MEASUREMENT OF TECHNICAL EFFICIENCY USING THE DEA AND SFA METHODS: A CASE STUDY ON MALAYSIAN TRANSPORT MANUFACTURING INDUSTRY

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Abstract: At present, there is limited research on the state of the transport manufacturing industry in Malaysia. This article presents an analysis on the technical efficiency (TE) of the Malaysian transport manufacturing industry using the established parametric and non-parametric approaches of Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), respectively based on Department of Statistics Malaysia (DoSM) data of 611 firms between 2005 and 2010. The results showed that within the DEA approach, the Variable Return to Scale (VRS) model gave higher average efficiency than the Constant Return to Scale (CRS) model, whereas the Translog function was found to be superior to the Cobb-Douglas function in the SFA approach. Overall, high efficiency values were found in both the parametric and non-parametric methods and the results were consistent. Spearman's coefficients showed weak correlations between the DEA and SFA approaches, with inconsistencies among the samples. Limited comparisons, however, could be made based on subsectors. Although inconsistencies were found in both approaches to identify firms with best and worst performances, the methods could still be useful in measuring TE through a careful selection of the input and output variables, depending on the context, objectives, and environment of the measurement.

Keywords: Technical efficiency, data envelopment analysis, stochastic frontier analysis.

Introduction

In recent years, the rapid development of the global transport industry has led to an increase in research on the level of efficiency in the transport and logistics industry. Examples include the works of Jarboui *et al.* (2013), Chang and Tovar (2014), Gonzalez (2015), Rhee and Kim (2015), and Fahmy-Abdullah *et al.* (2019).

Despite being one of the main industries in Malaysia, there has been limited research done on the technical efficiency (TE) of the Malaysian transport industry. Existing studies are non-exhaustive and generally involve whole sub-industries. Moreover, conflicting results from the various approaches used in the studies could confuse policymakers in the transport industry

and make it difficult for them to decide on the best courses of action to be taken to improve the industry's TE. TE is widely used as an indicator to gauge the efficiency level of a company or an industry (Mahadevan, 2004) and it has been used successfully to measure said levels in various organisations and industries (Cullinane *et al.*, 2006). In general, approaches to measuring TE can be classified into two, namely, parametric, and non-parametric (Jarboui *et al.*, 2012).

An example of a parametric approach is the Stochastic Frontier Analysis (SFA), which evaluates the cost, profit, or production functions based on the input, output, and environmental parameters (Aigner *et al.*, 1977). In the estimation, the effects of random errors and inefficiencies are considered immaterial

to these parameters (Boame, 2004). As SFA considers the problem structure and evaluates the performance determinants and factors (Cullinane *et al.*, 2006; Fahmy-Abdullah *et al.*, 2019, Latif *et al.*, 2019), the method is flexible and suitable for use in the hypothesis-testing of parameters in economic theories (Coelli, 1996; Coelli *et al.*, 2005).

On the other hand, a non-parametric approach such as the Data Envelopment Analysis (DEA) method (Farrell, 1957) estimates the input-output relationship in a given problem with minimal assumptions (Banker *et al.*, 1984). DEA can be used to evaluate the efficiency of an organisation, or a Decision-Making Unit (DMU) as it is known in the DEA literature, that is sensitive to unreliable data. An efficient DMU forms an efficiency boundary for units within the boundary (Avkiran, 2001). DEA ignores the effects of random errors in the hypothesis-testing, and the efficiency estimates are not based on statistics (Boame, 2004).

There is an ongoing debate on which are of the approaches is superior to measure TE and the use of both approaches is widely reported in the literature. Examples of DEA applications can be found in Yu and Fan (2009), Agarwal *et al.* (2010), Sun *et al.* (2015) and Sabli *et al.* (2019), while works on SFA include Coto-Millan *et al.* (2004), Mazumder and Adhikary (2010), Jarbouli *et al.* (2015) and Fahmy-Abdullah *et al.* (2017), among others.

A summary of studies comparing both approaches to measure TE in various industries was given by Lovell (1993). Ferrier and Lovell (1990) and Cullinane *et al.* (2006) compared the performance of the two approaches to measure cost efficiency in banking applications and port-related efficiency, respectively. Other similar comparison studies can be found in Karlaftis and Tsamboulas (2012), Odeck and Braten (2012), Randrianarisoa *et al.* (2015), Coelli and Perelman (1999) and Lin *et al.* (2013). The last two works focused on the comparison between the three approaches.

To the best of the author's knowledge, there is no previous work on the comparison

between different approaches to measuring efficiency in the Malaysian transport industry. This article presents a comprehensive analysis of the measurement of TE level of the Malaysian transport industry using the DEA and SFA methods. It is hoped that the comparative analysis would enable the evaluation of the suitable conditions in which each approach could be employed when measuring TE. Such results would be beneficial for stakeholders and policymakers and of the Malaysian transport industry to devise better action plans and recommendations to improve the industry.

Data and Methodology

Data Envelopment Analysis (DEA)

The DEA method is a non-parametric approach to measure the efficiency of a DMU based on the linear programming method (Farrell, 1957). Since its development, several improvements have been proposed to the original model. Follow-up studies by Charnes *et al.* (1978) and Coelli (1996) led to the development of an input-based model known as the Charnes, Cooper, and Rhodes (CCR) model. A major feature in this model was the assumption of a constant rate reduction and increase in the input and output, respectively, for each DMU.

Thus, the method is also known as the CCR-constant return to scale (CRS), or the CCR-CRS model, which can be used to compute General Technical Efficiency (GTE) scores (Nunamaker, 1985). The CCR-CRS model formulation can be written as:

$$\begin{aligned}
 & \min l_o^* - \varepsilon \left(\sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right) \\
 & \text{subject to: } \sum_{j=1}^N \lambda_j x_{ij} = l_o x_{io} - s_i^- \quad \text{where } i = 1 \dots m \\
 & \sum_{j=1}^N \lambda_j y_{rj} = s_r^+ - y_{ro} \quad \text{where } r = 1 \dots s \\
 & \lambda_j \geq 0, j = 1 \dots N, \quad s_i^-, s_r^+ \geq 0 \quad \forall i \text{ and } r
 \end{aligned} \tag{1}$$

Note: In Equation (1), x_{if} and y_{rf} are the i th input and r th output levels, respectively for DMU f ; N is the total DMUs; ε is a very small, non-Archimedean positive number as lower bound to inputs and outputs; λ_f is DMU f contribution in the efficiency of rated DMU f_o , at a point on the envelopment surface; S_i^+ and S_r^- are slack variables to represent the extra savings and gains in input i and output r , respectively; l_o^* is the radial efficiency factor indicating the possible reduction of inputs for DMU f_o . If l_o^* (optimal solution) = 1, and $S_i^+ = S_r^- = 0$, then DMU f_o can be taken as efficient. If $S_i^+ > 0$ and $S_r^- > 0$ at the optimal solution, the corresponding DMU f_o input and output can be improved further when the input levels contract to the proportion of l_o^* .

In the CCR model, the CRS assumption in calculating efficiency leads to the assumption that efficiency and DMU operating size are not significantly related. The CRS assumption, however, is only valid for a DMU that is operating at its optimum level. Since rise and fall in the economies of scale (SE) (minimal inputs causing maximum outputs) are foreseeable among the companies in the transport industry, the optimum level assumption may be invalid, leading to an inaccurate TE score.

The BCC model by Banker, Charnes, and Cooper (1984) attempted to improve the CCR-CRS model by introducing the Variable Return to Scale (VRS) to estimate a Local Pure Technical Efficiency (LPTE) score (Nunamaker, 1985). The VRS assumption enables TE calculation without SE. Once the TE score for a DMU is calculated, the value is compared to the LPTE score. The difference between the two values indicates that the scale inefficiency, as $TE = PTE \times SE$.

This implies that the firm can use the resources to exploit the SE on the border of production in the CRS case. The BCC-VRS formulation can be written as:

$$\begin{aligned} \min l_o^* - \varepsilon \left(\sum_{i=1}^m S_i^{-*} + \sum_{r=1}^s S_r^{+*} \right) \\ \text{subject to: } \sum_{f=1}^N \lambda_f x_{if} = l_o^* x_{ifo} - S_i^{-*} \quad \text{where } i = 1 \dots m \\ \sum_{f=1}^N \lambda_f y_{rf} = S_r^{+*} - y_{rfo} \quad \text{where } r = 1 \dots s \\ \lambda_f \geq 0, f = 1 \dots N, S_i^{-*}, S_r^{+*} \geq 0 \quad \forall i \text{ and } r \end{aligned} \quad (2)$$

Note, that the inclusion of the convexity constraint, $\lambda_f = 1$ in the BCC-VRS model prevents the scaling up or down of any interpolation point from the observed DMU, which can turn it into a reference point. The values of λ minimise l_o^* to l_o^* to identify a point, of which the lowest proportion of l_o^* is reflected by the input levels. At l_o^* , the DMU f_o input levels can uniformly contract without affecting the output. Thus, DMU f_o has an efficiency equals to l_o^* . The solution to Equation (2) can be written as: DMU f_o is Pareto-efficient if $l_o^* = 1$ and $S_i^+ = 0, S_r^- = 0, \text{ for } i = 1 \dots m, r = 1 \dots s$.

Stochastic Frontier Analysis (SFA)

The SFA model originally developed by Aigner *et al.* (1977) was further revised by Meeusen *et al.* (1977) and later Battese and Coelli (1995) to measure TE scores. In this article, the SFA model based on the Cobb-Douglas and Translog functions (Coelli *et al.*, 2005) that consists of three inputs and a single output are applied. The Cobb-Douglas and Translog functions are given in Equation (3) and Equation (4), respectively, as:

$$\ln Y_i = \hat{a}_0 + \hat{a}_1 \ln K_i + \hat{a}_2 \ln L_i + \hat{a}_3 \ln AV_i (v_i - u_i) \quad (3)$$

$$\begin{aligned} \ln Y_i = \hat{a}_0 + \hat{a}_1 \ln K_i + \hat{a}_2 \ln L_i + \hat{a}_3 \ln AV_i + \hat{a}_4 (\ln K_i)^2 \\ + \hat{a}_5 (\ln L_i)^2 + \hat{a}_6 (\ln AV_i)^2 + \hat{a}_7 (\ln K_i \times \ln L_i) \\ + \hat{a}_8 (\ln K_i \times \ln AV_i) + \hat{a}_9 (\ln L_i \times \ln AV_i) + (v_i - u_i) \end{aligned} \quad (4)$$

where Y_i is the log of the i -th firm nominal output amount; K_i is the log of the i -th firm nominal asset amount; L_i is the log of the i -th firm labor amount; AV_i the log of the i -th firm added value amount; v_i is the random variable or effect, independent and identically distributed (i.i.d), with $[N(0, \hat{\sigma}_v^2)]$; u_i is an assumed non-negative random variable to reflect inefficiency in production that is normally taken as i.i.d. and truncated at zero for distribution $[N(m, \hat{\sigma}_u^2)]$.

Specifications of the Firms' Input and Output Variables

Tingley *et al.* (2005) stated that the use of firm-level data in budgeting is desirable as more accurate analysis can be performed on the factors that affect the budgeting process. Battese and Coelli (1995) showed that using firm-level data enabled the determinant factors to be considered more accurately, leading to more accurate estimations of the efficiency level. However, collecting firm-level data is challenging due to issues on confidentiality and time constraint. This often resulted in the lack of responses from the employers in surveys, including those conducted at the national level

such as by the DoSM. Thus, previous related studies on the transport industry such as by Putri (2007), Rahmah and Idris (2008) and Noor Aini (2013) were based on industry-level data.

This study used the firm-level data from the DOSM Annual Survey of Manufacturing Industries between 2005 and 2010, which is the latest available data based on the Economic Census 2015. The input, output, and other study variables were carefully selected based on the current objectives and previous studies. Following the approach in Mankiw *et al.* (1995), three inputs were used for the models, namely, capital (x1), labor (x2) and production factor (x3). Capital (in RM) represented the firm's construction and improvement expenditure for the year in terms of the purchase value and fixed assets, while the workers represented the total value paid in wages including the benefits.

The production factor was an intermediate input that represented the total value of related materials and services used, including the utilities, fuels, and others. For the output variable, the firm's total product sales (y1) was selected. A summary of the input and output variables and their descriptive statistics are shown in Table 1.

Table 1: Summary of the input and output variables

Output	Mean	Minimum	Maximum	Standard Deviation
Sales (y1)	4176086	275896	21318011	4589477.059
Input				
Capital (x1)	942623	57964	4465787	919913.636
Labor (x2)	8508	894	22477	6679.767
Production Factor (x3)	4058439	201730	18044586	3944969.305

Source: Department of Statistics Malaysia (DOSM), 2005 to 2010

Based on Malaysia Standard Industrial Classifications (MSIC) for the years 2000 and 2008, the DOSM data was classified into six sub-industries at the three-digit level, according to the types of transport constructions. The six categories were for the manufacturing of

- 1) Motor vehicle, passenger car, and commercial vehicle,
- 2) Frames for motor vehicles, trailers, and semi-trailers,

- 3) Motor vehicles accessories and spare parts,
- 4) Ships and boats, floating structures, cruise, and sports boats,
- 5) Aircraft, spacecraft, and related machinery, and
- 6) Transport equipment with activities that are not elsewhere classified (n.e.c.), motorcycles, bicycles, and vehicles for persons with disabilities.

The selection of the DoSM data was performed at random, following a step-by-step identification and screening of the firms based on the size of the firms (large, medium, or small), employees count, capital, and the value added. During the screening, firms with incomplete information (missing values) and those that did not meet the small and medium company definition (number of employees less than five) were discarded as these would affect the subsequent analysis. The final selection resulted in a total of 611 firms, from which the input and output data in the year 2005 were taken for use in the analysis.

To determine the consistencies of the results and whether the study objectives were achieved, the efficiency results were compared

based on the five criteria as stated in Bauer *et al.* (1998), namely, efficiency distribution in each model, efficiency ranking, and identification of the worst and best performances among the firms.

Results and Discussions

Efficiency Values: DEA Model

The CCR-CRS and the BCC-VRS models were used to calculate efficiency scores of the six Malaysian transport manufacturing industry subsectors for the year 2005 until 2010. All calculations were performed using the DEAP Software, version 2.1 (Coelli, 1996). The calculated efficiency scores are tabulated in Table 2.

Table 2: Efficiency scores calculated using the CCR-CRS and BCC-VRS models for the year 2005 until 2010

CCR-CRS Model						
	2005	2006	2007	2008	2009	2010
1	0.201	0.287	0.437	0.482	0.446	0.184
2	0.211	0.490	0.373	0.258	0.379	0.172
3	0.281	0.426	0.396	0.343	0.347	0.250
4	0.274	0.327	0.381	0.312	0.310	0.172
5	0.345	0.464	0.270	0.340	0.152	0.225
6	0.282	0.383	0.331	0.447	0.327	0.279
Average	0.266	0.396	0.364	0.363	0.347	0.213
BCC-VRS Model						
	2005	2006	2007	2008	2009	2010
1	0.348	0.541	0.616	0.724	0.594	0.389
2	0.480	0.536	0.497	0.398	0.475	0.440
3	0.405	0.535	0.568	0.559	0.585	0.503
4	0.480	0.525	0.610	0.575	0.615	0.411
5	0.442	0.542	0.535	0.520	0.391	0.394
6	0.504	0.574	0.651	0.675	0.705	0.557
Average	0.443	0.542	0.579	0.575	0.560	0.449

Note: Subsector 1) motor vehicle, passenger car, and commercial vehicle, 2) frames for motor vehicles, trailers, and semi-trailers, 3) motor vehicles accessories and spare parts, 4) ships and boats, floating structures, cruise, and sports boats, 5) aircraft, spacecraft, and related machinery, and 6) transport equipment with activities that are not elsewhere classified (n.e.c.), motorcycles, bicycles, and vehicles for persons with disabilities

The results showed that the BCC-VRS model gave a higher average efficiency at 0.525, compared to the CCR-CRS at 0.325. This was expected as the BCC-VRS model calculated the LPTE without the use of SE and thus it was not limited to the assumption on constant input reduction and output increase as formulated in the CCR-CRS model. Results from the BCC-VRS model showed that the highest annual average efficiency score was in 2007 at 0.579, while the best-performing subsector within the period was subsector 6, with an average efficiency score of 0.611. For this study, the BCC-VRS model was selected for comparison with the SFA approach.

Efficiency Values: SFA Model

To compare the Cobb-Douglas and the Translog functions in the SFA model, the following hypothesis test was performed using the likelihood-ratio test, $LR(\lambda)$. The following null hypotheses were proposed:

H_0 = The Cobb-Douglas production function is suitable for data representation in this study

H_1 = The Translog production function is suitable for data representation in this study

The LR test ¹ ($H_0 : \beta_{ij} = 0$) was performed and the results were compared against the critical value for χ^2_6 distribution at a 5% significance level, as shown in Table 3.

Table 3: Hypothesis tests results for the Cobb-Douglas and Translog functions

Null Hypothesis	
	Cobb-Douglas ($H_0 : \beta_{ij} = 0$)
LR Statistics	36.09***
Critical Value	16.81***
Result	Reject H_0

Note: *** shows 1% significance level

Based on the results, the null hypothesis H_0 was rejected and the Translog function was selected for further analysis. Efficiency scores were calculated using the Translog function for the same input and output data used for the DEA model calculation previously and the results are shown in Table 4.

Table 4: Efficiency scores calculated using SFA model (Translog function) for the year 2005 until 2010

	SFA Model (Translog Function)					
	2005	2006	2007	2008	2009	2010
1	0.584	0.657	0.939	0.688	0.751	0.718
2	0.494	0.580	0.717	0.767	0.536	0.468
3	0.521	0.624	0.780	0.577	0.744	0.633
4	0.467	0.672	0.578	0.609	0.610	0.498
5	0.509	0.491	0.951	0.442	0.522	0.435
6	0.573	0.595	0.712	0.629	0.547	0.747
Average	0.525	0.603	0.780	0.619	0.618	0.573

Note: Subsector 1) motor vehicle, passenger car, and commercial vehicle, 2) frames for motor vehicles, trailers, and semi-trailers, 3) motor vehicles accessories and spare parts, 4) ships and boats, floating structures, cruise, and sports boats, 5) aircraft, spacecraft, and related machinery, and 6) transport equipment with activities that are not elsewhere classified (n.e.c.), motorcycles, bicycles, and vehicles for persons with disabilities

1 LR test statistic, $[-2 \{ \ln[(H_0) / (H_1)] \}] = -2 \{ \ln[(H_0)] \}$ has χ^2_q distribution, where q is the number of parameters, assumed zero in a null hypothesis.

The average efficiency scores showed that all subsectors operated at moderate efficiency levels. The lowest and highest annual efficiency scores were at 0.53 and 0.78 in 2005 and 2007, respectively. The highest average efficiency among the subsectors for the period was found in subsector 1 at 0.723, and the lowest in subsector 5, at 0.558.

Comparison of DEA and SFA Models Results

To perform a comprehensive comparison between the models, the results were compared in terms of the five criteria as stated in Bauer *et al.* (1998), namely, efficiency distribution in each model, efficiency ranking, and identification of the worst and best performances among the firms.

First Criteria: Efficiency Distributions in Each Model

Table 5 shows a comparison of the efficiency values calculated using the two models for three

sets of samples, namely, based on the subsector, year, and combined. The SFA model had a higher overall efficiency at 0.624, compared to the DEA model at 0.529. The mode was found to be 0.895 and 1.000 for the SFA and DEA models, respectively. The results showed that the average efficiency of the industry is at a modest level. The standard deviation found in the SFA model was lower at 0.127, compared to 0.136 for the DEA model, indicating closer positions of the respective firm to the full efficiency level in the parametric SFA approach. The skewness values showed that the distributions in both models were close to symmetrical, with a small bias to the left as the mode was larger than the average value. Based on the kurtosis values, the results in the SFA model seemed to be more dispersed and had higher average efficiency. Overall, the transport industry level of volatility can be interpreted as mesokurtic and consistent.

Table 5: Efficiency distributions of the DEA and SFA Models

	DEA Model			SFA Model		
	All	Year	Subsector	All	Year	Subsector
Mean	0.529	0.538	0.521	0.624	0.628	0.621
Median	0.449	0.564	0.522	0.662	0.619	0.620
Mode	1.000	-	-	0.895	-	-
Minimum	0.103	0.436	0.471	0.023	0.522	0.555
Maximum	1.000	0.593	0.603	1.000	0.736	0.717
Standard deviation	0.293	0.067	0.048	0.251	0.070	0.059
Skewness	0.488	-0.822	0.922	-0.451	0.114	0.691
Kurtosis	-1.138	-1.239	1.120	-0.939	1.382	0.208
Total number of firms	611	611	611	611	611	611

In summary, high efficiency values calculated by the two models, and the distribution of the results between the models were consistent. It should be noted that the good agreement between the parametric SFA model and the non-parametric DEA model was made possible through the careful filtering of the data. As non-parametric approaches are sensitive to

external factors, careful considerations of these factors would enable more reliable estimations of the efficiency values.

Second Criteria: Efficiency Ranking

Although the firms' efficiency values estimated by the DEA and SFA models may differ slightly,

the models may yield inaccurate firms' positions across the methods. For policymakers, the identification of more effective firms is more important than measuring the absolute efficiency

values. An adopted policy based on inaccurate results of firms' positions will be unstable and dependent on the applied boundary approach Bauer *et al.* (1998).

Table 6: Spearman's rank correlation coefficients for the DEA and SFA models

	DEA			SFA		
	All	Year	Subsector	All	Year	Subsector
DEA all	1.000					
DEA year	0.029	1.000				
DEA subsector	0.771*	-0.429	1.000			
SFA all	-0.143	0.257	0.086	1.000		
SFA year	-0.771*	0.429	-0.657	0.257	1.000	
SFA subsector	0.429	-0.714	0.771*	-0.371	-0.429	1.000

Note: * shows 10% significance level based on the Spearman's rank correlation coefficient table

Table 6 shows the calculated SFA and DEA models Spearman's rank correlation coefficients for different samples, namely, based subsector, year, and combined. For the SFA, the correlation between the subsectors' sample and the whole sample was -0.371. On the other hand, the same case in the DEA model gave a positive and significant value of 0.771.

Overall, weak and inconsistent correlations were found between the SFA and DEA results. As shown in Table 4, out of the nine values, four were negative, with one of them being significant. However, the DEA subsector and SFA subsector results had a positive and significant correlation, at 0.771. The findings indicated that results using

both models would be comparable if the input data were based on the subsector samples. Using other samples would lead to contradictory results due to the different firms' positions and could cause uncertainty for policymakers attempting to use the results for any decision-making.

Third Criteria: Identification of the Worst and Best Performances among the Firms

In cases where the firms' positions are different, consistent efficiency results could be calculated by identifying the worst and best performances among the firms. Table 7 shows the results of the DEA and SFA models.

Table 7: The worst and best performances among the firms as calculated by the DEA and SFA models

	DEA			SFA		
	All	Year	Subsector	All	Year	Subsector
DEA all		0.089	-0.213***	0.744***	-0.039	-0.156**
DEA year	0.370***		-0.009	0.199***	0.599***	-0.032
DEA subsector	0.332***	0.359***		-0.096	-0.247***	0.667***
SFA all	0.999***	0.371***	0.331***		-0.114	0.185**
SFA year	0.212***	0.935***	0.305***	0.213***		-0.310***
SFA subsector	0.022	0.215***	0.865***	0.021	0.228***	

Note: The upper-right triangle values indicate the top 25% performance while the lower-left triangle values indicate the bottom 25%; *** shows 1% significance level; ** shows 5% significance level

In Table 7, values above the diagonal line were based on samples comprising the top 25% of the firms. For instance, the results showed that 74.4% of the firms in the SFA all sample, which were the top 25% of all firms (153 firms from a total of 611), were also identified in the DEA all sample.

This value was at a 1% significance level. Similarly, values below the diagonal line of Table 7 represented the bottom 25% of the firms. Generally, the results showed a poor consistency between the results from the two approaches. In the parametric SFA model, only one positive value was recorded in the best-performing firms, which was 18.5%, at a 5% significance level. For the worst-performing samples, two out of three samples were positive with an average value of 22.05%, at a 1% significance level. For the non-parametric DEA model, results for the best-performing firms showed inconsistencies. On the other hand, all results for the worst-performing firms were consistent with an average value of 35.4% at a 1% significance level.

Comparison between the DEA and SFA samples for the best-performing firms showed a poor consistency, with four of the nine samples showing positive values at a 1% significance level and an average of 51.4%. The other five samples were negative, of which two were significant. The comparison between the worst-performing firms, however, showed better agreement with eight positive values at a 1% significance level and 52.91% average value.

Conclusion

This study compared the TE values calculated using two approaches, namely, the parametric SFA approach and the non-parametric DEA approach. Firm-level data from the DOSM Annual Manufacturing Industries Survey for the year 2005 to 2010 was applied. It was found that the average efficiency values calculated by the two approaches were at a high degree and the distributions of results in both approaches were consistent.

The results of Spearman's coefficients between the DEA and SFA results showed weak and inconsistent correlations between the two. Based on the results, the DEA method can be applied by policymakers to measure the TE of firms, while the SFA method is more suitable to identify inefficiency factors.

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