Analysis of Agricultural Technology Innovation Efficiency and Influencing Factors in Shandong Province Based on DEA-Tobit Model

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Abstract: Based on the statistical data of 17 cities in Shandong Province from 2008 to 2018, this paper analyzes the level of agricultural science and technology innovation efficiency and its related influencing factors based on DEA-Tobit model. The study found that the overall development level of agricultural science and technology innovation in Shandong Province is relatively high, and the gap between regions is small. But there are problems of insufficient scale advantages; scientific research investment, economic environment and fiscal expenditure have a significant impact on efficiency. Shandong Province should increase financial support for agricultural science and technology allocate input resources and attach importance to the efficiency of technology conversion evaluation.

1. Introduction

Agriculture plays a strategic role in the national economy. How to improve the ability of agricultural science and technology innovation in the context of rural revitalization and effectively allocate agricultural science and technology resources has become an important task of agricultural development. In recent years, the contribution rate of Chinese agricultural science and technology progress has increased from 53.5% in 2012 to 57.5% in 2017 and its role in agricultural development has become increasingly prominent. As a province which own traditional agricultural mode in China, Shandong has made outstanding achievements in agricultural modernization and plays an important role in the development of agriculture in the country. Therefore, this paper selects Shandong province as traditional example and makes a reasonable assessment of the level of agricultural science and technology innovation efficiency and analyses its influencing factors.

2. Literature review

At present, the domestic research on agricultural science and technology innovation efficiency is mainly carried out from two aspects: First, from the perspective of agricultural science and technology innovation efficiency evaluation methods, many scholars use DEA model to measure. Xiao Biyun (2016) used the DEA model to measure the efficiency of agricultural technology innovation in Chinese 31 provinces. The results show that the overall level of agricultural science and technology innovation efficiency in China is not high and the geographical gap is obvious. Zhang Lixia (2016) used SBM super-efficiency model to measure the efficiency of agricultural science and technology innovation in Beijing, Shanghai and Tianjin. At the same time, the DEA-Tobit two-step model was used to empirically test the influencing factors of agricultural technology innovation efficiency in three major cities. Zhang Jing (2014) used the non-parametric DEA-Malmquist index method to measure the efficiency of agricultural science and technology innovation in China from 1990 to 2008. Zhao Lianming (2018)
tested the allocation efficiency of agricultural science and technology resources in Chongqing by using the analytic hierarchy process and fuzzy evaluation. Second, from the perspective of the factors affecting the efficiency of agricultural technology innovation, Zhao Lijuan (2019) selected 30 provincial-level panel data from 2004 to 2015 to study the impact of environmental regulation and government R&D investment on Chinese agricultural science and technology innovation efficiency; Zhao Lijuan (2016) also combed the research on the impact of scientific and technological human resources and funds on the efficiency of agricultural science and technology innovation. In general, the relative researches are all based on the analysis of the impact of one certain factor on the efficiency of agricultural science and technology innovation after the construction of the indicator system, but using the DEA model, the Malmquist dynamic decomposition and Tobit model three research methods in the literature on the efficiency of agricultural science and technology innovation is relatively insufficient. The contribution of this paper is to integrate three kinds of research methods, adding technical variables to the construction of agricultural science and technology innovation efficiency, which further highlights the impact of efficiency value technology level. Besides, when using Tobit model to select influencing factors, it adds reflection of technology market and environmental indicators, which is a complement to the previous research.

3. Data and empirical analysis

3.1. Research model

The DEA-BCC method assumes that in each period \( t = 1, \ldots, T, k = 1, \ldots, K \) the \( K \) decision units use \( n = 1, \ldots, N \) inputs \( x_{k,n} \), thus obtaining \( m = 1, \ldots, M \) kinds of outputs \( y_{k,m} \). Specifically, the decision unit \( X_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T \) is the input variable and the output variable is \( Y_j = (y_{1j}, y_{2j}, \ldots, y_{mj})^T \), where \( X_{ij} \) is the total input of the \( j \)th decision unit (DMU) of the \( i \)th input and the constraint is \( i x_{ij} > 0 \); \( y_{mj} \) is the DMU to the output of the type of output variable and the constraint is \( y_{rj} > 0 \). The DEA-BCC model can be expressed as the following condition:

\[
\begin{align*}
\min \theta & \\
\text{s.t.} & \sum_{j=1}^{n} \lambda_j X_j + S^- = \theta X_0 \\
& \sum_{j=1}^{n} \lambda_j Y_j - S^+ = Y_0 \\
& \lambda_j = 1, \forall \lambda_j \geq 0
\end{align*}
\]

In above formula, \( S^- \) represents the vector value of the slack variable corresponding to the input. \( S^+ \) represents the vector of the variable corresponding to the output. \( \lambda_j \) is the coefficient of the linear combination of DMU, and \( \theta \) represents the relative effectiveness of the decision unit. Compared with the traditional DEA method, the DEA-Malmquist total factor productivity model can measure the efficiency of DMU's intertemporal dynamic panel in multiple periods. Besides, the Malmquist Index (TDF) can be decomposed into the product of technical efficiency (EC) and technological change (TC). Taking the 2-stage productivity calculation as an example, the formula shows as follows:

\[
\text{TDF} = \left[ \frac{D_i(X_{i+1},Y_{i+1})}{D_i(X_i,Y_i)} \right]^{1/2} \cdot \left[ \frac{D_i^{i+1}(X_{i+1},Y_{i+1})}{D_i^{i+1}(X_i,Y_i)} \right]^{1/2}
\]

\[
\frac{D_i^{i+1}(X_{i+1},Y_{i+1})}{D_i^{i+1}(X_i,Y_i)} \cdot \left[ \frac{D_i(X_{i+1},Y_{i+1})}{D_i(X_i,Y_i)} \cdot \frac{D_i^{i+1}(X_{i+1},Y_{i+1})}{D_i^{i+1}(X_i,Y_i)} \right]^{1/2}
\]
In the formula, $\frac{b^{i+1}(x_{i+1},y_{i+1})}{b^{i+1}(x_i,y_i)}$ is the technical efficiency change (EC), and $\left[ \frac{b^{i}(x_{i+1},y_{i+1})}{b^{i}(x_i,y_i)} \right]^{\frac{1}{2}}$ represents a technical change (TC), which is the movement of the production frontier in two periods. When the total factor production index (TDF), technical efficiency change (EC) and pure technology change (TC) are greater than (less than) 1, respectively, it indicates that the second-stage production status of the decision-making unit is improved (deteriorated). Because the inputs and outputs of agricultural science and technology are variable in scale, this paper first uses the output-based variable-scale compensation (VRS) method for agricultural technology of 17 cities in Shandong Province from 2008 to 2018 to measure the efficiency of innovation. At the same time, considering that technological innovation involves the dynamic process of technological progress and efficiency, this paper uses DEA-Malmquist total factor productivity model to decompose technological changes. Besides, the technical efficiency index measured by the DEA model takes the cutoff value (0-1), and the least squares method (OLS) is used to estimate the model parameters containing the censored data, thus the results of the estimation may be inconsistent; Based on the characteristics of the data, this paper uses the DEA-Tobit model based on Maximum Likelihood Estimation (MLE) to analyze the factors affecting the efficiency of agricultural science and technology innovation in Shandong Province. The Tobit model is as follows:

$$y_i = \begin{cases} y_i^* = x_i \beta + \varepsilon, & y_i^* > 0 \\ 0, & y_i^* \leq 0 \end{cases}$$

Where $\beta$ is the regression function, $\varepsilon$ is the error term, $x_i$ is the explanatory variable, and $y_i$ is the efficiency value vector calculated by the DEA-BCC model.

3.2. Research indicators and data selection

According to the theory of agricultural production factors, the basic elements of agricultural production inputs can be divided into land, labor, and capital. Referring to the index selection method of many scholars and combining with the availability of data, this paper takes the total output value of agriculture, forestry, animal husbandry and fishery in each city (unit: 100 million yuan) as the output index, and the planting area of crops in each city (unit: 10,000 hectares) as an indicator of land input, the number of employed people in agriculture (unit: 10,000) represents labor input. The main agricultural machinery at the end of each year (unit: 10,000 kW) and agricultural fertilizer application amount (unit: 10,000 tons) representing capital investment; in addition, in order to reflect the role of technical elements in the input and output process, this paper adds R&D expenditure internal expenditure (unit: 100 million yuan) as a variable representing technology investment into the model.

3.3. Research results and analysis

3.3.1. Analysis of static results of agricultural science and technology innovation efficiency

According to the DEA-BCC model, comprehensive efficiency is a comprehensive indicator for measuring factor input and output efficiency, while comprehensive efficiency is equal to the product of pure technical efficiency and scale efficiency. Using the DEAP2.1 software, this paper measures the agricultural input and output data of the 17 cities in Shandong Province from 2008 to 2018 under variable compensation conditions. As shown in Table 1, the average efficiency and ranking were obtained. It can be concluded from the table that Zaozhuang, Weihai, Rizhao and Heze have the highest agricultural science and technology innovation efficiency; from the perspective of comprehensive efficiency evaluation, 65% of the comprehensive efficiency value is above 0.9, indicating that level of agricultural science and technology investment innovation efficiency of Shandong Province is generally high. From a perspective of scale effect, only two cities have an increasing scale effect, indicating that there may be insufficient scale of technological innovation. From the perspective of regional differences, the standard deviation of the comprehensive efficiency value of agricultural science and technology innovation in various cities is 0.09, and the overall gap is small. In summary, the agricultural science...
and technology innovation in Shandong Province shows higher overall development level, smaller gap between regions and problem of insufficient scale.

3.3.2. Analysis of Dynamic Results of Agricultural Science and Technology Innovation Efficiency

Using the data in Table 2, this paper continues to perform Malmquist dynamic decomposition of agricultural science and technology innovation efficiency in Shandong Province from 2008 to 2018. Firstly, from the perspective of time trend, as shown in Table 2, the total factor productivity of agricultural science and technology innovation in Shandong Province increased by 4.8% between 2008 and 2018, and the technical efficiency and technological progress increased by 0.04% and 4.3% respectively, indicating that Shandong Province agricultural science and technology innovation Efficiency has generally maintained rapid growth and is largely explained by factors of technological advancement. In addition, from the trend of total factor productivity in Figure 1, it can be concluded that the Malmquist index has a small volatility and the overall stability remains stable, which indicates that the efficiency of agricultural science and technology innovation in Shandong Province is steadily increasing.

Table 1. Agricultural Science and Technology Innovation Efficiency from 2008 to 2018

| City       | TDF  | EC  | Scale Efficiency | Scale Effect |
|------------|------|-----|------------------|--------------|
| Jinan      | 0.932| 0.98| 0.95             | Increment    |
| Qingdao    | 0.871| 0.973| 0.896           | Decrement    |
| Zibo       | 0.724| 0.735| 0.985           | Constant     |
| Zaozhuang  | 1    | 1   | 1                | Increment    |
| Dongying   | 0.931| 0.981| 0.95             | Constant     |
| Yantai     | 0.93 | 1    | 0.93             | Decrement    |
| Weifang    | 0.818| 1    | 0.818            | Decrement    |
| Jining     | 0.968| 1    | 0.968            | Decrement    |
| Taian      | 0.981| 1    | 0.981            | Decrement    |
| Weihai     | 1    | 1    | 1                | Constant     |
| Zizhou     | 1    | 1    | 1                | Constant     |
| Laiwu      | 0.746| 1    | 0.746            | Increment    |
| Linyi      | 0.903| 1    | 0.903            | Increment    |
| Binzhou    | 0.76 | 0.826| 0.92             | Decrement    |
| Liaocheng  | 0.929| 0.989| 0.94             | Decrement    |
| Heze       | 1    | 1    | 1                | Constant     |
| Dezhou     | 0.885| 0.992| 0.891            | Decrement    |
| Mean       | 0.905| 0.969| 0.934            | -            |

Table 2 & Figure 1. Malmquist Index and Decomposition of Agricultural Science and Technology Innovation Efficiency in Shandong Province from 2008 to 2018

| Year        | TC   | TA   | TDF   |
|-------------|------|------|-------|
| 2008-2009   | 1.042| 1.042| 1.086 |
| 2009-2010   | 1.007| 1.144| 1.152 |
| 2010-2011   | 0.984| 1.047| 1.03  |
| 2011-2012   | 1.012| 1.084| 1.098 |
| 2012-2013   | 1.001| 0.929| 0.93  |
| 2013-2014   | 0.996| 1.155| 1.151 |
| 2014-2015   | 0.999| 0.891| 0.89  |
| 2015-2016   | 1.008| 1.017| 1.025 |
From the technical efficiency of dynamic analysis, we can find from Table 3 that the average factor productivity growth rate (ATP) of each city in Shandong Province is 4.4%, and the standard deviation is 0.04, indicating that the growth rate of agricultural technology efficiency is basically the same, and the difference is small. The top three growth rates of total factor productivity are Laiwu (9.3%), Yantai (7.4%) and Dongying (7.2%), which are different from the comprehensive efficiency obtained by using the DEA-BCC model; After that, the growth rate of Malmquist index was mainly explained by technological advances (TA), which is 4% and technological progress played an important role in improving the efficiency of agricultural science and technology innovation. As technological advancement can improve the level of agricultural intensive production and improve the efficiency of resource utilization, under the constraints of tight resources and environment, it is necessary to strengthen the investment in agricultural basic research and development, and pay more attention to the role of technological progress. In addition, the mean rate of change in pure technical efficiency is -0.01%, and the ratio of 47% is below 1, indicating that the lack of technical efficiency has a negative effect on the growth of total factor productivity, so in the investment in agricultural science and technology innovation, It is necessary to pay attention to the basic role of technological progress, and at the same time, improve the process of technological transformation and improve the efficiency of technology utilization.

Table 3. Malmquist Index and decomposition of Agricultural Science and Technology Innovation Efficiency in Cities

|       | ATP  | TA   | TC   | Scale Efficiency | TDF  |
|-------|------|------|------|------------------|------|
| Jinan | 1.001| 1.067| 0.996| 1.005            | 1.068|
| Qingdao | 1.002| 1.069| 1    | 1.003            | 1.071|
| Zibo  | 1.022| 1.045| 1.022| 1.001            | 1.068|
| Zaozhuang | 0.991| 1.045| 0.991| 1                | 1.035|
| Dongying | 1.003| 1.069| 0.998| 1.005            | 1.072|
| Yantai | 1.007| 1.067| 1    | 1.007            | 1.074|
| Weifang| 1.009| 1.062| 1    | 1.009            | 1.072|
| Jining | 1.003| 1.037| 1    | 1.003            | 1.04  |
| Taian  | 0.995| 1.062| 0.994| 1.001            | 1.056|
3.3.3. Analysis of Factors Affecting Agricultural Science and Technology Innovation Efficiency

This paper will set the Tobit model to calculate the factors affecting the efficiency of agricultural science and technology innovation as follows:

\[ Y_{it}^* = \alpha + \mu_i + X_{it}^*\beta + \varepsilon \]

Among them, \( Y_{it}^* \) is the DEA efficiency with the value range of 0-1, \( \mu_i \) is the individual effect, \( X_{it}^* \) is the influencing factor, and \( \varepsilon \) is the random disturbance term. In order to reduce the influence of the heteroscedasticity, all the independent variables are logarithmized. Referring to the research from Zhang Lixia (2016), this paper selects the following indicators of influencing factors:

Financial Expenditure: Agricultural science and technology research and development have the characteristics of long cycle, large investment and high risk. It requires government departments to provide necessary financial support for agricultural science and technology innovation. Therefore, this paper selects the amount of science and technology investment in the fiscal expenditure of local government's as the influencing factor of fiscal expenditure;

Technology market environment: The technology market promotes the market-oriented transformation of agricultural science and technology and inventions; through the market price discovery and incentive mechanism, the inventors of agricultural science and technology achievements can obtain the expected return, which can effectively promote the promotion and application of scientific and technological research and development results. Therefore, this paper selects the number of local patent grants between 2008 and 2018 as the indicator of the technical market environment.

Human resources input for scientific and technological personnel: Innovation is inseparable from talents. Agricultural science and technology talents like the research and development carrier of scientific and technological achievements can directly influence the scale and speed of research and development of agricultural science and technology innovation. Therefore, the number of R&D personnel selected in this paper represents the manpower input of scientific and technical personnel;

Investment in science and technology research and development: In addition to the financial expenditure, the research and development funds can directly affect the output of science and technology innovation. This paper selects the R&D expenditure as the proxy variable for the investment in science and technology research and development.

Economic environment: The innovation and practice of agricultural technology requires the support of the economic environment. This paper selects the per capita GDP of proxy variables as the measurement factor. The regression results are shown in Table 4 below:

| Influencing factor                  | Coefficient | Standard deviation | T-value | P-value |
|-------------------------------------|-------------|--------------------|---------|---------|
| Technology research investment      | 0.175***    | 0.428              | 4.085   | 0       |
| Scientific human-resource input    | 0.0299      | 0.417              | 0.717   | 0.473   |
| Economic environment               | 0.196***    | 0.304              | 6.425   | 0       |

Table 4. Regression Result using DEA-Tobit Model
Through the regression results of the model, it can be concluded that the investment in science and technology, economic environment and fiscal expenditure have a significant impact on the efficiency of agricultural science and technology innovation, in which the investment in science and technology research and development increases by 0.00175%, the output value of local GDP increases by 0.00196%, and the financial input increases by 0.00054%, the agricultural science and technology innovation efficiency index will increase by one unit. The impact of scientific and technological personnel input and technology market environment on the efficiency of agricultural science and technology innovation is not significant. Besides, the number of local patent authorizations may mainly include non-agricultural technology patents. In the estimation of the influencing factors of agricultural technology innovation efficiency, scientific research and development and scientific financial investment play a significant role, which reflects the importance of financial support in the process of agricultural technology research and development and cultivation.

4. Conclusion
From the static perspective of agricultural science and technology innovation efficiency, this paper mainly uses the DEA-BCC method to carry out efficiency accounting. The research finds that the development level of agricultural science and technology innovation efficiency in Shandong Province is generally high, and the regional differences are small, but there is a problem of insufficient scale effect. The allocation elements in the agricultural production process should be optimized, and the positive role of technical elements in improving the productivity of agricultural factors should be brought into play. For lower-efficient cities, the government should increase investment, introduction and promotion of agricultural technology and focus on the development of key agricultural technologies.

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