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R&D EFFICIENCY EVALUATION OF COMPUTER INDUSTRY IN CHINA BASED ON AN IMPROVED DEA MODEL

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ABSTRACT

The computer industry plays an important role in promoting the development of national economy and national comprehensive power of China. As an important evaluation indicator, the R&D efficiency of computer industry becomes one of the most important research fields currently. According to the shortages of traditional C2R model of DEA, this paper constructs an improved DEA model for measuring the R&D efficiency of computer industry and does an empirical research on R&D efficiency of computer industry in different regions. This research shows that: the improved DEA model overcomes the shortages of traditional C2R model and it is able to reflect the difference of R&D efficiency between different regions more effectively; Compared with efficiency frontier, the R&D efficiency of Chinese computer industry has potentials to improve; The R&D efficiency of Chinese computer industry is influenced by various factors, such as government support capacity, market structure and enterprise scale; Improve the environment of R&D activities is more effectively than increase the input of R&D resources in improving the R&D efficiency of Chinese computer industry.

Keywords: *Computer Industry, Evaluation of R&D Efficiency, Improved DEA Model, Influence Factor*

1. INTRODUCTION

As a typical high-tech industry, the computer industry not only has an important influence on the other industries and national economy, but also promotes the development of them. Therefore, developing the computer industry has become a high-effectively way to promote China's economic development. As one of the most important measure indicator of development situation, the R&D efficiency of computer industry becomes one of the most important research fields currently.

The outline of the paper is as follows. In section 2 we review previous research on previous improvement of traditional DEA model. In section 3, the improved DEA model is proposed. Evaluation of R&D efficiency by the improved DEA model of computer industry is discussed in section 4. Section 5 gives the conclusions and political suggestions.

2. PREVIOUS RESEARCH REVIEW

Previous researches on R&D efficiency of computer industry are seldom both in China and abroad. However, the research achievements on high-tech industry are more plenty and they provide a lot of useful reference information for studying the R&D efficiency of computer industry. From the previous research on efficiency evaluation we can see that, the DEA model is obviously different form the nonparametric evaluation methods, because it could analyze the DMU which with multiple input and output indicators. And this characteristic makes the DEA model exactly suitable for evaluating the efficiency of high-tech industry. Beside that, the DEA model does not need to set the specific function form, thus the DEA model avoids the errors and problems caused by wrong setting of frontier function. For these advantages, DEA model is widely used by a lot of scholars, such as Suzuki(1989) [1] and Encaoua(2000) [2]. However, there are still some shortages of the traditional DEA model. For example, the traditional DEA model can not distinguish DMU form each other effectively in some cases, as well as the weights of its input and output indexes are set up inconsistent with the actual. In view of the weaknesses of the traditional DEA model, the scholars have put forward a series of improved DEA model. The first kind of improved DEA model is given some prior information, such as weight restrictions

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information, preference structure information and value efficiency analysis information. Specifically, the improved DEA model with prior information includes the following: direct weight restrictions model, which is built up by Dyson, Thanassoulis(1988) [3] and Roll(1990)[4]; cone ratio model, which is built up by Charnes（1989, 1990）[5] [6]; assurance region model established by Thompson（1986）[7] and Beasley's virtual inputs and outputs restrictions model （1990）[8]. there second kind of improved DEA model is without prior information, such as super efficiency model(Andersen, Petersen（1993）[9], cross-evaluation model(Sexton（1986））[10] and multiple objective approach(Li, X. B, （1999）) [11]. In addition, scholars improved the traditional DEA model by changing the input and output variable type both abroad and in China. For example, Cooper（1999）analyzed the DEA model with categorical variables[12], Cook, Kress and Seiford（1993）given an improved DEA model with ordinal numbers as its input and output variables[13], Herbert and Thomas (2004) studied the efficiency network DEA model for evaluating efficiency of complex structured system[14]. The improved DEA models mentioned above still have some shortages: On one hand, the models with priority information cannot avoid the error or bias in judgment of value and priority information. And these shortages may cause the evaluation results are inconsistent with the facts. On the other hand, the improved DEA model without prior information always calculates the weight vector of input and output indicators from the most advantageous angle for their own DMU, which leads to low comparability of efficiency between different DMU. In order to solve the shortages of the DEA model mentioned above, this paper builds up an improved DEA model by drawing lessons from the previous academic achievements of Liu Yingping(2006) [15] and Sun Kai(2008) [16], and does an quantitative research on evaluation of R&D efficiency of computer industry in China based on the improved DEA model. According to the evaluation results, this paper analyzes the current situation and developing rules of computer industry, and provides policy reference for promoting the development of computer industry.

3. THE CONSTRUCTION OF IMPROVED DEA MODEL

3.1 Introduction of Traditional DEA Model- C²R Model

C2R is built up by Charnes, Cooper and Rhodes at 1978, its basic assumption is unchangeable scale to return. The essence of C2R is evaluating the relative efficiency of organization by mathematical programming techniques [17]. At present, most of the researchers are familiar with the traditional C2R model:

Set n comparable DMU, and denoted by DMU_{1-n}, each DMU has m types input and s types output. So the input vector can be written as $X_j = (x_{1j}, x_{2j}, \cdots, x_{mj})^T$, and the output vector can be written as:

$Y_j = (y_{1j}, y_{2j}, \cdots, y_{sj})^T, (j = 1, \cdots, n)$, and they are constant. $v = (v_1, v_2, \cdots, v_m)^T$ are m types of input weight vectors, and $u = (u_1, u_2, \cdots, u_s)^T$ are s types of output weight vectors, they are unknown variable.

So, the efficiency of K^{th} DMU can be rewritten as equation (1):

$$V_k = \frac{u^T Y_k}{v^T X_k} \tag{1}$$

Set V_k, the efficiency value of DMU_k, as objective function, and constraint to the efficiency value of all DMU, we get fractional programmed C²R model as equation (2):

$$\begin{cases} \max \dfrac{u^T Y_k}{v^T X_k} \\ \dfrac{u^T Y_j}{v^T X_j} \le 1, \quad j = 1, \cdots, n \\ u \ge 0, \quad v \ge 0 \end{cases} \tag{2}$$

Transform equation (2) into equation (3) :

$$t = \frac{1}{v^T X_k}, \quad \alpha = tv, \quad \beta = tu \tag{3}$$

Where α is m-dimension column vector, β is s-dimension column vector, so,
$\alpha = (tv_1, tv_2, \cdots, tv_m)^T$, $\beta = (tu_1, tu_2, \cdots, tu_s)^T$.

Accordingly, the model changes into equation (4):

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$$\begin{cases} \max \beta^T Y_k \\ \alpha^T X_j - \beta^T Y_j \ge 0, \quad j = 1,\cdots,n \\ \alpha^T X_k = 1 \\ \alpha \ge 0 \quad ,\beta \ge 0 \end{cases} \tag{4}$$

3.2 The Improved DEA Model: By Introducing Virtual DMU

The first step: construct virtual DMU. To construct two virtual DMU named DMU_{n+1} and DMU_{n+2}. DMU_{n+1} is the optimal decision making unit, its input vector can be written as

$$X_{n+1} = (x_{1,n+1}, x_{2,n+1}, \cdots, x_{i,n+1}, \cdots, x_{m,n+1})^T$$

and its output vector can be written as

$$Y_{n+1} = (y_{1,n+1}, y_{2,n+1}, \cdots, y_{r,n+1}, \cdots, y_{s,n+1})^T.$$

DMU_{n+2} is the worst decision making unit, its input vector can be written as

$$X_{n+2} = (x_{1,n+2}, x_{2,n+2}, \cdots, x_{i,n+2}, \cdots, x_{m,n+2})^T$$

And its output vector can be written as $Y_{n+2} = (y_{1,n+2}, y_{2,n+2}, \cdots, y_{r,n+2}, \cdots, y_{s,n+2})^T$. Set the input index of optimal decision making unit equal to the minimum value of X, as well as the output index of optimal decision making unit equal to the maximum value of X. So,

$$x_{i,n+1} = \min(x_{i1}, x_{i2}, \cdots, x_{in}),$$

$$y_{r,n+1} = \max(y_{r1,} y_{r2,} \cdots, y_{rn}).$$

Correspondingly, the input and output indexes of the worst decision making unit are maximum value and minimum value of X, that is

$$x_{i,n+2} = \max(x_{i1}, x_{i2}, \cdots, x_{in}),$$

Obviously, DMU_{n+1} and DMU_{n+2} may not exist inside the production possibility set, and their introduction is prepared for the following steps as a reference.

The second step: establish the efficiency evaluation model of optimal DMU_{n+1}. Take the efficiency evaluation of n +2 DMU as constraint; we build up the new DEA model by setting efficiency evaluation V^*_{n+1} of the optimal DMU as objective function. The new DEA model as equation (5) shows:

$$\begin{cases} \max \beta^T Y_{n+1} \\ \alpha^T X_j - \beta^T Y_j \ge 0, \quad j = 1,\cdots,n+2 \\ \alpha^T X_{n+1} = 1 \\ \alpha \ge 0 \quad ,\beta \ge 0 \end{cases}$$

(5)

So, DMU_{n+1} is obviously DEA efficiency, and $V^*_{n+1} \equiv 1$. But the optimum solutions α^* and β^* are infinite. So, choosing of the infinite weight vector is needed in order to identify "reasonable" public weight vector for all the n +2 DMU.

The third step: choose the public weight vector. From the equation $V^*_{n+1} = \dfrac{u^{*T} Y_{n+1}}{v^{*T} X_{n+1}} = \dfrac{\beta^{*T} Y_{n+1}}{\alpha^{*T} X_{n+1}} \equiv 1$ we can infer that, optimal decision making unit, DMU_{n+1} meet $\beta^{*T} Y_{n+1} - \alpha^{*T} X_{n+1} = 0$. In order to make sure there are "reasonable" public weight vector, we build model as:

$$\begin{cases} \min \beta^T Y_{n+2} \\ \alpha^T X_j - \beta^T Y_j \ge 0, \quad j \ne n+1 \\ \alpha^T X_{n+2} = 1 \\ \beta^T Y_{n+1} - \alpha^T X_{n+1} = 0 \\ \alpha \ge 0 \quad ,\beta \ge 0 \end{cases}$$

(6)

The model (6) aims at the minimum efficiency value of the worst decision making unit DMU_{n+2}, and adds constraint $\beta^T Y_{n+1} - \alpha^T X_{n+1} = 0$ into the model in order to get maximum value of the optimal decision making unit DMU_{n+1}. Change a kind of statement, form infinite group weight vector of optimal decision making unit, model (6) can choose a group of weight vector which makes the efficiency value of worst decision making unit to be minimum one.

The fourth step: to calculate efficiency value for DMU. By using the following equation (7) and optimal solutions α^{**} and β^{**} of equation (6), calculate efficiency value of every decision making unit.

$$V_j^{**} = \frac{\beta^{**T} Y_j}{\alpha^{**T} X_j} \quad (j = 1,\cdots,n)$$

(7)

The fifth step: Reset the optimal and worst DMU by using the evaluation results of the

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fourth step. V_j^{**} in fourth step is calculated by public weight vector, so it is objective and rational, and it can solve the problem of traditional C^2R model. The problem of traditional C^2R model is that, there are more than one DMUs' efficiency value is 1, and this caused difficulty in distinguishing and sequencing of all the DMU.

However, the efficiency value is far less than 1 sometimes because DMU_{n+1} and DMU_{n+2} are virtual ideal decision making unit. And more or less, this situation reduces the discrimination degree of different DMU on efficiency evaluation. Therefore, replace DMU_{n+1} by decision making unit DMU_α with maximum efficiency value, and replace DMU_{n+2} by decision making unit DMU_β ($1 \le \alpha, \ \beta \le n$) with minimum efficiency value, and introduced into models above. In this way, not only the results of the fourth step are used, but also makes optimal and worst decision making unit have actual significance (the optimal and worst decision making unit are come from production possibility set).

The sixth step: calculate efficiency value by repeating second step to fourth step. From the fifth step we can see that, DMU_α has the maximum efficiency value in all the DMU, and it is obviously effective compared with other DMU, so it is set as 1. To use DMU_α and DMU_β instead of DMU_{n+1} and DMU_{n+2} in equation (4) and equation (5), then repeat second step to fourth step until we get satisfying efficiency value of all DMU.

4. R&D EFFICIENCY EVALUATION OF COMPUTER INDUSTRY IN CHINA

4.1 Selection of Influencing Factors and Evaluation Indexes

R&D efficiency evaluation of computer industry in China by DEA model depends on two aspect endogenous factors: input resources of computer industry in R&D process, and final output results. In addition, exogenous influence factors, such as market structure, enterprise size, enterprise ownership, financial support of government departments and financial institutions and technical support of scientific research institutions have a certain degree influence on R&D efficiency of computer industry in China [18]. To establish R&D efficiency evaluation index system of computer industry in China as shown in figure 1:

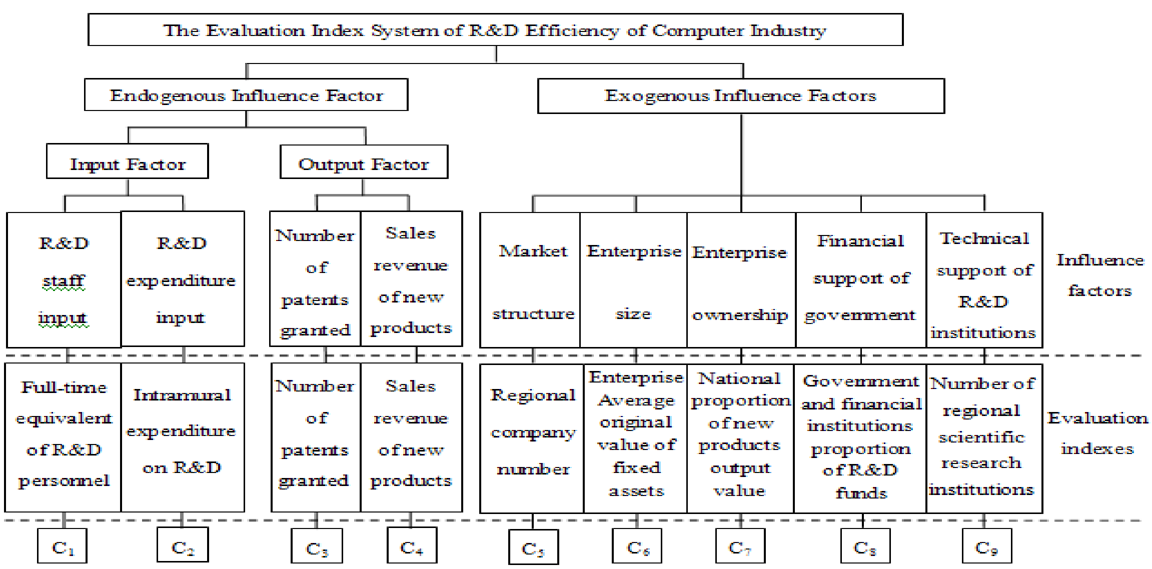

Fig. 1. The R&D Efficiency Evaluation Index System of Computer Industry

4.2 Determination of Evaluation Data

Considering the timeliness and availability of data in this paper, we choose "China statistical yearbook 2011", "China Industrial Economy Statistical Yearbook 2011", "China Statistics Yearbook on high technology industry 2011" and "China Statistical Yearbook on science and technology 2011" to be the data sources. By collecting and

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calculating, we got 23 group data of efficiency evaluation index of regional computer industry, and shown in table 1:

Table I Data Of Regional R&D Evaluation Indexes

DMU	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Beijing	1812	145904	891	496684	76	51368	0.1329	0.8899	38
Tianjin	1802	135983	672	259543	19	18263	0.1048	0.8431	32
Hebei	4211	7958	74	127386	11	14000	0.1428	0.8243	14
Shanxi	712	1333	14	18310	1	76000	0.1738	0.7732	9
Liaoning	1679	12212	412	571428	38	18947	0.3200	0.8936	26
Jilin	925	8226	16	84139	6	10833	0.0465	0.8873	2
Heilongjiang	2024	5719	217	55055	7	16000	0.6186	0.8830	15
Shanghai	2337	498408	806	235060	74	150243	0.0690	0.8447	37
Jiangsu	7327	754128	667	2055393	327	56358	0.0295	0.8240	81
Zhejiang	6761	203579	215	1255360	149	25470	0.0521	0.8989	22
Anhui	1172	46638	526	208837	21	8190	0.2404	0.8145	18
Fujian	605	197863	109	178	88	54330	0.0206	0.8481	8
Jiangxi	1025	8916	209	303573	19	10895	0.1940	0.8864	26
Shandong	7065	308055	1695	2116616	51	103471	0.1140	0.7982	41
Henan	2567	22340	495	269855	11	13636	0.1219	0.7627	32
Hubei	2101	125680	566	415263	23	25652	0.2634	0.8274	31
Hunan	1223	7212	358	287948	21	16143	0.1830	0.6379	18
Guangdong	4330	3019414	8238	5464131	641	78587	0.0777	0.7747	80
Guangxi	529	5096	6	45718	17	18235	0.0881	0.7751	1
Chongqing	1507	7654	207	209352	8	83500	3.2060	0.7586	36
Sichuan	558	139555	1141	339202	25	28480	0.0357	0.9588	34
Yunnan	848	1722	27	59878	4	46750	0.3489	0.8485	2
Shaanxi	520	36452	614	373721	2	8000	0.6514	0.9333	75

Descriptive statistics results of the computer industry R & D investment, R & D outputs and influence variables in this paper as shown in table 2:

TABLE 2 Results Of Descriptive Statistics

Variable	frequency	standard deviation	average	minimum	maximum
C_1	23	2133.13	2332.17	520	7327
C_2	23	631607.90	247828.10	1333	3019414
C_3	23	1675.12	790.22	6	8238
C_4	23	1196836.00	663157.80	178	5464131
C_5	23	142.97	71.26	1	641
C_6	23	36735.12	40580.48	8000	150243
C_7	23	0.65	0.31	0.0206	3.206
C_8	23	0.07	0.83	0.6379	0.9588
C_9	23	22.98	29.48	1	81

Using the improved DEA model above, this paper evaluates the R&D efficiency value of Chinese regional computer industry with and without influence factors of R&D process. The efficiency evaluation results are shown in table 3:

Table 3 Efficiency Evaluation Results Of Chinese Regional Computer Industry

No.	DMU	Without Influence Factors				With Influence Factors			
		Improved DEA Model		Traditional C^2R Model		Improved DEA Model		Traditional C^2R Model	
1	Beijing	0.5410	drs	0.2500	drs	0.7385	irs	0.9360	irs
2	Tianjin	0.5670	drs	0.2880	drs	0.7835	irs	1.0000	-
3	Hebei	0.9639	drs	1.0000	-	0.9320	irs	1.0000	-
4	Shanxi	0.9524	drs	1.0000	-	0.9262	irs	1.0000	-
5	Liaoning	0.5270	drs	0.2620	drs	0.5380	irs	0.5490	irs
6	Jilin	0.8783	drs	0.8370	drs	0.9392	irs	1.0000	-
7	Heilongjiang	0.7830	drs	0.6970	drs	0.8915	irs	1.0000	-
8	Shanghai	0.5647	drs	0.3470	drs	0.7824	irs	1.0000	-
9	Jiangsu	0.7800	drs	0.6700	drs	0.8900	irs	1.0000	-
10	Zhejiang	0.7993	drs	0.6990	drs	0.8997	irs	1.0000	-
11	Anhui	0.5377	drs	0.3780	drs	0.5644	irs	0.5910	irs
12	Fujian	0.9685	drs	1.0000	-	0.9843	irs	1.0000	-
13	Jiangxi	0.5527	drs	0.4600	drs	0.4539	irs	0.3550	irs
14	Shandong	0.4340	drs	0.1530	drs	0.6980	drs	0.9620	drs
15	Henan	0.5897	drs	0.3740	drs	0.7564	irs	0.9230	irs
16	Hubei	0.6017	drs	0.3270	drs	0.7934	irs	0.9850	irs
17	Hunan	0.5263	drs	0.3830	drs	0.4712	irs	0.4160	irs
18	Guangdong	0.4680	drs	0.2020	drs	0.7340	drs	1.0000	-
19	Guangxi	0.9426	drs	1.0000	-	0.9413	irs	1.0000	-
20	Chongqing	0.5933	drs	0.5230	drs	0.7472	irs	0.9010	irs
21	Sichuan	0.5067	drs	0.2680	drs	0.7529	irs	0.9990	irs
22	Yunnan	0.8280	irs	0.9900	irs	0.9225	irs	0.6170	irs
23	Shaanxi	0.5410	drs	0.3160	drs	0.7705	irs	1.0000	-

Note: DRS, decreasing returns to scale; -, constant returns to scale; IRS, increasing returns to scale

4.3 Analysis on R&D Efficiency Evaluation Result of Computer Industry in China

The analysis on evaluation result of computer industry R&D efficiency in China is based on the data in table 1 and table 3, and it shows that:

Firstly, from the perspective of industry, the average efficiency evaluation results of Chinese computer industry without and with influence factors are 0.6603 and 0.7787 respectively. According previous research result of reference [18], the R&D efficiency of Chinese computer industry is in the middle to upper level of high-tech industry. The reason is that, most R&D activities on Chinese computer industry are set focus on implicational research field, and the research results have a high market value and a high conversion rate.

Secondly, from the perspective of regions: the R&D efficiency with influences factors of developed regions of computer industry, such as Guangdong, Jiangsu and Zhejiang provinces, is lower than 0.9. This situation shows that, the current R&D efficiency of computer industry is low in China, and high level output is depends on high level input rather then high level R&D efficiency. At present, the output of Chinese computer industry does not reach the maximum output which the

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frontier production function showed. In the other word, redundancy of inputs or produce insufficient or both of them are existed, and these problems will grow bigger with the increasing investment of R&D activities.

Thirdly, from the perspective of returns to scale: 22 in 23 regions are decreasing returns to scale. But when the exogenous influence factors are considered, this figure dropped to 2 and 21 in 23 regions are increasing returns to scale. These data show that, to improve the R&D efficiency only by increasing R&D investment is not effectively. The exogenous influence factors, such as market structure, enterprise size, enterprise ownership, financial support of government departments and financial institutions and technical support of scientific research institutions should be considered in order to improve the R&D efficiency of computer industry in China.

Finally, from the perspective of influence factors: when the influence factors are considered, the average R&D efficiency value is 0.7787, and it is higher than 0.6603, which is the average R&D efficiency value without considering the influence factors. We can see that, the improvement of R&D efficiency of computer industry is depending on the R&D environment. Therefore, to improve the R&D environment is more effective than increasing R&D input in improving the R&D efficiency of Chinese computer industry.

5. CONCLUSIONS AND SUGGESTIONS

Through the research above, this paper got the following conclusions:

(1) The improved DEA model designed in this paper is superior to the traditional C^2R model on discrimination and disperse degree in R&D efficiency evaluation of Chinese computer industry.

(2) At present, R&D efficiency of computer industry is in the middle level of all high-tech industry in China, and the output of Chinese computer industry does not achieve the maximum output which the frontier production function showed. Input redundancy or output deficiency or both of them are existed, and these problems will grow bigger with the increasing investment of R&D activities.

(3) To improve the R&D environment is more effective than increasing R&D input in improving the R&D efficiency. So, exogenous influence factors, such as market structure, enterprise size, enterprise ownership, financial support of government departments and financial institutions and technical support of scientific research institutions should be considered in order to improve the R&D efficiency of computer industry. In addition, ways of financial support need to be changed form “process support” to "result support".

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