Research on R&D Efficiency Evaluation of Chinese Seed Industry Listed Companies Based on Three-Stage DEA Model

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Abstract. In this paper, we measure and analyze the R&D efficiency of 19 seed listed enterprises in China. In order to make the measurement more accurate, we used a three-stage DEA model to exclude the influence of environment variables. After removing the environmental factors, the R&D efficiency and scale efficiency decreased significantly than before, while the pure technical efficiency increased as a whole. This shows that the R&D efficiency of seed industry in China is low, mainly affected by the efficiency of scale, and 63% of enterprises are in the state of increasing scale returns. But enterprise scale, the government support, ownership concentration and economic environment for research and development personnel and R&D capital have positive influence on redundancy, which are not conducive to R&D efficiency. Therefore, enterprises should pay attention to the influence of environmental factors, by improving the environmental factors to expand the scale of research and development, and improve the efficiency of its R&D to a certain extent.

1. Introduction
Economist Schultz (1964) mentioned that traditional agriculture is no longer able to promote the rapid and stable growth of agriculture, and new factors of production need to be introduced for improvement of agricultural efficiency. Seed is the key factor to promote agricultural production. Since 2013, the research and development (R&D) input of seed enterprises in China have been increasing. The R&D investment of China's top 50 seed enterprises increased from 346 million yuan in 2011 to 1.38 billion yuan in 2016, indicating that the R&D investment scale of China's seed enterprises continues to expand. However, according to statistics from the international seed union (ISF), from 2014 to 2017, the trade deficit of China's seed industry continued to rise, reaching 227 million us dollars. China's seed import volume was 317 million us dollars in 2017. It showed that China's seed market is largely dependent on imported seeds. Why is the market share of China's seed enterprises still low in the case of increasing R&D investment? Has the government's policy implementation achieved the desired effect? Enterprise R&D efficiency represents the efficiency of R&D resource utilization in the process from R&D resource input to output, which to some extent reflects the innovation ability of enterprises. In this paper, the listed company of seed industry is selected as the representative of modern seed industry enterprises to objectively evaluate its R&D efficiency and explore factors influencing R&D efficiency, which is of great significance to the development of agriculture in China.

At present, Scholars mainly use two methods to measure R&D efficiency. One is the technology of Data Envelopment Analysis (Data Envelopment Analysis, DEA). Sharma & Thomas (2008) [1], Akihiro
& Shoko (2008) [2] and kai-hua Chen (2013) [3] have adopted the DEA analysis method to measure the efficiency of different levels of technology innovation. The other is the stochastic frontier production function method (SFA) proposed by Aigner in 1977. However, the SFA can only measure the efficiency of the Decision Making Unit (DMU) with multiple inputs and a single output. Data envelopment analysis (DEA) method can evaluate the efficiency of DMU with multiple inputs and multiple outputs, but it lacks consideration of environmental factors and random errors. Fied (2002) [4] think management inefficiency, environmental factors and statistical noise will affect the performance of DMU. Therefore, Fied proposed a three-stage DEA method based on the SFA and DEA model. This method combines the DEA with SFA, which not only retains the advantages of the traditional DEA method, but also can eliminate the impact on environmental factors and random error.

Therefore, in order to measure real R&D efficiency of seed industry, we adopt the three-stage DEA model, which exclude the influence of government subsidies, enterprise scale, ownership concentration and economic environment and other environmental factors on the R&D efficiency. The remainder of this paper is organized into four sections. Section 2 sets up and analyzes three stage DEA model. Section 3 describes the selection of data sources and variables. Section 4 analyzes the results, and checks the robustness of the results. Section 5 concludes the paper.

2. Method

Based on the above analysis, we use Fried's three-stage DEA model for reference to calculate the R&D efficiency of seed enterprises. Specific method corollary is as follows.

2.1. DEA-BCC model

First, we use the input-oriented BCC (Banker -charne -cooper) [5] model in DEA software to calculate the comprehensive technical efficiency of seed industry enterprises. The calculated efficiency (TE) can be decomposed into pure technical efficiency (PTE) and scale efficiency (SE), which is helpful for us to distinguish the influence of pure technical efficiency and scale efficiency on the comprehensive efficiency. The specific form of BCC model is as follows:

$$\text{Max}_{k} \left( \frac{\sum_{i=1}^{m} U_{r} Y_{rk} - u_{0}}{\sum_{j=1}^{a} V_{j} X_{jk}} \right)$$

subject to:

$$\sum_{j=1}^{a} V_{j} X_{ij} \leq s, i = 1, 2, \ldots, m$$

$$U_{r}, V_{j} \geq \xi > 0, r = 1, 2, \ldots, s, i = 1, 2, \ldots, m$$

In the formula, n represents the DMU, m and s are the number of input and output factors, $Y_{rj}$ is the rth type of R&D output of the jth seed industry listed company, $X_{ij}$ is the i type of R&D input of the jth seed industry listed company, and $\mu_{0}$ is the scale state variable of the DMU. If $\mu_{0}>0$, then the DMU is in the state of increasing return to scale; if $\mu_{0}=0$, then the return to scale of the DMU is unchanged; if $\mu_{0}<0$, then the DMU is in the state of decreasing return to scale.

The dual transformation of the above equation is as follows:
\[ \begin{aligned} &\min \theta - \varepsilon (e^T S^- + e^T S^+) \\
&\sum_{j=1}^{J} X_{i,j} \lambda_j - S_{i,k}^{-} = \Theta_k X_{i,k} \\
&\sum_{j=1}^{J} Y_{i,j} \lambda_j - S_{i,k}^{+} = Y_{i,k} \\
&s.t. \lambda_j \geq 0, S^{-}, S^{+} \geq 0 \\
&\sum_{j=1}^{J} \lambda = 1 \end{aligned} \]

\( \theta \) represents the efficiency of the DMU; \( \lambda \) represents the weights of input and output in the jth decision making unit. \( S^- \) and \( S^+ \) are the slack variables of input and output respectively. The slack variables are the difference between the actual input and the optimal input. When \( \theta = 1 \) and \( S = S^+ = 0 \), it indicates that the DMU reaches DEA efficiency. When \( \theta = 1 \) but \( S \neq 0 \) or \( S^+ \neq 0 \), DMU is weak DEA effective. If \( \theta < 1 \), then the DMU is not DEA effective.

2.2. Quasi-SFA model

Fried et al. believed that slack variables were caused by three factors, including management inefficiency, environmental effect and random error. Therefore, by constructing a quasi-SFA model, the influence of these three factors can be observed separately, with the purpose of adjusting the original R&D investment value of various listed companies in different industries to make them under the same external environment. In this stage, the quasi-SFA model is used to select appropriate environment variables. The slack value of input calculated by DEA in the first stage is taken as the dependent variable and the environment variable as the independent variable to construct the quasi-SFA model:

\[ S_{i,k} = f(z_{pk} ; \beta^p) + v_{ik} + \mu_{ik} \]

\( S_{i,k} \) is the slack value of the input of item ith of the kth DMU; \( z_{pk} \) is the environment variables that affect the efficiency of the DMU; \( \beta^p \) is the estimation coefficient corresponding to the environment variable; \( v_{ik} \) and \( \mu_{ik} \) respectively represents the influence of random error and management inefficiency on input relaxation variables, and \( v_{ik} + \mu_{ik} \) are mixed error terms.

We use maximum likelihood estimation to estimate \( \hat{z}_{i,a}; \hat{\beta}^p \) and \( \hat{v}_{ik} \). The adjusted input formula is as follows:

\[ \hat{X}_{i,a} = \hat{X}_{i,a} + \left[ \max(Z_{p,ik} \hat{\beta}^p) - (Z_{p,ik} \hat{\beta}^p) \right] + \left[ \max(V_{ik}) - V_{ik} \right] \]

\( \hat{X}_{i,a} \) is the adjusted input; \( \max(Z_{p,ik} \hat{\beta}^p) - (Z_{p,ik} \hat{\beta}^p) \) is the adjustment of external environmental factors; \( \max(V_{ik}) - V_{ik} \) is adjustment of the random error factor.

2.3. Adjusted DEA model

The input variables adjusted in the second stage were used to replace the input variables in the original sample data, and then the DEA-BCC model was used again to calculate the adjusted data, which get the real R&D efficiency value unaffected by environmental variables and random error terms.

3. Data and variable selection

We select 19 seed industry listed companies that continuously disclose R&D costs as DMU in the model from 2014 to 2016, which meet the evaluation requirements of DEA model and represent the
development status of China's seed industry. The data mainly came from the annual statements of listed companies and CSMAR database.

For R&D investment, most scholars use R&D expenditure and R&D personnel as indicators of R&D investment. But listed companies do not fully disclose the number of R&D personnel. Therefore, we take the number of technical personnel and R&D expenditure as the index of R&D investment.

In the selection of output indicators, we select the number of plant variety right applications, patent applications and the main business income to measure the enterprise's R&D output. This is because market return is the purpose of enterprise research and development. And The R&D output of listed companies in the seed industry include not only plant varieties but also patented inventions, both of which are the most direct R&D output of enterprises. In addition, compared with the application, authorization of plant variety rights and patents lags behind, and authorization is subject to subjective factors. Therefore, the number of applications for plant variety rights and patents can better reflect the output intensity of enterprises' R&D activities.

Based on the research of Wei Liu (2012) [6], Kaiwen Ji (2014) [7], Hongyu Gu (2017) [8] and other scholars, we select the following factors as environmental variables: (1) enterprise scale, which reflects the development scale of the enterprise. This paper use the natural logarithm of total assets to measure the size of an enterprise. (2) ownership structure, which represents the distribution of ownership in the enterprise and the corporate governance structure. Therefore, we select the shareholding ratio of the first largest shareholder to measure ownership concentration. (3) government support, which shows the government's support for enterprise innovation, such as R&D subsidy policies and R&D tax to encourage enterprise R&D. Therefore, we take the proportion of government subsidy in the operating revenue as the environmental variable supported by the government to the listed companies in the seed industry. (4) economic environment, finance environment and market environment reduce the survival and competitive pressure of enterprises. We select agricultural GDP growth rate of the province where the seed industry listed company is located to represent the economic environment of the enterprise.

The variables used in this paper and their descriptions are shown in table 1:

| indicator | variable | definition |
|-----------|----------|------------|
| input indicator | R&D personnel | number of technical personnel |
| | R&D expenditure | R&D expenditure |
| output indicator | operating income | Main product revenue |
| | plant variety rights | Number of applications for plant varieties |
| | patent | Number of patent applications |
| environmental variables | enterprise scale | Log of total assets |
| | ownership concentration | First shareholder shareholding ratio |
| | government support | The ratio of government subsidies to revenues |
| | economic environment | Growth rate of agricultural product in the province where the enterprise is located |

4. Empirical Result

4.1. Stage 1: Classical DEA estimation results

On the basis of the traditional DEA model, we use of DEAP2.1 software to measure R&D efficiency (TE), and TE is decomposed into pure technical efficiency (PTE) and scale efficiency (SE). Based on the traditional DEA model, we use the DEAP2.1 software calculates TE, and TE is decomposed into PTE and SE. PTE is the efficiency of DMU in the optimal size, which reflects the enterprise technical efficiency. SE is the gap between the optimal scale and the actual size, which reflects the influence of scale factor efficiency. The results are shown in table 2.
Table 2. R&D efficiency of listed seed companies before SFA adjusted

| Company stock code | TE 2014 | 2015 | 2016 | PTE 2014 | 2015 | 2016 | SE 2014 | 2015 | 2016 |
|--------------------|--------|------|------|----------|------|------|--------|------|------|
| 002385             | 1      | 0.89 | 0.68 | 1        | 1    | 1    | 1      | 0.89 | 0.68 |
| 002041             | 0.57   | 0.82 | 0.92 | 0.57     | 0.82 | 1    | 1      | 1    | 0.92 |
| 600354             | 1      | 1    | 0.49 | 1        | 1    | 0.58 | 1      | 1    | 0.85 |
| 000713             | 0.57   | 0.76 | 0.71 | 0.59     | 0.84 | 1    | 0.97   | 0.91 | 0.71 |
| 000998             | 0.72   | 0.76 | 0.48 | 1        | 1    | 1    | 0.72   | 0.76 | 0.48 |
| 300087             | 0.45   | 1    | 0.57 | 0.45     | 1    | 0.58 | 0.99   | 1    | 0.99 |
| 300189             | 0.44   | 0.63 | 1    | 0.44     | 0.65 | 1    | 1      | 0.97 | 1    |
| 600371             | 0.53   | 0.57 | 1    | 0.53     | 0.6  | 1    | 1      | 0.95 | 1    |
| 600313             | 1      | 1    | 1    | 1        | 1    | 1    | 1      | 1    | 1    |
| 430468             | 1      | 1    | 1    | 1        | 1    | 1    | 1      | 1    | 1    |
| 430625             | 1      | 0.41 | 0.59 | 1        | 0.6  | 0.67 | 1      | 0.68 | 0.88 |
| 430736             | 0.76   | 0.45 | 0.42 | 0.76     | 0.48 | 0.52 | 1      | 0.94 | 0.8  |
| 832019             | 1      | 1    | 0.64 | 1        | 1    | 1    | 1      | 0.64 | 1    |
| 831087             | 1      | 1    | 1    | 1        | 1    | 1    | 1      | 1    | 1    |
| 831888             | 0.43   | 0.41 | 0.52 | 0.47     | 0.51 | 1    | 0.93   | 0.8  | 0.52 |
| 831492             | 0.26   | 1    | 1    | 1        | 1    | 1    | 0.26   | 1    | 1    |
| 835626             | 0.33   | 0.23 | 0.25 | 0.47     | 0.41 | 0.54 | 0.7    | 0.56 | 0.46 |
| 832663             | 0.79   | 0.93 | 0.64 | 0.99     | 0.97 | 0.8  | 0.93   | 0.66 | 1    |
| 835662             | 1      | 1    | 0.89 | 1        | 1    | 1    | 1      | 1    | 0.89 |

It can be seen from the table that without considering environmental factors and the interference of random error terms, the inefficiency of R&D of most listed seed companies in China was mainly caused by low pure technical efficiency from 2014 to 2015. In 2016, scale efficiency was the main factor affecting the R&D efficiency of most listed seed companies in China. However, the efficiency values cannot reflect the real level and difference of R&D efficiency of listed seed companies in China because they are affected by environmental factors and statistical noise. Therefore, it is necessary to eliminate the interference of environmental factors and random error terms, and re-calculate the R&D efficiency after further adjustment of sample data.

4.2. Stage 2: SFA estimation results

we use slack variables from the first stage DEA as explained variables, and the enterprise scale, government support, ownership concentration and economic environment as explanatory variables to build two quasi-SFA models. The result was calculated by using Frontier 4.1 software.

Table 3. The SFA estimation results

|                    | R&D expenditure redundancy | R&D personnel redundancy |
|--------------------|---------------------------|-------------------------|
| coefficient        | standard-error            | coefficient             | standard-error |
| constant            | -14748.73**               | 99.80                   | -243.79 **    | 1.00        |
| enterprise scale    | 966.40**                  | 24.07                   | 17.25**       | 0.77        |
| government support  | 30608.99**                | 4.83                    | 172.42*       | 1.00        |
| ownership concentration | 1996.76**      | 300.00                  | 45.25**       | 1.00        |
| economic environment | 25530.56**               | 18.26                   | 194.92**      | 1.00        |
| $\sigma^2$         | 9386234.0**               | 1.00                    | 3114.31**     | 1.00        |
| $\lambda$          | 1.00**                    | 0.00                    | 1.00 **       | 0.00        |
| Loglikelihood      | -166.26                   | -89.25                  |             |
| LR                 | 9.7**                     | 10.61**                 |             |
In the table 3, both the unilateral generalized likelihood test values (LR) of the two quasi-SFA models have passed the test, indicating that the selected environment variables are reasonable. At the same time, the analysis results show that the influence of environmental variables on the two input redundancy has passed the significance test at the 5% level, which indicate that it is necessary to eliminate the influence of environmental variables. In addition, both models $\lambda$ tend to be close to 1, which show that the R&D efficiency is greatly affected by environment and random error.

If the regression coefficient of environmental factors in the model is negative, it means that input redundancy will reduce and help improve efficiency with increasing value of environmental variables. Conversely, if the regression coefficient of environmental factors in the model is positive, it indicates that increasing the value of environmental variables will increase input redundancy and cause waste. The effects of environment variables on the two relaxation variables are analyzed as follows:

1) Enterprise scale. The effect of this variable on the slack variable of R&D personnel and R&D investment is positive, manifesting that the larger the enterprise scale is, the more redundant the R&D funds and R&D personnel are, and it is the more unfavorable to improve the R&D efficiency of the company. When an enterprise scale is too large, it may lead to a large and complicated internal organization and redundant personnel, which is not conducive to work coordination and information transmission.

2) Government support. This variable significantly positively affects the slack variables for R&D personnel and funding. There are two main reasons for this results. On the one hand, enterprises may be affected by the "crowding-out effect" of government subsidies on research and development. On the other hand, that may be because the government's criteria for identifying recipients of subsidies are biased. Of course, it does not mean that the government should reduce subsidies to listed companies in the seed industry, but the government needs to improve the subsidy policy, which ensure that subsidies are invested in areas where they are really needed.

3) Ownership concentration. This results indicate that the increase of the shareholding ratio of the largest shareholder will increase the redundancy of R&D investment. Most of the seed enterprises in China are state-owned enterprises or family enterprises. State-owned enterprises are excessively dependent on the government, and family enterprises are basically directly controlled by the founders. The shareholding structure is often in the form of "one share being overwhelming big". Excessive concentration of ownership will make the largest shareholder have too much control over the board of directors, leading to the phenomenon of "insider control". When the interests of major shareholders and minority shareholders conflict, the decision-making subjectivity is strong, which is not conducive to the long-term development of enterprises.

4) Economic environment, agricultural GDP growth rate is an important indicator to measure macroeconomic environment. The results indicate that the macro-economy is in the stage of continuous expansion, which inhibits the R&D efficiency of enterprises. In the favorable financing environment and market environment, the survival pressure of seed industry listed companies is reduced, which may lead to lax management by managers and indirectly lead to the unreasonable distribution of internal resources.

In the above analysis, environmental factors have different degrees of influence on the slack variable of R&D investment of listed companies in seed industry, indicating that it is necessary to adjust the original input data and recalculate the R&D efficiency of enterprises with the adjusted input and output values by removing the influence of environmental factors, random factors and management inefficiency.

4.3. Stage3: DEA regression estimation results after SFA adjustment

In the third stage, we take the original output value and the adjusted input value in as the R&D output and R&D input, and use DEAP2.1 software to re-calculate the R&D efficiency of the enterprise. The calculation results are shown in the table below.
Table 4. R&D efficiency of listed seed companies after SFA adjusted

| Company stock code | TE 2014 | PTE 2014 | SE 2014 | TE 2015 | PTE 2015 | SE 2015 | TE 2016 | PTE 2016 | SE 2016 |
|--------------------|---------|----------|---------|---------|----------|---------|---------|----------|---------|
| 002385             | 1       | 1        | 1       | 1       | 1        | 1       | 1       | 1        | 1       |
| 002041             | 0.84    | 1        | 1       | 1       | 0.84     | 1       | 1       | 0.78     | 1       |
| 600354             | 1       | 1        | 0.6     | 1       | 1        | 0.76    | 1       | 1        | 0.78    |
| 000713             | 0.64    | 0.97     | 1       | 0.81    | 0.97     | 1       | 0.79    | 0.99     | 1       |
| 000998             | 1       | 1        | 0.78    | 1       | 1        | 1       | 1       | 0.78     | 1       |
| 300087             | 0.3     | 1        | 0.57    | 0.76    | 1        | 0.8     | 0.39    | 0.72     | 1       |
| 300189             | 0.39    | 0.6      | 1       | 0.8     | 0.97     | 1       | 0.49    | 0.63     | 1       |
| 600371             | 0.52    | 0.31     | 1       | 0.93    | 0.53     | 1       | 0.56    | 0.59     | 1       |
| 600313             | 1       | 1        | 0.76    | 1       | 0.67     | 1       | 0.17    | 0.3       | 0.76    |
| 430468             | 0.17    | 0.2      | 0.35    | 0.87    | 0.74     | 0.84    | 0.47    | 0.55      | 0.41    |
| 430625             | 0.85    | 0.19     | 0.4     | 0.85    | 0.19     | 0.4     | 0.85    | 0.34      | 0.62    |
| 430736             | 0.77    | 0.33     | 0.26    | 1       | 0.84     | 0.68    | 0.77    | 0.39      | 0.38    |
| 832019             | 0.93    | 0.31     | 0.1     | 1       | 0.74     | 0.69    | 0.93    | 0.42      | 0.15    |
| 831087             | 0.41    | 0.4      | 0.35    | 0.87    | 0.74     | 0.84    | 0.47    | 0.55      | 0.41    |
| 831888             | 0.65    | 0.58     | 0.77    | 0.72    | 0.59     | 0.73    | 0.91    | 0.98      | 0.77    |
| 831492             | 0.11    | 0.26     | 0.68    | 0.9     | 0.79     | 0.73    | 0.12    | 0.32      | 0.93    |
| 835626             | 0.19    | 0.11     | 0.1     | 1       | 0.7      | 0.68    | 0.19    | 0.16      | 0.15    |
| 832663             | 0.22    | 0.37     | 0.2     | 0.82    | 0.81     | 0.93    | 0.27    | 0.46      | 0.21    |
| 835662             | 0.55    | 0.81     | 0.43    | 1       | 1        | 0.92    | 0.55    | 0.81      | 0.47    |

As can be seen from table 4, the R&D efficiency of Dabeinong Technology Group (002385), Dunhuang seed industry (600354), zhongnongfa (600313) and Winall Hi-tech Seed (300087) has little change than before, indicating that R&D efficiency of these four companies is less affected by environmental variables and random factors. In terms of return to scale, Dabeinong Technology Group (002385), and zhongnongfa (600313) are in the optimal state of scale compensation from 2014 to 2016. In 2016, the number of enterprises with increasing returns to scale increased from 36% to 63.2%. This means that more than half of the listed companies in the seed industry have not yet reached the optimal size for research and development.

Figure 1. Comparison of the average efficiency before and after SFA adjusted
In general, after the adjustment of SFA, the average R&D efficiency and pure technical efficiency of listed companies in the seed industry rose slightly from 2014 to 2015, but declined in 2016. The mean value of R&D efficiency, the mean value of pure technology efficiency and the mean value of scale efficiency of listed companies in 2016 were 0.63, 0.88 and 0.69, respectively. Compared with before the adjustment, the technical efficiency was decreased, the pure technology efficiency was significantly improved, while the scale efficiency was significantly decreased, as shown in the figure 1.

5. Conclusion
This paper uses the three stage DEA model to analyze R&D efficiency of the seed listed companies in China between 2014 and 2016. The main conclusions are as follows: (1) after eliminating the random error and the external environment influences, pure technical efficiency and scale efficiency of sample companies, the comprehensive R&D efficiency than before all have different degree of change; (2) the R&D efficiency of listed companies in seed industries in China is low, which is mainly affected by the low scale efficiency; (3) about 60% of enterprises are in the state of increasing returns to scale; (4) the R&D efficiency of new three listed companies is relatively low, such as Lantron Seed Corporation (430625), Qiule Seeds Technology (831087) and damin seed industry (835626).

Based on the above conclusions, we can know that while increasing R&D investment, enterprises should establish a reasonable management system to make rational and effective use of R&D funds and avoid redundancy and waste of R&D funds. In addition, the government should change the direct financial support in the form of a single. For example, the government can provide diversified support such as capital, innovation services and innovation environment for enterprises at different development stages. When the government subsidizes enterprises, it should clearly specify the use of subsidies, strengthen supervision over the use and flow of subsidy funds, and determine the form and amount of follow-up subsidy funds according to the progress of the project, so as to maximize the utility of subsidy resources.

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