Robustness of efficient decision-making unit based on production model of stochastic frontier analysis with different distribution error

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ABSTRACT

In the empirical stochastic frontier analysis, there has been an increasing interest in exploring the consistency of the production model for decision-making units. Among it is the issue of consistency, which has been recognized as a complex process due to many factors such as different model estimations, the behavior of inefficiency effects and types of distributional errors. This paper focuses on analyses the technical efficiency of Malaysian stock performance over the period of 2013 to 2017. By utilizes SFA production function (Cobb-Douglas and Translog), which allows two decompositions of inefficiency effect into its time-variant and time-invariant, within two distributional assumptions known as truncated-normal and half-normal, which is predicted to estimate the technical efficiency score and provides a ranking efficiency based on the model estimation performance. Finally, to investigate the consistency of the estimated SFA efficiency score by examining its relationship with four models. These main findings figure out, using time-invariant inefficiency effect, Cobb-Douglas function with truncated-normal distribution more preferable for the dataset of study. By using four models with different distributional assumptions and production models, Spearman's rank-order was implemented and revealed that there was a high degree of correlation is found between efficiency estimates that derives from the models applied. Based on the empirical study, this research shows that the ranking efficiency for selected stock performance in Malaysia was said to be robust to different kinds of distributional errors and production models. This paper provides new evidence on consistency relative efficiency of stochastic frontier model based on the three assumptions; inefficiency effect, distribution error for technical inefficiency and production function.

1. Introduction

Efficient frontier methods such as Stochastic Frontier Analysis (SFA) models are widely used to identify the high and low performance of a firm. SFA model allows better separation of noise and inefficiency of error. Therefore, the separation of inefficiency of error from statistical noise requires specific assumptions on technical inefficiency such as half-normal distribution and normal distribution

(Aigner et al., 1977). Since limited theory is available in guiding the choice of technical inefficiency, various distribution assumptions are being explored in the literature. The information available in literature review reveals other types of distribution assumptions of technical inefficiency which are also used to estimate efficiency. For instance, Hasan et al. (2012), Hamidi (2016) and Yakob and Isa (2008) have used the truncated-normal distribution while the gamma distribution was implemented by Greene (1990), Stevenson (1980) and Ritter and Simar (1997), whereas exponential distribution was considered by Jondrow et al. (1982). However, half-normal distribution has become the standard choice by most studies (Yang, 2010; Ferreira et al., 2014; Iliyasu et al., 2016).

The types of distributional choices are guided by theoretical consideration and computational

convenience. Researchers tend to use half-normal and truncated-normal as inefficiency error distribution due to the ease of estimation and interpretation (Kirkley et al., 1995). Although there is no consensus on the type of distribution, one should choose to arrive at the inefficiency measure which most of the works that are available in the literature suggest different distributional assumptions that tend to yield similar efficiency. Based on a study conducted by Aigner et al. (1977), there are two ways for estimating inefficiency which they assumed that the distribution of the inefficiency term takes a half-normal and exponential distribution, and the result shows a little difference in inefficiency scores when different assumptions were used for the inefficiency term. Furthermore, few studies have been performed to test its robustness. Checking the robustness is one of the common procedures in the econometric field. Bauer et al. (1998) proposed a set of consistency condition of stochastic frontier models and the efficiency rank banks are roughly the same order and identify mostly the same banks as best practice and worst practice for the different distribution are used. Besides that, a study done by Yane and Berg (2013) examines the robustness of efficiency score ranking across four distributional assumptions (half-normal, truncated-normal, exponential and gamma distributions) for Translog stochastic production frontier models using data from Japanese water utilities. Findings show that efficiency rankings were quite consistent. Further, Zhou et al. (2012) used the SFA approach to estimate the economy-wide energy efficiency performance for the 21 OECD countries and applied half-normal and truncated-normal distributions for technical inefficiency distribution. It can be observed that the Spearman's rank correlation coefficient between the two sets of SFA approaches (normal-half normal and normal-truncated normal models) were larger than 0.97.

Moreover, a study conducted by Rosko and Mutter (2008) using Translog with truncated-normal distribution found that the relative inefficiency estimates were not sensitive to the choice of distributional alone. The production function of SFA models and inefficiency effect in SFA for panel data has to be appropriate in order for the measurement of efficiency performance to be accurate. However, both production function models of stochastic frontier should have an assumption on technical inefficiency distribution. Normally, different assumption and specification of the model will produce different prediction of technical efficiency. Nevertheless, some of the property's assumption will be robust for the model. Therefore, this study focuses on investigating the robustness of SFA model by evaluating the consistency of efficiency ranking score based on different distributional assumptions (half-normal and truncated-normal) of technical inefficiency for two production functions in SFA, specifically using Cobb-Douglas and Translog production function. In addition, using likelihood hypothesis testing, this study also proposes the best

model and inefficiency effect that represent the dataset of the study.

The remainder of the paper is organized as follow. The following section provides some discussion on the stochastic frontier model based on panel data. Section 3 describes the materials and methods, data sources and variables selection, production models of SFA as well as hypothesis testing. This is followed by the fourth section, which covers the result and discussion of this study and finally, conclusion and suggestions for future studies.

2. Stochastic frontier model

A stochastic model was proposed by Aigner et al. (1977) and Meeusen and Broeck (1977). SFA decomposes the error terms into two components. One part represents random events outside of the decision making unit's control and another part is a non-negative term that capturing inefficiency. SFA model is a parametric technique, which requires assumptions about the functional form of the production function and the distribution of the error terms.

The panel data models of SFA distinguish two approaches, concerning the assumption of whether or not efficiency changes over time. Time-invariant efficiency models assume efficiency to be constant over time. To observe changes over time, panel data need to consider as well as data of several firms at several time points. The panel form used is $y_{it} = x_{it}\beta + v_{it} - u_{it}$. The technical efficiency of the decision making unit (DMU) i at the time t was $TE_{it} = exp(-u_{it})$. Battese and Coelli (1992) proposed to represent the preceding u_{it} as $U_{it} = exp[-\eta(t-T)]u_i$; where eta, η is an unknown scalar parameter to be estimated which will determine whether inefficiencies are time-varying or time-invariant effects and u_i as technical inefficiency error that assumed to be independent and identically distributed (i.i.d) as truncated at zero of the $N(\mu, \sigma_u^2)$ distribution. If η is zero, it represents time-invariant inefficiency effects. Firm-specific inefficiency can be considered as inherent and structural residual between observed data and the corresponding production frontier. Without violent in economic environments (i.e. deregulation), firm-specific efficiency and its relative rankings will not likely to change drastically over a short period of time. On the other hand, positive η indicates decreasing inefficiency effects and a negative η represents increasing effects. Hence, the parameter β can be estimated using maximum likelihood estimator method.

Battese and Corra (1977) parameterized the log-likelihood function using $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and total variation in output from the frontier level of output, attributed to technical efficiency defined by $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$. The parameter gamma, γ lies between zero and one; $\gamma = 0$ indicates that all deviations from the frontier are due to random errors and $\gamma = 1$ means all deviation results are due to technical inefficiency.

3. Materials and methods

In this section, the model mentioned in Section 2 used to estimate the efficiency performance of selected companies. Through production function on the SFA model, variable's construction and the hypothesis testing based on this study, consistency of efficiency ranking will be identified.

3.1. Data sources

This paper analyzed the technical efficiency of Malaysian stocks of construction industry listed under Bursa Malaysia. The datasets include balanced panel data of twenty-five companies over a period of 5 years, from year 2013 to 2017, providing 125 observations. For this study, data was collected specifically from Eikon Thomson Reuter's database. The 25 selected construction listed companies as shown in Table 1.

3.2. Variable constructions

There are large numbers of financial ratios available. These ratios can be classified into few categories which are liquidity, profitability, leverage, assets turnover, market value and growth ratio. However, using all the available financial ratio variables in the stock evaluation seems impractical as it will complicate the evaluation process

computationally and analytically. There are various methodologies that have been implemented in order to identify the most important ratios. These methods include survey, which was carried out by expert judgments, namely Fuzzy Delphi Method (FDM), Globalization Grey Relational Analysis, Clustering Method, Principal Component Analysis, Decision Tree Method and Multiple Discriminant Analysis. Traditional methods for analyzing financial ratio under accounting and finance are Financial Ratio Analysis (FRA) and DuPont analysis. Many researchers who used both traditional methods are said to implement it due to the simple calculation and easiness to use. Financial ratios which have been calculated and found in financial statement provide the following benefits; measuring the performance of managers for reward, measuring the performance of department within multi-level companies, projecting the future by supplying historical information to existing or potential investors, providing information to creditors and supplier, evaluating competitive positions of rivals and evaluating the financial performance of acquisitions. Other than the benefits provided above, financial ratios are also used for the purpose of predicting future performance, business bankruptcy prediction, credit risk assessment decisions, financial valuation and credit analysis of companies and in-stock selecting and trading.

Table 1: List of selected Malaysians of construction industry companies

DMU	Companies	DMU	Companies	DMU	Companies
1	Ahmad Zaki Resources Bhd	10	Gadang Holdings Bhd	19	SBC Corporation Bhd
2	Benalec Holdings Bhd	11	Mitrajaya Holdings Bhd	20	Sycal Ventures Bhd
3	Bina Puri Holdings Bhd	12	Malaysian Resources Corporation Bhd	21	TRC Synergy Bhd
4	Brem Holdings Bhd	13	MTD ACPI Engineering Bhd	22	TRIplc Bhd
5	Crest Builder Holding Bhd	14	Mudajaya Group Bhd	23	TSY Capital Bhd
6	DKLS Industries Bhd	15	Muhibbah Engineering (M) Bhd	24	WCT Holding Bhd
7	Ekovest Bhd	16	PIB Engineering Bhd	25	YTL Corporation Bhd
8	Eversendai Corporation Bhd	17	Prinsiptek Corporation Bhd		
9	Fajarbaru Builder Group Bhd	18	Protasco Bhd		

Selection of output for this study is mainly based on the connection between efficiency and profitability that is known as the DuPont Model. DuPont Model or DuPont Analysis was created in the early 1900s, which is still considered as a valid model to be used for assessment of profitability (Sheela and Karthikeyan, 2012). DuPont Model is a useful tool for analyzing financial statement which the performance helps to predict future profitability (Chang et al., 2014). DuPont analysis decomposes return-on-net-operating assets (RNOA) into two multiplicative components which are profit margin and asset turnover. Soliman (2004) examined whether the use of industry benchmarks in conjunction with DuPont analysis improve forecasts of future RNOA. His study narrowed down to how market participants, such as equity analysts and stock market investors used DuPont components in assessing the prospects of the firm and examined the stock market's association with the information in the DuPont components. Study of Fairfield and Yohn (2001) demonstrated how the component of return

on assets used in DuPont analysis (namely asset turnover and profit margin) are relevant in forecasting changes in future. Specifically, DuPont analysis uses Return on Equity (ROE) to measure the percentage of earnings available to stockholders as per their total equity invested. DuPont analysis is different from the common calculation of ROE because it shows the relationship between profitability (net profit margin), assets management (total assets turnover) and financial leverage (debt ratio) in determining the ROE (Soliman, 2008). In other words, a company may use DuPont analysis to identify factors that cause the company to have low ROE. A company with the highest value of ROE can be considered as a high-performing company due to its ability in generating a high return on stockholders' investment. Therefore, the aim of this study is to maximize output production (ROE) when utilizing the inputs provided.

Assets turnover was selected as one of the inputs in this study. Assets turnover was measured by the value of a company's sales and revenue in relation to

the value of its assets and used as an indicator of the efficiency in which the assets were used to generate the revenue. The reason why asset turnover was selected as one of the input's variable is that the changes in the asset turnover ratio provide information on future profitability (Fairfield and Yohn, 2001; Bauman, 2014) as well as earnings management (Jansen et al., 2008). Identifying earning is important to access current economic performance in order to predict profitability and determine the firm's value (Jansen et al., 2012).

The market capitalization is also one of the selected inputs in this study. Market capitalization shows the size of a company which is known as the basic determinant of various characteristics, including risk which investors are interested in. Market capitalization is very essential to estimate stock return and risk. Dias (2013) studied the roles of market capitalization within the estimated value at risk (VaR) in order to have a portfolio with different market capitalization and it appeared that VaR methods performed differently. Furthermore, Reinganum (1983) investigated the relationship between stock return and market capitalization and the result further revealed that market capitalization was an excellent indicator for a long-run rate of return and the average portfolio return were systematically related to market capitalization. Prior to this, many studies in selection stock have used market capitalization based on the efficiency concept.

The debt to equity ratio input also referred to as risk or gearing ratio was used in this study to evaluate a company's leverage. Evidence of study conducted by Bhandari (1988) showed the expected returns on common stocks were positively related to the debt per equity ratio controlling for the beta (risk) and firm size. Based on another study was carried out by Mokhtar et al. (2014) using an approach which is known a Fuzzy Delphi Method (FDM), recognized debt-equity ratio as one of the most important financial ratios to evaluate stock performance.

3.3. Production model specification

A production function defines the technological relationship between the level of inputs and the resulting level of outputs. If the estimated econometrically from data on observed output and input usage, it indicates the average level of outputs that can be produced from a given level of inputs. The two forms of production function mostly used in literature to measure stock's inefficiency are the Cobb-Douglas (CD) and Translog (TL) functional form. The Cobb-Douglas form is easy to estimate, interpret and requires estimation of few parameters. The main drawback is that it assumes all companies would have a constant input of elasticity that substitute elasticity equals one and return to scale for all companies. On the other hand, the Translog form does not impose these restrictions and it tends

to be more flexible, however, it is susceptible to certain degrees of freedom and multicollinearity. Multicollinearity occurs when the independent variables are too highly correlated with each other. In this study, we implemented both models; Cobb-Douglas form and Translog form. For estimating the parameters, the method of maximum likelihood was applied for both models. The u_{it} term is a non-negative random variable associated with technical inefficiency in production.

For this study, truncated-normal and half-normal distribution were chosen for Cobb-Douglas form as well as Translog form because both distributions are easier and simpler for estimation and comparison with other types of distribution. For the assumption of technical inefficiency, we assumed that the technical inefficiency has time-varying and time-invariant effect. Therefore, by applying several different assumptions of distribution to the same dataset, this study will provide deeper insights into the implication of choosing different distributions, different models and behavior of inefficiency effect to technical inefficiency and performance ranking within the selected dataset. Estimation of technical efficiency of stocks was computed by statistical R-Programing, employing frontier package.

The empirical model of Cobb-Douglas prior to the estimation of stock performance is presented in Eq. 1:

$$ln(y)_{it} = \beta_0 + \sum_{j=1}^{3} \beta_j lnx_{jit} + e_{it}$$

$$ln(y)_{it} = \beta_0 + \sum_{j=1}^{3} \beta_j lnx_{jit} + v_{it} - u_{it} \qquad (1)$$

Subscripts i and t represent the ith company (decision-making unit) for $i = 1,2,...,25$; and t^{th} year of observation for $t = 1,2,....,5$; whereas the parameter of y_{it} refers to the individual Return on Equity (output production). "ln" represents the natural logarithm; β is a vector of unknown parameters to be estimated and $e_{it} = v_{it} - u_{it}$ is a stochastic composite error term. The v_{it} term corresponds to statistical noise, measurement error and other random events that are beyond the company's control and it is assumed to be independently and identically distributed (i.i.d) normal random variables with zero means and variances; $v_{it} \sim N(0, \sigma_v^2)$ and the u_{it} term is a non-negative random variable associated with technical inefficiency in production and are assumed to be independently and identically distributed (i.i.d). It is further assumed that v_{it} and u_{it} is independently distributed from each other. Variable x_1 is denoted as asset turnover (AT), x_2 is market capitalization (MC) and x_3 is the debt to equity ratio (DE).

The Cobb-Douglas functional model is presented in Eq. 2:

$$ln(ROE)_{it} = \beta_o + \beta_1 ln(AT)_{it} + \beta_2 ln(MC)_{it} + \beta_3 ln(DE)_{it} + v_{it} - u_{it} \qquad (2)$$

The Translog function is commonly used and it is generalized from the Cobb-Douglas function. It is a

flexible functional form providing a second-order approximation. The empirical of Translog function form is displayed in Eq. 3:

$$ln(y)_{it} = \beta_0 + \sum_{j=1}^{3} \beta_j \, lnx_{jit}$$
$$+ \frac{1}{2} \sum_{j=1}^{3} \sum_{k=1}^{3} \beta_{jk} lnx_{jit} lnx_{kit} + v_{it} - u_{it} \qquad (3)$$

Subscript j is the number of independent variables; for $j = 1,2,3$; i^{th} is the company for $i = 1,2,...,25$; and t^{th} year of time observation for $t = 1,2,....,5$. Parameter of y_{it} is the output production for i^{th} company at time t, x_{jit} is the corresponding level of inputs j of the ith company at time t, x_{jit} times x_{kit} is the interaction of the corresponding level of inputs j and k of the ith company at time t and β is a vector of unknown parameters to be estimated.

The Translog functional form of the current study is presented in Eq. 4:

$$ln(ROE)_{it} = \beta_0 + \beta_1 ln(AT)_{it} + \beta_2 ln(MC)_{it} + \beta_3 ln(DE)_{it}$$
$$+ \frac{1}{2}\beta_{11}(ln(AT)_{it})^2 + \frac{1}{2}\beta_{22}(ln(MC)_{it})^2 + \frac{1}{2}\beta_{33}(ln(DE)_{it})^2$$
$$+ \beta_{12} ln(AT)_{it} ln(MC)_{it} + \beta_{13} ln(AT)_{it} ln(DE)_{it}$$
$$+ \beta_{23} ln(MC)_{it} ln(DE)_{it} + v_{it} - u_{it} \qquad (4)$$

Parameter β_0, however, is the intercept of the constant term; β_1, β_2 and β_3 are first-order derivatives; β_{11}, β_{22} and β_{33} are own second-order derivatives and β_{12}, β_{13} and β_{23} are cross second order derivatives.

3.4. Hypothesis testing

The series hypotheses with generalized likelihood-ratio (LR) were obtained based on the performed hypothesis test from the model. A very first likelihood ratio test was conducted to test the null hypothesis from the Translog stochastic frontier production function which can be reduced to a Cobb-Douglas stochastic frontier production function. The test statistics used is $H_0: \beta_{jk} = 0$; $H_1: \beta_{jk} \neq 0$. This test aimed to determine the type of functions from the Cobb-Douglas model in order to see the adequateness of the dataset using maximum likelihood estimation.

The second test is to find out whether the effects of inefficiency exist or vice versa. The test statistics used is $H_0: \gamma = 0$, whereas the null hypothesis specifies zero technical inefficiency effects from the model. Another test is to identify types of distribution for technical inefficiency which the test statistics used is $H_0: \mu = 0$, the null hypothesis specifies that half-normal distribution is an adequate representation of the data, given the specifications of the generalized truncated-normal model.

Finally, is to test whether the inefficiency effects are time-invariant which can be done by running the two models; one without the parameter $\eta (\eta = 0)$, and the other with parameter. The test statistics $LR = -2[lnL_R(H_0) - lnL_U(H_1)]$ conform to $\chi^2(J)$

where $lnL_R(or H_0)$ and $lnL_U(or H_1)$ denote the value of the restricted and unrestricted for log-likelihood functions respectively, and J is the number of restrictions. The null hypothesis, H_0 will be rejected at the $\alpha\%$ level of significance if the likelihood ratio statistic exceeds the critical value $\chi^2_{1-\alpha}(J)$.

4. Results and discussion

This study was conducted on 25 construction companies in Malaysia from the year 2013 to 2017. The maximum-likelihood method was used to calculate the parameters in both Cobb-Douglas function and Translog function of time-invariant technical inefficiency effects, which can be referred to in Table 2.

4.1. Construction of SFA model

In order to construct the SFA model, likelihood ratio (LR) test was conducted to test whether Cobb-Douglas function is more suitable and adequate to represent the dataset under the study. Further, the null hypothesis from Translog function can be reduced to a Cobb-Douglas function. The result of the test statistic; $H_0: \beta_{jk} = 0$; $H_1: \beta_{jk} \neq 0$, is shown in Table 3.

The log-likelihood value of the restricted model is -136.08, and the log-likelihood value of the unrestricted model is -130.03. Thus, the LR statistics was noted as $-2[-136.08 - (-130.03)] = 12.1$ which clearly not greater than the 5% critical value of 12.59. This implied a failure to reject the null hypothesis. In other words, the Cobb Douglas function was more suitable and adequate to represent the data under this study. The Cobb-Douglas model provides an excellent fit. It has been shown in simulation studies that a misspecified Translog function performs rather poorly despite its flexibility if the sample size is small (Ruggiero, 1999). Next was to test whether technical inefficiency effect exists over time. The null hypothesis, $H_0: \gamma = 0$; specified that strictly stochastic technical inefficiency, σ_u^2 does not exist versus $H_1: \gamma > 0$. The log-likelihood function of the restricted model is -149.67, and the log-likelihood value for the unrestricted model is -134.13. Accordingly, the LR statistics was $-2[-149.67 - (-134.13)] = 31.08$ which has exceeded the critical 5% value of 7.82. Therefore, the test result rejected the null hypothesis, implying the existence of technical inefficiency.

The third test was on the technical assumption, whether the distribution technical inefficiency error term, u belongs to a half-normal or truncated-normal distribution. If μ is pre-assigned to be zero, then the distribution is considered as half-normal. The null hypothesis used is $H_0: \mu = 0$ versus $H_1: \mu \neq 0$; the log-likelihood value for the restricted model is -137.35 and the log-likelihood value for the unrestricted model is -135.35. Thus, LR statistic was $-2[-137.35 - (-135.35)] = 4$ which exceeded the

critical 5% value of 3.84. Therefore, this leads to a rejection of the null hypothesis and implies that the

technical inefficiency, u was associated with truncated-normal distribution.

Table 2: Parameters with different production function and distribution error for time-invariant

Inefficiency effect		Time-Invariant							
Production Function		Cobb-Douglas				Translog			
Distribution error		Truncated Normal		Half Normal		Truncated Normal		Half Normal	
Variable		Coeff	Pr (>|z|)	Coeff	Pr (>|z|)	Coeff.	Pr (>|z|)	Coeff.	Pr (>|z|)
Constant	β_0	-2.16	0.05.	-1.89	0.34	-16.75	0.00***	-15.60	0.35
ln(AT)	β_1	0.50	0.00***	0.43	0.01***	-3.58	0.19	-4.04	0.12
ln(MC)	β_2	0.23	0.00***	0.17	0.06.	1.40	0.00***	1.27	0.44
ln(DE)	β_3	0.65	0.00***	0.66	0.00***	1.08	0.46	1.62	0.30
$\frac{1}{2}(\ln(AT))^2$	β_{11}					0.03	0.92	0.09	0.78
$\frac{1}{2}(\ln(MC))^2$	β_{22}					-0.05	0.00**	-0.04	0.62
$\frac{1}{2}(\ln(DE))^2$	β_{33}					-0.02	0.11	-0.14	0.25
ln(AT)ln(MC)	β_{12}					0.20	0.15	0.22	0.09.
ln(MC)ln(DE)	β_{23}					-0.04	0.56	-0.07	0.40
ln(AT)ln(DE)	β_{13}					-0.27	0.04*	-0.24	0.10
Variance Parameters									
Sigma squared	σ^2	0.76	0.00***	1.31	0.00**	0.53	0.01**	0.79	0.00**
Gamma	γ	0.53	0.00***	0.70	0.00***	0.27	0.26	0.50	0.02*
Mu	μ	1.27	0.00***	0	0	0.76	0.25	0	0
Eta	η	0	0	0	0	0	0	0	0
Log-likelihood		-135.35		-137.35		-131.71		-131.99	

Table 3: Hypothesis testing result

Hypothesis Testing	Likelihood value of the reduced model	Likelihood value of the full model	DOF	$\mathbf{Pr}(> Chisq)$	Decision
$H_0: \beta_{jk} = 0$ $H_1: \beta_{jk} \neq 0$	-136.08	-130.03	6	0.05941	Fail to Reject
$H_0: \gamma = 0$ $H_1: \gamma \neq 0$	-149.67	-134.13	3	2.984e-07***	Reject
$H_0: \mu = 0$ $H_1: \mu \neq 0$	-137.35	-135.35	1	0.04582*	Reject
$H_0: \eta = 0$ $H_1: \eta \neq 0$	-135.35	-134.13	1	0.1174	Fail to Reject

Significance. Codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.' DOF: degrees of freedom

Finally, it is to test whether the inefficiency effects are time-invariant by applying the two models which is with or without the parameter $\eta(\eta = 0)$. The likelihood value for the restricted model is noted to be -135.35 and the unrestricted model is -134.13. The LR statistic used was $-2[-135.35 - (-134.13)] = 2.44$, which was lesser than the 5% critical value of 3.84. Therefore, again it leads to a rejection of the null hypothesis $H_0: \eta = 0$, and exclude η in the model.

After testing the four hypotheses using LR test, this study will follow the model proposed by Battese et al. (1989), using time-invariant inefficiency effect with truncated-normal distribution. Setting to be zero, it provides the time-invariant for SFA model as hypothesis test result. This result seems suitable due to the length of the panel data of this studies and the efficiency is thought unlikely to vary much over time The assumption of time-invariant inefficiency effect may hold in short panels but becomes less plausible when the number of time periods increases.

Therefore, this finding provides additional evidence for time-invariant studies and support by Kazukauskas et al. (2010) and Webster et al. (1998).

Hence, the Cobb-Douglas function, time-invariant inefficiency effect with truncated-normal distribution (Model 1) are selected for dataset of this study and the equation is as below:

$$ln(ROE)_{it} = \beta_o + \beta_1 ln(AT)_{it} + \beta_2 ln(MC)_{it} + \beta_3 ln(DE)_{it} + v_{it} - u_i \tag{5}$$

Based on Eq. 5 above, Table 2 (Model1) provides the estimation of the parameters. The value of gamma γ is 0.53. The parameter γ can be served as an index to identify whether the deviations from efficiency frontier is due to random error ($\gamma = 0$) or technical inefficiency ($\gamma = 1$). This value was consistent with the earlier hypothesis tests (technical inefficiency effects exist) and indicates that deviation results were more towards technical inefficiency.

Table 4 provides an efficiency score and ranking DMU or stock of companies for time-invariant effect for Model 1. Individual technical efficiencies for the company were estimated to range from 6.4 % to 83.6%, with an average mean efficiency of 30.8%. Based on Table 4, Model 1 clearly depicted that DMU_{22} (TRIplc Bhd) was at the top rank, while DMU_3 (Bina Puri Holdings Bhd) was the lowest

performance based on the ranking efficiency score. Other top performance companies were DMU_{19} (SBC Corporation Bhd), DMU_{10} (Gadang Holdings Bhd), DMU_{11} (Mitrajaya Holdings Bhd) and DMU_7 (Ekovest Bhd). While DMU_9 (Fajarbaru Builder Group Bhd), DMU_{21} (TRC Synergy Bhd), DMU_{17} (Prinsiptek Corporation Bhd) and DMU_2 (Benalec Holdings Bhd) were at the bottom rank performance.

Table 4: Ranking of DMU for time-invariant based on efficiency score and models

Rank	Model1		Model 2		Model 3		Model 4	
	CDTN	DMU	CDHN	DMU	TLTN	DMU	TLHN	DMU
1	0.836	22	0.914	22	0.814	22	0.890	22
2	0.546	19	0.826	10	0.738	19	0.873	19
3	0.525	10	0.808	19	0.674	10	0.849	10
4	0.481	11	0.806	11	0.621	6	0.815	6
5	0.428	7	0.715	7	0.593	11	0.798	11
6	0.421	5	0.704	6	0.588	7	0.793	7
7	0.415	6	0.692	5	0.565	4	0.756	4
8	0.345	4	0.634	15	0.553	5	0.743	15
9	0.335	15	0.597	4	0.540	15	0.733	5
10	0.294	16	0.526	16	0.535	16	0.730	25
11	0.272	12	0.512	18	0.485	20	0.729	16
12	0.271	24	0.511	12	0.484	25	0.688	20
13	0.262	18	0.510	24	0.451	12	0.658	12
14	0.251	20	0.442	20	0.449	13	0.635	24
15	0.246	23	0.424	23	0.444	23	0.621	13
16	0.206	13	0.387	25	0.437	24	0.620	23
17	0.204	14	0.378	14	0.413	17	0.571	18
18	0.201	1	0.374	8	0.412	18	0.563	17
19	0.201	8	0.354	1	0.410	1	0.542	1
20	0.196	25	0.354	9	0.360	9	0.508	9
21	0.193	9	0.354	13	0.344	8	0.462	8
22	0.178	21	0.328	21	0.339	21	0.458	21
23	0.171	17	0.280	17	0.318	2	0.403	2
24	0.153	2	0.259	2	0.313	14	0.402	14
25	0.064	3	0.099	3	0.238	3	0.250	3

Notes: CDTN: Cobb-Douglas function with Truncated-Normal distribution; CDHN: Cobb-Douglas function with Half-Normal distribution; TLTN: Translog function with Truncated-Normal distribution; TLHN: Tranlog function with Half-Normal distribution

4.2. Examination of consistency condition

Data presented in Table 5, Table 6 and Fig. 1 provide direct evidence on checking the consistency of conditions of the four models within the two types of production function and two types of distribution inefficiency suggested by Bauer et al. (1998).

4.2.1. Consistency condition (i)-Comparison of efficiency score based on distributions with each other's

Model 1 shows a comparison of the three models in checking the consistency of the SFA model. Based on Table 5, for Cobb-Douglas production function, the mean efficiency for Model 1 was 0.308 (with a mode 0.201) and Model 2 was 0.512 (with a mode 0.354). Meanwhile, for Translog production function within Model 3 and Model 4, the mean efficiency was rated at 0.485 and 0.644 respectively. The minimum value of efficiency scores for all the models was between the range of 0.064 and 0.250 and the maximum value of efficiency scores were between 0.814 and 0.914 which was closed to one. Value of efficiency scores that is close to one is referred to as efficient DMU. Standard deviation was slightly similar which the values were ranged between 0.139 and 0.207. Therefore, the results from the descriptive analysis show a slight difference in the

value of efficiency score between the four models and these findings was supported by Greene's (1990) claim.

Table 5: Descriptive statistics of the efficiency score by models

	Model 1	Model 2	Model 3	Model4
	CDTN	CDHN	TLTN	TLHN
Mean	0.308	0.512	0.485	0.644
Median	0.262	0.510	0.451	0.658
Mode	0.201	0.354	Null	Null
Minimum	0.064	0.099	0.238	0.250
Maximum	0.836	0.914	0.814	0.890
Standard Deviation	0.165	0.207	0.139	0.166
Skewness	1.330	0.213	0.460	-0.472
Kurtosis	1.858	-0.922	-0.384	-0.656

4.2.2. Consistency condition (ii)-Rank order correlations of the efficiency score based on distributions

Although the efficiency score for Cobb-Douglas and Translog production function (different distribution) were quite different, it is possible to note that these methods still have the tendency to generate similar rankings based on their efficiency score. Based on Table 4, few DMUs had similar ranking across the four models which refer to DMU_3, DMU_{21} and DMU_{22}. The ranking for other DMUs was quite consistent where the DMUs ranking performance was almost closed to one another.

Further investigation was computed to see the relationship between all models using Spearman's ranks order correlation. The result from Spearman's rank order is shown in Table 6. Based on the results, all models were said to have a strong relationship with a high coefficient correlation which was greater than 0.9. For the Cobb-Douglas production function, the degree of correlation between truncated-normal and half-normal distribution was highly correlated (0.978). This finding seems to be consistent with the studies conducted by Cullinane and Song (2006) and Zhou et al. (2012). For Translog production function, the degree of correlation between truncated-normal and half-normal distribution was also high (0.994) and it is in line with the study done by Yane and Berg (2013) which the correlation coefficient was reported to be greater than 0.9. In other words, it is proven that the same functional form with different distributions can still generate consistent ranking performance.

In addition, different functional forms within the production of the SFA model as well as the different assumptions of distribution are likely to produce high correlation. For instance, the degree of correlation between Cobb-Douglas function with truncated-normal distribution and Translog function with half-normal distribution was at 0.910. Another example, the degree of correlation between Cobb-Douglas function with half-normal distribution and Translog function with half-normal distribution resulted at 0.917. From the analysis, it can be concluded that the ranking results based on the efficiency score were quite robust with the distributional choice and SFA production function (Cobb-Douglas and Translog function). This was said

to be consistent with the conclusion drawn by Coelli et al. (2005).

Table 6: Spearman's rank-order correlation coefficient

Year	Time-Invariant			
2013-2017	CDTN	CDHN	TLTN	TLHN
CDTN	1	0.978	0.911	0.910
CDHN		1	0.907	0.917
TLTN			1	0.994
TLHN				1

* Correlation is statistically difference from zero at the 5% level (2- sided)

4.2.3. Consistency condition (iii)-Identification of best-practice and worst-practice firms

The implementation of one method to determine the best and worst performers may lead to a wrong conclusion, especially when ranking DMUs almost similar among different models (Silva et al., 2017). As discussed above, even though only 3 out of 25 (12%) DMUs have similar rankings, however, 88% of DMUs' ranking was still consistent. Based on the results, it was found that the top performance, as well as weak performance of DMUs, were in the same order across the four models. Moreover, Fig. 1 provides pictures of performance of DMUs based on the mean efficiency. DMU22 was placed at the top rank, while DMU3 was at the bottom rank across the four models. Fig. 1 also shows efficiency score for Model 4 (Translog function with Half-Normal distribution) which depicted the highest efficiency score compared to other models. Further, Model 1 (Cobb-Douglas function with Truncated-Normal distribution) shows the lowest efficiency score compared to other models across DMUs. However, even though their efficiency score were different, all models (four models) managed to be at the same rank for highest and bottom performance.
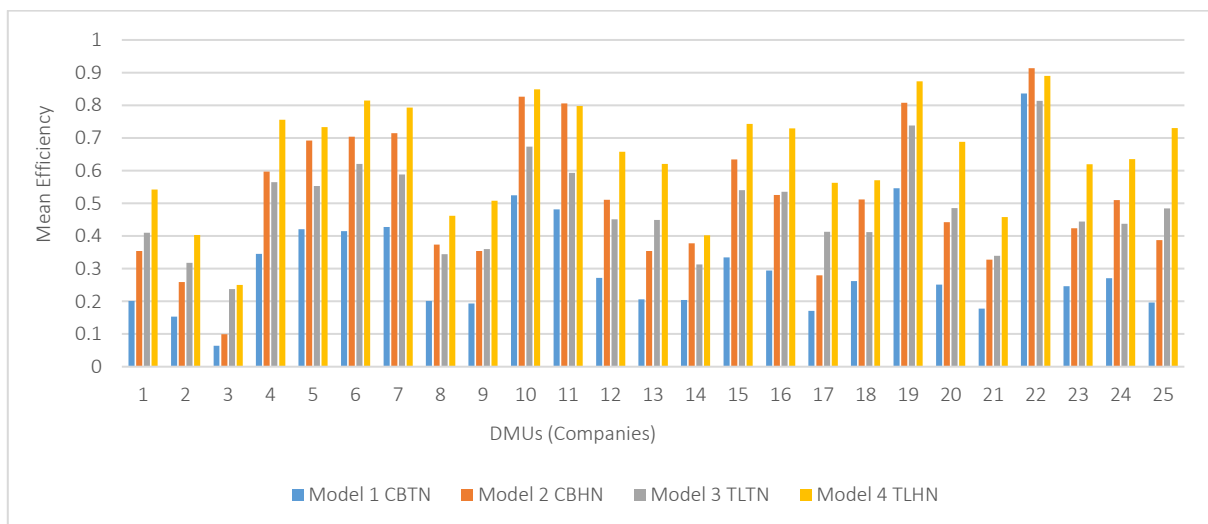

Fig. 1: Mean efficiency of DMUs by different model and distribution

5. Conclusion

This study applied two productions of a functional form of the SFA model created by Cobb-Douglas and Translog with different assumptions of inefficiency distributions for Malaysian stock

performance. Based on the likelihood ratio test, with different value of log-likelihood, the hypothesis findings show that Cobb-Douglas with truncated-normal distribution was much preferred for the dataset of this study. These findings also depicted that time was not the main contributor towards the efficiency performance of DMUs. This may due to the

usage of short panel data and without violence in the economic environment such as deregulation, firm-specific efficiency and its relative rankings, it will not likely to change drastically over a short period of time (Gong and Sickles, 1992).

Based on the empirical analysis, this study has figured out the assessment robustness of SFA model based on the three conditions. The impacts on different assumptions of distribution on technical inefficiency and different functional production form have generated different efficiency scores. However, obviously, it still can produce a consistent ranking across the four models. SFA approach is quite robust towards distributional choice and types of functional form because it can give a consistent ranking performance and it is proven to have a strong relationship with Spearman's ranks order correlation coefficient. Identification of top and bottom performance is crucial, especially in stock selection and investment decision. The findings will be significant if the result shows similar ranking across the four models.

For future research, four distributions can be applied towards inefficiency effects which are truncated-normal, half-normal, gamma and exponential distribution by using different samples of dataset. This can be done to check the consistency of the SFA model. Besides that, applying more panel data is advisable in order to check the time-varying for inefficiency effects across the four different distribution assumptions.

Compliance with ethical standards

Conflict of interest

The authors declare that they have no conflict of interest.

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