Can the digital economy enhance the agricultural production technical efficiency? An analysis based on panel data of prefecture-level cities in China

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Abstract

The digital economy facilitates the integration of digital resources and the upgrading of production processes in agriculture, thereby enhancing the efficiency of agricultural production technical and providing significant impetus for achieving agricultural modernization. This study utilizes a sample of 272 cities in China from 2010 to 2021, employs the entropy method to calculate the level of digital economic development, applies the SFA method to measure agricultural production technical efficiency, and empirically examines the impact of the digital economy on agricultural production technical efficiency as well as its moderating effects using panel fixed effects models, moderation effect models, and multi-period double difference models. The findings are as follows: The relationship between the digital economy and agricultural production technical efficiency follows an inverted U-shaped curve. Furthermore, analysis on moderation effects reveals that agricultural land resource endowment positively moderates this inverted U-shaped relationship while labor resource endowment negatively moderates it. Heterogeneity analysis indicates significant dimensional and regional variations in this inverted U-shaped relationship between the digital economy and agricultural production technical efficiency. Additionally, exogenous shock tests demonstrate that "Broadband China" pilot policy have a significantly positive impact on digitizing agriculture by improving agricultural production technical efficiency.

Keywords: Digital economy. Technical efficiency of agricultural production. Resource endowment. Fixed effects model. Moderation effects model.

1. Introduction

With the expansion of China's economy, the constraints on resource elements are gradually increasing. If we persist with the previous extensive development model, it will be challenging to ensure sustainability and continuity [1]. According to the data released by the National Bureau of Statistics of China, as of the end of 2023, there were approximately 477 million individuals engaged in agricultural activities residing in rural areas across China, constituting 33.84% of the total population. This represents a significant decline of 40.89% compared to the recorded figure of 807 million rural inhabitants in 2000 and a reduction by 30 percentage points relative to the overall population. Meanwhile, data indicates that China's per capita arable land area falls below half of the global average level, with agricultural labor and land resources increasingly constrained [2, 3]. In recent years, the agricultural sector has witnessed a significant surge in production costs encompassing various aspects such as seeds, pesticides, fertilizers, feedstuffs, fuel, and electricity consumption [4]. Simultaneously, labor costs have also experienced a rapid escalation. Moreover, the ongoing processes of industrialization and urbanization coupled with an increasingly aging population further exacerbate this situation by exerting additional pressure on agricultural production costs while simultaneously diminishing available arable land. The incremental increase in the supply of factors cannot sustain traditional high-speed development models that heavily rely on material input-intensive extensive agricultural growth patterns, which are no longer capable of meeting the current social development needs [5]. The optimization of resource allocation, the promotion of prosperity in agricultural and rural industries, and the enhancement of technical efficiency in agricultural production are imperative to address the current challenges pertaining to agricultural resources in China. The Chinese government has explicitly expressed its commitment to prioritize agriculture and rural development, aiming to expedite the establishment of a robust agrarian powerhouse while effectively promoting the revitalization of rural industries. This entails continuous enhancements in land output rates, labor productivity, and resource utilization.

Improved technical efficiency in agricultural production is crucial for the development of modern agriculture [6]. The key to transitioning from traditional to modern agriculture lies in the adoption of innovative technologies. Since the turn of the century, China has witnessed remarkable advancements in its digital infrastructure, with cutting-edge technologies such as big data, artificial intelligence, and mobile internet finding extensive applications across various socio-economic domains. The information infrastructure continues to undergo improvements and upgrades, while internet penetration rates are gradually increasing. Emerging technologies, such as digital technology, are rapidly integrating into various sectors, including agriculture which is deeply embracing digital elements. By effectively integrating digital resources and upgrading production processes, agricultural production technical efficiency can be significantly enhanced [7]. The advent of digital and information technology has presented innumerable opportunities for rural areas, garnering global interest and attention [8, 9].

Currently, extensive research has been conducted to investigate the impact of the digital economy on agricultural industry revitalization, income growth, and efficiency transformation [10-13]. In studies investigating the impact of the digital economy on agricultural production technical efficiency, some scholars argue for its positive influence [14], while also emphasizing the pivotal role played by digital technology [13, 15] and Agricultural Informatization [16, 17] in empowering agricultural development within the realm of the digital economy. However, divergent perspectives exist among scholars who posit challenges pertaining to power distribution, profit allocation, and policy incentives in fostering the nexus between the digital economy or digitization and technical efficiency in agricultural production [18-21]. The divergence in perspectives may stem from the limited utilization of simple linear relationships in existing research, which fails to capture the intricate and comprehensive nature of the correlation between the digital economy and agricultural production technical efficiency. Furthermore, contextual factors that exert influence on this relationship, particularly regional resource endowments, have been overlooked in previous studies.

Drawing upon an extensive review of existing literature, this study utilizes a sample of 272 prefecture-level cities and above in China from 2010 to 2021 as the basis for investigation. Firstly, it examines the intricate relationship between the digital economy and agricultural production technical efficiency. Secondly, it explores how agricultural resource endowment influences the aforementioned relationship between the digital economy and agricultural production technical efficiency. Finally, it conducts a comprehensive analysis on the heterogeneous impact of digitization as well as the exogenous effects of policies related to the digital economy, with an aim to offer valuable policy insights and practical guidance for advancing agricultural modernization.

2 Theoretical Analysis and Research Hypotheses

2.1 The direct impact

The agricultural production technical efficiency refers to the ratio between the actual output and the potential maximum output achieved by agricultural producers when inputting specific factors under existing technological conditions. It serves as an indicator of technology utilization and represents a crucial aspect of agricultural development quality. The digital economy has facilitated the organic integration of data elements with other factors, thereby driving the transformation, upgrading, and efficiency reform of traditional industries. It plays a pivotal role in fostering innovation and development of emerging business models [22]. Simultaneously, through enhancing the efficiency of information transmission and reducing acquisition costs [23], the digital economy can facilitate investment-production alignment, augment cognitive capabilities, as well as mitigate resource wastage and idle capacity. Requisite prerequisites are indispensable for fostering advancements in agricultural production technical efficiency. The initial stage of digital economy development has witnessed the driving force of scientific and technological advancements, leading to enhanced technical efficiency in agricultural production; However, the subsequent emergence of various constraining factors may result in a deceleration or even cessation of its growth [24]. Moreover, throughout this process, the costs associated with implementing technology exceed their incremental value [25]. For instance, in situations where education levels among the agricultural labor force are low or during early stages of digital economic development when the labor force encounters non-adaptive shocks, it is possible to observe a decrease in resource allocation efficiency while simultaneously widening the gap between agricultural production and the effective frontier [26]. The advancement of digital economic development at higher levels may pose greater challenges in bridging the urban-rural "digital divide" [27, 28], thereby presenting additional barriers for women and youth [29]. This aligns with the concept of "law disruption" - referring to the challenges faced by the economy and society in keeping pace with rapid technological advancements, particularly impacting vulnerable agricultural communities. Consequently, this article posits that as the digital economy evolves, there exists an initial increase followed by a subsequent decrease in technical efficiency of agricultural production. Based on this, we propose the hypothesis:

Hypothesis H1: *The impact of digital economy on agricultural production technical efficiency shows an inverted U-shaped relationship.*

2.2. Effect of adjustment

Given China's vast territory and complex terrain, there exist significant disparities in agricultural resource endowment across regions. Therefore, it is imperative to investigate how these institutional differences impact the relationship between digital economy and technical efficiency of agricultural production. Early economists held a favorable stance towards the role of natural resources in economic development; however, since the 1980s, an increasing number of economists have raised doubts regarding this perspective. Brunnschweiler and Bulte (2008) [30] contend that there exists no significant correlation between resource abundance and sluggish economic growth. Therefore, this paper posits that the overall level of resource endowment does not significantly moderate the relationship between the digital economy and agricultural production technical efficiency. However, as an indispensable component of agricultural resource endowment, land resources exert a profound influence on efficient allocation for farmers' employment [31], agricultural production, and macroeconomic growth. A higher per capita land operating scale facilitates the adoption and implementation of digital technology, addressing challenges such as an aging rural labor force in the agricultural labor market and escalating labor costs. Optimizing the allocation of land and labor factors contributes to enhancing agricultural production efficiency [32]. Therefore, this paper posits that the endowment of agricultural land resources can enhance an inverted U-shaped relationship between the digital economy and agricultural production technical efficiency. Conversely, the endowment of agricultural labor resources may attenuate this inverted U-shaped relationship. Based on the aforementioned rationale, we propose the following hypotheses:

Hypothesis H2a: *The agricultural resource endowment does not exert a significant moderating effect on the relationship between the digital economy and agricultural production technical efficiency.*

Hypothesis H2b: *The endowment of agricultural land resources serves as a positive moderator in the inverted U-shaped relationship between the digital economy and agricultural production technical efficiency, thereby reinforcing their association..*

Hypothesis H2c: *The endowment of agricultural labor resources acts as a negative moderator in the inverted U-shaped relationship between the digital economy and agricultural production technical efficiency, thereby attenuating their inverted U-shaped association.*

3 Materials and Methods

3.1. Model construction

The above research hypothesis is tested by constructing a fundamental model based on the direct transmission mechanism：

$$ATE_{it}=\beta_0+\beta_1 Dig_{it}+\beta_2 Dig_{it}^2+\beta_c Z_{ijt}+\mu_i+\delta_t+\varepsilon_{it} \tag{1}$$

In equation (1), ATE_{it} represents the agricultural production technical efficiency of city i in period t, Dig_{it} represents the level of digital economic development of city i in period t, and Dig_{it}^2 denotes the squared term of the level of digital economic development in period t for city i. Vector Z_{ijt} represents a series of control variables; μ_i denotes individual fixed effects that remain constant over time for city i, while δ_t controls for time fixed effects; ε_{it} accounts for random disturbances.

To investigate the potential moderating effect of agricultural resource endowment on the relationship between the digital economy and agricultural production technical efficiency, we constructed a digital economy index along with its quadratic term, as well as an interaction term incorporating resource endowment. The study investigated the moderating role by examining the relationship between the interaction term and agricultural production technical efficiency. Specifically, in addition to conducting significance tests for coefficients β_1 and β_2 in regression model (1), a moderation variable M was introduced, along with interaction terms involving Dig_{it} and Dig_{it}^2, resulting in formulation of regression equation (2) as follows.：

$$ATE_{it}=\beta_0+\beta_1 Dig_{it}+\beta_2 Dig_{it}^2+\beta_3 Dig_{it}M_{ijt}+\beta_4 Dig_{it}^2 M_{ijt}+\beta_5 M_{ijt}+\beta_c Z_{ijt}+\mu_i+\delta_t+\varepsilon_{it} \tag{2}$$

3.2. Variables selection

3.2.1. Dependent variable

Agricultural Production Technical Efficiency (ATE). This study employs five indicators, namely land, labor force, fertilizer, mechanical power, and electricity consumption as input variables. The land input is quantified by the total cultivated area of crops; the labor force input is represented by the number of employees in the primary industry; the fertilizer input is measured by the amount of pure applied agricultural fertilizers; the mechanical power input is assessed based on the total power of agricultural machinery; and finally, electricity consumption is determined through agricultural electricity usage. The output variable employed is the aggregate value of agricultural, forestry, animal husbandry, and fishery production. The stochastic frontier approach (SFA) model was selected as the evaluation methodology due to its appropriateness in estimating agricultural production efficiency [33]. The proposed approach considers the inherent randomness and diversity characteristics of agricultural production, thus enhancing its applicability. Given the uncertainty surrounding the specific form of the agricultural production function, this study employs a more flexible transcendental logarithmic production function for estimation purposes, thereby mitigating potential errors arising from incorrect assumptions.

3.2.2. Explanation of variables

Digital Economy (Dig). Based on Huang Huiqun et al.'s (2019) [34] approach, comprehensively assesses its developmental level using indicators such as internet penetration rate, employment status, output status, mobile phone adoption rate, and digital financial inclusion through the entropy method. The aforementioned indicators are quantified by statistics such as the number of individuals utilizing broadband access to the Internet, the proportion of computer service and software industry employees in urban areas, the overall count of telecommunications services per capita, and the mobile phone penetration rate (number of mobile phones used per 100 people). "Digital Financial Inclusion" employs the "China Digital Financial Inclusion Index," a collaborative effort between Peking University's Digital Finance Research Center and Ant Financial Group.

3.2.3. Regulation of variables

Resource Endowment Level (ResE). The term "resource endowment" in this article primarily refers to the abundance of factors that exert a substantial influence on agricultural production costs, encompassing land, labor force, technology, and policy support. In accordance with existing research, per capita arable land area (Land_ResE) is employed as a measure of agricultural land resource endowment. The density of agricultural practitioners per unit area (Lab_ResE) signifies the level of labor force resource endowment in agriculture. Agricultural machinery power per unit area (TE_ResE) serves as an indicator for technological resource endowment in agriculture. The allocation ratio of budget for agricultural forestry and water affairs (Pol_ResE) serves as an indicator of the level of policy resource endowment in agriculture. To ensure objective evaluation of agricultural resource endowments across different cities and mitigate potential biases arising from differences in measurement scales among indicators, each variable is first standardized using extreme value normalization to achieve mapping within the [0, 1] range. Subsequently, the standardized values for each aspect of agricultural resource endowments are aggregated to represent comprehensive resource endowment.

3.2.4. Control variables

According to the existing literature, control variables influencing agricultural and urban development include population density (PDe), city economic density (UED), level of financial development (Fina), degree of openness to the outside world (Open), extent of government intervention (Gov), and advancement in industrial structure (ISA). Population density refers to the number of individuals residing per unit area (people/km²), reflecting the concentration of population and efficiency in utilizing social resources within an urban setting. Urban economic density measures the strength or weakness of economic activities in a region by calculating the gross domestic product per unit area (thousand yuan/square kilometer). The level of financial development is evaluated by comparing the balance between loans and deposits from financial institutions at year-end with regional GDP; this indicator reflects the role played by the financial system in supporting the real economy. The degree of openness to international trade is measured by comparing import-export value with regional GDP, revealing a region's position in global commerce. The extent of government intervention is assessed by comparing local fiscal expenditure with regional GDP; this indicator primarily focuses on evaluating governments' size and role in economic operations, including provision of public services and infrastructure construction. Lastly, advancements in industrial structure can be calculated by comparing added value from tertiary industry with added value from secondary industry; this indicator reveals a city or region's transformation and upgrading process regarding its industrial structure.

3.3. Data source

The study examines the impact of the digital economy on agricultural production technical efficiency through balanced panel tests, focusing on 272 prefecture-level and above cities in China from 2010 to 2021. The selection of research samples primarily relies on the availability of sample data. Given the extensive collection work required for a large number of city samples, certain data needs to be manually collected and meticulously screened to ensure its quality and reliability. The time range from 2010 to 2021 was chosen as the research sample considering China's rapid economic development and flourishing digital economy during this period. By taking these factors into account, the selected samples can better reflect the general patterns and variations in the relationship between digital economy and agricultural production technical efficiency across different levels and types of cities in China, thereby providing a scientific basis and policy recommendations for further exploration of synergistic development between digital economy and agriculture. The data utilized are sourced from "China City Statistical Yearbook" as well as some national economic and social development statistical bulletins of prefecture-level cities, with inclusive finance data obtained from "Peking University Inclusive Finance Index" project team's released index.

4. Results and Analysis

4.1. Spatial and temporal characteristics of agricultural production technology efficiency

The kernel density estimation depicted in Figure 1 illustrates the distribution of agricultural production technical efficiency across Chinese cities during even-numbered years within the sample period. From a temporal perspective, it is evident that the kernel density function gradually shifts to the right, indicating an overall improvement in national agricultural production technical efficiency over time. Moreover, there is a trend of decreasing and then increasing kernel density gaps between 2010 and 2016, suggesting that during this timeframe, cities with high-level efficiency were more dispersed. However, from 2016 to 2020, there was an increase in peak values implying a concentration of cities with high-level efficiency once again. In terms of spatial dimensionality, all curves depicting agricultural production technical efficiency for different years exhibit a right-skewed pattern which indicates that most cities still have potential for improving their agricultural production technical efficiency. Additionally, compared to developed countries China's efforts to enhance its agricultural productivity face multiple challenges.

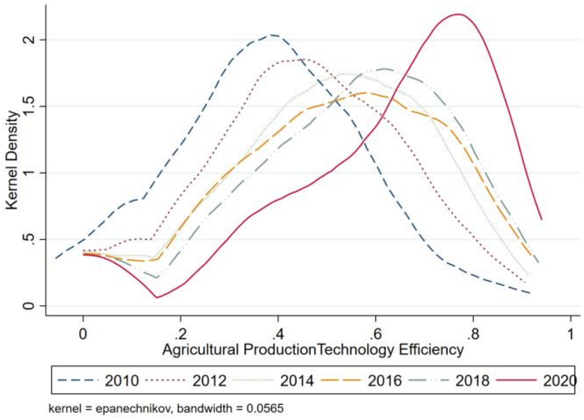

Figure 1: Kernel density of agricultural production technical efficiency.

4.2. Nonlinear relationship test between digital economy and agricultural production technical efficiency

In empirical studies, it is common to incorporate nonlinear terms into the model in order to examine U-shaped nonlinear relationships. However, some scholars have raised concerns regarding this approach [35, 36]. Therefore, following the general framework proposed by Jo (2010) [35], this study aims to assess whether a nonlinear relationship exists between two variables and specifically test for the presence of a U-shaped nonlinearity within a defined range. The results indicate that the calculated turning point of 0.79 falls within the range of digital economy values from 0.00 to 0.96, thereby confirming its alignment with the data range and enabling rejection of the null hypothesis at a significance level of 1%. Additionally, it is noteworthy that the results exhibit a negative slope, providing support for the hypothesis positing an inverted U-shaped nonlinear relationship between digital economy and agricultural production technical efficiency.

4.3. Benchmark regression results and analysis

The Hausman test is a commonly used method for determining whether to employ a fixed effects or random effects model in panel data analysis. The results of the test conducted using Stata16 are presented in Table 1, revealing a significant p-value of 0.0000. Consequently, we decisively reject the null hypothesis and establish that a fixed effects model should be employed instead of a random effects model. Subsequently, annual dummy variables are incorporated to investigate the presence of individual time effects. The results presented in Table 2 demonstrate the joint significance test for all annual dummy variables, accounting for time effects. The obtained p-value of 0.0000 strongly rejects the null hypothesis that there are no time effects in the model. Consequently, we opt for a two-way fixed effects model and employ cluster-robust standard errors to address potential heteroscedasticity issues.

Table 1: Hausman test.

Hypothesis test: Null hypothesis: The disturbance term is not correlated with the explanatory variables
chi2(8)=(b-B)'[(V_b-V_B)^(-1)](b-B) =70.86 Prob>chi2=0.0000 chi2(8)=(b-B)'[(V_b-V_B)^(-1)](b-B)(V_b-V_B Non-definite)

Table 2: Joint significance of annual dummy variables.

(1)year2=0	(7)year8=0
(2)year3=0	(8)year9=0
(3)year4=0	(9)year10=0
(4)year5=0	(10)year11=0
(5)year6=0	(11)year12=0
(6)year7=0	
F(9，282)=29.32	Prob>F=0.0000

The results of four regression models are presented in Table 3, encompassing (1) Fixed Effects Two-Way Dynamic Error Correction Model (FE_TW_DED), (2) Linear Correlation Fixed Effects Two-Way Dynamic Error Correction Model without squared terms (Lin_corr), (3) Ordinary Least Squares Mixed Regression Model (OLS), and (4) Fixed Effects Model (FE). The results indicate that column (1) exhibits the highest R-squared value, suggesting a superior overall fit. The comparison between column (2) and column (1) enables a more precise determination of the nonlinear relationship between digital economy and agricultural production technical efficiency. In column (1), a statistically significant positive correlation between the digital economy and agricultural production technical efficiency is observed at a significance level of 1%. However, at a significance level of 5%, there is an inverse correlation with the quadratic term of the digital economy. This implies that the digital economy exerts an inverted U-shaped influence on the agricultural production technical efficiency. This suggests that the development of the digital economy can significantly enhance the agricultural production technical efficiency to a certain extent. The widespread adoption of digital technology in agriculture enables farmers to access more precise information and data support through platforms such as the Internet and big data analysis, thereby optimizing agricultural production processes. However, it is important to acknowledge that when the growth of the digital economy surpasses a certain threshold, challenges arise due to agriculture's limited capacity to keep pace with exponential advancements in digital technology. Additionally, considering the prevalent issue of a "digital divide" resulting from disparities between countries with different national conditions, it becomes necessary to recognize that implementing a uniform policy may hinder technical efficiency in agricultural production. Therefore, flexible measures tailored to specific circumstances should be adopted when promoting the integration of traditional agriculture and digital economy development while also making adjustments and improvements based on local realities.

The control variables, namely the degree of openness and advancement in industrial structure, exhibit a positive correlation with enhancing agricultural production technical efficiency. A higher degree of openness typically leads to increased market competition and resource flow, thereby fostering a greater emphasis on efficiency and innovation within the agricultural sector. Simultaneously, advanced industrial structures in other industries such as manufacturing and services often offer enhanced support and demand, presenting additional opportunities for agricultural technological advancements and driving improvements in technical efficiency of agricultural production. Urban economic density, level of financial development, and extent of government intervention have significant negative impacts. An increase in urban economic density may lead to excessive utilization and improper allocation of agricultural resources, thereby constraining efficiency improvements and resulting in adverse consequences. A high level of financial development may foster an over-reliance on financial support within the agricultural sector, leading to inappropriate resource allocation, intensified market competition, increased risks, etc., which can negatively impact the efficiency of agricultural production technology. Excessive government intervention can result in irrational resource allocation, market failures, weakened market competitiveness, and diminished independent innovation capabilities within agriculture while impeding scientific advancements in farmland management and market-oriented development. Therefore, it is imperative to strike a balance during the process of urbanization when promoting enhanced productivity benefits through scientific means; make appropriate adjustments regarding strengthening financial support; adaptively modify government intervention strategies to facilitate higher levels of scientific cultivation.

Table 3: Results of the benchmark regression analysis.

	(1) FE_TW_DED	(2) Lin_corr	(3) OLS	(4) FE
Dig	0.258*** (2.74)	0.030 (0.66)	1.183*** (17.19)	1.217*** (17.83)
Dig2	-0.241** (-2.25)		-0.799*** (-9.32)	-0.835*** (-9.92)
PDe	0.001 (0.09)	0.001 (0.05)	-0.018 (-1.52)	-0.021 (-1.30)
UED	-0.020** (-2.24)	-0.024*** (-2.70)	-0.001 (-0.19)	0.003 (0.53)
Fina	-0.014** (-2.43)	-0.015** (-2.41)	-0.004 (-1.09)	-0.005 (-1.45)
Open	0.332* (1.90)	0.337* (1.91)	0.408** (2.52)	0.411** (2.52)
Gov	-0.146** (-1.97)	-0.144* (-1.92)	-0.267*** (-3.72)	-0.250*** (-3.45)
ISA	0.022* (1.77)	0.020* (1.65)	0.077*** (7.21)	0.078*** (7.20)
_cons	0.362*** （0.10）	0.403*** (4.39)	0.292*** (4.22)	0.298*** (3.17)
Time FE	YES	YES	YES	NO
City FE	YES	YES	YES	YES
Observations	3264	3264	3264	3264
Prob>chi2	0.000	0.000	0.000	0.000
R-sq	0.592	0.591	0.460	0.460

Note: t statistics in parentheses; ***, **, and * indicate significant at the 1%, 5%, and 10% statistical levels, respectively.

The study further conducted an analysis to examine the moderating effects of overall agricultural resource endowment and sub-category resource endowments on the relationship between digital economy and technical efficiency in agricultural production. The regression results for (1) comprehensive agricultural resource endowment (ResE), (2) agricultural land resource endowment (Land_ResE), (3) agricultural labor force resource endowment (Labor_ResE), (4) agricultural technology resource endowment (TE_ResE), and (5) agricultural policy resource endowment (Pol_ResE) are presented in Table 4. Overall, the results suggest that not all levels of resource endowments significantly moderate the relationship between digital economy and agricultural production technical efficiency. Specifically, as presented in Table 1, column (1), the interaction term coefficient between overall resource endowment level and digital economy is found to be statistically insignificant. This suggests that the overall level of resource endowment has no significant impact on the moderating effect, thus providing support for hypothesis H2a. Based on the regression results in column (2) and at a significance level of 1%, there is a positive association observed between the quadratic term of digital economy and the interaction term involving agricultural land resource endowment. This finding indicates that agricultural land resource endowment positively strengthens the inverted U-shaped relationship, thereby further validating hypothesis H2b. Conversely, in column (3) of the regression results, a statistically significant negative coefficient is observed for the interaction term between the quadratic term of digital economy and agricultural labor resource endowment at a significance level of 1%. This finding suggests that agricultural labor resource endowment has a detrimental effect on weakening the inverted U-shaped relationship, thereby providing further support for hypothesis H2c. However, it is noteworthy that columns (4) and (5) of the regression results reveal non-significant coefficients for both interaction terms, indicating no discernible influence from agricultural technology resource endowment or agricultural policy resource endowment on moderation effects.

Table 4: Regression results of the adjustment effect of agricultural resource endowment.

	(1) ResE	(2) Land_ResE	(3) Lab_ResE	(4) TE_ResE	(5) Pol_ResE
Dig	0.293*** (0.08)	0.296*** (0.07)	0.338*** (0.08)	0.292*** (0.07)	0.292*** (0.07)
Dig2	-0.292*** (0.07)	-0.274*** (0.07)	-0.337*** (0.07)	-0.291*** (0.07)	-0.291*** (0.07)
m	0.003*** (0.00)	0.544** (0.26)	0.069 (0.05)	-0.642*** (0.13)	0.003*** (0.00)
Dig×m	-0.011 (0.01)	-6.175* (3.24)	-2.228** (1.02)	2.482 (1.58)	0.011 (0.01)
Dig2×m	-0.009 (0.01)	17.325*** (5.32)	-4.643*** (1.38)	-2.018 (1.95)	-0.009 (0.00)
_cons	0.284*** （0.04）	0.371*** (0.04)	0.306*** (0.05)	0.207*** (0.05)	0.286*** (0.04)
Controlled	YES	YES	YES	YES	YES
TWFE	YES	YES	YES	YES	YES
Observations	3264	3264	3264	3264	3264
Prob>chi2	0.000	0.000	0.000	0.000	0.000
R-sq	0.612	0.595	0.597	0.612	0.612

Note: t statistics in parentheses; ***, **, and * indicate significant at the 1%, 5%, and 10% statisticallevels, respectively.

4.4. Robustness testing

4.4.1. Testing by adjusting the variable measurement method

In order to enhance the stability of the research findings, adjustments were made to the measurement methods for both the explanatory and dependent variables, followed by robustness tests. Firstly, in terms of adjusting the explanatory variable, Principal Component Analysis (PCA) was employed to compute a novel variable termed as Digital Economy Development Index. The estimation results are presented in column (1) of Table 5. Although there were slight variations in parameter estimates between alternative variables and the explanatory variable, their signs remained unchanged and all exhibited statistical significance at a 1% level. Meanwhile, the results from columns (2) and (3) demonstrate that land resource endowment and labor resource endowment continue to exert a regulatory influence, aligning with the analysis of benchmark regression findings. Moreover, in terms of adjusting the dependent variable, agricultural production technical efficiency was assessed using Data Envelopment Analysis (DEA), with the estimated outcomes presented in columns (4) to (6) of Table 5. The signs and significance levels of key parameters remain consistent. Consequently, it can be inferred that this study's findings are robust and reliable.

Table 5: The present study presents the robustness test results of adjusting explanatory variables and measuring methods for the dependent variable.

	(1) PCA	(2) P_Land_ResE	(3) P_Lab_ResE	(4) DEA	(5) D_Land_ResE	(6) D_Lab_ResE
Dig	0.020**	0.023***	0.024***	0.227***	0.231***	0.233***
	(2.42)	(3.14)	(3.29)	(2.13)	(3.14)	(3.53)
Dig2	-0.007*	-0.008***	-0.010***	-0.231**	-0.221***	-0.523***
	(-1.94)	(-3.43)	(-4.12)	(-2.42)	(-4.12)	(-3.93)
m		0.528**	0.069		0.678*	0.163
		(2.00)	(1.54)		(0.41)	(0.15)
Dig×m		-6.077*	2.125**		-7.051*	-3.481**
		(-1.87)	(2.09)		(3.08)	(2.11)
Dig2×m		17.010***	-4.485***		13.538**	-6.462**
		(3.20)	(-3.26)		(4.53)	(2.67)
_cons	0.407***	0.449***	0.402***	0.458***	0.476***	0.391***
	(4.38)	(10.39)	(9.80)	(0.13)	(0.51)	(0.31)
Controlled	YES	YES	YES	YES	YES	YES
TWFE	YES	YES	YES	YES	YES	YES
Observations	3264	3264	3264	3264	3264	3264
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000
R-sq	0.592	0.595	0.596	0.460	0.461	0.529

Note: t statistics in parentheses; ***, **, and * indicate significant at the 1%, 5%, and 10% statisticallevels, respectively.

4.4.2. Testing by instrumental variable method

In order to address potential endogeneity issues, this study has considered various factors that may influence agricultural production technical efficiency and has partially mitigated endogeneity problems caused by omitted variable bias. However, to eliminate the confounding effects of other factors on the results, an instrumental variable approach is further employed to validate the robustness of the findings. Firstly, in accordance with Huang et al. (2019)[34], the selection of the number of fixed telephone lines in each city in 1984 as an instrumental variable for measuring the level of digital economic development is a reasonable inference. Therefore, based on the research conducted by Yi Enwen et al. (2023)[37], we developed an instrumental variable to measure the digital economy index of each city in a specific year. This was achieved by multiplying the fixed telephone quantity in 1984 with the previous year's national internet user count. According to the reported results from the first-stage regression analysis, as shown in Table 6, column (1), it is evident that the instrumental variable exerts a statistically significant positive impact on digital economic development, thereby satisfying both theoretical and statistical requirements. The results of the second-stage regression demonstrate that even after accounting for endogeneity concerns, the digital economy continues to exert a significant positive impact on advancements in agricultural production technical efficiency. Moreover, we employed a two-stage least squares estimation technique and selected a lag of two periods in the development indicators of the digital economy as instrumental variables to assess their validity. When selecting instrumental variables, there exists a clear correlation between the instrumental variable of utilizing lagged values of digital economic development indicators and the dependent variable. Consequently, weak instrument heterogeneity is absent, and it satisfies the relevant constraint conditions. Moreover, incorporating lagged values of digital development indicators as external constraint conditions ensures that current disturbances do not impact previous results for this indicator, thereby satisfying the external constraint conditions. The analysis conclusion in column (4) of Table 6 demonstrates consistent results when employing fixed telephone lines per ten thousand people in each city as an exogenous instrument. Overall, after effectively addressing endogeneity concerns, it can be inferred that digital economic development continues to significantly enhance agricultural production technical efficiency, thereby indicating the robustness of our research findings.

Table 6: Robustness test results of instrumental variable method.

	IV：Fixed telephone lines per 10,000 people in each city			IV：The lag of two periods in the development indicators of the digital economy		
	First stage of regression	Second stage regression		First stage of regression	Second stage regression	
	(1)	(2)	(3)	(4)	(5)	(6)
	Dig	TE (Land_ResE)	TE(Lab_ResE)	Dig	TE (Land_ResE)	TE(Lab_ResE)
IV	0.004***			1.122***		
	(0.00)			(0.02)		
Dig		1.087***	1.569***		0.258**	0.723***
		(0.39)	(0.37)		(0.11)	(0.12)
Dig2		-0.887*	-1.676***		0.192	-0.540***
		(0.46)	(0.45)		(0.15)	(0.16)
m		1.267*	0.106*		2.343***	0.012
		(0.73)	(0.05)		(0.72)	(0.02)
Dig×m		-30.279***	4.282***		-27.247***	1.869***
		(8.91)	(1.46)		(9.18)	(0.67)
Dig2×m		65.861***	-9.238***		70.228***	-3.574***
		(15.12)	(2.03)		(15.17)	(0.94)
_cons	0.281***	0.380***	0.022	0.029***	0.447***	0.022**
	(0.01)	(0.06)	(0.03)	(0.01)	(0.04)	(0.01)

Note: t statistics in parentheses; ***, **, and * indicate significant at the 1%, 5%, and 10% statisticallevels, respectively.

5. Further analysis

5.1. Heterogeneity analysis

5.1.1. Analysis of heterogeneity in various dimensions of the digital economy

In current research, there is a lack of consensus regarding the dimensions for measuring the level of development in the digital economy. To address this gap and considering the intricate nature of agricultural production, this study further investigates the association between the digital economy and technical efficiency in agricultural production from five distinct perspectives: internet penetration rate, employment status related to internet usage, output status linked to internet activities, mobile phone adoption rate, and digital financial inclusion. The findings are presented in Table 7. Based on the results in column (1), it is evident that the one-time coefficient for internet penetration rate exhibits statistical significance, while the quadratic term shows a non-significant negative effect. This suggests that there may be a positive linear relationship between internet penetration rate and agricultural production technical efficiency. The increasing rate of internet penetration has provided a plethora of information resources, technological support, management tools, and market opportunities to enhance agricultural production efficiency. This phenomenon has facilitated the modernization and digitization of agricultural production methods, thereby augmenting productivity and quality. The coefficients in columns (2) and (3) do not exhibit a statistically significant impact on the technical efficiency of agricultural production with respect to internet employment status or internet output status. However, in columns (4) and (5), the linear term coefficient shows a significantly positive effect, while the quadratic term coefficient demonstrates a significantly negative effect, which is consistent with the findings of our benchmark results. The disparity in coefficient magnitude arises from the absence of standardized units across diverse dimensional variables. It is evident that the non-linear U-shaped impact of the digital economy on agricultural production technical efficiency primarily emanates from two dimensions: mobile phone adoption rate and digital financial inclusion. During the initial stages, as the number of mobile internet users increased, farmers gained enhanced access to information resources through devices like mobile phones. Digital financial inclusion has facilitated convenient access to financial services for farmers through electronic payments, online loans, and other digital means, thereby fostering the advancement of land transfer, large-scale cultivation, and modern facility construction. However, in subsequent stages of development, certain challenges have emerged. The progression of mobile internet and inclusive finance can further stimulate rural labor migration and entrepreneurial activities among farmers[38, 39], exacerbating the adverse effects of rural aging on agricultural production while also serving as a significant barrier impeding the enhancement of technical efficiency in agricultural production.

Table 7: Heterogeneity analysis of various dimensions in the digital economy.

	(1) Internet penetration rate	(2) Internet employment status	(3) Internet output status	(4) Mobile phone adoption rate	(5) Digital financial inclusion
Dig_i	0.003* (0.00)	0.812 (0.51)	0.515 (0.35)	0.004*** (0.00)	0.001*** (0.00)
Dig_i2	-0.000 (0.00)	-3.950 (3.43)	-1.919 (1.26)	-0.001** (0.00)	-0.001*** (0.00)
_cons	0.353*** (0.10)	0.375*** (0.10)	0.371*** (0.10)	0.324*** (0.10)	0.382*** (0.09)
Controlled	YES	YES	YES	YES	YES
TWFE	YES	YES	YES	YES	YES
Observations	3264	3264	3264	3264	3264

Prob>chi2	0.000	0.000	0.000	0.000	0.000
R-sq	0.592	0.591	0.591	0.592	0.594

Note: t statistics in parentheses; ***, **, and * indicate significant at the 1%, 5%, and 10% statistical levels, respectively.

5.1.2. Regional heterogeneity

Due to disparities in resource allocation and developmental stages, there exist substantial variations in both the level of digital economy development and the quality of economic progress concerning regional distribution. Based on their respective provincial geographical locations, these cities can be classified into two categories: eastern and central-western cities. Central cities encompass direct-controlled municipalities, sub-provincial cities, and provincial capitals, while outer cities comprise all others. According to the analysis results presented in Table 8, a consistent positive-negative relationship is observed between the coefficients of eastern cities/central cities and benchmark regression outcomes, indicating an inverted U-shaped association between digital economy and agricultural production technical efficiency. With the continuous innovation and application of digital technology, an ecosystem centered around internet, big data, artificial intelligence (AI), etc., has gradually emerged in eastern and central cities, leading to enhanced levels of technical efficiency in agricultural production. However, over time, these cities are also facing increasing challenges. In contrast to the benchmark regression results, a reverse U-shaped relationship is observed in central-western and outer cities, indicating a "mediocre middle" effect. When the level of digital economic development is either high or low, the benefits of agricultural production technical efficiency exceed those when the level of digital economic development is at a moderate level. This phenomenon may be attributed to increased investment in resources and efforts into agriculture during the early stages or saturation point of the digital economy, leading to enhanced agricultural production technical efficiency through the introduction of advanced technological methods. However, as the digital economy reaches a moderate level, attention may shift towards other industries, resulting in insufficient resources for promoting agricultural technological innovation and application.

Table 8: Analysis of regional heterogeneity.

	(1) Eastern Cities	(2) Central-Western cities	(3) Central Cities	(4) Outer Cities
Dig	1.226***	0.131	0.772***	-0.270*
	(0.35)	(0.08)	(0.18)	(0.14)
Dig2	-0.913**	0.546***	-0.717***	1.187**
	(0.37)	(0.12)	(0.20)	(0.22)
_cons	0.363***	0.413***	0.159***	0.493***
	(0.14)	(0.03)	(0.14)	(0.03)
Controlled	YES	YES	YES	YES
TWFE	YES	YES	YES	YES
Observations	1029	2235	349	2915
Prob>chi2	0.000	0.000	0.000	0.000
R-sq	0.141	0.274	0.176	0.147

Note: t statistics in parentheses; ***, **, and * indicate significant at the 1%, 5%, and 10% statistical levels, respectively.

5.2. External shock inspection

The article further employs the external policy intervention of upgrading network infrastructure in the pilot project "Broadband China" and utilizes a multi-period difference-in-differences (DID) method to assess the impact effects on both digital economy and agricultural production technical efficiency. The "Broadband China" strategy and implementation plan were formulated in accordance with the requirements outlined in the National Informatization Development Strategy for 2006-2020, aiming to progressively advance the construction of broadband and other network infrastructure. A total of 120 cities/groups were selected as demonstration sites for "Broadband China" during the years 2014, 2015, and 2016. Following their selection as demonstration cities/groups, local areas will endeavor to augment the number of broadband users, expedite broadband network speed, and expand network coverage to foster economic and social development.

Drawing on the research conducted by Beck et al. (2010) [40], we employ a multi-period Difference-in-Differences (DID) model to examine the overall impact of the "Broadband China" pilot policy on agricultural production technical efficiency. To address the potential estimation bias arising from non-random selection in the experimental group, which was determined based on crucial decision factors such as economic development level, geographical location, and resource endowment of each city, we adopt an approach similar to Edmonds et al. (2010) [41] by incorporating interaction terms between the potential decision factors and time linear trends into the control variables. Specifically, these decision factors encompass whether the city falls within the Yangtze River Economic Belt, whether it is located in the eastern region, and whether it qualifies as a central city (wherein definitions for both eastern region and central cities align with those previously mentioned). The precise formulation is presented as Equation (3).

$$ATE_{it}=\alpha_0+\alpha_1 DID+\alpha_c Z_{ijt}+\alpha_d T_t D_{ijt}+\mu_i+\delta_t+\varepsilon_{it} \quad (3)$$

The equation employs the use of a dummy variable, DID, to handle categorical variables. Specifically, if a city is chosen as a pilot city for "Broadband China" in a given year, it is assigned a value of 1; otherwise, it is assigned a value of 0. TtDijt represents the interaction term between decision factors and linear time trends.

According to the Difference-in-Differences (DID) methodology, a crucial assumption for assessing the pilot policy of "Broadband China" lies in employing parallel trend tests. Figure 2 illustrates the dynamic changes in technical efficiency of agricultural production prior to and subsequent to policy implementation. After conducting significance tests, the regression coefficients were validated two years following policy implementation, indicating that the pilot program of "Broadband China" has exerted an impact despite a lag effect lasting for two years. As the policy progresses, both the magnitude and statistical significance of the regression coefficients have increased, implying a gradual widening disparity in digital economic development between pilot cities and non-pilot cities.

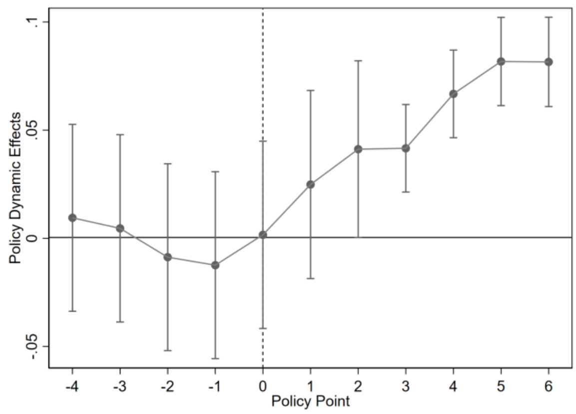

Figure 2: Parallel trend test.

The benchmark regression results are presented in Table 9. Column (1), which does not consider control variables, demonstrates a significant positive impact of the "Broadband China" pilot policy on agricultural production technical efficiency. To address the potential influence of increasing levels of urban digital economic development on policy implementation, column (2) incorporates individual and time fixed effects based on column (1) as controls. Remarkably, even after controlling for these factors, the "Broadband China" pilot policy remains statistically significant at the 1% level. After incorporating control variables, both with and without fixed effects (column (3)), as well as when considering fixed effects alone (column (4)), all exhibit positive and statistically significant regression coefficients for the "Broadband China" pilot policy at a 1% confidence level. The pilot policy of "Broadband China" facilitates a wide and high-speed network connection, thereby enhancing the efficiency of information transmission and improving farmers' access to advanced scientific knowledge and market information resources. Additionally, it stimulates the development of supporting infrastructure and enhances services in logistics, finance, and other domains. The pilot policy of "Broadband China" is of significant importance in promoting agricultural production technical efficiency and has consistently been validated by multiple models, demonstrating a stable and substantial positive impact.

Table 9: Effect analysis of the "broadband china" policy on agricultural production technical efficiency.

	(1)	(2)	(3)	(4)
DID	1.426***	0.281***	0.412***	0.275***
	(0.09)	(0.10)	(0.07)	(0.10)
_cons	0.414***	0.533***	0.319***	0.539***
	(0.04)	(0.05)	(0.11)	(0.07)
Controlled	NO	NO	YES	YES
TWFE	NO	YES	NO	YES
Observations	3264	3264	3264	3264
R-sq	0.341	0.464	0.367	0.447

Note: t statistics in parentheses; ***, **, and * indicate significant at the 1%, 5%, and 10% statistical levels, respectively.

6. Conclusions

The study employs a sample of 272 prefecture-level cities and above in China from 2010 to 2021 to examine the impact and moderation effects of the digital economy on agricultural production technical efficiency. To achieve this, we utilize panel fixed effects model, moderation effect model, and multi-period difference-in-differences model. The findings are as follows:

(1) The impact of the digital economy on agricultural production technical efficiency demonstrates a curvilinear relationship, characterized by an initial increase followed by a subsequent decrease. This relationship has been robustly validated through adjustments in variable measurement methods and the application of instrumental variable techniques.

(2) The moderation analysis reveals a curvilinear relationship between agricultural land resource endowment and the impact of the digital economy on agricultural production technical efficiency, characterized by an inverted U-shape. Similarly, there exists an inverted U-shaped relationship between agricultural labor resource endowment and the influence of the digital economy on agricultural production technical efficiency.

Heterogeneity analysis reveals significant heterogeneity in the inverted U-shaped relationship between the digital economy and agricultural production technical efficiency. Among different dimensions of the digital economy, internet penetration rate exhibits a positive linear impact on agricultural production technical efficiency, while the number of mobile internet users and inclusive digital finance development demonstrate an inverted U-shaped relationship with agricultural production technical efficiency. In terms of regional heterogeneity, an inverted U-shaped relationship between the digital economy and agricultural production technical efficiency is observed in eastern and central cities, while a U-shaped relationship exists in central-western and peripheral cities.

(4) The findings from the examination of exogenous shocks reveal that the pilot policy "Broadband China" in the digital economy has a significantly positive impact on technical efficiency in agricultural production.

7. Policy Implications

(1) Dialectical comprehension of the role played by the digital economy in facilitating advancements in agricultural production technology

In the development of the digital economy, it is crucial to differentiate between the digital economy and technological applications. Particular attention should be directed towards addressing the challenges encountered in digitizing agricultural production, with a primary focus on enhancing infrastructure and implementing intelligent transformations to bridge regional disparities within the digital economy. The promotion of the "Internet Plus Agriculture" model is imperative for optimizing the digitization of agricultural value chains and addressing production and sales challenges. Furthermore, concerted efforts should be made to enhance data resource integration, facilitate the sharing of digital technology support for agricultural production, foster the integration between the digital economy and agriculture, and ultimately achieve a comprehensive transformation towards digitization.

(2) Optimize the allocation of resources in different regions to effectively guide and direct targeted actions

Based on the diverse land and labor resources in each region, targeted guidance should be provided to facilitate the development of the digital economy. Differentiated policy measures ought to be implemented to foster the synergistic growth between the digital economy and agricultural production technical efficiency. The optimization of agricultural land resource utilization should be accompanied by a rational allocation of labor resources to enhance technical efficiency in agricultural production. In formulating strategies for guiding digital economic development in different regions, the principle of "teaching students according to their aptitude" applies. Effective and suitable policy measures can only be formulated by thoroughly understanding the advantageous resources and market demands specific to each region.

(3) Drawing on external shocks to promote policy implementation

The results of the exogenous shock test demonstrate that digital economy policies, such as the "Broadband China" pilot program, exert a positive influence on agricultural production technical efficiency. Consequently, policymakers can leverage these insights from exogenous shocks to further advance digital economy policies and facilitate the progress of agricultural modernization.

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9. Aditional Information

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writing—review and editing, H.P.; visualization, W.S.; supervision, L.W.; project administration, L.W.; funding acquisition, L.W.

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