

Article

Digital Economy and Industrial Structure Transformation: Mechanisms for High-Quality Development in China's Agriculture and Rural Areas

Jingruo Liu ¹, Xiuju Feng ², Jianxu Liu ^{1,3}  and Woraphon Yamaka ^{3,*} 

¹ School of Economics, Shandong University of Finance and Economics, Jinan 250014, China; jingruo_liu@126.com (J.L.); 20180881@sdufe.edu.cn (J.L.)

² School of Business, Shandong University of Political Science and Law, Jinan 250014, China; 002225@sdupsl.edu.cn

³ Faculty of Economics, Chiang Mai University, Chiang Mai 50200, Thailand

* Correspondence: woraphon.econ@gmail.com

Abstract: The digital economy's transformative impact on agriculture presents both opportunities and challenges for China's pursuit of high-quality agricultural and rural development. This study investigates the complex interplay between digital economy, industrial structure transformation, and agricultural advancement using panel data from 31 Chinese provinces spanning 2012–2021. We employed mediation analysis and threshold effect models to uncover several key findings: (1) The digital economy influences high-quality agricultural and rural development through the dual-mediating mechanisms of industrial structure intensification and upgrading in China. (2) These mediating effects exhibit heterogeneous patterns: while industrial intensification positively channels the digital economy's impact, industrial upgrading shows an initial negative indirect effect, suggesting potential short-term disruptions. (3) The relationship between digital economy and agricultural development is nonlinear, characterized by significant threshold effects. The digital economy's positive impact becomes more pronounced as industrial structure surpasses certain sophistication and advancement thresholds. Our findings reveal the nuanced dynamics of digital-driven agricultural transformation, highlighting the need for targeted policies that leverage industrial-structure changes while mitigating potential adverse effects. This research contributes to a more comprehensive understanding of how digitalization can be harnessed to promote sustainable and high-quality agricultural and rural development in China, with implications for other developing economies navigating similar transitions.

Keywords: digital economy; high-quality agricultural and rural development; mediation effect; threshold effect; China



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1. Introduction

In recent years, China's agricultural sector has faced significant challenges. These include resource constraints, increasing environmental pressures, and slowing growth in farmers' incomes. Consequently, promoting high-quality agricultural and rural development (HQARD) has become an urgent priority. China's agricultural labor productivity is much lower than that of developed countries like the United States, where one agricultural laborer in the U.S. supports significantly more people compared to one in China [1]. The contribution rate of agricultural science and technology progress stood at 61%, lagging behind the 80% level in developed countries. Moreover, agricultural pollution is severe, with non-point source pollution accounting for over 50% of total water pollution [2,3]. These issues underscore the pressing need for China's agricultural transformation and upgrading.

The burgeoning digital economy presents new opportunities for Chinese agriculture. Digital technologies such as big data, Internet of Things, and artificial intelligence are

reshaping agricultural production methods and value chains [4,5]. Many scholars focused on the impact mechanisms and pathways of the digital economy on agricultural development. Research indicates that the digital economy promotes sustainable and high-quality agricultural and rural development through various channels. Some studies demonstrated the significant impact of the digital economy on sustainable agriculture [6,7]. Research related to the digital economy and agricultural and rural development can generally be divided into three aspects.

(1). Digital Economy and Agricultural Production: The impact of the digital economy on agriculture has attracted increasing attention from scholars in recent years. Early studies have recognized the potential of digital technologies in transforming agricultural production and rural development [8,9]. More recent research has provided empirical evidence on the positive effects of the digital economy on various aspects of agriculture. For instance, Zheng et al. [10] found that the adoption of digital technologies has significantly improved agricultural productivity and farmers' income in China, while Chao et al. [11] demonstrated that the development of e-commerce has created new opportunities for farmers to access markets and increase their sales. Digital technologies, such as mobile phones and the internet, have significantly improved efficiency in agriculture by reducing transaction costs and facilitating market access for small-scale farmers [12]. Moreover, the digital economy has boosted green total factor productivity (GTFP) in agriculture through technology innovation and efficient resource use, particularly in China [13,14]. The integration of digital technologies in agriculture, such as automation and smart farming, has led to substantial improvements in productivity and sustainability [15]. Additionally, the application of digital technology can drive innovation and improvement in agricultural production methods and achieve differentiation and quality improvement of agricultural products, thereby increasing the added value and market competitiveness of agricultural products [16]. These findings collectively highlight that the digital economy plays a crucial role in promoting HQARD.

(2). Industrial Structure and Digital Economy: The development of the digital economy directly promotes industrial structure transformation. This is an inherent logical consequence. The widespread application of digital technologies facilitates the digital transformation of traditional industries. It also spawns new industries and business models, thereby optimizing the industrial structure [17]. Notably, industrial structure transformation may not only directly promote high-quality agricultural and rural development but also influence the impact of the digital economy on agriculture. This is due to several factors. First, it alters the efficiency of factor allocation, affecting the diffusion and application of digital technologies. Second, the degree of industrial structure optimization determines an economy's capacity to absorb digital technologies. Third, synergistic effects during industrial structure transformation may amplify or suppress the impact of the digital economy. Therefore, clarifying the relationships among the digital economy, industrial structure transformation, and high-quality agricultural and rural development has significant practical implications. This not only deepens our understanding of the digital economy's mechanisms but also provides a theoretical basis for formulating targeted policies to promote HQARD.

A limited body of studies has substantiated the impact of the digital economy on industrial structure transformation. Huang [18] and Liao [19] demonstrated that the digital economy facilitates technological innovation, accelerating the optimization and upgrading of industrial structures. Zhao [20] found that the digital economy enables manufacturing transformation by deeply integrating technological innovation with traditional industries. While direct research on the influence of industrial structure transformation on high-quality agricultural and rural development is scarce, studies have shown significant effects of structural transformation on economic growth and the shift from agricultural to non-agricultural sectors [21]. Briones and Felipe [22] observed that Asian economies adopted an agriculture-led industrialization path, wherein enhanced agricultural productivity laid the foundation for industrialization and economic growth. This existing literature suggests

a potential link between industrial structure transformation and agricultural development, though the specific mechanisms and impacts on high-quality agricultural growth remain to be fully explored.

(3). Impact of Digital Economy on Rural Development: Kichuk et al. [23] and Mei et al. [24] highlighted the importance of digital entrepreneurship and digital village construction in promoting high-quality rural economic development. These studies suggest that the digital economy not only enhances agricultural production efficiency but also provides comprehensive development opportunities for rural areas. Firstly, the digital economy fosters the development of rural infrastructure. Broadband internet accessibility, a critical component of the digital economy: Li [25] showed that rural broadband development significantly improves agricultural productivity, further validating the importance of digital infrastructure for high-quality agricultural and rural development. Secondly, the digital economy provides new economic opportunities for farmers. E-commerce platforms allow farmers to bypass traditional supply chains, directly reaching consumers and improving profit margins. Yao and Sun [26] and Wang [27] pointed out that the digital economy promotes high-quality development of agricultural enterprises by expanding market channels, improving logistics infrastructure, and enhancing professional talent quality. Thirdly, the digital economy contributes to the enhancement of rural quality of life. Regarding technological applications, several scholars emphasized the use of cloud computing and big data in organic and digital agriculture [28,29]. These technologies promote sustainable agriculture through precision farming and production quality monitoring and improve access to information and services through digital platforms. Overall, these studies collectively demonstrate that the digital economy's impact on high-quality agricultural and rural development encompasses technological innovation, socio-economic development, and environmental sustainability, etc. Numerous studies have explored the impact mechanisms and pathways of the digital economy on agricultural development, offering practical insights for promoting high-quality agricultural growth. However, the role of industrial structure transformation in the digital economy's promotion of high-quality agricultural and rural development in China remains understudied. The mechanism by which industrial structure transformation facilitates this process merits further investigation. Therefore, this study aims to address the following questions: (1) How does the digital economy influence China's high-quality agricultural and rural development? (2) What role does industrial structure transformation play in this process? (3) Are there nonlinear relationships or threshold effects among the digital economy, industrial structure transformation, and high-quality agricultural and rural development?

This study contributes to the existing literature in threefold. First, it reveals the mechanism of industrial structure transformation as a pathway through which the digital economy promotes high-quality agricultural and rural development in China. Second, to analyze the impact mechanism of industrial structure transformation on high-quality agricultural and rural development, we decompose it into industrial intensification and industrial advancement. Third, we not only examine the mediating mechanism of industrial structure transformation but also analyze its threshold effect in the digital economy's promotion of high-quality agricultural and rural development in China.

The remainder of this paper is structured as follows: Section 2 presents the data, detailing the sources and describing the key variables utilized in our analysis. Section 3 introduces the methodological framework, which includes the mediating effect model and the threshold effect model. Section 4 provides a comprehensive empirical analysis. Finally, Section 5 makes a conclusion by summarizing the main results, offering policy recommendations based on our findings, and suggesting directions for future research.

2. The Data

2.1. Data Sources and Definitions

This paper uses 31 provincial panel data in China from 2012 to 2021, with a total of 310 sample data. The data come from China Statistical Yearbook, China Rural Statistical

Yearbook, Green Food Statistical Yearbook, China Rural Business Management Yearbook, China Commodity Exchange Market Statistical Yearbook, China Energy Statistical Yearbook, China Water Resources Bulletin, and statistical yearbooks of each province.

- (1) Explained variables: Drawing upon the new development concept, this study constructs a comprehensive evaluation index system for HQARD from five dimensions: innovation, coordination, green development, openness, and sharing (Table 1). The HQARD index is calculated using the entropy method, as proposed by Wang and Kuang [30], to quantitatively assess the level of high-quality agricultural and rural development in different regions.

Table 1. Indicators of quality development in agriculture.

Dimension Layer		Evaluation Indicators	Specific Indicators	Causality	
blaze new trails developmental	Innovative foundations	Level of agricultural mechanization	Chief Motivator for Agricultural Mechanization	+	
		Percentage of financial investment in agriculture	Agriculture, forestry, and water fiscal expenditure/financial expenditure	+	
		Number of agricultural and economic institutions at the commune level	Data-direct (in LAN emulation)	+	
		Number of professional and technical staff in agricultural and economic institutions	Data-direct (in LAN emulation)	+	
	Benefits of innovation	Increased number	labor productivity	Gross output value of agriculture, forestry, animal husbandry, and fishery/number of employees in primary industry	+
			Land productivity	Gross agricultural output/area sown under crops	+
		Quality Enhancement	Number of green food enterprises	Number of green food units certified in the year	+
	Number of green food products		Number of green food products certified in the year	+	
	trade-off developmental	Industrial coordination	Agricultural industry structural adjustment index	1—(Agricultural output/gross value of agriculture, forestry, livestock and fisheries)	+
		Urban and rural coordination	Binary comparison coefficient	Comparative labor productivity in primary industry/Comparative labor productivity in secondary and tertiary industries	+

Table 1. Cont.

Dimension Layer	Evaluation Indicators	Specific Indicators	Causality		
greener developmental	Depletion of resources	Water consumption of 10,000 yuan of agricultural value added	Water use in agriculture/value added in agriculture	-	
		Intermediate consumption of agriculture, forestry, livestock and fisheries per unit of output value	Share of intermediate consumption in agriculture, forestry, livestock and fisheries in the value of production	-	
		Per capita electricity consumption of primary sector employees	Rural electricity consumption/primary sector employees	-	
		Energy consumption per unit of value added of agriculture, forestry, animal husbandry and fisheries	Energy consumption in agriculture, forestry and fisheries/value added in agriculture, forestry and fisheries	-	
	Environmental pollution	Strength of agricultural plastic films	Agricultural plastic film use/cultivated land area	-	
		Fertilizer application per unit area	Fertilizer application/cultivated land area	-	
		Pesticide use per unit area	Pesticide use/cropland area	-	
	Environmental protection	forest cover	Data-direct (in LAN emulation)	+	
	liberalization developmental	Resource optimization	Rural land transfer rate	Share of family-contracted land transfers in agricultural land	+
			Percentage of investment in fixed assets in agriculture	Investment in fixed assets in agriculture, forestry, animal husbandry and fishery/total fixed asset investment	+
External resources		Share of FDI in agricultural investment	FDI in agriculture/total investment in agriculture	+	
Market Optimization		Domestic market	Number of agricultural markets	data-direct (in LAN emulation)	+
			Agricultural market turnover as a percentage	Agricultural market turnover/value added in primary sector	+
		Foreign market	Dependence on exports and imports of agricultural products	China's agricultural import and export trade/added value of primary industry	+

Table 1. Cont.

Dimension Layer	Evaluation Indicators	Specific Indicators	Causality	
enjoy together developmental	Income level of the rural population	Per capita net income of rural residents	+	
	Overall level of affluence of the rural population	Rural Engel coefficient	-	
	Rising living standards	Enrichment of the life of the rural population	Per capita expenditure on education, culture and recreation/per capita consumption expenditure	+
		Value placed on health care by the rural population	Per capita health care expenditure/per capita consumption expenditure	+
	Benefit sharing	Ratio of income of urban and rural residents	Urban disposable income/rural disposable income	-
		Ratio of urban to rural consumption levels	Per capita consumption expenditure of urban residents/per capita consumption expenditure of rural residents	-
Gap in income distribution among rural residents		Rural Gini coefficient	-	

The concept of HQARD encompasses not only the efficiency and sustainability of agricultural production but also the economic, social, and environmental development of rural areas. Although there is no universally accepted definition of high-quality development in agriculture and rural areas, agricultural modernization and rural modernization are inherently intertwined. Therefore, high-quality agricultural and rural development is not a simple aggregate of high-quality agricultural and high-quality rural development. Instead, it represents a comprehensive and fundamental transformation in development concepts, orientation, impetus, and pathways under the goals of agricultural and rural modernization [31]. Innovation dimension captures the foundation and driving force of agricultural development, including indicators such as agricultural mechanization level and R&D investment. Coordination dimension reflects the balanced development of agriculture, focusing on the optimization of agricultural industrial structure and the integration of primary, secondary, and tertiary industries. Green dimension emphasizes the sustainability and eco-friendliness of agricultural growth, considering factors like the utilization rate of agricultural water resources and the application of green prevention and control technologies. Openness dimension measures the level of agricultural internationalization and market orientation, with indicators such as the export delivery value of agricultural products. Sharing dimension evaluates the inclusiveness and fairness of agricultural development, including rural residents' income level and the coverage of rural social security.

The multi-dimensional HQARD index provides a comprehensive assessment of the quality and sustainability of agricultural development, aligning with the United Nations' Sustainable Development Goals (SDGs). Previous studies have also highlighted the importance of evaluating agricultural development from multiple perspectives, such as resource efficiency, environmental protection, and social equity [32]. The HQARD index in this study extends the existing literature by incorporating the five dimensions of the new devel-

opment concept, offering a more holistic and balanced approach to assessing high-quality agricultural and rural development in the context of sustainability.

- (2) Explanatory variables: This study constructs a comprehensive digital economy index incorporating internet penetration rate, internet-related employment, internet-related output, and the number of mobile internet users, and the result is shown in Table 2 [33]. Internet penetration rate and the number of mobile internet users indicate the prevalence of digital infrastructure and the adoption of digital technologies by residents, which form the foundation of the digital economy. The proportion of internet-related employment and internet-related output directly measure the scale of the digital industry from the perspectives of employment and output, reflecting the direct contribution of the digital economy to economic growth. Innovatively, this research integrates the digital inclusive finance index into the existing framework, acknowledging digital finance as a critical component of the digital economy. The inclusive finance index measures the extent to which digital technologies have democratized access to financial services, providing a crucial gauge of the digital economy’s inclusiveness. The incorporation of the inclusive finance index highlights the inclusive characteristics of the digital economy, embodying the concept of shared benefits from digital economy development, which significantly supplements and innovates the existing digital economy measurement framework. To calculate the digital economy development level, this study employs an entropy weight method.

Table 2. Comprehensive development indicators for the digital economy.

Level 1 Indicators	Level 1 Indicators	Indicator Measurements	Indicator Properties
Digital economy Composite development index	Internet penetration	Internet users per 100 population	+
	Internet-related practitioners	Percentage of employees in computer services and software	+
	Internet-related outputs	Total telecommunication services per capita	+
	Number of mobile Internet users	Cell phone subscribers per 100 population	+
	Financial inclusion index	PKU-DFIIC	+

- (3) Mediating variables: Industrial structure upgrading is measured by ISI and ISU. Industrial structure adjustment refers to the reallocation of factors of production among the sectors of the economy and different industries and the change in the proportion of output value of the sectors of the economy and different industries [34]. A higher industrial structure refers to the process of evolution of industrial structure from lower level to higher level and the increase in labor productivity; higher industrial structure is the process of transferring primary industry to tertiary industry.

A. Industrial Structure Intensification (ISI)

The theoretical connotation of industrial structure intensification is highlighted by the process of industrial structure evolution from lower to higher levels and the increase in labor productivity. Among them, the quantity of industrial structure intensification (*ais1*) is expressed by the industrial structure hierarchy coefficient, i.e., the evolution process of the three major industries at the quantitative level is portrayed from the relative change in the share ratio, and the specific calculation formula is

$$ais\ 1_{i,t} = \sum_{m=1}^3 y_{i,m,t} \times m, m = 1, 2, 3 \tag{1}$$

where $y_{i,m,t}$ indicates the proportion of the m industry in the region i to GDP in the period t ; the index reflects the evolution of the proportional relationship of China’s three major industries from the dominance of the primary industry to the dominance of the secondary

industry and the tertiary industry gradually, which is the quantitative connotation of the heightened industrial structure.

B. Industrial Structure Upgrading (ISU)

According to the principle of industrial structure upgrading, such as the Cotyledon–Clark theorem, that is, in the process of economic development, the proportion of primary industry gradually decreases and the proportion of tertiary industry gradually increases, the industrial structure advanced is the process of transferring primary industry to tertiary industry. Therefore, this paper refers to the measurement of industrial advancement and uses the proportion of output value of secondary and tertiary industries as the measure of industrial structure advancement and reflects the process of industrial structure advancement by the proportion relationship of each industry [35].

- (4) Control variables: In this paper, urbanization rate (UR), government financial support level (GFSL), and regional openness level (ROL) are used as control variables for the study. Among them, GFSL is expressed as the proportion of public budget expenditure to GDP; UR is expressed as the proportion of the number of urban resident population to the total population; and the ROL is expressed as the proportion of the amount of actual utilization of foreign direct investment to GDP.

2.2. Comprehensive Indicator Measurement—Entropy Value Approach

Prior to the empirical analysis, the data need to be preprocessed:

First, the indicators are standardized. In this paper, the standardization process is carried out by using the method of polar deviation to transform the indicator values between (0,1) in order to eliminate the influence of the indicator’s scale.

Positive indicators:

$$x_{ij}^*(t) = \frac{x_{ij}(t) - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \tag{2}$$

Negative indicators:

$$x_{ij}^*(t) = \frac{x_j^{\max} - x_{ij}(t)}{x_j^{\max} - x_j^{\min}} \tag{3}$$

where x_{ij} denotes the observed value of the j^{th} indicator in the i^{th} province at time t . x_j^{\max} denotes the maximum value of the j^{th} indicator, and x_j^{\min} denotes the minimum value of the j^{th} indicator; $x_{ij}^*(t)$ denotes the pre-processed $x_{ij}(t)$.

Second, the indicators are normalized. The normalized value of the j^{th} indicator for sample area i is recorded as p_{ij} .

$$p_{ij} = \frac{\tilde{x}_{ij}}{\sum_{j=1}^m \tilde{x}_{ij}} \tag{4}$$

where $i = 1, 2, \dots, n; j = 1, 2, \dots, n$.

Third, in EWM, the entropy value of each indicator is calculated E_j :

$$E_j = - \ln(n)^{-1} \sum_{i=1}^n P_{ij} \ln(P_{ij}) \tag{5}$$

Fourth, the entropy redundancy of the indicators was calculated:

$$D_j = 1 - E_j \tag{6}$$

Fifth, the weights of the indicators were calculated:

$$W_j = \frac{D_j}{\sum_{j=1}^n D_j} \tag{7}$$

Sixth, the population quality development index was calculated for each region for each year:

$$A_{\lambda i} = W_j \times P_{\lambda ij} \quad (8)$$

3. Methodology

Mediation and threshold effect models have been widely applied in the literature on the digital economy and high-quality agricultural and rural development, providing powerful tools for revealing complex economic relationships and determining critical thresholds. In the digital economy domain, Gao and Lyu [36] explored the relationship between agricultural total factor productivity, the digital economy, and agricultural high-quality development using threshold regression models. Correspondingly, Qian and Zhang [37] utilized a threshold effect analysis to emphasize that the nonlinear influence of the digital economy on high-quality agricultural and rural development exhibits a pattern of initial strengthening followed by weakening. Concurrently, mediation effect models have gained extensive application in related research. Regarding the transformation of agricultural production methods, Wang et al. [38] highlighted that the development of the digital economy empowers green and intensive agricultural development through a threefold nonlinear mechanism: promoting green finance development, enhancing rural human capital, and alleviating agricultural resource misallocation. This paper employs mediation effect models and threshold effect models to thoroughly investigate the direct, indirect, and threshold impacts of the digital economy on high-quality agricultural and rural development. The specific methodologies employed are detailed below.

3.1. Mediation Model Construction

This paper selects two mediating variables (industrial intensification and industrial upgrading) to investigate the impact mechanism of the digital economy on high-quality agricultural and rural development. The empirical testing steps are as follows: (1) This paper conducts a regression analysis of the digital economy indicators and high-quality agricultural and rural development. If the results show a positive and significant coefficient, it indicates that the digital economy promotes high-quality agricultural and rural development. (2) This paper conducts a regression analysis of the digital economy and the above two mediating variables, respectively. If the regression coefficients are significant, it indicates that the digital economy can effectively influence the level of these mediating variables. (3) This paper simultaneously incorporates the digital economy and these two mediating variables into the model for regression analysis with high-quality agricultural and rural development. If the coefficient of the digital economy becomes insignificant or significant but with a reduced coefficient, it proves that the digital economy promotes high-quality agricultural and rural development by enhancing the level of these mediating variables. Therefore, this paper uses mediating effects and selects the stepwise regression method to verify the relationship among the three [39].

The model is set as follows:

Step 1: Examine the total effect of the core explanatory variable on the explained variable:

$$HQAD_{i,t} = \beta_0 + \beta_1 DE_{i,t} + \mu_i + \gamma_t + \epsilon_{i,t} \quad (9)$$

where $HQAD_{i,t}$ is the explained variable, representing the level of high-quality agricultural and rural development of individual i at time t ; $DE_{i,t}$ is the core explanatory variable, representing the development level of the digital economy; $ISI_{i,t}$ and $ISU_{i,t}$ are the mediating variables, representing industrial intensification and industrial upgrading, respectively; μ_i and γ_t represent individual fixed effects and time fixed effects, respectively; $\epsilon_{i,t}$ is the error term.

Step 2: Examine the impact of the core explanatory variable on the first mediating variable:

$$ISI_{i,t} = \alpha_0 + \alpha_1 DE_{i,t} + \alpha_2 UR_{i,t} + \alpha_3 GFSL_{i,t} + \alpha_4 ROL_{i,t} + \mu_i + \gamma_t + \eta_{i,t} \quad (10)$$

where $ISI_{i,t}$ is the mediating variable, representing industrial intensification.

Step 3: Examine the impact of the core explanatory variable on the second mediating variable:

$$ISU_{i,t} = \delta_0 + \delta_1 DE_{i,t} + \delta_2 UR_{i,t} + \delta_3 GFSL_{i,t} + \delta_4 ROL_{i,t} + \mu_i + \gamma_t + \theta_{i,t} \quad (11)$$

where $ISU_{i,t}$ is the mediating variable, representing industrial upgrading. In these two mediation models, the digital economy ($DE_{i,t}$) is expected to positively influence industrial intensification ($ISI_{i,t}$) and industrial upgrading ($ISU_{i,t}$), and these two mediating variables further influence high-quality agricultural and rural development ($HQARD_{i,t}$).

Step 4: Examine the joint impact of the core explanatory variable and mediating variables on the explained variable:

$$HQAD_{i,t} = \gamma_0 + \gamma_1 DE_{i,t} + \gamma_2 ISI_{i,t} + \gamma_3 ISU_{i,t} + \gamma_4 UR_{i,t} + \gamma_5 GFSL_{i,t} + \gamma_6 ROL_{i,t} \quad (12)$$

3.2. Threshold Model Construction

The mediation effect results show that the digital economy has a significant linear impact on high-quality agricultural and rural development through industrial structure intensification and industrial structure upgrading. However, since the impact of the digital economy on high-quality agricultural and rural development is multi-dimensional, its impact may exhibit different characteristics when the level of industrial structure intensification and industrial structure upgrading falls within different intervals, that is, there may be a nonlinear relationship between variables. To test whether there is a nonlinear relationship between variables, the panel threshold regression model is used to test the nonlinear relationship [40]. "Threshold regression", as a nonlinear econometric model, essentially searches for threshold variables in the variables reflecting causal relationships. The threshold value is estimated based on the sample data, and it is tested whether the parameters of the sample groups divided according to the threshold value are significantly different [41]. For the econometric model in this paper, the set panel threshold regression model is as follows:

$$HQAD_{it} = \beta_0 + \beta_1 DE_{it} \times I(ISI_{it} \leq \gamma) + \beta_2 DE_{it} \times I(ISI_{it} > \gamma) + \alpha X_{it} + \mu_1 \quad (13)$$

$$HQAD_{it} = \phi_0 + \phi_1 DE_{it} \times I(ISU_{it} \leq \delta) + \phi_2 DE_{it} \times I(ISU_{it} > \delta) + \lambda X_{it} + \mu_2 \quad (14)$$

where $I(\cdot)$ represents the indicative function. When the expression in parentheses is false, the value is 0; otherwise, the value is 1. According to whether the threshold variables of industrial structure intensification (ISI) and industrial structure upgrading (ISU) are greater than the threshold values γ and δ , the sample interval can be divided into two regimes, and the slope values β_1 and β_2 , ϕ_1 and ϕ_2 are used to distinguish the two regimes, respectively. X represents the control variables, including urbanization rate (UR), government fiscal support level (GFSL), and regional openness level (ROL). Similarly, based on the one-threshold model, the case where there are multiple threshold values in the model can be considered. The following takes the two-threshold model as an example:

$$HQAD_{it} = \beta_0 + \beta_1 DE_{it} \times I(ISI_{it} \leq \gamma_1) + \beta_2 DE_{it} \times I(\gamma_1 < ISI_{it} \leq \gamma_2) + \beta_3 DE_{it} \times I(ISI_{it} > \gamma_2) + \alpha X_{it} + \mu_1 \quad (15)$$

$$HQAD_{it} = \phi_0 + \phi_1 DE_{it} \times I(ISU_{it} \leq \delta_1) + \phi_2 DE_{it} \times I(\delta_1 < ISU_{it} \leq \delta_2) + \phi_3 DE_{it} \times I(ISU_{it} > \delta_2) + \lambda X_{it} + \mu_2 \quad (16)$$

where $\gamma_1 < \gamma_2$, $\delta_1 < \delta_2$, the calculation process of the two-threshold model is similar to that of the one-threshold model, which is to estimate the second threshold value under the condition that the first threshold value is fixed. In this model, β_1 , β_2 , β_3 and ϕ_1 , ϕ_2 , ϕ_3 represent the impact of DE_{it} on $HQARD_{it}$ at different levels, respectively.

4. Empirical Results

4.1. Descriptive Statistics and Correlation Analysis

Table 3 provides an overview of the variables’ descriptive statistics, including their mean values, standard deviations, and minimum and maximum values. The mean value of HQARD is 0.255, with a maximum of 0.625, a minimum of 0.112, and a standard deviation of 0.080. These figures indicate significant variations in high-quality agricultural development levels among cities nationwide. Similarly, DE has a mean value of 0.123, with a maximum of 0.552, a minimum of 0.017, and a standard deviation of 0.095, suggesting substantial disparities in digital economy development across cities. Moreover, the uneven distribution of HQARD and DE across cities may be attributed to factors such as regional resource endowments, industrial foundations, and policy support. Studies have shown that regions with better infrastructure, human capital, and institutional environments tend to have higher levels of agricultural development and digital economy growth. Moreover, the digital divide between urban and rural areas may exacerbate the imbalance in agricultural development, as rural areas often lag in terms of digital infrastructure and technology adoption.

Table 3. Descriptive statistics of variables.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
HQARD	310	0.255	0.080	0.112	0.625
DE	310	0.123	0.095	0.017	0.552
ISI	310	2.404	0.121	2.132	2.834
ISU	310	1.374	0.738	0.611	5.244
UR	310	0.602	0.118	0.363	0.896
GFSL	310	0.263	0.113	0.105	0.758
ROL	310	0.293	0.303	0.008	1.532

Table 4’s correlation analysis reveals a significant positive correlation between HQARD and DE, with a coefficient of 0.596, suggesting that the advancement of the digital economy may promote high-quality agricultural and rural development. Additionally, ISI and ISU, serving as mediating variables, show correlations of 0.664 and 0.639 with HQARD, respectively, indicating their potential bridging roles between the digital economy and agricultural development. Among the control variables, UR has the strongest correlation with HQARD, at 0.739, highlighting urbanization as a key factor in enhancing agricultural quality; GFSL is negatively correlated with HQARD at −0.341, possibly reflecting that excessive reliance on government support may hinder independent agricultural development. ROL also shows a positive correlation with HQARD at 0.557, suggesting that regions with higher levels of openness tend to have better agricultural development quality.

Table 4. Correlation analysis.

	HQARD	DE	ISI	ISU	UR	GFSL	ROL
HQARD	1						
DE	0.596 *** [0.517, 0.664]	1					
ISI	0.664 *** [0.596, 0.723]	0.639 *** [0.566, 0.701]	1				
ISU	0.639 *** [0.567, 0.702]	0.399 *** [0.299, 0.490]	0.731 *** [0.673, 0.779]	1			
UR	0.739 *** [0.683, 0.702]	0.617 *** [0.541, 0.682]	0.810 *** [0.767, 0.846]	0.537 *** [0.451, 0.613]	1		
GFSL	−0.341 *** [−0.437, −0.237]	−0.544 *** [−0.619, −0.459]	−0.192 *** [−0.298, −0.081]	0.0470 [−0.067, 0.159]	−0.323 *** [−0.421, −0.218]	1	
ROL	0.557 *** [0.473, 0.630]	0.615 *** [0.539, 0.681]	0.700 *** [0.638, 0.754]	0.454 *** [0.359, 0.539]	0.769 *** [0.718, 0.811]	−0.415 *** [−0.505, −0.317]	1

Note: *** are significant at the 1% level, with confidence interval in brackets.

4.2. Benchmark Regression

Table 5 presents a comparison of mixed-effects, random-effects, and fixed-effects models in examining the impact of DE, ISI, and ISU on HQARD. First, a Hausman test strongly favors the fixed-effects model over the random effects model (test statistic = 75.90, p -value = 0), indicating that the fixed-effects model is the most appropriate for this analysis. Second, the adjusted R-squared (r^2_a) of the fixed-effects model (0.832) is substantially higher than that of the mixed-effects (0.809) and random-effects (0.889) models, further confirming that the fixed-effects model provides the best fit for the data. Third, interpreting the results of the fixed-effects model, all variables exhibit significant effects on HQARD at various significance levels. The coefficient for DE is 0.081, suggesting that the growth of the digital economy has a significant positive influence on HQARD at the 5% level. The coefficients for the mediating variables, ISI and ISU, are -0.360 and 0.062 , respectively, both significant at the 1% level. The negative coefficient of ISI implies that a shift towards secondary and tertiary industries may adversely affect HQARD by diverting resources away from agriculture. Conversely, the positive coefficient of ISU indicates that the transition towards higher technological levels and value-added industries may promote HQARD by facilitating agricultural technological advancement and market expansion.

Table 5. Benchmark regression results.

	HQARD	HQARD	HQARD
	(1) ols	(2) re	(3) fe
DE	0.128 *** (0.043)	0.163 *** (0.051)	0.081 ** (0.036)
ISI	-0.138 *** (0.049)	-0.127 (0.081)	-0.360 *** (0.070)
ISU	0.052 *** (0.005)	0.059 *** (0.011)	0.062 *** (0.012)
UR	0.422 *** (0.043)	0.321 *** (0.071)	-0.403 *** (0.101)
GFSL	-0.134 *** (0.030)	-0.196 *** (0.057)	-0.266 *** (0.054)
ROL	-0.044 *** (0.014)	-0.019 (0.018)	0.087 *** (0.022)
Controlled variable	yes	yes	yes
Time effect	deny	deny	yes
Regional effect	deny	yes	yes
_cons	0.294 *** (0.099)	0.321 ** (0.158)	1.250 *** (0.160)
N	300.000	300.000	300.000
r^2	0.692		0.856
r^2_a	0.686	0.4462	0.832
Hausman			75.90 ***

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

4.3. Analysis of the Mediation Effect

Table 6 presents the mediation effect analysis of the impact of DE on HQARD, with ISI and ISU as mediating variables, while controlling for UR, GFSL, and ROL. First, the baseline regression in Model 1 shows that the direct effect of DE on HQARD is not significant. This result is contrary to theoretical expectations, possibly due to the opposing directions of indirect effects through the two mediators, which cancel each other out.

Table 6. The mediation effect.

	(1)	(2)	(3)	(4)
	HQARD	ISI	ISU	HQARD
DE	0.029	0.105 ***	−0.645 ***	0.081 **
UR	−0.484 ***	0.007	−1.862 ***	−0.403 ***
GFSL	−0.241 ***	0.147 ***	1.382 ***	−0.266 ***
ROL	0.026	0.138 ***	−0.694 ***	0.087 ***
ISU		0.084 ***		0.062 ***
ISI			3.106 ***	−0.360 ***
_cons	0.539 ***	2.143 ***	−5.227 ***	1.250 ***
N	300.000	300.000	300.000	300.000
r ²	0.836	0.905	0.864	0.856
r ² _a	0.809	0.889	0.841	0.832
P price	0.000	0.000	0.000	0.000

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

Second, in Models 2 and 3, the indirect effects of DE on ISI and ISU are significant at the 1% confidence level.

Third, the indirect effect of DE on ISI is positive (0.105), indicating that the development of the digital economy enhances industrial intensification.

Fourth, the indirect effect of DE on ISU is negative (−0.645), suggesting that the digital economy may hinder industrial upgrading in the short term. Fifth, Model 4 includes both mediating variables, revealing the positive and significant effects of DE (0.081), ISI (−0.360), and ISU (0.062) on HQARD. The insignificance of DE in Model 1 can be explained by the opposing indirect effects through ISI and ISU, which are now accounted for in Model 4. Sixth, combining the direct and indirect effects, we can infer that the digital economy influences agricultural development through complex mechanisms. While it directly promotes HQARD, it also indirectly affects it through industrial structure changes, with both positive and negative consequences.

4.4. Further: Bootstrap Mediation Effect Test

Baron and Kenny [42] believed that the intermediary variable refers to the variable between the independent variable and the dependent variable and can convey the influence of the independent variable on the dependent variable to a certain extent. Now, the conditions for the existence of mediation effect are further simplified. For example, Zhao et al. [43] confirmed that only the inclusion of a mediation variable in the model reduces the influence of the independent variable on the dependent variable. Because the mediation effect can occur even without the direct effect of the independent variable.

Based on the three-step method, bootstrapping was used to obtain standard error and confidence intervals [44], and the number of repeated sampling was set to 500 times [45]. The intermediary variables concerned in this study are ISI and ISU, and the test results are as follows:

Table 7 presents the results of the bootstrap mediation mechanism analysis, examining the direct and indirect effects of ISI and ISU on HQARD. First, both the direct and indirect effects of ISI and ISU on HQARD are significant at the 5% confidence level, as indicated by the 95% confidence intervals not including zero. Second, the direct effects of ISI and ISU on HQARD are positive, with coefficients of 0.806. This suggests that improvements in industrial structure, both in terms of intensification and upgrading, can directly contribute to the high-quality development of agriculture. This positive impact may be attributed to the spillover effects of technological advancements and resource optimization in other sectors on the agricultural industry.

Table 7. Results of the mediation mechanism test.

Effect		Observed Coefficient	Bootstrap Std. Err.	z	p > z	Normal-Based	
						[95% Conf. Interval]	
ISI	Indirect	−0.379	0.013	−2.880	0.004	−0.064	−0.012
	Direct	0.806	0.041	1.990	0.047	0.001	0.160
	Total Eff	0.427	0.039	1.080	0.278	−0.034	0.120
ISU	Indirect	−0.040	0.017	−2.380	0.017	−0.073	−0.007
	Direct	0.081	0.041	1.990	0.047	0.001	0.160
	Total Eff	0.041	0.040	1.030	0.303	−0.037	0.118

Third, the indirect effects of the digital economy on HQARD through ISI and ISU are negative, with coefficients of −0.379 and −0.040, respectively. This implies that the digital economy’s influence on HQARD, when mediated by changes in industrial structure, may have some adverse consequences. The negative indirect effects could be due to the reallocation of resources away from agriculture towards other sectors during the process of industrial restructuring driven by digitalization. Fourth, considering the contrasting signs of the direct and indirect effects, it is crucial to recognize the complex dynamics between the digital economy, industrial structure changes, and agricultural development. While the direct effects of ISI and ISU on HQARD are positive, the indirect effects of the digital economy through these mediators are negative. This finding highlights the need for targeted policies that can harness the benefits of industrial structure improvements for agriculture while mitigating the potential negative consequences of resource reallocation in the context of digitalization.

4.5. Test of the Threshold Effect

Table 8 presents the threshold effect test results for the impact of DE on HQARD, considering ISI and ISU as threshold variables, while controlling for UR, GFSL, and ROL. First, for the threshold variable ISI, the single-threshold model is significant at the 1% level, while the double and triple-threshold models are not significant at the 10% level. Thus, the single-threshold model is considered optimal for ISI. Second, similarly, for the threshold variable ISU, the single-threshold model is found to be optimal at the 10% significance level, as the double and triple-threshold models do not provide additional explanatory power.

Table 8. Results of the threshold effect test.

Variable	Threshold	Fstat	Prob	Crit 10	Crit 5	Crit 1
ISI	Single	63.730	0.000	22.113	27.483	41.278
	Double	17.500	0.106	17.684	24.966	64.481
	Triple	8.580	0.532	23.928	33.632	51.429
ISU	Single	34.020	0.014	20.974	26.495	35.395
	Double	20.780	0.090	19.986	26.947	39.394
	Triple	15.070	0.148	17.369	23.343	38.656

Table 8 presents the threshold effect test results for the impact of ISI and ISU on HQARD, while Table 9 shows the corresponding threshold estimates and their confidence intervals.

First, for the ISI model, the single threshold is significant, with an F-statistic of 63.730, passing the 1% significance level. The double and triple-threshold models are not significant at the 10% level, indicating that the single-threshold model is optimal for ISI. The threshold estimate is 2.706, with a narrow confidence interval of [2.704, 2.707], suggesting a precise estimate.

Table 9. The threshold estimation results and confidence intervals.

	Model	Threshold	Lower	Upper
ISI	Th-21	2.706	2.704	2.707
	Th-22	2.810	.	.
	Th-3	2.483	2.468	2.483
ISU	Th-21	2.445	2.283	2.466
	Th-22	3.231	2.982	4.016
	Th-3	3.895	3.231	4.032
DE	Th-21	0.257	0.248	0.268
	Th-22	0.217	0.210	0.218
	Th-3	0.049	0.047	0.050

Second, similarly, for the ISU model, the single threshold is found to be optimal at the 10% significance level, with an F-statistic of 34.020. The double- and triple-threshold models do not provide additional explanatory power. The single-threshold estimate for ISU is 2.445, with a confidence interval of [2.283, 2.466].

Third, based on the results, the single-threshold model is selected for both ISI and ISU. This choice can be explained from an economic perspective. As the industrial structure intensifies and upgrades, it reaches a critical point where its impact on agricultural development becomes more pronounced. This could be due to the spillover effects of technological advancements and resource optimization in other sectors on the agricultural industry. However, beyond this single threshold, the marginal effects of further intensification and upgrading may diminish, as the agricultural sector adapts to the new economic environment.

Table 10 presents the threshold model regression results, investigating the impact of DE on HQARD under different threshold variables, namely ISI and ISU. The results of the threshold regression are shown in Figures 1 and 2.

Table 10. Results of the threshold model regression results.

	ISI	ISU
VARIABLES	HQARD	HQARD
ISI	−0.265 ** (0.109)	−0.233 ** (0.0877)
ISU	0.0405 ** (0.0161)	0.0293 (0.0177)
UR	−0.123 (0.193)	−0.199 (0.170)
GFSL	−0.227 *** (0.0765)	−0.215 *** (0.0767)
ROL	0.0778 * (0.0419)	0.0941 ** (0.0431)
DE (ISI < 2.7056)	0.0386 (0.0510)	
DE (ISI > 2.7056)	0.304 *** (0.0726)	
DE (ISU < 2.4447)		0.0362 (0.0406)
DE (2.4447 ≤ ISU < 3.2308)		0.221 *** (0.0465)
DE (ISU ≥ 3.2308)		0.488 *** (0.0838)
Constant	0.893 *** (0.289)	0.861 *** (0.226)
Observations	300	300
Number of id	30	30
R-squared	0.882	0.879

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

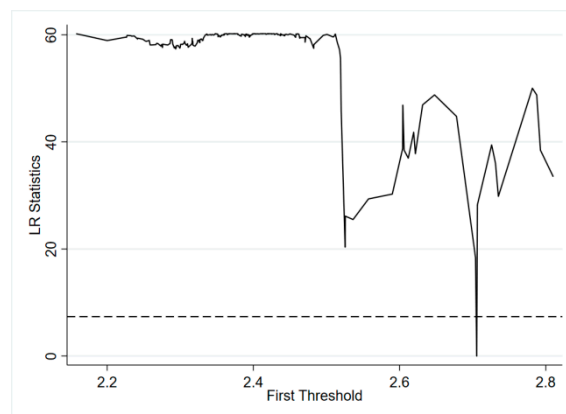


Figure 1. ISI single-threshold estimation results.

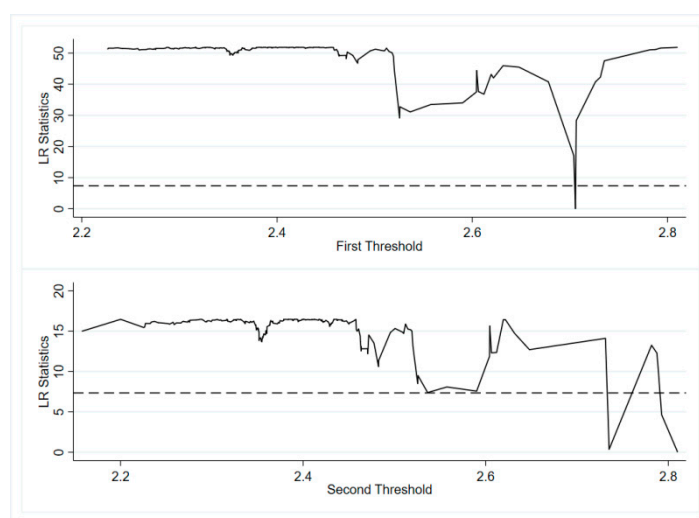


Figure 2. ISU double-threshold estimation results.

First, in the single-threshold model with ISI as the threshold variable (column 1), the coefficient of DE is 0.257 when ISI is below the threshold value of 2.706, indicating a positive impact on HQARD. However, when ISI exceeds the threshold, the coefficient of DE decreases to 0.049, suggesting a diminished effect. This finding implies that the relationship between DE and HQARD varies depending on the level of industrial structure intensification. The positive impact of the digital economy on agricultural development is more pronounced when ISI is below the critical level, while the marginal effect weakens once ISI surpasses the threshold. This result is consistent with the notion that as the industrial structure becomes more intensive, the spillover effects from other sectors to agriculture may diminish.

Second, the double-threshold model with ISU as the threshold variable (column 2) reveals a nonlinear relationship between DE and HQARD. When ISU is below the first threshold of 2.445, the coefficient of DE is 0.217, indicating a positive impact on agricultural development. As ISU increases and falls between the first and second thresholds (2.445 and 3.231), the coefficient of DE increases to 0.257, suggesting an enhanced positive effect. However, when ISU exceeds the second threshold, the coefficient of DE drops to 0.049, implying a reduced impact. This finding highlights the importance of industrial structure upgrading in moderating the effect of the digital economy on agricultural development. The initial upgrading process may facilitate the adoption of digital technologies in agriculture, but as the industrial structure becomes highly advanced, the focus may shift away from agriculture, leading to a diminished impact.

Third, our findings contribute to the growing literature on the relationship between the digital economy, industrial structure, and agricultural development. The threshold effects identified in this study provide a more nuanced understanding of how the impact of the digital economy on agriculture varies depending on the level of industrial structure intensification and upgrading. These results are in line with recent studies that emphasize the heterogeneous effects of technological advancements on different sectors and the importance of considering structural factors when assessing the impact of digitalization.

5. Conclusions and Policy Recommendations

This study analyzes the impact of the digital economy on high-quality agricultural and rural development in China using provincial data from 31 provinces between 2012 and 2021. The research highlights several key findings. First, the digital economy affects agricultural and rural development through the transformation and upgrading of the industrial structure, which in turn reflects how improvements in the country's economy can elevate the standard of living in rural areas. Second, this transformation can be divided into industrial structure sophistication and advancement. The digital economy facilitates the shift of resources from low- to high-productivity sectors, optimizing resource allocation and promoting development. However, it has a negative short-term impact on industrial advancement, potentially hindering immediate upgrades due to adaptation challenges faced by traditional industries. Despite this, the digital economy is a significant long-term driver of structural transformation and development. Third, the impact of the digital economy varies nonlinearly, with limited influence in early stages but increasing as the industrial structure reaches a certain level of advancement. This reinforces the connection between economic growth and digital technology development, highlighting their intertwined role in enhancing positive effects as digital integration in agriculture and rural sectors deepens.

Based on the findings of this study, we propose the following policy recommendations to promote the development of the digital economy and facilitate high-quality agricultural and rural development in China:

First, the government should prioritize the development of the digital economy as a key driver of industrial structure transformation, upgrading, and high-quality agricultural and rural development. This can be achieved by improving digital infrastructure, optimizing the institutional environment, and encouraging the widespread adoption of digital technologies in the agricultural sector. Specific measures may include increasing fiscal and financial support for digital agriculture initiatives, nurturing digital talent in rural areas, and refining the governance framework for digital agriculture.

Second, policymakers should formulate targeted digital economy development strategies that consider the distinct requirements of industrial structure intensification and upgrading. Tailored approaches should be implemented to promote the integration of digital technologies and agriculture, taking into account the varying stages of industrial development across regions. For areas with relatively lower levels of industrial development, the focus should be on promoting the application of digital technologies in agricultural production and management. In contrast, regions with more advanced industrial development should aim to foster the deep integration of digital technologies throughout the entire agricultural value chain.

Third, to ensure the effectiveness of policies aimed at promoting the digital economy and high-quality agricultural and rural development, it is crucial to conduct ongoing research on the evolving relationship between these two factors. As the industrial structure continues to upgrade, the impact of the digital economy on high-quality agricultural and rural development may exhibit new characteristics. Policymakers must remain vigilant, promptly optimizing and adjusting policies to provide sustained support for high-quality agricultural and rural development. Establishing and refining monitoring and evaluation mechanisms for digital agricultural development is essential, along with regularly assessing

the implementation effects of relevant policies and making timely adjustments based on the assessment results.

By implementing these policy recommendations, China can effectively harness the potential of the digital economy to drive industrial structure transformation and upgrading while promoting high-quality agricultural and rural development. This, in turn, will contribute to the overall goal of rural revitalization and sustainable economic growth.

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