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An Empirical Study on Innovation Efficiency of Strategic Emerging Industry

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Abstract: Strategic emerging industries have a significant leading role on the overall economic and the sustainable development of social economy. So making efforts to promote the development of strategic emerging industries is an advisable choice to strong its economic status. However, China's strategic emerging industries are still at a preliminary stage of development, the core competitiveness is not strong and the innovation efficiency is needed to be improved. This article will study the innovation efficiency of strategic emerging industry by DEA (Data Envelopment Analysis) and logit model which estimate the effective production based on a set of input-output observations and then investigate the influencing factors. According to the empirical study, it turned out that China's strategic emerging industries has reached an effective level and increase the input of labor productivity, R and D expenditures, R and D activities staff can increase the efficiency of innovation.

Key words: Innovation efficiency, strategic emerging industry, DEA

INTRODUCTION

Since, the financial crisis, the major developed countries in the world implemented the re-industrialization strategy in order to achieve economic recovery, including nurturing emerging technologies and industries. Countries attach great importance to the development of strategic emerging industry. China's development has entered a new era in its history. So, it must make the scientific development be the theme and the accelerating transformation of economic development as the main line. These are related to China's overall development strategy. In September 2009, Premier Wen Jiabao of the State Council held its third forum on the development of strategic emerging industries and listened to the economic expert and technological expert's advice and recommendations. In October 2010, to speed up the transformation of economic development, the State Council legislate the key directions, main tasks and support policies of strategic emerging industries. This rules could boost social economic embark on the innovation-driven and endogenous growth track of scientific development. In 2012, the State Council issued the "Twelfth Five-Year plan" to clarify the objectives, key areas and major tasks of the development of China's strategic emerging industries, accelerating the development of strategic emerging industries.

Strategic emerging industries are knowledge and technology-intensive industries which are based on technological breakthroughs and significant development needs, having a significant leading role on the overall economic and social and long-term development. Cultivate and develop strategic emerging industries can promote the development of economy and optimize the economic structure. However, china's strategic emerging industries are still at a preliminary stage of development, the core competitiveness is not strong and sustainable business model is still being explored. These are mainly due to China's current industrial core technological innovation capacity constraints. Therefore, this article will explore the performance of the scale of the industry, labor productivity, R and D funding and R and D personnel for strategic emerging industries.

Theoretical reviews: Domestic and foreign scholars have launched a lot of research for innovation performance. Shrieves (1978) analyzed the relationship between firm size and innovation and concluded that the firm size and innovation have a significant positive impact. It followed by some scholars Howe and Mcfetridge (1976) and Soete (1979) found that the non-linear relationship between firm size and innovation through empirical studies. Wu (2008) found an inverted U-shaped relationship between the market concentration and innovation strength and a non-linear incremental relationship between the firm size and innovation strength. This research revealed that the different nature of the structure of property rights in the R and D investment had a different incentive effects. Lian and Kai (2005) drew the conclusion that the non-state-owned scale enterprises have a significant role in promoting innovation which shows the relationship between firm size and innovation as a condition to certain corporate governance structure. A simple scale and the group do not necessarily guarantee the company's innovation capability. Zhengping and Wenliang (2011) constructed a model of social capital, absorptive capacity and innovation performance and validated and corrected the model through empirical analysis. Studies show that social capital will be obtained through the impact of innovative information, thus affecting the absorption ability and thus plays role in innovation performance. In the various dimensions of social capital, embedded resources are the most significant influence factors of innovation performance. In addition, contact strength and network size has a significant positive impact on innovation performance; cluster innovation centers and heterogeneity of networks are not significant. Xingzhi and Li (2011) used the SFA model to estimate the innovation performance of strategic emerging industry in China. And then the impact pathway of corporate scale and different innovative way of industrial innovation efficiency was revealed through the panel Tobit model. The influence degree of different ownership structure for innovation efficiency was also explained. The study found that China's overall innovation efficiency levels of strategic emerging industries is low and there was an inverted U-shaped nonlinear relationship between firm size and innovation efficiency. Innovation and the introduction of technology innovation have significant influence on innovation efficiency and the technological transformation and digestion and absorption's impact on innovation efficiency is not significant. Different structure of property rights have different influence on innovation efficiency: The state-owned property and innovation are negatively related but there was a positive relationship between non-state-owned property and innovation efficiency. Dongfeng (2012) divided the technical capacity into technology absorptive capacity and technological innovation capability and divided innovation strategy into exploratory innovation and the utilized innovative. The impact of technical capability and innovation strategy on the formation of innovative efficiency was put forward. The technological capabilities of enterprises and innovation strategies can have a significant impact on innovation performance. Specifically the utilized innovative is more significant than exploratory innovation on innovation performance and technical innovation and technology absorption capacity's impact on innovation performance is not significant.

This study utilizes data envelopment method and logit model to analyze the innovation efficiency and impact factors. This research methodology is more comprehensive and effective, so conclusions are more convincing than others.

METHODOLOGY AND MODELING

Judging from the characteristics and classification of strategic emerging industries, the connotation and characteristics of strategic emerging industries and high-tech industries are similar. They are of high-technology, high level of R and D, high input and high-risk characteristics. So, to some extent that strategic emerging industries rang from high-tech industries and high-tech industries is the central subject of strategic emerging industries. Therefore, adopt the data of high-tech industries to analysis innovation efficiency of strategic emerging industries, exploring the industrial scale, R and D investment, personnel investment, the production efficiency's influence on innovation efficiency.

To study the relative efficiency of strategic emerging industries in different year, usually adopt the input-output ratio indicator. It is easy to calculate the respective input-output ratio and sort the performance of their size when each of the input-output can be converted into the same unit of measurement performance sorting. However, strategic emerging industries have a number of inputs and outputs indicators and cannot be translated into a unified unit and numeric input-output ratio cannot be calculated. Thus, adopt a new approach to performance comparison. This method is generated at the end of the 1970s data envelopment analysis.

The Data Envelopment Analysis (DEA) was produced by the famous Operations Researchers (Charnes *et al*., 1978) to evaluate inter-sector relative effectiveness. DEA is the use of mathematical programming model (including linear programming, multi-objective planning, has a cone-shaped structure generalized optimization, semi-infinite programming, stochastic programming). It evaluate the relative effectiveness (called DEA efficient) of "sector" or "unit" (known as the" decision-making unit, of abbreviated DMU) with multiple input and multiple output. It often used to measure the relative efficiency of the operating units have the same goal. It can be proved that DEA effectiveness and multi-objective programming problems Pareto Efficient Solution (or non-dominated solutions) are equivalent. So, the DEA can be regarded as a new statistical method. It is based on a set of input-output observation to estimate the effective production frontier, has some outstanding features:

- Commonly in quantitative economics, statistical regression and other statistical methods are used to estimate effective production frontier but these methods are mostly limited to a single output. In contrast, DEA method has an absolute advantage for processing multi-input, multi-output problem

- DEA method can not only use linear programming to determine the corresponding point of the decision-making unit is in the efficient production frontier surface, at the same time it can get a lot of useful management information
- DEA can be used to study the relative effectiveness of a variety of programs (for example, investment project evaluation). Research the relative effect of a decision before making a decision to predict (such as the establishment of a new plant, the new plant with respect to already factory is efficient or not). DEA model can even be used for policy evaluation
- The DEA Method is purely technical and has nothing to do with the dimension. It only needs to distinguish inputs and outputs and does not need to dimensionless processing the indicators. Analyze the technical efficiency and scale efficiency directly and do not need to define a special function in the form. It does not ask for the number of samples
- Without any assume on weights, obtain the optimal weight through the decision-making unit of input and output data. It eliminates a lot of subjective factors, having a strong objectivity. Assume that each input is associated with one or more output and there is a link between input and output but do not need to determine the display expression of this relationship

DEA evaluation model selection: Because the DEA has the above advantages, since the first model CCR is proposed in 1978, a large number of scholars engaged in the study of DEA. Banker *et al.* (1984) drawn a model which is called BCC. Charnes *et al.* (1985) put forward another model, called CCGSS model. These two models are used to study the technology effectiveness of the production sector. Charnes *et al.* (1986) used the semi-infinite programming theory. Then reached an infinite number of decision-making unit, put forwarded a new Data Envelopment Analysis-CCW model. Charnes *et al.* (1987) got a model called cone ratio data envelopment model-CCWH model. This model can be used to deal with too much input and output and cone select can reflect the preferences of the decision-makers. Flexible application of this model can classify or queue the DEA effective decision-making unit which are identified in the CCR model and so on.

Among the DEA method, the CCR model and BCC model are the two classic models, used widely and mature. CCR model was put forward by Charnes *et al.* (1978), named by the initials of the three scholars. The model researches the relative efficiency of the decision-making unit under the assumption of constant returns to scale. BBC model was put forward by Banker *et al.* (1984), excluding the constant returns to scale factors of the CCR model and adding the changing returns to scale factors, to measure the relative efficiency of different returns to scale state. Strategic emerging industries of this study are limited by the internal management conditions, the external economic environment and many other conditions, so the returns to scale cannot be fixed. And the size of industry has an impact on the efficiency. Therefore this article selects BCC model of DEA method as the evaluation model for this study, to estimate DEA evaluation of the level of performance under variable returns to scale.

The BCC evaluation model: Generally named the measured performance organization for Decision-Making Unit (DMU) in the BCC. Assume that there are n decision-making unit (j = 1, 2,…, n), each decision-making unit has the same m items put into (i = 1, 2,..., m), each decision-making unit has the same s items put out (r = 1, 2,..., s). Make X_{ij} stand for i inputs of the decision-making unit j. Y_{rj} stand for r outputs of the j decision making unit. So, the matrix of input and output are:

$$\begin{pmatrix} X_{11} & X_{12} & \cdots & X_{1j} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2j} & \cdots & X_{2n} \\ X_{31} & X_{32} & \cdots & X_{3j} & \cdots & X_{3n} \\ \vdots & \vdots & & \vdots & & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mj} & \cdots & X_{mn} \end{pmatrix} \begin{pmatrix} Y_{11} & Y_{12} & \cdots & Y_{1j} & \cdots & Y_{1n} \\ Y_{21} & Y_{22} & \cdots & Y_{2j} & \cdots & Y_{2n} \\ Y_{31} & Y_{32} & \cdots & Y_{3j} & \cdots & Y_{3n} \\ \vdots & \vdots & & \vdots & & \vdots \\ Y_{s1} & Y_{s2} & \cdots & Y_{sj} & \cdots & Y_{sn} \end{pmatrix}$$

Calculate the relative efficiency value strategic emerging industries in year j_0:

$$\min \quad h_{j0} = \sigma$$

$$\text{st}\begin{cases} \sum_{j=1}^{n} X_{ij}\lambda_j \le \sigma X_{ij0} & i = 1, 2, \cdots m \\ \sum_{j=1}^{n} Y_{rj}\lambda_j \le Y_{rj0} & r = 1, 2, \cdots s \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j \ge 0, j = 1, 2, \cdots, n \end{cases} \tag{1}$$

σ stands for the value of efficiency of strategic emerging industries in year j, the constraint is:

$$\sum_{j=1}^{n} \lambda_j = 1$$

h_{j0} means the pure technical efficiency.

Dual conversion operator on model Eq. 1, the results are as follows:

$$\max \quad h_{j0} = \sum_{r=1}^{n} u_r Y_{rj0} - u_{j0} st$$
$$st \begin{cases} \sum_{j=1}^{m} X_{ij} v_i = 1 \\ \sum_{r=1}^{s} Y_{rj} u_j - \sum_{j=1}^{m} X_{ij} v_i - u_{j0} \le 0 \\ u_r, v_i \ge 0, \quad i = 1, 2, \cdots, m \quad r = 1, 2, \cdots, s \end{cases} \tag{2}$$

In Eq. 2, u_{j0} means the returns to scale index; u_r, $v_i \geq 0$, i = 1, 2,...,s are the constraint. $u_{j0}>0$ indicates that the strategic emerging industrial scale production is in the stage of increasing returns, producing under the scale smaller than production scale conditions. $u_{j0} = 0$ indicates that strategic emerging industries in the stage of constant returns to scale, the optimal scale production. $u_{j0}<0$ indicates that the strategic emerging industrial scale production in the stage of diminishing returns, greater than the optimal size.

The BCC model includes a measure of pure technical efficiency, scale efficiency and technical efficiency. The relationship among the three is Eq. 3 as following:

$$\text{Technical efficiency}_{CRS} = \text{Pure technical efficiency}_{VRS} \times \text{Scale efficiency} \tag{3}$$

Estimating the efficiency of strategic emerging industries through BCC model, get the value of technical efficiency, pure technical efficiency and scale efficiency and then certain the impact of input indicators on the strategic emerging industries. When the efficiency is 1, it means that in the case of the same outputs, the inputs of the elements achieve the optimal situation and the DEA is efficient. When the efficiency value is less than 1, the part input of the elements is wasted and not rational used, thereby increasing the level of performance can be achieved by reducing the amount of inputs.

RESULTS

The results of BBC evaluation model

Indicators selection: This study analyzes the innovation efficiency of strategic emerging industries, so select years' data from 2000-2010 under the principle of data aging line and easy access. When selecting the BCC input-output indicators combine with the two indicators of the production method and asset law principle and consider the selecting situation of strategic emerging industries indicators. Choose output value X_1, Labor productivity X_2, R and D (research and development) expenditures X_3 and R and D personnel X_4 as input indicators. Choose the total amount of patent applications Y_1 and new product sales Y_2 as output indicators. Showed in Table 1.

Result analysis: Use the software DEAP2.1 deal with the data and the BCC model results as shown in Table 2.

Table 1: Input and output indicators' value of high-technology industry from 2000-2010

Time	$X_{1(100\ million)}$	$X_{2(10,000/person)}$	$X_{3(100\ million)}$	$X_{4(10,000\ persons/year)}$	$Y_{1(item)}$	$Y_{2(100\ million)}$
2000	10411	15.9	111	9.2	2245	2483
2001	12263	23.7	157	11.2	3379	2875
2002	15099	32.6	187	11.8	5590	3416
2003	20556	43.1	222	12.8	8270	4515
2004	27769	47.3	292	12.1	11026	6099
2005	34367	51.8	363	17.3	16823	6915
2006	41996	56.4	456	18.9	24301	8249
2007	50461	59.9	545	24.8	34446	10303
2008	57087	60.4	655	28.5	39656	12880
2009	60430	63.1	774	32.0	51513	12595
2010	74709	68.4	968	39.9	59683	16365

Table 2: The efficiency and scale stage of high-technology industry calculated from BBC model

Time	Overall efficiency	Pure technical efficiency	Scale efficiency	Scale stage
2000	1.000	1.000	1.000	Constant returns to scale
2001	1.000	1.000	1.000	Constant returns to scale
2002	1.000	1.000	1.000	Constant returns to scale
2003	1.000	1.000	1.000	Constant returns to scale
2004	0.986	1.000	0.986	Increasing returns to scale
2005	1.000	1.000	1.000	Constant returns to scale
2006	1.000	1.000	1.000	Constant returns to scale
2007	0.979	1.000	0.979	Increasing returns to scale
2008	0.896	1.000	0.896	Increasing returns to scale
2009	1.000	1.000	1.000	Constant returns to scale
2010	0.979	1.000	0.979	Increasing returns to scale
Mean	0.985	1.000	0.985	

BCC: A method of the relative efficiency measurement of different returns to scale presented by Banker *et al.* (1984)

It can be seen that in 2000, 2001, 2002, 2003, 2006, 2009 the overall efficiency value is 1, reached the DEA efficient. In 2004, 2007, 2010 DEA value is more than 0.97 which is very close to the DEA efficient. In 2008, DEA value is below 0.9, so the performance level is not high. As can be seen from the fifth column, most of the time is in the stage of constant returns to scale; few years in the stage of increasing returns to scale, so expanding the scale of production further can achieve a higher level of performance. So, on the whole, the scale of China's strategic emerging industries has reached a more effective level.

According to the above method to analyze the performance of the different years of strategic emerging industries, usually people are more concerned about how to improve the level of performance; then use the logit model to analysis the factors affecting the performance.

Logit model: Logit model is the first discrete choice models and currently the most widely used model. It is a common method of sociology, biostatistics, clinical, quantitative psychology, econometrics, marketing and other statistical empirical analysis. Luce (1959) first proposed logit model according to the IIA characteristics. Marschak (1960) proved that the logit model was of maximum utility theory consistency. Luce and Suppes (1965) introduced the research achievement of Marley. The extreme value distribution can be deduced from the model of the Logit form. Logit form of non-deterministic model utility items must obey extreme value distribution.

Logit regression analysis is the regression analysis of qualitative variables on the dependent variable. It is a non-linear model. The basic feature is: the dependent variable must be dichotomous. Make the dependent variable y, then y = 1 commonly means that "yes" and y = 0 commonly means that "no". The argument can be dummy variables or continuous variables. From the point of view of the model, the DEA efficiency is defined as y = 1, the non-DEA is defined as 0, so that the value of 0 and 1 dependent variable can be written:

$$y = \begin{cases} 1 = \text{DEA efficient} \\ 0 = \text{DEA non efficient} \end{cases}$$

Then use a variety method to analysis the dependent variable valued 0, 1. Usually P means the effective probability DEA (DEA effective probability 1-P). Deal P as a linear function of x argument. Because y is the 0-1 Bernoulli distribution, the distribution is as following:

- **P = P (y = 1|x):** The probability of y = 1 when the variable is x. That is, the probability of DEA efficient when the input indicators is the x
- **1-P = P (y = 0|x):** The probability of y = 0 when the variable is x. That is, the probability of DEA non-efficient when the input indicators is the x

The probability of DEA effective and non-efficient becomes the ratio of occurring that is relative risk, expressed as:

$$\text{odds} = \frac{P}{1-P}$$

Because it appears as logarithmic form, the ratio of occurring is the log odds, expressed as:

$$\text{odds} = \ln\left(\frac{P}{1-P}\right)$$

The ratio of occurring of log odds is a specific function of probability P when the DEA is valid. Logistic transformed, the function can be written as a logistic regression logit model:

$$\log \text{it}\ (P) = \log_e\left(\frac{P}{1-P}\right)$$

On the one hand, logit expresses that it is conversion unit of the probability P; on the other hand, it can be used as dependent variable of the regression to maintain the traditional regression model between independent variables.

It can be obtained according to the definition of the expected value of a discrete random variable:

$$E(y) = 1(P)+0(1-P) = P$$

And then get $E(y) = P = \beta_0+\beta_1 x$.

Therefore, it can be seen from the above analysis, when the value of the dependent variable 0, 1, mean $E(y) = \beta_0+\beta_1 x$ always represents the probability of y = 1 when the argument is given. Although, this is derived from a simple linear regression analysis, it is also suitable for complex multivariate regression function (Eq. 4):

$$E(y) = \log \text{it}\ P = \beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k \quad (4)$$

β_0 is the constant term, β_1, β_2,..., β_k are regression coefficient of k independent variables.

The results of logit model: Follow the BCC model input indicators, the independent and dependent variables are shown in Table 3.

Table 3: The variables' definitions in the logit model

Type of variable	Name of variable	Definitions of variable
Dependent variable	Y	Whether the innovation efficiency is implement, 1 stands for implement 1, 0 reverse
Explanatory variables	X_1	Output value
	X_2	Labor productivity
	X_3	R and D expenditures
	X_4	R and D personnel
	ε	Residuals, follow a normal distribution
Variable coefficient to be estimated	β	

The fitting result is as follow:

$$Y = -3.849691-0.001044X_1+0.343341X_2+0.013996X_3+1.097711X_4$$

CONCLUSION

By the empirical study on innovation efficiency of strategic emerging industry, getting the results through the DEA model that on the whole the scale of China's strategic emerging industries has reached a more effective level. In the logit model results, labor productivity, R and D expenditures, R and D activities personnel's coefficient are positive; the total output value is negative. It indicates that in the case of other conditions remain unchanged, labor productivity, R and D expenditures, R and D activities staff have positive impact on corporate performance, so increase their input is good for efficiency of industrial innovation on the overall. It can promote the innovation efficiency of the strategic emerging industries. But the scale of the industry has reached an effective level; increasing industrial scale is negative for innovation efficient, hindering the efficiency of industrial innovation.

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