An International Comparison of R&D Efficiency: DEA Approach

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Summary

A prerequisite for making R&D more productive is to be able to measure its productivity. Most of the previous studies on this topic have attempted to measure R&D productivity at the firm or industry levels. In this study, however, R&D productivity is measured at the national level to provide R&D policy implications, particularly for Asian countries. Contrary to the previous studies where total factor productivity was adopted, this study employs the data envelopment analysis (DEA) approach to measure R&D productivity.

DEA is a multi-factor productivity analysis model for measuring the relative efficiency of each Decision Making Unit (DMU). In addition to the basic DEA model that includes all inputs and outputs, five additional models are constructed by combining single input with all outputs and single output with all inputs in order to measure specialized R&D efficiency. In this study, the twenty-seven countries are classified into four clusters based on the output-specialized R&D efficiency: inventors, merchandisers, academicians, and duds. Then, the characteristics of the Asian countries with respect to R&D efficiency are identified.

It is found that Singapore ranks high in total efficiency, and Japan in patent-oriented efficiency. Meanwhile, China, Korea, and Taiwanare found to be relatively inefficient in R&D. We expect that the findings from this study will be able to provide directions for R&D policy-making of the Asian countries.

Keywords: R&D productivity, R&D efficiency, R&D efficiency clusters, data envelopment analysis, Asian countries.

1. Introduction

An efficient and productive R&D operation is a major source of competitive advantage (Werner and Souder, 1997). A prerequisite for making R&D more productive is to be able to measure its productivity (Karlsson et al., 2004). Therefore, a number of studies have been done to measure R&D productivity. In terms of subject being measured, most studies have been conducted at the firm or industry levels (e.g. Zhang et al., 2003; Tsai, 2005; Hanel, 2000). However, very few have been done at the national level, although R&D management and policies at the national level are considered to be imperative. In this study, R&D productivity is measured at the national level in order to provide R&D policy implications, particularly for Asian countries, by identifying the characteristics of Asian countries with respect to R&D productivity. In terms of the measurement method, total factor productivity (TFP) has been mainly employed as a measure of overall productivity in the previous studies (Brown and Gobeli, 1992). However, it cannot be used when there are multiple outputs. In this study, data envelopment analysis (DEA) is used to measure R&D productivity so that the multiple outputs of outputs can be taken into consideration. Furthermore, DEA enables us to carry out relative comparisons among countries.

DEA is a multi-factor, productivity analysis model for measuring the relative efficiency of each DMU (Decision Making Unit) when there are multiple inputs and outputs. A standard way of measuring DEA efficiency is to estimate the model that includes all inputs and outputs. However, we need to consider various combinations of inputs and outputs since DEA efficiency highly depends on the combinations of inputs and outputs. Hence, the R&D efficiency scores in additional models are measured. The additional models are constructed by combining single input with all outputs and single output with all inputs. This enables us to measure specialized R&D efficiency in terms of each input or output. Based on the specialized R&D efficiency, the twenty-seven countries considered in this study are classified into four clusters. Finally, the characteristics of the Asian countries are identified by the efficiency scores and the clusters to which they belong. In summary, the purpose of this paper is to measure R&D efficiency using DEA at the national level; in turn, to identify the characteristics of Asian countries with respect to R&D efficiency.

The remainder of this paper is organized as follows. Section 2 deals with the concept of R&D productivity and DEA methodology. The research methodology is introduced in Section 3. Section 4 provides the results of DEA and clustering analysis. Finally, conclusions are then given in Section 5 with some policy implications.

2. Theoretical Background

2.1. R&D Productivity

Basically, productivity is defined as the ratio of output to input. Productivity is improved when more outputs are produced with the same inputs or less inputs with the same outputs. In most cases, factor productivity, such as labor productivity and capital productivity, is employed as a measure of productivity. It is merely a ratio of single output to single input. However, factor productivity does not tell us about overall productivity since it only considers a single input. To overcome the limitation of factor productivity, total factor productivity (TFP) has been widely used as an overall measure of productivity. TFP is calculated as the growth rate of output minus the average growth rate of each of the inputs (Bartelsman and Gray, 1996). Almost all of the studies on R&D productivity have employed this TFP concept (e.g. Zhang et al., 2003; Lichtenberg and Siegel, 1991; Tsai, 2005; Wakelin, 2001; Hanel, 2000). However, TFP has a limitation in that it cannot be used in the case of multiple outputs

Findings from recent studies of R&D returns to scale are somewhat mixed, but most suggest constant returns to scale or decreasing returns to scale (Graves and Langowitz, 1996). Scherer (1983) found out that about 60% of the industries in his study exhibited constant returns to scale, with 25% showing decreasing returns to scale and 15% showing increasing returns to scale. Bound, et al. (1984), found nearly constant returns to scale for firms whose R&D expenditures range from \$2 million to \$100 million, with decreasing returns to scale for those firms above \$100 million.

Inputs and outputs of R&D employed in the previous studies were not so different from each other. Inputs include the number of researchers or the number of R&D personnel as labor, and R&D expenditure or R&D intensity as capital. Also, the number of patents or the number of patents adjusted for technological importance or quality have been mainly used as outputs (Werner and Souder, 1997). Different types of outputs need to be considered because patents do not actually cover the overall output from the R&D effort (Tsai, 1995). In the studies of R&D performance measurement and technological knowledge measurement, the number of Ph. Ds and the technology balance of payment are also used as proxies of R&D inputs. R&D outputs have often taken the forms of the number of scientific and technical journal articles, technology balance of receipt, and the number of new products developed (e.g. Werner and Souder, 1997; Park et al., 2003; Wakelin, 2001).

2.2. DEA

DEA is a non-parametric approach that does not require any assumptions about the functional form of a production function. DEA provides efficiency as an overall measure of productivity that factor productivity cannot produce by measuring the relative efficiency with multiple inputs and outputs. The DEA efficiency of a DMU is measured by estimating the ratio of weighted outputs to weighted inputs and comparing it with other DMUs.

DEA models can be divided into the CCR model and the BCC model. The distinction between the two models has to do with the assumption on returns to scale (Cooper et al., 2000). The CCR model, which is the first DEA model suggested by Charnes et al. (1978), assumes constant returns to scale; whereas, the BCC model proposed by Banker et al. (1984) assumes variable returns to scale. Since R&D exhibits constant returns to scale in most cases, this paper employs the CCR model as mentioned in Section 2.1. DEA models are also distinguished by the objective of a model: maximize outputs or minimize inputs. As the objective of R&D lies in increasing outputs rather than decreasing inputs, the output-oriented models are employed here.

The output-oriented CCR model can be expressed by the following linear programming model.

$$\begin{aligned}
&\min \sum_{i=1}^{m} v_i x_{ik} \\
&s.t. \ \sum_{r=1}^{s} u_r y_{rk} = 1, \\
&\qquad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \ , \ j = 1, \cdots, n \\
&\qquad u_r \ge \varepsilon > 0, \ r = 1, \cdots, s \\
&\qquad v_i \ge \varepsilon > 0, \ i = 1, \cdots, m
\end{aligned}$$

Here, x_{ij} is the amount of the i-th input, y_{rj} is the amount of the r-th output, v_i is the weight given to the i-th input, u_r is the weight given to the r-th output, and k is the DMU being measured. In order to measure efficiency of every DMU, the model should be analyzed iteratively as many times as the number of DMUs. The ε constraints avoid any inputs or outputs being weighted at 0.

DEA has been widely used to measure the efficiency of organizations where there exist multiple inputs and outputs, such as hospitals, schools, militaries, banks, and fast food restaurants (Seiford, 1993).

3. Method

3.1. Research Framework

Figure 1 depicts the research framework. First, input variables and output variables were selected based on R&D productivity literature. Second, data for inputs and outputs were collected. Third, R&D efficiency scores were measured using DEA. Then, R&D efficiency clusters were identified by the R&D efficiency scores measured, using k-means clustering analysis. Finally, the characteristics of the Asian countries with respect to R&D efficiency were identified.

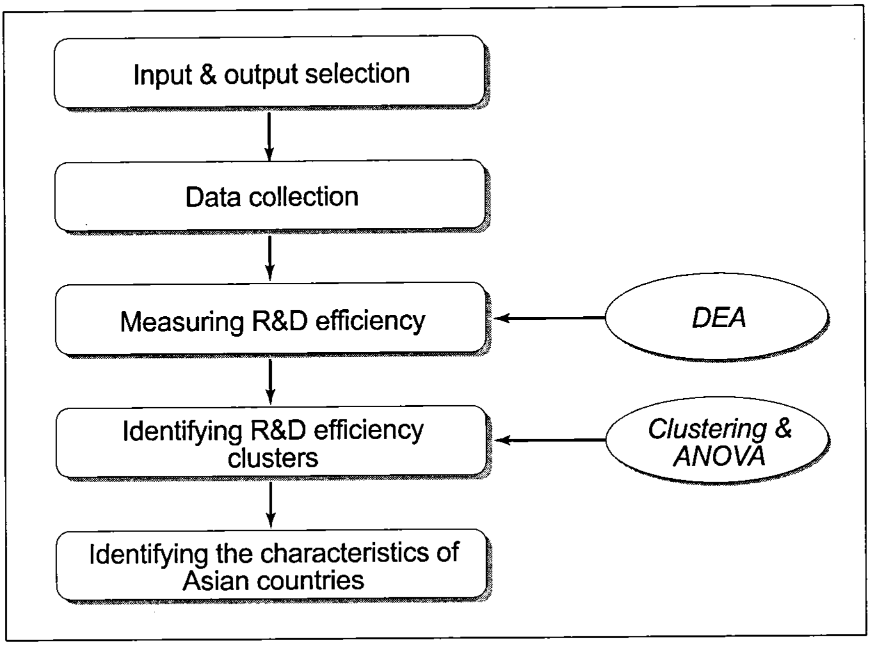

Figure 1 : Research Framework

3.2. Variables

Among a variety of inputs and outputs of R&D mentioned in Section 2, three inputs and two outputs were selected for this study. Table 1 summarizes the input and output variables. R&D expenditure and researchers have been selected as a proxy of capital input and labor input, respectively. Capital and labor are the typical inputs of this kind of study (Serrano-Cinca et al., 2005). Technology balance of receipts (TBR), articles, and patents have been selected as outputs. TBR can be considered as the direct commercial output of R&D activities of a country in that it reflects the ability to sell technology that is a main output of R&D activities. However, technology balance of payments was not selected as an input since it is merely payments for production-ready technologies (OECD, 2001). Articles published in journals are considered as the major output of research and widely used to evaluate performance of researchers (OECD, 2001). Patents are the most frequently used outputs of previous studies (Zhang et al., 2003). However, simple counts of patents filed at an intellectual property office are likely to be biased due to the home advantage for patent applications. Patent families, therefore, are employed to improve international comparability. A patent family is defined as a set of patents taken in various countries to protect a single invention (OECD, 2001). We used the triadic patent family indicators compiled by the OECD that relate to patents applied for at the European Patent Office (EPO), the US Patent & Trademark Office (USPTO), and the Japanese Patent Office (JPO).

Table 1 : Variables

Type	Variable	Description
Input	R&D expenditure	Average R&D expenditure of a country for the period 1994-1998
	Researchers	Average number of researchers of a country for the period 1994-1998
Output	TBR	Technology balance of receipts in 1999
	Articles	Number of scientific and technical journal articles published in 1999
	Patents	Number of triadic patent families in 1999

We need to be careful with selecting the time period of inputs and outputs since R&D inputs are not converted into outputs instantly. Although findings from previous studies vary slightly, it is assumed that, in general, there is a three-to-five year lag between R&D inputs and R&D outputs (Scherer, 1983; Acs and Audretsch, 1991). Graves (1996) suggested that a five-year average is a prudent middle ground given the variance of the previous studies. Therefore, in this study inputs were measured as the average for the period 1994-1998 and data in 1999 were used in the case of outputs.

3.3. Data

Data for two inputs and three outputs were mainly collected from the 2004 OECD Main Science and Technology Indicators (MSTI) database. However, data for the articles that cannot be found in the 2004 OECD MSTI were obtained from the 2004 World Bank's World Development Indicators (WDI) Database. The raw data set for DEA is attached in Appendix A. Originally, the 2004 OECD MSTI provided the data of thirty-eight countries, including eight non-member countries, but twenty-seven countries whose data were available were included as DMUs. In the case where there is no output data for a country for the year 1999, the data for 1998 were used instead. The Asian countries that are included are China, Japan, Korea, Singapore, and Taiwan as listed in Table 2.

Table 2 : Countries

No.	Ticker	Country	No.	Ticker	Country
1	AUS	Australia	15	NZL	New Zealand
2	AUT	Austria	16	NOR	Norway
3	CAN	Canada	17	POL	Poland
4	CHN	China	18	PRT	Portugal
5	CZE	CzechRepublic	19	ROM	Romania
6	FIN	Finland	20	RUS	Russian Federation
7	FRA	France	21	SGP	Singapore
8	DEU	Germany	22	SVK	SlovakRepublic
9	HUN	Hungary	23	SVN	Slovenia
10	IRL	Ireland	24	ESP	Spain
11	ITA	Italy	25	TAW	Taiwan
12	JPN	Japan	26	GBR	United Kingdom
13	KOR	KoreaRepublic	27	USA	United States
14	MEX	Mexico			

3.4. Methodology

The analysis process of this study is divided into two phases. In the first phase, R&D efficiency is measured using DEA with raw input and output data. The DEA models were solved by Frontier Analyst 3®, which is one of the DEA software. In the second phase, multivariate analyses were carried out using R&D efficiency scores obtained from the first phase. First, the k-means clustering analysis was run to identify R&D efficiency clusters. Then, ANOVA and post-hoc comparisons were conducted to test differences among clusters and identify the characteristics of each cluster. SPSS 11.5 was used for these multivariate analyses.

4. Results

4.1. Measuring R&D Efficiency

The R&D efficiency of the twenty-seven countries was measured using DEA. First, R&D efficiency was measured in the basic DEA model that included all the inputs and outputs. A standard way of measuring DEA efficiency is to estimate this basic model only. However, as DEA efficiency highly depends on the combinations of inputs and outputs (Jenkins and Anderson, 2003), it is necessary to study other combinations of inputs and outputs. This enabled finding the strengths and weaknesses of each country by examining the differences among the efficiency scores in various models (Serrano-Cinca et al., 2005). Hence, the R&D efficiency scores in additional models were also measured. The additional models were constructed by combining single input with all outputs and single output with all inputs. As a result, we were able to measure specialized R&D efficiency in terms of single input or single output. For instance, the DEA model that includes researchers only as an input and all outputs can be regarded as the labor efficiency model. Also, the efficiency scores measured in the DEA model that includes all inputs and patents only as an output represents patent-oriented efficiency. In this way, the additional five DEA models were estimated: capital efficiency model, labor efficiency model, TBR-oriented efficiency model, article-oriented efficiency model, and patent-oriented efficiency model. Table 3 shows the inputs and outputs included in the six DEA models.

Table 3 : Inputs & Outputs of the DEA Models

DEA model	Input		Output		
	R&D expenditure	Researchers	TBR	Articles	Patents
Basic model	O	O	O	O	O
Capital efficiency model	O		O	O	O
Labor efficiency model		O	O	O	O
TBR-oriented efficiency model	O	O	O		
Article-oriented efficiency model	O	O		O	
Patent-oriented efficiency model	O	O			O

Table 4 shows the R&D efficiency scores of the twenty-seven countries in the six DEA models. The first concern over the DEA results is which of the DMUs are 100% efficient in the basic model. Six countries, including Austria, Finland, Germany, Hungary, New Zealand,

and the United Kingdom have 100% overall efficiency. On the other hand, the other twenty-one countries whose efficiency scores are below 100% were found to be inefficient. Singapore was found to have the highest overall efficiency scores of 99.38% among the five Asian countries.

It should be noted that efficiency scores of each country are significantly different across the models. For instance, New Zealand is found to be 100% efficient in the article-oriented efficiency model, but only 1.5% efficient in the TBR-oriented efficiency model. It is clear that New Zealand has strength in producing science and journal articles, but is weak at gaining technology payment of receipt. These specific features would not have been revealed if only the full model had been estimated. Likewise, the characteristics of each country with respect to R&D efficiency can be identified by comparing the efficiency scores in the six DEA models.

Table 4 : R&D Efficiency Scores

	Overall efficiency	Capital efficiency	Labor efficiency	TBR-oriented efficiency	Article-oriented efficiency	Patent-oriented efficiency
AUS	67.78	64.67	67.44	2.1	62.89	29.34
AUT	100	100	100	100	57.86	59.33
CAN	74.25	63.46	74.25	21.56	66.11	28.28
CHN	14.75	14.75	6.57	0.43	14.64	1.77
CZE	56.61	54.28	55.55	25.96	47.85	3.94
FIN	100	100	98.51	5.49	59.14	100
FRA	78.5	56.54	78.5	14.76	54.07	54.12
DEU	100	100	100	44.48	48.29	100
HUN	100	100	59.87	39.82	79.76	25.86
IRL	86.62	85.65	86.29	74.07	58.06	39.03
ITA	90.26	68.28	90.26	38.5	72.3	41.28
JPN	87.34	87.34	72.35	12.86	22.41	86.48
KOR	28.75	24.26	28.55	1.32	20.44	21.31
MEX	39.05	29.43	39.05	3.5	37.98	2.97
NZL	100	100	100	1.5	100	29.54
NOR	80.57	80.25	66.09	64.21	47.03	35.54
POL	68.57	68.57	26.85	8.35	64.7	2.49
PRT	76.78	76.78	44.55	46.14	49.59	3.87
ROM	27.51	27.51	7.85	1.41	26.98	1.09
RUS	61.02	61.02	8.42	1.4	60.76	5.91
SGP	99.38	99.38	80.15	78.59	56.28	50.25
SVK	53.55	53.55	26.73	4.19	51.76	4.04
SVN	44.12	43.94	41.14	3.95	42.21	7.55
ESP	72.21	69.1	72.21	4.72	71.21	14.07
TAW	35.88	22.95	35.88	0.66	34.95	8.88
GBR	100	84.94	100	35.34	82.53	52.58
USA	74.14	57.33	74.14	28.43	47.07	57.15

4.2. R&D Efficiency Clusters

The R&D efficiency scores were measured in the basic model and five specialized efficiency models. Once R&D efficiency clusters were identified by the specialized R&D efficiency scores, it became easier to know the strengths and weaknesses of each country with respect to R&D efficiency. However, it is inappropriate to cluster countries by all of the specialized R&D efficiency scores since some are significantly correlated to each other at the 0.05 level, as shown in Table 5.

Table 5 : Pearson Correlation Coefficients

	Overall efficiency	Capital efficiency	Labor efficiency	TBR-oriented efficiency	Article-oriented efficiency	Patent-oriented efficiency
Overall efficiency	1					
Capital efficiency	0.963*	1				
Labor efficiency	0.859*	0.768*	1			
TBR-oriented efficiency	0.594*	0.597*	0.524*	1		
Article-oriented efficiency	0.699*	0.645*	0.567*	0.195	1	
Patent-oriented efficiency	0.696*	0.646*	0.768*	0.365	0.116	1

** $p<0.01$

Three types of output-specialized efficiency scores were chosen as clustering variables. Although correlations between two types of input-specialized efficiency and between each of two types of input-specialized efficiency and each of three types of output-specialized efficiency are too high; three types of output specialized efficiency are not significantly correlated to each other.

Table 6 : R&D Efficiency Clusters

Cluster	Number	Country
1	5	Finland, France, Germany, Japan, and United States
2	4	Austria, Ireland, Norway, and Singapore
3	7	Australia, Canada, Hungary, Italy, New Zealand, Spain, and United Kingdom
4	11	China, Czech Republic, Korea, Mexico, Poland, Portugal, Romania, Russian Federation, Slovak Republic, Slovenia, and Taiwan

It also may be interesting and implicative to classify countries by the three types of output-specialized efficiency in that it will reveal the strengths and weaknesses of a country in terms of R&D outputs. This also makes sense in that the DEA model employed was the output-oriented model.

Hierarchical clustering analysis was run using Ward's Method and its squared Euclidean distance. As a result, four clusters were identified as shown in Table 6.

ANOVA was then conducted on the three types of output-specialized efficiency to examine the characteristics of each cluster in detail. Post-hoc comparison was also run using Tukey's Honestly Significant Differences (HSD) for TBR-oriented efficiency and article-oriented efficiency that meet the equal variances assumption and using Dunnett T3 for patent-oriented efficiency. As a result, the four clusters were named Inventors, Merchandisers, Academicians, and Duds, respectively. Table 7 shows the result of ANOVA and post-hoc comparisons. This helped to describe the above-mentioned four clusters.

Table 7 : Results of ANOVA and Post-hoc Comparisons

	Inventors (Cluster 1)	Merchandisers (Cluster 2)	Academicians (Cluster 3)	Duds (Cluster 4)	p-value	Comparisons
TBR-oriented efficiency	21.20	79.22	20.51	8.85	0.000	2>1, 3, 4
Article-oriented efficiency	46.20	54.81	76.40	41.08	0.000	3>1, 2, 4
Patent-oriented efficiency	79.55	46.04	31.56	5.80	0.000	1>2, 3>4

Inventors A prominent feature of the Inventors is their high patent-oriented efficiency, but the other types of efficiency are low. These Inventors are G7 member countries with the exception of Finland. It is surprising that the United States, Japan, and Germany belong to this cluster whose TBR-oriented efficiency scores are low because they are ranked first, second, and third in TBR, respectively. A plausible explanation for this is that efficiency does not indicate an absolute size, but is a relative concept. As they also have high R&D expenditure and researchers, their TBR-oriented efficiency scores were found to be low.

Merchandisers This cluster was named Merchandisers because they are good at selling their R&D outputs. The countries of the Merchandisers were found to have high TBR-oriented efficiency, low article-oriented efficiency, and mid patent-oriented efficiency. The only Asian country that falls under this cluster is Singapore.

Academicians The countries of the Academician are good at publishing scientific and technical journal articles. Furthermore, they show only slightly low patent-oriented efficiency, and so is their TBR-oriented efficiency. No Asian country belongs to this cluster.

Duds As the name indicates, the countries of the Dud are not successful in producing R&D outputs. All of the three types of output-specialized efficiency are low. Unfortunately, this cluster has the highest number of countries, including the three Asian countries: China, Korea, and Taiwan.

4.3. Characteristics of the Asian Countries

This section deals with the characteristics of the Asian countries with respect to R&D efficiency in detail. The Asian countries considered in this study include China, Japan, Korea, Singapore, and Taiwan. Table 8 shows the Asian countries' R&D efficiency scores in the basic model and three types of output-specialized efficiency models. The numbers in parentheses are the ranking of each country with respect to the models. The reason why two types of input-specialized efficiency were excluded in Table 8 is because they are so highly and positively correlated with total efficiency that it need not to be examined.

Table 8 : R&D Efficiency Scores of the Asian Countries

	China	Japan	Korea	Singapore	Taiwan
Overall efficiency	14.75 (27)	87.34 (9)	28.75 (25)	99.38 (7)	35.88 (24)
TBR-oriented efficiency	0.43 (27)	12.86 (14)	1.32 (25)	78.59 (2)	0.66 (26)
Article-oriented efficiency	14.64 (27)	22.41 (25)	20.44 (26)	56.28 (13)	34.95 (23)
Patent-oriented efficiency	1.77 (26)	86.48 (3)	21.31 (16)	50.25 (8)	8.88 (18)
Cluster	Duds	Inventors	Duds	Merchandisers	Duds

In general, the Asian countries were found to be inefficient in R&D. Although Japan and Singapore show high ranking in total efficiency, the other three countries are seen to fall in last and belong to the Duds whose output-specialized efficiency scores are all low. China shows the worst performance among the Asian countries. It is ranked last in all models except the patent-oriented efficiency model. The reason for this is because it produces relatively low outputs in spite of their high R&D expenditure and number of researchers. The features of Korea and Taiwan are similar to China. They have very low efficiency scores, but their patent-oriented efficiency scores are not so bad. On the other hand, Singapore was found to be the best at R&D among the Asian countries. It is ranked second in TBR-oriented efficiency, which is why Singapore belongs to the Merchandisers and the other efficiency scores are relatively high. It shows an efficiency of almost 100% in the basic model. Japan has very high patent-oriented efficiency, but very low article-oriented efficiency. Although Japan produced the second most number of articles, a great volume of inputs lead to this result.

5. Conclusions

This study was aimed at measuring R&D efficiency at the national level using DEA. In addition to the basic DEA model, including all of the two inputs and three outputs, five additional models were constructed to measure specialized R&D efficiency. Then, the twenty-seven countries were grouped into the four clusters by output-specialized efficiency: Inventors, Merchandisers, Academicians, and Duds. Finally, the characteristics of the Asian countries with respect to R&D efficiency were identified in detail based on the efficiency scores and the clusters to which they belong.

The findings of this study are expected to provide directions for R&D policy-making of the Asian countries. The ultimate objective of DEA is to provide a way in which inefficient DMUs can improve their efficiency by benchmarking efficient DMUs. A simple calculation of DEA results will tell how many outputs should be increased to achieve 100% efficiency, but it does not tell us how to increase outputs themselves at the current input level. Finding how to increase outputs is what R&D managers are trying hard to do. The policy implications this study provides are not specific numbers to achieve 100% efficiency, but the current R&D efficiency levels of a country compared with other countries and their strengths and weaknesses. These implications will make it easy for R&D policy makers to decide whether they need to make an effort to improve R&D efficiency and what kinds of policies are required to enhance R&D efficiency to a satisfactory level. The R&D policy makers of China, Korea, and Taiwan must first know that their R&D efficiency level is very low compared to other countries. Then, they need to find out what the problems with in their current R&D, which will explain the reasons for their low efficiency level, and then find the solutions. Singapore has high efficiency, 99.38%, thanks to the high TBR-oriented efficiency. Once Singapore's R&D policies are focused on increasing article-oriented efficiency, which is where Singapore is weak, it will only be a matter of time before Singapore becomes 100% efficient in total efficiency. Japan will be able to obtain much more outputs even with a slight improvement in R&D efficiency, as it has a large R&D scale. In the case of Japan, R&D policy makers need to try to find out how to improve Japan's article-oriented efficiency to the level of its patent-oriented efficiency.

The limitations of this research are twofold. First, constant returns to scale of R&D activities are assumed. Even though this assumption was made based on literature, there has been little evidence showing that this is not the case. Therefore, R&D efficiency should be measured in the BCC model that assumes variable returns to scale and compared with the results from the CCR model. Second, two inputs and three outputs employed in this study may not be enough to discuss R&D as a whole. More types of inputs and outputs should be considered to enhance the reliability and applicability. These will be dealt with in future research.

An investigation into the relationship between R&D efficiency and GDP is a worthwhile area for future research as well. This is because R&D is a primary source of national wealth in the long-term (Acs and Audretsch, 1991). Whether this is true can be revealed by examining correlations between R&D efficiency and GDP or the discriminatory ability of R&D efficiency of the four clusters. We also are dealing with R&D efficiency at the national level; therefore, the notion of National Innovation System (NIS) needs to be introduced. The future research should measure R&D efficiency in the NIS context.

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Appendix A: DEA Data

Country	R&D expenditure (million dollars)	Researchers	TBR (million dollars)	Articles	Patents
AUS	6399	60245	103	12525	304
AUT	2973	18715	2282	3580	262
CAN	12058	90062	1995	19685	539
CHN	22975	539240	75	11675	66
CZE	1443	12674	287	2005	9
FIN	2586	20586	109	4025	419
FRA	27738	153148	2755	27374	2081
DEU	40906	233706	12673	37308	5867
HUN	707	11109	216	1958	30
IRL	928	6444	528	1237	56
ITA	12462	71749	3367	17149	740
JPN	85466	645588	8435	47826	11726
KOR	13911	98773	141	6675	459
MEX	2373	18248	64	2291	11
NZL	684	7184	8	2375	33
NOR	1878	16711	926	2598	108
POL	2014	52423	129	4523	8
PRT	876	12621	310	1508	5
ROM	838	30552	9	785	1
RUS	7424	563836	80	15654	71
SGP	1011	8884	610	1653	82
SVK	485	10022	16	871	3
SVN	409	4492	12	599	5
ESP	5273	52199	191	12289	120
TAW	7505	48948	38	5655	100
GBR	22424	145542	6081	39711	1767
USA	198354	1050900	36420	163526	15079