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Study on R and D Efficiencies of Chinese Science Parks: An Application of DEA Model and Malmquist Index

Guocun Zuo and Qiang Chen
School of Economics and Management, Tongji University, Shanghai, 200092, China

Abstract: China tries to build an efficient National Innovation System (NIS) in recent years. As Science Parks (SPs) are significant components of Chinese NIS, they are crucial to China. To evaluate Chinese SPs' R and D efficiency, this study takes fifty-two Chinese national SPs during the period 2007-2011 as objects. Firstly, three kinds of R and D technical efficiency scores were calculated by data envelopment analysis models, which were used to compare relative R and D efficiency and to analyze the major source of R and D inefficiency. Secondly, five kinds of R and D Malmquisit indexes were constructed from relative R and D efficiency scores, which were used to find the trends of R and D productivity change and to identify the major source of the change. The results show that most of these SPs are relatively inefficient in R and D activities; most of these SPs experience R and D productivity gains; lower pure technical efficiency score is the major source of poor technical efficiency score; technical efficiency change is the major source of R and D productivity change. The results imply that most Chinese SPs need R and D efficiency improvement rather than more R and D investments.

Key words: Science park, DEA, Malmquist index, R and D efficiency

INTRODUCTION

Since the mid-1980s, China have been trying to reform its scientific and technological system, one of the purposes is to bridge the deep gap between science and economy in China. Science Park (SP) is recognized as an effective vehicle to bridge the gap (Walcott, 2002). To take the advantages of SPs, many countries in the world established their own SPs, China with no exception. In March 1991, China central government approved the establishment of its first 27 national SPs, followed by yet another 25 in the following year. For sixteen years after that, there were only two other national SPs approved, one in 1997 and the other in 2007. Another wave of approving national SPs emerged during 2009-2011, in which 24 national SPs were approved. By the end of 2011, the number of Chinese national SPs was increased to 88. National SPs contribute a lot to China's economic. For example, eighty-eight national Sps created GDP of 4166 billion RMB (about 640 billion US dollars) that accounted for 8.8% of China's GDP and provided 10 million jobs in 2011(Source: Torch Center). SPs are expected to bring economic contributions through technology innovation and diffusion and synergies among agents within or near the parks but Chinese SPs' economic contributions are mostly attributed to factors accumulation (Hu, 2007; Macdonald and Deng, 2004). As it is ambitious to build an innovation-driven economy and national SPs are regarded as very important components of its national innovation system, China has been trying to improve its national SPs' innovation capabilities. In recent years, several initiatives such as "second-time pioneer", "first-class science park" and "innovation demonstrative science park", were launched to do so. And considerable R and D resources are poured into these SPs. In 2011, firms in national SPs expended 227 billion RMB (about 35 billion US dollars) that was 26.1% of China's total R and D expenditures in that year in R and D activities (Source: Torch Center). Although productive performance of these SPs were widely investigated (Hu, 2007; Hu *et al.*, 2010), R and D efficiencies of these SPs were neglected in literatures. On the other hand, this kind of information is valuable for China government, who need to allocate large sum of R and D resources to national SPs each year. So this study tries to analyze R and D efficiencies of fifty-two Chinese national SPs during the period 2007-2011.

METHODOLOGY

DEA model: Data Envelopment Analysis (DEA) model is a non-parametric mathematical programming approach to measure relative efficiency based on the technical efficiency concept. DEA selects the most efficient decision marking units (DMUs) among all DMUs concerned to form the "best-practice frontier", then each

Corresponding Author: Qiang Chen, School of Economics and Management, Tongji University, Shanghai, 200092, China

DMU gets an efficiency score comparing to the best-practice frontier (Chen *et al*., 2006). The following gives a brief description of CRS DEA models and VRS DEA models, used in this study.

Assume that there are K DMUs, each of them transforms M inputs into N outputs. The i-th DMU has an input vector x_i and an output vector y_i. All K input vectors make up the M*K input matrix X and all K output vectors make up the N*K output matrix Y. Then X and Y represent the data of all K DMUs. According to the technical efficiency concept, there is a measure of technical efficiency for the i-th DMU:

$$TE_i = u'y_i/v'x_i \tag{1}$$

Here, TE_i represents the technical efficiency of the ith DMU, u represents an N*1 vector of output weights and v represents an N*1 vector of input weights. To give a definite measure of TE_i, the weights u and v need be determined firstly. The mathematic programming problem in Eq. 2 can be used to determine the optimal weights:

$$\begin{aligned} &\max_{u,v} \quad TE_i \\ &\text{s.t.}\begin{cases} TE_k \le 1, \quad k = 1,2\ldots,K \\ \quad u, v > 0 \end{cases} \end{aligned} \tag{2}$$

This non-linier mathematic programming problem is very hard to be solved and has infinite number of solutions. To avoid these problems, Charnes *et al.* (1978) proposed an input-orientation DEA model that assumes Constant Returns to Scale (CRS). This model can be presented as Eq. 3:

$$\begin{aligned} &\max_{u,v} \quad (u'y_i / v'x_i) \\ &\text{s.t.}\begin{cases} v'x_i = 1 \\ u'y_k - v'x_k \le 0, \quad k = 1,2\ldots,K \\ u, v > 0 \end{cases} \end{aligned} \tag{3}$$

The mathematic programming problem in Eq. 3 has an equivalent duality form in Eq. 4, which is more convenient to use:

$$\begin{aligned} &\min_{\theta,\lambda} \quad \theta \\ &\text{s.t.}\begin{cases} -y_i + Y\lambda \ge 0 \\ \theta x_i - X\lambda \ge 0 \\ \lambda \ge 0 \end{cases} \end{aligned} \tag{4}$$

Here θ represents a scalar and λ represents a K*1 vector of constants. The obtained value of θ is the technical efficiency score of the i-th DMU, which satisfies the restriction $\theta \le 1$. If a DMU gets a value of θ equals to 1, it is on the best-practice frontier and technically efficient. Otherwise, it is not on the best-practice frontier and can be improved according to the best-practice frontier.

The CRS assumption is appropriate when all DMUs operate at an optimal scale. But sometimes it is not the case, therefore, Banker *et al.* (1984) proposed a new DEA model to deal with Variable Returns to Scale (VRS) situations. When not all DMUs operate at an optimal scale, the CRS model will result in measures of TE which are confounded by scale efficiencies. The VRS model fixes this problem.

The CRS model in Eq. 4 can be easily modified into a VRS one. When Eq. 4 is added the convexity constraint, N' λ = 1, it turns into a VRS model represented in Eq. 5:

$$\begin{aligned} &\min_{\theta,\lambda} \quad \theta \\ &\text{s.t.}\begin{cases} -y_i + Y\lambda \ge 0 \\ \theta x_i - X\lambda \ge 0 \\ N'\lambda = 1 \\ \lambda \ge 0 \end{cases} \end{aligned} \tag{5}$$

Here, N represents a K*1 vector of ones. The technical efficiency score obtained from a CRS model is usually called Technical Efficiency (TE), The technical efficiency score obtained from a VRS model is usually called Pure Technical Efficiency (PTE). The VRS model forms a convex hull of intersecting planes which envelope the data points more tightly than CRS conical hull. Thus PTE is greater than or equal to TE. The ratio of TE to PTE is called Scale Efficiency (SE). If SE of a DMU equals to one, it operates at an optimal scale. Otherwise this DUM suffers scale inefficiency. Accordingly, TE can be decomposed into two components: SE and PTE. This can be done by conducting both CRS and VRS models upon the same data of a DMU.

DEA model is capable of dealing with process with multiple outputs and multiple inputs, not requiring an explicit production function, to provide efficiency score relative to the most-practice frontier and not requiring price information (Odeck, 2000). These merits make it wisely used in measuring relative productive efficiency of all kind of entities (Chen *et al*., 2006). This study use DEA to calculate efficiency scores for 52 Chinese national SPs and also use it to compute R and D Malmquist indexes for these SPs.

Malmquist index (MI): MI is often used to measure productivity change. This study uses DEA efficiency scores to construct R and D MI. This kind of MI is defined as the ratio of the efficiency scores for the same DMU in two different periods (Guan and Chen, 2010).

According to Fare *et al.* (1994) there are two MIs, $M_0(0,1)$ and $M_1(0,1)$, to measure a DMU's productivity change over period 0 and 1. The former is calculated referencing the best-practice frontier in period 0 and the latter is calculated referencing the best-practice frontier in period 1. $M_0(0,1)$ and $M_1(0,1)$ can be calculated as following equation:

$$M_i(0, 1) = Te_{i1}/TE_{i0}, \qquad i = 0, 1 \tag{6}$$

Here, i represents that the best-practice frontier is of period i, TE_{i0} represents the efficiency score for the DMU observed in period 0, TE_{i1} represents the efficiency score for the same DMU observed in period 1. To avoid choosing an arbitrary benchmark best-practice frontier, Fare *et al*. (1994) defined geometric mean of $M_0(0,1)$ and $M_1(0,1)$ as the Malmquist index M(0,1):

$$M(0,1) = \sqrt{M_0(0,1) \bullet M_1(01)} \tag{7}$$

Using DEA models, it's easily to calculate M(0,1). It only needs to run four DEA models in Eq. 8 to compute TE_{ij} (i, j = 0, 1):

$$\begin{aligned} &(E_{ij})^{-1} = \min_{\theta,\lambda} \quad \theta \\ &\text{s.t.}\begin{cases} -y_i + Y_j\lambda \geq 0 \\ \theta x_i - X_i\lambda \geq 0 \\ \lambda \geq 0 \end{cases} \end{aligned} \tag{8}$$

Here, i and j (i, j = 0, 1) represent that the data come from period 0 or period 1.

Fare *et al*. (1994) also decomposed the productivity change into two mutually exclusive components: technical efficiency change and technical change overtime, which measure the change in technical efficiency and frontier shift, respectively. The technical efficiency change can be further discomposed into two exclusive components: scale efficiency change and pure technical efficiency change. For this, it needs to run another more four DEA models which need to introduce the convexity constraint, N' λ=1, into Eq. 8. With the approaches mentioned as above, five Malmquist indexes can be obtained for each DMU. They are Total Factor Productivity Change (TFPC), Technical Efficiency Change (TEC), Technical Change (TC), Pure Technical Efficiency Change (PTC), Scale Efficiency Change (SEC).

TFPC>1 (TFPC<1) indicates productivity gain (loss). Similarly, TEC>1 (TEC<1) represents that technical efficiency increases (decreases), TC>1 (TC<1) indicates technical progress (regress) and so on.

In addition, the major source of productivity gains or losses can be identified by comparing the values of TEC and TC. For example, if TEC is greater than TC and TFPC is greater than one, then productivity gain is mainly the result of improvements in technical efficiency. On the other hand, if TEC is less than TC and TFPC is less than one, then the productivity loss is primarily due to technical efficiency decrease. Similarly, the major sources of technical efficiency gains or losses can be identified by comparing the values of PTEC and SEC.

According to Guan and Chen (2010) it needs measure R and D technical efficiency in individual periods as well as R and D productivity change over two adjacent periods to comprehensive benchmarking entities' R and D efficiencies. Correspondingly, a study framework is constructed as Fig. 1. Firstly, CRS DEA model and VRS DEA model are run to provide three kinds of R and D efficiency scores, which are used to assess relative R and D efficiency in individual years and to analyze the major source of inefficiency. Then five kinds of Malmquist indexes are computed using efficiency score by DEA models, which are used to assess R and D productivity change over two adjacent years and to identify the major source of productivity change.

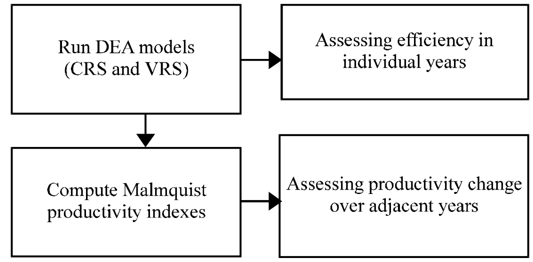

Fig. 1: Study framework

VARIALBE, SAMPLES AND DATA

The application of DEA requires a careful selection of input and output variables. There is no best rule about the input-output selection, availability and literature survey are two helpful criteria (Sun, 2011). In assessing R and D efficiency, R and D expenditure and R and D personnel are often elected as inputs and patent, publication are often elected as outputs (Guan and Chen, 2010; Hashimoto and Haneda, 2008; Wang and Huang, 2007). This study also chooses R and D expenditure and R and D personnel as input variables. But there is no detailed data about patent, publication of each of these SPs available. Furthermore, R and D activities have two functions, innovation and learning (Cohen and Levinthal, 1990) and many Chinese firms involve in R and D activities just for learning rather than innovation. Patent and publication are not perfect proxies for R and D outputs for these firms, thus for Chinese SPs, even if data are available. Since R and D activities can result in

Table 1: Descriptive statistics of variables

Variables	N	Min	Max	Mean	SD
TRev	260	0.00	244.08	11.07	28.95
Profit	260	0.23	130.64	9.44	14.45
Person	260	1.28	338.34	27.89	44.98
Expend	260	0.05	32.44	3.10	4.40

technical revenue (revenue from patent licensing, technical service and so on) and saving cost, technical revenue and profit are suitable proxies of outputs of R and D activities of these SPs. This study chooses them as output variables. Thus, variables in this study are defined as follows:

- **TRev:** Total technical revenue of all firms in a SP (hundred million RMB)
- **Profit:** Total profit of all firms in a SP (hundred million RMB)
- **Person:** Sum of R and D personnel of all firms in a SP (hundred persons)
- **Expend:** Sum of R and D expenditures of all firms in a SP (hundred million RMB)

The samples of this study are fifty-two national SPs of China established in 1991 and 1992. Although, China has established hundreds of SPs approved by different level of governments, these ones have longer history, larger scale and perform much more R and D activities. They can represent the best R and D performance of all SPs in China. The time period of this study is from 2007 to 2011, so there are 260 DMUs in total. All data were based on Statistical Yearbook of Chinese Torch (huoju) project 2008-2012 (Beijing: China Statistics Press). Table 1 gives the descriptive statistics of the variables. Table 1 presents that both input variables and output variables varied in a large range. It indicates that some of these SPs participated a lot of R and D activities while others just participated a little.

RESULTS AND DISCUSSION

Results of correlation analysis: DEA model assumes input variables and output variables satisfy the "isotonicity" relations. This requires that an increase in any input won't bring a decrease to any output. Otherwise, some variables need transform to satisfy the "isotonicity" requirement before analysis Charnes *et al.* (1978). Following Sun (2011) this study applies correlation analysis to test the "isotonicity". Table 2 gives the Pearson correlation coefficients of the four input/output variables. It shows correlation coefficients between two input variables and two output variables are all greater than 0.86, indicating these variables are significantly positively correlated. In other words, the

Table 2: Results of correlation analysis

	TRev	Profit	Person	Expend
TRev	1	0.895**	0.886**	0.864**
Profit	0.895**	1	0.926**	0.883**
Person	0.886**	0.926**	1	0.956**
Expend	0.864**	0.883**	0.956**	1**

Significant at the 0.01 level (2-tailed)

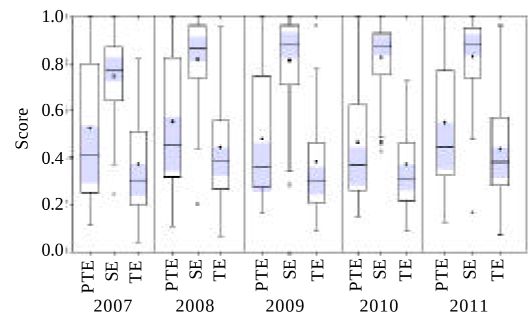

Fig. 2: Scale efficiey (SE), pure technical efficiency (PTE) and echnical efficiency (TE) in each year

four variables satisfy the requirement of "isotonicity" and are already properly represented for DEA analysis.

Results of DEA model: For each of these forty-two Chinese national SPs in each year of the period 2007-2011, three R and D efficiency scores are obtained. TE is obtained by CRS DEA model, PTE is obtained by VRS DEA model and then SE is calculated by equation SE = TE/PTE.

Figure 2 is the boxplot of scores of TE, SE and TE of these SPs in each year of 2007-2011. It presents that average SE score is about 0.8, average PTE score is about 0.4 and average TE score is about 0.3. Lower average TE score indicates that most SPs are relatively inefficient in each year. Lower average PTE score and higher average SE core indicate that most SPs' inefficiencies can be attributed to lower PTE score. Figure 2 also illustrates that there was a large efficiency disparity between these SPs (lower average TE score) and the disparity wasn't mitigated (average TE score wasn't increased obviously). Since these SPs locate in different regions of China, this may be a reflection of sustained R and D efficiency disparity between Chinese regions (Li, 2009).

To further identify the relationship of PTE and TE, Fig. 3 depicts total 260 tuples of (PTE, SE). A regression line and two histograms are also added to it. The regression line in Fig. 3 illustrates that PTE and SE were correlated negatively, so most of these SPs neglected either SE or PTE. Most points cluster in the area where SE∈[0.7,0.1] and PTE∈[0.2,0.4] in Fig. 3. This shows that most of these SPs have operated with a high SE and a low PTE. It signifies that more attentions should be pay to

Table 3: Arithmetic mean value of R and D efficiency score of each SP during 2007-2011

SP name	TE	PTE	SE	SP name	TE	PTE	SE
Chongqing	0.890	0.939	0.950	Chengdu	0.352	0.475	0.763
Changchun	0.863	0.988	0.870	Zibo	0.347	0.419	0.852
Lanzhou	0.839	0.947	0.880	Weihai	0.343	0.402	0.849
Shenyang	0.795	0.833	0.951	Taiyuan	0.325	0.356	0.914
Jinan	0.755	0.834	0.919	Wuhan	0.299	0.401	0.746
Tianjin	0.745	0.963	0.769	Zhuhai	0.296	0.476	0.724
Nanning	0.722	0.752	0.955	Changzhou	0.282	0.337	0.841
Urumqi	0.682	0.936	0.736	Zhengzhou	0.266	0.291	0.896
Hainan	0.636	1.000	0.636	Harbin	0.265	0.346	0.779
Hangzhou	0.634	0.927	0.675	Qingdao	0.262	0.295	0.889
Anshan	0.557	0.570	0.976	Nanjing	0.252	0.318	0.882
Xi'an	0.514	0.829	0.629	Jilin	0.249	0.288	0.855
Xiamen	0.501	0.628	0.825	Baotou	0.242	0.287	0.835
Beijing	0.482	1.000	0.482	Zhongshan	0.241	0.292	0.820
Shanghai	0.465	0.920	0.504	Changsha	0.237	0.290	0.831
Suzhou	0.441	0.511	0.901	Baoding	0.236	0.280	0.805
Kunming	0.439	0.500	0.872	Baoji	0.224	0.263	0.853
Dalian	0.437	0.518	0.866	Guilin	0.221	0.316	0.738
Wuxi	0.435	0.588	0.815	Foshan	0.202	0.229	0.885
Guangzhou	0.425	0.629	0.695	Huizhou	0.195	0.290	0.691
Weifang	0.419	0.511	0.845	Shenzhen	0.189	0.251	0.778
Daqing	0.414	0.450	0.915	Fuzhou	0.183	0.262	0.708
Shijiazhuang	0.395	0.413	0.940	Guiyang	0.182	0.369	0.514
Xiangfan	0.384	0.416	0.925	Nanchang	0.176	0.208	0.849
Hefei	0.368	0.406	0.919	Zhuzhou	0.150	0.203	0.730
Luoyang	0.358	0.380	0.942	Mianyang	0.089	0.317	0.424
				Mean	0.402	0.512	0.805

TE: Technical efficiency, PTE: Pure technical efficiency, SE: Scale efficiency

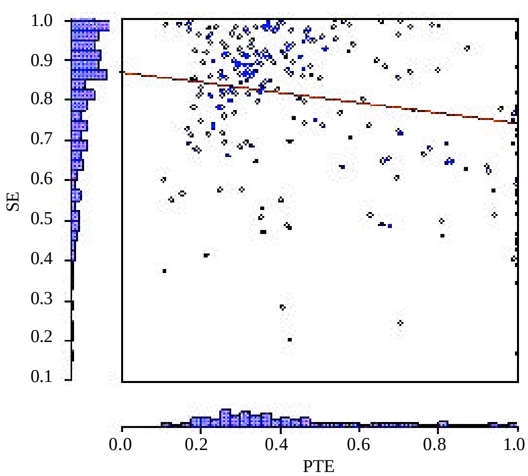

Fig. 3: Scale efficiey (SE) and pure technical efficiency (PTE) during 2007-2011

"soft factors" such as R and D management, institutional conditions and policy instruments (Guan and Chen, 2010).

Table 3 reports the arithmetic mean value of these three efficiency scores of each SP in the five years. Generally speaking, most of these SPs were relatively inefficiently, since the average TE was only 0.40 and only ten SPs got a TE score greater than 0.6. Chongqing SP, Changchun SP and Lanzhou SP were the three most relatively efficient, their TE were greater than 0.83. Nanchang SP, Zhuzhou SP and Mianyang SP were the three most relatively inefficient, their TE scores were less than 0.18. Table 3 also shows that most SPs got poor TE scores because of poor PTE scores, which indicate low utilization of inputs in R and D activities. Only several ones such as Beijing SP, Shanghai SP and Hainan SP got poor TE scores because of poor SE scores, which indicate operating at an unfavorable scale. Unfortunately, Guiyang SP and Mianyang SP not only got low utilization of inputs problem but also operated at an unfavorable scale.

Results of Malmquist indexes analysis: This study explore R and D productivity change by calculating five Malmquist indexes for each of these SPs: TFPC, TC, TEC, PTEC and SEC.

China as a whole got an impressive R and D productivity growth since 2000 but some regions of China improved little, some even became worse (Guan and Chen, 2010; Chen and Guan, 2011). These SPs followed a similar pattern during 2007-2011. Table 4 gives geometric mean value of the five R and D Malmquist indexes of each SP. Fifty-two SPs as a whole improved in the up-mentioned five aspects (see last row in Table 4). Forty-two SPs got a TFPC greater than one, showing that they experienced productivity gains. Ten SPs experienced productivity losses, their TFPC mean value were less than one. Mianyang SP, Jinan SP and Shijiazhuang SP were the three ones that experienced the largest R and D productivity gains; each of them got a TFPC greater than 1.4. On the other hand, Xiamen SP, Baoding SP and

Table 4: Geometric mean value of R and D Malmquist index of each SP during 2007-2011

SP name	PTEC	SEC	TEC	TC	TFPC	SP name	PTEC	SEC	TEC	TC	TFPC
Mianyang	1.737	0.818	1.421	1.176	1.671	Wuhan	1.035	1.018	1.054	1.063	1.12
Jinan	1.559	0.972	1.515	1.054	1.598	Shanghai	1	1.013	1.013	1.084	1.098
Shijiazhuang	1.369	1.039	1.423	1.01	1.438	Nanchang	1.032	0.993	1.025	1.065	1.091
Zhengzhou	1.23	1.063	1.307	1.063	1.389	Chongqing	1.091	1	1.091	0.985	1.074
Changchun	1.016	1.149	1.167	1.151	1.343	Hainan	1	0.937	0.937	1.144	1.071
Guiyang	1.159	1.043	1.209	1.069	1.293	Nanjing	0.841	1.175	0.987	1.078	1.065
Anshan	1.176	0.996	1.172	1.041	1.22	Zibo	0.912	1.103	1.007	1.05	1.057
Zhuzhou	1.094	1.052	1.151	1.058	1.218	Guilin	1.17	0.84	0.983	1.073	1.055
Shenzhen	1.061	1.102	1.169	1.041	1.217	Hefei	0.9	1.064	0.957	1.098	1.052
Xiangfan	1.141	0.996	1.136	1.069	1.214	Weifang	0.9	1.097	0.987	1.06	1.047
Foshan	1.155	1.006	1.163	1.042	1.212	Harbin	0.891	1.106	0.985	1.061	1.045
Baoji	1.132	1.001	1.133	1.061	1.202	Zhuhai	0.784	1.392	1.092	0.956	1.044
Weihai	1.086	1.02	1.107	1.084	1.201	Shenyang	0.967	0.982	0.95	1.098	1.043
Daqing	1.115	1.016	1.133	1.058	1.199	Xi'an	1.001	0.995	0.996	1.032	1.028
Kunming	1.103	1.044	1.152	1.039	1.197	Guangzhou	0.952	0.997	0.949	1.076	1.02
Beijing	1	1.11	1.11	1.075	1.193	Taiyuan	0.942	1.013	0.955	1.065	1.017
Tianjin	1.049	1.044	1.095	1.081	1.183	Fuzhou	0.941	1.011	0.95	1.036	0.985
Changzhou	1.029	1.072	1.104	1.07	1.181	Huizhou	0.979	0.938	0.918	1.07	0.982
Baotou	1.098	1.028	1.128	1.044	1.178	Suzhou	0.835	1.096	0.915	1.057	0.967
Chengdu	1.058	1.034	1.094	1.075	1.177	Hangzhou	0.956	0.943	0.901	1.072	0.966
Zhongshan	1.119	1.001	1.121	1.05	1.176	Wuxi	0.793	1.144	0.907	1.06	0.962
Urumqi	1.002	1.134	1.137	1.023	1.162	Jilin	0.93	0.946	0.88	1.064	0.936
Dalian	1.087	1	1.087	1.068	1.161	Nanning	0.829	0.988	0.819	1.111	0.91
Luoyang	1.098	0.998	1.096	1.057	1.158	Xiamen	0.764	1.141	0.871	0.992	0.864
Qingdao	1.061	1.02	1.082	1.059	1.146	Baoding	0.772	0.902	0.696	1.08	0.752
Changsha	0.959	1.11	1.065	1.068	1.137	Lanzhou	1	0.99	0.99	0.751	0.744
						Mean	1.024	1.029	1.053	1.055	1.112

PTEC: Pure technical change, SEC: Scale efficiency change, TEC: Technical efficiency change, TC: Technical change, TFPC: Total factor productivity change

Lanzhou SP got the three lowest TFPC, which were all less than 0.9, indicating that they actually experienced R and D productivity losses.

Thirty two SPs got a TEC greater than one; they improved in R and D experience, management and organization relative to the best-practice frontier. However, twenty SPs got a TEC less than one, they withdrew in R and D experience and management and organization relative to the best-practice frontier. TC measures the relative movement to best-practice frontier shift in R and D technology/skill, which is consequence of introducing new R and D experiment equipment or new R and D process and system (Guan and Chen, 2010). The average TEC was 1.055, showing that most SPs moved near to the best-practice frontier. Only four SPs got a TEC less than one, showing that they moved away from the best-practice frontier. Thirty-three SPs got a PTEC greater than one, showing that they were getting better in balancing R and D input and output. Thirty-five SPs got a SC greater than one, showing that their R and D size was under continuous optimization.

The TEC and TC are compared to identify the major source of R and D productivity change. Most of those SPs experienced productivity gains (28 of 42) got a TEC greater than TC, indicating that technical efficiency improvement was the major source of productivity gains for them. On the other hand, most of SPs experienced productivity losses (9 of 10) got a TEC less than TC, indicating technical efficiency regression was the major source of productivity losses for them. In conclusion, change in technical efficiency was the major source of R and D productivity change.

CONCLUSTIONS

This Study evaluated the R and D efficiencies of fifty two Chinese national SPs over the period 2007-2011 and analyzed the major source of R and D inefficiency and R and D productivity change. DEA is used to measure R and D technical efficiency in individual years and Malmquist index is computed to measure R and D productivity change over two adjacent years. The conclusions are as follows.

Most of these SPs performed R and D activities relatively inefficiently. Chongqing SP, Changchun SP and Lanzhou SP were the top three relatively efficient, while Nanchang SP, Zhuzhou SP and Mianyang SP were the three most relatively inefficient.

Most SPs' inefficiencies resulted from lower utilization of inputs (poor PTE score), just a few SPs such as Beijing SP, Shanghai SP and Hainan SP suffered inefficiency from an awful R and D activity scale (poor SE score).

Forty two SPs experienced productivity gains and only ten SPs experienced productivity losses. Mianyang SP, Jinan SP and Shijiazhuang SP were the three ones got the most productivity gains, while Xiamen SP, Baoding SP and Lanzhou SP were the three ones experienced the most productivity loss.

Technical efficiency change was the major source of productivity change. It majorly resulted in twenty-eight SPs' R and D productivity gains and also majorly resulted in nine SPs' R and D productivity losses.

The conclusions provided a policy implication for China government. To promote its SPs' innovation capabilities, policies aiming to how to use R and D resources efficiently will be better than more R and D investment. Since additional investment may be of little help, when R and D resources are not used efficiently (Wang and Huang, 2007).

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