Operational Efficiency Analysis and Improvement in Taiwan Computer Motherboard Industry

Ling-Lang Tang · Chunching Lien
Graduate School of Management, Yuan-Ze University, Taiwan
balltang@saturn.yzu.edu.tw · s867707@mail86.yzu.edu.tw

Abstract

Utilizing Data Envelopment Analysis (DEA), this paper examines the relatives efficiency of 24 companies over a period of 3 years in the Taiwan computer motherboard industry. Simultaneously, we employ BCG matrix to explain the difference between efficiency and profitability in these companies. We also utilize Benchmarking and Acquisition/Merger methods for corporations to improve their efficiency and productivity. DEA can identify benchmarking partners who are the best and show the way to improve their efficiency. Furthermore, we use DEA as a tool to find out who is the best candidate to be acquired/merged to get productivity. We believe that such computations hold the potential of becoming a useful tool assisting financial analysts and managers in their routine evaluation of the performance of corporations and industries.

(Key words: DEA; Efficiency; Profitability; Benchmarking; Acquisition/Merger)

1.Introduction

Taiwan manufacturers totally dominated 67.5%, 72.5% and 78.9% global market shares of computer motherboard in 1997, 1998 and 1999, respectively. However, the computer motherboard industry in Taiwan is highly competitive. To get more orders and to survive in the competitive market they demand achieving the highest levels of performance through continuous improvement and learning. It is therefore imperative that managers understand where they stand relative to competitors and best practices regarding their productivity.

Comparative and benchmarking information can provide impetus for significant improvements and can let institutions know new practices and new paradigms. Uncovering and understanding best practices, however, is often limited by the simplicity of the analytical framework. Simple gap analyses – probably the most commonly used technique for benchmaking – can provide important insights but are somewhat limited in scope because they take a one-dimensional view of a service, product, or process and because they ignore any interaction, substitutions, or trade-offs between key variables. Thus, a more inclusive multiple-input, multiple-output framework for evaluating productive efficiency and providing benchmarking information on how to become a well-managed company seems essential to improving decision making at poorly managed companies. Increasingly, Data Envelopment Analysis (DEA) is coming into general use as a tool to measure the relative cost effectiveness of industrial corporations. DEA is a linear programming-based technique that converts multiple inputs and multiple outputs into a scalar measure of relative productive efficiency. In this paper, we discuss how DEA may be further extended to measure the nature and extent of the motherboard industry in Taiwan and rank the companies in relation to each other.

In this study, we are interested in benchmarking the operation efficiency of Taiwan motherboard companies. This is accomplished by comparing the sales and resources used by each company with those of all other companies. To further utilize our result we choose two well-known methods for those inefficient corporations to improve their efficiency: Benchmarking and Acquisition/Merger. Benchmarking is an increasingly popular approach in the quest of increased efficiency. DEA can identify benchmarking partners who are the best and show the way to improve their efficiency. In the similar concept, we use DEA as a tool to find out who is the best candidate to be acquired/merged to further get efficiency or maintain original efficiency level. In a highly competitive industry like computer industry, the company would always consider acquisition/merger as a convenient tool to become more efficient and competitive quickly. Through the DEA we will know a hypothetical company whether could yield efficiency gains after adopting acquisition/merger.

For those inefficient companies, we find the procedures – choosing benchmarking partners and picking up objects for acquisition/merger through DEA could provide sufficient information and technique to improve their operational efficiency. We believe that such computations hold the potential of becoming a useful tool assisting financial analyst in their routine evaluation of the performance of corporations and industries.

2. The DEA Methodology

DEA relates the performance of each company in the industry to a piecewise linear industry production frontier. The frontier is an empirically estimated production function, based on the inputs and outputs of the efficient companies. DEA is an alternative and a complement to traditional central-tendency (statistical regression) analyses, and it provides a new approach to traditional cost-benefit analyses and frontier (or best-practices) estimation. For an introduction to the basic DEA models and theoretical extensions, readers are referred to Boissofiane (1991)[3] or Charnes et al. (1994)[5].

(1) Output-oriented Model: We use output-oriented data envelopment analysis (DEA) model to create a robust quantitative foundation to benchmark the operation efficiency of Taiwan motherboard companies.

Model (1): Output-oriented CCR Model

$$\max \phi_0 + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{S} s_r^+\right)$$

$$s.t.\ \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = x_{i0} \qquad i=1,2,\ldots,m;$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = \phi_0 y_{r0} \qquad r = 1,2,\ldots,s;$$

$$\lambda_j, s_i^-, s_r^+ \geq 0,$$

Model (2): Output-oriented BCC Model

$$\max \gamma_0 + \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+)$$

$$s.t.\ \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = x_{i0} \qquad i = 1,2,\ldots,m;$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = \gamma_0 y_{r0} \qquad r = 1,2,\ldots,s;$$

$$\sum_{j=1}^{n}\lambda_j = 1$$

$$\lambda_j, s_i^-, s_r^+ \geq 0.$$

(2) Windows Analysis: In this study, data from 24 companies over a period of 3 years are collected and presented in the form of a "windows analysis" of efficiency patterns. By the way, in the DEA literature, a company or a department is usually referred to as a decision making unit or DMU. In actual studies, observations for DMUs are frequently available over multiple time periods (time series data), and it is often important to perform a panel data analysis where interest focus on changes in efficiency over time. In such a setting, it is possible to perform DEA over time using a moving average analogue, where a DMU in each different period is treated as if it were a "different" DMU. Specifically, a DMU's performance in a particular period is contrasted with its performance in other periods in addition to the performance of the other DMUs. For detailed "windows analysis" see Bowlin (1987)[2].

(3) Data Collection: Since the purpose of DEA is to estimate a piecewise linear industry efficiency frontier, it is important to keep the list of participating companies fairly homogeneous, so that key production activities carried out by them are comparable. The main operational activity of these 24 companies discussed in this study is manufacturing motherboard. They are main motherboard manufacturers in Taiwan. So they are fairly homogeneous. In this study we employ Securities & Futures Institute (SFI) data base to perform DEA calculations of the relative efficiency of companies in the Taiwan motherboard industry. Data in 19997 and 19998 are complete but data in 1999 are incomplete at the time of this study. There are total 17 companies announced their financial statements at the time of this study. Hence, there are 65 (24*2+17=65) DMUs in our study. As measures of the inputs in this study we used the following indicators (in millions of dollars unless otherwise noted):

Input 1: Cash, Accounts Receivable and Inventory (Current Assets)

Input 2: Plant, Property, and Equipment (Fixed Assets)

Input 3: Other Assets and Long-term Investment

Input 4: Cost of Goods Sold

Input 5: Marketing and Administrative Expenditures

Input 6: Expenditures on R&D

Input 7: Other Expenses (Interest Expense, Allowance for Loss, etc.)

The inputs encompass a flow of total assets, raw materials, labor, research & development, and all expenditures, while the outputs encompass all the revenues a company earned within a year. To measure the flow of outputs, we used the following indicators (all in millions of dollars):

Output 1: Revenue from Motherboard

Output 2: Revenue from Other Products (namely, motherboard excluded)

Output 3: Other Revenues and Gains

Although the circumstance can creates no mathematical problems in the definition and calculation of the DEA rating by itself, we avoid to make obvious logical overlaps between the 7 input and 3 output variables. DEA can deal with inputs and outputs in different units simultaneously. But in this study all variables are measured in current dollars. We believe that dollar amounts are better indicators of the quantity and quality of high tech products than any measure of "volume" obtained by dividing by a price index. As a shorthand for a bewildering array of technical specifications, we shall use dollar amounts as measures of the size of the product. Thus, we choose to interpret concepts like "the production function of a firm" and "efficiency" in the computer industry as being defined in a space of variables measured in current dollars, and the DEA ratings will be calculated accordingly.

3. Data Analysis and Interpretation

In this section, we analyze the operation efficiency of the 24 Taiwan motherboard companies. We find a close association between our efficiency scores and profitability, suggesting that our model could be useful to managers as a complementary off-site monitoring tool.

(1) Efficiency Scores: According to model (1) and (2), we can calculate the efficiency scores of the 24 companies over a period of 3 years. Table 1 reports the CCR and BCC efficiency scores.

Table 1 **Efficiency Result**

No	Company	CCR	BCC	Scale Efficiency	$\sum\lambda$	RTS	Position in BCG Matrix	ROA (%)	ROS (%)
DMU 1	ACER97	1.023872	1.023196	1.000660	1.853987	DRS	Star	7.02	9.69
DMU 2	ACER98	1.000000	1.000000	1.000000	1.000000	CRS	Star	4.02	5.27
DMU 3	ACER99	1.000000	1.000000	1.000000	1.000000	CRS	Star	9.27	12.90
DMU 4	GVC97	1.065288	1.064629	1.000619	1.063272	DRS	Star	4.71	5.85
DMU 5	GVC98	1.066094	1.066080	1.000013	1.043789	DRS	Dog	-1.93	-8.58
DMU 6	GVC99	1.129819	1.129741	1.000069	0.729415	IRS	Dog	-23.86	-71.28
DMU 7	OSE97	1.000000	1.000000	1.000000	1.000000	CRS	Star	9.86	15.03
DMU 8	OSE98	1.000000	1.000000	1.000000	1.000000	CRS	Star	7.05	8.94
DMU 9	OSE99	1.000000	1.000000	1.000000	1.000000	CRS	Star	6.52	9.58
DMU 10	ECS97	1.247132	1.214210	1.027114	3.496140	DRS	Cow	-5.43	-24.28
DMU 11	ECS98	1.266738	1.252124	1.011671	3.742607	DRS	Cow	-13.44	-72.10
DMU 12	ECS99	1.000000	1.000000	1.000000	1.000000	CRS	Star	18.59	63.62
DMU 13	USI97	1.000000	1.000000	1.000000	1.000000	CRS	Star	13.90	23.20
DMU 14	USI98	1.082173	1.069034	1.012290	2.797683	DRS	Dog	-26.01	-61.97
DMU 15	USI99	1.069773	1.000000	1.069773	8.155197	DRS	Star	9.87	20.27
DMU 16	ASUS97	1.000000	1.000000	1.000000	1.000000	CRS	Star	44.03	53.39
DMU 17	ASUS98	1.000000	1.000000	1.000000	1.000000	CRS	Star	39.16	45.57
DMU 18	ASUS99	1.000000	1.000000	1.000000	1.000000	CRS	Star	33.88	38.97
DMU 19	GIGA97	1.000000	1.000000	1.000000	1.000000	CRS	Star	32.37	61.65
DMU 20	GIGA98	1.000000	1.000000	1.000000	1.000000	CRS	Star	36.58	58.10
DMU 21	GIGA99	1.000000	1.000000	1.000000	1.000000	CRS	Star	24.53	35.25
DMU 22	MSI97	1.058239	1.056173	1.001955	1.184264	DRS	Star	18.00	38.00
DMU 23	MSI98	1.034802	1.032771	1.001967	1.423900	DRS	Star	18.00	39.00
DMU 24	MSI99	1.023317	1.000000	1.023317	2.273795	DRS	Star	18.19	32.98
DMU 25	DFI97	1.067218	1.061595	1.005297	0.903428	IRS	Star	8.00	14.00
DMU 26	DFI98	1.000000	1.000000	1.000000	1.000000	CRS	Star	7.00	10.00
DMU 27	PROCOMP97	1.083692	1.000000	1.083692	0.190619	IRS	Star	6.56	11.27
DMU 28	PROCOMP98	1.000000	1.000000	1.000000	1.000000	CRS	Star	10.20	17.60
DMU 29	PROCOMP99	1.067193	1.057798	1.008882	1.709794	DRS	Star	10.84	18.01
DMU 30	BIOSTAR97	1.051685	1.051148	1.000511	0.742785	IRS	Star	10.54	28.93
DMU 31	BIOSTAR98	1.045580	1.044397	1.001133	0.867444	IRS	Star	10.04	21.00
DMU 32	BIOSTAR99	1.075011	1.061475	1.012752	2.774297	DRS	Star	7.87	16.49
DMU 33	SHUTTEL97	1.000000	1.000000	1.000000	1.000000	CRS	Star	13.94	35.58
DMU 34	SHUTTEL98	1.036083	1.028565	1.007310	1.593366	DRS	Star	11.91	22.87
DMU 35	KAIMEI97	1.000000	1.000000	1.000000	1.000000	CRS	Star	7.55	12.44
DMU 36	KAIMEI98	1.046869	1.046543	1.000312	1.010661	DRS	Dog	-5.01	-12.48
DMU 37	CHINATECH97	1.119036	1.117805	1.001101	0.937674	IRS	Star	9.45	19.30
DMU 38	CHINATECH98	1.091566	1.086890	1.004302	0.594116	IRS	Star	5.47	7.49
DMU 39	CHINATECH99	1.076117	1.075232	1.000823	0.938836	IRS	Star	6.05	8.68
DMU 40	SOYO97	1.000000	1.000000	1.000000	1.000000	CRS	Star	21.56	46.24
DMU 41	SOYO98	1.043409	1.010280	1.032792	0.752744	IRS	Star	11.21	23.54
DMU 42	SOYO99	1.163736	1.160533	1.002760	1.574826	DRS	Cow	-4.63	-11.49
DMU 43	EPOX97	1.000000	1.000000	1.000000	1.000000	CRS	Star	6.31	14.26
DMU 44	EPOX98	1.007595	1.005747	1.007595	1.247512	DRS	Star	10.65	22.45
DMU 45	EPOX99	1.000000	1.000000	1.000000	1.000000	CRS	Star	7.13	17.81
DMU 46	A-TREND97	1.000000	1.000000	1.000000	1.000000	CRS	Star	16.27	26.61
DMU 47	A-TREND98	1.060436	1.000000	1.060436	3.262732	DRS	Dog	-33.02	-78.36
DMU 48	ABIT97	1.079830	1.076211	1.003363	1.583853	DRS	Star	7.76	21.02
DMU 49	ABIT98	1.105354	1.101226	1.003748	0.644257	IRS	Star	8.81	16.30
DMU 50	ABIT99	1.179303	1.080416	1.091527	2.673636	DRS	Sleeper	9.93	19.49
DMU 51	SUPERPOWER97	1.000000	1.000000	1.000000	1.000000	CRS	Star	11.02	24.99
DMU 52	SUPERPOWER98	1.000000	1.000000	1.000000	1.000000	CRS	Star	4.01	4.64
DMU 53	LUCKYSTAR97	1.000000	1.000000	1.000000	1.000000	CRS	Star	7.60	25.00
DMU 54	LUCKYSTAR98	1.000000	1.000000	1.000000	1.000000	CRS	Star	6.60	14.30
DMU 55	AOPEN97	1.000000	1.000000	1.000000	1.000000	CRS	Star	3.34	9.59
DMU 56	AOPEN98	1.000000	1.000000	1.000000	1.000000	CRS	Star	12.48	34.22
DMU 57	AOPEN99	1.000000	1.000000	1.000000	1.000000	CRS	Star	15.59	38.47
DMU 58	IWILL97	1.000000	1.000000	1.000000	1.000000	CRS	Star	13.85	34.34
DMU 59	IWILL98	1.000000	1.000000	1.000000	1.000000	CRS	Star	13.90	27.39
DMU 60	IWILL99	1.000000	1.000000	1.000000	1.000000	CRS	Star	14.68	23.01
DMU 61	MYCOMP97	1.169893	1.160335	1.008238	0.747224	IRS	Cow	-14.80	-166.10
DMU 62	MYCOMP98	1.000000	1.000000	1.000000	1.000000	CRS	Star	4.60	5.10
DMU 63	ACORP97	1.000000	1.000000	1.000000	1.000000	CRS	Star	9.69	52.69
DMU 64	ACORP98	1.000000	1.000000	1.000000	1.000000	CRS	Star	8.61	22.67
DMU 65	ACORP99	1.000000	1.000000	1.000000	1.000000	CRS	Star	10.46	24.46

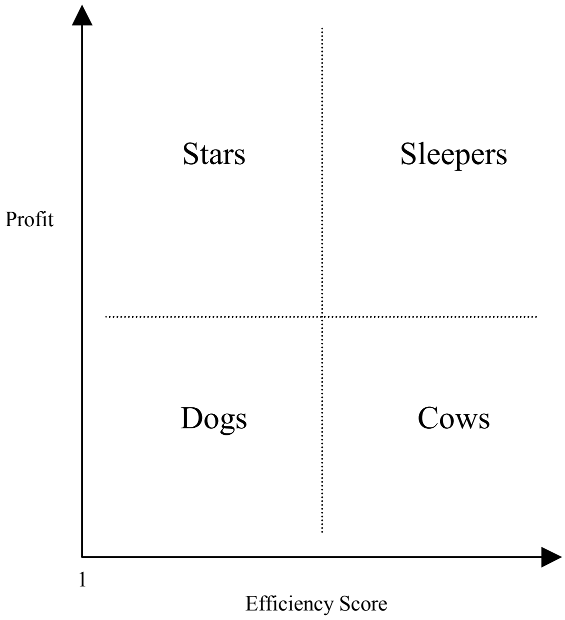
Now we define a scale efficiency measure by $\pi_0 = \dfrac{\phi_o}{\gamma_0}$. Obviously, $\pi \geq 1$. If $\pi = 1$, a DMU is called scale-efficient; otherwise, if $\pi > 1$, a DMU is called scale-inefficiency. We next determine whether increasing or decreasing returns to scale (IRS or DRS) is the primary cause of scale inefficiency. As shown in Banker (1984)[1], the optimal solution for λ_j^*(j = 1,…,n) in (1), *i.e.*, the magnitude of $\sum_{j=1}^{n} \lambda_j^*$, contains the information for RTS classification. Let DMU_0 be a company under evaluation and λ_j^* be an optimal solution to (1) associated with ϕ_0, then CRS prevail for DMU_0 if and only if $\gamma_0 = \phi_0$, *i.e.*, π_0=1; otherwise, if $\gamma_0 \neq \phi_0$,*i.e.*, $\pi_0 \geq 1$, then IRS prevail for DMU_0 if and only if $\sum_{j=1}^{n} \lambda_j^*$ <1, and DRS prevail for DMU_0 if and only if $\sum_{j=1}^{n} \lambda_j^*$ >1. Using this method, one does not have to worry about possible misclassification errors from multiple optimal solutions for λ_j^*, and the RTS classification are obtained from the optimal solutions to (1) and (2).

Note that the concept of RTS may be ambiguous unless a DMU is on the BCC-efficiency frontier, since we classified RTS for inefficient companies by their output-oriented BCC projections. Thus, a different RTS classification may be obtained for a different orientation, since the input-oriented and the output-oriented BCC models can yield different projection points on the VRS frontier. Thus, it is necessary to explore the robustness of the RTS classification under the input-oriented DEA model.

(2) BCG Matrix of Taiwan Motherboard: The premise of all DEA calculations is that efficiency can never be taken for granted, it has to be established empirically. As we shall see, in high technology industries such as the computer industry, efficiency may not even be the predominant mode of operations. There are other more pressing objectives that the management of a computer company has to tend to. Profitability is one of most important missions that they have to face every day.

The joint results of the analysis with the operation efficiency and profitability are illustrated in Figure1. DMUs fall into four quadrants similar to the ones observed in the BCG matrix: stars, dogs, sleepers, and cows (Hedley 1976[7]). Sleepers are those companies that are highly profitable, although they are inefficient in operations. Hence, their profitability can be further increased if they are awakened and improved their operational efficiency. Stars are the companies that match their superior operation efficiency with profitability, while cows are lagging in profits and a major reason for this is their operational inefficiency. Finally, for the dogs we conclude that enhancements of their profitability cannot come from improvements in operations, since they are already efficient on the operational side.

The subject matter dealt with in this paper, then, is the relationship between efficiency and the profitability. In Figure 2, the BCG Matrix can show what situation the company is. We can see there are many companies may be able to achieve efficiency and maintain high profitability. There are total 54 DMUs are classified into "Star" quadrant (ROA > 0 and efficiency score < 1.15). It implies most of motherboard manufacturers in Taiwan have good operation efficiency and profitability. Now we pick up DMU50 as an example. Abit99 is classified into "Sleeper" quadrant. If it can improve its operation efficiency, it could have better profitability. Next section will discuss how to improve efficiency.



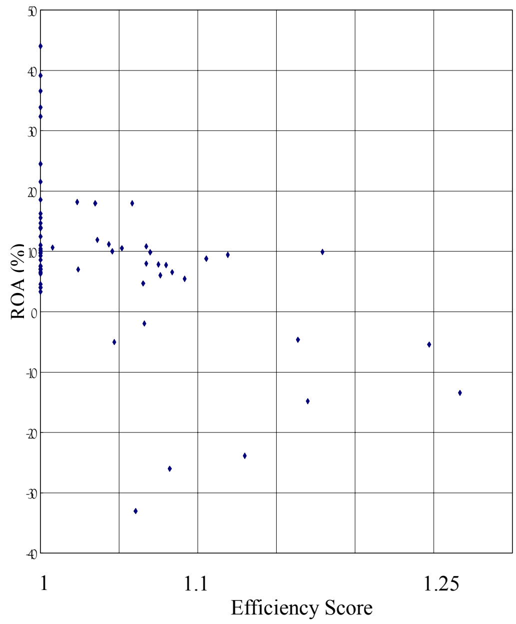


Figure 1 BCG Matrix.

Figure 2 The efficiency/profitability matrix

4. Improvement of Efficiency and Operation

Conventional wisdom holds that in competitive industries in the strongest institutions survive and that those institutions are among the most efficient and effective. In this section we will discuss how to improve operation to be efficient and effective.

4.1 Benchmarking

Benchmarking is a process of searching for the best products, service, practices or processes, adopting or adapting their good features and implementing them so that organizations could become "the best of the best". The practice of benchmarking, as detailed by Camp [4] and widely followed by practitioners, is dominated by the search for specific practices which will enhance performance (output); with a controlled allocation of resource (inputs); that result in increased efficiency. As a result, the search for benchmarking partners consists of seeking organizations that represent superior practices in a particular process that can be measure, modified if necessary, and then hopefully implemented in possibly a different operating environment. Collier and Storbeck [6] have proposed the use of DEA to aid in selecting benchmarking partners; their application utilizes a combination of technical and scale efficiency and is in the area of telecommunication.

This section focuses on a general philosophy for identifying a given company's "best practice" partners. Peer grouping approaches have been successfully used in evaluating productivity and efficiency for school, utilities, criminal superior courts, military recruiting districts, hospitals, banks *etc*. Hence, we are concentrating on a new tool for Step 2 of Camp's benchmarking process steps (For detailed benchmarking process see Camp, 1989[4]). Our approach will rely on the building of a peer group of other actual companies, operating in the same time period, and matched on size, service volumes, operating environment.

DEA is a powerful, non-parametric approach for identifying peer groups. For each inefficient unit, DEA identifies a set of corresponding efficient units to form a peer group for the inefficient unit. The efficiency calculations of the DEA methodology yield Pareto optimal measures of efficiency. For any inefficiency DMU, therefore, it should be of interest to estimate by how much it outputs could be increased and/or the magnitude of resources which it could be conserve – what we will refer to as "organizational slack". These estimates are based on empirical observations and on comparative calculations. They provide an indication of the relative magnitude of increases in output and conservation of resources which are reasonable to expect. If a unit is efficient, then the projected point is the same as the data point and there is no discrepancy. If a unit is inefficient, then the observed point and the projected point will be different. Now we pick up 5 DMUs for examples as illustrated in Table 2.

Table 2 Slacks Analysis (In millions of NT Dollars)

No	Company	Position in BCG Matrix	O1	O2	O3	I1	I2	I3	I4	I5	I6	I7
DMU 6	GVC99	Dog	0	0	0	2,993	0	398	0	1069	669	3782
DMU 10	ECS97	Cow	0	0	0	0	0	1,141	0	0	0	239
DMU 11	ECS98	Cow	0	0	33	0	117	1,081	0	0	0	916
DMU 12	ECS99	Star	0	0	0	0	0	0	0	0	0	0
DMU 42	SOYO99	Cow	0	0	125	444	0	0	0	16	29	190
DMU 50	ABIT99	Sleeper	0	0	158	0	0	0	0	0	0	58

Table 2 shows some parts of DEA calculation in section 3. GVC is in the red in the pass 3 years (see Table 1). If GVC can reduce input 1, 3, 5, 6 and 7 as table 2 shows, GVC's efficiency could be improved in 1999. ECS is also in the red in 1997 and 1998. The management of ECS was trying to close and dispose their losing-money departments in 1997 and 1998. In 1999 ECS began to be in the black. Hence, the "Sleeper" Abit99 should induce output 3 $158 million dollars and reduce input 7 $58 million dollars then it could be "Star".

4.2 Merger & Acquisition

Most observers agree that mergers are driven by a complex pattern of motives, and that no single approach can render a full account. In this section we focus on Efficiency and Monopoly Theories (see Trautwein, 1990[9]). We make a simulative situation to explain approach. Giga Byte Co.(DMU 19, 20 and 21, see table 1) is a professional motherboard manufacturer. Their products have good performance and earn excellent goodwill. In 1999, because of Y2K many PC assemblers made big orders for their desktop PCs in advance. But Giga was lacking of productivity always. Their supplies can't satisfy customers' demands – even Giga made outsourcing. It was too late to build new factories and machines. There was only way to get productivity right away – merger & acquisition. There are ten companies to be candidates to be merged. Hence, ten hypothetical DMUs are created to represent the result of merger and acquisition. Additivity is assumed in acquisition, *i.e.*, the input and output levels in the new company, DMU56 are the summations of the associated input and output levels of Giga99 and MSI99 (DMU 21 and DMU 24). The ten hypothetical DMUs replaced original ones in the DEA calculation in section 3. Table 3 reports some parts of outcomes after Merger & Acquisition. All efficiency scores of DMU 64 and DMU 65 are 1. Now we know the two companies, IWILL and ACORP are the best candidates to be merged/acquired by Giga.

Table 3 DEA Calculation for M&A

No	Company	CCR	BCC	Scale efficiency	RTS	ROA	ROS
DMU 55	GIGA99	1.000000	1.000000	1.000000	CRS	24.53%	35.25%
DMU 56	GIGA99+MSI99	1.011522	1.000000	1.011522	IRS	21.09%	34.15%
DMU 57	GIGA99+PROCOMP99	1.013051	1.006064	1.006944	IRS	20.39%	30.55%
DMU 58	GIGA99+BIOSTAR99	1.018139	1.010371	1.007688	IRS	19.27%	30.74%
DMU 59	GIGA99+CHINATECH99	1.015805	1.010361	1.005388	IRS	19.89%	28.57%
DMU 60	GIGA99+SOYO99	1.030787	1.017849	1.012711	IRS	15.60%	25.74%
DMU 61	GIGA99+EPOX99	1.000420	1.000000	1.000420	IRS	20.75%	32.85%
DMU 62	GIGA99+ABIT99	1.061602	1.000000	1.061602	IRS	18.68%	30.07%
DMU 63	GIGA99+AOPEN99	1.005885	1.000000	1.005885	IRS	20.58%	36.27%
DMU 64	GIGA99+IWILL99	1.000000	1.000000	1.000000	CRS	23.73%	34.34%
DMU 65	GIGA99+ACORP99	1.000000	1.000000	1.000000	CRS	23.83%	34.91%

5. Conclusion and Future Research

The paper analyzes the operation efficiency and profitability of the 24 Taiwan motherboard companies in 1997,1998 and 1999. Close to 83% of DMUs are classified into "Star" quadrant in BCG matrix. This can explain why these companies could survive to nowadays. To be more efficient and profitable, companies should adjust some inputs and outputs as DEA suggest (slack analysis).

The current study develops two ways to improve a company's operation efficiency and profitability. For those inefficient companies, we find the procedures – choosing benchmarking partners and picking up objects for acquisition/merger by DEA could provide sufficient information and technique to improve their operational efficiency. We believe that such computations hold the potential of becoming a useful tool assisting financial analyst in their routine evaluation of the performance of corporations and industries. And companies can use DEA as a assistant tool to choose candidates for M&A.

The current study does not attempt to incorporate "product life cycle theory" as was done in Thore *et al.* (1996)[8]. In addition, at the time of this study, some data for current year are incomplete. However, in future studies, we do expect to examine performance over time affected by PLC with Malmquist productivity change index techniques. Such an approach would allow a dynamic view of the company's operation efficiency and profitability over time. The incorporation of value judgement, *e.g.*, introduction of weight bounds will sharpen DEA scores and rule out possibly unreasonable values. Since the current study did not have access to such a prior information, we suggest employing a cone ratio or assurance region approach in the future research.

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