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Research on the effect of digital economy on new agricultural productivity

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Abstract

This article comprehensively explores the impact of the digital economy on the new quality of agricultural productivity. Leveraging the panel data of 31 provincial-level regions in China from 2011 to 2022, a series of advanced econometric models, such as bidirectional fixed-effect, intermediary effect, threshold effect, and spatial Durbin models, are established for in-depth empirical analysis. The results are multi-faceted. Firstly, the digital economy significantly elevates the new quality of agricultural productivity, yet with temporal and regional variances. Secondly, it acts as a catalyst for productivity growth by augmenting government revenue, spurring technological innovation, and enriching human capital. Thirdly, rural education, the urban-rural information chasm, and information infrastructure construction exert distinctive threshold effects on this promotional process. Notably, a significant spatial spillover effect exists. Consequently, based on these findings, suggestions for bolstering the new quality agricultural productivity are proffered from four perspectives: government governance, policy formulation, digital infrastructure construction, and human capital enhancement.

Keywords: Agricultural new quality productivity, Digital economy, Mediator effect, Rural revitalization, Spatial spillover effect, Threshold effect.
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Contents

Contribution of this paper to the literature

The possible innovation points of this article are as follows. First, there is an innovation in research perspective as it starts from the new angle of new-quality agricultural productivity related to the digital economy rather than traditional ones, providing a new understanding dimension. Second, it innovatively applies multiple complex models like bidirectional fixed effects, intermediary effects, threshold effects, and spatial Durbin models for comprehensive and in-depth analysis with more information than single-model approaches. Third, it innovatively explores various influencing factors, including rural education, urban-rural information gap, and infrastructure construction, considering their threshold and spillover effects. Fourth, based on empirical results, it innovatively gives practical suggestions from four aspects for promoting new-quality agricultural productivity development.

1. Introduction

The promotion of rural revitalization constitutes an internal requirement for the all-round construction of a modern socialist country, with industrial revitalization having become the basis and key to realizing rural revitalization. In the past ten years, China has witnessed significant accomplishments in agricultural development. As per the data from the National Bureau of Statistics, between 2011 and 2022, the grain output in China climbed from 588.4933 million tons to 686.5277 million tons, effectively safeguarding national food security. Additionally, the total output value of agriculture, forestry, animal husbandry, and fishery increased from 78836.98 billion yuan to 156665.94 billion yuan, registering an average annual growth of 6.4% and showing a steady enhancement in the quality of agricultural development.

Nevertheless, China's agricultural growth is still mainly extensive, beset with problems like large resource consumption, serious environmental pollution, and low production efficiency (Liu, Zou, & Wang, 2020; Tang & Chen, 2022). Hence, the transition from production-oriented to quality-oriented has emerged as a crucial issue for promoting the transformation and upgrading of China's agriculture and achieving high-quality agricultural development. The introduction of new quality productivity presents a new direction to solve this problem. Its high-tech, high-efficiency, and high-quality attributes can effectively boost the quality and efficiency of agricultural production, promoting the high-quality development of agriculture (Jie, 2024). In order to bring about industrial revitalization, and finally the full building of a modern socialist country (Lin, Gu, & Shi, 2024) it is very important to look into the factors that affect the promotion of new agricultural quality productivity.

The digital economy represents the world's future development direction and holds significant importance for China's transformation of its economic mode and attainment of high-quality economic development. With the continuous progress and wide application of digital technology, the integration of the digital economy with various industries has been deepening, driving the transformation and upgrading of different industries (Su, Su, & Wang, 2021). However, due to the relatively low economic level in the main areas of agricultural development and the lagging construction of information infrastructure, the penetration of the digital economy in these areas is small, and the level of integration with agriculture is low. According to the data of 2022, the penetration rate of China's digital economy into the primary industry is only 10.5%, far lower than that of the secondary industry (24.0%) and the tertiary industry (44.7%). Simultaneously, the digital economy's total factor productivity growth in the primary industry remains low throughout the year, significantly lower than that of the secondary and tertiary industries. To achieve high-quality development of agriculture, it is necessary to improve the impact of the digital economy on agriculture. Therefore, as agricultural development is in a critical period of transformation and upgrading, it is especially important to thoroughly study the impact effect of the digital economy on the new quality of agricultural productivity (Zhou, Chen, & Zhang, 2023).

2. Literature Review

The field of research on new agricultural productivity is increasingly attracting academic attention; however, there is relatively little research on the topic. Different scholars have adopted various dimensions for measuring and evaluating the topic. Zhu and Ye (2024) made comprehensive evaluation from three aspects: agricultural workers, agricultural labor materials, and agricultural labor objects; Song, Leng, and Zhou (2024) measured from three dimensions: scientific and technological productivity, green productivity, and digital productivity; while (Yang & Wang, 2024) evaluated the development level of new quality digital agriculture in China from three dimensions: "high quality" agricultural workers, "new medium" agricultural labor materials, and "new material" agricultural labor objects. In terms of the influencing factors, different studies have drawn different conclusions. Wang and Liu (2024) believe that the development of new quality productive forces in agriculture can enhance the level of food security in major countries; (Li, Xue, & Jiang, 2024) believe that agricultural digitization can significantly improve the productivity of new grain productivity; (Zhang & Gong, 2024) believe that the level of new agricultural productivity can be improved through the construction of high-standard agricultural farmland, thus increasing farmers grain income. In terms of theoretical analysis, the researchers also explored the concept of new quality productivity in agriculture from various perspectives. For example, Wang and Yang (2023) studied the mechanism of relationship between digital new agricultural productivity and the high-quality development in China; (Luo, 2014) analyzed the main obstacles, development priorities, and policy suggestions for the development of new agricultural productivity; (Jiang, 2024) made a logical analysis of new agricultural productivity from four aspects: connotation characteristics, development focus, constraints, and policy suggestions. These studies provide useful reference and enlightenment for understanding the connotation and influencing factors of agricultural productivity.

According to the comprehensive literature, scholars have not yet discussed the digital economy and the new quality productivity of agriculture, which shows that there is a lot of academic research space in this field. Therefore, based on the panel data of 31 provinces in China from 2011 to 2022, this paper makes a comprehensive evaluation of new agricultural productivity and tries to explore the effect of digital economy on the improvement of new agricultural productivity. This research aims to close this gap in academic circles and provide a specific reference for the formulation of relevant agricultural policies.

3. Mechanism Analysis

3.1. Analysis of the Direct Impact of Digital Economy on New Quality Productivity

The new agricultural quality productivity is a new productivity form with qualitative change produced by the optimization combination of productivity elements of laborers, labor materials, and labor objects. It has four main characteristics: innovation-driven, green and low-carbon, open integration, and human-oriented connotation, which represents the revolutionary improvement of production efficiency (Huang & Sheng, 2024). The impact of digital economy on new quality agricultural productivity can be explained from two aspects: technology promotion and population quality improvement. First, the booming development of the digital economy provides an efficient digital platform for the dissemination and exchange of information, breaking the constraints of geographical location and spatial constraints. In this context, emerging agricultural technologies can be promoted more widely, so that the agricultural community can adopt innovative technologies more quickly, improve production efficiency, and realize the effective improvement of new agricultural productivity (Ding, Liu, Zheng, & Li, 2021). Second, as a key support force for the development of China's digital economy, the popularization and development of the Internet have greatly reduced the learning cost of agricultural technology and business models (Hua & Zhang, 2023). Through various channels, such as online training provided by Internet platforms, agricultural practitioners are able to acquire knowledge and skills in a more convenient, efficient, and low-cost way. This not only enables them to continuously improve their personal quality without disrupting production but also promotes the continuous improvement of new agricultural quality productivity.

Based on the above analysis, hypothesis 1: Digital economy can promote the improvement of new agricultural productivity.

3.2. Analysis of the Action Mechanism of Digital Economy on the New Quality of Agricultural Productivity

3.2.1. Government Revenue Mechanism

The booming development of the digital economy has not only changed the business model and industrial pattern but also provided important support for improving the new quality of agricultural productivity. First, the rise of the digital economy has increased government tax revenue, resulting from the continued boom of emerging industries such as e-commerce and online services (Volkova, Kuzmuk, Oliinyk, Klymenko, & Dankanych, 2021) giving the government more money to support technological innovation and infrastructure construction in the agricultural sector. Secondly, digital transaction records and payment systems effectively reduce tax loopholes, improve the efficiency of tax collection (Zhu, 2021) further increase government revenue, and provide stable financial support for agriculture. Finally, the development of digital economy drives the growth of the overall economy (Tao, Zhang, & Shangkun, 2022) improves the level of national income and consumer demand, and promotes the demand for agricultural products, thus further expanding the tax base. To sum up, the digital economy provides strong financial support and policy guarantees for the promotion of new quality agricultural productivity by increasing government income.

3.2.2. Scientific and Technological Innovation Mechanism

Science and technology are the primary productive forces, and scientific and technological innovation is the core impetus for the progress of science and technology. By stimulating scientific and technological innovation, the digital economy can effectively enhance the productivity of new agricultural products. To begin with, the application of digital technology can speed up the agricultural informatization process (Quan, Zhang, Quan, & Yu, 2024). Digital technologies such as big data, cloud computing, blockchain, and Internet of Things can transform traditional agriculture into smart agriculture. This conversion can enhance the technological innovation capability of agriculture and subsequently improve the new quality productivity of agriculture. Moreover, the digital economy furnishes a digital medium for information dissemination and communication (Peng & Luxin, 2022). By removing regional limitations and accelerating the spread of knowledge, it stimulates the collision of innovative thoughts and the release of innovation spillover effects. As a result, the efficiency of agricultural technological innovation is increased, and the improvement of new agricultural quality productivity is promoted. Finally, the digital economy is characterized by being technological, digital, and intelligent as it reshapes the economic, digital, and cultural environments. This transformation of the environment not only shapes the behavior and expectations of innovation entities, but also drives the reform and improvement of the market economic system. Consequently, a better institutional environment and policy support are provided for agricultural scientific and technological innovation, ultimately driving the improvement of new agricultural productivity.

3.2.3 Human Capital Mechanism

Cultivating and expanding the new type of labor force is an important strategy to enhance the new quality of agricultural productive forces. The development of digital economy helps to improve the level of human capital, so as to effectively promote the improvement of new agricultural productivity. First, the booming digital economy accelerates the flow of knowledge and experience between different regions, allowing agricultural practitioners to keep abreast of the latest trends in agricultural techniques and management methods. Agricultural practitioners, through online training and other channels provided by the Internet platform, can continuously enhance their own quality, thereby promoting the rapid improvement of new agricultural productivity. Secondly, the application of digital technology has brought about the upgrading of agricultural production technology and the innovation of management mode and promoted the transformation and upgrading of traditional agriculture to modern agriculture. This not only gives birth to new agricultural forms and models but also provides a large number of new employment opportunities for agriculture, attracting more agricultural professionals to join and thus effectively promoting the improvement of new quality of agricultural productivity (Grigorescu, Pelinescu, Ion, & Dutcas, 2021).

Based on the above analysis, Hypothesis 2 is put forward: Digital economy promotes the improvement of new agricultural quality and productivity by improving the government income level, scientific and technological innovation level, and human capital level.

3.3. Analysis of the Threshold Effect of Digital Economy on the New Quality of Agricultural Productivity

3.3.1. Education Level in Rural Areas

The digital economy involves more complex digital technology applications such as big data, cloud computing, blockchain, and the Internet of Things. Agricultural practitioners need to master these technologies through professional education. When the level of education in rural areas is low, it means that agricultural practitioners receive insufficient professional education and have a low grasp of digital technology, thus having a restraining effect on the digital economy to promote the improvement of new quality agricultural productivity. When the level of rural education gradually improves, it means that agricultural practitioners usually receive deeper and specialized education and master higher levels of skills and knowledge. This enables it to deeper understand and apply the technologies and concepts involved in digital economy and makes it easier to master and apply advanced digital agricultural technology so as to promote the role of digital economy in improving the new agricultural productivity through the skilled use of digital agricultural technology. Therefore, the promotion effect of digital economy on new quality agricultural productivity will show the characteristics from low to high with the improvement of rural education level.

3.3.2. Information Gap between Urban and Rural Areas

Due to the huge differences in rural and urban areas in the access, use, and innovation of information resources and technologies, the serious information imbalance between urban and rural areas is caused (Chen & Wang, 2020). This may result in information asymmetry, which will affect the efficiency of resource allocation and ultimately inhibit the promotion of digital economy on new agricultural productivity. The information gap between urban and rural areas is small, the information asymmetry is light, and the allocation of urban and rural factors is relatively reasonable, which is conducive to the promotion of the new quality of agricultural productivity by digital economy. However, with the widening of the information gap between urban and rural areas, the information gap between urban and rural areas is also expanding, and the allocation of urban and rural factors gradually becomes inefficient, thus hindering the role of digital economy in promoting new agricultural productivity. However, with the acceleration of the urbanization process, a large number of people pour into cities, and the number of people receiving the same information keeps increasing, which alleviates the information asymmetry caused by urban-rural information imbalance, thus improving the efficiency of resource allocation and weakening the inhibitory effect of urban-rural information gap on the digital economy to promote new agricultural productivity. Therefore, the impact of digital economy on new agricultural productivity will show U-shaped characteristics from high to low to high with the widening of the information gap between urban and rural areas.

3.3.3. Information Infrastructure Construction

The construction of information infrastructure is the key pillar of the development of digital economy, and its level directly affects the promotion effect of digital economy on the new quality of agricultural productivity. When the level of information infrastructure construction is low, the role of digital economy in promoting the new quality of agricultural productivity is limited. This is because the lower level of information infrastructure can only cover the limited regional economies, and the cross-regional information flow is restricted, which restricts the cross-regional dissemination and communication of technology and knowledge, thus reducing the role of digital economy in promoting new agricultural productivity. When the level of information infrastructure construction is high, the digital economy plays a more significant role in promoting new agricultural productivity. This is because the high level of information infrastructure can cover a wider range of regional economy, break through the restrictions of regional information dissemination, promote the wide dissemination and exchange of agricultural technology and knowledge, and thus improve the promotion effect of digital economy on new agricultural productivity.

Based on the above analysis, the paper puts forward hypothesis 3: the influence of digital economy on new quality productivity has threshold effect based on rural education level, urban-rural information gap, and information infrastructure construction, which is manifested as non-linear increasing effect, non-linear effect of decreasing and then increasing, and a non-linear increasing effect, respectively.

3.4. Spatial Spillover Effect Analysis of Digital Economy on the New Quality of Agricultural Productivity

With the rapid development of the digital economy, the links between the provinces are becoming increasingly close. First of all, due to the frequent movement of agricultural trade activities and farmers among neighboring regions, coupled with the close geographical location and convenient transportation, to promote the flow of digital agricultural technology, agricultural management experience, and other information between regions. This flow of information provides local agricultural practitioners with the opportunity to learn from the advanced experience and technology in neighboring areas, thus effectively improving the level of local agricultural production and promoting the continuous improvement of new quality productivity. Secondly, due to the promotion of inter-regional economic activities and rural human capital flow, the advanced experience and technology of the regions leading in the development of digital economy will spread to other regions, while the wide application of digital media will further improve the speed and scope of diffusion. This diffusion effect drives more areas to benefit, thus promoting the improvement of agricultural production efficiency and improving the level of new agricultural productivity (Tian, Cai, & Zhang, 2024).

Based on the above analysis, the paper puts forward hypothesis 4: the development of digital economy has a positive spatial spillover effect on the improvement of new quality agricultural productivity.

4. Research Design

4.1. Model Construction

4.1.1. Benchmark Regression Model

The aim to examine how the digital economy affects the new level of agricultural productivity. The paper constructs the following benchmark model:

$$NQAP_{it} = \alpha_0 + \alpha_1 DE_{it} + \sum_{k=1}^{n} \eta_k \, Control_{it} + \lambda_i + \gamma_t + \mu_{it} \qquad (1)$$

In model (1), the notations "i" and "t" stand for the province and the year, respectively. "Control" denotes the control variable. Here, α_0 represents the constant term. The regression coefficients of each variable are indicated by

$\alpha1$ and η_k. The fixed effects of province and year are represented by λ_i and γ_t respectively. And μ serves as the random error term.

4.1.2. The Mediation Effect Model

On the basis of model (1), the intermediary effect model is constructed to test the role mechanism of digital economy in promoting the improvement of new quality agricultural productivity. The models constructs the following mediation effect:

$$Medium_{it} = \beta_0 + \beta_1 DE_{it} + \sum_{k=1}^{n} \eta_k\, Control_{it} + \lambda_i + \gamma_t + \mu_{it} \qquad (2)$$

$$NQAP_{it} = \beta_2 + \beta_3 DE_{it} + \beta_4 Medium_{it} + \sum_{k=1}^{n} \eta_k\, Control_{it} + \lambda_i + \gamma_t + \mu_{it} \qquad (3)$$

Where Medium represents the mediation variable, β_0 and β_2 represent the constant term, β_1, β_3, β_4, are the regression coefficients, and the other symbols have the same meaning as in the model (1).

4.1.3. The Threshold-Based Effect Model

The nonlinear effect of digital economy on agricultural new quality productivity is measured by constructing the threshold effect model. The model is as follows:

$$NQAP_{it} = \varphi_0 + \varphi_1 GAP_{it} \times I(Threshold_{it} \le \theta_1) + \varphi_2 DE_{it} \times I(\theta_1 < Threshold_{it} \le \theta_2) + \cdots + \varphi_n DE_{it} \times I(Threshold_{it} > \theta_{n-1}) + \sum_{k=1}^{n} \eta_k\, Control_{it} + \lambda_i + \gamma_t + \mu_{it} \qquad (4)$$

Where I (•) is the indicator function, when the conditions in parentheses are met, the value is 1, if not; the threshold is the threshold variable; φ 0 is the constant term, φ n is the regression coefficient; the other symbols have the same meaning as the model (1).

4.1.4. The Spatial Durbin Model

To explore the spatial spillover effect of digital economy on the new quality of productivity in agriculture by constructing the spatial Durbin model. The specific model is constructed as follows:

$$NQAP_{it} = \zeta_0 + \zeta_1 DE_{it} + \zeta_2 Control_{it} + \rho WNQAP_{it} + \zeta_3 WDE_{it} + \zeta_4 WControl_{it} + \lambda_i + \gamma_t + v_{it} \qquad (5)$$

$$v_{it} = \zeta_5 W v_{it} + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \delta^2 I) \qquad (6)$$

Where, ζ_0 represents the constant term, ζ_1, ζ_2, ζ_3, ζ_4, and ζ_5 are all coefficients, σ represents the spatial autoregressive coefficient, W is the spatial weight matrix, and v represents the residual term.

4.2. Description of the Variables

4.2.1. Explained Variables

The article explains agricultural new quality productivity as the variable under investigation. The basic connotation of new quality labor force is laborer, labor means, labor object, and its optimal combination (Research Center of Xi Jinping's Economic Thought, 2024) so the evaluation of agricultural new quality productive force is based on the three first-level indicators of laborer, labor means, and labor object. The research results of You and Tian (2024) primarily inform the selection of secondary indicators in the paper. First, as for workers, the study believes that new quality workers have higher cultural quality and labor productivity. Therefore, the paper describes the laborer from the two secondary indicators of labor quality and labor production efficiency. In terms of specific indicators, the quality of workers is represented by the average years of education in rural areas, per capita financial education expenditure, and the ratio of college graduates and permanent resident population; labor production efficiency is represented by the per capita output value of agriculture, forestry, animal husbandry, and fishery, per capita grain output and per capita disposable income of rural residents. Second, about labor data, the study elaborated on the characteristics and specific forms of traditional labor data and new quality labor data. Therefore, the paper describes the labor data from the two secondary indicators: traditional labor data and new quality labor data. Specifically, the ratio of agricultural machinery, the ratio of agricultural fertilizer application, and the ratio of rural broadband access users and rural population. Thirdly, about the labor object, the study explains the green development, land standardization, and other aspects. At the same time, considering the important role of innovation factors in upgrading the labor object, the article finally describes the labor object from three aspects of standardized farmland, green development, and innovative development. Specifically, standardized farmland is represented by the ratio of effective irrigated area and crop-sown area and the ratio of waterlogged area and crop-sown area; green development is characterized by the ratio of total afforestation area and agricultural water consumption and total grain output; and the ratio of local financial science and technology expenditure to local financial budget expenditure. The ratio of the amount of patent applications granted and the permanent resident population at the end of the year is represented. Finally, this paper constructs a new agricultural quality productivity measurement index system composed of three first-level indicators of labor, labor means, and labor object, including 7 second-level indicators and 18 specific indicators (Table 1). In terms of calculation method, the paper adopts four methods of standardization treatment, translation treatment, entropy value assignment, and linear weighting to calculate the comprehensive evaluation value of specific agricultural new quality productivity.

Table 1. Measurement index system of agricultural new quality productivity.

Evaluation target	Level 1 indicators	Secondary indicators	Specific indicators	Indicator attributes	weight
Agricultural new quality productivity	Labourer	Educational level of workers	Average years of education in rural areas (Years)	+	0.005
			Per capita financial expenditure on education (Yuan)	+	0.039
			Number of college graduates / Permanent resident population	+	0.024
		Labor production efficiency	Per capita output value of agriculture, forestry, animal husbandry and fishery (Yuan)	+	0.030
			Per capita grain output (kg)	+	0.061

Evaluation target	Level 1 indicators	Secondary indicators	Specific indicators	Indicator attributes	weight
			Per capita disposable income of rural residents (Yuan)	+	0.037
	Means of labor	Traditional labor data	Total power of agricultural machinery (Ten thousand kilowatts)	+	0.068
			Purity amount of agricultural chemical fertilizer application / Sown area of crops	-	0.011
			Number of reservoirs (Seats)	+	0.104
		New quality labor data	Optical cable laying line / Area area	+	0.125
			Rural delivery route / Area area	+	0.072
			Rural broadband access users / Rural population	+	0.065
	Subject of labor	Standardized farmland	Effective irrigated area / Crop sown area	+	0.024
			Waterlogging area / Crop sown area	+	0.121
		Green development	Total area of afforestation (Thousand ha)	+	0.059
			Agricultural water consumption / Total grain output	-	0.008
		Innovative development	Local financial expenditure on science and technology / Local fiscal budget expenditure	+	0.058
			Domestic patent application acceptance volume / Permanent resident population at the end of the year	+	0.089

4.2.2. Core Explanatory Variables

The core explanatory variable in this article is the digital economy. Referring to the research findings of Tao et al. (2022) this paper selects a comprehensive evaluation index system for digital economy development. This system encompasses Internet popularization, employment proportion, per capita telecom business volume, telephone penetration rate, and the digital financial inclusion index (Table 2). The same calculation method used for digital economy development is also applied to obtain the comprehensive evaluation value of the new agricultural quality productivity.

Table 2. Comprehensive evaluation index system of digital economy development.

Evaluation target	Level 1 indicators	Specific indicators	Indicator attributes	weight
Digital economy development	Internet popularization	Internet broadband access users / Permanent resident population at the end of the year	+	0.109
	The proportion of the employed personnel in the information industry	Information transmission, software and information technology services employed in urban units / Urban units	+	0.298
	Per-capita telecommunications business volume	Total telecom business volume / Permanent resident population at the end of the year	+	0.417
	Penetration	Number of phone users per 100 people	+	0.092
	The digital financial inclusion index	The China digital financial inclusion index	+	0.085

4.2.3. Intermediary Variables

The article sets up three intermediary variables to test the mechanism of action, including: (1) the government budget revenue in general (Hu, Shi, & Yang, 2022) using the numerical value of local fiscal science and technology expenditure and local education expenditure; (2) scientific and technological innovation (TI) and (3) human capital (HC).

4.2.4. Threshold Variable

The paper set up three threshold variables to study the threshold effect.(1) Rural education level (EDU) is expressed by the average number of years of education in rural areas. The calculation formula is: (primary school 6 + middle school 9 + high school 12 + 12 secondary college + 15 + 16 + graduate 19) / total number of population aged 6 and above.(2) Urban-rural information gap (GAP) (Wang & Xiao, 2021) is obtained from the ratio of rural per capita broadband quantity to urban per capita broadband quantity.(3) Information infrastructure construction (IIC), expressed by the ratio of the length of the optical cable line to the provincial area.

4.2.5. Control Variables

To eliminate the effect of other factors on the productivity of new agricultural quality, the article sets 6 control variables:

(1) the level of financial agricultural support (GAE), with the proportion of government expenditure on agriculture, forestry, and water resources in the total expenditure. The level of financial support for agriculture refers to the intensity of the government's financial support for agriculture, rural areas, and farmers within a certain period.

(2) Energy consumption level (ECO), By using the log value of rural electricity consumption. The energy consumption level means the degree of consumption of various types of energy in production, living, and other activities in a certain region or industry within a specific period.

(3) Mechanization level (ML), repressed by the ratio of the total power of agricultural machinery to the total sown area of crops. The mechanization level is an indicator used to measure the popularization and application level of mechanical operations in the process of agricultural production.

(4) Highway construction level (RND), The ratio of the highway's total mileage to the province's area determines the highway construction level. The highway construction level mainly refers to the construction scale, quality, and degree of perfection of highway infrastructure in a certain region.

(5) Reservoir construction level (RC), represented by the value of reservoir capacity (Li, Yin, & Wu, 2015). The reservoir construction level indicates the construction and development status of water conservancy facilities such as reservoirs in a certain area.

(6) Internet Development Level (IDL), reexpressed by the log of the number of rural broadband users. The Internet development level is an indicator that comprehensively reflects the construction of Internet infrastructure, the popularization degree of Internet applications, and the development status of Internet-related industries in a certain region.

4.3. Descriptive Statistics

Panel data from 31 provinces in China from 2011 to 2022 were selected for study (Table 3). The digital financial inclusion index is from Peking University Digital Financial Inclusion Index, and other data are mainly from China Statistical Yearbook and China Rural Statistical Yearbook. Among them, the minimum value of reservoir construction level and urban-rural information gap is zero, because the data is missing in some provinces in some years, and the value of adjacent years is very low. It is speculated that the missing reason is that the value is too small and the statistical difficulty is too large, so the zero treatment is conducted.

Table 3. Descriptive statistical results.

Type of variable	Variable	Variable interpretation	Observed value	Mean	Standard deviation	Least value	Crest value
Explained variable	ANQP	Agricultural new quality of productivity	372	0.208	0.073	0.064	0.419
Core explanatory variables	DE	Digital economy	372	0.217	0.148	0.0136	0.912
Controlled variable	GAE	Financial support for agriculture	372	0.115	0.034	0.040	0.204
	ECO	Energy consumption level	372	4.750	1.459	-0.139	7.575
	ML	Mechanized level	372	7.026	3.636	2.516	26.979
	RND	Highway construction level	372	0.934	0.526	0.052	2.269
	RC	Reservoir construction level	372	5.104	1.285	0	7.142
	IDL	The level of Internet development	372	4.843	1.710	-0.693	7.353
Metavariable	GI	Public Revenue	372	7.564	0.958	4.003	9.554
	TI	Technological Innovation	372	4.307	1.153	1.218	7.064
	HC	Human capital	372	6.565	0.713	4.354	8.261
The threshold variable	EDU	Level of education in rural areas	372	7.689	0.824	3.804	9.915
	GAP	Urban-rural information gap	372	0.500	0.364	0	1.777
	IIC	Information infrastructure construction	372	10.267	16.126	0.043	119.098

5. Interpretation of Result

5.1. Benchmark Regression Results

Before the empirical regression, the problem of multicollinearity was determined by whether the empirical data was present by performing multicollinearity tests on the core explanatory variables and control variables. The results demonstrate a maximum value of variance expansion factor (VIF) is 3.34, and the overall mean is 2.45, which is far less than 10, indicating that the core explanatory variables and control variables do not have multicollinearity problems, so the benchmark regression analysis can be conducted.

Table 4 shows the results of the benchmark regression analysis. In terms of core explanatory variables, in the model (1) without control variables, the regression coefficient of digital economy was 0.154, and it was significantly positive at the level of 1%, indicating that the development of digital economy has a promoting effect on the improvement of new quality agricultural productivity. In the model (2) - (7), gradually join the financial support of agriculture, energy consumption, mechanization level, highway construction, reservoir construction level, and the

Internet development level in the process of control variables; the regression coefficient of the digital economy is still significantly at 1% level, further proving the digital economy can effectively promote agricultural new quality productivity to verify the hypothesis 1. In terms of control variables, the regression coefficients of mechanization level, highway construction level, and the development level of the Internet are all significantly positive, indicating that the three also play an important role in enhancing the new quality of agricultural productivity and are also in line with the general cognition. The regression coefficient of the level of financial support for agriculture, energy consumption level, and reservoir construction level is significantly negative, indicating that these control variables have a certain inhibitory effect on the improvement of new agricultural productivity. The possible reason is that the high level of financial support for agriculture leads to agricultural developments excessive reliance on government subsidies, maintaining productivity at a low level and profitable, thus inhibiting the improvement of new agricultural quality productivity; new agricultural quality productivity represents higher production efficiency and higher utilization rate of resources, so lower resource consumption can produce more output than traditional productivity, thus concluding the reverse relationship of resource consumption level and new agricultural quality productivity; the improvement of reservoir construction level means the expansion of cultivated land and the limitation of agricultural water, thus inhibiting the improvement of new agricultural quality productivity.

Table 4. Benchmark regression results.

Variable	(1) ANQP	(2) ANQP	(3) ANQP	(4) ANQP	(5) ANQP	(6) ANQP	(7) ANQP
DE	0.154*** (0.043)	0.176*** (0.041)	0.163*** (0.038)	0.146*** (0.040)	0.149*** (0.039)	0.152*** (0.041)	0.136*** (0.041)
GAE		-0.482*** (0.080)	-0.420*** (0.077)	-0.418*** (0.071)	-0.380*** (0.076)	-0.368*** (0.074)	-0.413*** (0.073)
ECO			-0.00713*** (0.002)	-0.008*** (0.002)	-0.009*** (0.002)	-0.010*** (0.002)	-0.011*** (0.002)
ML				0.004*** (0.002)	0.004** (0.002)	0.004** (0.002)	0.005*** (0.0015)
RND					0.028** (0.011)	0.029*** (0.011)	0.027** (0.011)
RC						-0.009*** (0.003)	-0.011*** (0.003)
IDL							0.006** (0.003)
cons	0.174*** (0.009)	0.225*** (0.013)	0.254*** (0.017)	0.234*** (0.017)	0.209*** (0.019)	0.258*** (0.024)	0.247*** (0.025)
Time fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	372	372	372	372	372	372	372
R2	0.943	0.949	0.951	0.954	0.955	0.956	0.957

Note: ***, ** are significant at 1%, 5% and 10%, respectively, numbers in parentheses are robust standard error.

5.2. Analysis of the Mechanism of Action

It has been confirmed above that the development of digital economy has a significant positive impact on new agricultural productivity, but it remains to be confirmed by which mechanism this impact is achieved. The mechanism analysis has preliminarily identified that the digital economy will promote the improvement of new agricultural quality productivity through the government revenue mechanism, scientific and technological innovation mechanism, and human capital mechanism. Therefore, the above three mechanisms of action are further tested based on the model (Table 5).

Column (1) presents the total effect in the benchmark regression model. For the government revenue mechanism, in column (2), the coefficient of the digital economy is significantly positive at the 1% level, signifying that the digital economy significantly boosts government income. In column (3), the interaction term of the digital economy and government revenue is significantly positive at the 1% level, indicating that the digital economy significantly promotes the improvement of new agricultural productivity by increasing government revenue.

Regarding the scientific and technological innovation mechanism, in column (4), the coefficient of the digital economy is significantly positive at the 5% level, showing that the digital economy promotes technological innovation. In column (5), the coefficient of the interaction between the digital economy and technological innovation is significantly positive at the 5% level, meaning that the digital economy effectively promotes the enhancement of new agricultural productivity by facilitating scientific and technological innovation.

In terms of the human capital mechanism, in column (6), the coefficient of the digital economy is significantly positive at the 1% level, suggesting that the development of the digital economy can raise the level of human capital. In column (7), the coefficient of the interaction of the digital economy and human capital is significantly positive at the 1% level, indicating that the digital economy significantly promotes the improvement of new agricultural productivity by elevating the level of human capital.

Consequently, hypothesis 2 is verified.

Table 5. Test of the influence mechanism.

Variables	(1) Gross effect	Government revenue mechanism		Science and technology innovation mechanism		Human capital mechanism	
		(2) GI	(3) ANQP	(4) TI	(5) ANQP	(6) HC	(7) ANQP
DE	0.136*** (0.041)	0.795*** (0.288)	0.112*** (0.042)	1.223** (0.505)	0.105** (0.041)	0.641*** (0.228)	0.112*** (0.043)
GI			0.030*** (0.008)				
TI					0.026** (0.003)		
HC							0.037*** (0.010)
cons	0.247*** (0.025)	7.297* (0.217)	0.026 (0.063)	3.368*** (0.362)	0.160*** (0.024)	6.004*** (0.171)	0.02 (0.06)

Variables	(1) Gross effect	Government revenue mechanism		Science and technology innovation mechanism		Human capital mechanism	
		(2) GI	(3) ANQP	(4) TI	(5) ANQP	(6) HC	(7) ANQP
Controlled variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	372	372	372	372	372	372	372
R2	0.957	0.985	0.959	0.958	0.964	0.982	0.959

Note: ***, **, * are significant at 1%, 5% and 10%, respectively, numbers in parentheses are robust standard error.

5.3. Threshold Effect Analysis

The level of rural education, the information gap between urban and rural areas, and the information infrastructure construction may all have non-linear effects on the digital economy to promote the improvement of the new quality of agricultural productivity. First of all, the threshold effect of rural education level, urban-rural information gap, and information infrastructure construction were tested. Self-service method (Bootstrap) was sampled 300 times, and the test results are shown in Table 6. The results showed that the F value of single threshold effect of rural education level was 28.78, which passed the test at the 5% significance level, and the F value of double threshold effect was 12.93, which failed the test. The urban-rural information gap passed the two-threshold effect test, in which the single-threshold effect F value was 37.91, at the 1% significance level; the double-threshold effect F value was 19.54, at the 5% significance level; and the three-threshold effect F value was 13.51, which failed the significance test. The information infrastructure construction passed the single threshold effect test, and its F value was 83.07, which passed the 1% significance level. The F value of the double threshold effect was 43.06, which failed the significance test. According to the test results of the level of rural education, urban-rural information gap, and information infrastructure, single-threshold effect model, double-threshold effect model, and single-threshold effect model were constructed for threshold effect analysis.

Table 6. Results of the threshold effect tests.

The threshold variable	The threshold number	RSS	MSE	F price	P price	And the 95% confidence interval
EDU	Single threshold	0.110	0.0003	28.78	0.046**	[27.773， 39.942]
	Double threshold	0.106	0.0003	12.93	0.290	[29.820,36.598]
GAP	Single threshold	0.107	0.0003	37.91	0.006***	[25.669,33.848]
	Double threshold	0.102	0.0003	19.54	0.040**	[18.471,26.727]
	Three threshold	0.098	0.0003	13.51	0.670	[35.201,39.983]
IIC	Single threshold	0.096	0.0003	83.07	0.000***	[42.360,51.952]
	Double threshold	0.086	0.0002	43.06	0.143	[152.822,211.944]

Note: ***, ** are significant at 1%, 5% and 10%, respectively, numbers in parentheses are robust standard error.

Table 7 presents the parameter estimation results of the threshold effect values for each threshold variable. For the rural education level: When this level is less than or equal to the threshold value of 7.6880, the regression coefficient of the digital economy development level is 0.057, which is significant at the 1% level. When the rural education level exceeds 7.6880, the regression coefficient is 0.119, also significantly positive at the 1% level. The latter value is greater than the former, demonstrating that there is a non-linear increasing effect of the digital economy on the new-quality agricultural productivity. As the rural education level improves, the positive impact of the digital economy on the new-quality agricultural productivity gradually emerges. Regarding the urban-rural information gap: When this gap is less than the first threshold value of 0.0702, the regression coefficient of the digital economy is 0.236 and significant at 1%. When the urban-rural information gap is between the first threshold and 0.8725, the regression coefficient of the digital economy is 0.071, also significant at 1%. When the urban-rural information gap is greater than the second threshold value, the regression coefficient of the digital economy is 0.119, also significant at 1%. The regression coefficient undergoes a process from decreasing to increasing, indicating that the influence of the digital economy with the expansion of the urban - rural information gap shows a non - linear effect of first decreasing and then increasing. With the expansion of the information gap between urban and rural areas, the information asymmetry problem between them leads to inefficient factor configuration, which inhibits the digital economy's effect on the agricultural new-quality productivity. However, with the acceleration of urbanization and the influx of population into cities, the inhibition of the digital economy on the promotion of agricultural new-quality productivity is caused by the urban-rural information gap changes. Information infrastructure construction: when the information infrastructure construction is below the threshold value of 36.2734, the regression coefficient of digital economy is 0.081, and passes the significance test at the 1% level; when the information infrastructure construction is above the threshold value of 36.2734, the regression coefficient of digital economy is 0.242, which also passes the significance test at the 1% level. The former is higher than the latter, indicating that the construction of information infrastructure has effectively promoted the role of digital economy on the new agricultural productivity. Therefore, hypothesis 3 is proved.

Table 7. Results of the regression estimation of the threshold effect model.

Variable	(1) ANQP	(2) ANQP	(3) ANQP
DE (EDU≤7.6880)	0.057*** (0.015)		
DE (EDU＞7.6880)	0.119*** (0.022)		
DE (GAP≤0.0702)		0.236*** (0.030)	
DE (0.0702＜GAP≤0.8725)		0.071*** (0.016)	
DE (GAP＞0.8725)		0.119*** (0.021)	

Variable	(1) ANQP	(2) ANQP	(3) ANQP
DE (IIC≤36.2734)			0.081*** (0.017)
DE (IIC>36.2734)			0.242*** (0.038)
Controlled variable	Yes	Yes	Yes
cons	0.099** (0.042)	0.108*** (0.038)	0.095** (0.034)
N	372	372	372
R2	0.779	0.795	0.800

Note: ***, ** are significant at 1%, 5% and 10%, respectively, numbers in parentheses are robust standard error.

5.4. Spatial Spillover Effect Analysis

To determine whether an analysis of the spatial spillover effect is necessary, conduct a spatial autocorrelation test on the new productivity pf agriculture before employing the spatial measurement model. The global Moran index (Moran's I) was utilized to measure the spatial autocorrelation in each year under the second - order inverse distance spatial weight matrix (W1), the economic distance weight matrix (W2) based on per capita GDP, and the economic distance weight matrix (W3) based on per capita disposable income (see Table 8). The results reveal that the Moran's I index from 2011 to 2022 was significantly positive at the 1% level, and the z-value was greater than 4. This indicates the presence of a strong spatial autocorrelation and characteristics, such as spatial agglomeration. Hence, it is necessary to use the spatial measurement model for research.

Table 8. Global MoranI.

A particular year	W1		W2		W3	
	Moran's I	z	Moran's I	z	Moran's I	z
2011	0.399***	4.841	0.658***	4.514	0.661***	4.525
2012	0.415***	5.024	0.679***	4.652	0.682***	4.653
2013	0.415***	5.025	0.682***	4.676	0.684***	4.673
2014	0.425***	5.135	0.700***	4.795	0.701***	4.786
2015	0.388***	4.728	0.607***	4.192	0.612***	4.208
2016	0.418***	5.052	0.657***	4.507	0.661***	4.521
2017	0.409***	4.957	0.676***	4.635	0.677***	4.629
2018	0.430***	5.186	0.701***	4.795	0.703***	4.795
2019	0.438***	5.274	0.720***	4.913	0.721***	4.905
2020	0.437***	5.271	0.717***	4.901	0.718***	4.894
2021	0.469***	5.640	0.760***	5.197	0.761***	5.189
2022	0.472***	5.680	0.769***	5.262	0.773***	5.275

Note: *** are significant at 1%, 5% and 10%, respectively, numbers in parentheses are robust standard error.

Once the spatial spillover effect analysis has been determined, the next step is to determine the appropriate spatial measurement model. The spatial measurement model was initially determined by LM test (Table 9) on ordinary static panel regression. The results show that the two tests for spatial error passed one of the three spatial weight matrices at the 1% significance level and the two tests for spatial lag at the 1% significance level in the three spatial weight matrices. Therefore, it is necessary to choose the spatial measurement model with the dual effect of spatial error and spatial hysteresis and initially judge to choose the spatial Durbin model with two effects.

Table 9. Results of the spatial metrological model testing.

Inspection type	W1		W2		W3	
	Statistic	P price	Statistic	P price	Statistic	P price
Space error	45.693	0.000	42.713	0.000	43.118	0.000
	2.826	0.093	0.259	0.611	0.413	0.521
Space lag	111.835	0.000	85.351	0.000	87.489	0.000
	68.968	0.000	42.898	0.000	44.784	0.000

The LR and Wald tests were further used to determine whether the spatial Durbin model will degenerate into a spatial autoregressive model or a spatial error model (Table 10). It was found that the LR and Wald tests of the three spatial weight matrices were significant at the 1% level. This means that the SDM model is better than SAR and SEMM models. The Hausman test results for the three spatial weight matrices were all significant at the 1% level, and thus the spatial Durbin model with fixed effects was chosen. The effect test ultimately led to the decision to employ the individual time point double fixed effect spatial Durbin model for the analysis of spatial spillover effects.

Table 10. LR tests, Wald tests, and Houseman tests.

Test-target	W1		W2		W3	
	Statistic	P price	Statistic	P price	Statistic	P price
SDM VS SAR(LR)	67.330	0.000	43.890	0.000	44.760	0.000
SDM VS SEM(LR)	88.760	0.000	67.340	0.000	68.300	0.000
SDM VS SAR(Wald)	68.080	0.000	44.290	0.000	45.310	0.000
SDM VS SEM(Wald)	95.360	0.000	70.850	0.000	71.870	0.000
Hausman	39.420	0.000	99.170	0.000	105.810	0.000
Both VS ind	53.610	0.000	74.30	0.000	75.690	0.000
Both VS time	714.750	0.000	695.070	0.000	690.520	0.000

Table 11 shows the results of the spatial measurement regression of the new quality productivity in agriculture in relation to the digital economy for all three spatial weight matrices. This is done to make sure that the test results are reliable.

The results demonstrate that the regression coefficients of the digital economy are all positive and have passed the significance tests at the 1%, 5%, and 5% levels, respectively. This indicates that the development of the digital economy can promote the improvement of new agricultural productivity within this province. The regression coefficient of the spatial lag term of the digital economy is significantly positive at the 1% level, suggesting that the new agricultural productivity has a positive spillover effect among provinces that are adjacent in geographical space and have similar economic development levels. In other words, the development of the digital economy in this province can drive the improvement of agricultural new productivity in surrounding provinces.

Moreover, the rho values of the spatial Durbin model are significantly positive in the three spatial weight matrices, which also verifies the prominent spatial agglomeration characteristics.

Furthermore, the spatial Durbin model's effect decomposition of partial differentiation yields both the direct and spatial spillover effects of the digital economy on the new quality productivity of agriculture. The results reveal that the coefficients of the spatial spillover effect of the digital economy on the agricultural new productivity in the three spatial weight matrices are positive and have passed the 1% significance level test, accounting for 74.7%, 66.2%, and 68.3% of the total effect, respectively. This indicates that the digital economy has a strong positive spatial spillover effect on the agricultural new productivity.

Consequently, hypothesis 4 is proven.

Table 11. Results of the spatial Durbin model regression.

Variable	**(1) W1**	**(2) W2**	**(3) W3**
DE	0.101*** (0.034)	0.082** (0.034)	0.079** (0.034)
WxDE	0.241*** (0.085)	0.147*** (0.049)	0.159*** (0.049)
Direct effect	0.113*** (0.033)	0.095*** (0.033)	0.093*** (0.033)
Overflow effect	0.334*** (0.107)	0.186*** (0.053)	0.200*** (0.052)
Gross effect	0.447*** (0.099)	0.281*** (0.050)	0.293*** (0.050)
Controlled variable	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
Provincial fixed	Yes	Yes	Yes
rho	0.236*** (0.086)	0.187*** (0.052)	0.194*** (0.051)
Log-likelihood	1109.098	1099.577	1100.448
N	372	372	372
R2	0.616	0.636	0.631

Note: ***, ** are significant at 1%, 5% and 10%, respectively, numbers in parentheses are robust standard error.

6. Further Expansion

6.1. Robustness Test

To test the reliability of the empirical analysis, the robustness test was conducted by replacing the explained variables, shrinking the tail, and eliminating the municipality (Table 12). First, replace it with an explained variable. Total factor productivity is the core index of new quality productivity, so the agricultural total factor productivity as an alternative is explained variable (TFP), using the Malmquist index method to measure agricultural total factor productivity to replace agricultural new quality productivity. The input variables are, respectively agricultural machinery total power, fertilizer application, crop sown area, agricultural water consumption, and the first industry employment, output variables are for agricultural output value (Yin & Shen, 2014). Second, tail reduction processing. To avoid bias in empirical results, we eliminate the municipality, taking into account its particularity and policy bias. Third, eliminate the municipality. Considering the particularity and policy bias of the municipality, it is eliminated to avoid the bias caused to the empirical results. Column (1)--(3) are the regression results of replacing the explained variables, reducing tail reduction, and excluding the municipality, respectively. The regression results are significantly positive, which is consistent with the previous empirical conclusions, indicating that the empirical results are robust and reliable.

Table 12. Results of the robustness test.

Variable	**(1) TFP**	**(2) ANQP_w**	**(3) ANQP**
DE	0.109** (0.042)		0.143*** (0.033)
DE_w		0.162*** (0.038)	
Controlled variable	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
Provincial fixed	Yes	Yes	Yes
Cons	0.975*** (0.024)	0.257*** (0.026)	0.241*** (0.025)
N	372	372	324
R2	0.326	0.955	0.961

Note: * * *, * * are significant at 1%, 5% and 10%, respectively, numbers in parentheses are robust standard error.

6.2. Endogenous Discussion

In order to alleviate the endogenous problems of mutual causality, the paper adopts the instrumental variable method for endogenous discussion (Table 13). First, the digital economy (DE 1), which lags behind the first order, is used as the instrumental variable. The new agricultural quality productivity in that year could not affect the development level of digital economy last year, and the development of digital economy last year laid a foundation for the development of digital economy in that year. Therefore, choosing the lag of digital economy can avoid the endogenous problem of mutual causality. Second, the interaction term of post offices (POST) and fixed telephone numbers (TELE) in 1984 and the total length of the postal road in each province were taken as the instrumental variable (Huang, Yu, & Zhang, 2019). The number of post offices and fixed phones in history represents the basis of the development of digital economy in a region, which can have a certain impact on the development of current digital economy. Simultaneously, the current agricultural productivity cannot affect the distribution of post offices and fixed phones in history, so as to avoid the endogenous problem of mutual cause and effect. Given that the 1984 data on the number of post offices and fixed phones was cross-sectional, it was not suitable for direct panel data analysis. Therefore, we constructed the tool variable as an interaction term with the total length of the postal route in each province. The results show that the first-stage F value of the three instrument variables is greater than 10, indicating that these instrument variables are not associated with weak instrument variables, that is, the selected instrument variables are valid. After considering the endogenous problem, the regression coefficient of the digital economy is still positive, and it is significant at the levels of 1%, 5%, and 5%, respectively, which further confirms the robustness of the research conclusions.

Table 13. Results of the endogeneity test.

Variable	(1) DE	(2) ANQP	(3) DE	(4) ANQP	(5) DE	(6) ANQP
DE		0.209*** (0.069)		0.506** (0.234)		0.470** (0.233)
DE1	0.598*** (0.085)					
POST			1.20e12*** (3.66e-13)			
TELE					2.24e-10*** (6.90e-11)	
Controlled variable	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed	Yes	Yes	Yes	Yes	Yes	Yes
Cons	0.137*** (0.039)	0.162*** (0.034)	0.276*** (0.040)	0.055 (0.089)	0.275*** (0.040)	0.067 (0.088)
F	49.74		10.68		10.53	
N	341	341	372	372	372	372
R2		0.963		0.949		0.951

Note: ***, ** are significant at 1%, 5% and 10%, respectively, numbers in parentheses are robust standard error.

6.3. Heterogeneity Analysis

6.3.1. Temporal Heterogeneity

The research period of this article encompasses two stages: the explosive growth stage of digital economy development (2005-2015) and the integration and collaboration stage (2016-present).

In the former stage, the government mainly focuses on promoting the construction of digital infrastructure, thus laying the precondition for the digital economy's development. In the latter stage, the government not only continues to drive the construction of digital infrastructure but also endeavors to improve the policy support system for the digital economy. For instance, through the promulgation of the Outline of Digital Economy Development Strategy and the Fourteenth Five-Year Plan for Digital Economy, the government has attached greater significance to the digital economy during these two stages.

Consequently, taking 2016 as the cut-off point, by analyzing the impact of the digital economy on new agricultural productivity during 2011-2015 and 2016-2022, we can explore the role of government support within this context. Table 14, columns (1) and (2), display the regression results for these two time periods, respectively.

The results reveal that the regression coefficient of the digital economy from 2011 to 2015 is negative yet not significant. This implies that in the absence of government support during this period, the digital economy has little effect. In contrast, the regression coefficient of the digital economy during 2016-2022 is significantly positive at the 1% level, indicating that with the strong support of the government, the digital economy can significantly promote the improvement of new agricultural productivity.

One could attribute this situation to the early lack of guidance for the development of the digital economy. As a result, relevant factors continuously flowed out of the agricultural field, causing the digital economy to have an insignificant influence on the new agricultural productivity. In the later stage, however, through the formulation of relevant preferential policies and the government's active participation, the situation has changed.

Table 14. Results of temporal heterogeneity.

Variable	(1) ANQP (2011—2015)	(2) ANQP (2016—2022)
DE	-0.167 (0.284)	0.092*** (0.033)
Controlled variable	Yes	Yes
Time fixed	Yes	Yes
Provincial fixed	Yes	Yes
Cons	0.100** (0.044)	0.319*** (0.053)
N	155	217
R2	0.961	0.973

Note: ***, ** are significant at 1%, 5% and 10%, respectively, numbers in parentheses are robust standard error.

6.3.2. Spatial Heterogeneity

There are significant differences in policy support, climate environment, cultivated land conditions, agricultural technology, and market environment among major grain-producing areas, main grain marketing areas, and balanced areas. These differences lead to varying levels of agricultural development in different regions, which, in turn, result in different impacts of the digital economy on high-quality agricultural productivity.

To further examine the heterogeneity of the digital economy regarding new quality agricultural productivity, samples from the major grain-producing areas, main grain marketing areas, and production marketing balance areas were estimated separately (Table 15).

The results indicate that in the major grain-producing areas, the impact of the digital economy on new agricultural productivity is significantly positive at the 1% level, meaning that the digital economy can drive the improvement of new agricultural productivity in this region. In the main grain marketing area, the regression coefficient of the digital economy is positive yet not significant, suggesting that the effect of the digital economy in promoting new agricultural productivity in this region is not evident. In the production marketing balance area, the regression coefficient of the digital economy is also positive but not significant, indicating that the development of the digital economy fails to promote the improvement of new quality agricultural productivity in this region.

This situation could be caused by the following factors. In the major grain-producing areas, as agriculture bears the responsibility of maintaining national food security, the local government has long been dedicated to enhancing agricultural production efficiency. Hence, more attention is paid to the construction of agricultural information infrastructure and the application of digital technology, and thus the digital economy significantly promotes new agricultural productivity. Compared to other industries, the main grain marketing area experiences relatively low economic benefits from agriculture. As a result, both the government and the public pay less attention to agriculture, and there is less financial support for relevant technologies. Therefore, the effect of the digital economy on new agricultural productivity is not significant.

Table 15. Results for spatial heterogeneity.

Variable	(1) ANQP (Major grain producing area)	(2) ANQP (Staple area)	(3) ANQP (Production and marketing balance zone)
DE	0.331*** (0.045)	0.017 (0.080)	0.006 (0.038)
Controlled variable	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
Provincial fixed	Yes	Yes	Yes
Cons	0.075** (0.032)	0.251*** (0.068)	0.184*** (0.042)
N	156	84	132
R2	0.969	0.940	0.914

Note: ***, ** are significant at 1%, 5% and 10%, respectively, numbers in parentheses are robust standard error.

7. Conclusions and Suggestions

Based on the panel data of 31 provinces from 2011 to 2022, this paper adopts the two-way fixed effect model, mediation effect model, threshold effect model, and spatial Durbin model to conduct an in-depth empirical test of the impact of China's digital economy on new agricultural quality productivity. Firstly, the study reveals that the digital economy has a significant impact on new agricultural productivity. However, this impact shows different characteristics in different time periods and regions. From 2011 and 2015, the digital economy had a negative but not significant impact on new agricultural productivity. However, from 2016 to 2022, this impact significantly increased. In terms of space, the impact of the digital economy on new agricultural quality productivity is significantly positive in the main grain-producing areas but not significant in the main grain-marketing areas and the production-marketing balance areas. Secondly, the digital economy promotes the improvement of new agricultural quality and productivity by facilitating the increase in government income, the level of scientific and technological innovation, and the level of human capital. Thirdly, the study finds that the rural education level, urban-rural information gap, and information infrastructure construction have a nonlinear effect on the digital economy's role in promoting the improvement of new agricultural quality productivity. Specifically, the rural education level and information infrastructure construction exhibit a nonlinear increasing effect, while the urban-rural information gap shows a nonlinear effect of first decreasing and then increasing. Finally, it is found that the digital economy has a positive spatial spillover effect on new agricultural productivity. The spillover degree of new agricultural productivity in neighboring provinces is higher than that in the local region.

Based on the above research conclusions, the paper gives some suggestions: (1) to improve the level of government governance. First, it is necessary to strengthen information sharing and coordination among government departments, establish a digital government management system, promote the digital transformation of government governance, and improve the efficiency and transparency of government governance. Second, we should strengthen the government digital training and improve the digital skills and information level of government staff so as to better support and guide the development of digital economy in the agricultural field. (2) Formulate government policies in accordance with local conditions. First, according to the actual situation of agricultural development in different regions, differentiated digital economy policies should be formulated, including policies and measures on financial support, tax incentives, financial support, scientific and technological support, and other aspects. Second, according to the characteristics and advantages of regional agricultural development, we should innovate the regional agricultural development model and promote the deep integration of digital economy and agricultural development. (3) Strengthen the construction of digital infrastructure. First, we should encourage the participation of private capital, provide a stable investment environment, and provide support from capital, land, and other aspects to stimulate the enthusiasm of private capital to participate in the construction of digital infrastructure. Second, we should increase the investment in rural digital infrastructure construction, ease the information gap between urban and rural areas, and promote the rational allocation of factors. (4) Improve the level of agricultural human capital. First, we need to increase the investment in rural personnel training and education, introduce online education platforms, and promote the combination of online and offline education, so as to provide sufficient education opportunities for agricultural practitioners, so that they can fully master and apply relevant agricultural digital technologies. Second, we should strengthen the construction of agricultural professionals, establish and improve the system of talent cultivation and incentive, and attract professionals to engage in agricultural work by providing good welfare benefits.

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