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A New Internet DEA Structure: Measurementof Chinese R&D Innovation Efficiency in High Technology Industry

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Abstract

Studying from the characteristics of the two stagesin the high-tech industry, combining with the practice and deficiency of the actual measurement, wesummarize China's high-tech industry innovation efficiency calculation methodsand explore the one of DEA methodin depth to construct a new index system, on which a new internet DEA model (a methodological innovation) is constructed. This new model can be applied to get overall efficiency and the efficiency of the two phases in high-tech industry R&D activities. In the end, the article shows the application of this model: the ability to analyze China's high-tech industrial innovation efficiency and the efficiency of high-tech industry's R&D activity in different regions and will have implications for the governmental policy-making.

Keywords: internet DEA model, two-stage efficiency, R&D

1. Introduction

High-tech industry is a key and strategic industry in China, which takes a leading role to promote innovation and technology upgrading. Its competitiveness lies in the integration and rapid flow of technological innovation with all sorts of resources. In the high-tech industry, R&D innovation activities tend to be regarded as the most important driving force for high-tech development, but China's current relevant industrial policies is always on macro-level, such as the policy of increasing the overall input of governmental R&D funding, or introducing favorable tax policy to enterprises, neither is in connection with characteristics of existing stage of the high-tech industry nor allocating the resources efficiently, resulting in deficient government devotion and inefficiency, low capacity to transferring existing scientific and technological achievements into productivity in industrial R&D process and other defects in high-tech fields at present.

The consequences of the drawbacks mentioned above are always reflected in the statistics. According to the "Global Competitiveness Report 2012–2013" (2013), the GDP of China is ranked 2nd in the world, the technological innovation 20th–30th, the technology application 71th–105th. Unbalanced development of GDP and technological innovation, and that of technological innovation ability and technical application may bring about new risk. With the growth of high-tech, technological innovation has become the key factor in a long-term sustainable development, which is influential in regional economic growth and regional competitiveness. On condition that the innovative resources input are limited, a very important way to improve self-renovation capability is to gain more innovative fruit, which requires high-efficiency in technological innovation industry. In the process of enhancing the technological innovation efficiency, firstly we should know how to evaluate the efficiency of technological innovation. If the efficiency of innovation unit cannot be measured, wecannotdefine the innovation unit, nor find out the reasons for low efficiency of innovative resources application, let alone setting higher goals for innovation achievement. During the Technological innovation, from the generation of high-tech to its applications and lastly to commercialization, different innovative factors are of diverse influences and play different roles in different stages, so that characteristics in different stages might be different as well. Generally speaking, when we apply efficiency evaluation model (especially DEA model) to evaluate the high-tech industrial technology innovation input and output efficiency, it is necessary for us to pay more attention to the compatibility of input and output generated in different stages of technological innovation.

2. Literature Review

In recent years, the two high-tech efficiency calculation methods of overall analysis and phase analysis have been commonly adopted. More Chinese scholars choose the latter one of phase analysis and divide the high-tech into two phases: the high-tech R&D phase and the high-tech digestion and absorption phase. Besides, the research emphasis lies in specific aspects of industrial development but not the general aspects. Specifically, the high-tech R&D is the process that starts from innovative ideas. The research organization employs appropriate methods and means, using certain material in technical route, coming up with new varieties, new technologies, new services ;Technology digestion and absorption is the phase that enterprises make an improvement on technology patents and inventions , applied which to the production. The two phases of R & D and innovation digestion and absorption are inseparable. In China, R&D phase always occur in research institutes and universities, and in enterprises' R&D department, and the second phase of technology digestion and absorption always occur in the enterprises. The efficiency of the twophases (especially innovation efficiency of R&D activities in the first phase, directly affects growth of high-tech industries) is the object of study and a major focus of this paper.

Econometric circles advocate theparametric and non-parametric Frontiers Methods to measure the productive Efficiency. The representatives are stochastic frontier approach and data envelopment analysis, both of which have their own advantages and limitations. Aigner, Lovell, Schmidt and Broeck proposed their own stochastic frontier model independently.In the stochastic frontier model, they load a random error term on the frontier besides the existing extraneous variable of technical Inefficiency. In the beginning, people think it is impossible to estimate the technical efficiency of each evaluation unitin the stochastic frontier model, and they can only give an average evaluation to the overall units, while Battese and Coelli further get conditional mathematical expectation and optimum estimation of technical efficiency for each evaluation unit.

The data envelopment analysis (DEA) is a representative of non-parametric frontier method. Saaty A. Charnes, W. W. Cooper and E. Rhodes are the first oneswhopropose a method called data envelopment analysis (DEA) in 1978, which is used to evaluate relative effectiveness for sectors. Their first model was named the CCR model.From the perspective of the production function, this model is applied to rate the efficiency of DMU with multiple inputs and outputs. Banker, Charnes and Cooper (1988) create another DEA model called BCC. BCC model can generate the technical efficiency of the decision-making unit, and the CCR model can generate not only technical efficiency, but also the scale efficiency. Thereafter, many scholars extended DEA model, Chiang Kao proposed linear equationsunder the two levels. Andrew and Leon (2005): external investigation of the two-stage semi-parametric model; Jahanshahloo (2007) madethe cost-effectiveness model; Abdollah and Forough (2005): generic model; Wang Xiaohong (2004): E-DEA model. In order to further estimate the "effective production frontier", Charnes, Cooper and Wei Quan-ling (1986), made a research on a case with an infinite number of decision-making units, and got a new data envelopment model-CCW model.

Comparatively speaking, stochastic frontier model (SFA) only can evaluate the efficiency of the production process generating single-output, while non-parametric model can evaluate multi-output production process and single-output one. Because of diversity and complexity of the inputs and outputs in high-tech industry, More Chinese scholars choose DEA model to analysis the efficiency. In the past three decades, Chinese scholars have made a series innovative research on the high-tech industry with DEA, andmake a breakthrough in input-output analysis. Not only the macro-leveled input and output analysis, but also they make multi-stage efficiency analysis by combining value chain with technology transferring chain. Zheng Jian, Ding Yun long (2008) divide technological innovation process into the technicaloutput stage and technology-transfer stage, and make research on efficiency of high-tech industrial innovation by improvement of DEA. Fu Qiang, Ma Yucheng study the double-efficiency of China's high-tech industrial technology innovation based on value chain. Zhang Lei Yong &Ma Lei (2011) make a research on efficiency of China's S & T input-output in two-stage chain perspective. Although these scholars divide the high-tech industry into stages, it is defective in establishment of input and output index in different stages.For example, the index of R & D capital stock and R & D internal expenditures is classified by Zheng Jian (2008), Ding Yun long, Yu Yong Ze, Ma Lei (2011) as an input in the first stage , while Zhang Lei yong (2011) ranks them the index in second stage. His paper takes lead in innovation and practical application by the application of the CCR model which was commonlyused by most Chinese scholars to analyze. His thought and formulas is shown as below:

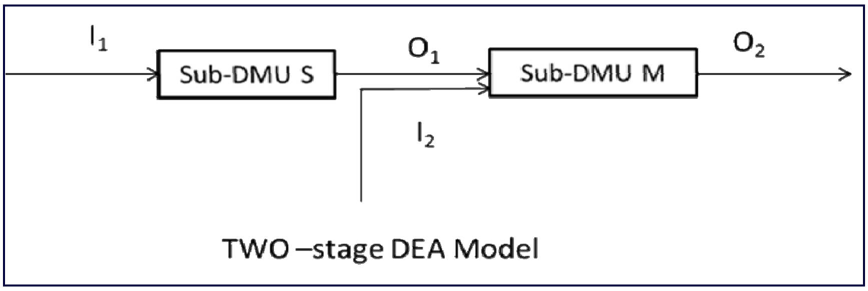

Figure 1. Ordinary two-stage DEA model

$$
\begin{aligned}
&\beta_o = Max \frac{U_M^T Y_{Mo}}{V_S^T X_{so} + V_M^T X_{Mo}} \\
&s.t. \quad \frac{U_M^T Y_{Mi}}{V_S^T X_{si} + V_M^T X_{mi}} \leqslant 1 \\
&\sum_{i=1}^{N} \lambda_i I_{1i} \theta_{1i}^{*} \leqslant I_{1i} \\
&\sum_{i=1}^{N} \lambda_i O_{2i} / \theta_{2i}^{*} \geqslant O_2 \\
&\sum_{i=1}^{N} \lambda_i O_{1i} \geqslant O_1, \sum_{i=1}^{N} \lambda_i O_{1i} \geqslant O_2 \\
&\sum_{i=1}^{N} \lambda_i I_{2i} \leqslant I_2, \quad \lambda_i \geqslant 0
\end{aligned}
$$

The network DEA modelsare used widely in worldwide.The scholars from different countries adopt network DEA method intheir fieldsfor input-output analysis stage by stage, and achieved a lot of excellent research results. For example, Samoilenko & Osei-Bryson (2011), applied the DEA in the United States competitive business environment. Also in the United States, Lewis, HF &Mallikarjun (2013), used a two-stage DEA model to analyze the United States Major League Baseball operating conditions in 2009. Liu, JS & Lu (2012) analyzed the efficiency of the group in internal combustion vehicles for the transport sector with the network DEA model. In Brazil, Wanke (2013) used network two-stage DEA to study the efficiency of Brazilian airport. There are many such examples.We can see that two-stage DEA model have already been used in various fields in many countries.

3. Improvements of Existing Models and Establishment of New Model

3.1 Defects of Existing Models

In practice, technological R & D and technological assimilation are the two phases in the course of production, during which the R&D activities take effect, therefore, it is unfeasible to classify R & D activities into any of the two phases. If weclassified it to one certain stage, it would be not real to the reality norallocate resources effectively. Besides, in this case, it would be not accurate for the calculated result of the input-output efficiency. The inaccuracy of efficiency is caused by CCR model, because the characteristic of CCR model is that the factors of input-outputin the two stages must be the same, while the factors are not identical in practice in the two stages. For example, many Chinese scholars classified the factors of R & D capital stock and R & D Intramural expenditure in the first phase of investment, however, in actual production; most R & D activities take place in scientific research institutes, universities and enterprises.Enterprises are not only implementer but also the main investors of the R & D activities. R & D department in enterprises carry out R&D activities andundertake the task of technical digestion and absorption. Therefore, it is inappropriate for the scholars to view R & D Intramural expenditure and other factors as the input in R&D stage.

In this article, a new DEA model isgenerated on the base of reality. When selecting factors, I take all the factors in the two phases that mentioned in the former literatures into consideration, combining with the functions of each factor in the actual innovation activities to establish a new index system. The factor of R&D activity is characterized by “full-time equivalent of R&D personnel” and “intramural expenditure on R&D”, which simultaneously work in the phases of technology R&D stage and technology digestion and absorption stage. The input-output model is shown asfollows:

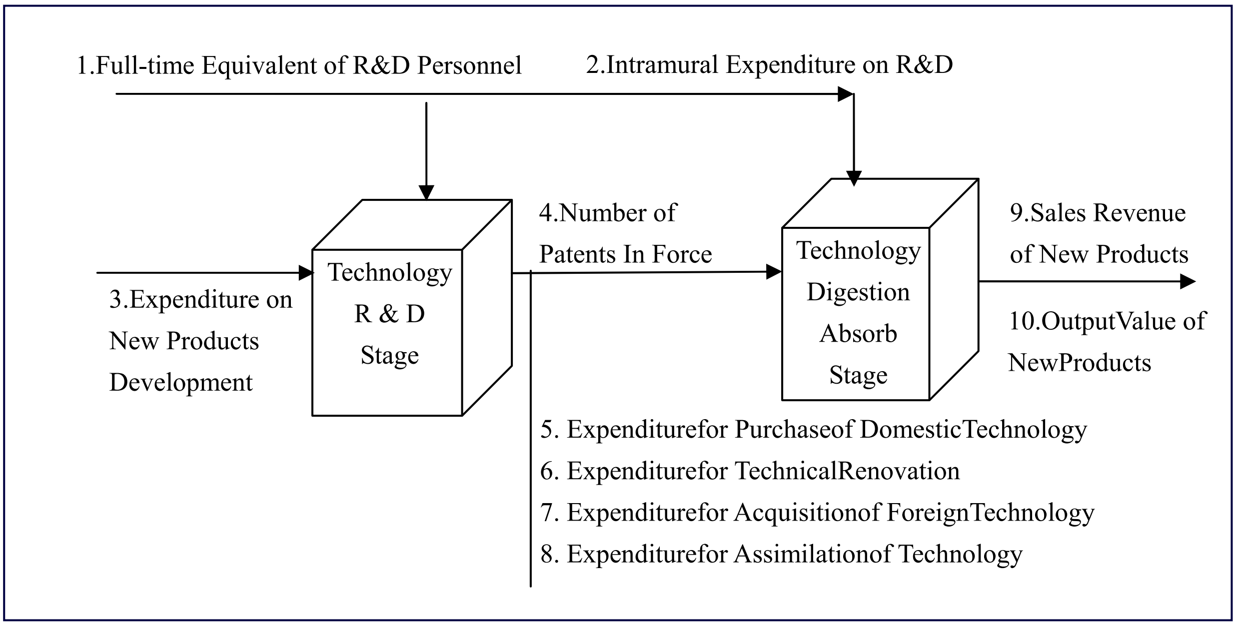

Figure 2. High-tech industry input-out put stage flowchart

Besides the indicators of "full-time equivalent of R & D personnel"and "intramural expenditure on R&D", I also conceive of "expenditure on new products investment" as the factor in the first stage, drawing out the indicator of "the number of patents" , which is regarded as the input in the second phase.In the second phase, in addition to the R&D activities, other indicators of "expenditures on technological activities" (Expenditure for Purchase of Domestic Technology, Expenditure for Technical Renovation, Expenditure for Acquisition of Foreign Technology and Expenditure for Assimilation of Technology) are viewed as input, which mainly function in the enterprises. The outputs of the second phase are "sales revenue of new products" and "output value of new products".

3.2 A new Network DEA Model

In this section, we build a network DEA model which is based on the two-stage input and output index system, to estimate the efficiency when certain inputs are used in the two phases at the same time. Suppose there are n decision-making units, set the$j$th DMU as $DMUj$ (j=1,..., n). Each $DMUj$ has m kinds of inputs. The ith input of DMUj is Xij (i=1,..., m). Some inputs are used in the first process, and other inputs are used in the second stage. These two inputs are set to$x_{i1j}(i_1 \in I_1)$and $x_{i2j}(i_2 \in I_2)$, $I_1 \cup I_2=\{1,...,m\}$.We define that the dth output of $DMUj$ (j = 1, ..., n) in the first stage isz_{dj} (d=1,......,t). t is the number of intermediate measure during production process, which is also the input indicator of the second stage. We define χ as the additional input for the second stage. The rth output of the second stage isy_{rj} (r=1,......,s). τ is the intermediate measure, which is the output of the first stage and also the input of the second stage.

If the input of$i_2 \in I_2$are both used in the two stages, when we evaluate the decision-making unit DMU0. Wedivide all the inputs into$\alpha_{i_2o} x_{i_2j}$ and $(1-\alpha_{i_2o})x_{i_2j}$, which are taken as the inputs of the first and second stage respectively. α_{i_2o} is limited in a certain interval, as $L^1_{i_2j} \le \alpha_{i_2o} \le L^2_{i_2j}$.

In the case of constant returns to scale, we measure the first and second stages of the efficiency by the model (1) and (2) independently.

$$\begin{aligned} \max \quad & \frac{\sum_{d=1}^{t}\eta_d^1\tau_{d0}}{\sum_{i_1=I_1} v_{i_1}x_{i_1 0} + \sum_{i_2=I_2} v_{i_2}^1 \alpha_{i_2 0} x_{i_2 0}} \\ s.t. \quad & \frac{\sum_{d=1}^{t}\eta_d^1\tau_{dj}}{\sum_{i_1=I_1} v_{i_1}x_{i_1 j} + \sum_{i_2=I_2} v_{i_2}^1 \alpha_{i_2 0} x_{i_2 j}} \le 1,\ j=1,\ldots,n \\ & L_{i_2 j}^1 \le \alpha_{i_2 0} \le L_{i_2 j}^2,\ j=1,\ldots,n, \\ & \eta_d^1, v_{i_1}, v_{i_2}^1 \ge \varepsilon,\ d=1,\ldots,t, i_1 \in I_1, i_2 \in I_2. \end{aligned} \tag{1}$$

$$\begin{aligned} \max \quad & \frac{\sum_{r=1}^{s}u_r y_{r0}}{\sum_{i_2=I_2} v_{i_2}^2(1-\alpha_{i_2 0})x_{i_2 0} + \sum_{d=1}^{t}\eta_d^2\tau_{d0} + \sum_{k=1}^{p}\delta_k \chi_{k0}} \\ s.t. \quad & \frac{\sum_{r=1}^{s}u_r y_{r0}}{\sum_{i_2=I_2} v_{i_2}^2(1-\alpha_{i_2 0})x_{i_2 j} + \sum_{d=1}^{t}\eta_d^2\tau_{dj} + \sum_{k=1}^{p}\delta_k \chi_{kj}} \le 1,\ j=1,\ldots,n \\ & L_{i_2 j}^1 \le \alpha_{i_2 j} \le L_{i_2 j}^2,\ j=1,\ldots,n, \\ & \eta_d^2, u_r, v_{i_2}^2, \delta_k \ge \varepsilon,\ d=1,\ldots,t, r=1,\ldots,s; k=1,\ldots,p; i_1=I_1, i_2=I_2. \end{aligned} \tag{2}$$

Model (1) measures the efficiency of the first stage, and model (2) measures the efficiency of the second stage. These two models are independent, which do not consider the relationship between each other. In order to build the relationship between the two stages, in this paper, we want to measure the performance of the two stages through the weighted average efficiency score, which can be seen in the formulate (3).

$$w_1 \cdot \frac{\sum_{d=1}^{t}\eta_d^1\tau_{d0} + u^A}{\sum_{i_1\in I_1} v_{i_1}x_{i_1 0} + \sum_{i_2\in I_2} v_{i_2}^1\alpha_{i_2 0}x_{i_2 0}} + w_2 \cdot \frac{\sum_{r=1}^{s}u_r y_{r0} + u^B}{\sum_{i_2\in I_2} v_{i_2}^2(1-\alpha_{i_2 0})x_{i_2 0} + \sum_{d=1}^{t}\eta_d^2\tau_{d0} + \sum_{k=1}^{p}\delta_k\chi_{k0}} \tag{3}$$

Where w_1 and w_2 is weights which satisfies $w_1 + w_2 = 1$. The overall efficiency of the DMU will be gained if and only if the efficiency of each stage is gained.

Because the investments related with η_d^1, η_d^2, and $v_{i_2}^1$, $v_{i_2}^2$ are the same, we assume that $\eta_d^1 = \eta_d^2 = \eta_d$, (d=1,......,t) in the model (1) and (2), that is, $v_{i_2}^1 = v_{i_2}^2 = v_{i_2}$, $i_2 \in I_2$. Similar with the work of Chen et al. (2010), we set

$$w_1 = \frac{\sum_{i_1\in I_1} v_{i_1}x_{i_1 0} + \sum_{i_2\in I_2} v_{i_2}\alpha_{i_2 0}x_{i_2 0}}{\sum_{i_1\in I_1} v_{i_1}x_{i_1 0} + \sum_{i_2\in I_2} v_{i_2}x_{i_2 0} + \sum_{d=1}^{t}\eta_d\tau_{d0} + \sum_{k=1}^{p}\delta_k\chi_{k0}} \quad \&$$

$$w_2 = \frac{\sum_{i_2\in I_2} v_{i_2}(1-\alpha_{i_2 0})x_{i_2 0} + \sum_{d=1}^{t}\eta_d\tau_{d0} + \sum_{k=1}^{p}\delta_k\tau_{k0}}{\sum_{i_1\in I_1} v_{i_1}x_{i_1 0} + \sum_{i_2\in I_2} v_{i_2}x_{i_2 0} + \sum_{d=1}^{t}\eta_d\tau_{d0} + \sum_{k=1}^{p}\delta_k\chi_{k0}} \tag{4}$$

Where w_1 and w_2 represent the importance or contribution of the first stage and the second stage. $\sum_{i_1\in I_1} v_{i_1}x_{i_1 o} + \sum_{i_2\in I_2} v_{i_2}x_{i_2 o} + \sum_{d=1}^{t}\eta_d\tau_{do} + \sum_{k=1}^{p}\delta_k\chi_{ko}$ represents the total amount of resources. $\sum_{i_1\in I_1} v_{i_1}x_{i_1 0} + \sum_{i_2\in I_2} v_{i_2}\alpha_{i_2 0}x_{i_2 0}$ and $\sum_{i_2\in I_2} v_{i_2}(1-\alpha_{i_2 0})x_{i_2 0} + \sum_{d=1}^{t}\eta_d\tau_{d0} + \sum_{k=1}^{p}\delta_k\tau_{k0}$ represent the absolute value of resource in the first and the second stage respectively. Then, we can transform formula (3) into $(\sum_{d=1}^{t}\eta_d^1\tau_{do} + \sum_{r=1}^{s}u_r y_{ro})/(\sum_{i_1\in I_1} v_{i_1}x_{i_1 o} + \sum_{i_2\in I_2} v_{i_2}x_{i_2 o} + \sum_{d=1}^{t}\eta_d\tau_{do} + \sum_{k=1}^{p}\delta_k\chi_{ko})$.

Through the linear transformation, we can obtain the model (5) as follows. We can get the overall system efficiency value by this model.

$$
\begin{aligned}
&\theta_o^* = Max\sum_{d=1}^{t}\pi_d\tau_{do} + \sum_{r=1}^{s}u_r y_{ro} \\
&s.t. \quad \sum_{d=1}^{t}\pi_d\tau_{dj} - \left(\sum_{i_1\in I_1}\omega_{i_1}x_{i_1 j} + \sum_{i_2\in I_2}\beta_{i_2 j}x_{i_2 j}\right) \le 0 \\
&\sum_{r=1}^{s}u_r y_{rj} - \left(\sum_{i_1\in I_1}(\omega_{i_2} - \beta_{i_2 j})x_{i_2 j} + \sum_{d=1}^{t}\pi_d\tau_{dj}\right) - \sum_{k=1}^{p}\varphi_k\chi_{kj} \le 0, \\
&\sum_{i_1\in I_1}\omega_{i_1}x_{i_1 j} + \sum_{i_2\in I_2}\omega_{i_2 j}x_{i_2 0} + \sum_{d=1}^{t}\pi_d\tau_{d0} + \sum_{k=1}^{p}\varphi_k\chi_{k0} = 1 \\
&L_{i_2 j}^1\omega_{i_2} \le \beta_{i_2 j} \le L_{i_2 j}^2\omega_{i_2}, \\
&u_r, \pi_d, \omega_{i_1}, \omega_{i_2}, \varphi_k \ge \varepsilon; \\
&j = 1,\ldots,n, r = 1,\ldots,s; d = 1,\ldots,t; k = 1,\ldots,p; i_1 = I_1; i_2 = I_2.
\end{aligned}
\tag{5}
$$

According to the optimal value of model (5), we can gain the efficiency of the first stage, i.e $\frac{\sum_{d=1}^{t}\pi_d\tau_{d0}}{\sum_{i_1=I_1}\omega_{i_1}x_{i_1 0} + \sum_{i_2=I_2}\beta_{i_2 o}x_{i_2 0}}$, andthe second stage's efficiency, i.e. $\frac{\sum_{r=1}^{s}u_r y_{rj}}{\left(\sum_{i_1\in I_1}(\omega_{i_2} - \beta_{i_2 j})x_{i_2 j} + \sum_{d=1}^{t}\pi_d\tau_{dj}\right) - \sum_{k=1}^{p}\varphi_k\chi_{kj}}$.

4. The Application of the Model

The referencedata are selected from "China Statistics Yearbook on High Technology Industry" and the calculation is on the ground of the data of five first-class high tech industries in the past 15 years recorded in the Yearbook. By the inputting data and MATLAB 9.0, we get the innovation efficiency of the high-techindustries. (Synthesizing the relevant papers of other scholars) IS the overall innovation efficiency of the industry as *E,* the first phase of the innovation efficiency as E1, the second phase of the innovation efficiency as *E2* and sequencethe average value of *E, E1* and *E2* by year. I also set *K = E2/E1*. *K* represents the ratioof efficiency E2 andE1. It can measure the difference between efficiency of an industry technology digestion and absorption stage and that of the technology research and development stage, in other words, it can indicate the coordination degree of high technology industry.

Table 1. The efficiency of 22 high-tech industry

High-tech industry	E1	E2	E	K(E_2/ E_1)
Manufacture of Medicines	0.436612	0.158498	0.360427	0.363018
Manufacture of Chemical Medicine	0.32037	0.183045	0.327627	0.571355
Manufacture of Finished Traditional Chinese Herbal Medicine	0.774321	0.110537	0.46209	0.142753
Manufacture of Biological and Biochemical Chemical Products	0.374426	0.224611	0.334219	0.599882
Manufacture of Aircrafts and Spacecrafts	0.117844	0.10838	0.175449	0.919692
Manufacture and Repairing of Airplanes	0.135101	0.123411	0.189656	0.913471
Manufacture of Spacecrafts	0.08283	0.042235	0.0888	0.509906
Manufacture of Electronic Equipment and Communication Equipment	0.299369	0.329579	0.461476	1.100911
Manufacture of Communication Equipment	0.354434	0.389508	0.481187	1.098958
Manufacture of Radar and Its Fittings	0.148562	0.15209	0.225812	1.023747
Manufacture of Broadcasting and TV Equipment	0.434378	0.219643	0.388727	0.50565
Manufacture of Electronic Appliances	0.304532	0.31644	0.467618	1.0391

Manufacture of Electronic Components	0.25683	0.265114	0.376195	1.032254
Manufacture of Domestic TV Set and Radio Receiver	0.734171	0.770901	0.874424	1.050029
Manufacture of Other Electronic Equipment	0.418974	0.222079	0.40642	0.530055
Manufacture of Computers and Office Equipments	0.552164	0.7887	0.870804	1.428381
Manufacture of Entired Computer	0.787635	0.849101	0.868827	1.078039
Manufacture of Computer Peripheral Equipment	0.870439	0.876598	0.95529	1.007076
Manufacture of Office Equipment	0.502309	0.688309	0.727753	1.370289
Manufacture of Medical Equipments and Measuring Instrument	0.476602	0.171324	0.378124	0.359469
Manufacture of Medical Equipment and Appliances	0.729298	0.143026	0.457905	0.196114
Manufacture of Measuring Instrument	0.437132	0.185128	0.366931	0.423505

We substitute the data form "The China High-tech Statistical", the results are obtained in table 1. We selected major industries'efficiency in table 2.

Table 2. The efficiency of high-tech industry league

	E	E1	E2	K(E2/E1)
Manufacture of Medicines	0.360427	0.436612	0.158498	0.363018
Manufacture of Aircrafts and Spacecrafts	0.175449	0.117844	0.10838	0.919692
Manufacture of Electronic Equipment and Communication Equipment	0.461476	0.299369	0.329579	1.100911
Manufacture of Computers and Officeequipment	0.870804	0.552164	0.7887	1.428381
Manufacture of Medical equipmentand Measuring Instrument	0.378124	0.476602	0.171324	0.359469

From Table 2, we can get the data ofthe efficiencyof the top-five high-tech industries (*E, E1, E2*) as well as coordination degree (*K)*, from which we can see that the overall efficiency of the industry "Manufacture of Computers and Office equipment" is as high as 0.87, the efficiency in the first and second phases of this industry tops as well, while the efficiency of the industry "Manufacture of Aircrafts and Spacecrafts" is the lowest; other three industries at the middle level. From the data, we can also find that "*K*" for "Manufacture of Computers and Office Equipment" is 1.4, indicating that for this industry, technology digestion and absorption is muchmore developed than technology R&D. *"K"* for "Manufacture of Aircrafts and Spacecrafts", "Manufacture of Electronic Equipment and Communication Equipment" is around 1, indicating the R&D achievement in the first stage can be applied in the second stage, which means the advanced technology can be turned into productive force. In the industry of "Manufacture of Medicines" and "Manufacture of Medical equipment and Measuring Instrument", "*K*" is far less than 1, indicating that digestion and absorption capacity of these two industries is relatively weak.

There are many reasons for the ranking as above.The industry of "Manufacture of Computers and Office Equipment" was the first that has been introduced to China and has developed for more than thirty years, for which the market extends abroad. Comparatively speaking, the industry of "Manufacture of Medical equipment and Measuring Instrument" was introduced to China in a rush, so that the market is immature. As the representative of the private "Manufacture of Electronic Equipment and Communication Equipment" enterprisein China, HUAWEI is still building itself in technological capability. "Manufacture of Aircrafts and spacecrafts Aerospace" is the key industry that the state needs to support and cultivate to some degree, and it will takes more time for the development. In the near future, the state will be expected to increase investment in resources of innovation.

5. Conclusions and Prospect

The traditional DEA model is based on the whole inputs and outputs, while the new network DEA model is based on the actual production which considering the internal structure.The whole process is divided into two parts: "R&D" stage and "technology digestion and absorption" stage. The latter model classified the former's inputs and outputs into each stage. Compared to the traditional DEA models, this new model improves both the accuracy of efficiency calculation and the analysis on practical applications.

This paper reviews the development of the DEA and sorts out the history of many scholars in using DEA method to estimate the efficiency of technological innovation, and summarizes the literature written by Chinese scholars on the accumulation of efficiency of technological innovation of high-tech industry. Besides, by analyzing Mare and Lei Yong's CCR model and making a research on rationality of the input-output index system of their model, I establish a newtwo-staged index system that is much more practical by integrating the actual characteristics of high-tech industry. Moreover, I make a reasonable assumption on the DMU so as to build a new DEA model whichcan be used to calculate the efficiency of the two stages and the overall efficiency.

Overall, this model isan efficiency-calculation method which is designed in connection with the Chinese high-tech industry characteristics, so that it is practicalin measuring R & D efficiency of the overall innovation in high-tech industry. In addition to overall efficiency, this model can also calculate R&D innovation efficiency in R & D stage and digestion and absorption stage. Taking Overall efficiency, the two-stage efficiency, and the China Statistical Yearbook panel data into consideration, we can analyze China's high-tech industry from two aspects of industry & region. On the one hand, in connection with the data of different industries, we canget characteristics of high-tech industries and the efficiency indifferent stages, andwe can determine the effect of R & D investment in science and technology as well as the efficiency of sub-industriesin the same category, which may help to select efficient Chinese Industries; on the other hand, in China Statistical Yearbook,the data of high-tech industries in all provinces can be found, with the calculation by the new DEA model, we can sequence efficiency of the high-tech industries in different regions, through the analysis of the sequence, more policy suggestions can be put forwarded to the Chinese government.

This model can also be used in the field of efficiency analyses on high-tech industries. Because the model was commenced in accordance with the characteristics of industrial development, we divide the technology development processinto two stages. The characteristics of this industry can be used in various countries, so that the model is applicable in a wide area. Except the field of industrial development, other areas with stage development charactersuch as transport and energy, multi-level sub- billing utilization, are also suitablefor using this model.

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