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# A Comparison of Ratios and Data Envelopment Analysis: Efficiency Assessment of Taiwan Public Listed Companies

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**Abstract** *The need to assess business firm's efficiency is important for all players involved in a business. Efficiency assessment has previously been conducted using financial ratio analysis. However, it failed when simultaneously considering multiple inputs and outputs. Because of this difficulty the data envelopment analysis (DEA) is proposed as an alternative approach for handling multiple inputs and outputs. This study introduces financial ratio analysis and the DEA model for assessing performance and uses panel data of 24 Taiwan public listed companies to demonstrate the merit of the model in assessing efficiency with quantitative guidance for policy formulation.*

**Key words** Efficiency, Ratio Analysis, Data Envelopment Analysis

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## 1. Introduction

Efficiency assessment of business firms is an important issue, which encompasses all business players, including managers, shareholders, and investors. Efficiency assessment demonstrates how shareholders and investors interests are affected, it informs on whether existing company resources are used effectively and efficiently, and motivate firms to implement strategies for further improvements. Various approaches have been used for this purpose, one of which is financial ratio analysis; financial ratios have been used as tools to plan and control firm activities and assess their efficiency. However, findings show that, they can only be an appropriated method when firms manage a single input to generate a single output. Financial ratio analysis does not provide sufficient information when considering the effects of economies of scale and estimation of overall efficiencies measures. Therefore, data envelopment analysis (DEA) has proven to be an essential tool, because it measures relative efficiencies by using multi-inputs and multi-outputs. The original purpose of DEA was to evaluate the relative efficiency of non-profit organizations such as schools and hospital; however, business firms and industries also use it to analyze monetary values (Erkut and Hatice, 2007). This study introduces financial ratio analysis and the DEA model for assessing performance. To illustrate the merit of DEA, this study uses panel data of 24 companies listed in the Taiwan Stock Exchange, which includes the effects of economies of scale, benchmarking firm efficiencies and quantitative guidance for further improvement.

## 2. Literature Review

Financial ratio analysis has historically been used for the explaining and predicting of firm' efficiency (Altman, 1968; Ambrose and Seward, 1988) and to evaluate the differences in financial management and goals between investor-oriented firms and cooperative enterprises. Chesnick (2000) identified various ratios, which can be used to evaluate firm' performance, including: liquidity ratios and profitability ratios. He documented that liquidity ratios measure the ability to fulfill short term commitments with liquid assets, whereas the profitability ratios measure the success of the firms in earning a net return on its operations. Initially, McNamara and Ducan (1995) used return on asset (ROA) to explain and predict firm efficiency; and found it to be a prior year of return on assets. Penman (2007) also found return on equity to be a pure measure of firm profitability and performance by investigating the properties of return on equity (ROE).

However, all these predictions have been found unsuccessful because of the univariate nature of ratio analysis, which presents a major limitation in assessing firm' performance. Conducting an analysis of complex organizations that produces multiple outputs is often limited to examining ratios of outputs to inputs (Ludwin and Guthrie, 1989). The result from ratio analysis is abstruse when considering the assessment of overall firm efficiency. This has led researchers to search for an alternative approach, among which is DEA. Because DEA was independently proposed by Charnes *et al.* (1978), studies to extend and apply the model have been numerous. Application of the model has involved an efficiency assessment of the public sector (schools and hospital) because of their given inputs and outputs which are not measureable in unified units (Friedman and Sinuany-Stern, 1998; Wei *et al.*, 2012). Similarly, it also has been used in efficiency evaluation of business and industries. Friedman and Sinuany-Stern (1998) used the ranking method in DEA to rank industrial branches in Israel according to their level of efficiency and performance. Researchers used two methods based on multivariate statistics, such as canonical correlation analysis (CCA) and discriminant analysis of ratio (DR/DEA). The inputs used in the study were assets, labor cost and average wage gained by employees per hour of work; the outputs were the revenue and export revenue.

Chandra *et al.* (1998) also used the DEA-CCR model to evaluate the efficiency of Canadian textile companies. The used inputs were the number of labor and average annual investment; whereas the used outputs were the annual sales values. Erkut and Hatice (2007) used the super slack based model of DEA with two inputs and three outputs to analyze the performances of 500 industrial enterprises in Turkey. The analysis result revealed that during 2003, only nine firms performed efficiently. El-Mashaleh *et al*. (2010) developed DEA with a CCR- oriented approach to benchmark the safety performance of 45 construction contractors. The authors demonstrated that after the research only eight contractors were considered to have superior safety performance. Tahir and Yusof (2011) adopted the DEA-CCR and DEA-BCC with inputs-oriented assumptions to estimate the technical and scale efficiency of 14 Malaysian public listed companies. Two inputs and one output were used. The inputs employed were total expenses and total assets, and the output was sales revenue. The estimate result disclosed that only one company was relatively efficient. Joshi and Singh (2009) estimated the production efficiency of the ready-made garment industry using DEA technology. They considered the number of stitching machines and number of operators as inputs-variables and the number of garment pieces produced as output variables. The result revealed that, under constant returns to scale (CRTS), firms should increase their outputs by 25% with the existing level of inputs.

Barros and Dieke (2007) evaluated the operational performance of 31 Italian airports using four data envelopment models. The types of model included: DEA-CCR, DEA-BCC, the cross- efficiency DEA model, and the super-efficiency DEA model. The outputs were measured by the number of planes, number of passengers, cargo, aeronautical receipts, handling receipts, and commercial receipts, and the inputs were labor costs, capital invested and operational costs. Liu *et al.* (2010) used DEA compared the relative efficiency of manufacturing companies of China and Turkey. They also used canonical correlation analysis, the same as the one conducted by (Friedman and Sinuany-Stern, 1998). The inputs variables included: the number of employees, inventory turnover, receivable turnover, total asset/total debt, cash flow, current ratio, and property plant and equipment/total asset, whereas the outputs variables included net income per employee, sales growth, net income per share, and EBIT margin. The results indicate that, Chinese manufacturing firms are more highly efficient than Turkish manufacturing firms. In conclusion, these studies affirm the application of DEA to assess firm efficiency by undertaking various process and models. They also differ on number and type of inputs and outputs. This means that the test for best specification with respect to the most appropriate variable for DEA is not clear-cut.

## 3. Research methodology and data acquisition

### 3.1. Research methodology

The DEA is a linear programming technique for evaluating the efficiency of multiple decision-making units (DMUs) when the production process presents multiple inputs and outputs structure. Charnes, Cooper and Rhodes first developed the technique based on the pioneer work of Farrell and his' efficiency measures (Farrell, 1957), also known as frontier analysis (Stancheva and Angelova, 2004). The efficiency of decision-making units (DMUs) is evaluated by comparing its performance with the best performing unit. The best performing unit should lie down on the efficiency frontier. If the unit is not on the efficiency frontier, it is considered inefficient. This decision- making units can be different type such as: business firms, number of schools, hospitals, and banks. DEA has been recognized as the best tool because of its well-known advantage, and has been credited for not requiring any specification of predetermined weights to the input and output variables. DEA can be used easily to handle multiple inputs and outputs simultaneously as opposed to other technique such as ratio analysis and regression.

The current study applied two DEA models with an output oriented version. The first model developed by Charnes *et al*. (1978) was called the CCR model. The second model was named the BCC model, developed by Banker (1984). The CCR model is built on the assumption of constant returns to scale (CRS), whereas the BCC model is built on the assumption of variable returns to scale (VRS). The relative efficiency evaluated by the CCR model is the overall efficiency score and the one estimated by the BCC model is the pure technical efficiency score. These scores are typically defined on the interval [0, 1].

### 3.2. The CCR Model

According to Charnes *et al*. (1978), the fractional form of the CCR liner programming model is given as follows:

$$\eta_O{}^{MA} = \frac{\sum_{r=1}^{S} u_r y_{rO}}{\sum_{i \in ID} v_i x_{iO}}$$

Subject to

$$\frac{\sum_{r=1}^{S} u_r y_{rj} - \sum_{i \in I_F} v_i \left(x_{ij} - x_{io}\right)}{\sum_{i \in I_D} v_i x_{ij}} \leq 1 \qquad j \in \{1........N\}$$

$$u_r, v_i \geq \in > \quad for \quad r \in (1........S) \quad and \ i \in I_D$$

$$v_i \geq 0 \quad for \ i \in I_F$$

Where *u* and *v* are the weights of the input and output, *i* and *r* are output and input of DMU. According to Liu *et al.* (2010), the model is difficult to solve because of its fractional model. Therefore, the dual liner model is required to reduce the number of constraints and facilitate solving the linear problem. However, the model is modified based on the Cooper' modification (Cooper *et al*., 2000).

$$Max \quad \phi_o + \varepsilon\left(\sum_{r=1}^{S} S_{ro}^{-} + \sum_{r=1}^{M} S_{io}^{+}\right)$$

Subject to

$$\sum_{j=1}^{N} \gamma_j y_{rj} - S_{ro}^{-} = \phi_O y_{ro} \ , \ r \in \{1,.........S\}$$

$$\sum_{j=1}^{N} \gamma_j x_{ij} + S_{io}^{+} = x_{io} \ , i \in \{1,........,M\}$$

$$\phi_O, \gamma_j, S_{rO}{}^{-}, S_{iO}^{+} \geq 0 .$$

Where, $\phi_O$ is the measure of efficiency of the $DMU$ $"O"$ in the set of $j = 1,2,.......n$ $DMU_S$ rate related to other, $\varepsilon$ is e an infinitesimal positive number used to make both the input and output coefficients positive; $S_{ro}^{-}$ is the slack variables for input constraints, which are all constrained to be non-negative, and $S_{io}^{+}$ is the slack variables for output constraints, which are all constrained to be non-negative. $\gamma_j$ is the dual weight assigned to DMUs.

### *3.3. The BCC- Model*

According to Banker (1984), the BCC-model enables expression of the (input) technical efficiency measure for DMU. Thus, it has the same equation employed in the CCR-model, but with convexity constraint for modification.

$$Max \quad \phi_o + \varepsilon\left(\sum_{r=1}^{S} S_{ro}^{-} + \sum_{r=1}^{M} S_{io}^{+}\right)$$

Subject to

$$\sum_{j=1}^{N} \gamma_j y_{rj} - S_{ro}^{-} = \phi_O y_{ro} \ , \ r \in \{1,.........S\}$$

$$\sum_{j=1}^{N} \gamma_j x_{ij} + S_{io}^{+} = x_{io} \ , i \in \{1,........,M\}$$

$$\sum_{j=1}^{N} \gamma_j = 1$$

$$\phi_O, \gamma_j, S_{rO}^{\ -}, S_{iO}^{+} \geq 0 \, .$$

If convexity constraint $\sum_{j=1}^{N} \gamma_j = 1$, it implies that the DMU $"O"$ is currently operating at the most productive scale size for the discretionary inputs, given the fixed level of non-discretionary inputs. However, if $\sum_{j=1}^{N} \gamma_j$ >1, it implies that DMU $"O"$ is operating at a scale greater than the most productive scale size for the discretionary inputs. Conversely, if $\sum_{j=1}^{N} \gamma_j$ < 1 then DMU $"O"$ is operating in the increasing return to scale region, at a scale smaller than the most productive scale size for the discretionary inputs, given the fixed level of non-discretionary inputs (Banker, 1984).

## 4. Data Acquisition and Variables

Data for this study were obtained from the database of the Taiwan' Stock Exchange which contains the annual report and financial statement of large public trade companies. The data obtained from the annual report consist of computer firms from 2006 to 2010. The 24 companies from which data were collected are the leading companies in the market, with total shares of 70%. A commonly held view of previously conducted studies is that specification of the most appropriate variable for the DEA program is not clear-cut. Therefore, this study specified the annual total fixed assets ($X_1$), operating cost ($X_2$) and number of employees ($X_3$) as three inputs, whereas the outputs are annual total sales revenue ($Y_1$) and non-operating income ($Y_2$). Table 1 shows the Pearson correlation matrix between inputs and outputs, and provides correlation coefficient and related p-value for each pair of variable. The coefficient measures the strength and direction of a linear relationship between variables. The results indicate that the variables are correlated at a significant level. For instance, revenue and operating cost are positively correlated with efficiency at .01 levels (two-tailed test). Table 2 shows the descriptive statistic of the variable employed in the study. A large variation exists in the distribution of each inputs and output across the investigation period. This is evidenced by the large standard deviation of variables.

*Table 1.* Correlation between inputs and outputs

| Variables | | $X_2$ | $X_2$ | $X_3$ | $Y_1$ | $Y_2$ |
|---|---|---|---|---|---|---|
| | Correlation | 1 | .750** | .777** | .756** | .809** |
| $X_1$ | p-value | | .000 | .000 | .000 | .000 |
| | Correlation | .750** | 1 | .805** | 1.000** | .767** |
| $X_2$ | p-value | .000 | | .000 | .000 | .000 |
| | Correlation | .777** | .805** | 1 | .811** | .811** |
| $X_3$ | p-value | .000 | .000 | | 0 | .000 |
| | Correlation | .756** | 1.000** | .811** | 1 | .773** |
| $Y_1$ | p-value | .000 | .000 | .000 | | .000 |
| | Correlation | .809** | .767** | .811** | .773** | 1 |
| $Y_2$ | p-value | .000 | .000 | .000 | .000 | |

**Note**: ** Correlation is significant at the .01 level (two tailed).

*Table 2.* Descriptive statistic for inputs and outputs

| Inputs/ Outputs | Variables | Mean | S.D | Max | Min |
|---|---|---|---|---|---|
| | $X_1$ | 1795683 | 1919909 | 7112855 | 472 |
| Inputs | $X_2$ | 110536213 | 188792428 | 726156455 | 412884 |
| | $X_3$ | 1585.2 | 1721 | 5894 | 20 |
| Outputs | $Y_1$ | 116931414 | 196463898 | 754152907 | 484019 |
| | $Y_2$ | 2271972 | 3612778 | 13925043 | 22292 |

## 5. Empirical Results and Discussion

Table 3 shows the average financial ratio per firm. For this analysis, we use standard financial ratios, which assess firm profitability and efficiency. The result indicates that companies $C_{11}$, $C_{12}$, $C_{18}$, and $C_{19}$ seem to satisfy the management efficiency criterion. For instance, company $C_{11}$ is considered more efficient on ROA and ROE. Its average return on asset and return on equity is 21.5% and 34.9% whereas the $C_{19}$ seems to be more efficient for profit from sales, with an average return on sale of 52.7%. Table 4 shows the average efficiency scores derived from the CCR and BCC models. The CCR efficiency of the DMU17 from 2006 to 2010 is 0.79; this implies that the consumption of all inputs could reduce by 21% while producing the same quantity of outputs. The scale efficiency indicates that the firms are on the optimum production scale when the score equals one. The return to scale analysis is also shown in Table 4. The table shows that only two companies exhibit an increase in returns to scale, indicating that manager' capabilities to use company' given- resources still need to be enhanced. They must reduce non-essential expenses to improve efficiency and performance. A slack variable analysis may improve the resource utilization of these inefficient firms. The result presented in Table 5 indicates an excess of fixed assets (FA) and a shortage of non-operating income (NOI). Thus, an increase in non-operating income followed by reduced of fixed assets is the most effective method for improvement.

*Table 3.* Average financial ratios per firm (2006~2010)

| Companies | ROA (%) | ROE (%) | ROS (%) |
|---|---|---|---|
| $C_1$ | 8.2 | 20.9 | 2.5 |
| $C_2$ | 7.5 | 12.8 | 5.4 |
| $C_3$ | 8.1 | 18.3 | 3 |
| $C_4$ | 6.6 | 13.4 | 3.3 |
| $C_5$ | 5.5 | 13.6 | 1.7 |
| $C_6$ | 7.1 | 12.1 | 6.4 |
| $C_7$ | 4.1 | 7.9 | 2.6 |
| $C_8$ | 3.1 | 6.2 | 1.6 |
| $C_9$ | 0.5 | 0.5 | 0.2 |
| $C_{10}$ | 4.9 | 6.9 | 3.4 |
| $C_{11}$ | 21.5 | 34.9 | 16.1 |

| Companies | ROA (%) | ROE (%) | ROS (%) |
|---|---|---|---|
| $C_{12}$ | 16.7 | 20.1 | 21.9 |
| $C_{13}$ | 8.2 | 11.2 | 5.9 |
| $C_{14}$ | 11.4 | 17.8 | 8.3 |
| $C_{15}$ | 7.9 | 13.9 | 4 |
| $C_{16}$ | 4 | 4.7 | 4.6 |
| $C_{17}$ | -3.8 | -4.6 | -10.3 |
| $C_{18}$ | 16.6 | 21.2 | 29.8 |
| $C_{19}$ | 16.6 | 20.4 | 52.7 |
| $C_{20}$ | -5.6 | -11.2 | -6.7 |
| $C_{21}$ | 12.6 | 15 | 17.2 |
| $C_{22}$ | -21.9 | -34.2 | -31.7 |
| $C_{23}$ | 4.3 | 5.2 | 2.5 |
| $C_{24}$ | -5.7 | -8 | -40.5 |

**Note:** ROA represents return on assets, ROE is return on equity, and ROS return on sales (net profit margin ratio)

*Table 4.* Average efficiency during the 2006~2010 period

| DMUs | CCR Efficiency | BCC Efficiency | Scale Efficiency | RTS |
|---|---|---|---|---|
| DMU1 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU2 | 0.99 | 1.00 | 0.99 | DRTS |
| DMU3 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU4 | 0.96 | 1.00 | 0.96 | DRTS |
| DMU5 | 0.97 | 0.98 | 0.99 | DRTS |
| DMU6 | 0.99 | 1.00 | 0.99 | DRTS |
| DMU7 | 0.98 | 0.99 | 0.99 | CRTS |
| DMU8 | 0.96 | 0.98 | 0.98 | CRTS |
| DMU9 | 0.94 | 0.95 | 0.99 | CRTS |
| DMU10 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU11 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU12 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU13 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU14 | 0.97 | 0.98 | 0.99 | CRTS |
| DMU15 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU16 | 0.92 | 0.93 | 0.99 | CRTS |
| DMU17 | **0.79** | 0.82 | 0.96 | IRTS |
| DMU18 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU19 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU20 | 0.82 | 0.85 | 0.96 | CRTS |
| DMU21 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU22 | 0.84 | 0.91 | 0.92 | CRTS |
| DMU23 | 1.00 | 1.00 | 1.00 | CRTS |
| DMU24 | 0.75 | 1.00 | 0.75 | IRTS |

**Note:** CCR Efficiency represents overall efficiency. BCC Efficiency represents pure technical efficiency.

RTS stands for returns to scales; CRTS, DRTS and IRTS represent constant, decreasing, and increasing returns to scale.

Table 5. Slack variable analysis for the 2006~2010 period

| DMUs | Excess FA | Excess OC | Excess E | Shortage Revenue | Shortage NOI |
|---|---|---|---|---|---|
| DMU1 | 0 | 0 | 0 | 0 | 0 |
| DMU2 | 0 | 0 | 0 | 0 | 0 |
| DMU3 | 0 | 0 | 0 | 0 | 0 |
| DMU4 | 0 | 0 | 0 | 0 | 0 |
| DMU5 | 907,034.7 | 0 | 0 | 0 | 4,608,757 |
| DMU6 | 0 | 0 | 0 | 0 | 0 |
| DMU7 | 688,406.8 | 0 | 0 | 0 | 377,694.7 |

| | | | | | |
|---|---|---|---|---|---|
| DMU8 | 633,682 | 0 | 0 | 0 | 371,362 |
| DMU9 | 1,923,525 | 0 | 0 | 0 | 1,191,624 |
| DMU10 | 0 | 0 | 0 | 0 | 0 |
| DMU11 | 0 | 0 | 0 | 0 | 0 |
| DMU12 | 0 | 0 | 0 | 0 | 0 |
| DMU13 | 0 | 0 | 0 | 0 | 0 |
| DMU14 | 27,093.18 | 0 | 0 | 0 | 158,896.3 |
| DMU15 | 0 | 0 | 0 | 0 | 0 |
| DMU16 | 0 | 0 | 0 | 0 | 176,886.9 |
| DMU17 | 0 | 0 | 0 | 0 | 0 |
| DMU18 | 0 | 0 | 0 | 0 | 177,999.1 |
| DMU19 | 0 | 0 | 0 | 0 | 0 |
| DMU20 | 0 | 0 | 0 | 0 | 0 |
| DMU21 | 0 | 0 | 0 | 0 | 147,042.1 |
| DMU22 | 0 | 0 | 0 | 0 | 0 |
| DMU23 | 442,794.3 | 0 | 0 | 0 | 463,253.4 |
| DMU24 | 0 | 0 | 0 | 0 | 0 |

**Note:** FA denotes fixed assets; OC: operating costs; E: employees; and NOI: non-operating income

All firms surveyed using the DEA approach have an acceptable level of efficiency, with CCCR scores ranging from 0.94 to 1.00, whereas BCC efficiency scores range from 0.75 to 1.00. This suggests that firms need to reduce their inputs cost up to 6% and 25%, while maintaining the same level of output. The average CCR, BCC, and scale efficiency score of DMU1, DMU3, DMU11, DMU12, DMU13, DMU15, DMU18, DMU19, DMU21, and DMU23 reached 1.00; this indicates that they are at an optimal level of efficiency, whereas the others are still inefficient, although their average CCR, BCC, and scale efficiency are close to 1.00. This implies that most of the large firms and their small counterparts are operating at a suboptimal level of efficiency. Therefore, necessary measures should be taken to improve their operational performance and efficiency. The empirical result from the Table 5 suggests that inefficient companies need improvement. For instance, the DMU5 exhibits an excess $NT 907,034 in fixed assets with a shortage of $NT 4,608,757 in non-operating revenue. The management must be improved by reducing investment in fixed assets and focusing more on revenue creation. For financial ratio approaches, this study uses each single ratio and compares it with benchmark ratios sequentially. However, using DEA-CCR and DEA-BCC with an output-oriented assumption, allows us to estimate the targets for measuring and explaining the determinants of each firm’s performance.

## 6. Conclusions

The usefulness of ratio analysis to estimate and predict firm efficiency has failed because of the univariate nature of ratio analysis, which presents major limitations in assessing firm’ performance. For this reason, DEA was introduced as an alternative approach for assessing the performance of such firms. To perform empirical analysis, this work used panel data of 24 firms listed as top Taiwan computer manufacturing firms in the market. The result derived from the DEA approach shows that all firms achieved an acceptable overall level of efficiency during the testing period, with an average CCR efficiency ranging from 0.94 to 1.00. The slack variable analysis identified possible ways to improve the performance of those inefficient firms. The results show that reduced investment in fixed assets followed by more non-operating revenue creation is the most effective method for improving the operational performance of inefficient firms. The financial ratio analysis shows that among the 24 analyzed companies, only four appear to satisfy the management efficiency criteria. Frontier analysis enables us to estimate the target for measuring and explaining the determinants of each firm performance, including the assessment of effect of economies of scale and an overall objective numerical score. Frontier analysis also suffers from drawbacks, which is the reason further research is needed with other input and output factors. The findings of this study can hopefully benefit managers of inefficient companies to help them restructure their organizational scope and business style and review resource utilization for improving their performance and efficiency.

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