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Using DEA to Evaluate R&D Performance of the Computers and Peripherals Firms in Taiwan

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ABSTRACT

Research & development (R&D) performance has been a competitive advantage for high-tech industries. This paper presents an empirical study in which we used Data Envelopment Analysis (DEA) to evaluate the R&D performance of 31 computers and peripherals firms located at Hsinchu Science-based Industrial Park in Taiwan. We found that the R&D performance is very different among the evaluated companies, though most of the companies are technically efficient. Moreover, we discussed possible directions for the inefficient companies to improve their R&D performance. In particular, we found that most of the inefficient companies should increase their scales to increase their relative efficiencies of R&D performance.

JEL: *C44, C67, M11*

Keywords: *R&D performance; High-tech industry; Efficiency; Data envelopment Analysis; Hsinchu Science-based Industry Park*

I. INTRODUCTION

New technologies and business models have had profound effect on how products and services are created and delivered, in particular as to the innovation, contents, delivery methods, systems, enabling technologies and management. The new information economy has been forcing high-tech companies to compete with each other through increasing R&D performance and decreasing cost simultaneously. An effective R&D operation is a major source of competitive advantage in today's rapidly globalizing economy. Thus, the evaluation of research & development (R&D) performance has been an important problem of both academic interest and practical need. To make decisions on R&D activity should be based on economic considerations more strongly, in order to estimate the opportunity cost and revenues of in-house R&D and to take these into account in costing (Brockhoff, 1998). In an exploratory investigation into R&D management practices, Cooper et al. (1997a, 1997b) conducted interviews in 35 leading firms in various industries and found the following key problems:

1) The portfolio of funded projects does not reflect the business strategy. There are disconnects between spending breakdowns on projects and the strategic priorities of the business.
2) The quality of R&D portfolio is poor. The success rates of funded projects are inadequate.
3) The Go/Kill decision points are weak. Funded projects tend to take on a life of their own.
4) There is a lack of R&D focus. Most firms confess to having too many projects for the limited resources available.
5) Some firms admitted to having too many trivial projects, i.e., modifications, updates and extensions, but too few projects to yield major breakthroughs and competitive advantage.

The computers and peripherals industry has been one of the most important components of the high-tech manufacturing industries worldwide. High-tech industry has the nature of high risks and high investment rewards. Because of the required creativity and innovation involved in R&D activities, evaluating R&D performance has been a difficult task. However, most of the managers of the high-tech companies rely on their experiences to evaluate R&D activities. In particular, the managers can hardly specify which factors contributing more or less to the R&D efficiency. Therefore, the managers do not know which factors they should enhance to increase the R&D performance of their companies. There are a number of R&D related studies on the selection of R&D projects (Chien, 2002), measuring R&D processes (Drongelen and Bilderbeek, 1999) the factors that affect R&D results (Brockhoff 1998; Morbey and Reithner, 1990) and measuring R&D performance (Brockhoff, 1998; Bilderbeek, 1999; Morbey and Reithner, 1990; Brown and Svenson, 1998; Gold, 1989; Werner and Souder, 1997). However, little research has been done on evaluating the relative efficiencies of R&D performances in the high-tech firms.

This paper present an empirical study in which we apply the data envelopment analysis (DEA) (Charnes et al., 1978; Banker et al., 1984) to evaluate the relative R&D efficiencies of 31 computers and peripherals firms in Hsinchu Science-based Industrial Park (HSIP) in Taiwan. Taiwan is now the leading supplier of computer monitors, modems, motherboards, keyboards, power supplies, scanner and pointing devices in the world. The computers and peripherals companies have high flexibility and capability to react quickly to the changing environment and to adjust the product line to meet the various customers' needs. For instance, Taiwan ranks as the world's second-largest producer of desktop and notebook computers. In 1997, Taiwan accounted for over 33% of the world's notebook personal computer production (HSIP, 1997).

The rest of the paper is organized as follows. Section 2 reviews related studies of R&D performance measurements. Section 3 describes the data envelopment analysis methodology. Section 4 presents the data and factors. Section 5 discusses the results. Concluding remarks are made in Section 6.

II. LITERATURE REVIEW

There are a number of quantitative and qualitative techniques and methods developed for R&D evaluation including profit/earning ratio and the R&D expenditure/sales (Brenner and Rushton, 1989; Morbey, 1988; Wallin and Gilman, 1986). However, these methods focus on a single point of view, e.g., R&D expenditure, paid-in-capital, and patents. To deal with the involved complexity of R&D activities, we need a method to understand the overall R&D performance and specify the directions for improvement for individual companies.

Considering the multiple attributes for evaluating R&D performance, some researchers developed empirically derived methods such as regression models for investigating R&D productivity. For example, Gilman Gilman (1978) studied stock price and optimum R&D spending. Morbey and Reithner (1990) used regression models to study the relation among R&D effects, productivity, and profitability. Zif et al. (1990) investigated the characteristics of business with high R&D investment used multiple regression models.

In addition, researchers also constructed subjectively derived models, grounded in decision sciences, such as the analytic hierarchy process (AHP), for priority setting and resource allocation in R&D management. For example, Liberatore (1987) developed a framework for applying AHP and supporting methods in the R&D evaluation. Werner and Souder (1997) reviewed the measurement of R&D performance. Rouse and Boff (1998) summarized the state of knowledge of R&D/technology management. Cordero (1990) studied an overview on the measurement of R&D performance in the firms.

However, as for the evaluation of R&D performance, the relations between the input factors and the output factors are usually not obvious. DEA model does not require the predetermination of the relative weights of the inputs and outputs, as do other approaches such as AHP. DEA has been effectively applied for measuring the relative efficiency in many fields including schools, hospitals, banks, and power delivery districts (Chien et al., 2003). Extensive literature review on DEA can be found in Seiford (1997). The special properties of DEA suit the characteristics of R&D activities. However, little research has been done to apply DEA to evaluate the R&D efficiency.

III. METHODOLOGY

In DEA, the efficiency is measured by the ratio of the aggregated outputs to aggregated inputs. DEA provides the means for assessing relative efficiencies of Decision Making Units (DMUs), with minimal former assumptions on input-output relations in these units and no predetermined weights. Following Charnes et al. (1978), a DMU is said to be efficient if it is not possible to increase (decrease) the value of an output (input) without increasing the use of at least one other input or decreasing the generation of at least one other output. This definition has the same concept as in the Pareto optimality that all the non-dominated DMUs have the highest efficiency score. Indeed, DEA is a fractional mathematical programming method that can deal with multiple inputs and multiple outputs simultaneously. DEA measures efficiency by estimating an empirical production function, which represents the highest values of outputs that could be form from relevant inputs, as completed from observed input-output vectors for the DMUs.

Three DEA formulations, i.e., the CCR model (Charnes et al., 1978), the BCC model (Banker et al, 1984), and P1 model (Chandra et al., 1998) are used in this study. In particular, we used the CCR model to measure the total efficiency. Then, we used the BCC model to measure technical efficiency and return to scale. A comparison of the two allows the determination of the extent to which the inefficient companies can be improved by increasing and decreasing the returns to scale, in addition to potential resource-allocation discrepancies. In addition, P1 model (Chandra et al., 1998) can be applied to consider the tradeoff between the increase and the decrease in inputs for the DMUs with increasing returns to scale. In the conventional DEA analysis, the efficiency can be adjusted by reducing input with surplus or increasing output with slack for all inefficiency DMUs. However, reducing input can be difficult, e.g., personal resources. Best projection of efficient DMUs for each inefficient DMU are obtained by P1 model (Chandra et al., 1998) that provides the direction to maximize the increase in outputs and minimize the increase in inputs.

In addition, the efficiency scores of all DMUs are set to be between 0 and 1 in the DEA models. The CCR model is as follows:

$$\text{Maximize} \quad E_k = \frac{\sum_{r=1}^{s} \mu_r Y_{rk}}{\sum_{i=1}^{m} \nu_i X_{ik}} \tag{1}$$

$$\text{Subject to} \quad \frac{\sum_{r=1}^{s} \mu r Y r j}{\sum_{i=1}^{m} \nu i X i j} \leq 1;\ j = 1, \ldots, n \tag{2}$$

$$\mu_r \geq \varepsilon > 0; r = 1,...,s \tag{3}$$

$$\nu_i \geq \varepsilon > 0; i = 1,...,m \tag{4}$$

where E_k : the relative efficiency of a DMU 'k'; μ_r : the weight given to output r; ν_i : the weight given to input i; Y_{rk} : the amount of output r from DMU k; X_{ik} : the amount of input i from DMU k; Y_{rj} : the amount of output r from DMU j; X_{ij} : the amount of input i from DMU j; ε : a small 'non-Archimedean' constant; n : the number of DMU; s : the number of outputs; and m : the number of inputs.

The BCC model produces variable returns to scale (VRS) efficiency frontier and evaluates both the technical efficiency and the scale efficiency. Thus, the overall efficiency can be decomposed into the technical efficiency and the scale efficiency. Indeed, the value of technical efficiency times the value of scale efficiency equal to the value of overall efficiency. That is,

$$\text{Maximize} \quad E_k = \frac{\sum_{r=1}^{s} \mu_r Y_{rk} + \mu_k}{\sum_{i=1}^{m} \nu_i X_{ik}} \tag{5}$$

$$\text{subject to} \quad \frac{\sum_{r=1}^{s} \mu_r Y_{rj} + \mu_k}{\sum_{i=1}^{m} \nu_i X_{ij}} \leq 1 \tag{6}$$

$$\forall j \geq 0, \mu_r, \nu_i \geq \varepsilon > 0 \tag{7}$$

Note that u_k indicates the returns to scale at specific points on the efficient frontier. The value of u_k can be positive, zero, or negative denoting that the corresponding DMU presents increasing, constant, or decreasing returns to scale, respectively. Therefore, a DMU is overall efficient if and only if it is both technical efficient and scale efficient. A DMU that is not overall efficient could be either technical inefficient or scale inefficient or both technical and scale inefficient. Using BCC model can specify the major sources causing overall inefficiency.

For each increase return to scale DMU, the P1 model (Chandra et al., 1998) is as follows:

$$\text{Maximize} \quad \sum_{k=1}^{K} I_k \left[\sum_{r=1}^{s} so_{rk} + \sum_{i=1}^{m} (si_{ik}^{-} - si_{ik}^{+}) \right] \tag{8}$$

$$\text{subject to} \quad \sum_{k=1}^{K} I_k \sum_{j \in J_k} x_{ij} \lambda_{jk} = x_{i0} + si_{ik}^{+} - si_{ik}^{-} \quad \text{for } i = 1,2,...m$$

$$\sum_{k=1}^{K} I_k \sum_{j \in J_k} y_{rj}\lambda_{jk} = y_{r0} + so_{rk} \quad \text{for } r = 1,2,...s$$

$$\sum_{k=1}^{K} I_k \sum_{j \in J_k} \lambda_{jk} = 1$$

$$\sum_{k=1}^{K} I_k = 1 \ \sum_{k=1}^{K} I_k = 1$$

$$I_k \in \{0,1\} \text{ for } k = 1,2,..., k$$

$$so_{rk}, si_{ik}^{+}, si_{ik}^{-}, \lambda_{jk} \geq 0 \quad \forall r, i, j, k$$

where K: the number of facet in an efficiency frontier; J_k: the set of the efficient DMUs that form k-th facet of the efficiency frontier; I_k=1, if k-th facet is chosen; I_k=0, otherwise; so_{rk}: the increase in output r if k-th facet is chosen for projection; si_{ik}^{+} : the increase in input i if k-th facet is chosen for projection; and si_{ik}^{-} : the decrease in input i if k-th facet is chosen for projection.

IV. AN EMPIRICAL STUDY

This empirical study involves the selection of input and output factors, the evaluation of total efficiency by CCR model, the evaluation of technical efficiency and scale efficiency by BCC model, and the discussion of improvement directions of the inefficient DMUs.

On the basis of the existing studies (Brenner and Rushton, 1989; Morbey, 1988; Wallin and Gilman, 1986; Zif et al, 1990; Chakrabarti, 1991; Hansen and Hill, 1991), we identified the factors affect R&D performance as follows: (1) R&D expenditure, (2) R&D employees, (2) paid-in-capital, (4) sales, (5) industrial classification, (6) companies' size, (7) the age of company, (8) the percent of market share, and (9) the number of patents. In sum, we selected four input factors and two output factors according to the criteria of complete, operational, decomposable, nonredundant, and minimal (Keeney and Raiffa, 1993). In particular, the four input variables are:

A: the age of the firm;

P: paid-in-capital of the firm;

R&D: annual R&D expenditure of the firm, including R&D current expenditure and R&D capital expenditure; and

R: number of R&D employees in R&D department /or section of the firm.

The two output variables are:

S: annual sales of the firm; and

T: number of patents approved by domestic and foreign patent office.

Researchers have found the relationship between R&D expenditure, the numbers of patents generated, the use of patent counts and R&D performance (Edwards and McCarry, 1973; McGrrath and Romeri, 1994; Robb, 1991; Werner and Souder, 1997). Thus, patents are useful indicators for identifying the fields where technological advances have been made. In addition, combining the data with sales, R&D expenditure, and R&D employees of the firms provides a basis for assessing the R&D performance. The data of the 31 computers and peripherals industry located at HSIP in Taiwan are collected for the period of year 1997 (Science park annual reports and HSIP annual reports). For the confidential reasons, these companies are coded as DMU1 to DMU31, respectively.

To estimate the construct validity, we used correlation analysis to check the isotonicity (Golany and Roll, 1985; Golany, 1988) among the inputs and outputs. We found significantly positive correlation among the inputs and outputs as shown in Table 1. Thus, the isotonicity assumption of the input/output factors in the DEA model is validated. Also, as suggested by Bowlin (1987), the number of inputs and outputs must be small or equal to one-third of the DMUs. In this study, we used 6 factors to evaluate 31 DMUs. The numbers of DMUs comparing to the number of the input and output factors should be large enough to make sure that the measurements of relative efficiencies are meaningful.

Table 1

Correlation between Input and Output

	A	P	R&D	R
S	0.459**	0.970**	0.574**	0.865**
T	0.380*	0.085	0.532**	0.188

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

V. RESULTS AND DISCUSSION

A. Total efficiency

We constructed the CCR model to evaluate the total efficiencies of the 31 computer and peripherals companies. The efficiency values of the 31 companies are very different as shown in Table 2. The efficiency ratio has an average value of 0.573. Among them, 13 companies have the total efficiency values to be 1 (i.e., at the efficient frontier). Although being inefficient, DMU31 presents a total efficient value of 0.988. Among the inefficient companies, 10% companies (3 of 31) presents the efficiency values more than 0.5 and 23% of companies (10 of 31) presents the efficiency values smaller than 0.1.

Table 2
Efficiency ratings and slack values

DMU	Efficiency	No. of facets for efficient DMU	Output slack			Input surplus		
			S	T	A	P	R&D	R
DMU1	1	4	0	0	0	0	0	0
DMU2	1	3	0	0	0	0	0	0
DMU3	0.501	NA	0	0	0	0	0	40.979
DMU4	1	17	0	0	0	0	0	0
DMU5	1	0	0	0	0	0	0	0
DMU6	1	1	0	0	0	0	0	0
DMU7	1	1	0	0	0	0	0	0
DMU8	1	0	0	0	0	0	0	0
DMU9	1	1	0	0	0	0	0	0
DMU10	0.747	NA	0	0	0	0	3314.279	11.586
DMU11	0.33	NA	0	0	0	0	4383.135	31.741
DMU12	1	2	0	0	0	7418.853	0	0
DMU13	0.432	NA	0	0	0	0	0	0
DMU14	0.205	NA	0	0	0	0	564.09	0.689
DMU15	0.417	NA	0	0	0	0	573.234	7.484
DMU16	0.046	NA	0	0	0	0	0	2.866
DMU17	1	0	0	0	0	0	0	0
DMU18	1	11	0	0	0.027	1642.974	0	0
DMU19	0.055	NA	0	0	0	0	21.906	0
DMU20	0.062	NA	0	0	0	0	17.568	0.441
DMU21	0.14	NA	0	0	0	0	149.268	1.847
DMU22	0.054	NA	0	0	1.058	0	95.979	0.455
DMU23	0.395	NA	11775	0	0	0	0	1.368
DMU24	0.026	NA	0	0	0.027	0	100.484	0.293
DMU25	0.146	NA	0	0	0	0	224.496	0
DMU26	1	1	0	0	0	0	0	0
DMU27	0.146	NA	0	0	0	0	293.286	1.703
DMU28	0.059	NA	0	0	0	0	33.011	0.192
DMU29	1	0	0	0	0	0	0	0
DMU30	0.015	NA	0	0	0	0	13.446	0.172
DMU31	0.988	NA	0	0	0	35447.54	0	0
MEAN	0.573	NA	379.82	0	0.036	1435.786	315.619	3.284

The efficiency frontiers that are formed by the efficient DMUs are so-called facets. The more the frequency of a facet is referenced by other inefficient DMUs, the higher strength the corresponding DMU has (Charnes et al., 1986, 1991). The numbers of facets that are referenced by the inefficient DMUs for each efficient DMUs are also given in Table 2. In particular, DMU 4 that is referenced 17 times by other inefficient DMUs reveals the highest strength. On the other hand, although DMU5, 8, 17, and 29 are also efficient, they are not referenced by other inefficient DMUs. This implies that these DMUs are located at the corner points of the efficient frontier.

B. Technical efficiency and scale efficiency

We constructed BCC model (Banker et al., 1984) to evaluate the technical efficiency and scale efficiency of the DMUs. The value of total efficiency (TOE) consists of two components: technical efficiency (TEE) and scale efficiency (SCE). Thus, the total efficient DMUs will also be technical efficient as well as scale efficient. From Table 3, the technical efficiency has an average value of 0.789. It means that most companies in this study present good technical efficiency. Only few companies need to improve in this way. Although DMUs 19, 28, 30, 31 are inefficient, their technical efficiency equal to 1. This implies their total inefficiencies are due to scales rather than their technology to make use of resources.

Table 3

Total efficiency, technical efficiency, and scale efficiency

	TOE	TEE	SCE	RTS
DMU1	1	1	1	CRS
DMU2	1	1	1	CRS
DMU3	0.501	0.523	0.958	DRS
DMU4	1	1	1	CRS
DMU5	1	1	1	CRS
DMU6	1	1	1	CRS
DMU7	1	1	1	CRS
DMU8	1	1	1	CRS
DMU9	1	1	1	CRS
DMU10	0.747	0.753	0.993	DRS
DMU11	0.33	0.396	0.883	IRS
DMU12	1	1	1	CRS
DMU13	0.432	0.561	0.769	IRS
DMU14	0.205	0.62	0.331	IRS
DMU15	0.417	0.595	0.7	IRS
DMU16	0.046	0.216	0.213	IRS
DMU17	1	1	1	CRS
DMU18	1	1	1	CRS
DMU19	0.055	1	0.055	IRS
DMU20	0.062	0.508	0.121	IRS
DMU21	0.14	0.391	0.357	IRS
DMU22	0.054	0.538	0.1	IRS
DMU23	0.395	0.588	0.672	IRS
DMU24	0.026	0.563	0.046	IRS
DMU25	0.146	0.55	0.265	IRS
DMU26	1	1	1	CRS
DMU27	0.146	0.651	0.224	IRS
DMU28	0.059	1	0.059	IRS
DMU29	1	1	1	CRS
DMU30	0.015	1	0.015	IRS
DMU31	0.988	1	0.988	IRS
mean	0.573	0.789	0.668	

Table 4

Projections for inefficient DMUs with increasing return to scale

DMU	DMUs in the Facet	S	T	P(+)	R&D(+)	R(+)	OBJECT	WEIGHT
DMU 11	DMU 1, 4	6075828	0	889256	110387	313	5075872	X1=1
DMU 13	DMU 4, 6, 7, 12	5887799	1	849429	114998	389	4922985	X1=0.958 X6=0.042
DMU 14	DMU 4, 18	6179774	0	904464	112208	410	5162692	X1=1
DMU 15	DMU 4, 18	6246068	0	938896	114207	397	5192568	X1=1
DMU 16	DMU 1, 2, 4	6249583	0	846201	110184	327	5292871	X1=1
DMU 19	DMU 4	6261999	0	885056	115065	417	5261461	X1=1
DMU 20	DMU 4, 18	6268681	0	928256	114876	405	5225144	X1=1
DMU 21	DMU 4, 18	6270104	0	939856	113857	395	5215996	X1=1
DMU 22	DMU 4, 18	6271243	0	929156	113719	407	5227961	X1=1
DMU 23	DMU 12, 26	6027293	1	889529	116675	394	5020697	X1=0.958 X6=0.042
DMU 24	DMU 4, 18	6275712	0	925056	111745	406	5238505	X1=1
DMU 25	DMU 4, 18	6275746	0	943856	113120	405	5218365	X1=1
DMU 27	DMU 4, 18	6277214	0	944056	113115	398	5219645	X1=1
DMU 28	DMU 4, 18	6277812	0	939556	115358	415	5222483	X1=1
DMU 30	DMU 4, 18	6281736	0	943181	115390	410	5222755	X1=1
DMU 31	DMU 1, 2, 4	6061232	0	883226	114915	415	5062676	X1=1

S: Annual sales (in 0,000 NT dollars)

R&D: Annual R&D expenditure (in 0,000 NT dollars)

R: Number of R&D employees

T: Number of patents approved by patent office

P: paid-in capital (in 0,000 NT dollars)

The scale efficiency is measured by the ratio of TOE to TEE. It denotes the percentage of resource usage of a company due to its size, i.e. to its scale of operation. Hence, (1 - TOE/TEE) is the percent of potential output lost due to scale inefficiency.

From the results shown in Table 3, the major portions of the inefficiencies are attributable to the scale, i.e. to the differences of firm sizes. Furthermore, a DMU is said to exhibit increasing (IRS), decreasing (DRS) or constant (CRS) returns to scale, if its returns to scale value is exceeding, less than or equal to 1, respectively. It gives an indication of the direction towards which resource allocation may have to be redirected to increase the efficiencies. The total efficient DMUs must have constant returns to scale.

As shown in Table 4, there are 18 inefficient companies. Most companies present increasing returns to scale. In particular, 11 companies have technical efficiency values bigger than scale efficiency values (i.e., DMUs 14, 16, 19, 20, 21, 24, 25, 27, 28, 30, 31). The resource inefficiencies of these companies may due to the scale factor rather than from the technical factor. This implies that they are not on the economic scale and they should enlarge the scale of company, e.g., by investment, to increase the efficiency.

Only DMU 3 and DMU 10 are decreasing returns to scale, i.e. their technical efficiency values are smaller than scale efficiency values. Thus, they should improve their technical factors to increase the efficiency of R&D performance.

C. The improvement direction

Most of the inefficient DMUs should increase their efficiency by reducing the input surplus. The quantities of output slack and input surplus are shown in the Table 2. In addition, the P1 model can be applied to find the way for improving the R&D performance of the DMUS that are increasing return to scale. The results are shown in Table 4. The second column is the reference facets correspond to efficiency frontier for each DMUs in first column. Columns 3 to 7 are the increment of the output factors, i.e., annual sales and patents, and the increment/reduction of the input factors, i.e., paid-in-capital, annual R&D expenditure, and R&D employees. The last column represents the convex combination's coefficient of the projection facet. It is noticed that most DMUs are projected to DMU1 and DMU 4. The results of P1 model given in Table 4 provide improvement directions for the inefficient DMUs.

VI. CONCLUDING REMARKS

Using data envelopment analysis, this paper evaluated the R&D performance of 31 Computers and peripherals firms located at Hsinchu Science-based Industrial Park in Taiwan. The use of DEA for evaluating the relative efficiencies of R&D activities shows a good understanding of the relations between the resource utilization and the output of the different companies. In particular, the results distinguish between efficient and inefficient companies according to the evaluations of total efficiency, technical efficiency, and scale efficiency, respectively. Furthermore, we examined the factors that affect R&D performance in a positive or negative manner, allowing the corresponding inefficient companies to identify the directions for improving their R&D performance.

In conclusion,

1. The efficiency values of 31 Computers and peripherals firms are very different. 42% of firms have the total efficient values to be 1.
2. The major portion of the inefficient firms are attributed to the scale component, i.e., to differences in resource allocation/usage patterns.
3. Most of the inefficient firms have increasing return to scale. It means most inefficient firms have technical resources, but the scale efficiency should be enhanced.

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