instrumental variables. The robustness of the exogeneity argument can be enhanced if over-identification tests further verify the stability of the instrumental variables in the subsample.

In the over-recognition test, the SW-F test rejected the null hypothesis concerning the weak instrument variable problem, indicating that the instrument variable is valid. The Anderson LM statistic was 239.74, and it also rejected the null hypothesis of under-recognition at the 1% significance level. 2SLS estimates are shown in Table 4. The F-statistic from the first-stage regression significantly exceeds 10, and individual missing values were addressed using an annual average growth method while controlling for all relevant control variables and fixed effects. The Sargan statistic is 0, which does not reject the null hypothesis, indicating that the instrumental variable is exogenous. The results from the second-stage regression indicate that the coefficient of agricultural new quality productivity is 1.3121, and the significance, positive and negative, of the coefficient is consistent with the baseline regression results. This indicates that hypothesis 1 remains supported even after accounting for endogeneity.

Table 4. 2SLS regression results.

Variables	First	Second
	agr	ACEE
Instrumental variable	0.9893*** (45.56)	-
agr	-	1.3121*** (16.24)
rjgdp	0.0115*** (3.17)	-0.0421*** (-3.04)
cxcj	-0.1890 (-0.84)	2.0116** (2.44)
gyhsp	0.1865** (2.37)	-0.2732 (-0.93)
dwkf	0.0049 (0.14)	-1.0876*** (-8.35)
nyzc	0.4363	1.4211
	(1.46)	(1.29)
lnrkmd	0.0050	0.0900***
	(0.71)	(3.44)
_cons	-0.1107	0.6589**
	(-1.38)	(2.23)
N	270	270
Adj-R^2	-	0.632

Table 5. Mediating effect test and moderating effect test regression results.

Variables	*TL*	*ACEE*	*ACEE*
	(1)	(2)	(3)
agr	1.425*** (3.47)	1.798*** (5.52)	2.774*** (5.67)
TL	-	1.561** (3.85)	-
DIV	-	-	1.247** (2.96)
DIV×agr	-	-	0.894*** (1.89)
_cons	2.190** (6.41)	3.961*** (8.49)	3.897** (4.73)
N	300	300	300
Controls	YES	YES	YES
STOCK/ YEAR	YES	YES	YES
Adj-R^2	0.876	0.944	0.925

Analysis of Mechanism: Mediating Effect and Moderating Effect

Testing the Mediating Effect of the Upgrading of Agricultural Industrial Structure

The mediating effect test results are shown in columns (1) and (2) of Table 5. In column (1), the regression coefficient for agricultural new quality productivity concerning the degree of agricultural industrial structure upgrading is significantly positive at the 1% level. This finding indicates that agricultural new quality productivity facilitates the upgrading of the agricultural industrial structure. In column (2) of Table 5, the regression coefficient of agricultural industrial structure upgrading on agricultural carbon emission efficiency is significantly positive at the 1% level. These results confirm the presence of a mediating effect exerted by agricultural industrial structure upgrading. Specifically, it suggests that improvements in agriculture's new quality productivity can enhance its carbon emission efficiency by accelerating upgrades to its industrial structure. Thus, Hypothesis 2 is supported.

To confirm the robustness of the mediating effect test results presented above, a bootstrap test with multiple uniform sampling was employed to verify the mediating role of agricultural industrial structure upgrading on the relationship between agricultural new quality productivity and agricultural carbon emission efficiency. The results are shown in Table 6. The results showed that the direct effect and indirect effect coefficients were significant, and the confidence intervals did not contain zero, but the sign of the regression coefficient of the direct effect was different from that of the indirect effect, indicating that there was a masking effect among variables; that is, although the indirect effect was positive, the negative direct effect masked the positive indirect effect, so it was partial mediation. Furthermore, these findings reinforce that there exists a partial mediating effect of agricultural industrial structure upgrading on how agricultural new quality productivity impacts agricultural carbon emission efficiency. This underscores the robustness of our previous analysis regarding mediating effects.

Further analysis using the Sobel test to examine the mediating effect of industrial structure upgrading is shown in Table 7. The findings from this test align with those obtained through the bootstrap method, thereby providing additional evidence that industrial structure upgrading serves a partially mediating role between the new quality productivity of agriculture and the efficiency of agricultural carbon emissions.

Testing the Moderating Effect of Industrial Diversity

The results of the moderating effect are shown in column (3) of Table 5. The coefficients of the interaction terms between agricultural new quality productivity and industrial diversity are both significantly positive. This finding indicates that industrial diversity exerts a positive moderating effect on the relationship between agricultural new quality

Table 6. Bootstrap test results of industrial structure upgrading.

Efficiency phase	Coefficient	P>|Z|	95% confidence interval	
			Lower limit	Upper limit
Direct effect	2.1486	0.000	0.8547	4.2916
Indirect effect	2.2596	0.000	0.7962	4.5327

Table 7. Sobel test for industrial structure upgrading.

Est	Std_err	Z	P>|Z|
0.005	0.001	2.2498	0.000

productivity and agricultural carbon emission efficiency. Thus, Hypothesis 3 is supported.

Heterogeneity Test

Heterogeneity Test for Geographical Differences

The development levels of agricultural new quality productivity and agricultural carbon emission efficiency may exhibit heterogeneity due to varying regional endowments. This paper explores the relationship between agricultural new quality productivity and agricultural carbon emission efficiency in relation to geographical location.

From the perspective of geographical location, China's economic geography divides its 30 provinces into three regions: eastern, central, and western. The regression results are shown in columns (1), (2), and (3) of Table 8. The findings indicate that a significant linear relationship exists only between agricultural new quality productivity and agricultural carbon emission efficiency in the eastern region. In contrast, the relationship in the central region is characterized by a significant negative linear correlation. Meanwhile, although there is a linear relationship in the western region, it lacks statistical significance. The underlying reasons for these observations may be attributed to several factors: The eastern region benefits from advanced economic development and high levels of scientific and technological innovation. As agricultural productivity improves, rapid advancements in agriculture can occur; continuous application of new technologies and management practices enhances agricultural carbon emission efficiency. Conversely, the central region is currently experiencing an economic rise where developments in agricultural new productivity exert a notable inhibitory effect on carbon emission efficiency. Furthermore, the western region lags economically; thus, the impact of agricultural new quality productivity on carbon emission efficiency remains relatively minimal.

Heterogeneity Test for Market Maturity

Market maturity is a crucial factor influencing the decision-making, production, and lifestyle of market participants. To investigate the differential impact of market maturity on the role of digital financial development in the domestic macro-circulation, this paper utilizes the total marketization index in the China Marketization Index Report compiled by Wang Xiaolu et al. as an indicator of market maturity; a higher index value indicates greater market maturity. Using the median of the marketization index of all provinces in the same year as the dividing line, the sample is divided into regions with higher market maturity and lower market maturity for group regression, and the results are shown in columns (4) and (5) of Table 8. The results show that the estimated coefficients for core explanatory variables are significantly positive in regions characterized by higher market maturity, whereas they lack significance in areas with lower market maturity. This discrepancy may stem from how rural new quality productivity differentially impacts agricultural carbon emission efficiency, which is closely linked to both institutional environments and technology diffusion capacities shaped by regional market maturity.

In provinces with high market maturity, barriers to factor mobility are diminished, allowing price signals to more effectively guide resource allocation. This facilitates the efficient market integration of low-carbon technologies, digital agricultural equipment, and innovative green management models that contribute to enhanced quality productivity. Agricultural operators in these areas demonstrate a heightened responsiveness to technology premiums and environmental regulations. The widespread implementation of carbon emission reduction technologies within the agricultural supply chain can distribute fixed costs through market trading mechanisms, thereby generating a positive feedback loop. Simultaneously, financial instruments and innovative service systems prevalent in mature markets can significantly mitigate financing constraints associated with technology adoption. These mechanisms enable the conversion of improvements in carbon emission efficiency into economic benefits through strategies such as carbon asset pricing and green credit initiatives. Consequently, this strengthens the interconnection between new quality productivity and carbon efficiency.

On the contrary, in provinces with lower market maturity, segmentation of factor markets and institutional transaction costs diminish the technology spillover effect associated with new quality productivity. The absence of effective market incentives complicates the alignment of private and social benefits derived

Table 8. Heterogeneity test.

Variable	Eastern region (1)	Central region (2)	Western region (3)	High market maturity (4)	Low market maturity (5)
agr	0.1073*** (3.43)	-0.1992*** (-3.20)	0.2686 (0.88)	0.2479** (2.54)	0.2153 (0.72)
_cons	3.35 (0.84)	-6.27*** (-2.84)	-1.405 (-0.46)	1.8547* (2.19)	2.7465 (0.53)
N	120	90	90	150	150
Controls	YES	YES	YES	YES	YES
STOCK/YEAR	YES	YES	YES	YES	YES
Adj-R^2	0.967	0.943	0.936	0.856	0.583

from low-carbon technologies, leading agricultural operators to favor traditional high-carbon production models. Particularly during the process of technology diffusion, information asymmetry and a lack of supporting services significantly elevate the barriers to adopting new quality productivity. Furthermore, poorly defined property rights deter long-term investments in environmentally friendly technologies. Additionally, dual constraints stemming from inadequate infrastructure and a shortage of human capital hinder the potential for carbon reduction through new productivity methods, even when policy interventions are implemented. This interplay between the institutional environment and techno-economic characteristics ultimately results in pronounced regional heterogeneity regarding the impact of new productivity on agricultural carbon emission efficiency.

Conclusion

This paper utilizes panel data from 30 provincial administrative regions, excluding Hong Kong, Macao, Taiwan, and Tibet, covering the period from 2012 to 2021. It empirically investigates the impact of new agricultural quality productivity on agricultural carbon emission efficiency and draws the following conclusions:

First, agricultural new productivity can significantly promote the efficiency of carbon emissions in agriculture. This finding remains robust even after conducting a series of robustness and endogeneity tests. Consequently, both the government and society must enhance agricultural productivity through innovation. This can be achieved by increasing investments in agricultural science and technology research and development, as well as encouraging scientific research institutions and enterprises to engage in cutting-edge agricultural science and technology initiatives. Simultaneously, efforts must be made to actively facilitate the transformation and dissemination of scientific and technological achievements. Establishing and improving an agricultural science and technology service system is essential to ensure that advanced agricultural technologies are effectively implemented in practice, enabling farmers to master and apply these innovations. In addition, constructing adequate agricultural infrastructure serves as a crucial foundation for enhancing the level of new quality productivity in agriculture. Therefore, it is necessary to improve farmland water conservancy facilities to guarantee that farmlands receive sufficient and timely irrigation, thereby enhancing the utilization efficiency of green resources.

Second, the upgrading of the agricultural industrial structure serves as a partial mediator between the new quality productivity of agriculture and its carbon emission efficiency. Therefore, to expedite this upgrading process, it is essential for both government and society to ground their efforts in a precise understanding of market demand. Utilizing advanced technologies such as big data and artificial intelligence, real-time collection, processing, and analysis of market information can be conducted to discern consumer preferences and trends regarding the variety, quality, and safety of agricultural products. Based on these insights, stakeholders should guide farmers and agricultural enterprises in rationally adjusting their production structures to yield marketable agricultural products. This approach aims to mitigate imbalances between supply and demand while preventing resource wastage that may arise from uncoordinated production practices.

Thirdly, industrial diversification plays a significant positive moderating role in the relationship between agricultural new quality productivity and agricultural carbon emission efficiency. Therefore, enhancing the integrated development of agriculture with other industries represents an effective strategy to accelerate the diversification of the agricultural sector. By promoting a deeper integration of agriculture with the processing industry, advancing the deep processing of agricultural products, and transforming primary agricultural goods into diversified processed foods, beverages, cosmetics, and other products, it is possible to enhance both the added value and market competitiveness of these agricultural outputs. Furthermore, it is essential for both government and society to facilitate the integration of agriculture with the service industry by establishing a comprehensive agricultural production service system that encompasses areas such as agricultural logistics, financial services for agriculture, and technological support in agriculture. This approach will provide holistic support for enhancing agricultural production efficiency.

Fourth, the impact of new agricultural quality productivity on carbon emissions in agriculture is more pronounced in the eastern region and provinces with high market maturity. Given the varying characteristics of how new productivity affects the efficiency of agricultural carbon emissions across different regions, policy design should be tailored to reflect the gradient of market development and incorporate a dynamic control mechanism. In eastern areas and regions with higher market maturity, it is essential to deepen reforms aimed at factor marketization. This can be achieved through mechanisms such as carbon emissions trading and innovations in green financial products, which would transform improvements in carbon efficiency resulting from new productivity into quantifiable asset returns. Additionally, employing a market bidding mechanism can guide agricultural management entities to cultivate endogenous motivation for technological iteration. Simultaneously, establishing a cross-regional technology diffusion network is crucial. A digital infrastructure-based platform for sharing low-carbon agricultural technologies should be constructed to facilitate the transmission of technology spillover effects from mature markets to central and western regions. For areas where market development lags, priority must be given to optimizing the institutional environment by addressing barriers that hinder factor flow through reductions in systemic transaction costs. Efforts should focus on enhancing the technology absorption capacity among new agricultural management entities while forming mechanisms that link technology subsidies with performance outcomes related to carbon emission reductions – leveraging financial expertise where necessary. Furthermore, supporting the establishment of regional green technology service centers will help mitigate issues stemming from information asymmetry.

Discussion

This study elucidates the roles of new agricultural productivity, industrial structure upgrading, industrial diversification, and carbon emission efficiency. The findings underscore the significant academic value and practical implications in both theoretical advancement and application-oriented contexts.

Firstly, the conclusion that new agricultural productivity significantly enhances carbon emission efficiency through technological integration and factor reorganization underscores the pivotal role of green technological innovation in promoting sustainable development of agriculture. The significance of this finding lies in its ability to transcend the limitations inherent in traditional productivity studies, which often prioritize economic output alone. By incorporating eco-efficiency into the analytical framework of production functions, this research provides a novel quantitative index for assessing the high-quality development of agriculture.

Secondly, the discovery of industrial structure upgrading as a partial mediator variable reveals the dynamic transmission path of agricultural green transformation. The findings indicate that industrial structure upgrading can account for the accelerated improvement in carbon emission efficiency associated with new quality productivity by facilitating the agglomeration of production factors within low-carbon sectors. This underscores the critical role of industrial policy in fostering a green transition; however, it also highlights the challenges inherent in fully realizing technological dividends through reliance on industrial restructuring alone. This suggests that synergies with other institutional innovations are essential. This insight carries significant implications for understanding the synergistic approach to enhancing production while mitigating pollution within Chinese agriculture, particularly amid ongoing agricultural industrialization processes that necessitate establishing a dynamic equilibrium model between carbon emission efficiency and industrial scale.

Finally, the moderating effect of industrial diversification on the relationship between these two factors underscores the applicability of system resilience theory within the realm of agricultural carbon emissions. This finding indicates that diversification not only mitigates environmental risks but also fosters synergistic effects through optimizing resource allocation and facilitating the diffusion of technological innovation. Particularly in the context of climate change, this insight provides a solid foundation for industrial integration policies within rural revitalization strategies, highlighting that the spillover benefits of green technologies can be significantly enhanced by cultivating a "production-processing-ecology" trinity in composite agricultural systems.

Overall, these three mechanisms have established a three-dimensional analytical framework of "technology-driven-structural optimization-system adaptation." The theoretical contribution of this framework lies in its ability to transcend the limitations of traditional linear causality and elucidate the complex processes involved in enhancing the efficiency of agricultural carbon emissions. In practical terms, the findings of this study provide a quantitative foundation for formulating differentiated policies aimed at promoting agricultural green transformation. At the level of technological application, it is essential to prioritize breakthroughs in core emission reduction technologies. At the industrial policy level, there is a need to enhance the synergy mechanism for carbon emission reductions across the entire industrial chain. Furthermore, at the regional development level, it is crucial to dynamically adjust the combination of policy tools based on varying levels of industrial diversity. This systematic knowledge holds significant decision-making support value for achieving carbon peaking goals within China's agriculture and rural sectors.

Research Prospects

The mechanism through which agricultural new-quality productivity influences agricultural carbon emission efficiency may exhibit a spatial spillover effect, warranting further exploration in future research. Additionally, the current study focuses exclusively on agriculture, potentially overlooking variations across different industry types. Subsequent investigations could also encompass other sectors, such as manufacturing and finance, to discern both the differences and similarities in how new-quality productivity affects carbon emission efficiency across various industries.

Acknowledgments

There are no acknowledgments for this paper.

Conflict of Interest

The authors declare no conflict of interest.

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