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An Empirical Study on the Relationship between Agricultural Science and Technology Input and Agricultural Economic Growth Based on E-Commerce Model

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Received: 28 September 2018; Accepted: 23 November 2018; Published: 28 November 2018

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Abstract: At present, e-commerce mode has been gradually applied to agricultural science and technology production, which has played an important role in agricultural economic growth and production efficiency. At the same time, the fundamental way out for sustainable and stable development of agriculture is science and technology. Generally speaking, part of the growth of the agricultural economy comes from agricultural production factors. The increase in input is partly due to the improvement of productivity of agricultural elements. Therefore, based on the background of the e-commerce environment, this paper chooses the entropy method to study the relationship between agricultural science and technology input and agricultural economic growth. Compared with the exponential method and the Bolat method, the entropy method can scientifically determine the specific weight of the indicators based on the variation of each quantitative index, so as to improve the accuracy and objectivity of the quantitative index analysis and avoid the adverse effects of human factors. The entropy method is used to evaluate and analyze the development level of agricultural e-commerce, which improves the accuracy and reliability of the evaluation results. Based on this, this paper makes an empirical study on the relationship between agricultural science and technology input and agricultural economic growth by using the method of entropy under the mode of e-commerce, constructs the index system of agricultural productivity, evaluates the situation of agricultural science and technology input and agricultural economic growth, and studies the relationship between them by using the method of regression analysis. Research shows that the application of agricultural science and technology investment and e-commerce mode can promote agricultural economic growth.

Keywords: e-commerce; agriculture; technology investment; economic growth

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1. Preface

Agricultural economic growth usually refers to the growth and change of the total output value of the agricultural sector in a certain period of time. It also refers to the change and growth of the ratio of the total input and the final total output of a country or a region. In China's "Internet +" strategic layout, "Internet + Agriculture" is a hot spot for government and related companies [1]. "Internet + agriculture" refers to the cross-border integration of information technology applications, such as the Internet, Internet of Things, cloud computing, and big data with agriculture, and innovation of modern agricultural models based on the Internet platform [2]. China's "Internet + Agriculture" is starting from agricultural e-commerce and it will promote the development of agricultural e-commerce [3]. Therefore, studying the development model of agricultural e-commerce in the new environment has important theoretical and practical value [4]. Mobile Internet technology, cloud computing technology, and big data processing technology provides a guarantee for the implementation of agricultural e-commerce [5]. With the improvement of rural informatization infrastructure, the popularity of 4G networks in rural areas, and the increasing availability of high-end smartphones, the number of rural netizens has grown rapidly [6]. According to statistics, as of the end of 2015, the number of rural netizens in China reached 195 million, and the penetration rate of rural Internet reached 28.4% [7]. Such large-scale rural netizens laid the foundation for the development of Internet agricultural e-commerce, and will promote the elimination of the information gap between rural and urban areas, so that information becomes equal and freely circulated [8]. Mobile commerce with smartphone means the client can impact the development trends of agricultural e-commerce. Cloud computing applied to agricultural e-commerce will hope to break the bottleneck of technology, talent, cost, management and terminal of agricultural e-commerce application [9]. Based on the e-commerce model, the relationship between agricultural science and technology investment and agricultural economic growth is studied, mainly analyzing the impact of agricultural informatization level on agricultural total factor productivity. Based on the background of the traditional "extensive" agricultural growth mode under the new normal to the modern "intensive" agricultural growth mode, and the agricultural informationization has become an important way and symbol of agricultural modernization. This paper selects the proposition of "the relationship between agricultural science and technology input and agricultural economic growth based on e-commerce model", and empirically studies the relationship between the two, with an aim of proposing targeted recommendations. The main purpose of this study is to analyze the development of China's current agricultural e-commerce model, to find out many problems that hinder the development of China's agricultural informatization and agricultural economic growth, and to explore the impact of agricultural informatization on the industry and its internal role. mechanism. In order to promote the construction of agricultural informatization and accelerate the transformation of modern agriculture from extensive growth to intensive growth, it provides a theoretical reference.

2. State of the Art

A lot of valuable research results have been obtained on the relationship between scientific research investment and economic growth and productivity growth [10]. "New Growth Theory" regards technological progress as an endogenous variable of economic growth. It holds that technological progress is the real driving force of long-term economic growth, and that investment in science and technology is the main factor of technological progress. It also points out that under the effect of technological progress, the diminishing marginal benefit of capital can be avoided and the sustained economic growth can be maintained (Paul Romer, 1986; Robert Lucas, 1986). Since then, Coe and Helpman (1995), Charles (1998), Guelec and Bruno (2001) have studied the relationship between total factor productivity and science and technology input through various econometric analysis models, and concluded that science and technology input is an important source of total factor productivity growth and the core factor of sustained economic growth. It plays a key role. R. Solow. (1957) used Cobb-Douglas function to analyze the relationship between technology change rate and output growth rate based on the statistics of 1909–1949 in the United States [11]. Domestic scholars have begun to study this issue in recent years. Li Rui (1991) studied the structure and proportion of agricultural scientific research investment in China, and concluded that we should strengthen the total investment in agricultural scientific research, and pay attention to structural adjustment. Huang Jitao et al. (2003) respectively analyzed the intensity of investment in agricultural scientific research, the theory and policy of investment in agricultural scientific research, and gave the countermeasures and suggestions of investment in agricultural scientific research in China. Zhao Zhijun et al. (2005) used Cobb-Douglas production function to calculate the total income, marginal income and long-term marginal income of agricultural scientific research input; Zhang Xiaohui et al. (2011) used empirical analysis method to study the impact of agricultural scientific and technological progress on labor employment in different sectors of rural areas, and the resulting labor for rural residents, The impact of power transfer and rural household income [12]. Thus, there is a very close relationship between investment in agricultural scientific research and the growth of the agricultural economy and agricultural productivity.

Meanwhile, in recent years, with the rapid development of e-commerce, many domestic scholars have begun to conduct theoretical research on agricultural e-commerce. The theoretical research on agricultural e-commerce in China began in 2000, focusing on development strategies and models [13]. Some scholars put forward the agricultural e-commerce development countermeasures of "government guidance, construction platform, improvement of environment, talent cultivation"; some scholars divided agricultural e-commerce mode into G2B and G2C mode, B2B mode, B2C mode, B2B2C mode, C2C mode, etc. Some scholars have proposed agricultural product management models, such as "supermarket + agricultural product processing enterprises + farmers", "direct agricultural products", "farm-to-food" and "membership agriculture" [14]. In terms of application, China's agricultural e-commerce application is still in its infancy [15].

To sum up, despite the differences in research methods and statistical caliber, the conclusions of different scholars differ. Agricultural technology input has a significant contribution to agricultural economic growth. However, there is less research on the technical input and economic growth of the "Internet + agriculture" mode of agricultural e-commerce, so this paper is based on electricity. E-commerce model has a wide range of economic significance and social benefits by empirically studying the relationship between agricultural science and technology investment and agricultural economic growth.

3. Methodology

3.1. Indicators and Data Sources

The agricultural input variables selected in this paper include agricultural labor force, land, total power of agricultural machinery, fertilizer application, large livestock and irrigation variables. Agricultural labor force is calculated by the number in the labor force in the primary industry, regardless of the quality difference of the labor force; the total planting area of crops is used to replace the arable land area for land input; the total power of agricultural machinery refers to the sum of all kinds of mechanical power used in agriculture, animal husbandry and fishery; and the input of chemical fertilizer is used in practice. The amount of chemical fertilizer applied in agricultural production is measured by the amount of reduced purity; the input of large livestock includes cattle, horses, mules, donkeys, camels and so on; and the input of irrigation is calculated by the effective irrigation area of agriculture every year. In order to eliminate the impact of price changes, agricultural output variables are converted by 1990 fixed prices, such as Table 1.

Since the beginning of the construction of agricultural e-commerce in China in the early 1990s, we considered the lag and significance of the impact of informatization construction on agricultural economic growth, and the availability of data. In addition, considering the special resource endowment conditions in Tibet and the sensitivity of DEA analysis methods to abnormal data, Tibet is not included in the accounting scope. In summary, the data used are the balance panel data formed by 30 provincial administrative units (excluding Taiwan, Hong Kong and Macau in China) from 2006 to 2017 over the past 12 years. The data is mainly from the China Statistical Yearbook and the China Rural Statistical Yearbook. This paper firstly analyzes the data through EXCEL, and then uses MaxDEAUltra6.14, Eviews7.0 and other software to carry out relevant statistical analysis.

Table 1. Statistical description of variables.

Variable	Number of sections	Sample Number	Minimum Value	Maximum Value	Average Value	Standard Deviation
Total output value of agriculture, forestry, animal husbandry and fishery (100 million yuan)	15	450	23.9	2116.5	516.4	408.7
Agricultural labor force (10000 people)	15	450	36.3	4039.6	1054.4	863.4
Land (1000 hectares)	15	450	216.5	14,248.7	5148.9	3671.8
Land (1000 hectares)	15	450	58.5	11,629.0	1946. 6	2132.5
Fertilizer application amount (10000 tons)	15	450	1.5	711.5	170.2	150.3
Number of large livestock (10000)	15	450	5.4	2509.0	534.0	485.6
Effective irrigation area (1000 hectares)	15	450	144.2	5081.0	1803.9	1381.7

Source: "China Rural Statistical Yearbook".

3.2. Research Hypothesis

Through the above-mentioned mechanism analysis, agricultural e-commerce can accelerate the advancement of agricultural technology to a certain extent, promote the accumulation of human capital elements, increase production capacity, and broaden sales channels. Based on this, the level of agricultural e-commerce is considered to have a certain degree of promotion to the improvement of agricultural total factor productivity. Therefore, the following hypothesis is drawn: Under certain other conditions, the higher the level of agricultural e-commerce, the more positive the positive effect on the growth of agricultural total factor productivity. The data is initially processed by EXCEL, with the related statistical analysis performed by using software, such as MaxDEAUltra6.14 and Eviews7.0.

3.3. Variable Design and Model Description

There are two main methods for measuring the level of agricultural e-commerce, namely the index method and the Bollard method. The index method is relatively simple and the results are clear, but the selected indicators are relatively aging, cannot adapt to the current research, lack of practicality [16]. The Polat method is suitable for quantitative analysis at the national level, but its shortcomings are also prominent. For example, the standards for the information industry division are not uniform, and some methods and data are not reasonable enough. The remaining methods and models are based on these two methods, and carry out in-depth research that is more integrated with the actual situation of each country. Compared with other scientific methods, the entropy method can scientifically determine the specific weight of indicators based on the variation of each quantitative index, thereby improving the accuracy and objectivity of quantitative indicators and avoiding the adverse effects of human factors. Based on the above advantages, the entropy method is used to scientifically determine the weights of various quantitative indicators, and then the evaluation level of agricultural e-commerce development level is based on the relevant weights to ensure the accuracy and reliability of the evaluation results.

Based on the development of China's agricultural e-commerce, based on the difficulty of obtaining the data required for comprehensive analysis, the agricultural e-commerce evaluation index system is constructed according to the following indicators. Information facility indicators: The number of computers used by households per 100 households in rural areas (the construction and application of rural computer networks are investigated), the number of telephones owned by farmers per 100 households (including fixed telephones and mobile phones), (rural telephones' construction and application of the network are investigated). The number of TV sets per 100 households (including black and white TV sets and color TV sets) (the construction and application of rural TV networks is investigated). Main indicators of information: The number of years of education in rural areas (measured by the cultural quality of rural labor in the region), and the proportion of colleges and above in every 100 rural areas (the cultural quality of rural labor in the region is measured). And the proportion of peasant property and wage income to total income (measured by the economic situation of rural labor in the region). Information Industry Indicators: The proportion of rural non-primary industry population in total rural total employment (the construction of agricultural information talents is measured).

All the data of the selected indicators in this study are from the Statistical Yearbook of China's "Provinces" from 2006 to 2017 and the Statistical Bulletin of National Economic and Social Development of the General Administration of Agriculture and Reclamation of the Provinces from 2006 to 2017. The data collected are from 2006 to 2017. According to whether it is necessary to set the production function in advance, the measurement of agricultural total factor productivity can be divided into two types, namely, parameter method and non-parametric method, wherein the parameter method includes Solow residual method, growth kernel algorithm and SFA, etc. The nonparametric method mainly includes two types, namely DEA and index method [17]. However, neoclassical production theories, such as Solow's residual method and growth kernel algorithm are based on the assumption of optimal production behavior, and the productivity is evaluated based on effective technology and configuration, fixed scale and efficiency. Methods, such as DEA and SFA do not require strict full efficiency assumptions. SFA requires the expression of the present production function in specific use, and it is difficult to avoid the adverse effect of the function form and the assumption of inaccuracy on the result, thus limiting its application level. The DEA is able to actively solve the SFA problem. It is the most commonly used measurement and analysis tool at this stage, and is represented by Malmquist. The DEA-Malmquist analysis tool does not require premise assumptions on the behavioral patterns of the research subjects, and the input and output data do not need to be dimensionless, and more focused on describing the dynamic changes of the decision-making units, further simplifying the workload of model analysis. Research efficiency has been improved. Therefore, it has been more fully applied and is currently the most popular analysis tool. Based on this, the DEA-Malmquist index method is used to measure the total factor productivity of agriculture. In agricultural production activities, the input of agricultural production factors will bring about undesired output and expected output. Based on this background, in order to have a comprehensive assessment and grasp of the agricultural production process, it is necessary to balance the content of the undesired output and the expected output. When measuring agricultural TFP, focus on the following indicators:

Input indicators: It mainly emphasizes the land input (unit—thousand hectares) measured by the total planting area of crops, the labor input calculated by the total labor force of agriculture, forestry, animal husbandry and fishery (unit—10,000 people), and the fertilizer input measured by the amount of chemical fertilizer applied for agricultural production this year (unit—10,000 tons). Agricultural machinery inputs (unit—10,000 kW) calculated on the basis of the total power of agricultural machinery, servant inputs (unit—10,000 heads) measured by the number of agricultural servants owned by provinces in the current year, and irrigation inputs (unit—thousand hectares) measured by the actual effective irrigated area per year.

Output indicators: The main emphasis is on two aspects, namely, agricultural expected output and agricultural "unexpected" output. The expected output is measured by the total output value of agriculture, forestry, animal husbandry and fishery, and the non-expected output is measured by agricultural non-point source pollution emissions. The unit survey evaluation method is applicable to the measurement of agricultural non-point source pollution in large-scale areas [18]. Based on the existing literature research and the actual situation in China, the source of pollution can be used to divide farmland fertilizer, rural life, farmland solid waste, livestock. Poultry farming is the main content of agricultural non-point source pollution. Combined with the availability and comparability of statistical data, the selected survey indicators include the amount of nitrogen fertilizer, phosphate fertilizer and compound fertilizer applied in various regions (unit—10,000 tons); the amount of livestock and poultry (unit—10,000 heads/only), with cattle, sheep and pig. Total output (unit—ten thousand tons), mainly wheat, potato, rice, oil; rural population (unit—million people). The specific formula is expressed as:

$$E = \sum_t EU_i \rho_i (1 - \eta_i) C_i (EU_i, S) = \sum_i PE_i (1 - \eta_i) C_i (EU_i, S). \tag{1}$$

In the above formula, E is the discharge of agricultural non-point source pollutants into the water body, expressed by the total nitrogen and total phosphorus emissions; EU_i, ρ_i, represent the unit i indicator statistics and the pollutant production intensity coefficient; The characterization symbol of the relevant resource utilization efficiency coefficient is η_i, and the representation of the unit i pollutant generation amount (soil production amount) PE_i is the product of EU_i and ρ_i. In the calculation process, the influence of management factors and comprehensive utilization factors of resources is ignored; The environmental characteristics (S) and the unit characteristics (EU_i) together determine the emission factor of the unit i pollutants, represented by C_i. The official statistical yearbooks of the past years are the statistical data sources of each unit, and the parameters, such as the pollution intensity coefficient and the emission coefficient are obtained through literature research.

The research focuses on the agricultural total factor productivity index of 30 provincial administrative units in China, intercepting the input and output index data of the time nodes from 2001 to 2012, and giving full play to the role of the Malmquist-Luenberger productivity index model.

Control variables: First, the natural environment variable (env). That is, the ratio of the area affected and the total planted area of crops, this variable is a direct reflection of the degree of deterioration of the natural environment. Objectively speaking, the natural environment will have a crucial impact on agricultural development [19]. At the same time, if the ecological environment shows a deteriorating trend, it will have a serious impact on agricultural growth and have a negative effect on agricultural TFP growth. Second, the expression pattern of agricultural planting structure (stru) is the ratio of the area planted with grain to the total planted area of crops. Considering the unique characteristics of China's agricultural resources, Chinese agriculture has comparative advantages in the production of labor-intensive agricultural products, such as vegetables, livestock products and aquatic products, but lacks comparative advantages in the production of land-intensive agricultural products, such as grain. Based on this background, agricultural production performance will be affected by the key role of agricultural planting structure. Financial support for agricultural strength variables (sup): It mainly reflects the government's support for agriculture. The evaluation index is the proportion of fiscal agricultural expenditure to total fiscal expenditure. From the field of agricultural infrastructure construction, it can be found that the government's financial support is extremely necessary. Only by formulating a sound fiscal support policy can we effectively promote the comprehensive agricultural production capacity. This will have an important impact on the growth of agricultural TFP. Rural human capital variable (huma): Measured by the average years of schooling of the rural workforce. The average number of years of education for rural laborers in each region is the product of two factors, which are the proportion of rural labor force in different regions, the proportion of people with different educational levels, and the educational years of education. The data is collected and clustered and normalized. The specific operation process of the algorithm is shown in Figures 1 and 2.

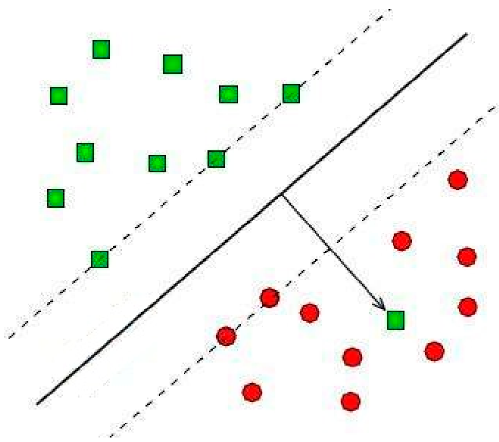

Figure 1. The specific operation process of the algorithm.

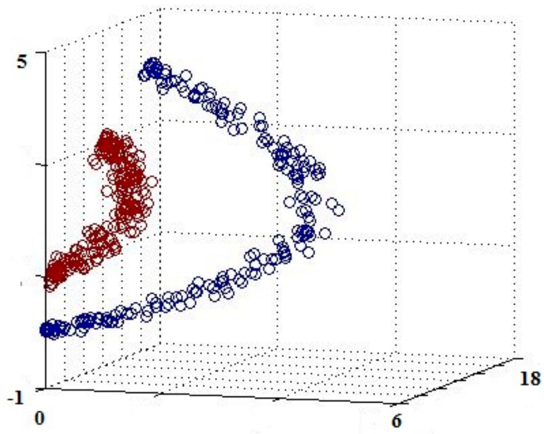

Figure 2. Data clustering processing.

4. Result Analysis and Discussion

4.1. Descriptive Statistics

According to the research needs, the relevant data obtained by each authoritative channel needs to be processed by the entropy method, and the data of some regions are listed, as shown in Figures 3 and 4. The data in the empirical data show that the difference in the level of agricultural e-commerce is still relatively large. The average value of agricultural e-commerce levels in Shanghai (4.8015), Beijing (4.7020) and Zhejiang (3.9871) is above 3.90. The average value of agricultural e-commerce levels in Yunnan (2.7355), Xinjiang (2.7821) and Guizhou (2.8368) is below 2.90. Secondly, after analyzing the relevant data, it can be seen that the level of agricultural e-commerce in various provinces in China shows a relatively significant change. According to this, it can be seen that the development of agricultural e-commerce itself will be constantly changing, due to the combined effects of many factors. Thirdly, whether it is analysis from the results of its overall mean calculation, or using the relevant data of the eastern, central and western regions over the years, the average level of agricultural e-commerce in the eastern region is at the lowest level, followed by the central region and the lowest in the western region. It is confirmed once again that there is a big difference in the level of agricultural e-commerce between different regions. The DEA-Malmquist index method is used to process the relevant data obtained by the authoritative channel, and the results are obtained. Figure 5 lists some data. The average agricultural total factor productivity in each provincial level in China is maintained at a level not lower than 1.00, but the specific levels of different provinces show significant differences, and the average of productivity shows significant fluctuation characteristics. Taking TFP as an example, the minimum TFP of agricultural TFP in nearly two-thirds of the provinces is less than 1.00. This result indicates that the agricultural TFPs in various provinces in China are showing large fluctuations at this stage, and are in a stage of continuous development and change.

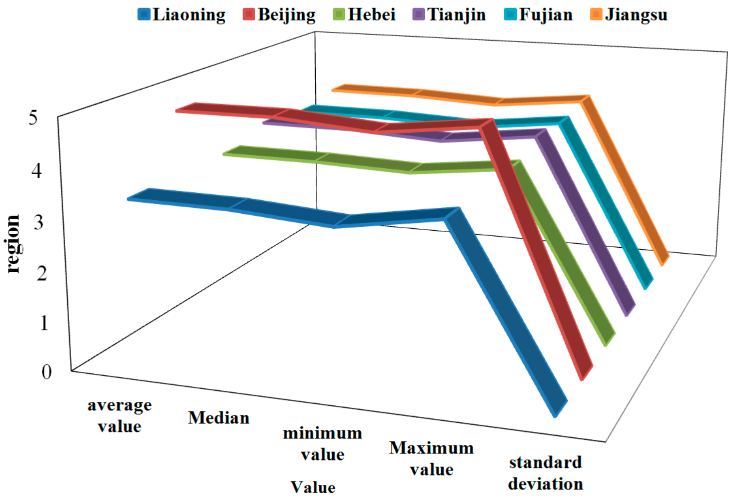

Figure 3. Table of agricultural informatization in different regions (part).

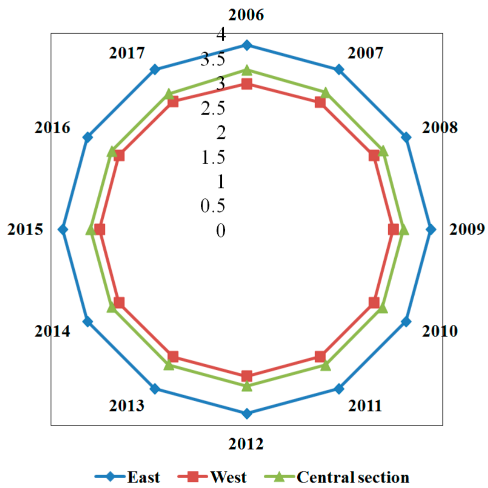

Figure 4. 2006–2017: Years of agricultural informatization level.

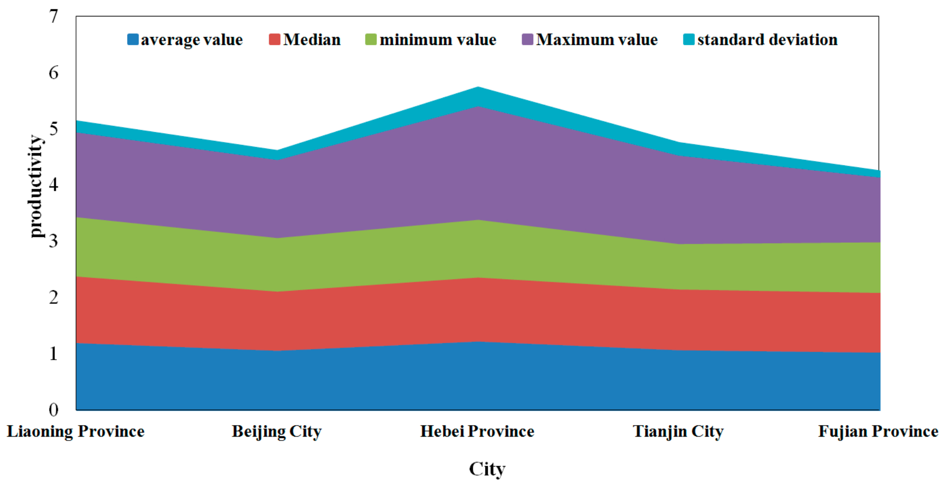

Figure 5. Agricultural: Total factor productivity tables by region.

Descriptive statistics on the relevant data required by the model are obtained in Figure 6. It can be seen that the difference between the minimum and maximum values of different variables is large. It shows that agricultural e-commerce level, agricultural total factor productivity index, financial support for agriculture, natural environment, agricultural planting structure and rural human capital are different in different provinces.

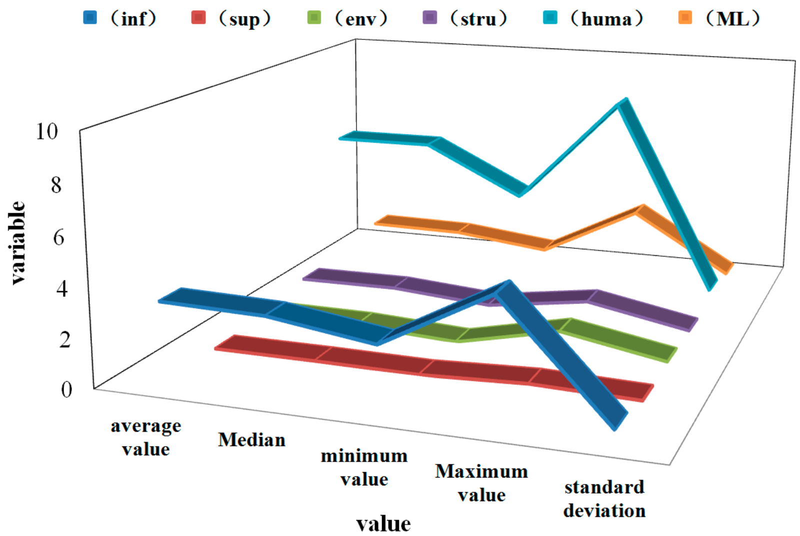

Figure 6. Model of variable descriptive statistics.

4.2. Regression Results and Analysis

Firstly, the ADF unit root test method is used to check the data for stationarity. The test results show that all the data are 0-order single-sequence sequences and pass the stationarity test. Next, the Granger causality test is used to test the specific relationship between agricultural e-commerce level and agricultural TFP. The test results show that accepting the agricultural TFP is not the null hypothesis of the Granger cause of agricultural e-commerce at a significant level of 10%. Rejecting agricultural e-commerce is not the original hypothesis of the Granger cause of agricultural TFP growth, that is, along with the increase in the level of agricultural e-commerce, it can bring about the growth of agricultural total factor productivity [20]. As can be seen from Table 2, the LR test results are obtained by using Eviews 7.0, where the accompanying probabilities of the F statistic and the LR test were 0.0054 and 0.0021, respectively, both of which were less than 0.1. Therefore, the assumption that the mixed cross-section model is more effective than the fixed-effect model is rejected, and the individual fixed-effect model is selected. It can be seen from the results of Table 3 Hausman test that the test statistic is 13.829439 and the accompanying probability is 0.0316. Therefore, the null hypothesis is adopted for the null hypothesis that there is no systematic difference between the random effect model and the fixed effect model, and the fixed effect model is selected.

Table 2. Results of LR test output of the model.

Effects Test	Statistic	d.f.	Prob.
Cross-section F	1.864760	(29,323)	0.0054
Cross-section Chi-square	55.573140	29	0.0021

Table 3. Results of Hausman test output of the model.

Test Summary	Chi-Sq.Statistic	Chi-Sq.d.f	Prob.
Cross-section random	13.829439	6	0.0316

The regression results obtained through Eviews7.0 are shown in Table 4. At the 10% level, agricultural total factor productivity has a significant positive correlation with agricultural e-commerce levels and fiscal support. It shows that the level of agricultural e-commerce has a positive impact on agricultural TFP. That is to say, when other conditions are unchanged, the level of agricultural e-commerce is increased by 1%, and the total factor productivity of agriculture is increased by 0.061%, which is consistent with the assumption. Moreover, the greater the government's support for agriculture, the more it can promote the growth of agricultural total factor productivity to a certain extent. Agricultural total factor productivity and structure and rural human capital are significantly positively correlated at 5%, and negatively correlated with the natural environment and agricultural planting structure at 5%. It shows that under certain other conditions, the higher the level of education of farmers, the more effective the promotion of the growth of agricultural total factor productivity. However, the greater the proportion of the affected area and the area planted with grain to the total sown area of crops, the more unfavorable the growth of total factor productivity in agriculture. At the same time, F-statistic reached 2.208 and its p value was 0.000187. The adjusted R2 fitting goodness reached 15.56%, and the fitting effect is good.

Table 4. Regression results of agricultural informatization level and total pactor Productivity of agriculture.

Variable	Coefticient	Std.Error	1-Statistic	Prob.
C	0.954894	0.203428	4.694019	0.0000
INF	0.067085	0.060835	1.102729	0.0709
SUP	0.096886	0.163293	1.171999	0.0635
ENV	−0.082096	0.099762	−1.822921	0.0111
STRU	−0.354161	0.139825	−2.532888	0.0117
HUMA	0.196266	0.124301	1.578951	0.0153
R-squared	0.193060	Mean dependent var		1.175905
Adjusted R-squared	0.155621	S.D.dependent var		0.256276
S.E.of regression	0.242364	Akaike info criterion		0.098135
Sum squared resid	18.97312	Sckwarz criterion		0.487549
Log likelihood	18.38472	Hannan-Quinn criter		0.252990
F-statistic	2.207932	Durbin-Wstson stat		2.166120
Prob (F-statistic)	0.000187			

To sum up, agricultural scientific research investment can effectively promote the growth of agricultural productivity. Its overall scale and structure are directly related to the supply of agricultural scientific and technological achievements, which is the core competitiveness of agriculture in China. The fluctuation of agricultural scientific research investment and agricultural productivity may occur in the following situations: The growth of agricultural scientific research investment promotes agricultural economic growth; the growth of agricultural economic growth promotes the growth of agricultural scientific research investment; there is no correlation between the growth of agricultural scientific research investment and agricultural economic growth, but there is another factor that affects both. The person. In these three cases, there is a relationship between the growth of investment in agricultural scientific research and the growth of the agricultural economy in the same direction.

5. Conclusions

In the e-commerce mode, an empirical study is conducted on the relationship between agricultural science and technology investment and agricultural economic growth. The 30 provinces in 2006–2017 are selected as samples, combined with information productivity theory, agricultural e-commerce service theory and economic growth theory. After calculation, it is found that there are relatively large differences in the level of agricultural e-commerce in various regions. The distribution characteristics are as follows: The eastern region has the highest level of informatization and the western region has the lowest. Based on the provincial panel data, the model analysis method is used to carry out the empirical analysis of the impact of agricultural e-commerce on agricultural total factor productivity and the internal mechanism. The analysis results indicate that with the improvement of the level of agricultural e-commerce, the total factor productivity of agriculture will increase simultaneously. The former has a significant positive effect on the latter, that is, under certain other conditions, for every 1% increase in the level of agricultural e-commerce, the total factor productivity of agriculture will increase by 0.061%. Therefore, Based on the research results, this paper believes that China still needs to adhere to the construction of agricultural informatization, improve the agricultural informatization management mechanism, increase investment in agricultural science and technology, increase the conversion rate of agricultural science and technology research results, and actively exert the talent cultivation ability of colleges and universities to meet the needs of agricultural informationization. Demand, thereby further improving the level of agricultural economic development in China.

Author Contributions: Conceptualization, T.W.; Methodology, T.W.; Software, L.H.; Validation, T.W.; Formal Analysis, T.W.; Investigation, L.H.; Resources, L.H.; Data Curation, L.H.; Writing-Original Draft Preparation, T.W.; Writing-Review & Editing, T.W.; Visualization, L.H.; Supervision, L.H.; Project Administration, L.H.

Funding: This research received no external funding.

Acknowledgments: I would like to extend my sincere gratitude to my friends for their considerable comments on the draft.

Conflicts of Interest: The authors declare no conflict of interest

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