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Technical efficiency in the Malaysian electric and electronic manufacturing industry: A stochastic frontier analysis approach

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ABSTRACT

This study measured the level of technical efficiency (TE) that exerted a significant impact on the Malaysian electric and electronic manufacturing industry, which consists of 13 sub-industries, from 2010 to 2015. Unbalanced panel data from 1880 firms was obtained from the Department of Statistics Malaysia. We used stochastic frontier (SFA) analysis with the transcendental logarithmic approach to estimate the empirical analysis parametric. The maximum likelihood estimated regression of the SFA parameters revealed a high total average TE of 0.944%. Both the manufacturing sub-industries for communications equipment (MSIC 263) and irradiation, electromedical, and electrotherapeutic equipment (MSIC 266) demonstrated the highest average TE value and consistency (0.989%). The consumer electronics manufacturing sub-industry (MSIC 264) yielded a notably lower TE level (0.846%). Changes in TE for all industries were monitored via standard deviation analysis. The low standard deviation (SD) for MSIC 263, 271, and 275 indicated continuous progress and demands for these industries, while the higher SD for MSIC 264, 266, 272, and 273 pointed out major changes that happened within the period. The findings demonstrated that studies on the TE levels indicate that the E&E manufacturing industry has highly expended and continuous efforts to update technologies and human capital innovations. Therefore, the practical implication is to achieve Sustainable Development Goal 9 for sustainable industrialization and fostering innovation by 2030.

Contribution/ Originality: The study found that the E&E manufacturing industry in Malaysia experienced positive growth from 2010 to 2015. It was observed that the economy was able to expand its own boundaries through innovations, resulting in improved productivity and the effective utilization of human capital.

1. INTRODUCTION

Productivity has been closely related to efficiency, effectiveness, and quality. According to Abdullah, Ismail, Sulaiman, and Abdul Talib (2017) efficiency can be defined as competence in input use, which depends on managerial and employee competencies as well as production technology and technological innovation. As the world moves towards the Fourth Industrial Revolution (IR 4.0), manufacturing industries should apply the latest technology to enhance production efficiency and optimise output. Thus, technical efficiency (TE) is vital for identifying the readiness of the manufacturing industry to adopt a technological approach for production methods, management, or labour. The TE is described as the competence and ability of a firm to use input to yield maximum output or minimise input consumption to generate the same amount of output using technology (Coelli, Rao, O'Donnell, & Battese, 2005; Fahmy-Abdullah, Sieng, & Isa, 2018; Farrell, 1957; Ismail, Sulaiman, & Norsi'ee, 2017;

Pargar, 2017; Syverson, 2011). A TE score of one indicates technical efficiency, and a score of less than one indicates technical inefficiency in production (Porcelli, 2009).

In the context of IR 4.0, the Malaysian Government has identified the electric and electronic (E&E) industry as a strategic sector in its plans for industrial upgrading and human capital development. Balakrishnan, Othman, and Zaidi (2021) stated that IR 4.0 implementation is linked to the E&E industry as it produces automation and digitalisation tools. Furthermore, IR 4.0 is not limited to the automation of one firm but redefines the entire network of the E&E chain, connecting it to a single digital ecosystem. The E&E industry can also minimise waste and defects, yield higher-quality products that drive the major exports of national products, and ensure business excellence (Balakrishnan et al., 2021; MITI, 2018; Mrugalska & Wyrwicka, 2017). Therefore, available input source use should be increased to enable determination of the efficiency level (Fakorede, Babatunde, & Ovat, 2014). In summary, TE is the relative productivity of best practices and levels of frontier production.

The E&E manufacturing industry plays a vital role in Malaysian economic, social, and technical development. The E&E industry has contributed to the Malaysian gross domestic product (GDP) at an average of 6.1% a year from 1970 to 2018, which is higher than that of advanced countries (OECD Economic Surveys: Malaysia 2019, 2019). Furthermore, the Department of Statistics (2018) has reported that the industry is the largest contributor to national total exports and a major player in the fast-growing E&E products market. The company exports its products to Singapore, Hong Kong, the United States, the People's Republic of China (PRC), Japan, and Europe. In 2019, the E&E industry was responsible for 37.8% of national total exports, representing exports worth RM372.67 billion, or 44.7% of all exported manufactured goods (MIDA, 2020).

Recognising the importance of TE in E&E manufacturing performance, Malaysia introduced the Seventh Malaysia Plan (7MP) to shift from input-driven growth to productivity growth. Due to strong external demand, positive growth of 8.0% was recorded in 2017 as compared to 7.2% in 2016 (Department of Statistics, 2018). Therefore, improved productivity is crucial for scaling-up countries, organisations, or individuals through higher profits or income generation, improved reputation, and reduced resource waste (Productivity Report 2018/2019, 2019). Due to its innovativeness and a firm commitment to capital investment, the E&E industry can catalyse the development of all other industries, limiting the area of study. Moreover, the E&E manufacturing space is evolving swiftly as more firms currently transition to advanced knowledge-intensive, high-tech, innovative, and higher value-add activities (MIDA, 2020a). The E&E industry has been emphasised as a National Key Economic Area (NKEA) under the Economic Transformation Programme (ETP) strategy to prime the nation towards a high-income economy by focusing on high-value and high-growth manufacturing activities for achieving world-class standards (MIDA ETP Annual Report, 2016). Nevertheless, the 2014 MITI (Ministry of International Trade and Industry of Malaysia) report stated that the Malaysian E&E industry is mutable and inconsistent. This issue is largely a result of the external environment, which in 2012 saw a 2.5% decline in demand for E&E manufacturing exports to RM231.2 billion. Significantly, this cutback also affected the labour market, as total redundancies increased by 35.2% to 7616 million, mainly due to higher manufacturing industry redundancies (MITI Report 2012, 2012). In this era of globalisation and an open economy, the Malaysian manufacturing industry, especially the E&E industry, is facing numerous challenges, such as a progressively competitive global environment, the sovereign debt crisis in Europe, the modest US economic recovery that has been dampened by domestic and external weaknesses, and the stagnant Japanese economy, which has affected export performance. Additionally, increasing competition from manufacturers in emerging markets like China and ASEAN (Association of Southeast Asian Nations) member countries has had an impact on export performance, particularly in higher value-added product assembly (Bank Negara Malaysia Annual Report, 2012). Hence, the 2012 Malaysian economic landscape became more challenging and uncertain due to the increasingly competitive global environment. Thus, E&E industry manufacturing firms should progress and achieve high productivity to compete with new operations, technology, and technological efficiency changes by improving industry efficiency and performance. Most previous studies on Malaysian E&E

manufacturing have compared it less favourably with other industries and focused only on the determinants of TE (Fahmy-Abdullah, Sieng, & Isa, 2019; Jajri & Ismail, 2014; Khalifah & Jaafar, 2017; Shaharudin, Hassam, Akbar, Rashid, & Noor, 2018). To the best of the authors' knowledge, this is the first attempt to compare the TE of 13 Malaysian E&E manufacturing sub-industries. The analysis will indicate the progress of efficiency in each sub-industry and its significant effect on the Malaysian economy. Thus, this study examined and compared the TE indicators for the 13 sub-industries from 2010 to 2015 via a stochastic frontier analysis (SFA) model and maximum likelihood estimation (MLE) using DOSM data. The changes in TE needed to produce the optimum output were evaluated using statistical analysis. The findings can spur the growth of the Malaysian global competitiveness environment with the implementation of new, innovative, and advanced technology.

2. LITERATURE REVIEW

The efficiency of a firm is determined based on its ability to yield output at minimum cost or to yield maximum profit. Numerous studies have analysed the TE of the E&E manufacturing industry. The concept of TE was first introduced by Kumbhakar and Lovell (2003) who stated that the decision-making ability to yield the maximum output with a set of output-oriented resources or to yield output with a lower amount of input-oriented resources determines efficiency. The TE can also can be defined as the ability of firms to yield maximum output with a given set of inputs (Fahmy-Abdullah et al., 2018; Farrell, 1957). Nonetheless, TE is a static concept involving the measurement of output from a specified input at a certain time point and measuring this relationship relative to an efficiency frontier would be of interest to government and investment agencies, economists, and management.

A firm's efficiency hinges on its capacity to achieve output at the lowest cost or maximize profits. Numerous studies have delved into the analysis of Technical Efficiency (TE) within the E&E manufacturing industry. Kumbhakar and Lovell (2003) were the first to introduce the idea of TE, which states that the capacity for making decisions to achieve maximum output using a particular set of output-oriented resources or to achieve output with fewer input-oriented resources is what determines efficiency. TE can also be defined as a firm's capability to achieve maximum output with a given set of inputs (Fahmy-Abdullah et al., 2018; Farrell, 1957). Nevertheless, TE is a static concept that involves measuring output based on a defined input at a specific time point. Examining this relationship in relation to an efficiency frontier holds significant interest for government and investment agencies, economists, and management professionals.The extent of technical inefficiency is captured by the difference between the efficiency frontier and the actual input–output relationship. Studies on TE have been conducted widely in various areas, such as the Indian manufacturing sector (Singh, Ashraf, & Ashish, 2019) carrot production (Abunyuwah, Yenibehit, & Ahiale, 2019) the Malaysian transportation industry (Hashim, Mohamed, Fahmy-Abdullah, & Sieng, 2021) and the Chinese energy industry (Wanke, Tan, Antunes, & Hadi-Vencheh, 2020) and agricultural production (Huang, Xu, & Guo, 2021). This evidence indicates that TE has been recognised as a relevant indicator for evaluating production efficiency and identifying weighted input that enhances efficiency. Moreover, this indicator helped economic and financial agencies identify specific industries for boosting national economic growth. Figure 1 illustrates the concepts of TE, describing it as a simple production process with a single output (Y) and input (X). Points A, B, and C indicate the relationship between the input and output of three firms and represent the productivity level of each firm. Firms producing on the production frontier operate at the highest possible productivity and are considered technically efficient. Firms demonstrating production below the frontier line are considered technically inefficient (Cullinane & Wang, 2010). Thus, firms producing at points B and C are considered technically efficient. The firm producing at point A is considered inefficient as its productivity could be increased by moving output Y1 to maximum productivity at output Y2. The firm at point C yields output level Y1 with a lower input level X1, while the firm at point B yields the same output level Y1 with a higher input. Accordingly, the firm at point A is considered technically inefficient. The TE is identified by obtaining the maximum possible output at a specific input level. The production frontier demonstrates all points of TE.

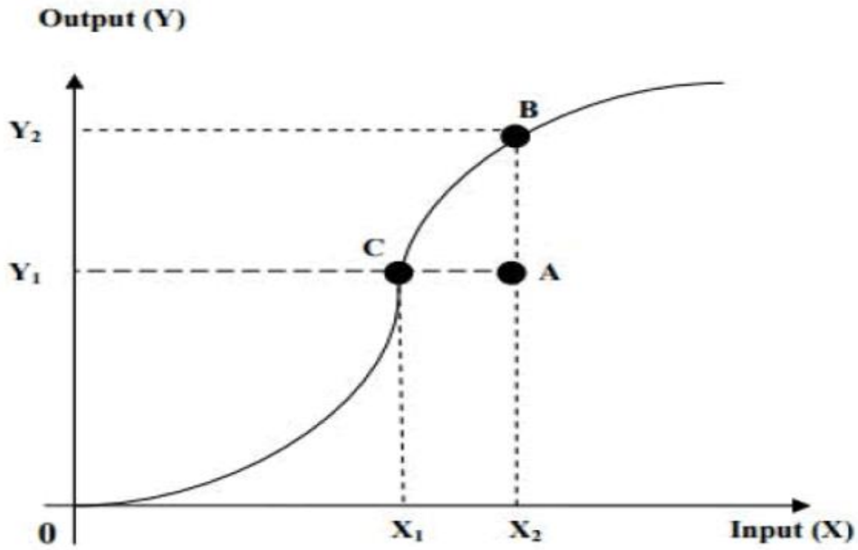

Figure 1. Production frontier and technical efficiency.
Note: Coelli, Rao, and Battese (1998).

Figure 1 visually represents the concept of Technical Efficiency (TE), depicting it as a straightforward production process involving a single output (Y) and input (X). In this diagram, we can identify three points: A, B, and C, each illustrating the relationship between input and output for different firms and reflecting their respective productivity levels. Firms operating along the production frontier, such as those at points B and C, achieve the highest possible productivity and are classified as technically efficient. Conversely, firms producing below this frontier line, like the one at point A, are considered technically inefficient (Cullinane & Wang, 2010). Hence, the firms positioned at points B and C are regarded as technically efficient. In contrast, the firm located at point A is deemed inefficient since its productivity could be enhanced by shifting from output Y1 to the maximum productivity point at output Y2. Point C represents a scenario where a firm achieves output level Y1 with a lower input level X1, while point B shows another firm achieving the same output level Y1 but with a higher input. To identify TE, we determine the maximum attainable output at a specific input level. The production frontier encompasses all points of TE, offering a comprehensive view of efficiency levels. Generally, TE can be calculated using parametric or non-parametric approaches. The SFA model is an example of a parametric approach. Aigner, Lovell, and Schmidt (1977) first developed the SFA, which involves input, output, and environmental parameters for evaluating cost, profit, or production functions. Battese and Coelli (1992) and Battese and Coelli (1995) continued developing this model specifically to evaluate corporate efficiency performance. Most TE research uses the SFA model as it presents several advantages, such as incorporating random error and uncontrollable factors in the calculation, more statistical parameters, user-friendliness, and simple equations (Abunyuwah et al., 2019; Zhang, Hu, & Xu, 2020). Battese, Rao, and O'donnell (2004) also emphasised that the SFA model can identify irrelevant factors contributing to technical inefficiency. In this research, the SFA model was used for measuring TE and was coupled with MLE for selecting the best output. Compared to the ordinary least square (OLS) method, the MLE is the most popular choice for estimating SFA output as it features advantages such as sufficiency, consistency, efficiency, and parameterisation invariance (Basri, Abdul Hamid, & Tan, 2006; Myung, 2003). Coelli et al. (2005) noted that using MLE solved heteroskedasticity and multicollinearity problems. The estimation model is crucial for evaluating the effectiveness of a proposed model and generating optimal output from random frontiers that is closer to the actual situation (BahooTorody et al., 2020; S. Yang et al., 2020). Ali et al. (2019) suggested that the principle of MLE is to select an estimated parameter that maximises the probability of finding the data. Ismiasih (2017) explained that MLE can describe the relationship between the maximum output and the input. Moreover, MLE can identify errors in probability distribution (Coelli et al., 2005; Gujarati, 2003; Wooldridge, 2006). Furthermore, MLE output can indicate the most significant parameters that mostly affect the TE. Thus, the organisation can focus on improving these factors and increasing production efficiency (Wagan, Memon, & Yanwen, 2020).

Fahmy-Abdullah et al. (2019) stated that there has been less research attention on Malaysian E&E manufacturing TE compared to that of other industries. Sulaiman and Rashid (2013) and Jajri and Ismail (2014) referred to the Malaysian E&E industry only in general. Information about the E&E industry is scarce, where firm-level data are used for measuring TE levels (Abd Ghafar & Ismail, 2015). Seong (2015) reported that the Northern Malaysian E&E industry can accommodate employees' needs by improving employee productivity to retain workers. In recent years, TE evaluation has become a popular indicator in economics, which has subsequently become the research focus for investigating empirical methods and approaches in specific areas (Fahmy-Abdullah et al., 2018; Hamdan, Fahmy-Abdullah, & Sieng, 2019; Latif, Fahmy-Abdullah, & Sieng, 2019; Nor et al., 2020). This discussion has demonstrated that there is a lack of studies on the E&E manufacturing industry. Therefore, this study was intended to bridge this gap and improve overall productivity in Malaysia using firm-level data.

Fahmy-Abdullah et al. (2019) pointed out that there has been relatively limited research attention dedicated to Technical Efficiency (TE) within the Malaysian E&E manufacturing sector compared to other industries. While Sulaiman and Rashid (2013) and Jajri and Ismail (2014) have made references to the Malaysian E&E industry in a general sense, detailed information about this sector remains scarce, particularly when it comes to utilizing firm-level data to gauge TE levels (Abd Ghafar & Ismail, 2015). Seong (2015) reported that the Northern Malaysian E&E industry has the potential to meet employees' needs by enhancing employee productivity, thereby retaining workers. In recent years, TE assessment has gained popularity as a key economic indicator, drawing increasing research attention for empirical methods and approaches in various specific areas (Fahmy-Abdullah et al., 2018; Hamdan et al., 2019; Latif et al., 2019; Nor et al., 2020). The discussion thus highlights a significant gap in the literature concerning TE within the E&E manufacturing industry. Therefore, the aim of this study is to bridge this gap and enhance overall productivity in Malaysia by utilizing firm-level data.

Mazorodze (2020) used SFA to identify the TE of 28 manufacturing industries in South Africa between 1970 and 2016. The research output highlighted that the industries operated 33% above their cost minimisation level through technical efficiency and could have reduced their input usage by 17% without affecting output levels. The average technical and cost efficiencies were 0.83 and 0.33, respectively. In Tanzania, Njiku and Nyamsogoro (2018) measured TE and reported that determinants such as firm age, location, ownership type, owner age, and education were production input factors that statistically contributed to the output. Yang, Chen, and Huang (2013) used firm-level panel data to measure TE levels and reported empirical results showing that the TE of Taiwanese manufacturing firms rose from 1987 to 2000. This means that the firms showed positive technological advances and TE. The SFA demonstrated that the overall average TE of rice farming in the Mekong Delta, Vietnam, was 0.77, exhibiting the potential to increase by 23% with the same input and technology (Ho & Shimada, 2019). Setiawan and Sule (2020) examined TE levels and their determinants in state-owned manufacturing enterprises in Indonesia. They found that these companies had operated inefficiently from 1980 to 2015, as the average technical efficiency demonstrated a decreasing trend during that period.

3. RESEARCH METHODOLOGY

3.1. Data Sources

This research used unbalanced panel data from 1880 firms obtained from the DOSM. The data were classified under the three-digit Malaysian Standard Industrial Classification (MSIC) codes based on the most recent 2015 census; the census is conducted every five years. The data were from the E&E manufacturing industry and were classified into 13 sub-industries, which are listed in Table 1.

3.2. The SFA Model

The production function was used in the SFA model, with input and output as components representing production activity. The concept of TE involves applying efficiency analysis to production functions, which is explained in the next section. The SFA model confers flexibility, where the estimated frontier can be specified with varied means based on the researcher's specific objectives. Furthermore, SFA has the advantage of being able to calculate an efficient production frontier in large-scale benchmarks with time series data (Mortimer, 2002). Moreover, the model is suitable for approximating cost frontiers (Schmidt & Lovell, 1979) and profit frontiers (Kumbhakar, 1987). These formulations diverge from the simple production model in the output and input choices and the effects and interpretation of inefficiency. Battese and Coelli (1995) used the SFA model, assuming that random variables exert effects on firms via the following specifications of the Coelli and Battese model:

The SFA (Stochastic Frontier Analysis) model offers a high degree of flexibility, allowing researchers to tailor the estimated frontier according to their specific objectives. Additionally, Mortimer (2002) provides evidence that SFA has the ability to compute an effective production frontier in large-scale benchmarks using time series data. Furthermore, Schmidt and Lovell (1979) and Kumbhakar (1987) demonstrated that the model is appropriate for estimating both cost frontiers and profit frontiers. These formulations represent departures from the conventional production model, particularly in terms of output and input selection, as well as considerations related to inefficiency effects and interpretation. Battese and Coelli (1995) employed the SFA model, incorporating random variables that exert influences on firms based on the specifications outlined in the Coelli and Battese model.

$$Y_{it} = X_{it}\,\beta + (v_{it} - \mu_{it}) \qquad i = 1, 2, \ldots, N \qquad t = 1, 2 \ldots, T \qquad (1)$$

Where;

Yit is the logarithm's production for firm i-th at the t-th year of observation.

Xit is a vector (k x 1) multi quantity input for firm i-th at the t-th year of observation.

β is a vector (k x 1) of the unknown parameters.

$v_i v_{i_t}$ = random variables or random error terms assumed to be independent and identically distributed (*i.i.d*) as [*N*(0, $\sigma_v^2 \sigma_v^2$)] random variables, similar and normally distributed and independent of the non-negative variables,

$\mu_i \mu_{i_t}$ = [$u_t$exp (-| (t-T))], non-negative random variables assumed to be independent and identically distributed (*i.i.d*) truncations (at zero) of the [*N*($\mu \mu_{i}$, $\sigma_u^2 \sigma_u^2$)] distribution.

$v_i v_{i_t}$ is a random variables or random error terms are assumed to be independent and identically distributed (*i.i.d*) as [*N*(0, $\sigma_v^2 \sigma_v^2$)] random variables, similar and normally distributed and independent of the non-negative.

$\mu_i \mu_{i_t}$ is [$u_t$exp (-| (t-T))] is a non-negative random variables, which are assumed to be independent and identically distributed (*i.i.d*) truncations (at zero) of the [*N*($\mu \mu_{i}$, $\sigma_u^2 \sigma_u^2$)] distribution.

N is represents the number of sample firms for which observations are available.

| is the parameter to be estimated, and the panel data are not necessarily complete (unbalanced panel data). The inefficiency in the time interval before *T* is the sum of the inefficiencies at each year end and exp (| (*T*-*t*))]. If | is positive, then inefficiency decreases over time. However, if | is negative, inefficiency increases over time.

For this study, unbalanced panel data of 1880 firms on three digits of Malaysian Standard Industrial Classification (MSIC) were used for calculating TE within a six-year period (2010–2015).

The secondary data are based on the most recent 2015 Department of Statistics Malaysia (DOSM) census. The data is from the E&E manufacturing industry and has been classified into 13 sub-industries, as listed in Table 1.

Table 1. The E&E manufacturing sub-industries in Malaysia.

No.	Code	E&E manufacturing sub-industry
1	MSIC 261	Electronic components and boards
2	MSIC 262	Computers and peripheral equipment
3	MSIC 263	Communications equipment
4	MSIC 264	Consumer electronics
5	MSIC 265	Measuring, testing, navigating and control equipment, watches, and clocks
6	MSIC 266	Irradiation, electromedical, and electrotherapeutic equipment
7	MSIC 267	Optical instruments and photographic equipment
8	MSIC 271	Electric motors, generators, transformers, and electricity distribution and control apparatus
9	MSIC 272	Batteries and accumulators
10	MSIC 273	Wiring and wiring devices
11	MSIC 274	Electric lighting equipment
12	MSIC 275	Domestic appliances
13	MSIC 279	Other electrical equipment

Sources: Economic Census 2011 and 2016, DOSM.

3.3. Model Specification by Transcendental Logarithm (Translog)

A translog stochastic production function was used to characterise the stochastic frontier production of the listed manufacturing firms. Based on the Battese and Coelli (1995) model, Equation 2 is a modification of Equation 1, to which the translog function has been added, as follows:

$$\ln Output_{it} = \ln O_{it} = \beta_0 + \beta_1 \ln C_{it} + \beta_2 \ln L_{it} + \beta_3 \ln II_{it} + \frac{1}{2}\beta_4 (\ln C_{it})^2 + \frac{1}{2}\beta_5 (\ln L_{it})^2 + \frac{1}{2}\beta_6 (\ln II_{it})^2 + \beta_7 (\ln C_{it} \times \ln L_{it}) + \beta_8 (\ln C_{it} \times \ln II_{it}) + \beta_9 (\ln L_{it} \times \ln II_{it}) + (v_{it} - \mu_{it})$$

$$i = 1, 2, ..., N \qquad t = 1, 2 ..., T \qquad (2)$$

Where $\ln O_{it}$ is the logarithm for the total output of firm i-th at the t-th year of observation.

$\ln C_{it}$ is the logarithm for the total assets of firm i-th at the t-th year of observation.

$\ln L_{it}$ is the workforce number of firm i-th at the t-th year of observation.

$\ln II_{it}$ is the intermediate input for firm i-th at the t-th year of observation.

i = 1, 2, ..., N is the number of firms.

t = 1, 2, ..., 4 is the number of years of observation (from 2010 to 2015).

v_i = *i.i.d* with [N(0, σ_v^2)].

u_i = non-negative random variables assumed to be independent and identically distributed truncations (at zero) of the [$N(\mu_i, \sigma_u^2)$].

3.4. Data Analysis

The stochastic frontier production function can also investigate the TE of a firm. All empirical results were derived using Frontier 4.1 computer software. The DOSM data were analysed using Microsoft Office Excel 2016. The analysis was processed using Frontier 4.1, which uses the Fortran 77 programming language that specialises in estimating stochastic production frontiers. Frontier is a medium for estimating the TE of a firm from the translog function.

4. RESULTS

The TE of Malaysian E&E manufacturing firms from 2010 to 2015 was calculated using descriptive statistics, which included the data, average, minimum and maximum value, and standard deviation. Abdul-Ghafar (2003) emphasised that descriptive statistics are a simple, popular, and accurate statistical method for identifying relevant study variables and describing phenomena that occur over time. This study used a DOSM data panel categorised according to three digits under the MSIC 2000 and MSIC 2008 classifications. This study included 1880 E&E

manufacturing firms, encompassing 13 sub-industries. Variables β1 to β5 were selected for the study and consisted of output (O), capital (C), labour (L), capital–labour ratio (C/LR), and intermediate input (II).

Table 2. Summary descriptive statistics of the variables (2010–2015).

Variable	O	C	L	C/L	II
Unit	**MYR (million)**	**MYR (million)**	**Number**	**Ratio**	**MYR (million)**
2010					
Average	15,058	2,711	27,894.615	77.581	12,402
Minimum	587	129	2,002.000	26.420	434
Maximum	88,203	20,374	156,485.000	144.722	71,072
Standard deviation	25,086	5,559	41,896.984	39.797	20,449
2011					
Average	13,909	2,497	26,772.615	75.464	10,999
Minimum	657	193	2,350.500	24.940	488
Maximum	81,871	19,164	154,536.500	150.445	62,504
Standard deviation	22,918	5,179	41,136.193	37.848	17,682
2012					
Average	12,761	2,283	25,650.615	73.580	9,595
Minimum	679	186	2,699.000	20.774	459
Maximum	75,540	17,954	152,588.000	154.689	53,936
Standard deviation	20,905	4,814	40,439.917	37.514	15,038
2013					
Average	13,383	2,539	24,445.846	86.504	9,993
Minimum	586	182	3,355.000	24.714	414
Maximum	80,147	20,564	138,749.500	261.164	56,598
Standard deviation	21,979	5,493	36,377.184	63.463	15,673
2014					
Average	14,006	2,794	23,241.077	97.047	10,391
Minimum	493	171	2,897.000	19.500	369
Maximum	84,754	23,174	124,911.000	332.810	59,259
Standard deviation	23,081	6,187	32,364.673	84.995	16,318
2015					
Average	22,097	3,913	30,853.231	129.228	17,591
Minimum	438	96	1,844.000	52.287	298
Maximum	144,133	29,153	180,145.000	396.603	115,845
Standard deviation	39,234	7,661	47,355.272	96.300	31,648

Note: O = Output; C = Capital; L = Labour; C/LR = Capital–labour ratio; II = Intermediate input.

4.1. Descriptive Information of the Sample

Table 2 lists the descriptive statistics of the variables. The maximum and minimum value of the output (O) of the firms to production was MYR22, 097 million (2015) and MYR12, 761 million (2012), respectively. The highest and lowest average capital (C) were MYR3, 913 million (2015) and MYR2, 283 million (2012), respectively. The highest average labour (L) was recorded in 2015 with 30,853 people, while the lowest average was recorded in 2014 with 23,241 people. The highest average capital–labour (C/L) ratio was recorded in 2015 at MYR129, 000 per employee as compared to the lowest average C/L ratio recorded in 2012, which was MYR73, 000 per employee.

The highest average intermediate input (II) was recorded in 2015 at MYR17, 591 million, while the lowest average II was MYR9, 595 million in 2012. Throughout 2015, the variable recorded the highest average overall value of the six-year period as the E&E manufacturing industry is export-oriented and generated an added value of MYR53.8 billion in 2015 (Economic Planning Unit, Eleventh Malaysia Plan - 11MP). As the E&E manufacturing industry can potentially become more multifaceted and yield high value-added products, which is crucial for the development and production activities of other products under the 11MP initiative and Malaysia Productivity Blueprint (MPB). Therefore, higher productivity growth is expected for the other manufacturing industries (Productivity Report 2018/2019, 2019). Therefore, the efficiency values were obtained using the descriptive statistics summary of the internal variables.

4.2. The TE Results

4.2.1. Estimated SFA Parameter Results

Battese and Coelli (1992) and Battese and Coelli (1995) developed a parametric approach using SFA production functions for data panels. Table 3 illustrates the results of parameter estimation using the translog production function for 2010-2015. The results were obtained according to the MLE of the parameter production function in Frontier 4.1.

The gamma parameter (γ) value was between one and zero. The TE refers to the ability of a firm to achieve maximum output with a given input. Therefore, the SFA approach of the translog production function model was appropriate in this study as it could determine the expected value and estimate the level of efficiency at firm level more accurately. The SFA focused on overall observation and forming marginal efficiency based on optimisation through statistics. The SFA was based on marginal output and thought that firms that didn't produce the marginal output were affected by technical inefficiency, measurement error, disturbance term, and other non-systems that couldn't be controlled. This was one of the SFA model's benefits over other models (Admassie & Matambalya, 2002; Coelli, 1996).

The regression results demonstrated that most of the parameters ($\beta 0$ to $\beta 14$) were significant for determining the output in the stochastic boundary production model. The value of the II coefficient was 0.626, indicating that a 1% increase in II input leads to a 0.626% increase in output. The value of the significant t-ratio was 2.488 at a 5% significance level. The role of II dominated the increase in output. For parameters $\beta 5$ and $\beta 6$, the coefficient values were 0.082 and 0.104 at a 1% significance level, respectively. Parameters $\beta 10$ and $\beta 12$ were effective but affected the efficiency level negatively. The two parameters were significant at 5% and 1% significance levels, with coefficient values of 0.026 and 0.158, respectively. Parameters $\beta 11$ and $\beta 13$ demonstrated positive coefficient values for the efficiency levels of the firms at 0.198 and 0.018, respectively, and the t-ratio was significant.

The regression results demonstrated that most of the variables (parameters $\beta 0$ to $\beta 14$) were significant. Overall, the estimation for the gamma parameter (γ) yielded a positive and significant value of 8.237 at a 1% significance level. This value implied that technical inefficiency was a significant contributor and demonstrated an extremely strong relationship with the level and change of firm output. In addition, the sigma squared ($\sigma^2 = \sigma_v^2 - \sigma_\mu^2$) value was 3.319 at a 1% significance level and was consistently significant from 2010 to 2015. This means that some firms operated inefficiently.

Nevertheless, the Malaysian E&E manufacturing industry demonstrated a high average TE value from 2010 to 2015 (0.944). This demonstrated that almost all firms operated at a high level to produce optimal output. Even the firms that recorded the lowest average TE value had to increase their output by only 5.6% using the same amount of input to achieve maximum efficiency (100%). In other words, these firms had either exceeded the output limit or had used inputs optimally. The increase can be seen in the 9.3% rise in E&E product exports equivalent to MYR145.8 billion, while sales increased by 16.3% to MYR169.5 billion (MOF Economic Report 2017/2018, 2018).

Table 3. Estimated SFA parameter results (2010–2015).

Variable	Parameter	Coefficient of MLE		
		Coefficient	Standard error	t-value
Constant	β_0	1.469	0.904	1.626
Ln capital (C)	β_1	0.329	0.222	1.482
Ln labour (L)	β_2	-0.083	0.395	-0.211
Ln intermediate input (II)	β_3	0.626	0.252	2.488**
Year (t)	β_4	-0.051	0.045	-1.126
0.5 × (ln capital)^2	β_5	0.082	0.031	2.615***
(Ln capital) × (ln labour)	β_6	0.104	0.042	2.488**
(Ln capital) × year	β_7	0.002	0.008	0.306
0.5 × (Ln labour)^2	β_8	-0.034	0.093	-0.363
(Ln labour) × (ln intermediate input)	β_9	-0.062	0.054	-1.159
(Ln labour) × year	β_{10}	-0.026	0.011	-2.493**
0.5 × (ln intermediate input)^2	β_{11}	0.198	0.037	5.274***
(Ln intermediate input) × (ln capital)*	β_{12}	-0.158	0.027	-5.821***
(Ln intermediate input) × year	β_{13}	0.018	0.007	2.541**
0.5 × (Year)^2	β_{14}	-0.004	0.004	-0.999
Sigma squared	$\sigma^2 = \sigma_v^2 + \sigma_\mu^2$	0.006	0.002	3.319***
Gamma	Γ	0.901	0.109	8.237*
Log likelihood		125.416		
Likelihood ratio test (LR test) of the one-sided error		1.471		
Average TE		0.944		

Note: Representative level of significance: * = 10%, ** = 5%, and *** = 1%.

4.2.2. Results of TE Analysis

The average total TE in the E&E manufacturing industry plays a vital role in the Malaysian GDP. Figure 2 illustrates the average TE of the Malaysian E&E manufacturing industry from 2010 to 2015. The data indicated that the overall average TE value was 0.944, which was close to the calculated average TE in Table 3. This value proved that the E&E manufacturing industry operated at optimum efficiency and productivity. The finding also indicates that the firms operated at higher efficiency levels during the six-year period to produce optimum output, as each firm is closely linked and forms a symbiotic system that uses other industry products as basic input, enhancing the efficiency progress of each sub-industry.

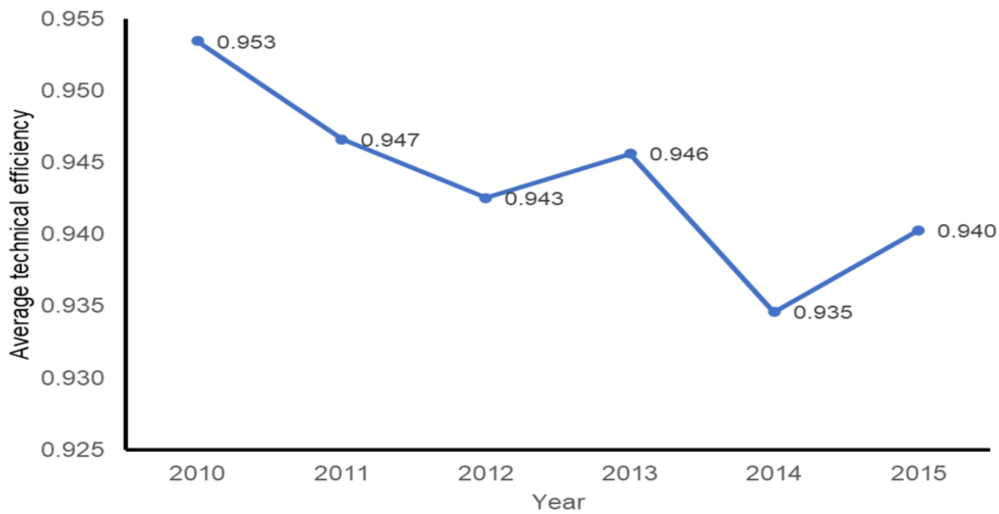

Figure 2. Average TE from 2010 to 2015.

The 2017/2018 Economic Report stated that an increase in the global electronics cycle for the E&E manufacturing industry, which contributed RM138.4 million in 2015 and RM151.8 million in 2016, supported export-led productivity (Productivity Report 2018/2019, 2019). Compared to small firms, large firms were better able to operate and contribute to efficiency (Ismail, Abidin, & Saukani, 2019). After the Asian financial crisis (1997–1998), the E&E industry was further supported by government efforts through a strategic initiative in the 10MP to create a conducive environment for independent economic growth, especially the E&E manufacturing industry, as evidenced by the E&E manufacturing industry contributing 6.4% productivity performance growth (RM80.06 billion) to the overall Malaysian manufacturing industry growth of 9.4% in 2010 (Productivity Report 2018/2019, 2019).

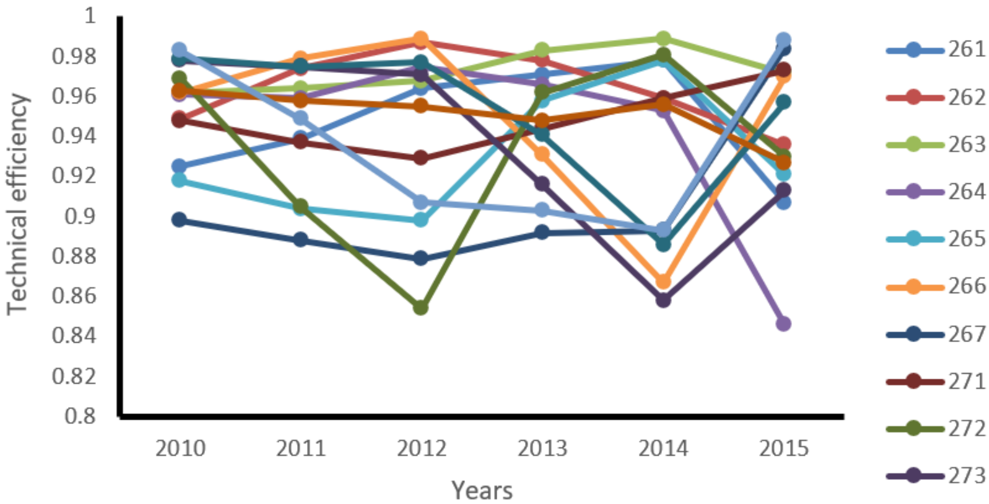

Figure 3. Changes in TE in all E&E sub-industries.

Figure 3 depicts the changes in the TE value in the E&E sub-industries from 2010 to 2015. Most sub-industries demonstrated positive efficiency in their operations, as there were minimal changes to the TE values within the year. However, there were big changes in TE for the following sub-industries: computers and peripheral equipment (MSIC 262), batteries and accumulators (MSIC 272), and irradiation, electromedical, and electrotherapeutic equipment (MSIC 266). In 2012, TE went down for MSIC 272 and MSIC 262. The MSIC 266 demonstrated decreased TE in 2014. Nevertheless, these sub-industries all bounced back to increase production efficiency after this decreasing trend. These phenomena might have started as a result of the rising demand for these sub-industries' products on a global scale, which encouraged more effective operations to produce maximum output. Nevertheless, the consumer electronics sub-industry (MSIC 264) demonstrated a declining trend from 2012 to 2015 as TE reached a nadir of 0.846 in 2015. Several factors may have caused this decline, such as industry relocation to lower-cost countries such as China and Vietnam, the Malaysian government introducing new policies that affected tax, and trade-related restrictions. In addition, reduced global demands for consumer electronic products after the Asian financial crisis significantly worsened industry productivity, consequently affecting TE (Raj-Reichert, 2020).

According to Economic Census (2011) the increase was a result of an increase in three factors: gross output value (RM4,365,336 billion), intermediate input value (RM3,102,652 billion), and wages and salaries (RM223,585 million). The Economic Outlook 2021 (MOF, 2019) predicted that the Malaysian E&E industry would leap forward in the wake of digital transformation through work from home (WFH) and virtual communication, which are part of new work practices. The lowest TE values for 2010 and 2015 were recorded for the optical instruments and photographic equipment sub-industry (MSIC 267, TE = 0.898) and the consumer electronics sub-industry (MSIC 264, TE = 0.846), respectively.

Table 4. Average TE scores and standard deviations for all E&E sectors in 2010–2015.

MSC code	Average TE score for 2010–2015	Standard deviation
261	0.947	0.0257
262	0.964	0.018
263	0.973	0.010
264	0.943	0.044
265	0.930	0.029
266	0.950	0.041
267	0.906	0.036
271	0.948	0.014
272	0.934	0.044
273	0.935	0.044
274	0.953	0.033
275	0.951	0.012
279	0.937	0.039
Average	0.944	0.012

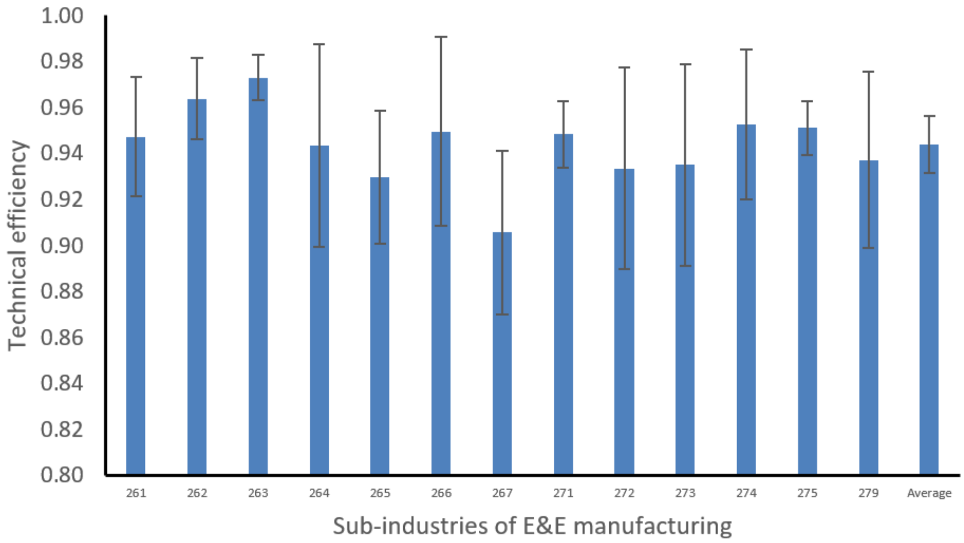

Figure 4. Average TE of all E&E sub-industries.

This study attempted to introduce the standard deviation as an indicator for monitoring TE value changes in the selected years. Recent scientific publications have used the standard deviation as an important indicator, such as for monitoring leaf phenology (Denéchère et al., 2021) the real-time growth stage of thin films (Wagner et al., 2022) and dipolar magnetic fields (Peqini & Duka, 2018).

Hypothetically, a low standard deviation indicates minimal TE changes and that the sub-industry progressively controls its production efficiency without significant factors inhibiting optimum output production. However, a high standard deviation might indicate the existence of important factors that influence TE value changes. In this study, the average standard deviation of the TE value was 0.012 (Table 4), indicating the continued growth of this sector and that its contribution to the GDP as the output (Table 2) increased from 2010 to 2015.

From 2010 to 2015, Figure 4 shows that the average TE values for MSIC 263 (communications equipment), MSIC 271 (electric motors, generators, transformers, and electricity distribution and control apparatus), and MSIC 275 (home appliances) were all close to each other.

This finding indicated that significant TE parameters such as demand and intermediate input continuously increased over time, indicating positive progress. The average TE values of MSIC 264 (consumer electronics), MSIC 266 (irradiation, electromedical, and electrotherapeutic equipment), MSIC 272 (batteries and accumulators), and MSIC 273 (wiring and wiring devices) exhibited higher standard deviations compared to those of the other E&E sub-industries.

As discussed earlier, these sectors have encountered several problems, including factory relocation to lower-cost nations, decreasing global demand, and stress from recent government policies inhibiting positive changes in the TE value.

5. CONCLUSIONS, IMPLICATIONS, AND SIGNIFICANCE

The study assessed the TE levels of Malaysian E&E manufacturing sub-industries using unbalanced panel data from 1880 firms recorded from 2010 to 2015. The translog production findings revealed significant efficiency for the E&E manufacturing sub-industries, implying that almost all firms operated efficiently to produce optimum output with an overall average TE value of 0.944%.

The MSIC 263 (communications equipment) and MSIC 266 (irradiation, electromedical, and electrotherapeutic equipment) demonstrated the highest average TE and consistency (0.989%) during the study period. The MSIC 264 (consumer electronics) demonstrated a notably lower TE level (0.846%) during the study period. The findings on the TE levels indicate that continued efforts to update technologies and innovation for human capital to address the E&E manufacturing sub-industries are highly limited. Better technology transfer and innovations would increase efficiency in converting input into output.

Therefore, Malaysia should leverage its strong E&E industry to spur the growth of these enabling technologies. Moreover, IR 4.0 technologies can be used to significantly improve E&E product manufacturing, and industry outputs should embrace digitalisation (EPU, 2021). Therefore, it is of great importance for E&E firms to become more efficient. This will lead to higher added value and a more competitive environment to strengthen the economy and withstand future economic and financial crises.

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