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Research article

The coordinated impacts of agricultural insurance and digital financial inclusion on agricultural output: Evidence from China

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A R T I C L E I N F O

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A B S T R A C T

The coordinated development of agricultural insurance and digital financial inclusion is crucial to agricultural production, previous research on the subject is unclear. Based on the data of some provinces in China from 2011 to 2019, the entropy method is used in this paper to construct indexes measuring the development of agricultural insurance and digital financial inclusion. Their coupling coordination index is calculated, and the basic characteristics of the coupling coordination degree are analyzed. The influence of the coupling coordination degree of agricultural insurance and digital financial inclusion on agricultural output is empirically analyzed by constructing a regression model. The results show that the coupling coordination degree of agricultural insurance and digital financial inclusion significantly improves farmers' agricultural output, and the promotion effect is more prominent in eastern China and mountainous areas. And the threshold effect analysis show that there is a nonlinear relationship between the coupling coordination degree of agricultural insurance and digital financial inclusion on agricultural output. The conclusion of this paper provides a theoretical basis and empirical evidence for the coordinated development of rural financial system and agricultural construction.

1. Introduction

Agricultural production is the basis of human survival. Since the reform and opening up, China's agricultural production has been continuously improved, and the added value of agriculture has increased by year, from 1653.6 billion yuan in 2002–8677.5 billion yuan in 2021 [1,2]. With the development of agriculture, more studies have analyzed the reasons affecting agricultural production, such as credit [3], technology and system [4], climate change [5] and trade [6]. The factors affecting agricultural production are divided into the following three categories: system reform, factor input and total factor productivity (TFP) [3,4]. System reform include the land property right system reform, tax and fee reduction and price [7–9]. Throughout the process of agricultural development, the milestone of the land property rights system reform is the household contract responsibility system [10,11], and the implementation of the household contract responsibility system is of great significance to the improvement in agricultural productivity [12–14]. In 2006, agricultural taxes were completely abolished, which promote agricultural development [14]. The factor inputs of agricultural production are mainly divided into land, capital, labor and intermediate inputs [3,4]. Feder et al. [3] showed that credit satisfied the source of funds needed for agricultural production. Fan [4] found the agricultural labor force, land and farm machinery

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elements significantly improved the agricultural output. The input and output of factors follow the law of marginal decline, and existing studies have shown that the agricultural output elasticity of intermediate inputs (farm machinery, fertilizer, etc.) is gradually increasing [15], Gong [15] analyzed the output elasticity of various agricultural production factors, and it was found that the output elasticity of intermediate inputs gradually increased, the labor elasticity decreased. TFP is determined by technological innovation. Sheng [16] measured China's TFP from 1978 to 2016, and the results showed that TFP growth accounted for 40% of output growth before 2009, and the average growth rate gradually slowed down after 2009.

Although China's agricultural production has made outstanding achievements at the global level, there are also some obstacles [17]. In recent years, with the industrialization and urbanization, a large amount of the agricultural labor force has poured into the secondary and tertiary industries [18–20]. The cross-regional flow of the labor force has led to the phenomenon of farmland and wasteland abandonment in rural areas [21]. The promotion and popularization of frontier science and technology in rural areas are facing obstacles. In addition, farmers faced the trouble of capital factors because traditional finance entails guarantee or mortgage procedures, the process is complicated, and the examination and approval are strict, such that farmers find it difficult to obtain loans from financial institutions [22,23], which to a large extent hinders the process of agricultural economic development. With the impact of COVID-19 and extreme weather, agricultural production have been severely hampered [24–26]. In general, agricultural production problems worthy of attention. The development of the rural financial system can solve some problems in agricultural development. This paper selects two important components of the rural financial system, agricultural insurance and digital financial inclusion, and analyzes the coordination effect of the two in agricultural output [27].

As a risk management tool, agricultural insurance effectively compensates for farmers' post-disaster losses and is conducive to the continuity and stability of agricultural production [28]. Many scholars have carried out research on agricultural insurance and its effects on household income, agricultural output and the rural economy [29–31]. Li et al. [30] analyzed the impact of agricultural insurance and air pollution on agricultural green TFP in China, and the results showed that agricultural insurance could improve agricultural green TFP. Similar studies include Ahmed et al. [29]. Zou et al. [31] studied the impact of agricultural insurance on China's agricultural output and pointed out that agricultural insurance promoted the growth of agricultural output by improving labor productivity and arable area. Some scholars believe that agricultural insurance affects agricultural output by changing factor inputs, such as chemical fertilizers and pesticides, but there is no consensus on whether there is a substitution relationship or a mutually promoting relationship between agricultural insurance and factor inputs [32,33]. Other scholars have analyzed whether agricultural insurance affects agricultural production by changing the agricultural land management area [34,35]. Yamauchi [34] pointed out that the promotion of agricultural insurance increases the crop planting area to make the grain yield increase significantly, Lafrance J.T. et al. [35] found that would not affect the planting area. Besides, there are scholars attention moral hazard and adverse selection, which can lead to the loss of agricultural production [36–38]. Digital financial inclusion, as another important part of rural finance, can provide credit support for farmers and solve the problem of insufficient financial services in rural areas [39]. In the literature, most studies separate agricultural insurance and digital financial inclusion [34,40]. Moreover, existing literatures are mostly studied in the framework of "insurance and credit" [41,42], and the role of insurance and digital financial inclusion in agriculture is unclear. The improvement in agricultural requires the coordination and cooperation of financial system. Therefore, it is imperative to study the impact of the coupling coordination degree of agricultural insurance and digital financial inclusion on agricultural production.

Agricultural insurance and digital inclusive finance are important components of rural finance, and whether the two coordinated development will have an impact on agricultural production deserves further consideration. In order to analyze the impact of the coupling coordination degree of agricultural insurance and digital financial inclusion on agricultural output, this research constructed the coupling coordination degree index of agricultural insurance and digital financial inclusion, and mainly studied the following two aspects by using regression analysis method: (1) The influence of their coupling coordination degree on agricultural output; (2) Verify whether there is a nonlinear relationship between the coupling coordination degree and agricultural output. The main contributions are as follows: (1) The research can enrich the literature in related fields; (2) Innovation in research ideas, construction of coordination index and threshold test; (3) It provides reference for the improvement of rural financial system.

2. Theoretical model

In this part, the theoretical model related to the coupling coordination degree of agricultural insurance and digital inclusive finance on agricultural output will be established. The commonly theoretical models of agricultural output include Solow growth model [43] and Ramsey-Cas-Koopmans (RCK) model. This study constructs the theoretical model on the basis of Solow growth model [43]. The premise is that the production function satisfies constant returns to scale. Based on the Solow model, the agricultural production function is set as follows [43]:

$$Y(t) = F(K(t), A(t)L(t)) \tag{1}$$

Y is the level of agricultural output, A is technology, K is capital, and t is time. Among them, agricultural production is characterized by labor enhancement. The effect of agricultural insurance and digital inclusive finance on agricultural output is essentially that they have effects on L, K and A, and they realize the increase of agricultural output by eliminating the distortion of factor prices, resource allocation and other ways.

2. Materials and methods

2.1. Data

This study uses two data sources: micro survey data and macro data. The micro survey data used in this paper are from the China Family Panel Studies (CFPS) conducted by Peking University (http://www.isss.pku.edu.cn/cfps/index.htm, accessed on January 5, 2022). The survey data from 2014, 2016 and 2018 are used in this study. The explained variables for agricultural output and some control variables are from the CFPS, the explanatory variables for digital financial inclusion are from the digital financial inclusion index released by Peking University (website: https://idf.pku.edu.cn/yjcg/zsbg/513800.htm, accessed January 5, 2022) [44], and the agricultural insurance and other control variables are from the annual macro data released by the National Bureau of Statistics (website: http://www.stats.gov.cn/, accessed January 5, 2022). To prevent endogeneity problems, which may be caused by bidirectional causality, this paper follows the treatment methods used in the existing literature and selects the predetermined variables in the macro variables involved in the analysis.

The main object of this paper is agricultural output, then only sample families engaged in agricultural production are retained in this paper when processing micro data. After the removal of invalid and missing samples, the final sample size was 15,816 households.

2.2. Variables

2.2.1. Dependent variables

Agricultural output measures usually involve macroscopic and microscopic investigations with different statistical caliber. The dependent variable in this paper is the total output value of farmers' agricultural and sideline products provided by the CFPS. Compared with macro data, micro data better addresses the reverse causality problem and can observe individual heterogeneity.

2.2.2. Key variables

To study the coordinated agricultural output effect of agricultural insurance and digital financial inclusion, the core explanatory variable of this paper is expressed by the coupling coordination degree of agricultural insurance and digital financial inclusion, which reflects the coordinated development degree of agricultural insurance and digital financial inclusion. The higher the index value is, the higher the coordinated development degree of agricultural insurance and digital financial inclusion, and vice versa. The single-dimensional index of agricultural insurance premium income only represents the insurance level of agricultural insurance, which cannot comprehensively and systematically cover other necessary factors, such as insurance claims. Therefore, this study synthesizes the agricultural insurance index from agricultural insurance premium income and agricultural insurance claims. Premium income is insurance company based on the obligation of insurance contract which needs the cost that policy holder pays. In the event that a claim is required in the future under the contract, the amount required to be paid is insurance claims. Both agricultural insurance premium income and agricultural insurance claims come from the annual macro aggregate data. The development level of digital financial inclusion takes the digital financial inclusion index released by Peking University as the indicator to measure the development of digital financial inclusion [44]. The index includes three levels: coverage breadth, coverage depth and digitalization degree. It is the most authoritative and widely used index evaluation system for the development of digital financial inclusion in China. This study uses the processing methods in the existing literature to synthesize indices to measure the development degree of provincial digital financial inclusion from the three aspects of coverage breadth, depth of use and degree of digitalization by using the entropy weight method. The coupling coordination degree of agricultural insurance and digital financial inclusion indicators is also taken as the explained variable. In this paper, the entropy weight method is used to measure the index weight. The indicator system and weight information of agricultural insurance and digital financial inclusion are shown in Table 1 below.

2.2.3. Control variables

To alleviate the possible endogeneity problem linked to omitted variables, this paper considers the three aspects of family features, village characteristics and macroeconomic situation as selected control variables. Household characteristics mainly include the proportion of the population engaged in agricultural labor, land management area, whether the land is leased in or out, agricultural machinery value, social capital and household assets and liabilities. The village features mainly concern the economic level of the village, the terrain characteristics of the village and the traffic situation of the village. The household characteristic variables and village characteristic variables are obtained from the publicly available data in the CFPS. Macroeconomic characteristic variables at the regional level include the regional economic development level and the added value of the secondary and tertiary industries. The

Table 1
Evaluation index system of agricultural insurance and digital financial inclusion.

Coupling Subsystem	Index layer	Units	Attributes	Weights	Mean	S.D.
Agricultural insurance	Agricultural insurance premium income	Million (RMB)	+	0.508	1266.758	1121.111
	Agricultural insurance claims	Million (RMB)	+	0.492	842.785	903.562
Digital Financial Inclusion	Coverage	–	+	0.332	182.251	90.474
	Depth of coverage	–	+	0.334	197.018	91.456
	Degree of digitization	–	+	0.335	278.400	117.673

regional aggregate data come from the data published on the official website of the National Bureau of Statistics. The definitions and descriptive statistical analysis of the variables are shown in Table 2.

2.3. Method

2.3.1. Coupling coordination degree model

In the operation of society and the economy, there are internal coupling relations among resources, the environment and the economy, and the evaluation system of the social economy has been transformed from a single dimension to a comprehensive evaluation system of overall balance and coordination. Coupling is the phenomenon of dynamic correlation between two or more systems. This concept comes from physics. The coupling coordination degree model is the most intuitive and effective method to measure coupling relationships [45–47]. Song [45] points out that the coupling coordination degree model can reveal the coupling degree and interrelationship of subsystems. Similar views are held on this method [46,47]. In conclusion, the coupling coordination degree model is suitable for analyzing the coupling degree of the two subsystems of agricultural insurance and digital financial inclusion. The coupling coordination degree model can be used to quantitatively analyze the evolution of the coupling coordination between agricultural insurance and digital financial inclusion. The coupling coordination degree model is usually divided into the coupling model and the coordination model. The coupling model mainly measures the coupling degree C of the system, while the coordination model reflects the synergistic effect of the coupling system by measuring the coordination degree D and the comprehensive coordination index T. C indicates the interaction relationship between two or more systems, D and T reflect the benign coupling level and the state of coordinated development between different systems. With the promotion and deepening of agricultural insurance and digital financial inclusion in rural areas, the impact of their coordinated development and interaction on agricultural output is also worth further discussion. Once the internal development of the financial system is not coordinated, the effect of financial support for agricultural production may be affected by non-negligible. In addition, there are relatively few studies on this aspect, so this paper uses the coupling coordination degree model to measure the coupling level of rural financial system. The evaluation system and specific formula of the coupling coordination degree model are as follows [45–47]:

$$C = \left[\frac{\prod_{i=1}^{n} U_i}{\left(\frac{1}{n} \sum_{i=1}^{n} U_i \right)^n} \right]^{1/n} \tag{2}$$

In Formula (2), C is the coupling degree of the system, and Ui is the subvalue of each system. Ui in this paper is the comprehensive variable obtained through the entropy method, and the value range of C is [0, 1]. The higher the value of C is, the higher the coupling degree among subsystems. According to the classification of existing literature [48], $C \in (0,0.3)$ indicates that agricultural insurance and digital financial inclusion are in the state of a cooperative game, belonging to a low level coupling stage; $C \in (0.3, 0.5)$ indicates the stage of noncooperation; $C \in (0.5, 0.8)$ indicates the stage of benign coupling; $C \in (0.8, 1.0)$ indicates that the systems are at a high level of coupling; $C = 1$ means that the systems realize benign resonance coupling and tend to a new ordered structure. Since only two subsystems of agricultural insurance and digital financial inclusion are involved in this paper, the value of n is 2, and the expression of the coupling degree of the system can be simplified as follows [45–47]:

Table 2
Variable definitions and descriptive statistics in the model.

Variables	Definition	Mean	S.D
Dependent variable			
Agricultural output	Agricultural and sideline products take logarithm value	5.195	6.087
Key variable			
D	Measured index	0.524	0.102
Control variable			
Agricultural labor population proportion	Agricultural population as a proportion of the total number of households	0.538	0.268
Area of land management	Based on questionnaire data	9.692	31.048
Land rented	Farmers rents land (yes = 1, no = 0)	0.179	0.383
Land rent out	Farmer leases land (yes = 1, no = 0)	0.091	0.288
Agricultural machinery	Take logarithm of farmer machinery input	1.259	6.281
Social capital	Expenditure on gifts, in logarithm	6.316	4
Household financial assets	Cash and deposits	3.427	7.091
Household financial liabilities	Financial liabilities other than mortgages	−1.446	6.092
Village economy	Per capita net income of the village	7.447	3.262
Village topography	Mountains and hills take the value of 2, plain takes the value 1, other takes the value 0	1.275	0.726
Village traffic	Distance to the nearest town	13.321	52.31
GDP	Regional economic development level	10.631	0.352
Secondary industry	Proportion of added value of the secondary industry	0.456	0.058
Tertiary industry	Proportion of added value of the tertiary industry	0.438	0.062
Observation	15,816		

$$C = \frac{2\sqrt{U_1 U_2}}{U_1 + U_2} \tag{3}$$

Agricultural insurance and digital financial inclusion show a dynamic development trend, and the coupling degree and coordination degree should be used together to reflect the coupling interaction and synergistic effect of agricultural insurance and digital financial inclusion. The coordination model includes the comprehensive coordination index T and coordination degree D, which is the comprehensive index of the system coupling degree C and coordination index T. The coordination degree model used in this paper is shown as follows [45–47]:

$$T = aU_1 + bU_2 \tag{4}$$

$$\mathrm{D} = \sqrt{\mathrm{C} * \mathrm{T}} \tag{5}$$

In equation (4), a and b are the weights of the subsystems, and $a + b = 1$. In most studies, the values of a and b are assumed to be the same, and each subsystem is considered to be of the same importance [48]. The value range of T and D is [0,1], and the existing studies often divide the degree of coordination D into five categories [48], where $D \in [0,0.2]$ is the stage of serious disorder. $D \in (0.2, 0.4)$ is moderate disorder; $D \in (0.4, 0.5)$ is the basic coordination stage; $D \in (0.5, 0.8)$ indicates moderate coordination; and $D \in (0.8, 1.0)$ indicates high coordination.

2.3.2. Kernel density method

Kernel density estimation is used to study the evolution characteristics of the coupling coordination degree between agricultural insurance and digital financial inclusion. Kernel density estimation is a method commonly used to study unbalanced distributions. The principle of this method is to treat the distribution characteristics of the research object as a probability distribution and analyze the variation trend of the distribution over time. Dai [49] point out that kernel density estimation by estimating the probability distribution of random variables is expressed in the continuous density curve distribution of random variables. The kernel density estimation method can be used to fit the three dimensional graph of the variable, which is convenient to observe the evolution of the coupling coordination degree. The kernel density estimation formula is as follows [49]:

$$\mathrm{f}(x) = \frac{1}{Nh} \sum_{i=1}^{\mathrm{N}} \mathrm{K}\left(\frac{X_i - x}{h}\right) \tag{6}$$

In equation (6), $f(x)$ is the density function of random variable X, $K(\cdot)$ is the kernel function, which is a kind of weighting function or smoothing function, N is the number of observed values, h is the bandwidth, X is an independent and identically distributed random variable, and x is the mean value. Parameter estimation and nonparametric estimation are two methods of function estimation, and kernel density estimation is a nonparametric estimation. Nonparametric estimation relies on graph changes and comparative analysis of the evolution of the distribution of random variables.

2.3.3. Spatial autocorrelation analysis

In this study, the spatial correlation global moran index was used to analyze the spatial correlation characteristics of the coupling coordination degree [50]. Spatial data analysis is helpful to clearly identify the spatial evolution process and regional structure of the coupling coordination degree between agricultural insurance and digital financial inclusion. The specific formula is as follows [50]:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \overline{x})(x_j - \overline{x})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \tag{7}$$

$$S^2 = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} (x_i - \overline{x})^2}{n} \tag{8}$$

Formula (7) is the global spatial autocorrelation, where n is the number of provinces in the sample, w_{ij} is the element in the spatial weight matrix W, x_i and x_j are the coupling coordination degrees of provinces i and j, respectively, and is the mean value of the coupling coordination degree. The value range of I is $[-1, 1]$. When $I = 0$, it indicates that there is no spatial autocorrelation and the distribution is random in space. When $I > 0$, there is a positive spatial correlation, and the larger the value is, the more obvious the spatial correlation is. When $I < 0$, there is a negative spatial correlation [51].

2.3.4. The regression model

Based on the above analysis, the benchmark model is set as follows:

$$Agricultural\ output_{ijt} = \alpha_1 D_{jt} + \alpha_2 X_{ijt} + \alpha_3 V_{ijt} + \alpha_4 Z_{jt} + \mu_i \tag{9}$$

where i is the farmer, j is the region, $Agricultural\_output_{ijt}$ represents the farmer's agricultural output, the core explanatory variable is the composite index D_{jt} of agricultural insurance and digital financial inclusion, X_{ijt} is the control variable of family characteristics, V_{ijt} is the control variable of village characteristics, Z_{jt} is the control variable of regional macroeconomic characteristics, and μ_i is the unobservable random disturbance term.

A threshold regression model considers the nonlinear relationship between variables. Hansen [52] pointed out that when a parameter reaches a specific value, the development form of another parameter can change, and the regression results exhibit the phenomenon of structural mutation. The point of structural mutation is the threshold value. The basic principle of threshold regression is to use sample data to estimate the threshold of the structural break point and test whether there are differences in regression coefficients between different groups. Since the impact of D on agricultural output may vary between intervals with different levels of economic development, there may be a nonlinear relationship. In order to test whether there is a nonlinear relationship and estimate the threshold value, this paper constructs a threshold regression model [53]. On the basis of the benchmark model, the single threshold regression model is set as follows [52,53]:

$$Agricultural\ output_{ijt} = \beta_1 D_{jt} * I\left(T_{ijt} \le \gamma\right) + \beta_2 D_{jt} * I\left(T_{ijt} > \gamma\right) + \beta_3 X_{ijt} + \beta_4 V_{ijt} + \beta_5 Z_{jt} + \varepsilon_i \tag{10}$$

T_{ijt} is the threshold variable, γ is the threshold value in the case of a single threshold, and $I(\cdot)$ is the indicative function, When the expression in parentheses is true, the value is 1; otherwise, it is 0.

3. Results

3.1. Analysis of the coupling coordination degree between agricultural insurance and digital financial inclusion

3.1.1. Analysis of the coupling coordination degree between agricultural insurance and digital financial inclusion in different regions

Based on the calculation principle of the coupling coordination degree, the coupling degree and coordination degree indexes of agricultural insurance and digital financial inclusion in each region from 2011 to 2019 were obtained, and the data were used to preliminarily measure the coordinated development level of agricultural insurance and digital financial inclusion. It can be seen from Table 3 that in the whole sample, the coupling degree level is high, first decreasing and then rising, and reaches a high level of coupling in 2019. The coordination degrees T and D increase year by year, but the overall coordination level is not high. According to the data, system coupling C is higher than 0.65, indicating benign coupling and a high level state. Regional coupling C appears to fall after an initial rising trajectory, and the coupling in the central region is ahead of that in the eastern and western regions. Since 2015, coupling C in the eastern region system has been behind that in the central and western regions. The level of coordination in the central region is still ahead of that in the eastern and western regions. There is a gap between the coupling coordination degrees of agricultural insurance and digital financial inclusion in different regions. This paper uses the kernel density estimation method to further analyze the differences across regions.

Kernel density estimation can reflect the dynamic evolution process of the coupling coordination degree between agricultural insurance and digital financial inclusion. The shift in the kernel density curve and the height and width of the crest show the development trend and regional difference in the coupling coordination degree. Fig. 1 shows the dynamic changes in the coupling coordination degree for the whole sample and each region. Fig. 1 (a) is the three-dimensional kernel density diagram of the coupling coordination degree. During the observation period, the curve shifted to the right as a whole, indicating that the coupling coordination degree of each region gradually increased. The height of the curve did not change significantly during the sample period, but the width increased, indicating that the difference degree of each region increased. Fig. 1 (b), (c) and (d) are the kernel density maps of the eastern, central and western regions, respectively. The kernel density maps of the eastern, central and western regions all show a trend of moving to the right, indicating that the coupling coordination degree of each region increased to varying degrees during the observation period. There is no significant change in wave height in the eastern region, but the width increases, indicating that the coupling coordination degree difference between the eastern regions gradually became obvious. The peak height of the central and western regions gradually increases, indicating that the regional gap was significantly reduced. This result indicates that although the coordination degree of agricultural insurance and digital financial inclusion between regions has improved, the phenomenon of regional imbalance still exists.

Table 3
Coupling coordination degree of agricultural insurance-digital financial inclusion.

Year	C				T				D			
	Full sample	East Area	Central Area	West Area	Full sample	East Area	Central Area	West Area	Full sample	East Area	Central Area	West Area
2011	0.7806	0.7681	0.9407	0.6658	0.0744	0.0816	0.0796	0.0063	0.2356	0.2483	0.2697	0.1950
2012	0.7441	0.7047	0.8872	0.6590	0.1669	0.1778	0.1758	0.1481	0.3506	0.3519	0.3945	0.3110
2013	0.7174	0.6705	0.8396	0.6568	0.2606	0.2711	0.2683	0.2377	0.4306	0.4241	0.4745	0.3938
2014	0.7273	0.6816	0.8120	0.6796	0.2859	0.2885	0.2891	0.2732	0.4543	0.4415	0.4843	0.4291
2015	0.7116	0.6666	0.7866	0.6670	0.3646	0.3697	0.3585	0.3515	0.5076	0.4943	0.5307	0.4825
2016	0.7483	0.6974	0.8210	0.7141	0.3749	0.3687	0.3941	0.3555	0.5286	0.5057	0.5687	0.5030
2017	0.7498	0.6829	0.8285	0.7272	0.4293	0.4253	0.4528	0.4111	0.5662	0.5372	0.6124	0.5461
2018	0.7805	0.7090	0.8570	0.7702	0.4853	0.4929	0.5173	0.4565	0.6142	0.5895	0.6656	0.5925
2019	0.8122	0.7438	0.8798	0.8050	0.5400	0.5466	0.5673	0.5054	0.6607	0.6362	0.7062	0.6366

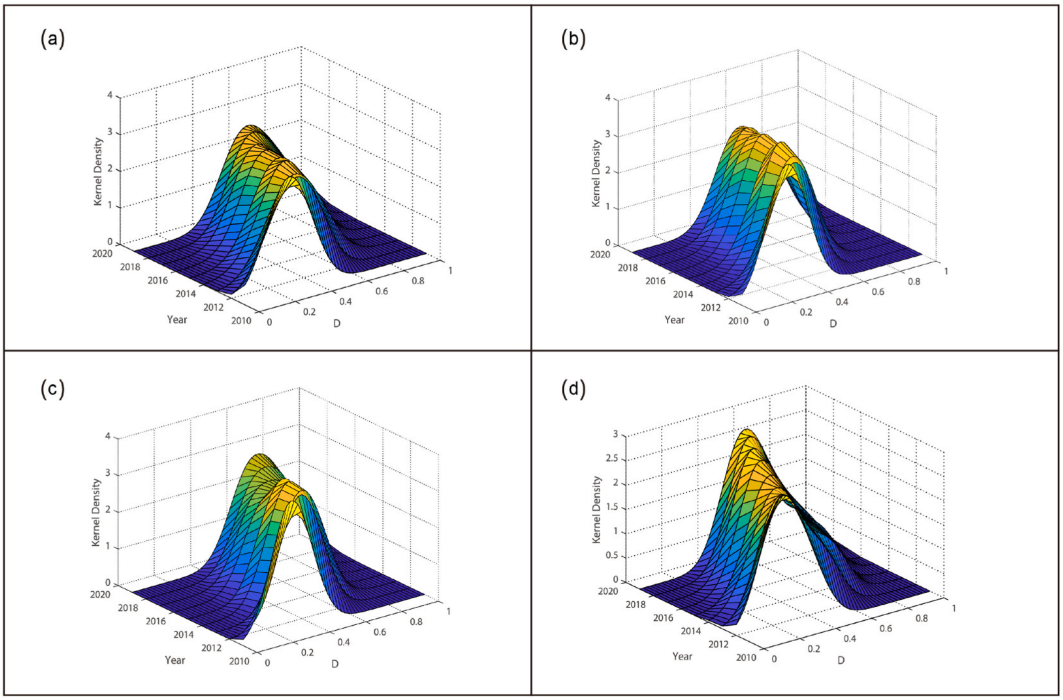

Fig. 1. Evolution of d from 2011 to 2019.

3.1.2. Spatial autocorrelation analysis

From 2011 to 2019, the global Moran autocorrelation indexes of the coupling coordination degree of agricultural insurance and digital financial inclusion were all greater than 0, fluctuating from 0.046 in 2011 to 0.059 in 2019, the graph is shown in Fig. 2. The Moran in digital financial inclusion index is greater than 0, indicating that there is a positive spatial correlation between the coupling coordination degree of agricultural insurance and digital financial inclusion between different regions. There is a synergistic development trend among regions, and the spatial autocorrelation becomes higher with the increase in Moran's value.

3.2. Analysis of agricultural output coordinated by agricultural insurance and digital financial inclusion

3.2.1. The benchmark return results

Table 4 reports the benchmark regression results of agricultural output coordinated by agricultural insurance and digital financial inclusion coupling. Regression 1 shows the empirical results of the whole sample. The coefficient of the coupling coordination index D of agricultural insurance and digital financial inclusion is 4.592 and significant at the 1% level, indicating that the coordinated development level of agricultural insurance and digital financial inclusion promotes the level of agricultural output. The proportion of people involved in agricultural production, rented land, value of agricultural equipment, social capital, total value of cash and deposits, and village economic conditions significantly promote agricultural output, while land rental, terrain characteristics, village

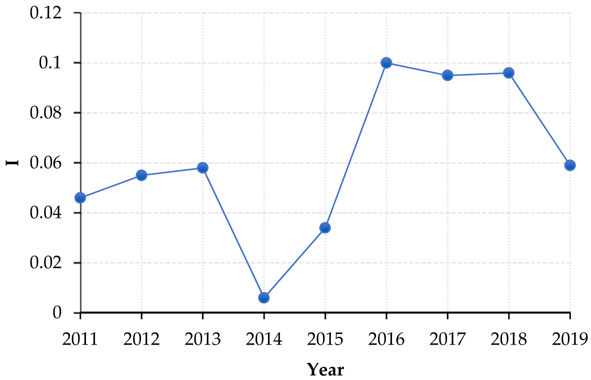

Fig. 2. The global Moran index in 2011–2019.

Table 4
Baseline regression analysis results: full sample and subregion.

Variables	(1)			(2)			(3)		
	Full sample			East Area			West Area		
D	4.592	(0.683)	***	19.247	(1.91)	***	0.897	(0.793)	
Agricultural labor population proportion	1.588	(0.174)	***	1.777	(0.268)	***	1.076	(0.224)	***
Area of land management	0.0004	(0.001)		0.043	(0.007)	***	−0.001	(0.002)	
Land rented	1.506	(0.122)	***	1.235	(0.201)	***	1.609	(0.150)	***
Land rent out	−1.361	(0.160)	***	−0.729	(0.271)	***	−1.503	(0.194)	***
Agricultural machinery	0.132	(0.008)	***	0.095	(0.012)	***	0.148	(0.009)	***
Social capital	0.144	(0.012)	***	0.146	(0.018)	***	0.109	(0.016)	***
Household financial assets	0.038	(0.007)	***	0.068	(0.011)	***	0.048	(0.009)	***
Household financial liabilities	0.009	(0.008)		−0.011	(0.013)		0.018	(0.009)	*
Village economy	0.045	(0.015)	***	−0.014	(0.025)		0.023	(0.018)	
Village topography = 2	−2.098	(0.109)	***	−1.372	(0.157)	***	−2.602	(0.150)	***
Village topography = 0	−2.150	(0.154)	***	−1.315	(0.317)	***	−2.676	(0.185)	***
Village traffic	−0.005	(0.001)	***	0.007	(0.004)	**	−0.005	(0.001)	***
GDP	−0.985	(0.246)	***	4.231	(0.585)	***	−2.750	(0.557)	***
Secondary industry	0.423	(2.603)		−28.056	(5.394)	***	20.379	(3.378)	***
Tertiary industry	−5.725	(2.443)	**	−41.495	(5.008)	***	11.927	(2.864)	***
_cons	12.658	(1.509)	***	−19.871	(5.333)	***	18.81	(4.725)	***
Year	YES			YES			YES		
R^2	0.114			0.174			0.123		
Obs	15,630			5781			9866		
P value				−2.959**					

Note: (1) *p < 0.10, **p < 0.05, ***p < 0.01, the standard errors of coefficients are in parentheses; (2) "P value" was used to test the significance of the D coefficient difference between groups.

traffic conditions and GDP significantly suppress agricultural output. Regressions (2) and (3) are the regression results of the eastern region and the western region, respectively. The regression coefficient of D in the eastern region is significantly positive at the level of 1%, while the coefficient of D in the western region is not significant. The P value is obtained through self-sampling 100 times and is the result of the intergroup coefficient difference test. The results show that there is a significant difference in the regression results between the eastern and western regions. Agricultural insurance and digital financial inclusion have significant promoting effects on agricultural output in eastern regions. Moreover, this regression result confirms that there is regional imbalance in the coupling coordination degree between agricultural insurance and digital financial inclusion. In addition, the existence of endogeneity problems may lead to errors in estimation, so this paper further selects instrumental variables for two stage least square (TSLS).

Endogeneity problems, such as measurement error, bidirectional causality and missing variables, may exist in the model estimation. Based on this, this paper uses the instrumental variable method to estimate. The selection of instrumental variables should meet the conditions of externality, correlation with endogenous explanatory variables and exclusivity. On the basis of existing references, the coupling coordination degree between agricultural insurance and digital financial inclusion, which lags 2 periods, is selected as an instrumental variable [54,55]. The regression analysis results of the instrumental variable method are shown in Table 5 below. The regression coefficients of the first stage and the second stage are significantly positive at the 1% level. To verify the effectiveness of the instrumental variables, the problem of weak instrumental variables is tested according to the regression results. The Wald F test is passed, so there is no problem of weak instrumental variables, indicating that the selection of instrumental variables was effective. The regression results of the TSLS are consistent with the conclusion of the whole sample, which verifies the authenticity and reliability of the regression results.

3.2.2. *Threshold effect analysis*

As shown from the regression results, there are significant differences between the regression coefficients of core explanatory variables in the regional regression. Therefore, agricultural output may vary with the level of economic development and industrial

Table 5
IV estimation regression results.

Variables	(1)			(2)		
	D			Agricultural output		
L (−2)	1.034	(0.0026)	***			
D				4.135	(0.715)	***
Control variables	YES					
Year	YES					
_cons	0.025	(0.005)	***	12.750	(1.508)	***
R^2	0.963			0.114		
Obs	15,630			15,630		

Note: *p < 0.10, **p < 0.05, ***p < 0.01, the standard errors of coefficients are in parentheses.

structure among regions; that is, there is a nonlinear relationship between the coupling coordination degree of agricultural insurance and digital financial inclusion and agricultural output. Therefore, on the basis of group regression, the threshold effect proposed by Hansen [52] is selected to test and measure whether there is a nonlinear relationship between variables and determine the threshold of the nonlinear relationship. In this paper, per capita GDP and industrial structure are selected as threshold variables to test the nonlinear relationship, and industrial structure is measured by the proportion of added value of the tertiary industry based on the existing literature. Threshold effect analysis mainly consists of two steps: the first step is to check whether there is a threshold effect; if there is, then the threshold value is estimated. The second step is to test whether there is a difference in the parameter estimation results. Table 6 shows the threshold effect test and threshold estimation results. The F statistic of the threshold variable economic development level and industrial structure is significant at the 1% level, and the results of the P value are all less than 0.01, which rejects the null hypothesis of the three-threshold model. Therefore, there are three threshold values for both the economic development level and industrial structure. Table 6 lists the threshold values of the estimated results. This shows that when the level of economic development and industrial structure exceed the threshold, the impact of the coupling coordination degree of agricultural insurance and digital financial inclusion on agricultural output changes. Fig. 3 shows the likelihood ratio function of the threshold estimate. The dotted line is higher than the lowest point of the curve in the picture, indicating that the threshold value is real and valid. In Fig. 3, (I), (II) and (III) are the threshold estimates of GDP respectively, the three threshold estimates are 11.088, 11.005 and 11.120, while (IV), (V) and (VI) are the threshold estimates of industrial structure, the three threshold estimates are respectively 0.354, 0.351 and 0.451. Fig. 3 is correspond to the results in Table 6.

Table 7 reports the threshold regression results of the economic development level and industrial structure. The three thresholds divide the samples into four intervals. As shown from the regression results, when the value of the economic development level and industrial structure of threshold variables exceeds a certain range, the intensity of agricultural output coordinated by agricultural insurance and digital financial inclusion changes. When the economic development level of the threshold variable is at a low level, that is, lnGDP$\leq$11.005, the estimated coefficient of the coupling coordination degree of agricultural insurance and digital financial inclusion is 3.145 and passes the significance test at the 1% level. When the level of economic development keeps improving but lnGDP$\leq$11.088, the regression coefficient of coupling coordination degree D increases to 7.528. When the level of economic development reaches another level (11.088 $<$ lnGDP$\leq$11.120), the estimated coefficient of coupling coordination degree D decreases to 3.964, which is significant at the 1% level. When the level of economic development crosses the third threshold and reaches a high level (lnGDP $>$11.120), the estimated coefficient corresponding to the core explanatory variable is stable at 3.322. With the improvement in the economic development level, the regression coefficient of coupling coordination degree D on agricultural output first increases, then decreases and gradually stabilizes, indicating that agricultural insurance and digital financial inclusion have significant nonlinear threshold characteristics on agricultural output under different economic development levels. When the threshold variable industrial structure is low (T_industry $\leq$0.351), the estimated coefficient of coupling coordination degree D on agricultural output is 2.337. When the proportion of added value of the tertiary industry increases but the value is less than 0.354, the regression coefficient of coupling coordination degree D decreases sharply, and its estimated value is $-$2.534. When the proportion of the added value of the tertiary industry is greater than 0.354, the regression coefficient of the core explanatory variable gradually stabilizes. The threshold regression coefficients of industrial structure are significant at the 1% level. Within a certain range, the rise of the tertiary industry in GDP leads a large part of the agricultural population to transfer to the secondary and tertiary industries. This shift in population and resources to a certain extent can go against the development of agriculture. When the value added of the tertiary industry accounts for more than 0.354, there is a steady transformation of the economic structure, and short-term structural stability is formed between different industries. At this time, the coupling coordination degree D significantly promotes the growth of agricultural output, which also indicates a process of coordinated development among different industries. In conclusion, when lnGDP is the threshold variable, the higher the economic level is, the more the coupling coordination degree promotes the intensity of agricultural production, but the intensity of the coupling coordination degree is different in different ranges. When industrial structure is used as a threshold variable, the tertiary industry develops to a certain stage, and the tendency of factor resources leads to lower levels of agricultural output; only when the flow of elements between the three major industries stabilizes can the coupling of agricultural insurance and digital financial inclusion continue to promote the increase in agricultural output.

3.2.3. Heterogeneity analysis and robustness test

To ensure the accuracy and robustness of the regression results, on the basis of existing studies [56,57], this paper studies whether topographic heterogeneity exists in the impact of coupling coordination degree D on agricultural output and conducts a robustness test by screening samples. The results of the heterogeneity analysis and robustness test are shown in Table 8 below. Because agricultural

Table 6
Threshold effect test and threshold estimation results.

Threshold variable	Threshold number	F	P	Threshold value
lnGDP	Single threshold	18.068	0.000	11.088
	Two threshold	90.844	0.000	11.005
	Three threshold	12.896	0.000	11.120
T_industry	Single threshold	49.775	0.000	0.354
	Two threshold	57.834	0.000	0.351
	Three threshold	9.489	0.003	0.451

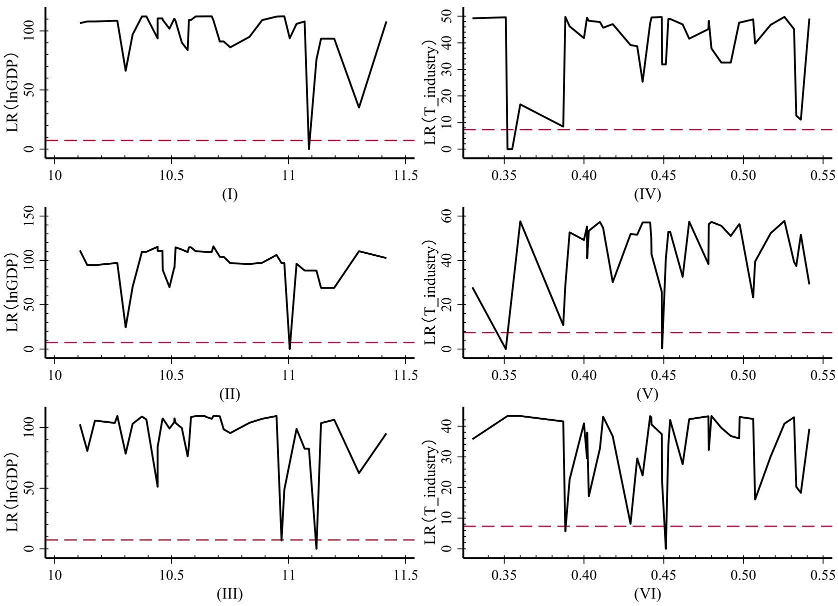

Fig. 3. Threshold estimation results.

Table 7
Threshold effect test and threshold estimation results.

Variables	lnGDP			T_industry		
lnGDP≤11.005	3.145	(0.545)	***			
11.005<lnGDP≤11.088	7.528	(0.784)	***			
11.088<lnGDP≤11.120	3.964	(0.734)	***			
lnGDP>11.120	3.322	(0.747)	***			
T_industry ≤0.351				2.337	(0.690)	***
0.351 < T_industry≤0.354				−2.534	(0.688)	***
0.354 < T_industry≤0.451				3.238	(0.541)	***
T_industry>0.451				3.280	(0.631)	***
Control variables	YES					
R^2	0.119			0.119		

Note: *p < 0.10, **p < 0.05, ***p < 0.01, the standard errors of coefficients are in parentheses.

Table 8
Regression results of heterogeneity analysis and robustness test.

Variables	Heterogeneity			Robustness test		
D	1.944	(1.123)	*	4.419	(0.707)	***
Village topography = 2	−3.123	(0.357)	***			
Village topography = 0	−1.227	(0.332)	***			
D*Village topography	1.982	(0.649)	***			
_cons	12.658	(1.509)	***			
Control variables	YES					
Year	YES					
R^2	0.116			0.113		
Obs	15,647			15,299		

Note: *p < 0.10, **p < 0.05, ***p < 0.01, the standard errors of coefficients are in parentheses.

production is closely related to the terrain characteristics of the region, heterogeneity is considered to analyze the interaction between topographic features and the coupling coordination degree. Based on the CFPS classification of topographic characteristics, this paper classifies topographic characteristics into three categories, namely, mountain and hilly areas with Village topography = 2, plain areas with Village topography = 1, and Village topography = 0 for grasslands, fishing villages, and other situations. According to the results of heterogeneity in Table 8, regions located in the plain support the improvement in agricultural output. The regression coefficient of the interaction term between terrain features and the coupling coordination degree is 1.982, showing that agricultural insurance and digital financial inclusion have a stronger effect on agricultural output in mountainous areas. Due to the different industrial structures of different provinces and cities, agriculture accounts for a relatively low proportion of the economic composition of municipalities directly under the central government. With reference to the treatment methods of the existing literature, municipalities directly under the central government were removed for the robustness test [58]. In Table 8, The coefficient of the core explanatory variable in robustness test is 4.419, which significant at the 1% level. It is consistent with the conclusion of the benchmark regression. The accuracy and reliability of the regression results are verified by heterogeneity analysis and robustness test.

4. Discussion

This study uses the method of empirical analysis to analyze the influence of the coupling coordination degree of agricultural insurance and digital financial inclusion on agricultural output. The findings are helpful to understand the logical relationship between rural financial system and agricultural output.

The degree of coupling coordination between agricultural insurance and digital financial inclusion is gradually increasing, which is similar to the results of relevant studies [59]. In practical terms, this is closely related to economic development, technological change and the spread of knowledge. With the popularization of agricultural insurance knowledge, farmers are more willing to buy agricultural insurance. The premium income of agricultural insurance increased from 17.4 billion yuan in 2011 to 67.248 billion yuan. In addition, the number of rural financial institutions' outlets and employees has achieved breakthrough development in all provincial regions. Both agricultural insurance and digital inclusive finance are increasing in depth, breadth and coverage, which, to a certain extent, makes the rural financial system develop comprehensively and the degree of coordination among subsystems is also improved. By comparing D in eastern, central and western, it can be seen that there is a regional imbalance phenomenon, with D in western China being the lowest and the highest in central China, which is consistent with the results of similar study [59]. The development of agriculture in the western region is mainly limited by the characteristics of the terrain. The overall level of economic development in the eastern region is relatively high, but it is not dominated by the primary industry. The central region is suitable for the development of agriculture and its convenient geographical location also provides good conditions for the development of agriculture and rural finance [60]. The kernel density figure reflects the subtle differences of the whole and different regions, and the results obtained are similar to the existing research [61]. The D of the three regions increased continuously and the degree of difference in each region expanded continuously, but did not show a trend of polarization. The difference is that Shen et al. [61] measured the kernel density of the financial development level of each province, while this study took the coupling coordination degree of the two subsystems of agricultural insurance and digital financial inclusion passes the Moran index test and is greater than 0, which means the financial system in rural areas is mutually reinforcing. This provides suggestions for the coordinated development of the financial system between regions, and the introduction of financial industry policies conducive to the balanced. It can help to narrow the imbalance between regions and provide reference for the construction of multi-level rural financial system.

With the impact of technological innovation, the financial demand in agricultural production becomes more prominent. The construction of agricultural infrastructure and rural financial system are of great significance to agricultural production and rural revitalization. It is found that D has a significant positive effect on agricultural output, which is consistent with the results of similar studies [62,63]. Karlan et al. [62] pointed out that the investment of smallholder farmers in developing countries depends on their financial environment, and improving the financial environment can bring significant welfare changes. Stefanija [63] shows that remittances remove credit constraints and insurance restrictions and increase fertilizer inputs. Research on the synergy mechanism between insurance and credit also include Dick [41] and Han [42]. It shows that the factors of production and the supporting market system do not exist in isolation, that many parties work together to affect agricultural output. However, the influence of coupling coordination degree D on agricultural production has regional differences, and this result is significantly positive in the eastern region, while there is no significant influence in the western region, which confirms the regional imbalance characteristics of coupling coordination degree. The western region is limited by natural environment and social attributes, which increases the difficulty in the development of agricultural insurance and digital inclusive finance in this region. This study can provide certain reference for the government to carry out rural financial business in the western region. In addition, factor input such as the proportion of agricultural labor force, leased land, agricultural machinery, social capital, and the total value of cash and deposits all significantly promoted agricultural output. The threshold effect analysis and regional heterogeneity test verified the regional difference of coupling coordination degree on agricultural production. In the future, it is necessary to adopt relevant policies, measures and development plans according to local conditions, combined with local social and natural attributes, which is to narrow the regional imbalance of the rural financial system.

There are several differences between this study and previous studies. Most scholars analyze the impact of "credit - insurance" on agriculture [62–64], but few studies have analyzed the effect of coordinated development of agricultural insurance and digital financial inclusion on agricultural output. In addition, the existing analysis of the internal coordination of rural financial system rarely uses comprehensive indicators to quantify [62]. Our study provides empirical evidence for the construction and improvement of agricultural insurance, digital inclusive finance and rural financial system. Here are still some problems worth further consideration. Limited by the data, the allocation of resources and new technologies were not included in the research. In the subsequent research, the effect analysis of factor allocation and technological change on agricultural output can be considered.

Based on the results, relevant policy implications are proposed as follows: First, The dual role of government and market mechanisms can be used to continuously improve the rural financial system, optimize the rural financial resource allocation system according to local conditions, narrow the differences in financial insurance services between regions and prevent polarized development [65]. Second, We will vigorously develop agricultural insurance, strengthen the promotion and scope of agricultural insurance, and increase subsidies for agricultural insurance premiums so that agricultural insurance benefits farmers [66,67]. In addition, it is crucial to promote the development of digital financial inclusion. While improving the required technical level, relevant departments should also strengthen support for the construction of digital financial inclusion in rural areas, reduce service costs, improve incentive mechanisms, enhance the integration of digital financial inclusion in agricultural production [39,68–70]. Moreover, a model suitable for the coordinated development of agricultural insurance and digital financial inclusion should be found [71,72]. Finally, the government should strengthen the construction of agricultural modernization demonstration areas, strengthen interregional exchanges and innovation [73].

5. Conclusion

Agriculture is a prerequisite for the smooth progress of other production activities. In this study, the coupling coordination degree of agricultural insurance and digital financial inclusion is measured by macro data in China, and the basic characteristics of the coupling coordination degree are observed. Micro survey data are used to analyze the impact of the coupling coordination degree of agricultural insurance and digital financial inclusion on agricultural output in China. The main conclusions of this paper are as follows: (1) The coupling degree of agricultural insurance and digital financial inclusion is relatively high and shows a trend of decreasing first and then rising, while the coordination degree increases year by year, but the overall level is not high. When observed by region, the coupling degree C and coordination degree D in the central region are ahead of those in the eastern and western regions. As shown in the kernel density diagram, although the coordination degree of agricultural insurance and digital financial inclusion among regions continues to improve, the phenomenon of regional imbalance still exists. (2) The coupling coordination degree of agricultural insurance and digital financial inclusion significantly improves farmers' agricultural output, and the promotion effect is more prominent in eastern China and mountainous areas. The threshold effect analysis results show that there is a nonlinear relationship between the coupling coordination degree of agricultural insurance and digital financial inclusion on agricultural output. This conclusion remains consistent following treatment of the endogeneity problem and a robustness test.

Author contribution statement

Chaofan An; Xiaoxia He: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Lin Zhang: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no conflict of interest.

Appendix A

Entropy weight method is based on the basic principle of variability index to determine the size of the objective weight [74,75]. Compared with subjective weighting, entropy weighting method is an objective weighting method with higher accuracy and simpler algorithm, but it has a high dependence on samples. The weighting step of entropy weight method is as follows [74,75].

(1) Standardized treatment of indicators. In order to eliminate the dimensional differences of different indicators in agricultural insurance and financial inclusion, the standardization process is first implemented. The specific formula is:

$$\omega_{ij} = \frac{X_{ij} - X_{min}}{X_{max} - X_{min}} \tag{A1}$$

$$\omega_{ij} = \frac{X_{max} - X_{ij}}{X_{max} - X_{min}} \tag{A2}$$

Where, i represents the sample, j represents the index, and Xij is the j index of the i province. The dimensionless index is obtained by standardization, A1 is a positive indicator and A2 is a negative indicator.

(2) Calculate the weight coefficients of indicators in agricultural insurance and digital financial inclusion.

$$H_{ij} = \frac{\omega_{ij}}{\sum_{i=1}^{n} \omega_{ij}} \tag{A3}$$

(3) Calculate the entropy of the index.

$$e_j = -r \sum_{i=1}^{n} H_{ij} \ln \left(H_{ij} \right) \tag{A4}$$

Where $r > 0$, $r = 1/(\ln n)$, and e_j ranges from (0,1).

(4) Calculate the difference coefficient of the index.

$$y_j = 1 - e_j \tag{A5}$$

The larger the difference coefficient y_j, the higher the importance of the index.

(5) Calculate the weight of each index.

$$Z_j = \frac{y_j}{\sum_j y_j} \tag{A6}$$

(6) The comprehensive score of each index was calculated.

$$D = \sum_j \left(Z_j \omega_{ij} \right) \tag{A7}$$

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