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R&D EFFICIENCY AND THE NATIONAL INNOVATION SYSTEM: AN INTERNATIONAL COMPARISON USING THE DISTANCE FUNCTION APPROACH

Jin-Li Hu, Chih-Hai Yang† and Chiang-Ping Chen†*
*National Chiao Tung University, Taiwan, and †National Central University, Taiwan

ABSTRACT

This paper applies the distance function approach for stochastic frontier analysis (SFA) to compare research and development (R&D) efficiency across 24 nations during 1998–2005. In this multiple input–output framework, R&D expenditure stock and R&D manpower were inputs, while patents, scientific journal articles, and royalties and licensing fees (RLF) were outputs. Intellectual property rights protection, technological cooperation among business sectors, knowledge transfer between business sectors and higher education institutions, agglomeration of R&D facilities, and involvement of the government sector in R&D activities significantly improve national R&D efficiency.

Keywords: distance function approach, national innovation system, R&D efficiency
JEL classification numbers: O32, O57

I. INTRODUCTION

Endogenous growth theory emphasizes the crucial role played by research and development (R&D) in the fostering of economic growth.[1] Discrepancies in the level of economic development mean that not all nations were able to devote substantial resources to R&D expenditure in the past decade.[2] However, the more critical concern for governments should be whether R&D resources are used efficiently. Efficient and productive R&D processes can provide the impetus for national competitive advantages (Werner and Souder, 1997). Conversely, inefficient usage of national R&D resources slows economic development. Therefore, evaluating R&D

Correspondence: Jin-Li Hu, Institute of Business and Management, National Chiao Tung University, 118 Chung-Hsiao W. Rd., Sec. 1, Taipei City 100, Taiwan. Tel: +886-2-23812386 × 57641; Fax: +886-2-23494922; Email: jinlihu@gmail.com. The authors are indebted to an editor, an associate editor, and two anonymous referees of this journal for their helpful comments. The authors also thank seminar participants at National Taiwan University and Ming Chuan University. Partial financial support from Taiwan's National Science Council (NSC-99–2410-H-009–063) is very much appreciated. Responsibility for any errors remains with the authors.

[1] See Acemoglu *et al*. (2006) for a comprehensive survey of the theoretical and empirical literature on the innovation-economic growth nexus.
[2] See both Main Science and Technology Indicators of OECD and World Development Indicators online.

efficiency across nations and understanding its determinants are the prerequisites for designing R&D policies to improve resource allocation.

The parametric approach of stochastic frontier analysis (SFA) and the non-parametric approach of data envelopment analysis (DEA) are major methods of evaluating efficiency scores. SFA, which starts by estimating the production function, is more appealing than DEA, because it takes into account the statistical noise (Coelli *et al*., 2005). It is thought to be applicable to the estimation of technical efficiency drawn from a single output production function. From a national perspective, R&D outputs are multidimensional, including patents, royalties and licensing fees (RLF) and academic publications. It is therefore difficult to compare the R&D efficiency of various national R&D programmes in the same context, which implies that the comparison of R&D efficiency across nations in terms of one output may only provide a partial view of national R&D efficiency. Mindful of this potential limitation, the main purpose of this paper is to apply the distance function approach to the multiple input–output framework of SFA in order to compare R&D efficiency across nations.

A nation's R&D environment, as per the national innovation system (NIS) proposed by Lundvall (1992) and Nelson (1993), is a crucial influence on R&D performance. Whether a nation can efficiently transform its R&D inputs into outputs is heavily dependent on the health of the R&D networks linking industry, government and academia.[3] Under the legal environment of stronger intellectual property rights (IPR) protection, the frequent interaction through joint activities between R&D performers enables them to exchange ideas and research experience, which results in a more efficient R&D process (Tödtling *et al*., 2009). However, the influence of NIS on R&D efficiency is not well considered in the existing literature.

This paper mainly evaluates national R&D efficiency and aims to provide the following distinct types of empirical evidence. First, it estimates national R&D efficiency with reference to the multiple input–output R&D production process. It also explores the role of NIS, using the distance function approach of SFA proposed by Coelli and Perelman (2000). This approach not only possesses the advantages of DEA by considering multiple outputs and being free of behavioural assumptions, but also remedies its drawback of not considering the individual effect of each nation.[4] Second, as few studies have examined R&D efficiency at the national level, this study provides a fresh method to evaluate national R&D efficiency. Third, examining the relationship between NIS and national R&D efficiency can provide insightful policy implications for each individual nation to help establish a healthy and well-functioning environment. These should in turn help foster economic development and improve the allocation of R&D resources.

The remainder of this paper is organized as follows: Section II briefly reviews literature regarding the evaluation of national R&D efficiency. Section III proposes the empirical methodologies and introduces the dataset. Section IV displays the estimated R&D efficiency scores and conducts model tests. Section V explores the impacts of NIS factors on national R&D efficiency. The final section includes concluding remarks and policy implications.

II. LITERATURE REVIEW

Two main streams are used to evaluate national R&D efficiency. The first uses the technique of DEA to capture the multiple outputs feature of R&D activity. Lee and Park (2005) compared

[3] The interaction between universities, industrial enterprises and public research institutions within the NIS is the so-called triple-helix (Etzkowitz and Leydesdorff, 1997, 2000).

[4] As for examining the determinants of inefficiency, two-stage (or three-stage) DEA may encounter the problem of inconsistent estimates due to the inadequate assumptions on error term distributions of various stages (Kumbhakar and Lovell, 2000).

R&D efficiency across 27 nations by considering three kinds of output: technological balance, articles and patents. Their results showed that Singapore ranks highly in terms of total efficiency, whereas patent-oriented efficiency is distinctive in Japan. Meanwhile, China, Korea and Taiwan were found to be relatively inefficient with regard to their R&D resource allocation across Asia. The characteristics of Asian nations that affect R&D efficiency were then identified. Considering two outputs of patents and scientific journal articles, Wang and Huang (2007) evaluated national R&D efficiency across 30 nations using the three-stage DEA. Their results showed that less than one-half of the nations are fully efficient in R&D activities, and that more than two-thirds are at the stage of increasing returns to scale. Sharma and Thomas (2008) considered patents and scientific journal articles as outputs to examine the relative efficiency of the R&D process across 22 developed and developing nations. They found some developing nations emerging on the efficiency frontier, indicating that these can also serve as benchmarks for their efficient use of R&D resources.

The other line of literature uses the parametric approach of SFA, while the technical efficiency of the production function is estimated using a single output. The drawback is that this approach compares national R&D efficiency without adequately dealing with the feature of multiple R&D outputs at the national level. Wang (2007) used the weights to integrate multiple to single outputs and then employed SFA to evaluate R&D efficiency across the sampled nations. Fu and Yang (2009) estimated the innovation production frontier for a panel of 21 OECD nations. However, they only considered patents as a proxy for output. Evaluating national R&D efficiency in terms of a single output may only lead to a partial view of national R&D performance.

This literature review demonstrates how, despite the DEA approach taking multiple outputs into account, it cannot simultaneously consider the environmental factor, the consistency of statistical distribution in various stages, and the decision-making unit's (DMU) individual effects when evaluating the R&D efficiency scores. The main drawback of the SFA approach is that it cannot include multiple outputs in its analysis. However, it can capture the statistical noise produced by random disturbance.[5] In light of these shortcomings, this study attempts to compare national R&D efficiency by applying the distance function approach to the multiple input–output framework of SFA. Moreover, this approach can simultaneously recognize the relationship between NIS and national R&D efficiency.

III. EMPIRICAL METHODOLOGY AND DATA

Following Farrell's (1957) concept that evaluates efficiency measures by estimating the frontier production function, many researchers have refined this approach to efficiency evaluation of time-varying panel data model.[6] If efficiency varies, then it is natural to explore the determinants of efficiency variation. Early studies examined the determinants of efficiency scores using the two-stage approach developed by Pitt and Lee (1981). The first stage is specifying the stochastic frontier function to estimate technical efficiency. The second stage identifies the determinants of technical inefficiency by conducting adequate regression analysis. However, the two-stage procedure involves inconsistent assumptions regarding the identical distribution of efficiency effects in the two estimation stages. Kumbhakar *et al*. (1991) and Battese and Coelli (1995) developed a single-stage approach that directly incorporated explanatory variables into the efficiency error component. The Monte Carlo simulation shows that the two-stage models may

[5] For more detailed comparative discussions of the advantages and disadvantages of SFA and DEA, see Coelli *et al*. (2005).
[6] For the development of SFA models, see Battese and Coelli (1995).

be seriously biased, which suggests the single-stage SFA is more adequate (Wang and Schmidt, 2002).

This study expands the firm level innovation production function proposed by Pakes and Griliches (1984) to the national level. In one nation's R&D production process, R&D expenditure stock and R&D manpower are the inputs used to produce multiple outputs, including patents, royalties and licensing fees (RLF), and scientific journal articles. This study thus applies the distance function approach of SFA to evaluate the national R&D efficiency by considering multiple outputs. This approach is more flexible since it can estimate the production function of multiple outputs without needing to specify a behavioural objective such as profit maximization or cost minimization (Coelli *et al*., 2005). Crucially, this approach can simultaneously estimate the parameters of the distance function and the efficiency effects of NIS factors.

III.1 The distance function approach for R&D efficiency

As the objective of R&D activities focuses on producing new and original outputs rather than saving R&D inputs, this study employed the output distance function approach. An output-expanding approach was applied to the measurement of the distance, which is the maximal proportional expansion of output vector, given an input vector. According to Shephard's (1970) specification, the output distance function can be defined as follows:

$$D_{\mathrm{O}}(X, Y) = \min\left\{\theta : \left(\frac{Y}{\theta}\right) \in P(X)\right\}, \tag{1}$$

where $P(X)$ presents the output sets of the production technologies that describe the sets of output vectors that are feasible for each input vector X. That is:

$$P(X) = \{Y : X \,\text{can produce}\, Y\}. \tag{2}$$

This gives the minimum amount by which an output vector can be deflated and remains producible with a given input vector. The output distance function $D_{\mathrm{O}}(X, Y)$ is non-decreasing, positively linearly homogeneous and convex in Y, and non-increasing in X (Kumbhakar and Lovell, 2000). $D_{\mathrm{O}}(X, Y) \leq 1$ and $D_{\mathrm{O}}(X, Y) = 1$ represent how Y belongs to the production possibility set of ($Y \in P(X)$) and Y is located on the frontier of the production possibility set of X, respectively.

The formulation of the output distance function defined in Equations (1) and (2) can be specified as:

$$D_{\mathrm{O}}(X, Y) = f(X, Y, \delta)\, e^{\lambda+\nu} \tag{3}$$

where δ is a vector of unknown coefficients to be estimated, term λ captures the individual-specific effect of a nation which is invariant with time,[7] and term ν is the random disturbance term, capturing the statistical noise, which is assumed to be $iidN(0, \sigma_{\nu}^{2})$.

An appropriate functional form $f(\cdot)$ in Equation (3) should ideally be flexible, easy to calculate, and permit the imposition of homogeneity. A commonly used functional form of production is the translog form, which satisfies the above criteria and has been widely adopted in previous studies (Grosskopf *et al*., 1996; Coelli and Perelman, 2000). The Cobb–Douglas form is the alternative functional form that satisfies only the latter two criteria, because of the restrictive elasticity of substitution and scale property. This study used the likelihood ratio (LR) test to identify whether the Cobb–Douglas functional form or the translog specification was the most adequate. The translog distance function with M outputs and J inputs in the year t is

[7] This study follows the 'true fixed-effects' model of Greene (2005), in which fixed effects are estimated by dummy variables.

specified as:

$$\ln D_{Ont} = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{nt}^m + \frac{1}{2}\sum_{m=1}^{M}\sum_{k=1}^{M} \alpha_{mk} \ln y_{nt}^m \ln y_{nt}^k + \sum_{j=1}^{J} \beta_j \ln x_{nt}^j$$
$$+ \frac{1}{2}\sum_{j=1}^{J}\sum_{h=1}^{J} \beta_{jh} \ln x_{nt}^j \ln x_{nt}^h + \sum_{m=1}^{M}\sum_{j=1}^{J} \psi_{mj} \ln y_{nt}^m \ln x_{nt}^j + \lambda_n + \nu_{nt},$$
$$n = 1, \ldots, N \quad \text{and} \quad t = 1, \ldots, T \tag{4}$$

where n denotes the n-th DMU in the sample. The restriction of linear homogeneity in outputs requires:

$$\sum_{m=1}^{M} \alpha_m = 1,\ \sum_{m=1}^{M} \alpha_{mk} = 0, m = 1, \ldots, M; \quad \text{and} \quad \sum_{m=1}^{M} \psi_{mj} = 0, j = 1, \ldots, J. \tag{5}$$

Furthermore, the restriction of symmetry requires:

$$\alpha_{mk} = \alpha_{km}, m, k = 1, \ldots, M, \quad \text{and} \quad \beta_{jh} = \beta_{hj}, j, h = 1, \ldots, J. \tag{6}$$

One essential problem in estimating Equation (4) is that the dependent variable $\ln D_{Ont}$ is unobservable. Fortunately, we can solve this problem by imposing the linear homogeneity in outputs (Lovell *et al*., 1994; Färe and Primont, 1995):

$$\ln\left(\frac{D_{Ont}}{y_{nt}^M}\right) = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \tilde{y}_{nt}^m + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{k=1}^{M-1} \alpha_{mk} \ln \tilde{y}_{nt}^m \ln \tilde{y}_{nt}^k + \sum_{j=1}^{J} \beta_j \ln x_{nt}^j$$
$$+ \frac{1}{2}\sum_{j=1}^{J}\sum_{h=1}^{J} \beta_{jh} \ln x_{nt}^j \ln x_{nt}^h + \sum_{m=1}^{M-1}\sum_{j=1}^{J} \psi_{mj} \ln \tilde{y}_{nt}^m \ln x_{nt}^j + \lambda_n + \nu_{nt}$$
$$n = 1, \ldots, N \quad \text{and} \quad t = 1, \ldots, T \tag{7}$$

where $\tilde{y}_{nt}^m = y_{nt}^m / y_{nt}^M, m = 1, \ldots, M-1$. Equation (7) can be rewritten as:

$$-\ln y_{nt}^M = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \tilde{y}_{nt}^m + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{k=1}^{M-1} \alpha_{mk} \ln \tilde{y}_{nt}^m \ln \tilde{y}_{nt}^k + \sum_{j=1}^{J} \beta_j \ln x_{nt}^j$$
$$+ \frac{1}{2}\sum_{j=1}^{J}\sum_{h=1}^{J} \beta_{jh} \ln x_{nt}^j \ln x_{nt}^h + \sum_{m=1}^{M-1}\sum_{j=1}^{J} \psi_{mj} \ln \tilde{y}_{nt}^m \ln x_{nt}^j + \lambda_n + \nu_{nt} - \ln D_{Ont},$$
$$n = 1, \ldots, N \text{ and } t = 1, \ldots, T. \tag{8}$$

We next replace the unobservable component $-\ln D_{Ont}$ by the non-negative random term u_{nt} that is assumed to be independently distributed, truncated at zero of $N(u, \sigma_u^2)$, and independently distributed of ν_{nt}. The predicted value of the output distance for the n-th DMU, $\hat{D}_{Ont} = \exp(-u_{nt})$, is unobservable, because u_{nt} only appears as part of the composed error term, $\varepsilon_{nt} = \nu_{nt} + u_{nt}$. The conditional expectation of u_{nt}, given $\varepsilon_{nt} = \nu_{nt} + u_{nt}$, is used to obtain the predicted value of the output distance function. The output distance would hence be predicted as:

$$\hat{D}_{Ont} = E\left[\exp\left(-u_{nt}\right) | \varepsilon_{nt}\right] \tag{9}$$

which is consistent with the Farrell output-oriented measure of technical efficiency (Kumbhakar and Lovell, 2000). Equations (8) and (9) can be estimated using the maximum likelihood method (Coelli and Perelman, 2000).

As the one-step model is more adequate (Wang and Schmidt, 2002), we further specify the efficiency model as follows:

$$-u_{nt} = \delta_0 + \delta_1 IPRP_{nt} + \delta_2 HUM_{nt} + \delta_3 TechCoop_{nt} + \delta_4 KT_{nt} + \delta_5 RDF_{nt} + \delta_6 SGRD_{nt} + \omega_{nt}, \tag{10}$$

where $-u_{nt} = \ln D_{Ont}$ and the random disturbance ω_{nt} is assumed to be independently distributed as truncated at zero of:

$$N\left(-(\delta_0 + \delta_1 IPRP_{nt} + \delta_2 HUM_{nt} + \delta_3 TechCoop_{nt} + \delta_4 KT_{nt} + \delta_5 RDF_{nt} + \delta_6 SGRD_{nt}), \sigma_u^2\right)$$

Therefore, this study can simultaneously estimate the parameters of distance function and the efficiency model.

III.2 Data and description of inputs and outputs

This study collected a panel dataset of 24 nations, including 16 European, four Asian, and four North and South American, from 1998 to 2005.[8] The two inputs were R&D expenditure stock and full-time researchers and technicians.[9] Due to the unavailability of data on R&D expenditure stock, this study converted R&D expenditure flow into R&D expenditure stock using the perpetual inventory method. The R&D expenditure stock is defined as follows:

$$K_t = K_{t-1}(1-\delta) + R_{t-1} \tag{11}$$

where K_t and K_{t-1} are the respective R&D expenditure stock in the current year and previous year, δ is the depreciation rate of stock, and R_{t-1} is the R&D expenditure flow in the previous year. If the R&D series starts in year $t = 1$ and the pre-sample accumulation of stock is given by Equation (11) with R&D growing at a fixed rate of$g$, then the R&D expenditure stock at the beginning of the first year is defined by the following equation:

$$K_1 = R_0 + (1-\delta)R_{-1} + (1-\delta)^2 R_{-2} + \cdots = \sum_{s=0}^{\infty} R_{-s}(1-\delta)^s = R_0 \sum_{s=0}^{\infty}\left[\frac{1-\delta}{1+g}\right]^S = \frac{R_1}{g+\delta}, \tag{12}$$

The assumed depreciation rate of R&D expenditure was 15 percent (Hall and Mairesse, 1995; Mairesse and Hall, 1996). Moreover, the growth rate is set to be an individual nation's average annual rate of growth of R_t (Guellec and van Pottelsberghe de la Potterie, 2004).

The three outputs included patents, RLF and scientific journal articles. Patents are the most widely adopted R&D output measure in the existing literature. However, the simple count of patent applications at home is likely to be biased due to the home advantage for patent applications and the qualitative difference in patents between nations. We adopted the number of patent applications in the European Patent Office (EPO) and the US Patent and Trademark Office (USPTO), because they provided the clearest indication of R&D performance and can be treated as 'new-to-the-world' innovations.[10] RLF reflect the ability to sell advanced technologies, and they can be treated as one of the direct commercial outputs from a nation's R&D activities.

[8] The 24 nations were Belgium, the Czech Republic, Finland, France, Germany, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Spain, Romania, Slovenia, the United Kingdom, Israel, Japan, South Korea, the Russian Federation, Singapore, Argentina, Mexico, Canada, and the United States.

[9] Total R&D expenditure refers to both the public and private sector and covers the expenditure of basic research, applied research and experimental development, such as land, buildings, instruments and equipment, and other current costs of creative work undertaken systematically to increase the stock of knowledge.

[10] For the pitfalls and advantages of equating patent counts with innovation, see Furman *et al.* (2002) for a survey.

TABLE 1
Summary statistics of input and output variables

ID	*Name*	*Mean*	*SD*	*Maximum*	*Minimum*
	Output variables				
y^1	Patents[a]	16556.1	43277.0	240902.8	15.71
y^2	Scientific journal articles[b]	21428.6	39326.1	205320	623
y^3	Royalty and licensing fees[b] (million US$ in year 2000)	346.2	925.1	5631.103	0.143
	Input variables				
x^1	Total R&D manpower[a] (full-time equivalent units)	230297.2	344040.9	1415873	6805
x^2	R&D expenditure stocks[c] (million US$ in year 2000)	137276.3	309116.1	1600433	2080.073

Sources: [a]Main Scientific Technology Indicators, Paris: OECD. [b]World Bank: World Development Indicators database. [c]R&D expenditure flows are collected from Main Scientific Technology Indicators, Paris: OECD, then transformed into R&D expenditure stocks using the perpetual inventory method.

Journal articles published in the scientific and engineering fields are considered another major output of research that is widely used to evaluate the performance of researchers (OECD, 2001). This study counted the number of journal articles published in physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences, as one of the outputs. Since the dataset covered eight years, we transformed all variables in monetary units into real variables in terms of a million US dollars in the year 2000. Table 1 displays summary statistics and data sources of the input and output variables.

III.3 Variable description of efficiency model

With regard to the explanatory variables in Equation (10), the term *IPRP* is the strength of IPR protection, representing the legal environment. This study adopted the IPR index surveyed by the International Institute for Management Development (IMD). A higher value on the index indicates a stronger level of protection. This index has been widely adopted, and found to be highly correlated with the Ginarte–Park IPR index (Nunnenkamp and Spatz, 2003).[11] It should be positively related to R&D efficiency, as an environment with strong IPR protection is favourable for firms to undertake R&D activity and reduces the risk of imitation. The term *HUM* denoted the accumulation of human capital that is measured by the proportion of total education expenditure compared to GDP. A higher ratio strengthens the accumulation as well as the quality of human capital and, in turn, enhances R&D efficiency (Furman *et al*., 2002). Fu and Yang (2009) also indicated that a higher amount of investment in education strengthens national innovative capacity. Mastromarco (2008) found that human capital is a channel to improve technical efficiency in less-developed nations. Thus, a positive and significant coefficient for the *HUM* variable was expected.

The NIS focuses on a textured description of the organization and patterns of cooperative activity that contribute to innovative behaviour in a nation.[12] This study concentrated on two kinds of linkage among R&D performers. First, the term *TechCoop* denoted the strength of technological cooperation within the business sector in each nation. Second, the term *KT*

[11] Although the IPR index developed by Ginarte and Park (1997) has been adopted in previous studies, there is no consecutive index for our sample period of 1998–2005.
[12] See Nelson (1993) for a comprehensive review of the national innovation system.

described the strength of knowledge transfer between the business sector and higher education institutions. We adopted the measures surveyed by IMD – ranging from 0 to 10 – to capture the strength of technological cooperation and knowledge transfers. A higher value of *TechCoop* indicated more frequent technological cooperation among the business sector in a nation. Beath *et al*. (1998) characterized technological cooperation as a form of R&D joint venture that can economize scarce R&D resources and lower the unit cost. A nation with more technological cooperation among its business sector can cultivate a favourable environment for firms to learn advanced knowledge and further obtain the complements of the technology, resulting in an R&D efficiency-enhancing effect. A higher value of *KT* represents more frequent knowledge transfers between the business sector and higher education institutions. An environment full of knowledge transfer is helpful for firms to enhance their technological capability. The higher education sector can collaborate with industry and transfer academic researches into commercial applications, and it also benefits from the financial support of cooperative firms.

In addition, the R&D facilities play an important role in the development of new technologies. The IMD survey contains one index that measures whether the relocation of R&D facilities is a threat to the nation. A lower value of the index denotes this as a high threat. That is, the R&D facilities are more important for R&D activity. For the sake of clarity, we constructed the term *RDF*, which is calculated by 10 minus the IMD index. This new index also ranges from 0 to 10. A higher value of *RDF* implied the R&D facilities were more important, which meant that a nation's government would devote more effort to attracting the establishment of R&D facilities to promote national R&D activities. A positive relationship between RDF and R&D efficiency was expected.

Finally, the term *SGRD* denoted the degree to which the government sector was involved in the national R&D activities, measured by the ratio of government R&D expenditure to total R&D expenditure. Wang (2007) argued that the government's R&D is usually less efficient than the private sector's due to the interference of bureaucratic red tape. Conversely, Guellec and van Pottelsberghe de la Potterie (2004) argued that government R&D has a public mission to enhance the stock of knowledge for society by focusing on basic research that may have positive effects on national R&D efficiency. Thus, the influence of *SGRD* is uncertain. Table 2 summarizes the definition and data sources of all variables in the efficiency model.

IV. ESTIMATION OF DISTANCE FUNCTION AND R&D EFFICIENCY

IV.1 Estimation results of distance function

Table 3 presents the results obtained by estimating the distance function of SFA and model diagnosis.[13] The estimated sign and significance of coefficients on inputs and outputs were as expected, implying that the properties of non-decreasing in Y and non-increasing in X were satisfied in the output distance function. Although there were some insignificant values, the magnitude of inputs and transformed output variables were also as expected and fulfilled the properties of monotonicity.[14] We also applied the LR test for separability between inputs and

[13] R&D expenditure and the number of researchers may overlap. The salary of part-time R&D manpower is sometimes included in the accounting title of R&D expenditure. While this double counting problem is not serious, we also estimated the empirical model, including only R&D expenditure as the independent variable, and obtained similar results. We then adopted the likelihood ratio test to determine which model is more appropriate. Finally, we confirmed that the specification of including two inputs was the most adequate.

[14] See Färe and Primont (1995) for more details about the properties of the output distance function.

TABLE 2
Definition of independent variables in the efficiency model

Variables	*Definition*	*Mean*	*SD*
IPRP	The degree of intellectual property rights protection (0–10)	6.3740	1.7089
HUM	The percentage of total education expenditure on GDP (%)	5.2785	1.4123
TechCoop	The strength of technological cooperation in the business sector (0–10)	5.3229	1.2991
KT	The strength of knowledge transfer between the business sector and higher education institutions (0–10)	4.5415	1.3819
RDF	The importance of the R&D facilities' agglomeration (0–10)	4.9913	1.0368
SGRD	The share of government R&D expenditure in total R&D expenditure (%)	0.3985	0.1425

Sources: IPRP, TechCoop, KT and RDF were collected from International Institute of Management Development: World Competitiveness Yearbook. HUM and SGRD were collected from World Bank: World Development Indicators database and Main Scientific Technology Indicators, Paris: OECD, respectively.

outputs: $H_0 : \psi_{mj} = 0, m = 1, \ldots, 3, j = 1$ and 2. The value of the LR test was 114.1758, which proved significantly larger than the critical value 13.28 ($= \chi^2_{4,0.01}$). This suggested that the input–output separability model could be rejected. This is reasonable since efficiency measures take outputs and inputs into account. Therefore, we were unable to judge whether the production of output is efficient without the input vector, and vice versa.

The estimated σ^2 and γ were significantly greater than zero, which showed that the sum of the variance of the error component, and the ratio of the variance of u_{nt} to error component, were substantial. It suggested that the random variables of v_{nt} and u_{nt} need to be considered in the R&D efficiency evaluation. Specifically, the estimated $\gamma = 0.9819$ indicated that the variance of technical inefficiency was the major source of total variance for both technical inefficiency and random noises. Also, the statistic of the LR test for an absence of technical inefficiency was 108.8564, which was larger than the critical value 20.09 ($= \chi^2_{8,0.01}$). This indicated that the null hypothesis of no technical inefficiency effects in R&D across nations should be rejected.

It remained to be determined whether the Cobb–Douglas formulation or the translog specification was a more adequate representation of the production function. We tested the null hypothesis that the square-term of inputs and outputs and interaction terms between inputs and outputs are simultaneously zero. As shown in the lower part of Table 3, the coefficients of the interaction terms between inputs and outputs, as well as the outputs square terms, were statistically significant. The statistics of the LR test, 59.2369, was larger than the critical value 23.209 ($= \chi^2_{10,0.01}$). Hence, the null hypothesis that the distance function is the Cobb–Douglas form could be rejected. It follows that the specification of the translog functional form was a more satisfactory fit than the Cobb–Douglas functional form.[15]

Before discussing the estimated efficiency scores, we were attentive to the question of whether the efficiency scores were affected by y^M_{nt} in the distance function approach. This study included three outputs and treated each as one choice of y^M_{nt} when estimating R&D efficiency in the

[15] The Cobb–Douglas functional form is a first-order flexible form, but the translog functional form is a second-order flexible form. Coelli *et al*. (2005) indicated that the second-order flexible functional form is usually more preferable in the literature.

TABLE 3

Estimated results of the output distance function and efficiency model

Distance function		*Coefficients*	*Standard error*	*t-value*
Constant	Constant	11.0626[a]	1.1457	9.6551
$\ln \tilde{y}^1$	α_1	1.2292[a]	0.2699	4.5542
$\ln \tilde{y}^2$	α_2	0.2713	0.2865	0.9467
$\ln \tilde{y}^1 \ln \tilde{y}^1$	α_{11}	0.0996[a]	0.0486	2.0491
$\ln \tilde{y}^2 \ln \tilde{y}^2$	α_{22}	0.0764[c]	0.0416	1.8348
$\ln \tilde{y}^1 \ln \tilde{y}^2$	α_{12}	−0.1016[a]	0.0382	−2.6594
$\ln x^1$	β_1	−2.4648[a]	0.6114	−4.0309
$\ln x^2$	β_2	−0.7197	0.5996	−1.2001
$\ln x^1 \ \ln x^1$	β_{11}	0.2185	0.1458	1.4980
$\ln x^2 \ \ln x^2$	β_{22}	0.0635	0.1819	0.3492
$\ln x^1 \ \ln x^2$	β_{12}	−0.0202	0.1526	−0.1325
$\ln \tilde{y}^1 \ \ln x^1$	ψ_{11}	−0.1059[b]	0.0484	−2.1872
$\ln \tilde{y}^1 \ \ln x^2$	ψ_{12}	0.0137	0.0804	0.1707
$\ln \tilde{y}^2 \ \ln x^1$	ψ_{21}	0.0156	0.0852	0.1838
$\ln \tilde{y}^2 \ \ln x^2$	ψ_{22}	0.4221[a]	0.0708	5.9605
Efficiency model				
Constant	δ_0	−2.4316[a]	0.1527	−15.9227
IPRP	δ_1	0.0720[a]	0.0137	5.2250
HUM	δ_2	−0.0139	0.0124	−1.1214
TechCoop	δ_3	0.2185[a]	0.0399	5.4743
KT	δ_4	0.0926[a]	0.0250	3.6996
RDF	δ_5	0.0664[a]	0.0182	3.6340
SGRD	δ_6	0.9992[a]	0.1678	5.9547
$\sigma^2 = \sigma_v^2 + \sigma_u^2$		0.0211[a]	0.0027	7.5762
$\gamma = \sigma_u^2/\sigma^2$		0.9819[a]	0.0907	108.2253
Log-likelihood function				278.5257
LR test of one-sided error				108.8564[a]
LR test for H_0: Cobb–Douglas formation				59.2369[a]
No. of observations				192

Notes: The nation's individual fixed effect is included in the estimation of the distance function. The results of the distance function were estimated by using RLF as y_{nt}^M. The results of the efficiency model and the parameters of the distance function are simultaneously estimated by the maximum likelihood method.
[a], [b], and [c] represent significance at the 1%, 5%, and 10% levels, respectively.

distance function approach. If the efficiency scores are affected by different choices of y_{nt}^M, then an improper explanation of each nation's efficiency scores will be produced. This study thus tested whether the estimated efficiency scores were affected by using different choices of y_{nt}^M. According to the *H* statistic of the Kruskal–Wallis test displayed in Table 4, the result showed that the estimated R&D efficiency scores for each nation were unaffected by different choices of y_{nt}^M as we estimated the distance function.

IV.2 Estimation results of national R&D efficiency

Table 5 displays the R&D efficiency scores with and without NIS factors across regions and groups. As shown in the bottom of Table 5, the average R&D efficiency with NIS factors

TABLE 4

Results of the Kruskal–Wallis H test

Year	*1998*	*1999*	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*
H statistic	0.007	0.009	0.069	0.106	0.012	0.084	0.085	0.005
Null hypothesis	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept

Notes: The null hypothesis is that the estimated efficiency scores were unaffected by using different choices of y_{nt}^{M}. The critical value of the χ^2 distribution with *d.f.* 2 is 5.991 at the 5% level.

TABLE 5

R&D efficiency with/without NIS factors across regions and groups

	NIS factors	*1998*	*1999*	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*	*Average*
Regions										
Europe	with	0.8779	0.8817	0.9081	0.9149	0.9210	0.9365	0.9577	0.9478	0.9182
	without	0.4339	0.4399	0.4458	0.4517	0.4577	0.4578	0.4697	0.4757	0.4540
Asia	with	0.8159	0.8413	0.9007	0.8544	0.9239	0.9465	0.9753	0.9497	0.9010
	without	0.3024	0.3097	0.3171	0.3245	0.3319	0.3394	0.3469	0.3545	0.3283
America	with	0.8759	0.8959	0.9145	0.9188	0.9247	0.9243	0.9124	0.9001	0.9083
	without	0.3871	0.3927	0.3984	0.4041	0.4099	0.4157	0.4215	0.4274	0.4071
Groups										
OECD	with	0.8907	0.8983	0.9174	0.9194	0.9298	0.9444	0.9615	0.954	0.9269
	without	0.488	0.4941	0.5003	0.5065	0.5126	0.5188	0.5249	0.5311	0.5095
Non-OECD	with	0.7969	0.8144	0.8796	0.8636	0.8989	0.9112	0.9278	0.8986	0.8739
	without	0.1529	0.1588	0.1648	0.171	0.1772	0.1679	0.1901	0.1966	0.1724
Total	with	0.8673	0.8773	0.9079	0.9055	0.9221	0.9361	0.9531	0.9401	0.9137
	without	0.4042	0.4103	0.4164	0.4226	0.4288	0.431	0.4412	0.4475	0.4253

Notes: These efficiency scores were estimated by using the RLF as y_{nt}^{M}. Efficiency scores with and without NIS factors were estimated by the maximum likelihood method using the model of Battese and Coelli (1992, 1995).

was between 0.8673 and 0.9531. This implied that the potential for improvement of resource allocation was, on average, between 4.69 and 13.27 percent over the sampling periods. With regard to the average regional R&D efficiency with NIS factors, Asian nations had a lower overall R&D efficiency, whereas American and European nations experienced comparably high levels of R&D efficiency. However, Asian nations had higher overall R&D efficiency than the other two regions after 2002. As the Asian nations in the dataset included Japan and emerging 'technology tigers', such as Israel, South Korea and Singapore, this suggested that Asian nations are more efficient than the other two regions. On the other hand, the average R&D efficiency of OECD nations is obviously higher than that of non-OECD nations. Since OECD members are advanced nations with better R&D management skills, this result suggested that making well-designed policies is important to national R&D activities.

Comparing two sets of results in Table 5, several interesting findings are worth noting. First, when taking the National Innovation System (NIS) factors into account, the estimated R&D efficiency scores for all regions and groups are larger than those obtained without including the NIS effect. This finding implies that without considering NIS factors, the penalty incurred by regions or groups operating under a less healthy NIS will be larger than the benefit brought about by operating under a robust NIS. Second, the average gaps in R&D efficiency between Asian and European nations were 0.0172 and 0.1257, with and without taking the external effects into account, respectively. The corresponding gaps between Asian and American nations were 0.0073 and 0.0788, respectively. This highlights the importance of constructing a healthy

TABLE 6
National R&D efficiency with/without NIS factors during 1998—2005

	With NIS factors					*Without NIS factors*				
Nations	*Mean*	*Min*	*Max*	*Groups*	*Rank*	*Mean*	*Min*	*Max*	*Groups*	*Rank*
Belgium	0.9329	0.8532	0.9897	2	14	0.4594	0.4308	0.4876	2	10
Czech	0.9021	0.7873	0.9913	2	18	0.2515	0.2242	0.2793	3	15
Finland	0.9824	0.9530	0.9929	1	1	0.4288	0.3999	0.4575	2	11
France	0.9659	0.9388	0.9883	1	9	0.8361	0.8239	0.8477	1	4
Germany	0.9801	0.9745	0.9911	1	2	0.9511	0.9472	0.9548	1	2
Hungary	0.9666	0.9207	0.9895	1	8	0.2301	0.2036	0.2572	3	17
Ireland	0.9570	0.8745	0.9876	1	12	0.2242	0.1979	0.2511	3	18
Italy	0.9162	0.8442	0.9842	2	16	0.7393	0.7212	0.7567	1	5
Netherlands	0.9714	0.9370	0.9947	1	4	0.5733	0.5477	0.5983	2	8
Poland	0.9281	0.8693	0.9874	2	15	0.3288	0.2999	0.3579	2	13
Portugal	0.8107	0.6089	0.9853	3	20	0.1606	0.1378	0.1843	3	20
Romania	0.7798	0.6535	0.9250	3	22	0.0502	0.0389	0.0626	3	24
Spain	0.9400	0.9200	0.9794	2	13	0.6064	0.5820	0.6302	2	6
Slovenia	0.7391	0.5237	0.9762	3	24	0.0856	0.0105	0.1159	3	23
UK	0.9582	0.9281	0.9899	1	11	0.9756	0.9736	0.9775	1	1
Russia	0.9608	0.9125	0.9906	1	10	0.3637	0.3345	0.3929	2	12
Japan	0.9672	0.9238	0.9855	1	7	0.5921	0.5672	0.6165	2	7
S. Korea	0.7579	0.5183	0.9896	3	23	0.3230	0.2941	0.3521	2	14
Israel	0.9103	0.7454	0.9832	2	17	0.2315	0.2049	0.2586	3	16
Singapore	0.9685	0.8687	0.9932	1	6	0.1666	0.1433	0.1907	3	19
Argentina	0.8848	0.7921	0.9822	2	19	0.1370	0.1159	0.1590	3	21
Canada	0.9711	0.9310	0.9937	1	5	0.5255	0.4985	0.5522	2	9
Mexico	0.8053	0.7355	0.8493	3	21	0.1247	0.1047	0.1458	3	22
U.S.A.	0.9721	0.9452	0.9931	1	3	0.8412	0.8294	0.8525	1	3
Average	0.9137	0.8316	0.9797			0.4253	0.4013	0.4475		
Two-sample mean test (H_0: *with* is smaller than *without*)					$t = 8.1475^*$	Mann–Whitney U test (H_0: *with* is indifferent from *without*)			$Z = 5.011^*$	

Notes: These efficiency scores were estimated by using the royalties and licensing fees as y_{nt}^{M}. Efficiency scores with and without NIS factors were estimated by the maximum likelihood method using the model of Battese and Coelli (1992, 1995). The group was classified by K-means clusters analysis. Notations 1, 2, and 3, represent good, middle, and poor groups, respectively.
*represents significance at the 1% level.

and well-functioning NIS for Asian nations to facilitate R&D, in order to catch up with their European and American counterparts. Finally, the average gaps in the efficiency scores between OECD and non-OECD nations were, respectively, 0.053 and 0.3372, with and without taking the external effects into account. Non-OECD nations normally devote fewer resources to R&D relative to OECD nations. They can improve their R&D efficiency by enacting appropriate policies and constructing a well-functioning NIS, which will help to reduce any discrepancies between their R&D efficiency relative to OECD nations. In sum, these findings confirmed that NIS indeed plays a pivotal role in promoting R&D efficiency for regions and groups.

Table 6 displays the levels of national R&D efficiency obtained with and without considering NIS factors during the sampling periods. An efficiency score close to unity means that a nation has a more efficient R&D production process. When taking NIS factors into account, Finland, Germany, the Netherlands, Canada and the United States had a higher R&D efficiency score – greater than 0.97, on average. Moreover, France, Hungary and the UK had R&D efficiency scores that were higher than 0.95, on average. For Asian nations, the R&D efficiency scores of Japan and Singapore were higher than the average during the sampling periods. On the other hand, the R&D efficiency of Romania and Slovenia was lower from 1998 to 2005. Compared with developed nations, emerging economies generally lack high-quality R&D personnel, well-established knowledge management, and other innovation complements, which limit their R&D efficiency. Therefore, emerging nations cannot efficiently transform R&D inputs into outputs. This is the reason why the emerging nations experienced lower national R&D efficiency than their developed counterparts.

Table 6 also displays the ranking and classification of each nation according to two scenarios. The sampled nations are classified into three groups by cluster analysis. Compared with the results of the two scenarios in Table 6, we first discovered that the average R&D efficiency scores of all nations became larger after the NIS factors were taken into account. This difference is supported by using the two-sample mean test and the Mann–Whitney U test, as shown in the bottom of Table 6. Second, the number of group members with higher efficiency scores increased from five nations to twelve when considering NIS factors. Finland, the Netherlands, Russia, Japan and Canada switch from the second group to the first after considering NIS factors. Additionally, the classification of Hungary, Ireland and Singapore jumps from the last group to the first after considering NIS factors. This implies that a well-functioning NIS is essential for these nations. Finally, when considering NIS factors, ten of 24 nations improved their rankings significantly. Specifically, Finland ranked first and eleventh on R&D efficiency with and without taking NIS factors into account, respectively. The corresponding rankings of Singapore are sixth and nineteenth, respectively. Again, these findings support the claim that NIS indeed plays a crucial role in improving national R&D efficiency.

V. THE RELATIONSHIP BETWEEN NATIONAL R&D EFFICIENCY AND NIS

As discussed in the previous section, constructing a well-functioning NIS is critical to the enhancement of R&D efficiency. This section further examines how the interaction of triple helix within the NIS affects R&D efficiency. The middle part of Table 3 displays the estimated influence of NIS factors on efficiency. First, the estimated coefficient of *IPRP* is significantly positive, implying that a stronger IPR protection provides a favourable R&D environment and then induces a higher R&D efficiency, *ceteris paribus*. However, the R&D efficiency score seems not to be significantly influenced by the investment of human resources.

Second, we turn to an investigation of potential impacts of the interaction of various R&D performers within a nation. The coefficient of *TechCoop* is associated with a significantly positive sign. That is, more cooperative R&D activities among the business sector not only enhance the level of R&D itself, but also help obtain complementary technologies from cooperating firms. From the viewpoint of NIS, more interaction among business sectors can further enhance the national R&D efficiency. On the other hand, the coefficient of *KT* is positive and significant at the 1 percent statistical level. This suggests that a nation with a close linkage of knowledge transfer between higher education institutions and the business sector is helpful in transferring academic R&D outputs into commercial technologies. In other words, firms can improve their R&D performance by frequently collaborating with universities and research organizations (Tödtling *et al*., 2009). From the perspective of higher education institutions, cooperation with firms can help them obtain more financial support to sustain their R&D activities. Since a well-functioning NIS depends on the interaction of various

R&D performers, more intensive interactions between business and academic sectors can enhance the national R&D efficiency through the exchange of ideas and knowledge spillover. The above finding implies that, policy-wise, the government should enhance the mechanisms of knowledge transfer from higher education institutions to the private sector, as it is beneficial to promote national innovative capacity and improve national R&D efficiency.

Third, we find that the estimated coefficient of *RDF* is positive and significant at the 1 percent statistical level, which supports the claim that R&D facilities make important contributions to the improvement of national R&D efficiency. This result suggests that devoting greater efforts to attracting more multinationals and local enterprises to establish R&D facilities is beneficial to domestic R&D efficiency. Indeed, many nations have established science parks and enacted various R&D measures to attract knowledge-intensive enterprises to set up R&D facilities, as the agglomeration of R&D facilities can enhance national innovative capability and improve national R&D efficiency.

Finally, it is important to understand the role that government R&D plays in national R&D efficiency. Does more government R&D improve national R&D efficiency? We found that a nation with a high ratio of public-funded R&D tends to experience higher R&D efficiency. This is consistent with the findings of Guellec and van Pottelsberghe de la Potterie (2004) and Wang (2007). Government R&D generally focuses on basic research, with a view to developing the fundamental technologies needed to meet the needs of industrial upgrading. It also serves as the groundwork of national R&D activity to enhance the national R&D efficiency. Wang (2007) indicated that the reduction of bureaucratic red tape is beneficial to domestic R&D performance when the government is directly involved in national R&D activities. Hence, government R&D overall has a significantly positive impact on national R&D efficiency.

VI. CONCLUDING REMARKS AND POLICY IMPLICATIONS

To attain stable and sustainable growth, most nations have aggressively invested in R&D activities. However, a more essential issue is the efficient utilization of R&D expenditure. Existing studies using SFA to estimate and compare R&D efficiency across nations adopt only one R&D output. This study differs by applying the distance function approach to estimate national R&D efficiency through the inclusion of multiple R&D outputs in its stochastic frontier approach. Using a panel dataset of 24 nations from 1998 to 2005, this study simultaneously estimated the translog distance function and the determinants of national R&D efficiency, especially for the role of NIS.

The average R&D efficiency manifested as a relatively stable magnitude between 0.8673 and 0.9531, indicating that the potential for improvement ranges from 4.69 to 13.27 percent. It was also found that the gaps in R&D efficiency between Asia and Europe, as well as between Asia and the Americas, are reduced after NIS factors are taken into account. For Asian nations, this highlights the importance of NIS in terms of facilitating their R&D activities, and suggests that a healthy and well-functioning NIS can serve as a key strategy for technology catch-up. Similarly, non-OECD nations can improve their R&D efficiency by implementing adequate R&D policies and constructing a robust NIS to improve R&D efficiency and reduce their efficiency gap relative to OECD nations.

With regard to the relationship between NIS and national R&D efficiency, IPR protection is integral to the promotion of R&D efficiency. Technological cooperation in the business sector, and knowledge transfer between higher education institutions and the business sector, are positively related to national R&D efficiency. This finding supports the argument that an active NIS is characterized by close interactions among various R&D performers within a nation, which can promote technological capabilities and improve national R&D efficiency. Moreover, the agglomeration of R&D facilities and the government's R&D also play a considerable role in improving national R&D efficiency.

There are several key policy implications for national R&D activities. First, due to the essential feature of multiple outputs from the perspective of national R&D activities, national R&D efficiency cannot be properly evaluated by considering only a single output. Moreover, constructing a healthy and well-functioning NIS is a plausible strategy for developing nations to catch up developed nations. Second, in addition to direct devotion to R&D, government should make more effort by providing stronger IPR protection, clustering R&D laboratories, and establishing science parks as necessary. Third, since technological cooperation and knowledge transfer contribute to the improvement of national R&D efficiency, the government should try to establish a channel and implement adequate policies to enhance the interactions of R&D activities among various performers.

Finally, some directions for future research can be offered. First, this study focused on evaluating the overall R&D efficiency at the national level. If sufficient data becomes available, the R&D efficiency of individual sectors is certainly worthy of study in its own right. Moreover, a cross-national comparison of individual sectors' R&D efficiency could shed light on its determinants that might assist policymakers when designing R&D policies. Second, this study collected data on 24 nations and included only six non-OECD nations. Readily available data on more non-OECD nations, along with a sufficient period to contextualize it, would make the comparative study of R&D efficiency between non-OECD and OECD nations a realistic, and worthwhile, future possibility.

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