

Identification of DEA Determinant Input-Output Variables : an Illustration for Evaluating the Efficiency of Government-Sponsored R&D Projects

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DEA 효율성을 결정하는 입력-출력변수 식별 : 정부지원 R&D 과제 효율성 평가를 위한 실례

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In this study, determinant input-output variables are identified for calculating Data Envelopment Analysis (DEA) efficiency scores relating to evaluating the efficiency of government-sponsored research and development (R&D) projects. In particular, this study proposes a systematic framework of design and analysis of experiments, called “all possible DEAs”, for pinpointing DEA determinant input-output variables. In addition to correlation analyses, two modified measures of time series analysis are developed in order to check the similarities between a DEA complete data structure (CDS) versus the rest of incomplete data structures (IDSs). In this empirical analysis, a few DEA determinant input-output variables are found to be associated with a typical public R&D performance evaluation logic model, especially oriented to a mid- and long-term performance perspective. Among four variables, only two determinants are identified : “R&D manpower” (x_2) and “Sales revenue” (y_1). However, it should be pointed out that the input variable “R&D funds” (x_1) is insignificant for calculating DEA efficiency score even if it is a critical input for measuring efficiency of a government-sponsored R&D project from a practical point of view *a priori*. In this context, if practitioners’ top priority is to see the efficiency between “R&D funds” (x_1) and “Sales revenue” (y_1), the DEA efficiency score cannot properly meet their expectations. Therefore, meticulous attention is required when using the DEA application for public R&D performance evaluation, considering that discrepancies can occur between practitioners’ expectations and DEA efficiency scores.

Keywords: Data Envelopment Analysis, Design of Experiments and Analysis, Determinant Input-output Variables, Efficiency, R&D Performance Evaluation

1. Introduction

1.1 Motivation

The program logic model of public research and development (R&D) performance evaluation can be defined as a pictorial model that explains how a program does its work. The pro-

gram logic model links resources with planned activities and performance (Wholey, 1983; Bickman, 1987; Wholey, 1987; McLaughlin and Jordan, 1999). W. K. Kellogg Foundation (WKKF) (2004) classifies performance according to three different time periods : (1) short-term (1~3 years) outputs, (2) mid-term (4~6 years) outcomes and (3) long-term (7~10 years) impacts-most of which have occurred since the com-

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pletion of a program. Ruegg and Feller (2003) propose a program logic model for the performance evaluation of the Advanced Technology Program (ATP) at National Institute of Standards and Technology (NIST) under the U.S. Department of Commerce (DOC). McLaughlin and Jordan (1999) propose a flow-chart type program logic model to describe the process of “a research and technology development and deployment program” of the Office of Energy Efficiency and Renewable Energy (EERE) under the U.S. Department of Energy (DOE).

In recent years, the performance efficiency and effectiveness of public R&D investment has been analyzed using a variety of methodologies based on program logic models. Quantitative and qualitative evaluation obtained from the formative as well as the summative perspective can be fed back into subsequent decisions so as to enhance the overall relevance and accountability of an R&D program. For example, Government Performance Results Act (GPRA) was enacted by the U.S. Congress in 1993; all government affairs have been evaluated for performance since then (GPRA, 2003). Similarly, the Korean government also established a national R&D program performance assessment and management system in 2006; all activities and performance of each government-sponsored R&D project (i.e., GSP) is monitored yearly during the subsequent five-year performance follow-up period (MST · KISTEP 2007).

1.2 Statement of the Problem

Bitman and Sharif (2008) mention that Data Envelopment Analysis (DEA) is one of the representative methodologies for measuring R&D performance efficiency. But they point out that practitioners tend to be reluctant to use it due to its mathematical complexity. Rouse and Putterill (2003) proposed “an integral performance framework”; they discussed three major components: performance measurement, analysis and evaluation. Also, they selected three typical methods for the analysis of performance productivity-Stochastic Frontier Analysis (SFA), Total Factor Productivity (TFP) and DEA. Chiesa and Masella (1996) emphasized the importance of identifying tangible performance measures as a prerequisite step for successful R&D performance evaluation. Meanwhile, this study is initiated from pondering the three biggest difficulties in practical use of DEA as pointed out by Seiford and Thrall (1990): (1) model specification, (2) variables’ weights (i.e., multipliers) restrictions and (3) variables selection.

First, regarding model development and selection, a variety of DEA-related literature has been reported since the CCR (Charnes, Cooper and Rhodes) model was proposed. The CCR model is based on the assumption of Constant Returns

to Scale (CRS) for the first time (Charnes *et al.*, 1978). Then, the BCC (Banker, Charnes and Cooper) model was established with a Variable Returns to Scale (VRS) assumption, which can be regarded as a variant of the CCR model (Banker *et al.*, 1984). Additionally, Banker and Morey (1986a) developed a DEA model that can handle exogenously fixed variables. Banker and Morey (1986b) presented a mixed-integer programming-based DEA model to deal with categorical variables. Also, Charnes *et al.* (1985), widened the model selection, providing a DEA/Window Analysis (DEA/WA) model that can encompass the passage of time (i.e., dynamic) analysis. Applications of DEA-based Malmquist Index (MI) can be found, associated with analyzing R&D performance productivity changes between two points in time. Here, productivity changes are separated by two components : “catch-up” (i.e., rate of efficiency change) and “frontier-shift” (i.e., rate of technical change) (Wu *et al.*, 2006; Guan and Chen, 2010).

Second, to date some types of DEA multiplier constraints are designed with the aim of improving the reliability of the DEA efficiency score. Typically, two types of multiplier constraints are proposed : the Cone-Ratio (CR) model by Charnes *et al.* (1990) and the Assurance Region (AR) method by Thompson *et al.* (1990). Generally, AR multiplier constraints are classified into three subordinate types as follows : (1) absolute Weights Restrictions (WRs), (2) relative WRs or AR Type I (AR-I), (3) input-output WRs or AR Type II (AR-II) (Cooper *et al.*, 2004). Furthermore, the AR Global Model (ARGM) can restrict virtual input-virtual output (Wong and Beasley, 1990; Allen *et al.*, 1997; Pedraja-Chaparro *et al.*, 1997). Asmild *et al.* (2007) also reported experimental results on the sensitivity of DEA efficiency scores associated with CR model-type multiplier constraints.

But, disappointingly, it is still not easy to find DEA-related literature with empirical analyses as well as theoretical discussions explaining a systematic procedure, especially for DEA input-output variables selection, sampling of homogeneous data (i.e., outliers elimination) and so on. Particularly, due to the model’s aforementioned mathematical complexity, practitioners tend to doubt DEA efficiency scores. Regarding DEA input-output variables like this, they may ask : “Do they really work in the calculation of DEA efficiency scores in accordance with their own importance?” But until now, the literature has not offered many clear-cut answers about that.

With this question in mind, this study aims to bridge this gap. First, determinant input-output variables are identified that overwhelm the other remaining insignificant variables in DEA efficiency score calculation when evaluating the efficiency of government-sponsored R&D projects. Second, it is examined whether or not determinants match the variables that practitioners consider relatively more important a priori. Fi-

nally, statistical characteristics are summarized using an empirical analysis. In particular, the experimental design and analysis framework developed in this study with so-called “all possible DEAs” is based on the concept of “all possible regressions”-that is, a typical regression variable selection and model building procedure. In addition to correlation analyses, two modified accuracy measures of time series analysis are developed and examined in order to check the similarities between a DEA complete data structure (CDS) versus incomplete data structures (IDSs). Section 2 of this paper provides background and theory, Section 3 provides design of experiments, Section 4 provides analysis of experiments and Section 5 offers practical implications and conclusions.

2. Background and Theory

2.1 R&D Performance Evaluation and Generic Program Logic Models

<Figure 1> is a generic program logic model for public R&D performance evaluation (McLaughlin and Jordan, 1999; Ruegg and Feller, 2003; WKKF, 2004). In particular, Ruegg and Feller (2003), illustrate some representative factors of the inputs as well as the three-phased subsequent performance in the ATP Toolkit, Part I. Inputs include budget, staff, etc. Meanwhile, some intellectual property-related outputs are listed including publications and patents. Commercialization-related outcomes are new-improved products, processes

and services, firm growth, etc. For the socio-economic long-term impacts, we can see employment gains, international competitiveness and so on.

Lee *et al.* (2009), utilize a DEA/AR model in their public R&D performance efficiency study in order to consider the importance of input-output variables associated with six heterogeneous R&D programs. Hsu and Hsueh (2009), evaluate DEA efficiency of 110 GSPs; consequently, they emphasize the need for an appropriate upper limit on the ratio of the amount of government support in the R&D budget. Bitman and Sharif (2008), compare characteristics of five common methodologies for R&D performance evaluation : (1) scoring model, (2) Analytic Hierarchy Process (AHP), (3) Boston Consulting Group (BCG) or growth-share matrix, (4) Balanced Scorecard (BSC) and (5) DEA. Abramo *et al.* (2008), reported a DEA application for bibliometric data in the Italian university system for measuring the technical efficiency of research activities. Sharma and Thomas (2008), compared the national R&D programs of 22 countries and found that a small number of R&D programs conducted by developing countries were benchmarks located on the DEA efficiency frontier. Meng *et al.* (2006), analyzed the relative efficiency of investments for some basic research programs in China using statistical regressions and DEA method. They found that there were significant improvements in overall efficiency from 1991 to 1996. Oral *et al.* (1991), presented three R&D project evaluation and selection models : self-evaluation model, cross-evaluation model and selection model.

Farris *et al.* (2006), presented a case study of how DEA was applied to compare engineering design projects of the

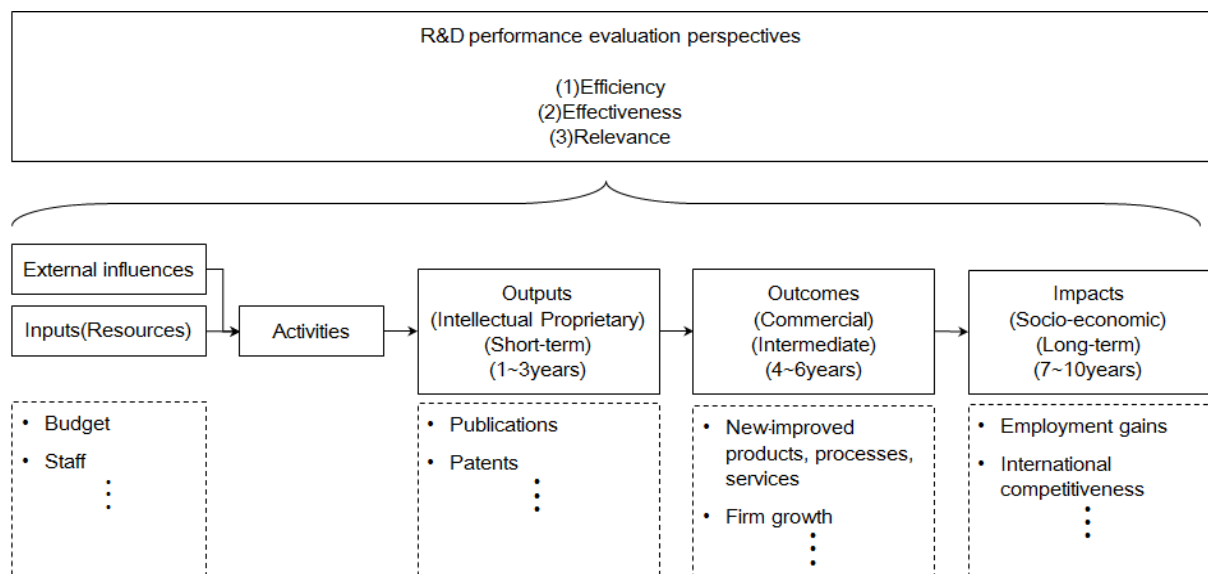


Figure 1. R&D performance evaluation logic model (An integrated model excerpted from McLaughlin and Jordan, 1999; Ruegg and Feller, 2003; WKKF, 2004)

Belgian Armed Forces, and they explained a variable reduction process where the initial 23 input-output variables were reduced to the final five input-output variables. Zhu (2003), discussed some DEA sensitivity studies regarding the variable and model selection, and a regression-based model was proposed for identifying critical input performance measures related to a case with only one output variable. Treatment of data variations by statistical methods has been proposed in related literature as well. Simar and Wilson (2000), used a bootstrap method which could deal with multiple input-output variables, and they proposed a general method for bootstrapping in nonparametric frontier models to remedy the sampling variations resulted from a finite sample of observed production units.

2.2 DEA Models and All Possible Regressions

DEA is a methodology of Operations Research (OR) that calculates relative efficiency scores of a set of peer entities in the range of $[0, 1]$. Each entity pursuing the same objective that is called Decision Making Unit (DMU) has common multiple input-output variables. Initially, active fields of DEA applications are education programs (Charnes and Cooper, 1980; Charnes *et al.*, 1981; Bessent *et al.*, 1982), urban police department (Parks, 1983), banking center (Sherman and Gold, 1985), hospitals (Banker *et al.*, 1986) and so forth. Moreover, Seiford and Thrall (1990), Callen (1991), Zhu (2003), Cooper *et al.* (2004) and Cooper *et al.* (2007), presented excellent explanations particularly on mathematical formula and computational implementation for various DEA models.

Unlike typical statistical analysis methodologies (e.g., regression analysis) that mainly focus on the analysis of central tendency, DEA explores the extreme surface of data (i.e., frontier). Statistical analysis is used to find the relative position of the individual from the center of data, while DEA is used to measure the relative position of the individual from the frontier of data. Therefore, DEA as an extreme-point technique is very sensitive to data measurement error and outliers which can lead to a serious problem (Seiford and Thrall, 1990). From the input-oriented perspective, DEA frontier is the minimum input to achieve a given output. On the contrary, it means the maximum output with given input from the output-oriented point of view.

Assume a set of n DMUs ($j = 1, \dots, n$) having m input variables ($i = 1, \dots, m$) and s output variables ($r = 1, \dots, s$). Then, for each DMU j , "semipositive" vectors of input-output variables are defined as $x_j \in R^{m \times 1}$, $y_j \in R^{s \times 1}$. For all DMUs, matrices of input-output variables are defined as $X = (x_j) \in R^{m \times n}$, $Y = (y_j) \in R^{s \times n}$. Eq. (1) is a CCR ratio model that calculates DEA efficiency score $h_0(v, u)$

of DMU₀ (Zhu, 2003; Cooper *et al.*, 2004; Cooper *et al.*, 2007). In Eq. (1), $v \in R^{1 \times m}$, $u \in R^{1 \times s}$ are vectors of input-output multipliers respectively and every element of $\mathbf{0}_{(1 \times m)} \in R^{1 \times m}$, $\mathbf{0}_{(1 \times s)} \in R^{1 \times s}$ has a value of zero.

$$\begin{aligned} \max_{v, u} \quad & h_0(v, u) = \frac{u y_0}{v x_0} \\ \text{subject to} \quad & u y_j / v x_j \leq 1 \quad \forall j \\ & v \geq \mathbf{0}_{(1 \times m)} \\ & u \geq \mathbf{0}_{(1 \times s)} \end{aligned} \quad (1)$$

By applying Charnes and Cooper transformation such as (1) $t^{-1} = u x_0$, (2) $\mu = t u$ and (3) $\nu = t v$ to Eq. (1), a non-linear fractional programming model Eq. (1) can be converted into a linear programming model Eq. (2) that is a CCR multiplier model (Seiford and Thrall, 1990; Callen, 1991).

$$\begin{aligned} \max_{\nu, \mu} \quad & z_0(\mu) = \mu y_0 \\ \text{subject to} \quad & \mu Y - \nu X \leq \mathbf{0}_{(1 \times n)} \\ & \nu x_0 = 1 \\ & \nu \geq \mathbf{0}_{(1 \times m)} \\ & \mu \geq \mathbf{0}_{(1 \times s)} \end{aligned} \quad (2)$$

By adding VRS assumption, Eq. (2) is modified to an input-oriented multiplier infinitesimal VRS model Eq. (3). In Eq. (3), the decision variable μ_0 is a VRS scalar. To distinguish between "efficiency" and "weak efficiency", constraints are also modified so that ν , μ have values greater than or equal to infinitesimal or non-Archimedean ϵ . Every element of $\epsilon_{(1 \times m)} \in R^{1 \times m}$, $\epsilon_{(1 \times s)} \in R^{1 \times s}$ has a value of ϵ and all elements of $e \in R^{1 \times n}$ are ones. Hence, "the production possibility set" P enveloped by the frontier is defined as Eq. (4). In Eq. (4), $\{(L, U)\} = \{(0, \infty), (1, 1), (1, \infty), (0, 1)\}$ corresponds to four different Returns To Scale (RTS) assumptions such as CRS, VRS, IRS (Increasing Returns to Scale), DRS (Decreasing Returns to Scale) respectively and a semi-positive $\lambda \in R^{n \times 1}$ is a vector of DMU intensity (Cooper *et al.*, 2007).

$$\begin{aligned} \max_{\nu, \mu, \mu_0} \quad & z_0(\mu, \mu_0) = \mu y_0 - \mu_0 \\ \text{subject to} \quad & \mu Y - \nu X - \mu_0 e \leq \mathbf{0}_{(1 \times n)} \\ & \nu x_0 = 1 \\ & \nu \geq \epsilon_{(1 \times m)} \\ & \mu \geq \epsilon_{(1 \times s)} \\ & \mu_0 \text{ free in sign} \end{aligned} \quad (3)$$

$$P = \{(x, y) \mid x \geq X\lambda, y \leq Y\lambda, L \leq e\lambda \leq U, \lambda \geq \mathbf{0}_{(n \times 1)}\} \quad (4)$$

Meanwhile, in regression analysis, a variety of computational methodologies have been developed associated with regression variable selection, especially for building parsimonious models (Montgomery *et al.*, 2001). The most

widely used methods are : (1) all possible regressions, (2) directed search on *t*-statistic and (3) stepwise regression. Furthermore, the stepwise regression can be classified into three types : (1) forward selection, (2) backward elimination and (3) stepwise regression. Basically, the full model which includes all regression variables acts as the reference for regression variable selection. By checking statistics between the full model and reduced models, statistically significant regression variables can be identified, which is the core of these methodologies. Key statistics examined are (adjusted-) coefficient of multiple determination, residual mean square, Mallows C_p and so on.

3. Design of Experiments

3.1 DEA Data Structures for All Possible DEAs

<Figure 2> shows that the DEA data structure analyzed in this study consisted of four input-output variables of a GSP (i.e., DMU) associated with “2012 R&D Program of Technology Development and Application Support (PTDAS)”, described in detail in Section 3.2. In fact, “2012 PTDAS” is one of the major R&D programs sponsored by the Ministry of Knowledge Economy (MKE) of Korea; the budget spent from 2006 to 2010 was approximately 0.6 billion U.S. dollars (MKE · NIPA, 2012). To establish the data structure, this study considered the availability of the MKE · NIPA database and the data reliability. As seen in a generic R&D performance evaluation logic model in <Figure 1>, short-term intellectual property outputs (e.g., publications, patents, etc.) should be included in the data structure along with mid-term commercialization outcomes and long-term socio-economic impacts. However, most beneficiaries of “2012 PTDAS” are small and medium-sized enterprises (SMEs) or venture businesses involved in the information and communication technology industry, so intellectual property outputs are not the

main interest of this study. Therefore, the data structure in <Figure 2> can be considered as a design of limited scope, coping with the chain of “R&D funds” (x_1) and “R&D manpower” (x_2) → “Sales revenue” (y_1) and “New employment” (y_2).

In order to identify determinants in calculating DEA efficiency scores among four input-output variables shown in <Figure 2>, a total of nine different data structures for all possible DEAs are generated. This is shown in <Figure 3>. In <Figure 3>, “CDS0” is the complete data structure (CDS) with (the number of inputs the number of outputs) = (2 × 2) as in <Figure 2>. Compared with “CDS0”, the other eight incomplete data structures (IDSs) are presented on both sides of the compartments in <Figure 3>. On the left-hand side, four (${}_2C_1 \times {}_2C_1 = 2 \times 2 = 4$)(1×1) IDSs are listed from “IDS1” to “IDS4.” On the right-hand side, the upper two (${}_2C_2 \times {}_2C_1 = 1 \times 2 = 2$)(2×1) and the lower two (${}_2C_1 \times {}_2C_2 = 1 \times 2 = 2$)(1×2) IDSs are arranged from “IDS5” to “IDS8.” Similar to the computational procedure of all possible regressions, “CDS0” serves as a reference in the comparisons of data structures explained hereafter.

3.2 Data collection and Sample

<Table 1> explains the DEA input-output variables considered in this study. The first input variable, “R&D funds” (x_1) is the sum of two sub-items such as “Amount of government support” (x_a) and “Corporate matching funds” (x_b). The second input variable, “R&D manpower” (x_2) is the sum of two sub-items such as “Technical manpower” (x_c) and “Non-technical manpower” (x_d). Meanwhile, the first output variable, “Sales revenue” (y_1) is the aggregate of pure sales of products and services through a GSP occurring during the five-year performance follow-up period from 2006 to 2010. The second output variable, “New employment” (y_2) is also the aggregate of pure new employment in the same manner as “Sales revenue” (y_1). Two variables, “R&D manpower” (x_2) and “New employment” (y_2) are collected in the units of man-years. For measuring these two output variables, each GSP’s contribution is reflected as well.

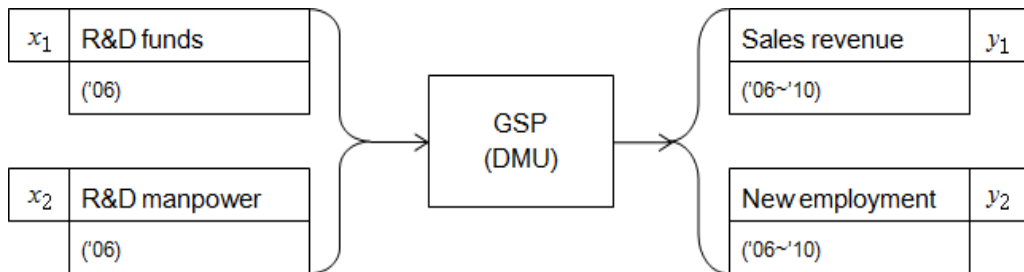


Figure 2. DEA’s complete data structure(i.e., a mid- and long-term performance oriented model of “2012 PTDAS”)

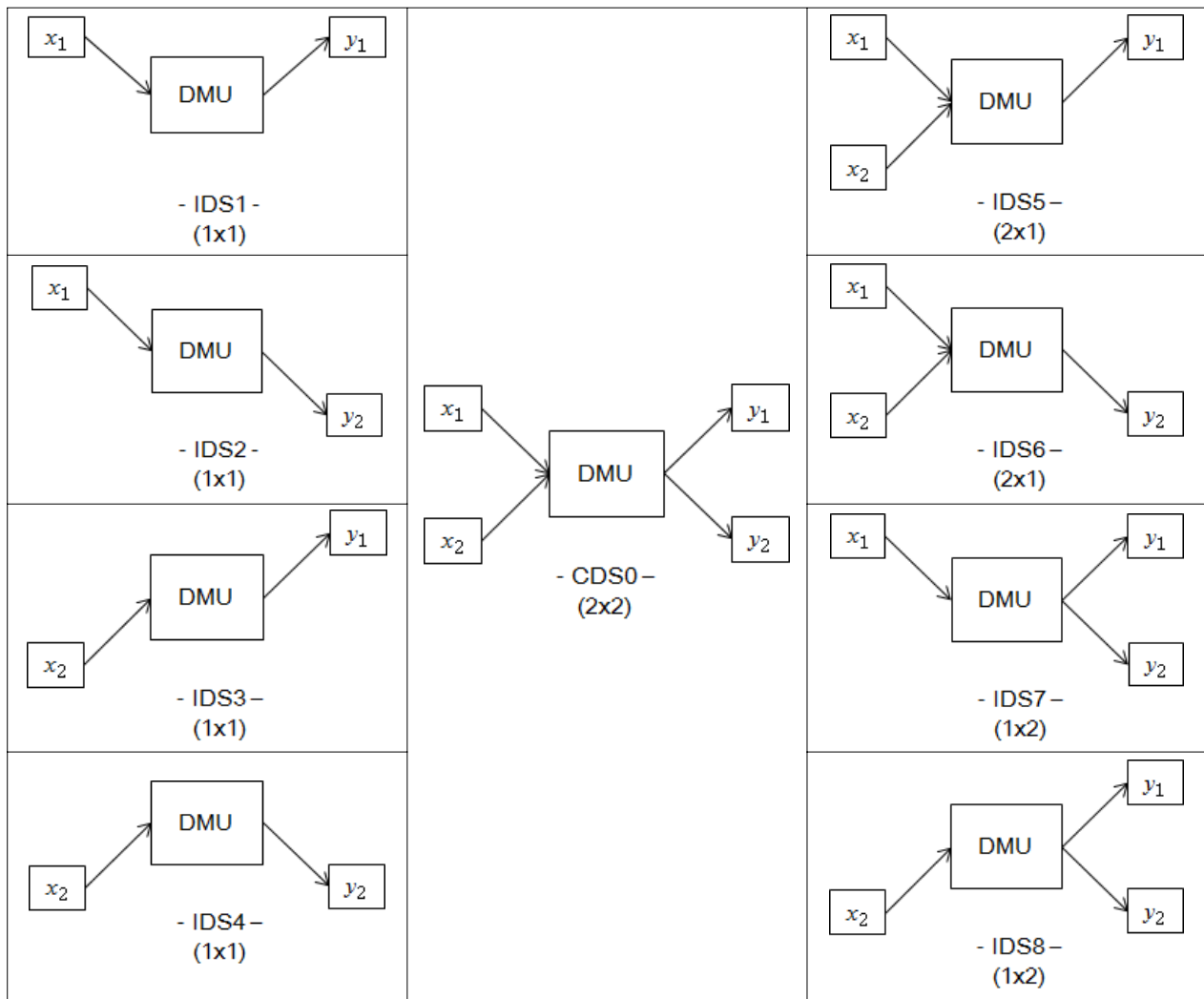


Figure 3. DEA's complete data structure versus incomplete data structures

Table 1. DEA input-output variables

DEA input variable	Variable name	Year of input	Sub-items
R&D funds	$x_1 = x_a + x_b$	2006	Amount of government support (x_a) Corporate matching funds (x_b)
R&D manpower	$x_2 = x_c + x_d$	2006	Technical manpower (x_c) Non-technical manpower (x_d)
DEA output variable	Variable name	Performance follow-up period	Sub-items
Sales revenue	y_1	2006~2010	
New employment	y_2	2006~2010	

In “2012 PTDas”, all activities and performance of all 796 GSPs that launched between 2006 and 2010 were investigated and assessed by MKE of Korea. Among them, 218 GSPs that started and finished in 2006 provide a good sample for this study; the R&D performance time-lag can be fully reflected.

Among the initial sample, 133 companies responded to the “2012 PTDas” survey and submitted their GSPs-related observations (response rate = $133/218 \times 100 = 61\%$). Only 37 GSPs reported “Sales revenue” (y_1) and “New employment” (y_2) created during the five-year performance followup period (the ratio of performance creation = $37/133 \times 100 = 28\%$).

Out of 37 GSPs, only 19 obtained foreign and/or domestic patents applications and registrations (the ratio of patents application and registration creation = $19/37 \times 100 = 51\%$). The-

refore, it can be supposed that the majority of the sample were carried out by SME or venture companies primarily pursuing mid-term commercialization. <Table 2> summarizes

Table 2. Box-plot outliers screening for DEA data set

Descriptive statistics	x_1 (1,000 U.S. dollars)	x_2 (Man-years)	y_1 (1,000 U.S. dollars)	y_2 (Man-years)
Min	130	5	56	2
Q ₁	500	6	400	6
Median	763	9	1,950	9
Q ₃	1,350	14	11,530	26
Max	3,030	24	229,390	341
IQR	850	8	11,130	20
IF ₂	2,625	26	28,225	56
Number of outliers	2	0	6	6

Table 3. DEA data set

GSP ID	DMU ID	x_1 (1,000 U.S. dollars)	x_2 (Man-years)	y_1 (1,000 U.S. dollars)	y_2 (Man-years)
3B-06-0008-00	1	445	15	1,950	6
3B-06-0027-00	2	2,000	6	10,000	9
3B-06-0058-00	3	600	9	19,300	19
3B-06-0164-00	4	523	12	3,828	12
3B-06-0192-00	5	765	6	450	14
3B-06-0194-00	6	564	10	300	4
3Z-06-0044-00	7	300	6	1,600	36
3Z-06-0054-00	8	200	5	180	8
3Z-06-0060-00	9	945	5	428	2
3Z-06-0073-00	10	959	24	56	7
3Z-06-0074-00	11	2,047	23	400	27
3Z-06-0078-00	12	300	6	800	3
3Z-06-0085-00	13	249	7	11,416	2
3Z-06-0091-00	14	1,161	23	384	3
3Z-06-0098-00	15	697	8	3,167	24
3Z-06-0111-00	16	997	13	760	6
3Z-06-0126-00	17	572	7	3,280	6
3Z-06-0137-00	18	509	6	340	6
3Z-06-0139-00	19	1,975	13	1,802	10
3Z-06-0158-00	20	180	5	360	8
3Z-06-0177-00	21	500	6	1,464	8
3Z-06-0181-00	22	560	8	100	3
3Z-06-0182-00	23	763	8	2,020	2
3Z-06-0206-00	24	890	6	60	6
3Z-06-0230-00	25	1,200	14	690	9
3Z-06-0241-00	26	150	5	4,150	8
3Z-06-0246-00	27	130	5	160	5
3Z-06-0262-00	28	764	12	10,409	12
Mean		748.00	9.75	2,852.00	9.46
StDev		534.00	5.67	4,533.00	8.09
CoefVar		0.71	0.58	1.59	0.85
Min		130.00	5.00	56.00	2.00
Q ₁		336.00	6.00	345.00	4.25
Median		586.00	7.50	780.00	7.50
Q ₃		956.00	12.75	3,252.00	11.50
Max		2,047.00	24.00	19,300.00	36.00
IQR		619.00	6.75	2,907.00	7.25

descriptive statistics for box-plot outliers screening.

Among the 37 observations extracted above, the number of outliers that exceed “the upper inner fence” IF2 for each variable are: two for x_1 , zero for x_2 , six for y_1 and six for y_2 . Consequently, for the total of four input-output variables in <Figure 1>, nine GSPs are sorted out as outliers. Finally, after the outliers removal, a DEA data set is prepared in <Table 3> In <Table 3>, for the input variables, “R&D funds” (x_1) has greater values of mean, standard deviation (StDev) and coefficient of variation (CoefVar) compared with “R&D manpower” (x_2). Similarly, for the output variables, “Sales revenue” (y_1) has greater values of those three descriptive statistics as compared with “New employment” (y_2).

4. Analysis of Experiments

4.1 Comparisons of DEA Efficiency Scores

In parallel with the main analysis, the sample’s DEA efficiency scores are examined. First, <Table 4> summarizes the value of Pearson’s r correlation coefficient between each pair of variables. Particularly, the correlation coefficient $r = 0.522$ between x_1 and x_2 has a statistical significance (p -value = 0.004 < significance level $\alpha = 0.05$) which implies “R&D manpower” (x_2) increases proportionally according to “R&D funds” (x_1). The other two correlation coefficients for x_1 versus y_1 and y_2 show a positive (+) relationship between every two corresponding variables, but they have a lack of statistical significance. Hence, it cannot be asserted that “Sales revenue” (y_1) and “New employment” (y_2) are increased by the amount of “R&D funds” (x_1). Additionally, although not statistically significant, the correlation coefficient $r = -0.115$ of “R&D manpower” (x_2) compared with “Sales revenue” (y_1) shows a negative (-) relationship. Theoretically, it can be assumed that “R&D manpower” (x_2) has a positive (+) correlation with “Sales revenue” (y_1). However, in this real data set which might be usually confounded with some noises including the R&D performance time-lag, measurement or

survey errors and so on, an expected relationship between the two variables was not detected apparently.

For 28 DMUs in <Table 3>, DEA efficiency scores are summarized in <Table 5> by the CCR-I (input-oriented CCR) model Eq. (2) and <Table 6> shows another DEA efficiency scores by the BCC-I (input-oriented BCC) model Eq. (3). Meantime, Park *et al.* (2011), summarized some public R&D performance efficiency evaluation studies using various input-oriented DEA models. In addition, Paradi *et al.* (2004), presented a table of DEA orientation possibilities associated with the three approach perspectives (i.e., production, profitability and intermediation) which shows that input-oriented DEA models can be used for the three approach perspectives. Based on the literature mentioned above, the present study adopts an input-oriented DEA model. <Table 5> shows nine different series of DEA efficiency scores; the first one is obtained using CDS0. The rest of the eight series correspond with IDS1 to IDS8 respectively. In the column of CDS0, three DMUs-DMU ID 3, 7, 13-are efficient. However, in the column of CDS0 in <Table 6>, the number of efficient DMUs is nine (DMU ID 2, 3, 7, 8, 9, 13, 20, 26, 27), which can be regarded as an effect of VRS assumption (DEA-Solver-Pro 2012).

<Figure 4> visualizes DEA efficiency scores in <Table 5>, sorted by CDS0 ascending order for the comparisons of nine different data structures in <Figure 3> Also, <Figure 5> is presented to depict <Table 6> in a similar manner. In both <Figure 4> and <Figure 5>, it can be seen that the series of CDS0 is greater than or equal to the remaining eight IDSs. That can be interpreted as a natural behavior of DEA caused by “the space dimensionality” mentioned by Seiford and Thrall (1990).

4.2 Finding Highly Correlated Data Structures

Here, some interesting facts are found. Actually, there are some highly positive (+) correlations detected between CDS0 and a few IDSs. First, in <Table 7>, $r = 0.394$ (p -value = 0.038) is the lowest between CCR-I and BCC-I efficiency scores associated with (1×1) IDS3 ($x_2 \rightarrow y_1$). This means

Table 4. Correlation coefficients of DEA input-output variables

		x_1	x_2	y_1
r (p -value)	x_2	0.522 (0.004)		
	y_1	0.015 (0.939)	-0.115 (0.561)	
	y_2	0.163 (0.408)	0.107 (0.588)	0.170 (0.387)

Table 5. DEA efficiency scores of CCR-I model

GSP ID	DMU ID	CDS0	IDS1	IDS2	IDS3	IDS4	IDS5	IDS6	IDS7	IDS8
3B-06-0008-00	1	0.18995	0.09558	0.11236	0.06062	0.06667	0.09558	0.11236	0.18995	0.10214
3B-06-0027-00	2	0.77720	0.10906	0.03750	0.77720	0.25000	0.77720	0.25000	0.13595	0.77720
3B-06-0058-00	3	1	0.70160	0.26389	1	0.35185	1	0.35185	0.89480	1
3B-06-0164-00	4	0.32217	0.15965	0.19120	0.14876	0.16667	0.18092	0.19120	0.32042	0.25345
3B-06-0192-00	5	0.38889	0.01283	0.15251	0.03497	0.38889	0.03497	0.38889	0.15251	0.38889
3B-06-0194-00	6	0.07053	0.01160	0.05910	0.01399	0.06667	0.01519	0.06667	0.06355	0.07053
3Z-06-0044-00	7	1	0.11633	1	0.12435	1	0.14267	1	1	1
3Z-06-0054-00	8	0.33333	0.01963	0.33333	0.01679	0.26667	0.02113	0.33333	0.33333	0.26667
3Z-06-0060-00	9	0.08810	0.00988	0.01764	0.03992	0.06667	0.03992	0.06667	0.02500	0.08810
3Z-06-0073-00	10	0.06083	0.00127	0.06083	0.00109	0.04861	0.00137	0.06083	0.06083	0.04861
3Z-06-0074-00	11	0.19565	0.00426	0.10992	0.00811	0.19565	0.00811	0.19565	0.10992	0.19565
3Z-06-0078-00	12	0.13289	0.05816	0.08333	0.06218	0.08333	0.07133	0.08333	0.12891	0.11845
3Z-06-0085-00	13	1	1	0.06693	0.76050	0.04762	1	0.06693	1	0.76050
3Z-06-0091-00	14	0.02640	0.00721	0.02153	0.00779	0.02174	0.00889	0.02174	0.02596	0.02518
3Z-06-0098-00	15	0.58298	0.09911	0.28694	0.18460	0.50000	0.18460	0.50000	0.34875	0.58298
3Z-06-0111-00	16	0.08892	0.01663	0.05015	0.02726	0.07692	0.02726	0.07692	0.06030	0.08892
3Z-06-0126-00	17	0.27892	0.12507	0.08741	0.21850	0.14286	0.21850	0.14286	0.19547	0.27892
3Z-06-0137-00	18	0.17053	0.01457	0.09823	0.02642	0.16667	0.02642	0.16667	0.10119	0.17053
3Z-06-0139-00	19	0.16121	0.01990	0.04219	0.06464	0.12821	0.06464	0.12821	0.05629	0.16121
3Z-06-0158-00	20	0.37088	0.04362	0.37037	0.03358	0.26667	0.04396	0.37037	0.37088	0.26695
3Z-06-0177-00	21	0.28061	0.06386	0.13333	0.11378	0.22222	0.11378	0.22222	0.17880	0.28061
3Z-06-0181-00	22	0.06250	0.00389	0.04464	0.00583	0.06250	0.00583	0.06250	0.04464	0.06250
3Z-06-0182-00	23	0.11796	0.05774	0.02184	0.11775	0.04167	0.11775	0.04167	0.07376	0.11796
3Z-06-0206-00	24	0.16667	0.00147	0.05618	0.00466	0.16667	0.00466	0.16667	0.05618	0.16667
3Z-06-0230-00	25	0.11369	0.01254	0.06250	0.02298	0.10714	0.02298	0.10714	0.06746	0.11369
3Z-06-0241-00	26	0.96330	0.60345	0.44444	0.38705	0.26667	0.60345	0.44444	0.96330	0.50653
3Z-06-0246-00	27	0.32051	0.02684	0.32051	0.01492	0.16667	0.02684	0.32051	0.32051	0.16667
3Z-06-0262-00	28	0.43802	0.29717	0.13089	0.40449	0.16667	0.41406	0.16667	0.39602	0.42679
Mean		0.34652	0.13189	0.16642	0.16724	0.19652	0.18829	0.21808	0.27410	0.30308
StDev		0.31594	0.24025	0.20151	0.26369	0.19544	0.29410	0.20266	0.30885	0.28094
Min		0.02640	0.00127	0.01764	0.00109	0.02174	0.00137	0.02174	0.02500	0.02518
Max		1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000

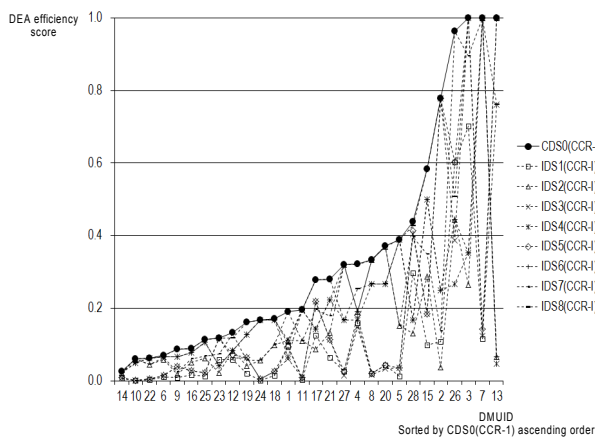


Figure 4. DEA efficiency scores sorted by CDS0 (CCR-I) ascending order

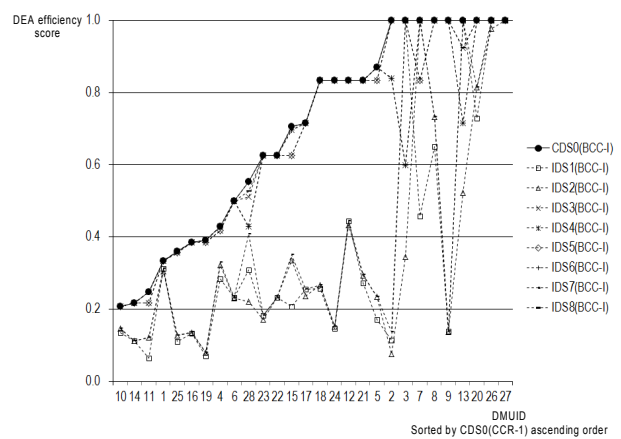


Figure 5. DEA efficiency scores sorted by CDS0 (BCC-I) ascending order

that those two variables x_2 and y_1 are more sensitive to VRS constraint $e\lambda = 1$ in Eq. (4) than the other two variables x_1 and y_2 . In other words, x_1 and y_2 are inactive in calculating BCC-I efficiency score.

For a more detailed analysis of the determinants identification, <Figure 4> is separated into three distinct panels in <Figure 6> and each panel is comprised of the series having highly positive (+) correlations in <Figure 4>. Similarly,

Table 6. DEA efficiency scores of BCC-I model

GSP ID	DMU ID	CDS0	IDS1	IDS2	IDS3	IDS4	IDS5	IDS6	IDS7	IDS8
3B-06-0008-00	1	0.33333	0.31229	0.30446	0.33333	0.33333	0.33333	0.33333	0.31229	0.33333
3B-06-0027-00	2	1	0.11485	0.07597	1	0.83928	1	0.83928	0.13745	1
3B-06-0058-00	3	1	1	0.34462	1	0.59920	1	0.59920	1	1
3B-06-0164-00	4	0.42914	0.28372	0.32196	0.41666	0.42857	0.41666	0.42857	0.32936	0.42914
3B-06-0192-00	5	0.86904	0.17183	0.23445	0.83333	0.86904	0.83333	0.86904	0.23445	0.86904
3B-06-0194-00	6	0.50000	0.23174	0.23049	0.50000	0.50000	0.50000	0.50000	0.23174	0.50000
3Z-06-0044-00	7	1	0.45739	1	0.83333	1	0.83333	1	1	1
3Z-06-0054-00	8	1	0.65049	0.73225	1	1	1	1	0.73225	1
3Z-06-0060-00	9	1	0.13899	0.13756	1	1	1	1	0.13899	1
3Z-06-0073-00	10	0.20833	0.13556	0.14699	0.20833	0.20833	0.20833	0.20833	0.14699	0.20833
3Z-06-0074-00	11	0.24689	0.06409	0.12244	0.21739	0.24689	0.21739	0.24689	0.12244	0.24689
3Z-06-0078-00	12	0.83333	0.44402	0.43333	0.83333	0.83333	0.83333	0.83333	0.44402	0.83333
3Z-06-0085-00	13	1	1	0.52208	0.92239	0.71428	1	0.71428	1	0.92239
3Z-06-0091-00	14	0.21739	0.11294	0.11197	0.21739	0.21739	0.21739	0.21739	0.11294	0.21739
3Z-06-0098-00	15	0.70604	0.20814	0.33600	0.62499	0.69642	0.62499	0.69642	0.35146	0.70604
3Z-06-0111-00	16	0.38461	0.13341	0.13589	0.38461	0.38461	0.38461	0.38461	0.13640	0.38461
3Z-06-0126-00	17	0.71428	0.25461	0.23686	0.71428	0.71428	0.71428	0.71428	0.25461	0.71428
3Z-06-0137-00	18	0.83332	0.25717	0.26617	0.83333	0.83333	0.83333	0.83333	0.26642	0.83333
3Z-06-0139-00	19	0.39011	0.06999	0.07971	0.38461	0.39011	0.38461	0.39011	0.08036	0.39011
3Z-06-0158-00	20	1	0.72778	0.81361	1	1	1	1	0.81392	1
3Z-06-0177-00	21	0.83333	0.27307	0.29290	0.83333	0.83333	0.83333	0.83333	0.29505	0.83333
3Z-06-0181-00	22	0.62499	0.23214	0.23214	0.62499	0.62499	0.62499	0.62499	0.23214	0.62499
3Z-06-0182-00	23	0.62499	0.18260	0.17038	0.62499	0.62499	0.62499	0.62499	0.18260	0.62499
3Z-06-0206-00	24	0.83332	0.14607	0.15223	0.83333	0.83333	0.83333	0.83333	0.15223	0.83333
3Z-06-0230-00	25	0.35969	0.11055	0.12661	0.35714	0.35969	0.35714	0.35969	0.12688	0.35969
3Z-06-0241-00	26	1	1	0.97634	1	1	1	1	1	1
3Z-06-0246-00	27	1	1	1	1	1	1	1	1	1
3Z-06-0262-00	28	0.55205	0.30796	0.22040	0.51099	0.42857	0.55205	0.42857	0.40817	0.52704
Mean		0.69622	0.35791	0.34849	0.68007	0.66119	0.68431	0.66119	0.40154	0.69256
StDev		0.28426	0.30964	0.28735	0.27932	0.26887	0.28137	0.26887	0.33043	0.28206
Min		0.20833	0.06409	0.07597	0.20833	0.20833	0.20833	0.20833	0.08036	0.20833
Max		1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000

Table 7. Correlation coefficients of DEA efficiency scores between CCR-I and BBC-I model

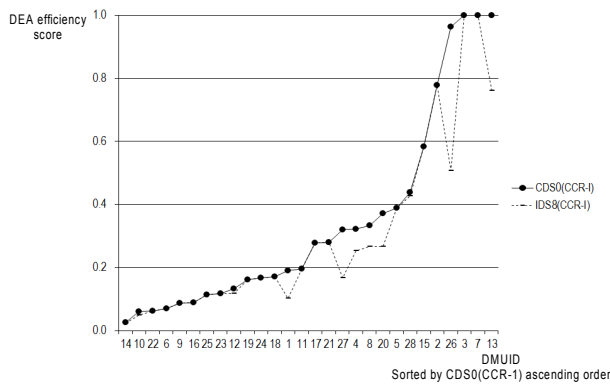
	CDS0	IDS1	IDS2	IDS3	IDS4	IDS5	IDS6	IDS7	IDS8	Min	Max
Pearson's <i>r</i>	0.606	0.702	0.809	0.394	0.434	0.435	0.517	0.882	0.550	0.394	0.882
(<i>p</i> -value)	(0.001)	(0.000)	(0.000)	(0.038)	(0.021)	(0.021)	(0.005)	(0.000)	(0.002)		

<Figure 7> has two panels that are extracted from <Figure 5> In the preparation of <Figure 6> and <Figure 7>, each panel has the series that satisfy their correlation coefficient $r \geq 0.950$ (p -value $\leq \alpha = 0.05$) in <Table 8> and <Table 9>.

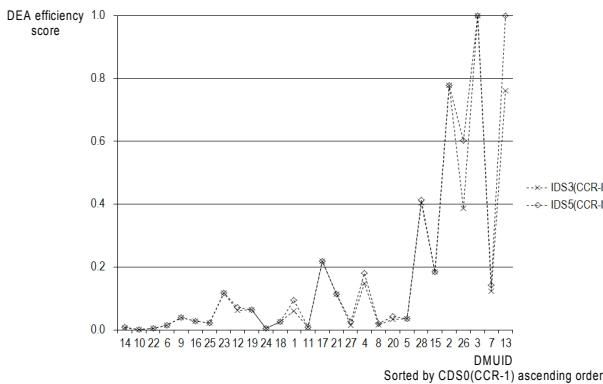
In particular, determinants are more clearly identified in <Figure 7> and <Table 9>, associated with the BCC-I model. From <Figure 7>(a), it can be seen that four distinct data structures-CDS0, IDS3, IDS5 and IDS8-generate approximately identical DEA efficiency scores. Furthermore, <Figure 7>(b) reveals that IDS4 and IDS6 generate exactly the same DEA efficiency scores. Two common variables are "R&D manpower" (x_2) and "Sales revenue" (y_1), shared by the four data structures in <Figure 7>(a). Conversely, the other two variables, "R&D funds" (x_1) and "New employment" (y_2), are in-

active or insignificant in calculating DEA efficiency scores whether or not they are included in the four data structures. Also, the sole difference between (1×1) IDS4 ($x_2 \rightarrow y_2$) and (2×1) IDS6 (x_1 and $x_2 \rightarrow y_2$) is the presence or absence of "R&D funds" (x_1). It implies again that "R&D funds" (x_1) is a thoroughly insignificant variable.

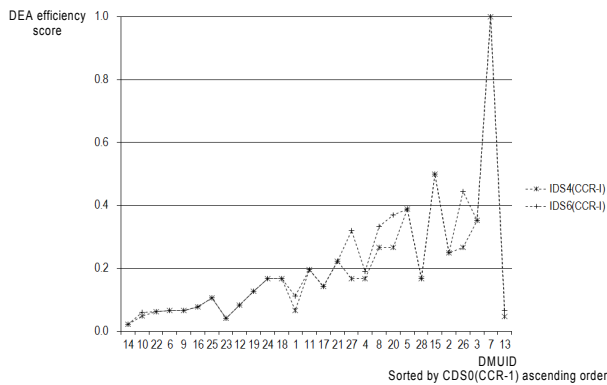
As for the CCR-I model, <Figure 6> presents three panels. <Figure 6>(a) has two series of DEA efficiency scores-CDS0 and IDS8 and <Figure 6>(b) has another two series-IDS3 and IDS5. Therefore, it is seen that <Figure 7>(a) is just split into two panels as per <Figure 6>(a) and <Figure 6>(b). In summary, <Figure 6> and <Figure 7> accompanied by <Table 8> and <Table 9> prove clearly that the two determinants are "R&D manpower" (x_2) and "Sales revenue" (y_1) and the



(a)



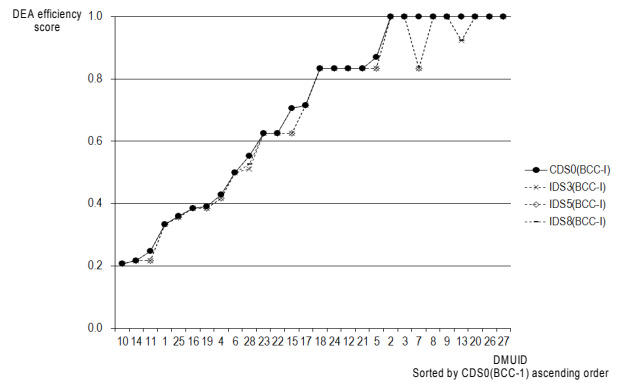
(b)



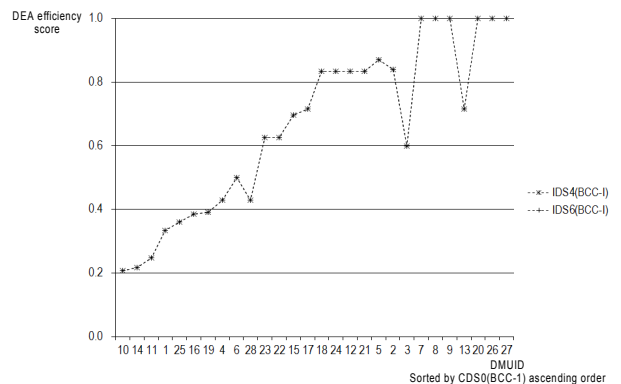
(c)

Figure 6. Highly correlated DEA efficiency scores sorted by CDS0 (CCR-I) ascending order

other two are insignificant variables in calculating DEA efficiency score. From <Table 3>, the size and dispersion of the determinant input “R&D manpower” (x_2) are less than those of the insignificant input “R&D funds” (x_1). On the contrary, the size and dispersion of the determinant output “Sales revenue” (y_1) are greater than those of the insignificant output “New employment” (y_2). Also, aforementioned, it is noted that there is a negative (-) correlation between “R&D manpower” (x_2) and “Sales revenue” (y_1) even though it is not statistically significant.



(a)



(b)

Figure 7. Highly correlated DEA efficiency scores sorted by CDS0 (BCC-I) ascending order

In addition, four different tables are provided in the <Appendix>. The first two contain nonparametric correlation coefficients such as Kendall’s τ_B and Spearman’s ρ_s corresponding to <Table 8>. The latter two summarize the same kinds of nonparametric correlation coefficients associated with <Table 9>. As we can see in <Table A.1> through <Table A.4>, correlation analyses based on the parametric Pearson’s r accord with the nonparametric correlation analyses.

4.3 Modified MAPE and MAD

To check the similarity between incomplete data structures and the complete data structure, two well-known accuracy measures of time-series analysis - “Mean Absolute Percentage Error” (MAPE) and “Mean Absolute Deviation” (MAD)- are modified as Eq. (5) and Eq. (6) to fit the context of this analysis (Minitab^R, 2005; Berenson *et al.*, 2012). In Eq. (5) and (6), ES_j^{CDS0} notes a DEA efficiency score of DMU_j with CDS; ES_j^{IDS} notes a DEA efficiency score of DMU_j with one of IDSs.

In <Table 10>, compared with CDS0, the most similar incomplete data structure is (1×2) IDS8 ($x_2 \rightarrow y_1$ and y_2) and

Table 8. Correlation coefficients of DEA efficiency scores of CCR-I model

		CDS0	IDS1	IDS2	IDS3	IDS4	IDS5	IDS6	IDS7
Pearson's <i>r</i> (<i>p</i> -value)	IDS1	0.770 (0.000)							
	IDS2	0.608 (0.001)	0.152 (0.439)						
	IDS3	0.783 (0.000)	0.816 (0.000)	0.058 (0.768)					
	IDS4	0.622 (0.000)	0.064 (0.745)	0.882 (0.000)	0.142 (0.470)				
	IDS5	0.819 (0.000)	0.893 (0.000)	0.086 (0.664)	0.983 (0.000)	0.120 (0.544)			
	IDS6	0.663 (0.000)	0.112 (0.572)	0.941 (0.000)	0.134 (0.495)	0.972 (0.000)	0.135 (0.493)		
	IDS7	0.915 (0.000)	0.817 (0.000)	0.694 (0.000)	0.627 (0.000)	0.560 (0.002)	0.699 (0.000)	0.630 (0.000)	
	IDS8	0.952 (0.000)	0.652 (0.000)	0.584 (0.001)	0.789 (0.000)	0.709 (0.000)	0.777 (0.000)	0.687 (0.000)	0.815 (0.000)

Table 9. Correlation coefficients of DEA efficiency scores of BCC-I model

		CDS0	IDS1	IDS2	IDS3	IDS4	IDS5	IDS6	IDS7
Pearson's <i>r</i> (<i>p</i> -value)	IDS1	0.624 (0.000)							
	IDS2	0.596 (0.001)	0.795 (0.000)						
	IDS3	0.992 (0.000)	0.620 (0.000)	0.559 (0.002)					
	IDS4	0.941 (0.000)	0.484 (0.009)	0.636 (0.000)	0.936 (0.000)				
	IDS5	0.992 (0.000)	0.636 (0.000)	0.559 (0.002)	0.998 (0.000)	0.927 (0.000)			
	IDS6	0.941 (0.000)	0.484 (0.009)	0.636 (0.000)	0.936 (0.000)	1.000 (*) (0.000)	0.927 (0.000)		
	IDS7	0.652 (0.000)	0.948 (0.000)	0.889 (0.000)	0.614 (0.001)	0.536 (0.003)	0.628 (0.000)	0.536 (0.003)	
	IDS8	0.999 (0.000)	0.608 (0.001)	0.596 (0.001)	0.992 (0.000)	0.949 (0.000)	0.990 (0.000)	0.949 (0.000)	0.639 (0.000)

Table 10. MAPE_{mod} and MAD_{mod} of DEA efficiency scores of CCR-I and BCC-I model

	CCR-I	CCR-I	BCC-I	BCC-I
	MAPE _{mod}	MAD _{mod}	MAPE _{mod}	MAD _{mod}
IDS1	0.7322	0.2146	0.5061	0.3383
IDS2	0.4562	0.1801	0.5054	0.3477
IDS3	0.6274	0.1793	0.0230	0.0161
IDS4	0.3096	0.1500	0.0388	0.0350
IDS5	0.5918	0.1582	0.0176	0.0119
IDS6	0.2495	0.1284	0.0388	0.0350
IDS7	0.2540	0.0724	0.4450	0.2947
IDS8	0.0975	0.0434	0.0044	0.0037
Mean	0.4148	0.1408	0.1974	0.1353
StDev	0.2217	0.0575	0.2396	0.1597
Min	0.0975	0.0434	0.0044	0.0037
Max	0.7322	0.2146	0.5061	0.3477

two modified accuracy measures : (1) CCR-I model, the minimum $MAPE_{mod} = 0.0975$ and the minimum $MAD_{mod} = 0.0434$, (2) BCC-I model, the minimum $MAPE_{mod} = 0.0044$ and the minimum $MAD_{mod} = 0.0037$. If four (1×1) incomplete data structures are considered, the most similar ones are: (1) CCR-I model, $IDS4 (x_2 \rightarrow y_2)$ with $MAPE_{mod} = 0.3096$ and $MAD_{mod} = 0.1500$, (2) BCC-I model, $IDS3 (x_2 \rightarrow y_1)$ with $MAPE_{mod} = 0.0230$ and $MAD_{mod} = 0.0161$. On the basis of the similarity check, almost the same conclusions are achieved as in Section 4.2.

$$MAPE_{mod} = \sum_{j=1}^n \left| \frac{ES_j^{CDS0} - ES_j^{IDS}}{ES_j^{CDS0}} \right| / n \quad (5)$$

$(ES_j^{CDS0} \neq 0)$

$$MAD_{mod} = \sum_{j=1}^n \left| ES_j^{CDS0} - ES_j^{IDS} \right| / n \quad (6)$$

4.4 Identification of DEA Determinant Input-Output Variables

To sum up Section 4.2 (the correlation analysis) and Section 4.3 (the similarity analysis) in the DEA complete data structure of <Figure 8>, DEA determinant input-output variables are “R&D manpower” (x_2) and “Sales revenue” (y_1) and the insignificant input-output variables are “R&D funds” (x_1) and “New employment” (y_2). Even if “New employment” (y_2) can be one of the determinant output variables along with “R&D manpower” (x_2) and “Sales revenue” (y_1) from the similarity analysis in Section 4.3, the overlapping determinants identified between the two sections above are only “R&D manpower” (x_2) and “Sales revenue” (y_1).

However, it should be noted that the insignificant input “R&D funds” (x_1) could be the critical input in public R&D performance evaluation logic models from a practical perspective. Therefore, if practitioners focus on or are interested in the efficiency reflecting the relationship between “R&D funds” (x_1) and “Sales revenue” (y_1), then DEA methodology cannot satisfy their expectations.

5. Practical Implications and Conclusions

This study illustrates empirically that only a small number of input-output variables actually determine DEA efficiency score. Notably, in this analysis, “R&D funds” (x_1) is classified as an insignificant input in calculating DEA efficiency score. However, in reality, it can be the foremost input based on public R&D performance evaluation logic models. Therefore, careful attention is required when a DEA model is adopted for measuring R&D performance efficiency. Additionally, two modified accuracy measures are developed and scrutinized to check the similarities between a DEA complete data structure versus incomplete data structures. Furthermore, statistical characteristics are summarized regarding the determinants as well as the insignificant variables.

In the future, a remedial procedure is required to make all input-output variables act as determinants in calculating DEA efficiency scores. For example, future study could consider to what extent AR and ARGM constraints can control the influence of each variable over DEA efficiency scores. Also, statistical characteristics of the determinants described in this study should be verified more rigidly in terms of both theoretical and empirical perspective. The present study proposed a systematic procedure for identifying DEA determinant input-output variables with a small-scale application. As aforementioned, this framework of design and analysis of experiments can be called “all possible DEAs.” On the other hand, with a large-scale data structure, the computation complexity of this procedure can be worsened due to the enumeration feature. Hence, a more selective step should be incorporated into the procedure to sort out less influential variables effectively in advance. Finally, in order to alleviate the drawback of DEA as an extreme-point technique, it is necessary to establish a systematic procedure to detect outlier DMUs as well as to measure the influence of those upon the whole set of DEA efficiency scores.

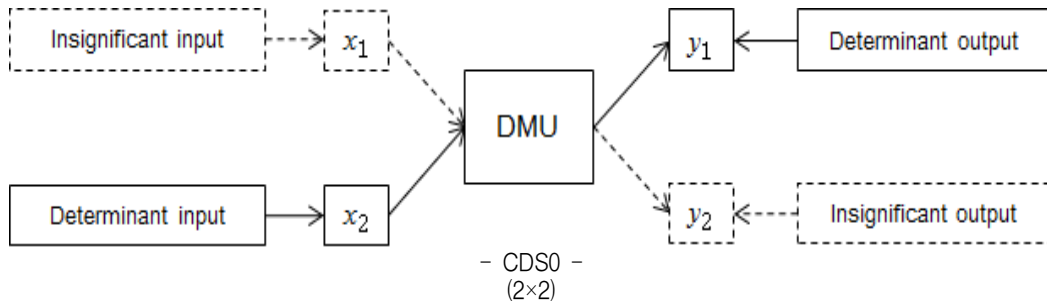


Figure 8. DEA determinant input-output variables based on the correlation analyses

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<Appendix>

Table A.1. Kendall's τ_B correlation coefficients of DEA efficiency scores of CCR-I model

		CDS0	IDS1	IDS2	IDS3	IDS4	IDS5	IDS6	IDS7
Kendall's τ_B (p-value)	IDS1	0.614 (0.000)							
	IDS2	0.571 (0.000)	0.317 (0.018)						
	IDS3	0.550 (0.000)	0.783 (0.000)	0.175 (0.192)					
	IDS4	0.670 (0.000)	0.287 (0.035)	0.589 (0.000)	0.260 (0.057)				
	IDS5	0.566 (0.000)	0.845 (0.000)	0.209 (0.119)	0.940 (0.000)	0.236 (0.084)			
	IDS6	0.713 (0.000)	0.324 (0.016)	0.681 (0.000)	0.282 (0.036)	0.913 (0.000)	0.274 (0.042)		
	IDS7	0.753 (0.000)	0.633 (0.000)	0.686 (0.000)	0.469 (0.000)	0.474 (0.001)	0.509 (0.000)	0.546 (0.000)	
	IDS8	0.895 (0.000)	0.568 (0.000)	0.472 (0.000)	0.584 (0.000)	0.686 (0.000)	0.555 (0.000)	0.677 (0.000)	0.645 (0.000)

Table A.2. Spearman's ρ_s correlation coefficients of DEA efficiency scores of CCR-I model

		CDS0	IDS1	IDS2	IDS3	IDS4	IDS5	IDS6	IDS7
Spearman's ρ_s (p-value)	IDS1	0.782 (0.000)							
	IDS2	0.713 (0.000)	0.486 (0.009)						
	IDS3	0.723 (0.000)	0.928 (0.000)	0.268 (0.169)					
	IDS4	0.750 (0.000)	0.357 (0.062)	0.761 (0.000)	0.343 (0.074)				
	IDS5	0.738 (0.000)	0.955 (0.000)	0.308 (0.111)	0.991 (0.000)	0.321 (0.095)			
	IDS6	0.816 (0.000)	0.444 (0.018)	0.831 (0.000)	0.380 (0.046)	0.975 (0.000)	0.383 (0.044)		
	IDS7	0.903 (0.000)	0.823 (0.000)	0.835 (0.000)	0.653 (0.000)	0.604 (0.001)	0.697 (0.000)	0.700 (0.000)	
	IDS8	0.966 (0.000)	0.751 (0.000)	0.629 (0.000)	0.750 (0.000)	0.776 (0.000)	0.742 (0.000)	0.800 (0.000)	0.828 (0.000)

Table A.3. Kendall's τ_B correlation coefficients of DEA efficiency scores of BCC-I model

		CDS0	IDS1	IDS2	IDS3	IDS4	IDS5	IDS6	IDS7
Kendall's τ_B (<i>p</i> -value)	IDS1	0.476 (0.001)							
	IDS2	0.495 (0.000)	0.793 (0.000)						
	IDS3	0.953 (0.000)	0.463 (0.001)	0.454 (0.001)					
	IDS4	0.869 (0.000)	0.361 (0.009)	0.454 (0.001)	0.840 (0.000)				
	IDS5	0.963 (0.000)	0.479 (0.001)	0.456 (0.001)	0.990 (0.000)	0.834 (0.000)			
	IDS6	0.869 (0.000)	0.361 (0.009)	0.454 (0.001)	0.840 (0.000)	1.000 (*)	0.834 (0.000)		
	IDS7	0.518 (0.000)	0.892 (0.000)	0.886 (0.000)	0.471 (0.001)	0.407 (0.003)	0.488 (0.001)	0.407 (0.003)	
	IDS8	0.982 (0.000)	0.448 (0.001)	0.487 (0.000)	0.965 (0.000)	0.881 (0.000)	0.954 (0.000)	0.881 (0.000)	0.493 (0.000)

Table A.4. Spearman's ρ_s correlation coefficients of DEA efficiency scores of BCC-I model

		CDS0	IDS1	IDS2	IDS3	IDS4	IDS5	IDS6	IDS7
Spearman's ρ_s (<i>p</i> -value)	IDS1	0.633 (0.000)							
	IDS2	0.609 (0.001)	0.928 (0.000)						
	IDS3	0.980 (0.000)	0.606 (0.001)	0.555 (0.002)					
	IDS4	0.916 (0.000)	0.519 (0.005)	0.581 (0.001)	0.904 (0.000)				
	IDS5	0.984 (0.000)	0.621 (0.000)	0.565 (0.002)	0.996 (0.000)	0.894 (0.000)			
	IDS6	0.916 (0.000)	0.519 (0.005)	0.581 (0.001)	0.904 (0.000)	1.000 (*)	0.894 (0.000)		
	IDS7	0.657 (0.000)	0.969 (0.000)	0.954 (0.000)	0.605 (0.001)	0.549 (0.002)	0.620 (0.000)	0.549 (0.002)	
	IDS8	0.994 (0.000)	0.609 (0.001)	0.592 (0.001)	0.983 (0.000)	0.929 (0.000)	0.978 (0.000)	0.929 (0.000)	0.634 (0.000)