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Study on the Impact of the Digital Economy on Green Total Factor Productivity in Agriculture

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Abstract

This study employs panel data from 30 Chinese provinces spanning 2011–2022, utilizing the SBM model and GML index to measure agricultural green total factor productivity. It empirically examines the impact mechanism of the digital economy on agricultural green TFP, while also investigating the mediating role of rural revitalization and regional heterogeneity. Findings reveal: First, the digital economy significantly enhances agricultural green TFP, with this conclusion remaining robust after a series of stability tests. Second, mechanism analysis indicates that rural revitalization plays a significant mediating role between the digital economy and agricultural green TFP. Third, heterogeneity analysis reveals pronounced regional variations in the digital economy's promotional effect. It exerts a significant positive impact on green agricultural TFP in western regions, whereas its influence on eastern regions fails to pass significance tests. This reflects that the enabling effects of the digital economy are closely tied to regional development stages and resource endowments. This study provides empirical evidence for deepening understanding of the intrinsic mechanisms through which the digital economy drives green agricultural development and offers policy implications for promoting digital rural construction and high-quality agricultural development tailored to local conditions.

Keywords: digital economy, rural revitalization, green total factor productivity in agriculture

1. Introduction

Agriculture serves as the foundational industry of the national economy, with its development quality directly impacting national food security and sustainable socioeconomic progress. In recent years, China has achieved remarkable agricultural development, yet challenges such as excessive resource consumption, intensified environmental pollution, and ecosystem degradation have become increasingly prominent. Traditional extensive development models are no longer compatible with the intrinsic requirements of high-quality development. Against this backdrop, enhancing the green total factor productivity (GTFP) of agriculture has become a key pathway for promoting agricultural transformation and upgrading. It not only improves resource utilization efficiency but also serves as the core for achieving coordinated development between agricultural production and the ecological environment. As emphasized in the "14th Five-Year Plan for Advancing Modernization in Agriculture and Rural Areas," it is imperative to "promote green agricultural development and strengthen resource conservation and environmental protection"[1] .

In response to this policy direction, the digital economy—a new economic form centered on data as its core element and modern information networks as its primary vehicle—is increasingly becoming a vital force driving agricultural modernization and green development[2] . Digital technologies offer novel solutions to overcome resource and environmental constraints in agricultural development by optimizing production processes and enhancing resource allocation efficiency. In recent years, scholarly research on green total factor productivity (TFP) in agriculture has grown significantly, exploring various influencing factors and their mechanisms. From a technological perspective, informatization is recognized as a key means to boost agricultural production efficiency, significantly improving TFP through optimized production processes and resource utilization[3] . The indirect constraints of rural population aging on agricultural productivity have also drawn significant attention, as shifts in the labor supply structure may become a bottleneck for enhancing agricultural TFP[4] . Additionally, environmental regulations and fiscal agricultural support policies are recognized as crucial external factors influencing agricultural TFP[5][6] . Concurrently, infrastructure development provides substantial support for TFP growth by improving production conditions over the long term[7] .

In the realm of rural revitalization, scholars similarly emphasize the enabling role of the digital economy. They contend that it can promote the revitalization of rural industries, talent, and ecosystems by introducing data elements, driving intensive development, and advancing intelligent governance[8] . Alternatively, it can inject new momentum into rural revitalization by narrowing urban-rural income gaps and improving resource allocation[9][10] .

However, existing research still faces the following limitations: First, most studies focus on the direct effects of the digital economy without systematically revealing its underlying pathways of action; Second, although the digital economy and rural revitalization have been extensively discussed separately, the linkage mechanism between them and their synergistic impact on green agricultural development have not received sufficient attention. Crucially, existing literature has not adequately examined or answered whether rural revitalization, as a national strategy, plays a mediating role in the digital economy's influence on green agricultural total factor productivity.

Based on this, this paper attempts to construct a theoretical framework incorporating mediation effects, aiming to systematically elucidate the mechanism through which the digital economy influences agricultural green TFP via the integrated pathway of rural revitalization. Utilizing provincial-level panel data from China spanning 2011 to 2022, this study empirically tests the direct effects of the digital economy. It further reveals the mediating transmission mechanism of rural revitalization and meticulously examines its regional heterogeneity. This research not only deepens our understanding of the relationship among the digital economy, rural revitalization, and green agricultural development but also provides theoretical foundations and policy insights for promoting the deep integration of agricultural digital transformation and rural revitalization strategies tailored to local conditions

2. 2. Theoretical Analysis and Research Hypotheses

2.1 The Relationship Between the Digital Economy and Agricultural Green Total Factor Productivity

Agricultural green total factor productivity (GTFP) typically comprises technological progress and technical efficiency. Regarding technological progress, the digital economy effectively enhances agricultural green productivity by introducing innovative technologies and improving traditional production methods. For instance, the widespread application of digital technologies such as big data, artificial intelligence, and the Internet of Things in agriculture can unlock data value to advance green production models like precision agriculture and smart farming, significantly optimizing resource utilization efficiency. Simultaneously, the digital economy accelerates the dissemination of new technologies and sharing of advanced practices through information networks, drastically shortening technology diffusion cycles. This transforms the traditional "weather-dependent" production model, enabling rapid adoption of green agricultural technologies. Furthermore, digital inclusive finance alleviates financing difficulties caused by geographical constraints and information asymmetry in traditional financial services through online and digital means. This further promotes the adoption of green technologies by small and micro agricultural entities, providing financial support for enhancing the green total factor productivity of agriculture[11][12] .

In terms of technological efficiency, the digital economy comprehensively enhances the utilization efficiency of agricultural factors and green production efficiency by optimizing resource allocation, improving agricultural management, and promoting industrial chain collaboration. For instance, the application of agricultural IoT enables precise land resource management, significantly improving soil fertility utilization efficiency. Intelligent equipment can optimize water and fertilizer application based on crop needs, reducing waste and environmental pollution while enhancing marginal productivity of resources. This dual effect of technological innovation and factor optimization not only markedly increases agricultural green TFP but also promotes the coordinated development of agricultural modernization and ecological conservation, providing crucial support for achieving high-quality agricultural development[13] .

Based on this analysis, this paper proposes Hypothesis 1:

H1: The digital economy can significantly promote the improvement of agricultural total factor productivity.

2.2 The Mediating Role of Rural Revitalization

As a key mediating mechanism through which the digital economy influences agricultural green total factor productivity (GTFP), rural revitalization exerts positive effects by optimizing resource allocation, promoting green technology diffusion, and reducing transaction costs. According to classical economic growth theory, improvements in agricultural total factor productivity depend not only on the optimal combination of factor inputs but also on efficiency gains driven by technological progress. Under the "green development" paradigm, enhancing GTFP further requires emphasizing the synergistic effects of resource conservation and environmental protection. The rapid development of the digital economy has injected new momentum into this process. Through means such as inclusive finance, e-commerce, and smart agriculture, it improves the efficiency of rural resource allocation, reduces information asymmetry and transaction costs, and significantly promotes the adoption of green agricultural technologies and enhances resource utilization efficiency[14][15] .

Moreover, rural revitalization provides systematic support for rural economic and agricultural green development through multidimensional pathways including industrial revitalization, talent revitalization, and ecological revitalization. Specifically: - Industrial revitalization drives deep integration and structural optimization between agriculture and secondary/tertiary industries, extending green agriculture's value chain; - Talent revitalization accelerates the adoption of green technologies in agricultural production by enhancing farmers' qualifications and skills; - Ecological revitalization boosts agriculture's ecological benefits and resource sustainability by promoting green agricultural practices and sustainable development. Based on this, the digital economy can not only directly enhance the green total factor productivity of agriculture but also exert an indirect influence through the intermediary variable of rural revitalization. The synergistic promotion of both ultimately achieves high-quality agricultural development and comprehensive rural revitalization[16] .

This indicates that elevating the level of rural revitalization represents a crucial pathway for the digital economy to empower agricultural modernization and green transformation, as well as a key driver for promoting sustainable rural economic development.

Based on this analysis, this paper proposes Hypothesis 2:

H2: The digital economy indirectly enhances agricultural total factor productivity through the mediating variable of rural revitalization.

3. Results

3.1 Benchmark Model Construction

This paper constructs the following econometric model to assess the impact of the digital economy on green agricultural total factor productivity:

$$GTFP_{it} = \beta_0 + \beta_1 DE_{it} + \sum_{k=1}^{K} \beta_k X_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Where i and t denote region and year, respectively. $GTFP_{it}$ represents the dependent variable, agricultural green TFP. DE_{it} is the core explanatory variable, the digital economy. X_{kit} serves as the control variable. β_0 is the constant term. μ_i is the region fixed effect, capturing the specific impact of individual regions (i). λ_t is the time fixed effect, reflecting the influence of time (t) on agricultural green TFP. ε_{it} constitutes the error term.

3.2 Mediation Effect Model

Based on equation (1), the key to the mediation effect analysis is to examine the mediating role of rural revitalization (RR) between the digital economy (DE2) and agricultural green total factor productivity (GTFP).

$$RR_{it} = \alpha_0 + \beta_1 DE_{it} + \sum_{k=1}^{K} \beta_k X_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

$$GTFP_{it} = \alpha_0 + \beta_2 DE_{it} + \beta_3 RR_{it} + \sum_{k=1}^{K} \beta_k X_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

Where RR_{it} represents the level of rural revitalization as the mediating variable. DE_{it} denotes the level of the digital economy as the independent variable. X_{kit} signifies control variables (e.g., labor force level, human capital, social consumption level). μ_i indicates the regional fixed effect to control for the influence of regional characteristics on rural revitalization. λ_t represents the time fixed effect to control for common effects across years. ε_{it} denotes the error term.

3.3 Construction of Key Indicators

3.3.1 Dependent Variable

Table 1. Input-Output Indicators for Agricultural Green Total Factor Productivity

Indicator Type	Name	Meaning	Unit
Input indicators	Agricultural Labor Input	Primary industry employees	Ten thousand people
	Agricultural Land Input	Cropping area and aquaculture area	Thousand hectares

	Agricultural Fertilizer Input	Agricultural fertilizer (purely calculated) usage	Ten thousand tons
	Agricultural Machinery Input	Total power of agricultural machinery	Ten thousand kilowatts
	Agricultural Diesel Input	Agricultural diesel usage	Ten thousand tons
	Agricultural Plastic Film Input	Agricultural plastic film usage	Ten thousand tons
	Pesticide Input	Pesticide usage	Ten thousand people
	Agricultural Water Input	Primary industry employees	Thousand hectares
Output Indicators	Expected Output	Total output value of agriculture, forestry, animal husbandry, and fishery	Hundred million yuan
	Non-expected Output	Agricultural carbon emissions	Ten thousand tons

3.3.2 Core Explanatory Variables

Digital Economy (DE). Drawing on relevant research, this paper constructs a framework for measuring inter-provincial digital economic development levels in China using four primary indicators: digital infrastructure, digital industrialization, industrial digitalization, and digital innovation capacity. Entropy values are employed for scoring. Data sources include the Digital Finance Research Center at Peking University, annual editions of the China Industrial Statistical Yearbook and China Statistical Yearbook, and provincial statistical yearbooks. The specific indicator system is detailed in Table 2.

Table 2. Digital Economy Development Level Indicators

Indicator Type	Name	Meaning	Unit
Digital Infrastructure	Internet Penetration Rate	Number of Internet Broadband Access Ports	10,000
		Number of Broadband Internet Access Users	10,000
		Number of Internet domain names	10,000
	Mobile phone penetration rate	Mobile phone base station density	per square kilometer
		Mobile phone penetration rate	units per 100 people
	Information transmission coverage	Length of long-distance optical cables per unit area	Kilometers per square kilometer
Digital Industrialization	Software and Information Technology Services	Software Business Revenue as a Percentage of GDP	%
		Number of employees in information transmission, software, and information technology services	10,000 people
	Development level of electronic information manufacturing	Information technology services revenue as a percentage of GDP	%
		Telecommunications service volume as a percentage of GDP	Ten thousand people
		Telecommunications Service Volume per Capita	RMB/person
	Level of Development in the Postal and Telecommunications Industry	Per capita postal service volume	Yuan/person
		Express Delivery Volume	10,000 pieces
		Enterprise E-commerce Transaction Volume	billion yuan
Industrial Digitalization	Enterprise digitalization level	Percentage of enterprises engaged in e-commerce transactions	%
		Number of Computers Used per 100	persons

		Employees	
		Number of websites per 100 enterprises	sites
	Digital Inclusive Finance	Digital Inclusive Finance Index	/
Digital Innovation Capability	Research and Experimental Development Level	Full-time equivalent R&D personnel in industrial enterprises above designated size	Person-years
		R&D Expenditures of Industrial Enterprises Above Designated Size	Ten Thousand Yuan
		Number of R&D projects (topics) in industrial enterprises above designated size	Projects
	Technological Innovation Capability	Total value of technology contracts concluded	Ten thousand yuan
		Number of patent applications granted	item

3.3 Intermediate Variable

Rural Revitalization (RRL). The Rural Revitalization evaluation index system comprises four primary indicators: Thriving Industry, Ecological Livability, Rural Culture, and Effective Governance. Entropy values were assigned using the entropy method, with data primarily sourced from the China Statistical Yearbook, China Energy Statistical Yearbook, China Rural Statistical Yearbook, China Population and Employment Statistical Yearbook, China Urban and Rural Construction Statistical Yearbook, and provincial statistical yearbooks. The specific indicator system is shown in Table 3.

Table 3. Rural Revitalization Indicators

Indicator Type	Name	Meaning	Unit
Industrial Prosperity	Total Agricultural Machinery Power per Capita	Reflects agricultural mechanization level and agricultural production capacity	kW/person
	Comprehensive Grain Production Capacity	Measures regional grain production capacity and stability	tons
	Agricultural labor productivity	Ratio of agricultural output value to labor force size	Yuan/person
	Main business revenue of agricultural product processing enterprises above designated size	Reflects the level of industrialized operations	¥100 million
	Application volume of pesticides and chemical fertilizers	Measures agricultural green development	ton
Eco-friendly and Livable	Percentage of Administrative Villages with Domestic Sewage Treatment	Administrative village sewage treatment coverage rate	%
	Percentage of administrative villages with domestic waste treatment	Administrative village waste management coverage rate	%
	Sanitary toilet coverage rate	Improvement level of villagers' sanitation facilities	%
	Proportion of Nature Reserves in Jurisdictional Area	Reflecting ecological conservation level	%
Rural Civilization	Rural residents' expenditure on education, culture, and entertainment as a percentage of total expenditure	Rural cultural living standards	%
	Proportion of full-time teachers with bachelor's degrees in rural compulsory education schools	Educational Faculty Quality	%
	Average Years of Education Among Rural Residents	Reflecting the level of education accessibility	Year
	Comprehensive population coverage rate of television programs in rural areas	Information dissemination and cultural accessibility	%

	Number of Rural Cultural Stations	Level of Cultural Service Facility Development	Units
Effective governance	Percentage of Administrative Villages with Broadband Internet Access	Level of information infrastructure development	%
	Proportion of villages where the village chief and Party secretary positions are held by the same person	Grassroots governance capacity	%
	Proportion of administrative villages with development plans	Implementation status of village planning	%
	Percentage of administrative villages that have implemented village improvement initiatives	Level of village environmental improvement	%

3.4 Control Variables

Based on existing research, the following control variables were selected for this study. Labor force level (LL) is measured by taking the natural logarithm of the number of employed persons; human capital level (HCL) is calculated as the number of higher education students divided by the total population; social consumption level (SCL) is the total retail sales of consumer goods divided by the regional gross domestic product; fiscal support intensity (DGI) is the general fiscal budget expenditure divided by the regional gross domestic product; transportation infrastructure level (TIL) is the logarithm of the total road mileage and the logarithm of the total freight volume.

4. Data Sources and Statistical Descriptions

Given data availability, this study employs interprovincial panel data from 30 Chinese provinces, municipalities, and autonomous regions (excluding Tibet, Hong Kong, Macao, and Taiwan) for the period 2012–2022. All research data originate from the following sources for respective years: Peking University Digital Finance Research Center, annual editions of the China Industrial Statistical Yearbook and China Statistical Yearbook, and provincial statistical yearbooks.The specific indicator system is shown in Table 4.

Table 4. Descriptive Statistics

Variable Classification	Variable	Mean	Standard Deviation	Minimum	Median	Maximum
Dependent variable	Agricultural Total Factor Productivity (AGTFP)	1.512	0.540	0.649	1.357	4.581
Explanatory Variables	Digital Economy (DE)	0.185	0.165	0.034	0.131	0.669
Control Variables	Labor Force Level (L)	7.601	0.768	5.545	7.658	8.864
	Human Capital Level (H)	0.021	0.006	0.009	0.021	0.044
	Social Consumption Level (S)	0.389	0.059	0.180	0.394	0.504
	Fiscal Support Intensity (D)	0.260	0.111	0.105	0.232	0.758
	Transportation Infrastructure Level (T)	11.651	0.834	9.501	11.925	12.981

5. Empirical Findings and Analysis

5.1 Benchmark Regression Analysis

Table 5 Regression Table

	(1)	(2)
	z_agtfp	z_agtfp
z_de		0.383***

		(2.852)
z_l	-0.111	-0.164
	(-0.354)	(-0.530)
z_h	0.388***	0.386***
	(3.971)	(3.992)
z_s	-0.065	-0.081*
	(-1.454)	(-1.828)
z_d	-0.453***	-0.439***
	(-4.259)	(-4.171)
z_t	0.142	0.158
	(0.835)	(0.940)
_cons	-0.638***	-0.562***
	(-7.532)	(-6.384)
N	330	330
R^2	0.865	0.868
F	121.383	117.152

***p<0.01", "**p<0.05", "*p<0.10

Table 5 reports the benchmark regression results for the relationship between the digital economy and agricultural total factor productivity (AGTFP) based on the sample data after capping treatment. To avoid the interference of extreme values on the regression results, the main variables in this paper were capped at the 1% and 99% percentiles. Column (1) presents regression results excluding the digital economy variable, while Column (2) incorporates digital economy (DE) alongside control variables. Findings indicate that digital economy exerts a statistically significant positive impact on agricultural TFP at the 1% confidence level, with a coefficient of 0.397. This implies that a 1% increase in digital economy levels corresponds to an approximate 0.397 standard deviation increase in agricultural TFP. Among the control variables: - Labor level (L) is significantly negative, suggesting excessive labor input may reduce efficiency; - Human capital level (H) is significantly positive, indicating education and skill enhancement boost agricultural productivity; Social consumption level (S) is significantly negative at the 10% level, potentially reflecting the crowding-out effect of rural consumption expansion on agricultural production; fiscal support intensity (D) is significantly negative, indicating inefficient fiscal allocation; transportation infrastructure level (T) is positive but not significant, suggesting its limited role in enhancing agricultural productivity. Overall, the model's R^2 exceeds 0.84, indicating a high degree of fit.

5.2 Robustness Test

To validate the reliability of the benchmark regression results, this study conducted robustness tests from two dimensions: excluding special years and lagged explanatory variables. The results are shown in Table 6. Column (1) reports the estimation results after excluding samples from specific years. The coefficient of the core explanatory variable (DE) is 0.37 and remains significant at the 1% level, consistent with the benchmark regression conclusion. Column (2) employs a one-period lagged explanatory variable, yielding a coefficient of 0.547 that remains statistically significant at the 1% level, further supporting the robustness of the conclusion. The magnitudes and significance levels of the coefficients for the remaining control variables show no significant changes. The overall model fit ($R^2 = 0.873$) and F-statistic (117.378) indicate that the estimation results possess good explanatory power and validity. Furthermore, potential endogeneity issues were addressed through endogeneity tests (Column 3), and the conclusions remained valid. In summary, the benchmark regression results demonstrate robustness across different testing strategies.

Table 6. Robustness Tests

	(1) Excluding exceptional years z_agtfp	(2) One-period lag z_agtfp
z_de	0.370***	
	(2.623)	
l_z_de		0.547***
		(3.077)
z_l	-0.371	-0.241
	(-1.069)	(-0.563)

z_h	0.373***	0.397***
	(3.617)	(2.789)
z_s	-0.086*	-0.070
	(-1.852)	(-1.580)
z_d	-0.414***	-0.501***
	(-3.712)	(-2.889)
z_t	0.211	0.261
	(1.163)	(1.187)
_cons	-0.564***	0.054**
	(-6.184)	(2.399)
N	300	300
R2	0.873	0.884
F	117.378	5.228

***p<0.01", "**p<0.05", "*p<0.10

5.3 Endogeneity Test

To mitigate potential endogeneity issues in the model, this study employs propensity score matching (PSM) for estimation. By matching the treatment group with the control group, sample self-selection bias is effectively controlled. Post-matching balance tests passed, and the average treatment effect (ATT) was significant, indicating that the benchmark regression results remain robust after accounting for endogeneity concerns.

Table 7. Endogeneity Tests

	(1) OLS	(2) PSM
	z_agtfp	z_agtfp
z_de	0.383***	
	(0.131)	
Treatment Effect (ATT)		0.625***
		(0.116)
Control Variables	Yes	Yes
Individual Fixed Effects	Yes	No
Year Fixed Effects	Yes	Yes
N	300	300

***p<0.01", "**p<0.05", "*p<0.10

5.4Mediation Effect

Empirical results indicate that the digital economy not only directly promotes the improvement of agricultural total factor productivity but also generates indirect pull effects by advancing the implementation of the rural revitalization strategy. Column (1) in Table 7 shows that the digital economy (z_de) has a significant positive impact on agricultural total factor productivity (z_agtfp) (coefficient = 0.383, significant at the 1% level), providing a prerequisite for testing the mediating effect. Column (2) results indicate that the digital economy (z_de) also significantly promotes the mediating variable "rural revitalization level" (z_r) (coefficient = 0.603, significant at the 1% level).

These findings indicate that the level of rural revitalization serves as a crucial channel through which the digital economy influences agricultural total factor productivity. By improving rural infrastructure, optimizing factor allocation, and strengthening policy support, the digital economy provides the material foundation and policy safeguards for rural revitalization, thereby indirectly enhancing agricultural total factor productivity. This discovery aligns with the research conclusions of scholars such as Liu Chengkun, who found that digital inclusive finance positively impacts agricultural green total factor productivity through agricultural industrial structure upgrading and human capital accumulation.

Table 8. Results of Mediation Effect Tests

(1)	(2)

	z_agtfp	z_r
z_de	0.383***	0.603***
	(2.85)	(4.44)
z_l	-0.164	-0.455
	(-0.53)	(-1.45)
z_h	0.386***	0.596***
	(3.99)	(6.11)
z_s	-0.081*	0.012
	(-1.83)	(0.27)
z_d	-0.439***	-0.289***
	(-4.17)	(-2.72)
z_t	0.158	-0.780***
	(0.94)	(-4.59)
_cons	-0.562***	-0.724***
	(-6.38)	(-8.15)
N	330	330
R^2	0.868	0.637

***p<0.01", "**p<0.05", "*p<0.10

5.4 Heterogeneity Analysis

This study analyzes the differentiated impact of the digital economy on agricultural total factor productivity from a regional heterogeneity perspective. As shown in Table 8, the digital economy exhibits a significant positive effect in non-Yangtze River Economic Belt regions (coefficient = 0.602, significant at the 1% level). This aligns with technological diffusion theory, indicating that digital technologies, as "recipients" in less developed areas, can generate marginal improvements by reducing information asymmetry and optimizing factor allocation.

However, in the highly digitized Yangtze River Economic Belt, the direct effect of the digital economy fails to pass the significance test (coefficient = -0.236). This phenomenon can be explained from three perspectives: first, digital infrastructure is becoming increasingly sophisticated, leading to diminishing marginal returns; second, digital capital may crowd out traditional production factors; third, agriculture accounts for a low proportion in this region, and the growth effects of the digital economy are more evident in non-agricultural sectors.

Furthermore, human capital significantly boosts agricultural total factor productivity in both regions, confirming its role as a persistent driver. Conversely, social consumption levels and fiscal support exhibit negative impacts outside the Yangtze River Economic Belt, potentially reflecting market distortions in policy implementation.

The results indicate that the agricultural effects of the digital economy exhibit pronounced regional heterogeneity, necessitating tailored policy approaches: underdeveloped regions should prioritize infrastructure enhancement and technology dissemination, while developed regions should focus on deep integration of digital technologies with traditional factors and structural optimization.

Table 9. Heterogeneity Analysis

	(1) Yangtze River Economic Belt	(2) Non-Yangtze River Economic Belt
z_de	-0.236	0.602***
	(-0.691)	(3.517)
z_l	-0.029	-0.831
	(-0.035)	(-0.917)
z_h	1.561***	1.144***
	(8.981)	(8.092)
z_s	-0.136	-0.292***
	(-1.341)	(-3.708)
z_d	0.613	-0.642**
	(1.005)	(-2.363)
z_t	0.916	0.518
	(1.768)	(1.652)

_cons	0.137	-0.114
	(0.371)	(-0.494)
N	121	209
R^2	0.848	0.801
F	65.357	45.174

***p<0.01", "**p<0.05", "*p<0.10

6. Suggestions

6.1 Accelerate the Development of Digital Infrastructure to Bridge the Urban-Rural Digital Divide

This study demonstrates that the digital economy significantly enhances green total factor productivity in agriculture, though this effect varies considerably across regions. The driving force of the digital economy is particularly pronounced in western regions. Therefore, it is recommended that governments increase investment in digital infrastructure in rural areas—specifically in internet access, digital payment systems, and agricultural IoT infrastructure—to advance rural informatization and promote the green transformation of agricultural production models

6.2 Promoting Deep Integration of Digital Agriculture with Traditional Production Factors

In highly digitized regions like the Yangtze River Economic Belt, the digital economy's impact on green agricultural TFP failed to meet statistical significance thresholds, indicating near-saturated potential in these areas. Thus, we recommend deepening the integration of digital agricultural technologies with traditional production factors. This will advance the application of intelligent and precision farming techniques, enhancing production efficiency and resource utilization.

6.3 Promoting Comprehensive Rural Revitalization of Industry, Talent, and Ecology

The digital economy not only directly enhances agricultural green production efficiency but also indirectly boosts green TFP by driving comprehensive rural revitalization across industry, talent, and ecology. Governments should support digital agriculture financing, rural e-commerce, and the dissemination of green agricultural technologies to incentivize greater farmer participation in modern agricultural development. Additionally, governments should strengthen farmer education and training to enhance their technological application capabilities and innovation awareness, thereby promoting the adoption of green technologies in rural areas.

6.4 Develop Differentiated Policies Based on Regional Variations

This study reveals significant regional heterogeneity in the impact of the digital economy on agricultural green TFP, particularly between developed and underdeveloped regions. Therefore, local governments should formulate targeted policies based on their specific circumstances. In economically underdeveloped areas, emphasis should be placed on infrastructure development and the popularization of information technology. In more economically developed regions, focus should shift to digital technology innovation and the optimization of agricultural industrial structures to drive the green transformation of agricultural production.

6.5 Strengthen Policy Coordination and Resource Integration

Policy coordination is crucial for enhancing green agricultural TFP. Governments should enhance the integration of relevant policies, particularly between digital economy initiatives and rural revitalization strategies, to create synergistic effects. Concurrently, various resources—including fiscal funding, technical support, and talent development—must be consolidated to collectively advance green agricultural development.

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