International Journal of Academic Research in Business and Social Sciences
July 2012, Vol. 2, No. 7
ISSN: 2222-6990

A Study of Estimating the Technical Efficiency of Optoelectronic Firms: An Application of Data Envelopment Analysis and Tobit Analysis

Yaw-Shun Yu
Department of Finance, Chung-Hua University, No. 707, Sec. 2, WuFu Rd., HsinChu, Taiwan

Ambrosio Barros
Department of Finance, Chung-Hua University, No. 707, Sec. 2, WuFu Rd., HsinChu, Taiwan

Ming-Lang Yeh
Department of Business Administration, Chung-Hua University, No. 707, Sec. 2, WuFu Rd., HsinChu, Taiwan

Min-Jer Lu
Department of Food and Beverage Management, Yuanpei University, No. 306, Yuanpei Street, Hsin-Chu, Taiwan

Chih-Hung Tsai
Department of Information Management, Yuanpei University, No. 306, Yuanpei Street, Hsin-Chu, Taiwan
E-mail: imtch@mail.ypu.edu.tw

Abstract

The aim of this study is to investigate the efficiency and the determinants of efficiency of optoelectronic firms in Taiwan. Initially, the efficiency of each firms were evaluated using data envelopment analysis (DEA) approach. To investigate the determinants of efficiency, the Tobit regression model was used with the intention to explain variation in calculated efficiencies to a set of explanatory variables, such as firm's size, number of employees, profitability and ownership. The data collected cover the period of year 2010, from the database of the Taiwan' Stock Exchange. The finding reveals that profitable firms are more likely to operate at higher levels of efficiency. In addition, the study also reveals that firm's size has a positive impact on efficiency, but its effect is statistically insignificant. Also another finding suggests that the size of employees has a statistically insignificant adverse impact on the performance, indicating that the increase size of employees may have increased the cost and affects efficiency negatively. Thus necessary measures should be taken.

Keywords: Efficiency, Data Envelopment Analysis, Tobit Model, Optoelectronics firms

1. Introduction

Given the increasing level of competition between firms in the industry, it is of considerable interest to measure the efficiency of involving firms and investigate the determinants of their efficiencies. Studies have being carried out to analyze efficiency issues of industries using data envelopment analysis (DEA) approach. Recent examples of these studies were conducted by Chandra *et al.* (1998), Zhu (2000), Keh and Chu (2003), Erkut and Hatice (2006), and Tahir and Yusuf (2011). Evidence suggested that few studies have made use of Tobit regression analysis to investigate the determinants of firms' efficiency. However, some studies use ordinary least squares (OLS) regressions to estimate the variation in calculated efficiencies. Favero and Papi (1995) investigated the determinants of efficiency and found that efficiency is explained by product specialization and firm size. Miller and Noulas (1996) conducted OLS regressions to find the effects of firm's size, profitability, and market power on efficiency and stated that firm size and its profitability are significant and positively related to its efficiency. However, recent study by Aggrey *et al.* (2010) using similar approach found a negative association between firm's size and efficiency. In addition, they also found a positive relation between foreign ownership and efficiency. According to this study, the efficiency increases until a firm size threshold is reached and technical efficiency decreased with an increase in the firm size. Similarly, Le and Harvie (2010) examines the factors influencing efficiency and find that firm age, size, location, ownership, cooperation with a foreign partner, product innovation, competition, are significantly related to technical efficiency.

Based on these different approaches to find the determinants of firm's efficiency, the study tries to find the determinants of efficiency of optoelectronic firms using Tobit regression analysis. Initially, the performance efficiency of each firm was evaluated using CCR model of the DEA. In addition, the determinants of efficiency were also investigated using censored regression analysis of the Tobit model, with the intentions to explain the variation in calculated efficiencies to a set of explanatory variables. The rest of this study is organized as follows: Section 2, details methodology and data acquisition; Section 3, provides the empirical study and illustrates the results of DEA; Section 4, explains the determinants of efficiencies; and finally, section 5 offers a conclusion.

2. Methodology

Data envelopment analysis (DEA) was first developed by Charnes, Cooper and Rhodes in 1978 based on the pioneer work of Farrell and his efficiency measures (Farrell, 1957), henceforward the CCR model. DEA is mathematical liner programming method that produces a single measure of efficiency for each unit relative to its peers. DEA is oriented to evaluate the efficiency of organization such as business firms, schools, hospitals, and banks where the presence of multiple inputs and outputs make comparison difficult (El-Mashaleh *et al*., 2010; Wei *et al.*, 2012). The organization evaluated by DEA is called decision making units (DMUs). In this study, the DMUs refer to 26 optoelectronic firms which the entities responsible for converting inputs (i.e., resources, money, etc.) into outputs (i.e., sales and profits). The DEA is a mathematical liner programming method used to determine which DMU lie down on the efficiencies frontier. DEA provides the analysis of efficiencies for multiple inputs and outputs, by evaluating each DMU and compare 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.

Cooper *et al.* (2000) and Coelli *et al*. (1998) claimed that DEA has gained popularity because of its well-known advantage. First, it has ability to handle multiple inputs and multiple outputs simultaneously as a result of the use of linear programming. Linear programming can handle large number of inputs and outputs variables. Second, DEA has no prior assumptions to allocate weights to the different inputs and outputs. The weights are derived directly from arbitrary subjective weighting. DEA delivers a set of weights, which optimize unit' efficiency subjected to the weights not leading the bounds of the frontier to be violated by other units. Third, the measurement units of the different inputs and outputs variables need not be consistent. This study makes use of the Charnes–Cooper–Rhodes (CCR) model of DEA, built on the assumption of constant returns to the scale (CRS). According to Charnes *et al.* (1978), the fractional form of the CCR liner programming model is given as follows:

$$\text{Max } \mathrm{K_o} = \frac{\sum_{p=1}^{s} u_{po} y_{po}}{\sum_{r=1}^{m} v_{ro} x_{ro}} \tag{1}$$

Subject to

$$\frac{\sum_{p=1}^{S} u_{po} y_{pj}}{\sum_{r=1}^{m} v_{ro} x_{rj}} \leq 1 \qquad j \in \{1.........n\} \tag{2}$$

$$u_{po}, v_{ro} \geq 0 \quad for \quad p \in (1.........S) \;\; and \;\; i \in (1..........m) \tag{3}$$

Where *o* is the decision making units (DMUs) being estimated in the set of *j* = 1,..., *n* DMUs, k_o is the measure of efficiency of DMUs $''o''$ in the set of $j = 1.........n$ DMUs rate relative to others. y_{po} are the amount of outputs *p* produced by DMU $''o''$ and x_{ro} are the amount of input "r" utilized by DMU $''o''$, u_{po} and v_{ro} are the weight of inputs and outputs computed by DEA model, *m* is the number of inputs utilized by DMUs to produce the number of outputs. 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's modification (Cooper *et al*., 2000):

$$Max \quad \phi_o + \varepsilon \left(\sum_{p=1}^{S} S_{po}^{-} + \sum_{r=1}^{m} S_{ro}^{+} \right) \tag{4}$$

Subject to

$$\phi_o x_{po} - \sum_{j=1}^{n} \gamma_j x_{pj} - S_{po}^{-} = 0 \ , \ p \in \{1,.........s\} \tag{5}$$

$$y_{ro} + \sum_{j=1}^{m} \gamma_j y_{ro} + S_{ro}^{+} = 0 \ , \ r \in \{1,........, m\} \tag{6}$$

$$\phi_O, \gamma_j, S_{po}^{-}, S_{rO}^{+} \geq 0 \, . \tag{7}$$

Where, ϕ_O is the measure of efficiency of the DMU $''o''$ in the set of $j = 1,2,.......n$ DMU_S rate related to other, ε is e an infinitesimal positive number used to make both the input and output coefficients positive; S_{ro}^{-} is slack variables for input constrains, which are all constrained to be non-negative, and S_{io}^{+} is slack variables for output constraints, which are all constrained to be non-negative, γ_j is the dual weight assigned to DMUs. The objective of Eq.1 is to maximize the efficiency of the DMUs under evaluation. Eq.2 means that the efficiencies of all DMUs are ≦1.0. Eq.3 suggests that, the outputs and inputs weights are ≧0. This implies that all DMUs are either on the efficiency frontier or below it, and that efficiencies scores range between 0 and 1.0. Briefly stated, the CCR model of DEA will be used to evaluate the efficiency of 26 firms has previously mentioned. The model yields efficiency scores that range between 0 and 1, making the dependent variable a limited dependent variable. According to previously conducted studies the use of Tobit model is more accurate in estimating the variation of performance measurement and thus provides a precise result which may serve as guidance for further improvement, whereas the estimation with an ordinary least square (OLS) may lead bias to variation estimated. The efficiency scores obtained from DEA in the first stage are the dependent variables in the second stage of the Tobit model. Tobit models refer to regression models in which the range of the dependent variable is constrained or limited (Amemiya, 1984). In statistics literature, Tobit model is an extension of profit analysis developed by Tobin (1958) which is also called censored normal regression model (Goldberger, 1964).

Recently, many DEA applications employ two-stage procedure involving both DEA and Tobit. Kirjavainen and Loikkanen (1998) conducted two-stage procedure to estimate the efficiency and the determinants of efficiency of Finnish senior secondary schools. Pasiouras (2008) used DEA and Tobit regression model to estimate both efficiency and the determinants of inefficiencies of Greek commercial banks. Javed *et al.* (2010) also used similar approaches to investigate the efficiency and the determinants of efficiency of rice- wheat system. The Tobit model is defined as follows:

$$y = \begin{cases} y^*, & if \ y^* > 0 \\ 0, & if \ y^* \leq 0 \end{cases} \tag{8}$$

$$y_i^* = \beta X_i + \varepsilon_i \, , \, \varepsilon_i \sim N(0,\sigma^2) \quad (9)$$

Where, y is the DEA efficiency score, y^* is the latent variable, β is the vector unknown parameter which determines the relationship between the independent variables and the latent variable, X_i represents the vector of explanatory variables.

3. Data collected and Variables

Taiwan's optoelectronics industry consists of big and small sized firms, measured by employments and total assets in millions NT$. With regard to ownership, the shares are distributed according to different type of shareholders such as government with 1% of shares, domestic companies plus domestic natural person with total shares of 60%, and foreign shareholders with 39% of shares. The shares are distributed in unity ranging from 20,000.00 to 400,000.00 unities. Data were obtained from the database of the Taiwan's Stock Exchange, which contains the annual report and financial statement of large public trade companies. The data obtained from the 2010 annual report consists of 26 firms. As mentioned earlier, DEA considers DMUs as the entity responsible for converting inputs variable (i.e., resources, money, etc.) into outputs variable (i.e., sales and profits). However, in the DEA literature there is considerable disagreement on the specification of inputs and outputs variables. Sigala (2004) argued that one of the major problems associated with the DEA model is that it is difficult to define and identify the measurement of inputs and outputs being provided. In particular, the accurate measurement of inputs and outputs is complicated because of perishability and the heterogeneous nature of the business (Johnston and Jones, 2004). Previous studies showed that inputs are associated with capital, human, and environmental conditions (Goldman, 1992). Donthu *et al.* (2005) argued that factors associated with direct costs to the business firms are good candidates for input variables. On the other hand, output variables, such as profit, should reflect the goal or objectives of the company. Financial variables related to sales and net income are excellent candidates for outputs to measure the financial viability of an individual operating institution. Following the above considerations, we specified the annual total fixed assets (X_1), operating cost (X_2) and the number of employees (X_3) as three inputs, whereas the outputs are the annual total sales revenue (Y_1) and non-operating income (Y_2). It is important to note that net income was excluded from analysis because DEA is sensitive to negative value. Table 1 shows descriptive statistics for the collected data.

Table 1: Descriptive statistic for data collected

Inputs/Outputs	Variables	Mean	S.D	Max	Min
	X_1	18,458,328	58,763,706	305,683,998	63,111
Inputs	X_2	30,782,782	79,970,310	416,614,357	293,526
	X_3	2,174.9	3,831.3	19,416	28
Outputs	Y_1	32,965,152	84,624,266	442,996,298	294,315
	Y_2	905,789	1,468,995	7,423,412	28,830

Note: All variables are except X_3 is measured in millions of NT dollars. X_3 is measured in term of number of employees.

4. Empirical findings

The performance of 26 companies is examined in terms of their ability to provide outputs with minimum input consumption. The DEA efficiency scores can be interpreted to show how much each company could reduce its input usage without reducing output. For example, if a particular firm has an efficiency score of 0.62, this implies that this particular firm needs to reduce its inputs by 38%, to achieve 100% efficiency. The DEA-Solver software of Cooper *et al*. (2000) was used to run the CCR model. Table 2 summarizes the descriptive statistics of the results. Out of 26 companies only six are efficient under constant returns to the scale (CRS). The efficiency score average is 0.87, indicating that, the input for an average unit could be reduced by 13%. Also, the results show that there is slight variation between the efficiencies.

Table 2: Descriptive statistic for DEA result

Total number of evaluated DMUs	26
Number of efficient DMUs	6
Number of inefficient DMUs	20
Average scores	0.8673
Scores standard deviation	0.1205
Maximum score	1
Minimum score	0.6084

Having derived the measurements of efficiency, we now concentrate our investigation to identify the factors that affects the levels of efficiency of each firm. As Lovell (1993) recommended that, the identification of factors that explain differences in efficiency is essential for improving the results of firms. Although, economic theory does not supply a theoretical model of the determinants of efficiency, however, according to Caves and Barton (1990) and Caves (1992), several studies have developed a strategy for identifying the determinants of efficiency. These determinants include: factors external to the firm (i.e., competition) and characteristics of the firm (i.e., size, ownership, profitability and location). Technical efficiency can be associated with the size of firm; however, according to Torii (1992) improving efficiency demands, a cost of how much should be invested in preserving the firm's results. Whilst according to Caves (1992), this cost is not proportional to the firm's output, but on the contrary, the larger the size of the firm, the lower the unit cost in terms of the firm's management. All due to insufficient empirical studies, which focuses on the efficiency and analysis of the determinants of optoelectronic firms' efficiency, motivated this study.

4.1. Explaining differences in efficiency

This section reports an attempt to explain differences in the calculated efficiency of these firms after implementing Tobit model. Following the prior studies, we suggest a number of potential factors which affects efficiency such as, effects of firm's size, profitability and ownership. Size is measured in two ways: the total assets measured in millions of NT$ and the number of employees hired by each firm. Whilst firm's profitability is the net income to total assets. We employed a dummy variable that takes value one if firms have foreign ownership and zero otherwise. Thus the Tobit model used is this study may be specified as follows:

$$y_{it}^{*} = \beta_0 + \beta_1 SOE_{it} + \beta_2 TA_{it} + \beta_3 P_{it} + \beta_4 Dummy_{it} + \varepsilon_{it} \tag{10}$$

Table 3 reports the result of Tobit estimation. It is significant to note that the dependent variable in the model is DEA efficiency scores. Positive coefficients imply a rise in efficiency, whereas negative coefficients mean fall in efficiency. The results of the regression are significant at 95% level or higher. Firm's profitability has significant positive effects on efficiency, indicating that the more profitable firms have the higher its efficiency. Total assets have positive effects on efficiency, however is not statistically significant. Excitingly, the size of employees as the second proxy for firms' size yields negatively and insignificant coefficient, indicating that the increases size of employees may have increased the cost and affects efficiency negatively. Another insignificant coefficient with positive sign is the ownership dummy. The positive coefficient on the ownership dummy variable confirms that foreign ownership may improve efficiency. However, the effect is not statistically significant. This indicates that firms with foreign ownership share may enjoy a superior efficiency. This is evidenced by the fact that foreign ownership has been view as a key channel for transferring knowledge, skills, technology and managerial know-how; hence enhance the efficiency of domestic firms. Thus, we can speculate that one of the source of efficiency of such firms is due to their connection with foreign own firms.

Table 3: Tobit regression result

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.856676199	0.027465884	31.19055614	4.48046E-19
SOE	-3.68263E-05	1.96188E-05	-1.87709295	0.074468601
P	0.008408958	0.001848379	4.549368483	0.000174768
TA	9.88869E-10	7.2692E-10	1.360354685	0.188142196
Dummy	0.001765273	0.000966109	1.827197783	0.081917533

Note: SOE denotes size of employees; TA: total assets; P: profitability; and Dummy represents ownership

5. Conclusion

This study used two-stage procedures to investigate the performance and assess the determinants of performance of Taiwan optoelectronic firms. In the first step, technical efficiency measurements were calculated using DEA approach on 26 firms taken in 2010. Having obtained the efficiency measures, the censored normal regression model of Tobit was used to explain the variation in calculated efficiencies to a set of explanatory variables. These variables were firm's size, firm's profitability, and ownership. The result estimated using censored normal regression model offers useful economic insights. The significance of firms' profitability is an indication that the more profitable firms achieved the higher technical efficiency. The number of employee's variable is negatively associated to efficiency, indicating that an expansion in size of employees may be an obstacle for being efficient in the optoelectronic industry in Taiwan, however the effects is not statically meaningful. The ownership dummy and total assets have positive sign, but they are statically insignificant. However, we can speculate that foreign ownership can be a key factor for improving firm's efficiency. They bring with them technology, skills, managerial know-how and access to foreign market to enhance the efficiency of domestic firms. Therefore, it is suggested that the connection with foreign owned firms should be well come by policy makers, since the presence of foreign partnership may enhance local firms' efficiency and competitiveness.

References

Altman, E.I., (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. Journal of Finance, 23(4), 589-609.

Ambrose, J.M., and Seward, J.A., (1988). Best Rating Financial Ratios and Prior Probabilities in Insolvency Prediction. Journal of Risk and Insurance, 55(2), 229-244.

Aggrey, N., Eliab, L., and Joseph, S., (2010). The Relationship between Firm Size and Technical Efficiency in East Africa Manufacturing Firms. Journal of Sustainable Development in Africa, 12(4), 226-236.

Amemiya, T., (1984). Tobit models: A survey. Journal of Econometrics, 24(1/2), 3-61.

Caves, R.E and Barton, D., (1990). Efficiency in US manufacturing Industries. MIT Press: Cambridge, MA.

Caves, R., (1992). Determinants of Technical Efficiency in Australia. In Caves, R (ed.) Industrial Efficiency in Six Nations, MIT Press, 241-272.

Charnes, A., Cooper, W.W., and Rhodes, E., (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, 2(4), 429-444.

Chandra, P., Cooper, W.W., Shanling, Li., and Rahman, A., (1998). Using DEA to evaluate 29 Canadian textile companies — considering returns to scale. International Journal of Production Economics, 54(2), 129-141.

Coeli, T., Rao, D., and Battese, G., (1998). An introduction to efficiency and productivity analysis. Boston/Dordrecht/ London: Kluwer Academic Publishers.

Cooper, W.W., Seiford, L. and Tone, K., (2000). In: Data Envelopment Analysis: A Comprehensive Text with Models, Application, References, and DEA-Solver Software, Kluwer Academic Publishers, Norwell, Massachusetts.

Donthu, N., Hershberger, E.K. and Osmonbekov, T., (2005). Benchmarking marketing productivity using data envelopment analysis. Journal of Business Research, 58(11), 1474-1482.

El-Mashaleh, M.S., Rababeh, S.M., and Hyari, K.H., (2010). Utilizing data envelopment analysis to benchmark safety performance of construction contractors, International Journal of Project Management, 28(1), 61–67.

Erkut, D., and Hatice, D., (2007). Measuring the performance of manufacturing firms with super slacks based model of data envelopment analysis: An application of 500 major industrial enterprises in Turkey. European Journal of Operational Research, 182(3), 1412-1432.

Farrell, M.J., (1957). The measurement of productive efficiency. Journal of the Royal Statistical Society, 120(3), 253-290.

Favero, C.A. and Papi, L., (1995). Technical efficiency and scale efficiency in the Italian banking sector: a non-parametric approach. Applied Economics, 27(4), 385-395.

Goldberger, A.S., (1964). Econometric Theory. New York: Wiley.

Goldman, A., (1992). Evaluating the performance of the Japanese distribution system. Journal of Retailing, 68(1), 11-39.

Javed, M.I., Adil, S.A., Asghar, A. and Raza, M.A., (2010). Measurement of Technical Efficiency of Rice-Wheat system in Punjab, Pakistan using DEA Technique, Journal of Agricultural Research, 48(2), 227-237.

Johnston, R., and Jones, P., (2004). Service productivity towards understanding the relationship between operational and customer productivity. International Journal of Productivity and Performance Management, 53(3), 201-213.

Keh, H.T., and Chu, S., (2003). Retail productivity and scale economics at the firm level: A DEA approach. Omega, 31(2), 75-82.

Kirjavainen, T. and Loikkanen, H.A., (1998). Efficiency differences of Finnish senior secondary schools: An application of DEA and Tobit analysis. Economics of Education Review, 17(4), 377-394.

Le, V. and Harvie, C., (2010). Firm performance in Vietnam: evidence from manufacturing small and medium enterprises. Department of Economics, University of Wollongong, Working Paper 04-10.

Liu, C.H., Lin, S.J., and Lewis, C., (2010). Evaluation of thermal power plant operational performance in Taiwan by data envelopment analysis. Energy Policy, 38(2), 1049–1058.

Lovell, K., (1993). Production frontiers and productive efficiency, in: H. Fried, C.A.K. Lovell, and S. Schmidt, Eds. The Measurement of Productive Efficiency: Techniques and Applications, Oxford, Oxford University Press, 3-67.

Miller, S.M. and Noulas, A.G., (1996). The technical efficiency of large bank production. Journal of Banking and Finance, 20(3), 495-509.

Pasiouras, F., (2008). Estimating the technical and scale efficiency of Greek commercial banks: the impact of credit risk, off-balance sheet activities, and international operations. Research in International Business and Finance. 22(3), 301-318.

Sigala, M., (2004). Using data envelopment analysis for measuring and benchmarking productivity in the hotel sector. Journal of Travel and Tourism Marketing, 16(2/3), 39-60.

Tahir, I.M., and Yusof, K.N.K., (2011). Estimating Technical and Scale Efficiency of Malaysian Public Listed Companies: A Non Parametric Approach. Interdisciplinary Journal of Research in Business, 1(7), 1-7.

Tobin, J., (1958). Estimation of relationships for limited dependent variables. Econometrica, 26(1), 24-36.

Torii, S., (1992). Technical Efficiency in Japanese Industries. in Caves, R (ed.) Industrial Efficiency in Six Nations. MIT Press, 31-120.

Wei, C.K., Chen, L.C., Li, R.K., Tsai, C.H. and Huang, H.L., (2012). A Study of Optimal Weights of Data Envelopment Analysis – Development of a Context-Dependent DEA-R Model. Expert Systems with Applications, 39(4), 4599-4608.

Zhu, J., (2000). Multi-factor performance measure model with an application to Fortune 500 companies. European Journal of Operational Research, 123(1), 105-124.