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Determinant of Technical Efficiency of Small and Medium Enterprises in Malaysian Manufacturing Firms

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ABSTRACT

Technical efficiency is the ability of an enterprise to produce the maximum output using a set of input or minimizing the use of input in producing a certain level of output. When an enterprise is operating at its most efficient, operating costs can be reduced and profits can be increased. This article attempts to analyses the level of technical efficiency of Small and Medium Enterprises (SMEs) in the Malaysian manufacturing firms and identifies the determinants of their efficiency. The analysis uses the data obtained from the Department of Statistics of Malaysia 2009 Manufacturing Survey, which covers 4661 SMEs. In the analysis, SMEs will be divided into three categories, namely, the micro-sized enterprises (CSEs) the small-sized enterprises (SSEs) and the medium-sized enterprises (MSEs). To achieve the objectives of this study, we estimate the frontier production model to obtain technical efficiency scores simultaneously with technical inefficiency determinants model. In this study, we adopt the translog production model in obtaining the technical efficiency scores and the linear technical inefficiency model to determine factors affecting the firms' inefficiency level.

Keywords: Technical efficiency, small and medium enterprises, manufacturing firms, frontier production model.

INTRODUCTION

The efficiency of an enterprise is measured by the ability to produce output with minimum cost or making maximum profit. The issue of technical efficiency (TE) was first introduced by Kumbhakar and Lovell (2000), who stipulated that efficiency is the decision-making ability to produce to get the maximum output from a set of input (output oriented) or to produce output using the lowest amount of input (input oriented). According to Greene (1993), the level of TE of a firm can be characterized by the relationship between the present and potential level of production (Herrero & Pascoe, 2002). TE differs from allocative efficiency (AE), which refers to the use of inputs at an optimal rate in order to achieve maximum profit.

Beginning with efforts by Farrell (1957), frontier efficiency analysis has been used to assess the technical and distribution efficiency; scale efficiency; and allocative efficiency. Many different methods have been developed to analyses frontier efficiency. The most clear differences are in the use of boundary specifications (i.e., parametric or nonparametric); approaches in boundary computation (i.e., programming or statistical techniques); and the formula for the standard deviation from the frontier (i.e., inefficiency or a mixture of inefficiency and statistical disorder). Among these methods, the nonparametric approach to the analysis of the efficiency frontier is very attractive due to the minimum data requirements and its flexibility. It does not impose restrictions on the form of the function to calculate the efficiency index for each firm or on the distributional assumptions about the error structure. Furthermore, this method does not impose restrictions on the possible beginning of input substitution. The nonparametric approach allows for explicit TE and does not assume it is a permanent hypothesis. Finally, the nonparametric approach is very simple since it requires only a standard linear algorithm. The principal weakness of the approach is that it is not stochastic, an issue similar to other frontier efficiency analysis methods.

The issue of efficiency is often associated with the quality of labor or human capital, which is often identified as the main input in production of output, and helping the process of economic growth. An increase in human capital investment through education and training will produce a more knowledgeable labor force. Human capital will improve labor quality and productivity; and ultimately improve the efficiency of manufacturing firms. Rahmah (2012) explains that firms that have a high number of educated workers are able to maintain and control technologies and adapt to new technologies. Labor quality is more able to make further investments in human capital, creating knowledge workers who are able to learn quicker and are more innovative (Bosworth & Wilson, 1993;

Bishop, 1990; Chapman & Tan, 1990). In fact, a decline in the proportion of skilled labour in a firm will reduce productivity (Yokohama, 1991). Further, the positive relationship between the length of the education of employees and productivity has been repeatedly proven (Black & Lynch, 1996; Rahmah & Idris, 2009). The rationale is that education improves skills in people, while enabling them to be more innovative and think critically.

The present study seeks to examine the extent and determinants of TE of SMEs in Malaysia. Data analysis to achieve the objective of this study is estimated simultaneously. They involve obtaining the TE index using the Stochastic Frontier Approach (SFA) through estimating a translog production model and identifying determinants of TE using the regression equation. The remaining of the paper is divided into five sections. The second section discusses the theoretical framework and empirical literature review. The third section describes the model specification and data. The fourth part discusses the research findings, which is followed by a presentation of the conclusions and policy implications in the fifth section.

METHODOLOGICAL FRAMEWORK AND EMPIRICAL LITERATURE

The present study integrates an existing methodological framework to examine the TE of SME firms in Malaysia, which is presented in the present section. First, the theoretical frameworks relating to TE extant studies and the empirical findings of such studies are examined. Emphasis is placed upon the SFA since the present study adopts this approach for the purpose of data analysis. Additionally, existing empirical literature examining the determinants of TE is also reviewed.

Methodological framework

Farrell (1957) was the first to measure the productive efficiency in terms of frontiers and argues that economic efficiency should be divided into (a) TE, which measures the ability of a firm to maximize output using a given amount of input; and (b) Allocative efficiency (AE), which measures the ability of firms to use inputs at optimal proportions at a given price to produce certain level of output. The measurement of production frontier and efficiency can be classified into two groups:

a) non- parametric model, known as the *Data Envelopment Analysis* (DEA) developed by Farrell (1957) and Charnes et al. (1978); and
b) Parametric model known as Stochastic *Frontier Analysis* (SFA) which was developed by Aigner et al. (1977); Meeusen and Van den Broeck (1977).

Farrell (1957) defines TE as the production of output in relation to certain fixed inputs. Farrell (1957), the pioneer of efficiency measurement, characterized several instances of how production can be inefficient. Normally, the stochastic production frontier model is used to estimate the TE. The estimated model is often based upon the Cobb-Douglas or translog production function. The present study uses a translog production function to analyse the production frontier. In general, a translog production function is expressed as follows:

$$Y_i = (X_i \dots \dots X_n) \tag{1}$$

$$= \alpha_0 \prod_{i=1}^{n} X_i^{\alpha i} \prod_{i=1}^{n} X_i^{1/2[\sum_{i=1}^{n} \beta_{ij} lnX_j]} \tag{2}$$

The tranlog stochastic production frontier model is as follows;

$$lnY_i = ln\alpha_0 + \sum_{i=1}^{n} \alpha_i lnX_i + 1/2 \sum_{i=1}^{n} \sum_{i=1}^{n} \beta_{ij} lnX_i lnX_j + v_i - u_i \tag{3}$$

where, Y is output, α is efficiency parameter, X_i, X_j are inputs, v_i is a random variable that is assumed to be independent and normally distributed, $N(0, \sigma_V{}^2)$; and u_i is a non-negative random variable which refers to the impact of inefficiency in the production of the firms. The variable is assumed to be independently distributed with truncation, $N(0, \sigma_u^2)$ and *i* is firm i.

The efficiency of firms in the production of output can be achieved when a firm is able to produce output at the frontier level where the firm is at its best performance. Firms operating below the boundary are considered inefficient. The way to enhance efficiency is to improve the existing technology or enhance employee skills through education and training so that the existing technology can be used more efficiently. Existing studies that use SFA include Farrell (1957), Aigner and Chu (1968), Aigner et al. (1977), Kumbhakar et al. (1991), Greene (1993), Coelli (1994, 1996) and Battese & Coelli (1995).

The variance parameter for the model is written as follows:

$$\sigma^2 = \sigma^2_v + \sigma_u^2; \;\; \lambda = \sigma_u^2 / \sigma_v^2 \text{ and } \gamma = \sigma_u^2 / \sigma^2$$

where, parameter γ having a value between zero and one (Battese & Coelli, 1995; Coelli, et al. 1998), and the λ parameter could be any non-negative value. The value of TE for each firm is derived from the following formula:

$$TE = \frac{Yi}{\exp(x,\beta)} = \frac{\exp(x,\beta - ui)}{\exp(x,\beta)} = \exp(-ui) \qquad (4)$$

The index of TE is between zero and one or 0< TE_i < 1. The manufacturer i achieves maximum output if $TE_i = 1$.

The method of maximum likelihood (ML) estimation procedure is used for the frontier production model (equation 4). To determine the appropriateness of the frontier model, the value γ is observed. If the value is large and significant, than frontier production model is better than the ordinary production model for analyzing firm production processes.

Empirical Literature

Studies that employ firm data to obtain TE values include Wu (2000, 2003), Yao & Zhang (2001), Danlin et al. (2001), Byrnes et al. (1987) and Wu et al. (2003). Two most commonly adopted approaches by the researchers are the DEA and the SFA. Byrnes et al. (1987), using DEA approach, finds that the inefficiency of firms in Illinois is better explained by the inefficiency of scale. Weersink et al. (1990) also uses the same approach to find that efficiency of firms in Ontario is attributed to pure TE. Danlin et al. (2001) examine the TE of the cotton industry in the Soviet Union and find that at least 84 percent of the firms are efficient. Meanwhile, other studies that examine the determinants of TE find that firm size, financial structure and the degree of specialization is an important factor (e.g., Kalaitzandonakes et al., 1992, Chavas & Aliber, 1993; Featherstone et al., 1997).

Wu (2003) and Yao and Zhang (2001) examine the link between the efficiency of firms in China and macro variables; and find that government incentives, location, reward systems, capital, foreign direct investment and expenditure on research and development are key factors in efficiency. Both studies also find that nearly all of the factors included in the estimation process of the TE model are significant. These factors include the percentage of training expenditure; the percentage of research and development; the percentage of professional workers; the level of education of entrepreneurs; the number of employees who attend training; and firm size.

Researchers frequently employ SFA to measure the TE of firms. Nonetheless, the results from previous studies are not uniform. Idiong (2007) studies 112 rice farmers in Cross River State, Nigeria and explains that productivity will increase through improvements in efficiency and technology. SFA is used by researchers and the results show that most farmers are technically efficient, resulting in a mean efficiency of 0.77 or that 77 percent are efficient, while the other 23 percent should be improved to achieve maximum efficiency. The study also shows that various factors have a significant impact on the TE of the farmers examined, including the level of education of farmers; cooperative membership or farmers' association membership; and access to credit.

Sinani et. al (2007) use SFA to investigate the extent and determinants of firm efficiency. The study estimates the two models of production and determinants of efficiency of production simultaneously. Using data from Estonian firms (Northern Europe) for the period of 1993 to 1999, the study finds that foreign ownership can improve TE. Increased firm size and high labor quality also improves efficiency. Budget constraints, however, will negatively affect the efficiency of firms. Largely, firms in Estonia operate on constant returns to scale (CRS).

Meanwhile, Obwona (2006) examines the potential to improve the efficiency of the production of tobacco and identifies the factors that affect the efficiency of the farmers. The study uses cross-sectional data of 65 small and medium-scale farmers in Uganda using SFA to assess specific TE. Most of the determinants of efficiency are socioeconomic and demographic factors. The results show that education, accessibility of credit and additional services contribute positively towards improving efficiency. The study also suggests that the efficiency of farmers in Uganda will increase following the investment of further resources in additional services; increased credit availability; and reduced land fragmentation.

Existing studies also compare the SFA and DEA approaches when measuring efficiency and identifying determinants of efficiency. For example, Odeck and Brathen (2012) perform a meta-analysis of various mean scores of TE in the port industry based on 40 studies published in academic journals. The study uses the DEA and SFA approaches to measure the TE scores for different factors. The study produces five principal findings: (1) the random effects model is better than the fixed effects model in explaining variations in TE; (2) TE scores are lower in more recent studies compared to previous studies; (3) studies using the DEA model recorded scores higher than those using the SFA model; (4) panel data studies have lower TE scores than cross-sectional data studies; and (5) studies using data on port industries in Europe produces lower TE scores than data obtained from other industries and locations around the world.

Tingley et al. (2005) also compare the SFA and DEA approaches in the study of TE of the fishing industry in the English Strait. The study finds that TE scores from the SFA are consistently better than the scores recorded by the DEA; and have a smaller variance. The study also argues that the DEA can be used as an alternative to the SFA when difficulty exists in selecting the correct production model for SFA. Diaz and Sanchez (2008) study technical inefficiency and its determinant for SMEs in Spain using the manufacturing sector data of 1995- 2001. Using panel data and SF production, they find that SMEs have greater tendency to be inefficient compared to the large sized firms. Philips et.al. (2012) study the determinants of efficiency in the 120 manufacturing firms in Nigeria in 2011. Using Cobb-Douglass SF model, his study shows that the main determinant of efficiency total expenditure on unskilled workers development, cost of intermediate inputs and net productive asset. Apart from this, status of registration and year of establishment positively affect firms' technical efficiency, whereas firms' size have negative impact.

Zulridah and Rahmah (2005) use the DEA method to analyze the TE of 138 small and medium-sized firms in Malaysia and find that scores for constant returns to scale (CRS) are higher than the variation returns to scale (VRS) scores. Under the CRS approach, 6.31 percent of the sample is found to demonstrate full efficiency (TE = 1). Meanwhile, 92.63 percent of the sample firms are not efficient (TE < 1) with efficiency scores of less than 0.50. When the VRS technology is used, 17 firms are found to be efficient and only 56 firms, or 58.94 percent of firms, are found to have an efficiency score of less than 0.50. Meanwhile, 22 firms demonstrate efficiency scores between 0:50 - 0.99. With regard to the determinants of efficiency, the study finds that the level of mechanization employed and firm size have a significant positive impact, suggesting that larger firms with a more sophisticated level of mechanization have higher TE.

Rahmah and Syahida (2009) find that the mean TE index is 0.5334 for Malay firms in the services sector. The SFA approach is used and the results show that the TE index of the sub-sector of finance, insurance, real estate and commerce is higher than the other sub-sectors with a mean efficiency of 0.5536. The aforementioned sub-sector is followed by the transport, storage and communication sub-sector with a mean TE value of 0.5454. The mean value is relatively modest and service firms need to increase productivity in order to further improve their TE.

Rahmah and Norlinda (2008) examine 478 Malay enterprises in the manufacturing sector in Malaysia using the SFA approach. The study shows that the average TE of Malay firms in the manufacturing sector under review stood at 0.4484. The findings indicate that firms should increase their output by 55.16 percent using the same input to achieve 100 percent efficiency. The sub-sectors examined include wood and wood products; chemical petroleum, coal, rubber and plastic; basic metal products, iron and steel; metal products, machinery, electrical and transport equipment; and other manufacturing industries. The highest efficiency levels are achieved by metal products industry and related capital-intensive heavy industries. Non-metal, glass and ceramic industries, which are more labor intensive, record the lowest TE scores. The number of years of education and firm size are two very important determinants of TE. The coefficient for years of schooling of entrepreneurs and firm size are 0.0088 and 0.1676, respectively; and both are significant at the 1 percent significance level.

MODEL SPECIFICATION AND DATA

The model specifications and data utilized in the present study are now surveyed. The first part explains the model specifications utilized in the present study, which consist of a SFA production model; and two TE models. The two TE models are differentiated by the manner in which human capital is measured. The second part explains the source of data utilized in the present study.

Model specifications

The SFA production model, which is based upon the translog production function, is expressed as follows:

$$lnVA_i = \beta_0 + \beta_1 lnLAB_i +_i \beta_2 lnCAP_i + 0.5\beta_3 (lnLAB)_i^2 + 0.5\beta_4 (lnCAP)_i^2 + \beta_5 lnLAB_i lnCAP_i + v_i - u_i \quad (5)$$

where VA is firms' value added; LAB is quantity of labor, CAP is value of fixed asset; i is firm ith and v and u are error terms.

The determinants of TE in the present study are selected based upon the Productivity Report 2011/2012 (MPC, 2012). The factors include the development of human capital; technological capacity; accelerating demand; the efficient allocation between sectors; reducing business regulation; innovation; and creativity. In accordance with the available data, the determining factors are expressed in the model below. The estimation of the model is accomplished using the ML procedure.

$$TIE_i = \beta_{02} + \beta_{12} lnRDE_i + \beta_{22} lnICTE_i + \beta_{32} lnTRNE_i + \beta_{42} WTEC_i + \beta_{52} GEN_i + v_i - u_i \quad (6)$$

$$TIE_i = \beta_{01} + \beta_{11} lnRDE_i + \beta_{21} lnICTE_i + \beta_{31} lnTRNE_i + \beta_{41} WUSEC_i + \beta_{51} WLSEC_i + v_i - u_i \quad (7)$$

where TIE is the technical inefficiency derived through SFA approach; RDE is the ratio of research and development expenditures to total expenditures of enterprises; ICTE represents the ratio of information and communication technology (ICT) and telecommunication expenditure; TRNE is the ratio of training expenses; WTEC is the ratio of employees in the category of technicians and associate professionals; WUSEC is the ratio of employees with education levels of STPM and SPM; WLSEC is the ratio of workers with education levels below the SPM level. Data is divided into three categories of size, namely micro sized enterprise (CSEs), small sized enterprises (SSEs) and medium sized enterprises (MSEs).

Source of Data

The data used for the analysis in the present study is obtained from the Annual Survey of Manufacturing Industries in Malaysia for 2009, which is conducted by the Department of Statistics Malaysia (DOSM). The data utilized in the present study consists of 30.0 percent of the total samples from the manufacturing survey data in 2009 according to the 3-digit classification standard. DOSM arranges the data according to firm size, based upon the definition by SMECORP (www.smecorp.gov.my), and randomly selects 30 percent of the data available for each category of firm. DOSM does not provide all available data to researchers due to the existence of a rule that mandates that a researcher can only be provided access to a maximum of 30.0 percent of the available data. The data contains 4,937 firms in 71 sub-industries of the manufacturing sector in Malaysia. Of the 4937 firms, there are 4661 SMEs are utilized in the analysis whereby all required information are available.

RESULTS

Table 1 presents the descriptive statistics of the independent variables for the inefficiency model. The mean for research and development (R&D) expenditure per year is RM2358.28, for ICT expenditure is RM6400.69 and for training expenditure is RM749.97. The small amount of expenditure for these three categories reflects a low or may be no expenditures are allocated for these purposes for some firms. The CSEs and SSEs for example rarely allocate their expenses on training their workers, conducting proper R&D or even expenses on ICT. The mean ratio of workers with upper secondary and lower secondary education are 0.3782 and 0.5766 respectively. The mean ratio of the technical workers is very low at only 0. 0383, but the ratio for the general workers is quite high at 0.7228.

As shown in Table 2 the mean of the technical efficiency for the whole sample is 0.6547. The MSEs and SSE demonstrate a higher technical efficiency as compared to the CSEs. The result shows that only one firm in the MSEs reach full level of efficiency. But the majority of the firms are at the efficiency level of between 0.70-0.79. The number of the firms at the efficiency below 0.50 is quite large, especially for the CSEs. Table 3 present the TE scores by the manufacturing sub industry. It is shown that the electrical and electronics industry is the most efficient with the TE score of higher than 0.7326. This is followed by the transport equipment; the plastics and rubber based products and metal products with the TE of higher 0.7. The lowest TE is observed in the textile and wearing apparel industry with the mean of less than 0.6. Therefore, the results do show that the heavy industries are relatively more efficient than the light industries.

Table 4, 5 and 6 present the simultaneous estimation results for the production frontier models and technical inefficiency determinants for the CSEs, SSEs and MSEs. In Table 4 and 5, it is shown that the value of gamma is quite large and significant at 1% significance level, which implies that the deviation from the production frontier is due to technical inefficiency. Therefore, the frontier production model is better than the ordinary production model in explaining the firm's production processes. But this value is very small and not significant for the MSEs model, which implies that the deviation is due to noise. For the CSEs, most of the incorporated variables are statistically significant in determining the output level of the firms. The quantity of labor is positively significant, the capital input is not significant in the first model but both variables are significant in model 2. The significant determinants of technical inefficiency for the CSEs are expenditure on R&D, ICT and training, in which the increase in these expenditures will reduce the technical inefficiency in CSEs. The quality of labor which are measured by their job categories and level of education are also a significant determinant of inefficiency for CSEs except the ratio of workers with education level of lower than SPM.

The results of the estimation for the production model in the SSEs as shown in Table 5 are almost similar to the results for CSEs. All independent variables for the production frontier model are significant and give correct signs as predict by the theory. The technical inefficiency level of the SSEs is mainly determined by their expenditure on R&D and ICT, which are negative and highly significant. However, the ratio of technical and general workers will increase technical inefficiency. On the other hand, the ratio of the workers with level of education does not significantly affect SSEs technical inefficiency

The results for the MSEs in Table 6 show the significant level of the capital input in determining the firms output. But only the expenditure on ICT and training has a significant negative effect on the technical inefficiency level of the MSEs. Other incorporated variables are not significant. Therefore, there are different determinants of the technical inefficiency for the three firms' size. This shows different emphasis has to be formulated in a strategic policy. For the CSEs and SSEs the most significant determinant of their technical inefficiency with the largest negative coefficient is ICT expenditure, but for the MSEs the training expenditure is particularly important in reducing their technical inefficiency level. With regards to the labor quality, the results show that most coefficients for the ratio of workers by level of education are not statistically significant. However, the ratio of workers by job categories does give a significant negative impact on the inefficiency level especially for the CSEs. This implies that CSEs still require less educated workers to equip with their low technological level. In contrast, for the SSEs, an increase in the ratio of workers at the technical and general level will increase their inefficiency level, which shows the need for workers at the higher job categories like the professional level.

CONCLUSION

The paper examines the TE scores for the three firms' size, CSEs, SSEs and MSEs and identifies the determinants of technical inefficiency for these firms. The results show that the overall TE is at the moderate level with the SSEs and MSEs have the higher efficiency level compared to CSEs. This shows that firms' size is important for a higher technical efficiency. One of the reasons for higher TE for larger firm's size is that they can enjoy economics of scale that will reduce their production cost. The heavy manufacturing sub industries are proven to have higher TE scores than the light industries. Most of the incorporated variables significantly determine the output level of the firms under study and the signs are in accordance with production theory. The expenditure on R&D, ICT and training seem to be particularly important for reducing inefficiency for the CSEs and SSEs. For the medium-sized firms, the expenditure on ICT and training is very important in reducing their inefficiency level. Labor quality which is measured by the ratio of workers at different job categories is also important in reducing the technical inefficiency level of the firms especially in the CSEs. However, for the SSEs the increase in this ratio will increase inefficiency, which implies the need for a higher rank job category to be more efficient. When labor quality is measured by the level of education, the study does not show any significant results, except the workers with upper secondary education for the CSEs, who contribute negatively to the technical inefficiency.

The results of this study can be related to several policy implications especially regarding the determinants of technical inefficiency. The TE level is still moderate for the three firms' size and the number of firms that operating at the optimum level is quite small. Therefore, in order to increase the efficiency level and increase the number of firms with maximum score, efficiency determinants must be known. As we know expenditure on R&D, ICT and training are still low in the SMEs. Therefore, based on their negative contribution to the technical inefficiency, firms should increase these types of expenditures. With regards to workers quality; for the micro-sized firms, in line with their low level of technology, they can continue hiring lower rank workers as they contribute negatively to their inefficiency. However, with a better technological adoption in the SSEs firms, a more quality workers are needed. These firms cannot rely on workers at the technical and general levels because the result indicates negative consequences when their ratio increases.

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TABLE 1: Descriptive Statistics for Determinants of Technical Efficiency

Variable	Number of Firms	Mean	Standard Deviation	Skewness
RDE	4661	2358.28	56849.12	41.672
TRNE	4661	749.95	7654.91	22.419
ICTE	4661	6400.69	93311.13	62.106
WUSPM	4661	0.3782	0.3490	0.554
WLSPM	4661	0.5766	0.3706	-0.407
WTEC	4661	0.0383	0.1161	5.250
WGEN	4661	0.7224	0.3958	-1.128

Source Computed from data provided by the Department of Statistics, 2009

TABLE 2: Technical Efficiency by Firm's Size

Technical Efficiency	Micro	Small	Medium	Total (Percentage)
1.00	0	0	1	1 (0.02)
0.90-0.99	1	13	19	33 (0.71)
0.80-0.89	246	724	84	1054(22.61)
0.70-0.79	827	594	68	1489 (31.95)
0.60-0.69	649	131	18	798 (17.12)
0.50-0.59	398	32	7	437 (9.38)
<0.50	809	30	10	849 (18.21)
Total	0.5842	0.7742	0.7741	0.6547

Source Computed from data provided by the Department of Statistics, 2009 using SFA

TABLE 3: Technical Efficiency by Sub industry

Num	Sub industry	Mean
1	Food (101-108)	0.6561
2	Beverage and Tobacco (110-120)	0.6240
3	Textile and Wearing Apparel (131-152)	0.5637
4	Wood Based Products (161-182, 310)	0.6756
5	Chemical Products (201-210)	0.6881
6	Plastic and Rubber Based Products (221-222)	0.7089
7	Non-Metal Mineral Products (231-239)	0.6555
8	Metal Products (241-259)	0.7027
9	Electrical Electronics (231-239)	0.7326

10	Transport Equipment (291-309, 331-332)	0.7140
11	Others (321-329)	0.6272
	Total	0.6547

Note: Sub industries are categorized based on Malaysian Standard Industrial Classification (MSIC) 2008, Department of Statistics.

TABLE 4: Estimation Results for Production Frontier Model and Determinants of Technical Inefficiency for Micro-sized Firm

	Model 1		Model 2	
Variable	Coefficient	t-ratio	Coefficient	t-ratio
Intercept	10.295	198.11***	10.10	245.88***
lnLAB	0.730	11.77***	0.995	18.01***
lnCAP	-0.086	-0.075	-8.581	-7.41***
0.5 $(\ln LAB)^2$	0.029	0.468	-0.105	-1.71*
0.5 $(\ln CAP)^2$	0.024	11.20***	0.024	11.11***
lnLAB X lnCAP	-0.003	-4.06***	-0.003	-3.88***
Determinants of Technical Inefficiency				
Intercept	0.611	2.52**	-0.848	-1.35
lnRDE	-0.878	-3.59***	-0.963	-3.15***
lnICTE	-3.084	-9.01***	-0.484	-8.42***
lnTRNE	-0.248	-1.79*	-0.411	-2.59***
WTEC	-7.671	-5.82***		
WGEN	-2.84	-8.18***		
WUSEC			-1.354	-2.21**
WLSEC			0.045	0.08
sigma-squared	2.875	-8.18***	3.722	8.63***
gamma	0.938	128.39***	0.950	139.43***
Log Likelihood	-3170.47		-3260.95	
LR test of the one-sided error	880.76		699.79	

Note: * significant at 10%, ** significant at 5%, *** significant at 1%.

TABLE 5: Estimation Results for Production Frontier Model and Determinants of Technical Inefficiency for Small-sized Firm

Variable	Model 1		Model 2	
	Coefficient	t-ratio	Coefficient	t-ratio
Intercept	10.459	50.0***	10.395	46.44***
lnLAB	1.285	8.13***	1.366	8.25***
lnCAP	-0.166	8.66***	-0.165	-8.51***
0.5 $(\ln LAB)^2$	-0.265	-3.78***	-0.288	-4.03***
0.5 $(\ln CAP)^2$	0.025	8.71***	0.025	8.46***
lnLAB X lnCAP	0.001	3.37***	0.001	3.07***
Determinants of Technical Inefficiency				
Intercept	-6.147	-5.93***	-0.531	-0.94

lnRDE	-0.374	-15.95***	-0.383	-3.29***
lnICTE	-0.419	-0.001	-0.158	-5.07***
lnTRNE	0.203	3.59	0.050	1.95*
WTEC	2.843	2.55***		
WGEN	2.381	4.09***		
WUSEC			0.132	0.21
WLSEC			0.650	1.14
sigma-squared	2.792	6.50***	0.941	8.87***
gamma	0.924	76.56***	0.782	25.89***
Log Likelihood	-1273.14		-1285.49	
LR test of the one-sided error	164.57		139.88	

Note: * significant at 10%, ** significant at 5%, *** significant at 1%.

TABLE 6: Estimation Results for Production Frontier Model and Determinants of Technical Inefficiency for Medium-sized Firm

Variable	Model 1		Model 2	
	Coefficient	t-ratio	Coefficient	t-ratio
Intercept	14.576	14.78***	14.153	1.61
lnLAB	0.986	1.05	1.564	0.45
lnCAP	-0.467	-2.68***	-0.409	-2.64***
0.5 $(\ln LAB)^2$	-0.160	-0.366	-0.357	-0.487
0.5 $(\ln CAP)^2$	0.05	1.58	-0.038	1.22
lnLAB X lnCAP	-0.0001	-0.06	0.0005	0.215
Determinants of Technical Inefficiency				
Intercept	-0.517	-0.67	0.072	0.07
lnRDE	0.006	0.25	0.008	0.54
lnICTE	0.112	1.85*	0.030	0.91
lnTRNE	-0.057	-3.48***	-0.050	-3.33***
WTEC	-1.267	-1.52		
WGEN	0.248	0.29		
WUSEC			0.658	0.66
WLSEC			0.884	1.04
sigma-squared	0.746	9.55***	0.764	10.14***
gamma	0.012	0.20	0.000	0.00
Log Likelihood	-265.67		-265.80	
LR test of the one-sided error	15.64		15.38	

Note: * significant at 10%, ** significant at 5%, *** significant at 1%.