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Technical Efficiency of Malaysian Manufacturing Small and Medium Enterprises

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ABSTRACT

Small and medium sized enterprises (SMEs) make up over 90 percent of all enterprises and generated more than 50 percent of total workforce in Malaysia. Given their importance as the backbone of the Malaysian economy, the objectives of this study are to measure firm-level efficiency and to identify sources of inefficiency in the Malaysian manufacturing SMEs, especially micro enterprises, using a stochastic frontier analysis approach. This study utilizes firm-level data from The Survey of Manufacturing collected by The Department of Statistics of Malaysian for SMEs in 2010. Results of the analysis indicate that over 90 percent of the total variation from the frontier for micro enterprises is due to technical inefficiency and the simple average of technical efficiency is only 56.2 percent. Small & medium sized enterprises are technically more efficient. Salary and wages per worker, research and development expenditure, training expenditures have positive and significant effects on the technical efficiency in micro enterprises, whereas ratio of unskilled labor is negatively related with technical efficiency. The positive impact on efficiency level by increasing the investments in technological capabilities and workforce and the negative impact on efficiency level by increasing unskilled labor ratio are found to be higher in micro enterprises as compared to small & medium sized enterprises.

Keywords: Technical efficiency, stochastic frontier analysis, small and medium enterprises

ABSTRAK

Lebih daripada 90 peratus perusahaan di Malaysia merupakan Perusahaan Kecil dan Sederhana (PKS) dan telah menjana lebih daripada 50 peratus jumlah tenaga kerja. Memandangkan PKS adalah tulang belakang kepada pembangunan ekonomi Malaysia, objektif kajian ini adalah untuk mengukur tahap kecekapan firma dan mengenal pasti sumber ketidakcekapan dalam PKS sektor pembuatan, khasnya perusahaan mikro dengan berdasarkan pendekatan analisis stokastik frontier. Kajian ini menggunakan data peringkat firma daripada Tinjauan Sektor Pembuatan yang dijalankan oleh Jabatan Perangkaan Malaysia pada tahun 2010. Keputusan kajian menunjukkan peratusan variasi daripada frontier yang disebabkan oleh ketidakcekapkan adalah melebihi 90 peratus bagi perusahaan mikro dan purata kecekapan teknikal hanyalah 56.2 peratus. Perusahaan bersaiz kecil dan sederhana secara teknikalnya lebih cekap. Gaji dan upah per pekerja, perbelanjaan penyelidikan dan pembangunan, perbelanjaan latihan memberi kesan positif yang signifikan ke atas kecekapan teknikal dalam perusahaan mikro, manakala nisbah buruh tidak mahir berhubung secara negatif dengan kecekapan teknikal. Kesan positif ke atas tahap kecekapan berikutan peningkatan pelaburan dalam keupayaan teknologi dan tenaga kerja serta kesan negatif ke atas tahap kecekapan dengan meningkatkan nisbah buruh tidak mahir adalah lebih besar dalam perusahaan mikro berbanding perusahaan bersaiz kecil dan sederhana.

Kata kunci: Kecekapan teknikal, analisis stokastik frontier, perusahaan kecil dan sederhana

INTRODUCTION

Small and medium sized enterprises (SMEs) have been identified as one of the growth engines for various countries in the world since they make up over 90 percent of all enterprises and generated more than 50 percent of total workforce. They have been recognized as a key business sector and provided more jobs than large companies (National SME Development Council 2009). Their contributions to the economy are likely to be increasingly important as the economy becomes more global. National governments and international lending institutions have supported SMEs in several developing countries with credit and technical assistance for decades (Mini & Rodriguez 2000). The rationale behind supporting SMEs is that the development of SMEs is more effective than large scale industrialization to achieve higher employment, income equality and a more geographically dispersed distribution of wealth. In Malaysia, since 1980s the government has launched a number of development programs and invested a substantial amount of budgets for implementation of these programs. However, does achieving those goals through SME support come at a hidden price due to the possibility that SMEs are less technically efficient than larger firms? (Mini & Rodriguez 2000). The technical efficiency (TE) of small firms is central to the debate about the role of SMEs in generating growth and employment in developing countries. Knowing the levels, distributions and sources of inefficiency will tell us whether firms have utilized all inputs into efficient production. The knowledge on TE is also crucial if policymakers wish to determine whether policies targeting SMEs are needed, and if so, what kinds of policies and delivery mechanisms are appropriate.

The aims of this study are to measure firm-level efficiency and to identify sources of inefficiency in the Malaysian manufacturing SMEs using a stochastic frontier production approach. This paper augments the existing studies on TE in Malaysia in two ways. First, this is the first attempt to study TE of various manufacturing SMEs in Malaysia including micro enterprises using firm-level data. To our knowledge, the World Bank (1997) is the only other TE study on Malaysia using firm-level data. Most studies on efficiency in Malaysia have focused on measuring the TE of SMEs in particular manufacturing industries such as food processing (Rashilah *et al*. 2010, Alias *et al*. 2008, Mad Nasir *et al*. 2013) and food, wood, chemical and metal (Idris & Rahmah 2007). The second contribution of this study is the empirical investigation of the impact of labor quality and technology capability, together with a set of other factors, on TE of the firms.

The rest of the paper is organized as follows. The next section describes briefly on manufacturing SMEs in Malaysia and followed by the discussion of literature reviews. Section 4 details the production frontier model, the inefficiency effect model, and the data used for estimation and section 5 presents the empirical evidence obtained. Finally, conclusions are presented in Section 6.

AN OVERVIEW OF MALAYSIAN MANUFACTURING SMALL AND MEDIUM SIZED ENTERPRISES

SMEs are the backbone of the Malaysian economy. As of 2012, they accounted for large proportion of businesses in Malaysia; 97.3 percent of total registered business establishments (645,136). Based on the previous SMEs' definition, the majority of SMEs are in the services sector (90%), followed by manufacturing (5.9%), construction (3%), agriculture (15) and mining and quarrying (0.1%). The contribution of SMEs to GDP increased from 31 percent in 2009 to 32.7 % in 2011. They also contributed 19 percent to exports and about 60 percent to employment. Most of the SMEs were micro enterprises, forming 77 percent of total SMEs in Malaysia in 2010 (2003: 79.3%). Small sized SMEs accounted for 20 percent, while medium sized SMEs constituted the balance 3 percent (Malaysia 2012). SMEs manufacturing play a significant role in the Malaysian economy in terms of business numbers, output, value added, employment and exports. As of 2012, there were 39,669 establishments in manufacturing sector represented about 5.9 percent of all establishments in Malaysia (662,939). SMEs represented 95.4 percent (37,861) of all establishments in manufacturing. Even though the share of SME GDP to overall GDP was 32.7 percent in 2012, the share of SMEs manufacturing to GDP decreased from 8.1 percent in 2005 to 7.9 percent in 2012 (Malaysia 2012). However, the contribution of SMEs manufacturing towards employment has increased. Majority of SMEs in the manufacturing was micro enterprises (57.1%), followed by small sized (36.8%) and the remaining was medium sized (6.1%). In terms of distribution by industry, SMEs manufacturing were mostly in the wearing apparel sub-sector, followed by food product (15.1%), others sub-sectors (paper, electrical equipment) (14.6%), fabricated metal product (10.5), and printing & reproduction of recorded media (7.7%).

LITERATURE REVIEW

Many empirical studies have estimated stochastic frontiers production models, predicted firm-level efficiencies and identified determinants of inefficiency between firms in an industry. Harris (1999a) used a frontier production function approach to estimate efficiency in Northern Ireland (NI) manufacturing sector for the year 1987-88 and found that the mean TE in NI was approximately 80 per cent. Tybout (2000) provided an extensive summary of inefficiency studies for developing countries with a comparison, from Caves (1992), of efficiency measures from Australia, Japan, Korea, UK and US. The latter reported country averages of the efficiency index ranging between 0.67 and 0.70. Mahadevan (2000) studied the TE of manufacturing industries in Singapore from 1975-94 and found that the average TE was 73 per cent. In her later study, Mahadevan (2002) investigated TE of the Malaysian manufacturing sector from 1981-1996 and found that TE in the 1980s increased gradually while the score decreased reversibly in the 1990s. A similar study by Idris & Rahmah (2007) using data from 1985-2000 showed that the food, wood, chemical and iron industries were more efficient compared to other industries. Both studies showed consistent results in terms of the trend in TE in Malaysia, i.e., increased in the 1980s and decreased in the 1990s. Battese *et al*. (2001) used stochastic frontier for firms in five different regions of Indonesia for the period 1990-1995 and found that there were substantial efficiency differences among the garment industry firms across the five regions. Rozilee (2010) estimated the TE for all manufacturing industries in Malaysia for the period 1986-1995. The author found that the TE for all sectors constantly increased at 0.01 percentage points each year and the resource based industries (RBI) were more technically efficient compared to non-RBI groups.

Mad Nasir *et al*. (2013) investigated the partial productivity and TE of SMEs in the Malaysian food processing industry for the period 2000-2006. They found that capital productivity was relatively unchanged and material productivity showed a declining trend during the period of observation. Five sub-industries, namely, refined palm oil, kernel palm oil, feed, alcohol and soft drink were technically efficient. In contrast, five sub-industries, namely, canning of pineapple, sugar, glucose, coconuts and other flour, experienced lower TE with the TE scores varying between 35.9 percent up to 48.1 percent. In earlier study, Mad Nasir *et al.* (2011) evaluated the market competitiveness of SMEs in the Malaysian Food Processing Industry (FPI) in terms of TE and productivity growth and found that TE was 0.756 during the period of 2000-2006. Alias *et al*. (2008) studied the technical efficiency of SMEs in Malaysia for the year 2004 and found that the number of firms considered technically efficient was only 3.06 percent of the total firms, while total TE varied from 0.30 to 97.10 percent. Rashilah *et al*. (2010) focused on measuring the TE of SMEs in the food processing industry in Malaysia and found that the majority of the companies (96.84%) attained a level of TE of around 80 per cent. Zalina & Marziah (2007) assessed industrial level of efficiency among the Malaysian SME and found that the average TE for all industry sub-sectors was 0.7609.

With respect to determinants of firm-level TE, most previous studies drew attention to characteristics of firms such as size, age of firm, ownership and international linkages such as exporting, direct foreign investment, foreign technology licenses and transfer and outsourcing. Only a few studies examined impacting factors such as low-or-high priority sectors, regional differences, workforce capability such as labor quality, education and training of employees and technology capabilities such as expenditures on research and development (R&D) and ICT. The relationship between firm size and TE has been and still remains a debatable issue. From empirical and theoretical viewpoints, the relationship between firm size and efficiency is not clear cut. Some researchers advocate promotion and support of small firms on the basis of both economic and welfare arguments. It is argued, for instance, that an expansion of the small firm segment leads to more efficient resource allocation, less unequal income distribution and less underemployment because small firms tend to use more labor-intensive technologies. Agell (2004) argued that employees of smaller firms may be more motivated by competitive-based incentive schemes rather than financial ones, thus possibly making small firms more efficient.

Lundvall & Battese (2000) found that the relationship between firm size and TE was mixed. Yang & Chen (2009) compared the TE of SMEs with that of large firms and studied the factors influencing technical efficiency for Taiwan's electronics industry. They found that the average TE for large firms was higher than that of SMEs, without considering the size effect, and lower when considering the endogenous choice on firm size. They also found that being a subcontractor had a statistically significant positive influence on SMEs' TE, but the effect decreased with firm size. Amornkitvikai *et al*. (2014) employed a stochastic frontier and data envelopment analysis (DEA) to analyze inefficiency effect models for Thai manufacturing SMEs and found that Thai manufacturing SMEs experienced decreasing returns to scale even though their technical efficiency in production was found to be relatively high. Their results using both approaches also revealed that firm age, medium sized enterprises compared with small-sized enterprises, firm location in Bangkok, foreign investment and government assistance are significantly and positively related to TE.

In earlier study, Amornkitvikai *et al*. (2013) employed a stochastic frontier analysis (SFA) and found that the average TE was 69.72 percent and variables firm size, firm age, foreign ownership, location and government assistance were firm-specific factors that significantly affected the technical inefficiency of production. Le & Harvie (2010) evaluated and firm-level TE and identified the determinants of technical efficiency of domestic non-state manufacturing small and medium enterprises (SMEs) in Vietnam. The results revealed that manufacturing SMEs in Vietnam had relatively high average TE ranging from 84.2 percent to 92.5 percent. Factors such as firm age, size, location, ownership, cooperation with a foreign partner, subcontracting, product innovation, competition, and government assistance were significantly related to TE, albeit with varying degrees and directions. Batra & Tan (2003) derived firm-level estimates of TE, compared the distribution of efficiency across firms of different sizes and identified its most important correlates. They used firm-level data from six countries; Malaysia, Indonesia, Mexico, Colombia, Taiwan (China) and Guatemala. The results showed that while TE increased with firm size, there was substantial overlap in the distribution of efficiency across firm sizes, with some small firms operated at the same or higher levels of efficiency than some large firms. Thus, small firms were not inherently inefficient. Mini & Rodriguez (2000) examined the relationship between size and TE in the Philippines textile industry and found that TE increased with size and both exports and government interventions were positively associated with efficiency, although the link between government support and technical efficiency was somewhat weaker.

Badunenko *et al*. (2008) investigated the determinants of TE of German manufacturing firms for the period 1992-2002 and linked TE to firm characteristics e.g. organization, location, outsourcing and R&D. Most surprisingly and in contrast to many previous studies, they found that firm size and R&D did not exert any positive influences on differences of TE across firms. Sinani *et al*. (2008) investigated the determinants and dynamics of firm efficiency in Estonian firms for the period 1993-1999. Their findings provided support for hypotheses that a firm’s ownership structure and its characteristics such as firm size, labor quality, soft budget constraints and time of privatization were important for TE. Niringiye *et al*. (2010) investigated the relationship between firm size and TE in East African manufacturing firms. Contrary to their expectation, the results showed a negative association between firm size and TE in both Ugandan and Tanzanian manufacturing firms. The existence of a positive association between size squared and TE and a negative association between firm size and TE in Ugandan and Tanzanian manufacturing firms suggests an inverted U-relationship between firm size and TE. Sangho (2003) identified and estimated sources of technical inefficiency of Korean manufacturing firms and found that firm size had a positive and significant effect in every sector. The effects of the other factors such as dependency on external funds, research and development investments, and exports were less systematic and varied across sectors.

There are evidence of relationship between ownership and efficiency. For example, Linz & Rakhovsky (2011) found that non-state ownership more likely to improve efficiency, but the ownership effect varied by industry and over time. Sheehan (1997) examined TE in firms in NI over the period 1973-85 and found that foreign ownership was an important factor in determining average efficiency levels. On the other hand, the study by Soderbom & Teal (2004) found that technical inefficiency was not lower in African manufacturing firms with foreign ownership or older firms and its dispersion across firms was similar to that found in other economies**.** Zhang *et al*. (2003) investigated the influence of ownership on the research and development (R&D) efficiency of Chinese firms and found that ownership was the contributing factor in the relationship between R&D and productive efficiencies. The state sector had significantly lower R&D and productive efficiency than the non-state sector. Within the non-state sector, foreign firms had higher R&D and productive efficiency than domestic collective owned enterprises and joint stock companies.

Harris (1999a) studied productive efficiency in five UK manufacturing industries and found that plants in data processing equipment, motor vehicles and aerospace were relatively around the higher end of the efficiency distribution whereas plants in brewing and newspapers sectors had much lower levels of efficiency compared to the frontier. He also found that scale effects and foreign ownership had a positive effect in determining TE. Harris (1999b) provided estimates for over 200 manufacturing sectors using the same approach in a more extended study of efficiency in UK manufacturing sector. Using estimates from Harris (1999b), Harris (2001) compared the differences in efficiency of manufacturing firms in NI and other UK regions and found that NI had generally the lowest level of average efficiency throughout the period 1974-94. He also found that foreign plants operating in Northern Ireland had higher efficiency levels compared to their domestic counterparts.

Linz & Rakhovsky (2011) investigated which firm characteristics contributed to variation in TE in Russia and found that firms in low-priority sectors exhibited higher efficiency in 1992 than firms in high-priority sectors. Efficiency gains were relatively higher in industries which experienced the largest percentage output declines. Batra & Tan (2003) found that a common set of factors appear to distinguish more-efficient firms from less-efficient firms in all six countries; Malaysia, Indonesia, Mexico, Colombia, Taiwan (China) and Guatemala were education and training of workers, investments in new technology, automation, and quality control. Aw & Batra (1998) estimated the TE of manufacturing firms and the determinants of efficiency using micro data from Taiwan. They then used expenditures on research and development and on-the-job training as proxies for firm-level efforts at modifying or adapting technology and international linkages (such as exporting, direct foreign investment, and foreign technology licenses) to find their correlation with efficiency of firms. They found that efficiency was positively correlated with the firm's investments in training and research and development and with its informal contacts with foreign purchasers through export sales. Deraniyagala (2001) examined the effects of technology accumulation on firm-level TE in the Sri Lankan clothing and agricultural machinery industries and found that adaptive technical change to have a significant and positive effect on efficiency in both industries and variables relating to technological skills and training also emerged as significant determinants of firm-level efficiency. Ng & Li (2003) investigated underlying reasons why low efficiency was constantly found in enterprises in China. They focused their attention on the effect of training provision on enterprise efficiency and found a positive relationship between training provision and TE in enterprises.

Previous studies also investigated other determinants of efficiency such as labor quality, capital intensity, wages, export intensity and activities and other international linkages including trade liberalization, experience of workers, modernization of physical capital and innovation in product, owner education, participation in public programs, and outsourcing. It is expected that the higher the level of labor quality, the more efficient will be both the use of existing technology and the absorption of new technology, which will consequently result in higher efficiency levels. Mahadevan (2000) studied on the TE of manufacturing industries in Singapore from 1975-94 and found that capital intensity and labor quality were important factors in determining the efficiency levels. Alvarez & Crespi (2003) explored the factors that could explain the observed differences in TE and the factors lying beneath the differences such as experience of workers, modernization of physical capital and innovation in products using Chilean manufacturing firms and non-parametric deterministic frontier methodology. They found that efficiency was positively associated with the experience of workers, modernization of physical capital and innovation in products. In contrast, other variables such as outward orientation, owner education and participation in some public programs did not affect the efficiency of the firms. McIntyre & Martin (2013) studied the efficiency of Eastern Europe countries firms and the determinants of inefficiency and found that, on average, Romanian firms were 10 percent less efficient than firms in Poland, Hungary and Czech Republic. Evidence suggested that the measurable industrial drivers of TE tend to be consistent across countries, suggesting that the relative inefficiency of Romanian enterprise is due to institutional factors.

Mokhtarul (2004) estimated TE of Australian textile & clothing firms and the inefficiency effects model revealed that TE varied significantly according to firms' age, size, capital intensity, proportion of non-production to total workers and type of legal status. Mahadevan & Mansor (2007) investigated impacts of human capital and technology development and other range of factors on TE of firms in the Malaysian micro-electronics sector using a random coefficient stochastic production approach. They found that on average, firm's overall TE (not accounting for size and ownership) was about 84 per cent. The effects of ICT, firm size, skilled labor and exports were positive and significant but the capital labor ratio, firm age, and foreign ownership were insignificant. The effect of training was ambiguous as results were inconsistent and the effect of R&D was only significant at the 10% level. Khalifah *et al*. (2008) studied efficiency of foreign and local establishments in Malaysia's automotive sector for the period 2000-2004 and found that the small size of plants and the lower share of white-collar workers were significant in explaining plant inefficiency. Foreign multinationals were significantly more efficient than locally owned plants. Unexpectedly, a higher capital-labor ratio was positively related to plant inefficiency and this might be due to excess capacity in the automobile sector as a result of a small domestic market. Kim & Shafi'i (2009) decomposed total factor productivity growth into technical progress, TE change, allocative efficiency change, and scale efficiency change to Malaysian manufacturing data for the period 2000-2004. The results showed that total factor productivity was driven mainly by technical progress but was hurt by deteriorating TE. The skill and quality of workers were the most important determinants of TE, whereas foreign ownership, imports, and employee quality underpinned technical progress.

METHODOLOGY, MODELS AND DATA

Productivity and efficiency are important to characterize the production and market competitiveness. For this reason theoretical and empirical works on firm performance focus on measuring enterprise productivity and efficiency. Average labor productivity had been used as a measure of efficiency until Farrell (1957) introduced a method to measure efficiency in his seminal paper. Farrell's efficiency measure contains an efficient production frontier which is the output that a perfectly efficient firm could obtain from any given combination of inputs. The performance of a productive unit will be measured against that efficient frontier (Farrell 1957). He also discussed in detail the factors that lead to inefficiency in production.

A number of techniques have been developed to estimate this frontier. Several authors broadly classified them into two main groups: parametric and non-parametric (Kumbhakar & Lovell 2003, Coelli *et al*. 2005). The parametric method uses an econometric technique by specifying a stochastic production function which assumes that the error term is composed of two elements. One is the typical statistical noise which represents randomness. The other represents technical efficiency which is commonly assumed in the literature to follow a one-sided distribution (Alvarez & Crespi 2003). The stochastic frontier production model was developed independently and simultaneously by Aigner *et al*. (1977) and Meeusen & Van den Broeck (1977). In this model there is a composed error term which captures the effects of exogenous shocks beyond the control of the analyzed units in addition to incorporating technical inefficiency. Errors in measurement of outputs and observations are also taken into consideration in this model (Kumbhakar & Lovell 2003). In this model the parameters for the inefficiency effects model are jointly estimated with the stochastic frontier model.

Battese and Coelli (1995) proposed a model that captures inefficiency effects for panel data based on earlier work by Kumbhakar *et al*. (1991). For cross-sectional data and generalized functional form in the Cobb-Douglas case the stochastic production function can be specified as,

$$Y_i = x_i \beta + (v_i - u_i), \ \ i = 1, \dots\dots, N \tag{1}$$

or, in logarithmic form,

$$lnY_i = \beta \ lnx_i \ + (v_i - u_i) \tag{2}$$

where lnY_i is the logarithm of the scalar output of firm i, β is the vector of unknown parameters to be estimated, x_i is the vector of value of known functions of inputs associated with firm i, v_i are random errors which are assumed to be iid N(0, σ_v^2) and independent of u_i, u_i is non-negative random variables which are assumed to account for technical inefficiency in production and assumed to be independently distributed as truncations at zero of the N(μ_i, σ_u^2) distribution. With the assumption of a linear functional relationship, the mean distribution of u_i is a function of the explanatory variables and can be specified as,

$$\mu_i = z_i \ \delta \tag{3}$$

where z_i is a p x 1 vector of variables which may influence the efficiency of a firm; δ is an 1 x p vector of unknown parameters to be estimated. Individual firm technical efficiencies from stochastic frontiers are defined as,

$$TE_i = \frac{Exp(\ln Y_i/u_i, x_i)}{Exp(lnY_i//u_i{=}0, x_i)} = e^{-u_i} \tag{4}$$

where Y_i is the production of firm i. TE_i will take a value between zero and one in the stochastic production frontier. It measures the output of firm i relative to the output that could be produced by a full efficient firm using the same vector. For both the stochastic frontier model and the inefficiency effects model, the maximum likelihood method can be used to estimate the coefficients of the two functions simultaneously. The likelihood function is expressed in terms of the variance parameters of the frontier function as follows,

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

where σ_v^2 is variance of noise and σ_u^2 is variance of inefficiency effects. If the value of σ_u^2 is equal to zero, then u_i is also zero which means the firms are fully efficient. γ has a value between one to zero. If the value of γ is one, the deviations from the frontier are attributed to random error. If it has the value of one, the deviations are due to technical inefficiency.

There exists no well-grounded methodological framework to analyze the determinants of technical efficiency and the choice of the variables to include in the technical efficiency model is justified by common reasoning. Most of the factors in inefficiency effect model used in this study are derived from previous empirical studies. The firm specific exogenous variables that we include in our inefficiency model is firm size, labor quality in terms of education, expenditures on workers in terms of wages and training, as well as research and development (R&D) expenditures. Findings on relationship between establishment sizes and efficiency have suggested in many sectors that large establishments tend to be more efficient that small establishment. For two categories of SMEs, namely, micro and small & medium, we utilize one dummy variable, *SZ* which take on values of 1 if firm is small & medium sized enterprises and 0 otherwise.

Other factors that may raise productivity are investment in training and investment in new technology. Training provides workers with skills to perform a wide variety of tasks and to upgrade job skills as new technologies are introduced. Worker training plays a key role in adapting, modifying, and improving new technology. Meanwhile, investment in equipment and new technology may enable output per worker to increase. Aw & Batra (1998) proxied firm-level efforts at modifying or adopting technology by expenditures on R&D and investments in training and found that efficiency is positively correlated with the firm's investments in training and R&D. Variables *RD* and *TR* in our inefficiency effect model represent the firms' own investments in technological capabilities and workforce.

Several studies have found that labor quality plays a very important role in determining inter-industry differences in productivity in a number of developed countries as well as developing countries. The skills gained from formal educational qualifications in school and/or post-school (tertiary) are a key element of a worker's labor quality. The use of education to proxy human capital is in line with the literature on labor quality and is informed by economic theory about the main determinants of human capital. In Malaysia, Idris & Rahmah (2010) used level of education obtained by employee as indicator to measure quality of labor. We introduce a variable *ED* to represent ratio of employees with the education level below SPM to the total workers as a determinant of inefficiency.

The human capital measures that we use may not capture all aspects of worker quality such as workers' abilities. For example, Fox & Smeets (2011) used wage bill as a measure of quality-adjusted labor and found that it might be picking up some unobserved input quality since it was better at predicting output than their other human capital measures. In fact, traditional economic theory upholds a positive relationship between wage level and productivity. This comes from the fact that a greater wage level makes it possible for the company to reduce the corresponding rotation ratio and improving productivity (Carey & Otto 1978). In virtue of the above, and as technical efficiency includes the capacity of companies to generate outputs based on certain production resources, it could be expected that an increase in productivity as a consequence of a greater average wage level would also have a positive effect on technical efficiency (Sellers & Mas, 2009, Giroh *et al*. 2012). Therefore, we have introduced salaries and wages per worker (*WG*) as one of the determinants of technical efficiency in this study.

A Cobb-Douglas production function is commonly used to predict technical efficiency and to estimate inefficiency effects models. The Cobb-Douglas stochastic production function can be expressed as follows:

$$lnY_i = \beta_0 + \beta_1\, lnK_i + \beta_2\, lnL_i + (v_i - u_i) \tag{5}$$

where Y_i is value added of firm i, K_i is value of capital of firm i, L_i is labor of firm i, v_i is random error in which $v_i \sim N(0, \sigma_v^2)$ and u_i is technical inefficiency in which $u_i \sim N(\mu_i, \sigma_u^2)$. We also model the factors influencing technical inefficiency including the firm specific variables as follows,

$$\mu_i = \delta_0 + \delta_1\, lnWG_i + \delta_2\, RD_i + \delta_3\, TR_i + \delta_4\, ED_i + \delta_5\, SZ + w_i \tag{6}$$

We have used the software package FRONTIER 4.1 developed by Coelli (1996) to obtain the maximum likelihood estimates for parameters of the stochastic frontier model and technical inefficiency effects model as shown in Equations (5) and (6) for overall manufacturing enterprises, micro enterprises and small & medium enterprises. The dummy variable, *SZ* is omitted from Equation (6) when estimating the technical inefficiency effects model for micro enterprises and small & medium enterprises. This study utilizes firm-level data from The Survey of Manufacturing collected by The Department of Statistics of Malaysian for SME in 2010.

Two hypothesis tests need to be conducted for the technical inefficiency effects model as presented in Equations (5) and (6). The first hypothesis test is about the absence of technical inefficiency effects. Thus, there is no inefficiency function and no deviation from technical inefficiency. This is equivalent to imposing the restriction specified in the null hypothesis as follows,

$$H_0^1: \ \gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0 \tag{7}$$

The second hypothesis tests whether exogenous variables included in Equation (6) have a significant influence upon the degree of technical inefficiency. A test of the null hypothesis for this is as follows,

$$H_0^2: \ \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0 \tag{8}$$

A likelihood-ratio test (LR test) was used to test these hypotheses:

$$\lambda = -2\{ln\ [L(H_0)] - ln\ [L(H_1)]\} \tag{9}$$

where, $L(H_0)$ and $L(H_1)$ are the maximized value of likelihood function for the frontier model under the null and alternative hypothesis. The LR test statistic has an asymptotic chi-square distribution with parameters equal to the number of restricted parameters imposed under the null hypothesis (H_0), except H_0^1, which have a "mixed" chi-square distribution (Kodde & Palm 1986). The restrictions imposed by the null hypothesis are rejected when λ exceeds the critical value.

RESULTS OF ESTIMATION

Table 1 summarizes the results of the two set of hypothesis tests for overall manufacturing SMEs, micro enterprises and small & medium sized enterprises separately. The first hypothesis, which specifies that technical inefficiency effects are absent from the model, is strongly rejected at the 1% level of significance. This indicates that technical inefficiency effects model exists for overall manufacturing SMEs, micro enterprises and small & medium sized enterprises, given a Cobb-Douglas production function and inefficiency effects model as specified by Equations (5) and (6). The second hypothesis which specifies that all estimated parameters of the exogenous variables in the inefficiency effects model are jointly equal to zero, is also strongly rejected at the 1% level of significance for overall manufacturing SMEs, micro enterprises and small & medium sized enterprises. This shows that the exogenous variables used in this study have a significant influence upon the degree of technical inefficiency, given a Cobb-Douglas production function and inefficiency effects model.

Table 2 summarizes the results of the maximum likelihood estimation for overall manufacturing SMEs, micro enterprises and small & medium sized enterprises separately. All the slope coefficients in the Cobb-Douglas production function are highly significant at the 1% level of significance with an expected positive signs. The elasticities of capital (β_1) are 0.056 (overall manufacturing SMEs), 0.044 (micro enterprises) and 0.090 (small & medium sized enterprises). The elasticities of labor (β_2) are 1.060, 0.636, and 0.948 respectively for overall manufacturing SMEs, micro enterprises and small & medium sized enterprises. It can be observed that the elasticity of labor is much higher than capital. These imply that Malaysian manufacturing SMEs are labor intensive, and that this is the most important characteristic in the production function. Adding the two elasticities, the overall manufacturing SMEs and small & medium sized enterprises are found to have increasing returns to scale. In contrast, micro enterprises experienced decreasing returns to scale as the combined values of the estimated input coefficient (0.68) is less than unity.

The estimate of the variance parameter of gamma (γ) for overall manufacturing SMEs is 0.785 implying that the deviation in the production function is mainly due to technical inefficiency. Analyzed by the size of enterprises, over 90 percent of the total variation ($\gamma = 0.927$) from the frontier for micro enterprises is due to technical inefficiency. However, for small & medium sized enterprises, almost all deviations from the production function are attributable to noise or random error as the gamma value, 0.008 is close to zero. As shown in the table, the simple average of technical efficiency (TE) is 56.2 percent in micro enterprises and 83.2 percent in small & medium sized enterprises with an overall average of 62.7 percent. After grouping into categories, it can be observed that the percentages of small & medium sized enterprises with TE more than 0.8 (59.27 percent) is relatively higher than micro enterprises (11.09 percent). None of the small & medium sized enterprises exhibited TE less than 0.4 as compared with almost one-quarter of the micro enterprises.

The estimated results for Equation (6) are also summarized in Table 2. All negative coefficients signs of the technical inefficiency effects model represent the relationship relative to technical inefficiency. Hence all negative signs must be converted to positive for their relationship to technical efficiency or vice versa (Charoenrat & Harvie 2012). The estimated coefficient for firm size (*SZ*) in the technical inefficiency effects model is significant and negative, implying that small & medium sized enterprises are technically more efficient than micro enterprises. Large firms are able to obtain new technology faster than small firms, because they have less capital constraints and able to benefit from economies of scale (Phan 2004, Le & Harvie 2010). Besides firm specific factor, investments in technological capabilities and workforce are among other factors that may raise productivity. Training provides workers with skills to perform a wide variety of tasks and to upgrade job skills as new technologies are introduced. Worker training plays a key role in adapting, modifying, and improving new technology. Meanwhile, investment in equipment and new technology may enable output per worker to increase. Results from the analysis indicate that research and development expenditures (*RD*) and training expenditures (*TR*) contribute positively to technical efficiency in overall manufacturing SMEs, micro enterprises and small & medium sized enterprises. These findings are in line with previous studies by Batra & Tan (2003), Ng & Li (2003), and Deraniyagala (2001). For the micro enterprises, the impact on efficiency level by increasing the training and R&D expenditures are found to be higher as compared to small & medium sized enterprises. However, the coefficient of *RD* for small & medium sized enterprises is not statistically significant.

It is expected that the higher the level of labor quality, the more efficient will be both the use of existing technology and the absorption of new technology, which will consequently result in higher efficiency levels (Mahadevan & Mansor 2007, Zahid & Mokhtar 2007, Charoenrat & Harvie 2012). The estimated coefficients for ratio of employees with the education level below SPM to the total workers (*ED*) in the technical inefficiency effects model are positive and highly significant at the 1% level of significance for overall manufacturing SMEs, micro enterprises and small & medium sized enterprises. This implies that by increasing the unskilled labor ratio will deteriorate the technical efficiency. For the micro enterprises, the negative impact on efficiency level by increasing unskilled labor ratio is relatively higher as compared to small & medium sized enterprises.

Estimates of the coefficients for salaries and wages per worker (*WG*) have negative signs, and statistically significant at the 1% level of significant for overall manufacturing SMEs, micro enterprises and small & medium sized enterprises. These results support the traditional hypothesis that the wage level is positively related with productivity. Further, a high salary level reduces employee rotation; and a low employee turnover diminishes hiring and training costs (Thomas *et al*. 1998), which can be reflected in efficiency increases. For the micro enterprises, the impact on efficiency level by increasing the salaries and wages per worker is found to be higher as compared to small & medium sized enterprises.

CONCLUSION

As the majority of SMEs in the manufacturing are micro enterprises, the efficiency of these enterprises will directly affect the Malaysian economy in terms of business numbers, output, value added, employment and exports. However, using the Cobb-Douglas production function, our results from the stochastic frontier analysis show that they operate inefficiently in which about 25 percent of them recorded TE value below 0.4 with an overall average of 0.562 as compared to 0.832 by small & medium sized enterprises. The negative sign of the coefficient of firm size from the inefficiency effects model for overall manufacturing SMEs indicate that small & medium sized enterprises are relatively more efficient. In addition, micro enterprises also experienced decreasing returns to scale, implying that the inputs are not efficiently used as the increases in output is less than that proportional change in inputs. It can further supported by the gamma coefficient where more than 90 percent of the total variation from the frontier for micro enterprises is due to technical inefficiency. The results of hypothesis tests also reveal that technical inefficiency effects model exists for overall manufacturing SMEs, micro enterprises and small & medium sized enterprises. In addition, the firm size, R&D and training expenditures, ratio of unskilled labor and wage level jointly have a significant influence upon the degree of technical inefficiency.

In term of firms' investments in technological capabilities and workforce, results from the analysis indicate that R&D expenditures, training expenditures, salaries and wages per worker contribute positively to technical efficiency in overall manufacturing SMEs, micro enterprises and small & medium sized enterprises. For the micro enterprises, the impact on efficiency level by increasing the investments in technological capabilities and workforce are found to be higher as compared to small & medium sized enterprises. In other words, human resource management and financial policies and practices are of vital importance for micro enterprises. Efforts on the reallocation of budget for R&D expenditures to promote innovation, reviewing the current wage levels and encouraging employees to attend training according to their level of employment are suggested to enhance firms' efficiency. On the other hand, the government, through its relevant ministries also plays an important role by giving the financial assistance to encourage R&D activities, conducting various types of training programs and subsidizing the SMEs in term of training expenditures. The empirical results also show that by increasing the unskilled labor ratio (employees with qualification below SPM) will deteriorate the technical efficiency more abruptly in micro enterprises. It is suggested that government should provide sufficient technical and vocational training to those students who dropping out of school before completing their Form Five, or SPM prior to entering labor market. For the existing unskilled labor, firms are suggested to enhance workers' skills by sending them to participate in necessary training program.

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TABLE 1: Statistics For Hypothesis Tests Of The Stochastic Frontier Model And Inefficiency Effects Model

	Overall SMEs	Micro Enterprises	Small & Medium Enterprises
Null hypothesis, H_0	No technical inefficiency effects $\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$	$\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$	
LR Statistics	582.09	833.25	168.89
* Critical value at $\alpha = 0.01$	17.755	16.074	16.074
Decision	Reject H_0	Reject H_0	Reject H_0
Null hypothesis, H_0	No joint inefficiency variables $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$	$\delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$	
LR Statistics	195.50	336.81	130.90
** Critical value at	15.086	13.277	13.277

$\alpha = 0.01$			
Decision	Reject H_0	Reject H_0	Reject H_0

Note: * contain a mixture of a χ^2 distribution obtained from Table 1 of Kodde and Palm (1986).

** obtained from a χ^2 distribution.

TABLE 2: Maximum Likelihood Estimates For Parameters Of The Stochastic Frontier Model And Technical Inefficiency Effects Model

Variables	Overall SMEs	Micro Enterprises	Small & Medium Enterprises
Stochastic Frontier Model			
Constant	9.651 (0.033) ***	10.243 (0.037) ***	9.423 (0.093) ***
Capital, *lnK*	0.056 (0.003) ***	0.044 (0.003) ***	0.090 (0.005) ***
Labor, *lnL*	1.060 (0.014) ***	0.636 (0.025) ***	0.948 (0.026) ***
Technical Inefficiency Effects Model			
Constant	-0.280 (0.170) *	-0.311 (0.329)	1.249 (0.165) ***
Salaries & Wages per worker, *lnWG*	-0.280 (0.027) ***	-0.761 (0.086) ***	-0.301 (0.009) ***
R&D Expenditure, *RD*	-0.0000019 (0.0000008) **	-0.0012 (0.0005) **	-0.0000002 (0.0000002)
Training Expenditure, *TR*	-0.000020 (0.0000009) ***	-0.0036 (0.0001) ***	-0.0000084 (0.000001) ***
Ratio under SPM, *ED*	0.756 (0.099) ***	0.885 (0.152) ***	0.867 (0.045) ***
Size (dummy), *SZ*	-1.214 (0.175) ***	-	-
Variance Parameters			
Sigma-squared, σ^2	1.656 (0.108) ***	2.622 (0.319) ***	0.586 (0.008) ***
Gamma, γ	0.785 (0.018) ***	0.927 (0.009) ***	0.008 (0.002) ***
Log-likelihood Function	-5399.622	-3273.943	-1822.556
No. of observations	4661	2930	1731
Technical Efficiency			
< 0.200	154 [3.30]	288 [9.83]	0 [0.00]
0.200 - < 0.400	264 [7.81]	412 [14.06]	0 [0.00]
0.400 - < 0.600	988 [21.22]	666 [22.73]	140 [8.09]
0.600 - < 0.800	2780 [59.62]	1239 [42.29]	565 [32.64]
≥ 0.800	375 [8.05]	325[11.09]	1026 [59.27]
Simple Average	0.627	0.562	0.832

Note: Standard errors are in ( ); percentages are in [ ]

* significant at 10%, ** significant at 5%, *** significant at 1%