International Journal of Engineering & Technology, 7 (4.33) (2018) 25-31

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Estimating Efficiency Performance of Decision-Making Unit by using SFA and DEA Method: A Cross-Sectional Data Approach

Roslah Arsad[1,2]*, Zaidi Isa[2], Siti Nabilah Mohd Shaari[3]

[1]*Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Perak Branch, Tapah Campus, Tapah Road, 35400 Perak, Malaysia*
[2]*School of Mathematical Sciences, Faculty Science and Technology, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, Malaysia*
[3]*Faculty of Accountancy, Universiti Teknologi MARA, Perak Branch, Tapah Campus, Tapah Road, 35400 Perak, Malaysia*
**Corresponding author E-mail: rosla280@perak.uitm.edu.my*

Abstract

In this paper, a cross-sectional samples data of 115 Malaysian stocks have been employed to compare both Data Envelopment Analysis (DEA) method and Stochastic Frontier Analysis (SFA) method. These approaches are used to provide a review of frontier conceptual measurement, strength and limitation of the parametric and non-parametric models. Stochastic frontier production function of Cobb-Douglas type was utilized for the estimation. The function was estimated using the maximum likelihood estimation technique. Two models in DEA, DEA-CCR and DEA-BCC are applied in this study and the ranking correlation between SFA method and both models DEA are determined by using the Spearman rank method. The result revealed using SFA, the mean technical efficiency of sample consumer product companies is 37.5% and implies that companies operating at means level of technical efficiency could produce 80.1% more output for given level of inputs if they become technically more efficient. From empirical results of the SFA method, we determined that the deviations from the efficient frontiers of production functions are largely attributed to inefficiency effects (technical inefficiency). Finally, the findings also showed that the difference in ranking stocks performance using DEA-CCR, DEA-BCC and SFA methods. The main contribution of the paper is showing the comparative performance based on both model, DEA and SFA method using financial ratio.

Keywords: *Efficiency; Frontier Analysis; Non-Parametric; Parametric; Productivity.*

1. Introduction

Evaluation of performance can be measured using productivity ratio. A process of the decision-making unit (DMU) will employ the resource inputs to produce the desired products or services called as productivity ratio. The literature on measurement performance using frontier estimation has been widely used in economic studies of productivity and technical efficiency in hospital costs, electric power, commercial fishing, farming, manufacturing of many sorts, public provision of transportation and sewerage services, education, labor markets and a huge array of other settings. Generally, efficiency can refer to the ability of the inputs converted into outputs production process and proficiency of producers achieving their economic objectives, such as production at minimum cost, generation of maximum revenue and maximization of profit. The technique of production frontier is used as a tool to measure the relationship between the input and output. For non-parametric approach, the DMU is called technically efficient due to the fact that the DMU operates on the production frontier and they are not technically efficient when it is below the frontier. If information on price and behavioral assumption such as cost minimization or profit maximization are available, the allocative efficiency will be considered as a tool of the performance measurement. Allocative efficiency in input selection involves selecting that mix of inputs (labor and capital) that produces a given quantity of outputs at minimum cost. Combination of allocative and technical efficiency will provide overall economic efficiency performance [1].

Many researchers have studied the parametric technique, Stochastic Frontier Analysis (SFA) method for analyzing various DMU disciplines such as investigating on the technical efficiency of the Malaysian domestic banks listed in the Kuala Lumpur Stock Exchange (KLSE) market [2] and comparing the performance farms in the Swiss mountain region [3]. For non-parametric technique, Data Envelopment Analysis (DEA) method applies to study the improvement and management level enhancement within the large port of Korea and China [4]. Researchers also employed the DEA method to calculate the efficiency of stock market in Bursa Malaysia [5] and portfolio selection on the Mumbai Stock Exchange [6]. Due to lack of information about some parameters, the theory of probability is imported into the model of DEA and Stochastic Data Envelopment Analysis (SDEA) is introduced.

At present, there are numerous comparative studies for both methods, parametric and non-parametric approaches. There is a comparative study on between DEA and SFA methods by [7] that compare the efficiency of the syndicates, an insurance company in a regular insurance. Other comparative study using DEA and SFA approaches applied in commercial and rural banks, biomass power plants and prestigious hotels. In the market economies, decision-making units (DMUs) are expected to achieve the maximum in production or consumption. The failure of DMUs to produce at the best practicing frontier called as production inefficiency. The concept of the production frontier and technical efficiency were first discussed by [8] and [9]. It was followed by [10] who first discussed on input-oriented and implemented it practically in the U.S agriculture, where the author classified efficiency into two components; technical efficiency and allocative efficiency. The DMU is called technically efficient when it is impossible to produce more outputs without producing less of some other outputs or using more and refers to organizing available resources in such a way that the maximum feasible output is produced. On the other hand, allocative efficiency or price efficiency refers to the use of the budget in such a way that, given relative prices, it is able to obtain the most productive combination of resources. In other words, no alternative combination of the resources, given the budgetary constraint, would enable the organization to produce a higher output.

There are many studies using financial ratio but most of them are based on DEA approach. However, there is a limitation in the study when the SFA method only restricted to one output instead of DEA that can employ multiple inputs and to produce multiple outputs. Furthermore, there is less study that has been done to measure the efficiency of stocks performance listed in the Bursa Malaysia using the financial ratio based on the parametric approach. We are interested to investigate the efficiency performance by using two techniques; parametric method (e.g., SFA) and non-parametric method (e.g., DEA). It can be done by applying a samples data of the Malaysian stock market. The result of the performance by using both methods can be compared to provide a review of frontier conceptual measurement, strength and limitation of parametric and non-parametric methods. The remainder of this paper is organized into four more sections. The second section of this paper will briefly explain on the literature review related to the measurement of efficiency. Section three is devoted to the methodology in relation to efficiency by using empirical data. The discussion and results of the sample data are explained in section four. The final section presents the overall conclusion of this research analysis and suggestion for future studies.

2. Measurement of Efficiency

There are various types of measurements which have been applied in determining the efficiency of DMUs. Researchers investigated the efficiency of performance in financial institutions by using frontier analysis and they assumed that the difference between these frontier analyses is based on the data relating to the functional form of the best practice frontier, whether the random error is taken into account or not. The efficiency measurement using frontier can be divided into two categories; parametric and non-parametric.

2.1. Parametric frontier approach

The first category measurement of efficiency is the parametric approach. This approach can be divided into deterministic models and stochastic models. In the deterministic model, we have statistical and non-statistical models. Deterministic non-statistical models when the models does not have statistical properties. Linear and quadratic programming techniques are employed to construct the frontier. Goal programming technique will be used to calculate the technology parameter vector to obtain an estimation of technical inefficiency, while the technical efficiency will be solved by optimization problems. The shortcoming of these approaches is the parameters are not estimated in any statistical sense but calculated using mathematical programming techniques. However, it is complicated to make a statistical inference concerning the calculation and precludes any hypothesis testing. The deterministic models are statistical when the error term is specified by a given distribution of probability and the estimators have statistical properties. The model's based statistical properties will be used in the econometric approach to estimate the parameter of the frontier functions and how statistical inference will do based on those estimates. The main advantage of deterministic statistical models is the ease of obtaining individual estimates of efficiency for productive units. The estimation of a deterministic frontier to all common productive units will assume that all the deviation from the frontier is entirely interpreted as inefficiency. The deterministic statistical frontier of maximum production given by a function where the error term only reflects the DMU's technical efficiency. However, there are other factors outside its control which affect its behavior and also captured by the unilateral error term. So, the residual estimation provided by deterministic methods are overvalued. A deterministic and statistical frontier means that all observations (except one) are situated below the production frontier (or in case of a cost function, above the cost frontier). This restriction is the limitation of using deterministic statistical frontier. The non-existence of the asymmetric component in the error term means that it is able to capture random or uncontrollable shocks. That is the principal censure of statistical deterministic frontier models. Corrected Ordinary Least Squares (COLS) and the standard regression technique are the most models commonly used. Parametric models are seen as the relative importance for different cost drivers or to the parameters in the possibly random noise and efficiency.

Three major models in parametric approach are Stochastic Frontier Approach (SFA), Distribution Free Approach (DFA) and Thick Frontier Approach (TFA). DFA must specify a functional form for the frontier but separates the inefficiencies in a different way. DFA assumes that the efficiency of each firm is stable, does not change over time, whereas random errors will average out to zero. This approach sets no specific types of distribution to the inefficiency term. The last one is TFA, in which this approach assumes that the deviations from the predicted cost of each quartile represent random error and difference between the lowest cost and highest average cost quartile denotes inefficiencies. In [12] were among the first authors to estimate a parametric deterministic frontier begins by assuming a function giving maximum possible output as certain inputs.

A deterministic parametric frontier specified as:

$$y_i = f(x_i, \beta)\exp(-\mu_i) \;;\; \mu_i \geq 0 \tag{1}$$

where y_i represents the dependent variable and translate the production observed for a productive unit i where variable $i = 1,2,.......N$, β represents a vector of unknown technological, μ_i represent the shortfall of output from the frontier (technical inefficiency) for each producer. Early research in error term able to capture random or uncontrollable shocks was proposed by [13]. They did a study on the SFA approach, which also referred to as the Econometric Frontier Approach (EFA). It specifies a functional form for the cost, profit or production relationship among inputs, outputs, and environmental factors and allows for random error. The stochastic term is included because it is able to consider random noise and other measurement errors. The inefficiency terms can be defined as the increasing cost above the minimum estimated cost frontier (cost efficiency) or reducing profit below the profit frontier (profit efficiency). The distribution assumption for the stochastic term components is illustrated by two-sided distribution while the inefficiency term is assumed to be one-sided distribution. This type of model also covers errors in the observation and in the measurement of outputs. Generally, many of different functional forms are used in the literature to model production functions such as Cobb-Douglas (linear logs of outputs and inputs), Quadratic (in inputs), Normalized quadratic and Translog function. Translog function is very commonly used. It is a generalization of the Cobb-Douglas function. It is a flexible functional form providing a second order approximation. Cobb-Douglas and Translog functions are linear in parameters and can be estimated using least squares methods. It is possible to impose restrictions on the parameters (homogeneity conditions). For estimation of the parameter, Ordinary Least Squares (OLS) estimates cannot be used to compute measures of technical efficiency. However, a better solution is to make some distributional assumptions concerning the two error terms and estimate the model using the method of maximum likelihood. The Cobb-Douglas equation in logarithmic terms, the single output stochastic frontier can be represented as:

$$\ln q_i = \beta_0 + \sum_{n=1}^{N} \beta_n \ln X_{ni} + v_i - u_i \quad (2)$$

The technical efficiency, TE_i of DMU i is defined as:

$$TE_i = \frac{q_i}{\exp(x_i\beta + v_i)} = \frac{\exp(x_i\beta + v_i - u_i)}{\exp(x_i\beta + v_i)} = \exp(-u_i) \quad (3)$$

where $\exp(\beta_0 + \beta_1 \ln x_i)$ is called deterministic component, $\exp(v_i)$ is noise error and $\exp(u_i)$ is inefficiency error. The advantage of the SFA approach is allowing the random shocks and measurement error. Measurement error and random factors such as regulatory-competitive environments, weather, luck, socio-economic and demographic factors call for uncertainty. SFA can analyze the structure and investigates the determinant of producer's performance. Therefore, the SFA approach has more strength in economic theory. The difficulty of SFA is, it is risky to impose strong a priori assumptions on the production technology by choosing a functional form (e.g. Cobb Douglas, translog, etc.) given most of the distributional characteristic of the production technology are a priori unknown. The exact specification for the error structure is difficult and impossible. In addition, such specification is likely to introduce another potential source of error. The continuity in this approach may lead to approximation errors. Another problem in SFA is the non-existence of consensus on the type of distribution to be selected in order to arrive at the inefficiency measurement.

2.2. Non-parametric frontier approach

The second category measurement of efficiency is the non-parametric approach. This approach also can be divided into deterministic and stochastic models. DEA method is an example of a deterministic model in the non-parametric approach. For DEA, mathematical programming will be used to observe data that provides for the construction of frontier as well as for the calculation of efficiency score relatives to those constructed frontiers. The initial model of DEA developed by Charnes, Cooper and Rhodes is known as the CCR model [14]. CCR model is used to measure the relative efficiency of a decision making units by utilizing multiple inputs to produce multiple outputs. The set of relatively efficient DMUs creates the efficient frontier and any deviation from the frontier identified as inefficiency. CCR model in DEA imposed three restrictions on the frontier technology; constant return to scale (CRS), the convexity of the set of feasible input-output combinations and strong disposability of input and output. Banker, Charnes and Cooper then proposed BCC model to allow a variable return to scale (VRS) [15]. In the DEA method, there is no statistical hypotheses and tests required.
The efficiency score unit is between zero and one. If the efficiency score unit is equal to one, the DMU assumed to be technically efficient and lies on the efficiency frontier. The observed data that enveloped by the frontier is called relatively inefficient DMU. The objective of Banker, Charnes and Cooper (BCC) model is assumed to be the pure technical efficiency (PTE). The PTE measures how a DMU utilizes the resources under exogenous environment, and a low PTE implies that the DMU ineffectively manages its resources. Advantages of the DEA method are the ability to create prospective improvements for inefficiency units and identify the units for benchmarking. DEA also does not require information about the process or relationship between input and output. Hence, DEA is more flexible compared to those parametric approaches. In DEA, no functional form for the frontier or the distribution of inefficiency is assumed. The outcome of an efficiency analysis based DEA is that communicate made easy for decision makers. Equally important, the outcome extends beyond the estimation of measures of inefficiency.
The main limitation of non-parametric is deterministic approaches. Production relationships are often stochastic in nature. If this situation is ignored, the efficiency calculation outcomes will be biased and give misleading conclusions. DEA could not distinguish between technical inefficiency and statistical noise effects. The deterministic in non-parametric approach generally ignore prices and the account (measurement error and random factors) only for technical inefficiency in using too many inputs or producing too few outputs. DEA could not measure error and random factors for allocative inefficiency. It is because allocative inefficiency is not responding to relative prices in choosing inputs and outputs, nor can they compare firms that tend to specialize in different inputs or outputs. It is because there is no way to compare one input or output with another without the benefit of relative prices. Similar to the cost function, there is no way to determine whether the output being produced is optimal without value information on the outputs. Thus, the non-parametric techniques typically focus on technological optimization rather than economic optimization. However, the SDEA was introduced where the flexible structure and the possibility are combined, and that some of the variations in data may be noise and only requires most of the points to be enveloped. DEA model has extended to the stochastic DEA model where the case of stochastic inputs and outputs through the use of chance-constrained programming. This can be interpreted as a way of allowing for statistical or probabilistic considerations into the conventional (standard) DEA model.

3. Methodology

This paper employed both techniques; DEA method and SFA methods in analyzing technical efficiency of samples data from 115 companies' consumer product industry traded in Bursa Malaysia for the year 2015. The efficiency score using both methods, SFA and DEA will be calculated using R-programming software, employing Benchmarking package. Generally, the Malaysian stock exchange is called Bursa Malaysia. The stock market is where the stock in companies are bought and sold, providing company's options to access capital, and investor's opportunities to own a stock of the company and enjoy potential gains from the company's future performance. Decision makers or investors can only invest their stocks through a stock exchange, an organized marketplace where stocks are bought and sold under strict rules, regulations and guidelines.

3.1. Data sources

Data of the non-financial companies in Bursa Malaysia used taken from Thomson Reuters Eikon datastream. Financial data that are taken from the datastream are selected as inputs and outputs variables. A survey technique was carried out based on an expert judgment, named the Fuzzy Delphi Method (FDM).
The results of [16] study, indicated on the return on equity, return on assets, net profit margin, operating profit margin, earnings per share and debt to equity are the most important ratios in identifying the most significant financial ratios to focus on, in order to evaluate the stock's performance.

3.2. Selection and definition of variables

Clarification of inputs and outputs in this study are based on experts' information. Expert information is selected in an industry that may have been formed over many years of experience. Researchers refer to experts' opinions in defining these variables. Normally, profitability and growth perspective are considered as outputs because revenue or income generation is a major objective criterion for a company. Asset utilization, liquidity and leverage perspectives are considered as inputs because they are concerned with planning and operational strategies of a company. Table 1 shows the definition for all the variables selected in this study.

Table 1: Definition of variables

Variables	Definition
Return on equity	The amount of net income returned as a percentage of shareholders' equity and measures a Corporation's profitability by revealing how much profit a company generates with the money shareholders have invested.
Return on assets	Indicator profitable a company is relative to its total assets, meaning that how efficient a company's management using its assets to generate earnings.
Earnings per share	The portion of a company's profit allocated to each outstanding share of common stock.
Operating margin profit	Indicates profit a company makes after paying for variable costs of production associated with business operations.
Net profit margin	The ratio used to calculate the percentage of profit a company produces from its total revenue.
Price earnings ratio	The ratio for valuing a company that measures its current share price relative to its per-share earnings.
Asset turnover	Indicates successful a company is in utilizing its assets in the generation of sales revenue.
Debt to equity ratio	Measure a company's financial leverage and indicates debt a company is using to finance its assets relative to the value of shareholders' equity.

Therefore, for DEA method, the outputs selected in this study are return on equity, return on assets, earnings per share, operating profit margin, net profit margin and price to earnings ratio, while debt to equity ratio and assets turnover are identified as input variables as shown in Table 2.

Table 2: Input and output variables

	Selection Output and Input Variables	
	SFA	DEA
Output	Return on equity (ROE)	Return on equity (ROE)
		Return on assets (ROA)
		Earnings per share (EPS)
		Operating margin profit (OPM)
		Price earnings ratio (PER)
		Net profit margin (NPM)
Input	Asset turnover	Asset turnover
	Debt to equity ratio	Debt to equity ratio

All the financial data selected are based on the Fuzzy Delphi Method (FDM) and previous studies of input and output variables. The finding of this study will reveal the limitation and strength of each result of both methods. Based on DuPont theory, the highest value of return on equity will be considered as a well-performed company because the company can generate a high return on stockholders' investment. A company`s goal is to maximize profit as to benefit the owners or stockholders. Therefore, for the SFA method, we choose to return on equity as the output variable (profitability to investors), while debt to equity ratio and assets turnover as input variables.

By using logarithm models in analyzing, data will be problematic when companies incur losses or zero since the logarithm of non-negative and zero number are not defined in the SFA model. A study by [17] will be used in this study as they proposed censoring method that can be applied to data losses and zero. This method assigns the negative observation in the dependent variable (output) with 1. This method improves the rank stability of the estimated efficiency score and adds to the discriminatory power of their log (π) model and making them less likely to be biased.

3.3. Empirical of SFA method

The empirical model version of the stochastic frontier analysis is used on 115 companies in the year of 2015. We assume $t = 1$ that can be expressed with the specification of Cobb-Douglas functional form as follows:

$$\ln(y_i) = \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + v_i - u_i \tag{4}$$

where subscripts i represent the i^{th} company for $i = 1,2,......,115$, parameter of y_i represents the return on equity, β is the vector of unknown parameters to estimate, x_{1i} is debt to equity, x_{2i} is asset turnover, u_i captures the technical inefficiency in production and assumes is to be independent and identically distributed (i.i.d) as half-normal, $u_{it} \sim \left|N(0,\sigma^2)\right|$ and v_i assumed to be independent and identically distributed (i.i.d), as $v \sim \mathrm{N}(0,\sigma_v^2)$ and captures statistical noise, measurement error and other random events that are beyond the company's control. The parameter β is estimated using the maximum-likelihood method.

The parameterized of the log-likelihood function using:

$$r = \frac{\sigma_u^2}{\sigma^2} = \frac{\sigma_u^2/\sigma_v^2}{\sigma_u^2/\sigma_v^2 + \sigma_v^2/\sigma_v^2} = \frac{\lambda^2}{\lambda^2+1}, \quad \lambda = \sqrt{\frac{\sigma_u^2}{\sigma_v^2}} \tag{5}$$

Parameter r lies in the range between 0 and 1; $r = 0$ indicates that all the deviation from the frontier due to random error (noise), while $r = 1$ means all deviation result from the technical inefficiency. However, if the value of r is closer to zero, it means that the variation between actual output and the maximum possible output mainly comes from another uncontrolled pure random factor (noise).

In contrast, if the value of r is closer to one, the variation comes mainly from the effect of one or more exogenous (independent) variables that are used in the model (technical inefficiency). A series of a formal hypothesis were obtained using a t-test or a likelihood ratio test statistics for performing the hypothesis test. However, this study will apply a t-test. The null hypothesis is rejected when test statistic exceeds the critical value.

The following hypothesis will be tested in this paper:

- $H_0 : \sigma_u^2 = 0$; It expresses that no variance between companies in terms of efficiency in the model.
- $H_0 : r = 0$; It expresses that no stochastic inefficiency effect.

3.4. Empirical of DEA method

DEA is a mathematical model used to measure the relative efficiency of a set of DMUs with multiple inputs and multiple outputs without specifying a priori a production function.

Consider a set of 115 companies. For DMU k , let y_{rk} denote the level r^{th} outputs, and x_{ik} denote the level of the i^{th} input. To measure the efficiency of DMU k , the weights u_r and v_i will be found to maximize the following ratio E_k subject to a set of constraints:

$$\begin{aligned} &Max\ E_k = \sum_{r=1}^{6} u_r y_{rk} \\ &\text{Subject to } \sum_{r=1}^{6} u_r y_{rj} - \sum_{i=1}^{2} v_i x_{ij} \le 0, \quad j = 1,......,115 \\ &\sum_{i=1}^{2} v_i x_{ik} = 1 \\ &u_r, v_i \ge 0, \quad r = 1,2......,6\ ,\ i = 1,2 \end{aligned} \tag{6}$$

The value E_k is between zero and one, with higher values indicating greater efficiency. After transformation, the CCR model is:

$$Min\ \vartheta$$

$$\text{Subject to } \vartheta_{xik} - \sum_{j=1}^{115} \lambda_i x_{ij} \geq 0, \quad i = 1,2 \tag{7}$$

$$\sum_{j=1}^{115} \lambda_j y_{rj} \geq y_{rk}, \qquad r = 1,2,\ldots\ldots, 6$$

$$\lambda_j \geq 0, \quad j = 1,\ldots\ldots\ldots, 115$$

Taking variable return to scale into account, the model in (7) extended to obtain the following model, which is commonly referred to as the BCC model is:

$$Min\ \theta$$

$$\text{Subject to } \theta_{xik} - \sum_{j=1}^{115} \lambda_j x_{ij} \geq 0, \quad i = 1,2 \tag{8}$$

$$\sum_{j=1}^{115} \lambda_j y_{rj} \geq y_{rk}, \qquad r = 1,2,\ldots.., 6$$

$$\sum_{j=1}^{115} \lambda_j = 1,$$

$$\lambda_j \geq 0, \quad j = 1,2\ldots., 115,$$

Entire companies' ranking in the industry will be presented with a problem when efficiency scores are calculated the same. Balance index is to be calculated based on the second restriction. In (9), when the shadow price is derived from technology, the profit of DMU is zero. This situation is called a balanced situation. The second restriction to get a profit for j^{th} DMU is presented as follows:

$$\left[\sum_{r=1}^{6} u_r y_{rj} - \sum_{i=1}^{2} v_i x_{ij} \right] \leq 0, \quad j = 1,2,\ldots\ldots., 115 \tag{9}$$

Next, using the model ranking of [18], the profit restriction and sum are used to describe a new index in addition to the efficiency score for each DMU. This situation is called a balance index. Therefore, when the profit restriction by shadow price becomes zero, we say that p^{th} DMU is efficient. When the profit for other DMUs is equal to or less than zero, the current DMU has overcome the others in this profit competition. Otherwise, the DMU is inefficient because its profit restriction is not zero, thus it is considered a loss. As a conclusion, the lesser the sum is, the more the profit of the evaluated DMU differs from the profits from other DMUs. Thus, the higher the evaluated DMU should be ranked.
We can also conclude that if the efficiency scores of DMU_A and DMU_B is the same, while the same time DMU_A obtains more negative quantity value in balance index than DMU_B, then DMU_A has a higher rank than DMU_B. The balance index was computed for the year 2015 is as follows:

$$\begin{aligned} \text{Balance Index}_{2015} = \; & (6.22u_1 + 21.7u_2 + 1.33u_3 + 2660.83u_4 + 5.53u_5 + 3.67u_6) \\ & -(45.88v_1 + 113.73v_2) \end{aligned} \tag{10}$$

4. Results and Discussion

We have applied two models in the DEA model, DEA-CCR, DEA-BCC and SFA method to compute the efficiency score of the companies. SFA method is only limited to a single output and multiple inputs while DEA can calculate multiple outputs and multiple inputs.

4.1. Empirical result SFA method

The Maximum Likelihood Estimates (MLE) for the parameters of the Cobb-Douglas stochastic frontier analysis model were presented in Table 3. The result in Table 3 shows that the estimates of the parameters debt to equity input and assets turnover input are 1.498 and 1.982 respectively.

Table 3: Estimates of maximum likelihood of Cobb-Douglass Function

Variable Production Elasticity	Cobb-Douglas Production Function		
	Parameter	Coefficient	t-Value
constant	β_0	5.783	2.634
debt to equity	β_1	1.498	575.755
assets turnover	β_2	1.982	212.663
Variance Parameter			
lambda	λ	3.611	2.678*
sigma-square	σ^2	3.159	
$\sigma_u^2 = 2.933954$, $\sigma_v^2 = 0.2250623$			
Log-likelihood function		-171.632	

*statistically significant at the level $\alpha = 0.05$

Table 3 shows the parameter of sigma-square or variance of the observed DMU with the deterministic function of maximum production. The sigma-square for u (σ_u^2) is the variance of the technical inefficiency error and sigma-square for v (σ_v^2) is the variance of noise or random error. Therefore, the total error of variance for observed DMU and maximum function of production is the sum of σ_u^2 and σ_v^2. The MLE of debt to equity ratio and assets turnover were significant at $\alpha = 0.05$. The estimated of maximum likelihood coefficients found that elasticity of the return on equity for asset turnover is the highest at 1.982. This means that with an increase of 1% in the input of asset turnover, it will increase by 1.982% on the return on equity of companies. For the input of the debt to equity, the elasticity of the return on equity is 1.498. This means that 1% increase in debt-equity ratio input resulted in an increase of 1.498% in the return on equity companies. The estimate of sigma-squared σ^2 is different from zero, indicating a good fit.
The result of the efficiency score, ranking of companies and list of consumer product companies are shown in Table 4, Table 5 and Table 6. The top-ranked company is DMU_{83} (Poh Kong Holdings) and the bottom-ranked is DMU_{54} (Kuantan Flour Mills). The other five top companies are DMU_5 (Apollo Food Holdings), DMU_{36} (Hong Leong Indus Bhd), DMU_{110} (Xian Leng Holdings), DMU_{79} (Pelangi Publishing) and DMU_{20} (Cocoaland Holdings). On the contrary, the other most five bottom rank of companies are DMU_{49} (Karex), DMU_{25} (Eka Noodles Bhd), DMU_3 (Amtek Holdings Bhd), DMU_{15} (Carlsberg Brewery) and DMU_{108} (Upa Corp Bhd). From the investigation, it was observed that the mean technical efficiency of sample consumer product companies is 0.375 (37.5%) ranging from 0.814 (81.4%) to 0.013(1.3%), this implies that companies operating at means level of technical efficiency could produce 80.1% more output for given level of inputs if they become technically more efficient.
Next, the t-test is carried out in this study to test out the hypothesis. First, we tested whether there is no difference in efficiency in the model between the companies, $H_0 : \sigma_u^2 = 0$ versus $H_1 : \sigma_u^2 > 0$. In (5), the null hypothesis is equivalent to $H_0 : \lambda = 0$; versus $H_1 : \lambda > 0$. The calculated-t for lambda is 3.611 and it is greater than the critical value, 2.678. Therefore, the null hypothesis was rejected at the level significant $\alpha = 0.05$. This implies that there are differences in efficiency between the companies whereby the sigma-squared is significantly greater than zero.
Second, we tested whether there is no stochastic inefficiency effect existed. $H_0 : r = 0$ versus $H_1 : r > 0$, that specifies the inefficiency are no stochastic effect. Therefore, the null hypothesis was

rejected and this result implies the stochastic inefficiency (noise) existed, where the value r is significantly greater than zero. The value of the parameter r is 0.9288. Recall that r can serve as an index to identify whether the deviations from the efficient frontier are due to random error ($r = 0$) or technical inefficiency ($r = 1$). Therefore, it shows that the value of the variance r in this study is close with one. Suggesting that the companies' efficiency variation are 92.88% due to the inefficiency effects (technical inefficiency) and 7.12% due to random error or noise effects and this suggestion supported by the result of hypothesis testing.

4.2. Empirical result DEA method

The efficiency score companies using DEA-CCR and DEA-BCC models shown in Table 4. From the result, shows that 8 (7%) companies have the same efficiency score at 1 and the rest are inefficient units when DEA-CCR model is employed. The efficient companies when using DEA-CCR model are DMU_{63} (Maxwell Inter), DMU_{97} (Spritzer Berhad), DMU_{31} (Fed Furn Hldgs (M)), DMU_{84} (Ppb Group Bhd), DMU_{77} (Paragon Union Berhad), DMU_{20} (Cocoaland Hldgs), DMU_{36} (Guan Chong Berhad) and DMU_{1} (Acoustech Bhd). However, the number of efficiency companies increase to 16 (14%) companies when DEA-BCC model is employed to the data. DMU_{97} (Spritzer Berhad), DMU_{63} (Maxwell Inter), DMU_{9} (Bonia Corporation), DMU_{18} (China Ouhua), DMU_{31}(Fed Furn Hldgs (M)), DMU_{84} (Ppb Group Bhd), DMU_{77} (Paragon Union Berhad), DMU_{36} (Guan Chong Berhad), DMU_{20} (Cocoaland Hldgs), DMU_{1} (Acoustech Bhd), DMU_{43} (Hup Seng Industries), DMU_{60} (Ltkm Bhd), DMU_{24} (Dutch Lady Milk), DMU_{68} (New Hoong Fatt), DMU_{8} (Bio Osmo Berhad) and DMU_{91} (Saudee Group) are identified as efficient companies using DEA-BCC model. When the results of the efficiency score for companies are the same for both models, we are unable to rank the performance by only using the efficiency score. Balance index by Alirezae and Afsharian method is computed to rank the entire companies.

The ranking result using balance index for both methods are compared and it is illustrated in Table 5. The result indicates that by using the DEA-CCR method, 14 companies could not be ranked using values of balance index. This is due to the values of the balance index for those companies are zero. Thus, all the 14 companies are ranked at the bottom of the list. On the other hand, the other 101 companies are able to be ranked completely using efficiency score and values of balance index. It can also be seen that the companies, which have the same efficiency score, can be ranked using values of their values of balance index. Examples of inefficient companies with the same efficiency scores are DMU_{23} (Degem Bhd) and DMU_{103} (Teo Guan Lee Corp) where the efficiency score is 0.225.

We reset the rank and re-rank the DMU based on the value of balance index. The ranking for DMU_{23} (Degem Bhd) and DMU_{103} (Teo Guan Lee Corp) are at 52th and 53th place respectively. However, the result indicates that Alirezae and Afharian ranking method is unstable through DEA-CCR approach because it fails to rank entirely the 115 companies. For DEA-BCC model, the result shows that all of the samples companies are successfully and completely ranked based on the ranking method of balance index. Using Balance Index, the top ranking companies is DMU_{63} (Maxwell Inter), by DEA-CCR approach and DMU_{97} (Spritzer Berhad) by DEA-BCC approach model.

We can also distinguish a different total number of efficient companies based on efficiency score of DEA model based on Table 4. The value of efficiency score for inefficient companies under DEA-BCC model is also greater than the efficiency score for inefficient companies under DEA-CCR model. It is due to the different assumptions of technology. DEA-CCR model assumes that all the companies are a constant return to scale. However, DEA-BCC model assumes all the companies are a variable return to scale.

Table 4: Efficiency score using DEA method and SFA method

DMU	SFA	DEA		DMU	SFA	DEA		DMU	SFA	DEA		DMU	SFA	DEA	
		CCR	BCC			CCR	BCC			CCR	BCC			CCR	BCC
1	0.369	1	1	30	0.190	0.192	0.250	59	0.659	0.244	0.350	88	0.046	0.191	0.214
2	0.651	0.375	0.406	31	0.303	1	1	60	0.139	0.723	1	89	0.345	0.204	0.378
3	0.027	0.547	0.614	32	0.260	0.152	0.184	61	0.096	0.372	0.394	90	0.102	0.728	0.730
4	0.508	0	0.109	33	0.510	0.403	0.559	62	0.664	0	0.951	91	0.343	0.459	1
5	0.807	0.814	0.932	34	0.342	0	0.182	63	0.441	1	1	92	0.166	0.036	0.133
6	0.049	0.055	0.205	35	0.301	0.023	0.082	64	0.435	0.047	0.119	93	0.465	0	0.331
7	0.347	0.453	0.453	36	0.799	1	1	65	0.595	0.003	0.145	94	0.051	0.149	0.208
8	0.648	0.383	1	37	0.453	0	0.102	66	0.693	0.491	0.589	95	0.658	0.315	0.318
9	0.699	0	1	38	0.619	0.233	0.524	67	0.600	0.527	0.680	96	0.455	0.005	0.118
10	0.652	0.207	0.240	39	0.671	0.236	0.259	68	0.551	0.325	1	97	0.338	1	1
11	0.745	0.043	0.096	40	0.177	0.401	0.672	69	0.309	0.337	0.422	98	0.702	0.337	0.369
12	0.307	0.116	0.230	41	0.621	0.309	0.358	70	0.072	0.229	0.447	99	0.114	0.074	0.115
13	0.302	0.082	0.126	42	0.195	0.486	0.515	71	0.553	0.162	0.550	100	0.610	0.285	0.335
14	0.044	0.244	0.691	43	0.563	0.896	1	72	0.088	0.281	0.312	101	0.405	0	0.905
15	0.025	0.057	0.110	44	0.468	0.208	0.258	73	0.435	0	0.153	102	0.065	0.031	0.128
16	0.156	0.674	0.719	45	0.609	0.269	0.278	74	0.716	0.210	0.233	103	0.113	0.225	0.282
17	0.729	0.062	0.110	46	0.281	0.112	0172	75	0.284	0.251	0.325	104	0.186	0.255	0.288
18	0.249	0	1	47	0.314	0.060	0.103	76	0.566	0.176	0.181	105	0.475	0.031	0.112
19	0.390	0.598	0.621	48	0.433	0.210	0.243	77	0.218	1	1	106	0.132	0.165	0.195
20	0.780	1	1	49	0.036	0.714	0.715	78	0.476	0.102	0.181	107	0.530	0	0.155
21	0.179	0.089	0.145	50	0.571	0.645	0.661	79	0.781	0	0.067	108	0.021	0.308	0.358
22	0.242	0	0.092	51	0.204	0	0.116	80	0.093	0.229	0.238	109	0.272	0.103	0.155
23	0.076	0.225	0.334	52	0.416	0.168	0.278	81	0.391	0.084	0.106	110	0.796	0.336	0.678
24	0.205	0.927	1	53	0.152	0.059	0.118	82	0.151	0.082	0.154	111	0.385	0.121	0.666
25	0.032	0	0.096	54	0.013	0.070	0.226	83	0.814	0.181	0.193	112	0.278	0.843	0.916
26	0.175	0.067	0.176	55	0.090	0.291	0.442	84	0.582	1	1	113	0.717	0.103	0.175
27	0.341	0.666	0.768	56	0.431	0.077	0.106	85	0.762	0.138	0.334	114	0.180	0.286	0.316
28	0.248	0.152	0.238	57	0.208	0.140	0.173	86	0.680	0.118	0.137	115	0.157	0.422	0.449
29	0.370	0.053	0.140	58	0.451	0.221	0.283	87	0.150	0.113	0.223				

Table 5: Ranking using DEA method and the SFA method

DMU	Rank			DMU	Rank			DMU	Rank			DMU	Rank		
	SFA	CCR	BCC		SFA	CCR	BCC		SFA	CCR	BCC		SFA	CCR	BCC
1	56	8	10	30	82	60	65	59	18	46	49	88	108	61	74
2	21	30	43	31	66	3	5	60	94	14	12	89	58	59	45
3	112	20	32	32	73	68	79	61	99	31	44	90	98	13	22
4	37	102	106	33	36	27	34	62	17	110	17	91	59	24	16
5	2	12	18	34	60	107	80	63	45	1	3	92	88	96	95
6	107	92	76	35	68	99	114	64	47	94	98	93	41	113	53
7	57	25	38	36	3	7	8	65	28	101	91	94	106	69	75
8	22	29	15	37	43	108	110	66	13	22	33	95	19	36	55
9	14	103	2	38	24	49	36	67	27	21	26	96	42	100	99
10	20	58	67	39	16	48	63	68	34	35	14	97	62	2	1
11	8	95	112	40	86	28	28	69	64	32	42	98	12	33	46
12	65	74	71	41	23	37	48	70	104	50	40	99	96	85	102
13	67	83	97	42	81	23	37	71	33	66	35	100	25	41	50
14	109	47	25	43	32	10	11	72	102	42	57	101	51	114	20
15	113	91	105	44	40	57	64	73	46	111	90	102	105	97	96
16	90	16	23	45	26	43	61	74	11	55	70	103	97	53	60
17	9	88	104	46	70	76	86	75	69	45	54	104	83	44	58
18	74	104	4	47	63	89	109	76	31	63	82	105	39	98	103
19	53	19	31	48	48	56	66	77	77	5	7	106	95	65	77
20	6	6	9	49	110	15	24	78	38	79	81	107	35	115	87
21	85	80	92	50	30	18	30	79	5	112	115	108	114	38	47
22	76	105	113	51	80	109	101	80	100	51	69	109	72	78	88
23	103	52	52	52	50	64	62	81	52	81	107	110	4	34	27
24	79	9	13	53	91	90	100	82	92	82	89	111	54	72	29
25	111	106	111	54	115	86	72	83	1	62	78	112	71	11	19
26	87	87	83	55	101	39	41	84	29	4	6	113	10	77	84
27	61	17	21	56	49	84	108	85	7	71	51	114	84	40	56
28	75	67	68	57	78	70	85	86	15	73	94	115	89	26	39
29	55	93	93	58	44	54	59	87	93	75	73				

Table 6: List of companies

DMU	Companies' Name	DMU	Companies' Name	DMU	Companies' Name
1	Acoustech Bhd	40	Hong Leong Indus Bhd	79	Pelangi Publishing
2	Ajinomoto Malaysia	41	Hovid Berhad	80	Pelikan Int'l Corp
3	Amtek Holdings Bhd	42	Hume Industries Bhd	81	Pensonic Holdings
4	Apex Healthcare Bhd	43	Hup Seng Industries	82	Poh Huat Res Hldgs
5	Apollo Food Holdings	44	Hwa Tai Industries	83	Poh Kong Holdings
6	Asia Brands Bhd	45	Iq Group Hldgs	84	Ppb Group Bhd
7	Asia File Corp Bhd	46	Jaycorp Bhd	85	Prolexus Berhad
8	Bio Osmo Berhad	47	Jerasia Capital Bhd	86	Pwf Consolidated
9	Bonia Corporation	48	Johore Tin Berhad	87	Ql Resources Bhd
10	British Amer Tobacco	49	Karex	88	Salutica
11	C.I. Holdings Berhad	50	Kawan Food Berhad	89	Sand Nisko Cap
12	Cab Cakaran Corp Bhd	51	Khee San Berhad	90	Sasbadi Holdings Bhd
13	Caely Holdings Bhd	52	Khind Holdings	91	Saudee Group
14	Cam Resources Bhd	53	Kotra Industries Bhd	92	Sern Kou Resrcs Bhd
15	Carlsberg Brewery	54	Kuantan Flour Mills	93	Shh Resources Hldgs
16	Cck Consol	55	Latitude Tree	94	Signature Inter
17	Ccm Duopharma	56	Lay Hong Berhad	95	Sinmah Capital
18	China Ouhua	57	Lee Swee Kiat Group	96	Spring Gallery Bhd
19	Classic Scenic Bhd	58	Lii Hen Industries	97	Spritzer Berhad
20	Cocoaland Hldgs	59	London Biscuits Bhd	98	Sws Capital Bhd
21	Cwg Holdings Bhd	60	Ltkm Bhd	99	Syf Resources Bhd
22	D.B.E. Gurney	61	Magni Tech	100	Tafi Industries Bhd
23	Degem Bhd	62	Malayan Flour Mills	101	Tan Chong Motor
24	Dutch Lady Milk	63	Maxwell Inter	102	Tek Seng Holdings
25	Eka Noodles Bhd	64	Milux Corp Bhd	103	Teo Guan Lee Corp
26	Emico Holdings Bhd	65	Mintye Industries	104	Teo Seng Capital
27	Eng Kah Corporation	66	Msm Malaysia	105	Tomei Cons Bhd
28	Euro Holdings Bhd	67	Nestle (Malaysia)	106	Tpc Plus Bhd
29	Eurospan Holdings	68	New Hoong Fatt	107	Umw Holdings Berhad
30	Fcw Holdings Berhad	69	Ni Hsin Resrcs Bhd	108	Upa Corp Bhd
31	Fed Furn Hldgs (M)	70	Niche Capital	109	Wang Zheng Bhd
32	Formosa Prosonic Ind	71	Ntpm Holdings Bhd	110	Xian Leng Holdings
33	Fraser & Neave	72	O&C Resources	111	Xidelang Holdings
34	G3 Global Bhd	73	Oriental Food Ind	112	Xingquan
35	Goldis Bhd	74	Oriental Holdings	113	Yee Lee Corporation
36	Guan Chong Berhad	75	Padini Holdings	114	Yoong Onn
37	Hb Global Ltd	76	Panasonic Mfg	115	Ysp Southeast Asia
38	Heineken Malay	77	Paragon Union Berhad		
39	Homeritz Corp	78	Pccs Group Berhad		

Table 7: Spearman's rank order correlation coefficients

Method	Spearman's Rank Order Correlation		
	SFA	DEA-CCR	DEA-BCC
SFA	1	0.0246	0.0971
DEA-CCR		1	0.766
DEA-BCC			1

We continued to compute the Spearman rank correlation coefficient as shown in Table 7. Referring to the Table 7, shows the correlation between SFA and DEA-CCR model, SFA and DEA-BCC model, DEA-CCR and DEA-BCC models. It is interesting to note that, the correlation between the SFA and DEA-CCR model, SFA and DEA-BCC model, are not as great as compared to DEA-BCC and DEA-CCR models.

5. Conclusion

We have analyzed three different technique for measure efficiency of 115 samples of Malaysian companies. These efficiency measurement techniques may be classified in different ways. Our study has been to distinguish between parametric and non-parametric methods. A vast literature has treated the measurement of performance efficiency by using of both parametric and non-parametric approaches. Based on the findings of empirical studies, seem to confirm it, we decided, no approach is strictly preferable. As has been shown throughout this study, each technique has its own advantages and weaknesses. A careful consideration of them, of the data set utilized, and the intrinsic characteristics of the industry under analysis will help us in the correct implementation of these techniques.

DEA method is easier to interpret the analysis and it is not compulsory for hypothesis and functional form. SFA approach is allowing the random shocks or measurement error and has more strength in economic theory since the nature of production has a strong relation with stochastic. However, the difficulty of SFA is risky to impose strong a priori assumptions on the production technology by choosing a functional form. Therefore, it would be desirable to introduce more flexibility into the SFA approach, as well as to go more deeply into the analysis of stochastic non-parametric methods and their statistical properties.

Overall, the findings show evidently the stocks efficiency with three different models and all of them show different results and ranking performances. Future studies are recommended to include more variables of inputs and outputs. Since SFA are only limited for one output, extra investigation for SFA method so that multiple outputs can be applied. We will also focus to test the SFA model with the issues of time-variant that affect efficiency by using of panel data and dynamic context for DEA method. So that, the study is more comprehensive.

References

[1] Coelli TJ, Rao DSP, O'Donnell CJ & Battes GE (2005), *An introduction to efficiency and productivity analysis*. Springer Sciences.

[2] Hasan MZ, Kamil AA, Mustafa A & Baten MA (2012), A Cobb Douglas stochastic frontier model on measuring domestic bank efficiency in Malaysia. *PLoS One* 7(8), 1–5.

[3] Flubacher M (2015), Comparison of the economic performance between organic and conventional dairy farms in the Swiss mountain region using matching and stochastic frontier analysis. *Journal Socio-Economics Agriculture* 8, 76–84.

[4] Bin Zheng X & Park NK (2016), A study on the efficiency of container terminals in Korea and China. *Asian Journal of Shipping and Logistics* 32(4), 213–220.

[5] Ling OP & Kamil AA (2010), data envelopment analysis for stocks selection on Bursa Malaysia. *Archives of Applied Sciences Research* 2(5), 11–35.

[6] Zamani L, Beegam R & Borzoian S (2014), Portfolio selection using data envelopment analysis (DEA): A case of select indian investment companies. *International Journal of Current Research and Academic Review* 2(4), 50–55.

[7] Nektarios M, Xenos P, Nektarios G, Poulakis K & Chouzouris M (2015), Efficiency analysis of Lloyd's syndicates: A comparison of DEA and SFA approaches. *Spoudai-Journal of Economics and Business* 65(1–2), 27–46.

[8] Koopmans TC (1951), *Activity analysis of production and allocation*. John Wiley Sons.

[9] Debreu G (1951), The coefficient of resource utilization. *Econometrica-Journal of Econometric Society* 19(3), 273-292.

[10] Farrell MJ (1957), The measurement of productive efficiency. *Journal of the Royal Statistical Society* 120(3), 253–290.

[11] Bogetoft P & Otto L (2011), Benchmarking with DEA, SFA, and R. Springer Sciences.

[12] Aigner DJ & Chu SF (1968), On estimating the industry production function. *American Economic Review* 58(4), 826–839.

[13] Aigner D, Lovell CAK & Schmidt P (1977), Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6(1), 21–37.

[14] Charnes A, Cooper WW & Rhodes E (1978), Measuring the efficiency of decision making units. *European Journal of Operational Research* 2(6), 429–444.

[15] Banker RD, Charnes A & Cooper WW (1984), Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* 30(9), 1078–1092.

[16] Mokhtar M, Shuib A & Mohamad D (2014), Identifying the critical financial ratios for stocks evaluation: A fuzzy Delphi approach. *Proceedings of the 3rd International Conference on Quantitative Sciences and Its Applications: Fostering Innovation, Streamlining Development*, pp. 348-354.

[17] Bos JWB & Koetter M (2011), Handling losses in translog profit models. *Applied Economics* 43(3), 307–312.

[18] Afsharian M & Alirezaee MR (2007), A complete ranking of DMUs using restriction in DEA models. *Applied Mathematics and Computation* 189, 1550–1559.