PARAMETRIC AND NON-PARAMETRIC TECHNIQUES IN ESTIMATING TECHNICAL EFFICIENCY OF CRUDE PALM OIL PRODUCTION IN MALAYSIA

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2019

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by

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Thesis submitted in fulfilment of the requirements for the degree of Master of Science

May 2019

ACKNOWLEDGEMENT

I am deeply grateful to my supervisors, Dr. Adli bin Mustafa of the School of Mathematical Sciences, Universiti Sains Malaysia, as well as Prof. Dr. Anton Abdulbasah Kamil, who was formerly at the Mathematics Section, School of Distance Education, Universiti Sains Malaysia, for their continuous encouragement, advice and support throughout the course of this research. May Allah accepts their ‘amal.

I would like to acknowledge receiving financial support and scholarship from the Jabatan Perkhidmatan Awam (JPA) and the Program Pelajar Cemerlang (PPC) of the Government of Malaysia throughout my study.

Last but not least, I would like to express my boundless appreciation to my family for their love, motivation and patience. May this effort be beneficial to all mankind.

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LIST OF ABBREVIATIONS

COLS	Corrected ordinary least squares
CPKO	Crude palm kernel oil
CPO	Crude palm oil
CRS	Constant returns to scale
DEA	Data envelopment analysis
DFA	Distribution free approach
DMU	Decision making unit
DOSM	Department of Statistics Malaysia
FDH	Free disposal hull
FELDA	Federal Land Development Authority
IRS	Increasing returns to scale
LP	Linear programming
LR	Likelihood ratio
MAD	Minimum absolute deviation
MC	Mill capacity
MPC	Malaysian productivity corporation
MPI	Malmquist productivity indices
MPOB	Malaysian Palm Oil Board
PORIM	Palm Oil Research Institute of Malaysia
PORLA	Palm Oil Registration and Licensing Authority
OLS	Ordinary least squares
SAA	Sample average approximation
SE	Scale efficiency

SFA	Stochastic frontier analysis
SDEA	Stochastic data envelopment analysis
TC	Technological change
TE	Technical efficiency
TFA	Thick frontier approach
TFP	Total factor productivity
VRS	Variable returns to scale

TEKNIK BERPARAMETER DAN BUKAN BERPARAMETER DALAM MENGANGGARKAN KECEKAPAN TEKNIKAL PENGELUARAN MINYAK KELAPA SAWIT MENTAH DI MALAYSIA

ABSTRAK

Tujuan utama kajian ini adalah untuk menggunakan teknik berparameter dan bukan berparameter dalam menilai kecekapan teknikal (TE) pengeluaran minyak sawit mentah (CPO) oleh negeri-negeri di Malaysia. Untuk mencapai matlamat ini, pendekatan analisis perbatasan stokastik berparameter (SFA) serta kaedah analisis penyusutan data (DEA) tak berparameter dan kaedah penyusunan data stokastik (SDEA) telah digunakan. Kajian ini melibatkan data panel yang terdiri daripada 12 negeri pengeluar CPO di Malaysia, dalam tempoh 18 tahun dari tahun 1999 hingga 2016. Pembolehubah output yang dipilih ialah pengeluaran CPO tahunan dan pembolehubah input dianggap sebagai kawasan perladangan, kapasiti kilang buah, buruh dan pembolehubah masa. Kami mendapati kapasiti kilang buah, buruh dan masa sebagai pembolehubah input yang ketara menjejaskan tahap output CPO. Kawasan perladangan terbukti secara statistik tidak bererti. Kecekapan teknikal didapati meningkat dari semasa ke semasa. Ia juga didapati bahawa ketidakcekapan dalam industri ini disebabkan oleh ketidakcekapan teknikal 'tulen' dan bukannya kecekapan skala. Keluaran yang dihasilkan daripada SFA, DEA dan SDEA telah dibandingkan. TE keseluruhan SFA, DEA dan SDEA masing-masing adalah 0.79, 0.88 dan 0.97. Di samping itu, telah didapati bahawa DEA menghasilkan nilai kecekapan yang mempunyai korelasi positif yang lemah kepada kedua-dua skor kecekapan yang dihasilkan daripada SFA dan SDEA. Sementara itu, keputusan dari SFA dan SDEA tiada korelasi. Kami mendapati bahawa pilihan teknik dalam

pengukuran kecekapan sangat mempengaruhi nilai kecekapan yang dianggarkan dan kedudukan kecekapan negeri dalam populasi. Johor, Sabah dan Perak adalah antara negeri pengeluar CPO yang paling cekap di bawah DEA dan SDEA tetapi berada di kedudukan sederhana di bawah SFA. Ini juga berlaku bagi Selangor yang merupakan negeri yang paling cekap mengikut SFA, namun hanya berjaya menduduki tahap sederhana di bawah DEA dan SDEA. Kami membuat kesimpulan bahawa negeri Kelantan dan Melaka secara keseluruhannya adalah negeri-negeri yang paling kurang cekap kerana ranking yang rendah dalam semua kaedah. Jumlah pengeluaran produktiviti faktor (TFP) pengeluaran CPO juga diperiksa menggunakan indeks perubahan Malmquist TFP, dianggarkan menggunakan kaedah DEA. Pulau Pinang mempunyai pertumbuhan purata tertinggi TFP pada purata peningkatan 3.7% setahun manakala negeri Sabah menjadi negeri dengan penurunan produktiviti purata tertinggi sekitar 7.6%.

PARAMETRIC AND NON-PARAMETRIC TECHNIQUES IN ESTIMATING TECHNICAL EFFICIENCY OF CRUDE PALM OIL PRODUCTION IN MALAYSIA

ABSTRACT

The main purpose of this study is to apply parametric and non-parametric techniques in evaluating the technical efficiency (TE) of crude palm oil (CPO) production by the states in Malaysia. To achieve this, the parametric stochastic frontier analysis (SFA) approach as well as the non-parametric data envelopment analysis (DEA) and stochastic data envelopment analysis (SDEA) methods were applied. This study involves a panel data consisting of 12 CPO producing states in Malaysia, over a 18 year time period from year 1999 to 2016. The output variable chosen was the annual CPO production and the input variables considered were plantation area, fruit mill capacity, labour and time variable. We found fruit mill capacity, labour and time as input variables that significantly affect the level of CPO output. Plantation area was proven to be statistically insignificant. Technical efficiency was found to be increasing over time. It was also found that the inefficiencies in the industry were mainly caused by 'pure' technical inefficiency rather than scale inefficiency. The outputs produced from SFA, DEA and SDEA were compared. The overall mean TE of SFA, DEA and SDEA are 0.79, 0.88 and 0.97 respectively. It was found that DEA produced efficiency values that have weak positive correlation to both the efficiency scores produce from SFA and SDEA. Meanwhile, the results from SFA and SDEA were uncorrelated. We discovered that the choice of technique in efficiency measurement greatly influences the efficiency values estimated and the efficiency rankings of the states. Johor, Sabah and Perak are

among the most efficient CPO producing states under DEA and SDEA but ranked average under SFA. This is also the case for Selangor which is the top efficient state according to SFA, however only managed to ranked average under DEA and SDEA. We concluded that the state of Kelantan and Malacca are overall the least efficient states due to their low ranking in all methods. The total factor productivity (TFP) change of CPO production was also examined applying the Malmquist TFP change index, estimated using the DEA method. Penang had the highest mean TFP growth at 3.7% average increase per year while the state of Sabah becomes the state with the highest mean productivity decline of around 7.6%.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Oil palm is the world's most rapidly increasing oil producing crop because of its low production cost and high oil yield per unit area per year compared to any other oil crop (Carter et al., 2007). The crop produces between eight to ten times more oil per hectare per year compared to annual oilseeds such as rapeseed or soybean (Basiron, 2007). World palm oil production increased 336% from 1980 at 5.0 million tonnes to 21.8 million tonnes in year 2000 (Abdullah & Sulaiman, 2013). Over the years it has been used for many different purposes; about 80% of the product is consumed by human, whilst the remaining goes to animal feeds, energy source and various industrial uses (Johnson, 2013).

Malaysia is one of the biggest palm oil producers in the world (Basiron, 2007). The country accounts for 44% of the world's exports of palm oil making the industry the fourth major revenue for the nation (MPC, 2014). The industry plays a huge role in the development of the country by reducing poverty rate from 50% in the 1960s, to less than 5% today. The success of the Malaysian palm oil industry, however, did not come without a price. From health campaign claiming the oil increased risk of heart diseases, alleged land grabs, deforestation and the extinction of the orang utan to the recent resolution by the European Parliament calling for the EU to phase out the use of palm oil in biodiesel that are allegedly produced in an unsustainable way, leading to deforestation.

With the continuous pressure and controversies surrounding the manufacturing of palm oil, it is only ideal that the Malaysian palm oil industry demonstrate sustainability by being more efficient in the usage of resources. Measuring efficiency is important not only to have a reliable record of the industry's progress, but also to be able to investigate the impact of any new and already existing implemented policies. Methods for estimating efficiency can be categorized into two, parametric approach and non-parametric approach. These approaches can either be deterministic or stochastic (Bogetoft & Otto, 2011).

Among the various methods developed, non-parametric data envelopment analysis (DEA) and parametric stochastic frontier analysis (SFA) are the most commonly used techniques for estimating technical efficiency (Baten et al., 2009; Hassan et al., 2012). The DEA and SFA techniques involve mathematical programming and econometric methods, respectively (Coelli et al., 2005). Both techniques have their own advantages and limitations. None of the approach can be said to be more superior to the other (Berger & Humphrey, 1997).

There is no need to impose any assumptions about the production functional form when applying DEA. The non-parametric frontier constructed by DEA is more flexible than a parametric frontier (Coelli et al., 2005). However, one of the limitations of DEA is that it does not deal with measurement errors or any other sources of statistical noise. Thus, the estimated efficiencies could be biased if the production process largely involves stochasticity (Baten & Kamil, 2010). Banker (1986), Sengupta (1992), Land et al. (1993), Olesen and Petersen (1995) and Cooper et al. (1998) are some authors who have suggested stochastic approaches to DEA to accommodate the existence of random error.

Previous literatures used various methods in studying the performance of the Malaysian palm oil industry; such as ordinary least squares (Azman, 2014; Ramasamy et al., 2005), data envelopment analysis (Afzal et al., 2018; Bushara & Mohayidin, 2007; Mohamad & Said, 2010; Wadud, 2008), system dynamics method (Lee, 2011), qualitative approach (Man & Baharum, 2011), techno-economic and sensitivity analysis (Ong et al., 2012) and Order-m frontier approach (Afzal et al., 2018).

The Malaysian palm oil industry is a highly regulated industry (MPC, 2014). The industry must abide by several Federal Acts concerning land access, environment, labour and occupational safety and health. Even though land matters fall under the Federal Act, the state authorities are empowered to make rules for enforcing this regulation in their respective states. Regulations on planning, construction of building, property taxes and licensing are also under the jurisdiction of the local government. Thus, it is of interest to see whether efficiency of palm oil production is affected under different state authorities. Previous works have not yet explored this possibility. The performance of the Malaysian palm oil industry had been evaluated based on plantation-based public companies (Ramasamy et al., 2005), different oil and fat sector (Bushara & Mohayidin, 2007), various manufacturing industries (Afzal et al., 2018; Mohamad & Said, 2010; Wadud, 2008) and palm oil mill's capacity (Azman, 2014; Man & Baharum, 2011).

1.2 Statement of the Problem

Palm oil is one of the biggest produce commodities in Malaysia (MPC, 2014). Its significance to the country's economy is high as Malaysia has become one of the top producers in the world (Basiron, 2007). The industry is highly regulated at the federal, state and local government levels with the states having authority on matters such as land. As available resources would eventually reach a limit, being efficient and becoming more efficient in production has become more crucial. To improve in this matter, measuring technical efficiency is important as an indicator of whether available resources are used to the fullest to produce the maximum potential crude palm oil (CPO) output. To our knowledge, no study has yet used the most applied parametric SFA and non-parametric DEA techniques to find the efficiency of producing CPO by the states in Malaysia. There is also an interest to view the results obtained from the SDEA method that has the advantages of a non-parametric technique but also allows for stochasticity in the data. The result could be an indicator to where each state stands in terms of producing CPO efficiently among the states in Malaysia. This can serve as a planning aid for management and policy makers to draw conclusion on existing and new regulations.

1.3 Purpose of the Study

To apply parametric and non-parametric techniques in estimating the technical efficiency of crude palm oil production by the states in Malaysia.

1.4 Objectives of the Study

1) To estimate the technical efficiency of producing crude palm oil in Malaysia using SFA, DEA and SDEA.
2) To measure the total factor productivity change using the Malmquist index by applying a DEA like linear program.
3) To compare the outputs from SFA, DEA and SDEA techniques as well as identifying the advantages and limitations of implementing the different analytical methods.

1.5 Scope of the Study

The technical efficiency (TE) of crude palm oil (CPO) production is estimated by using stochastic frontier analysis (SFA), data envelopment analysis (DEA) and stochastic data envelopment analysis (SDEA) methods. This study is applied to a panel data consisting of 12 CPO producing states in Malaysia, over an 18-year time period from year 1999 to 2016. The states involved are the state of Johor, Kedah, Kelantan, Malacca, Negeri Sembilan, Pahang, Penang, Perak, Selangor, Terengganu, Sabah and Sarawak. The annual CPO production is chosen as the output variable. A total of four input variables are considered in this study. They are plantation area, fruit mill capacity, labour and time variable. For the SFA approach, we will apply the model specification of Battese and Coelli (1992) while for the SDEA part, the model proposed by Banker (1986) is applied. For the DEA approach, the constant returns to scale (CRS) model by Charnes et al. (1978) and the variable returns to scale (VRS) model by Banker et al. (1984) are both applied. The total factor productivity (TFP) change of CPO production is also examined by applying the Malmquist TFP change index by Färe et al. (1994), estimated using the DEA method. The data analysis for the SFA, DEA and SDEA methods are carried out using the computer software FRONTIER 4.1, DEAP 2.1 and LINDO 6.1, respectively.

CHAPTER TWO

LITERATURE REVIEW

2.1 Basic Theory: Efficiency Measurement

According to Farrell (1957), the efficiency of a firm could be looked at from two components; technical efficiency and allocative efficiency. Technical efficiency is the ability of a firm to produce the maximum amount of output from a given set of inputs. Meanwhile, allocative efficiency represents the firm's ability to use the optimal proportions of inputs given their respective prices and the production technology. This study focuses on technical efficiency (TE). Consider Figure 2.1 which displays a production process with a single input (*x*) that is used to produce a single output (*y*).

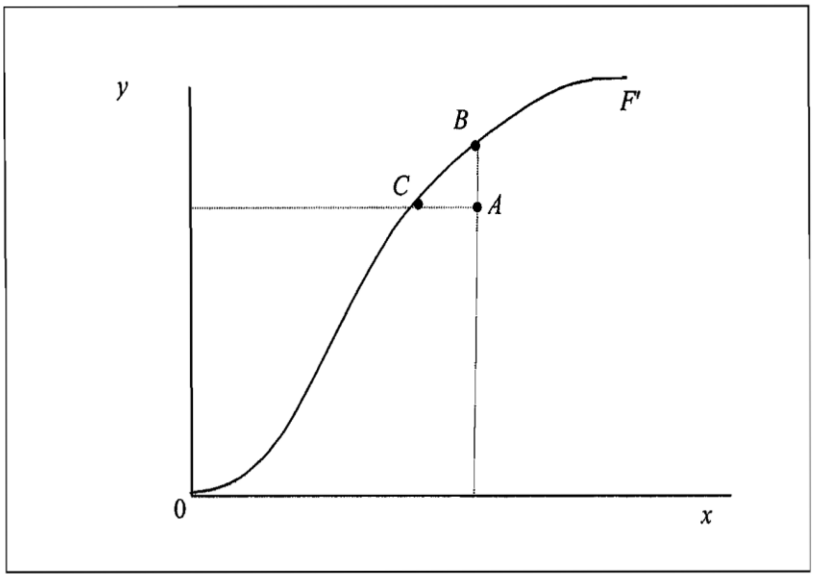

Figure 2.1: Production frontiers and technical efficiency. Source: Coelli et al. (2005).

The line $0F'$ represents the production frontier where the maximum potential output could be produced from the respective input level. The firms operating at point B and C are technically efficient firms. If a firm operates at point A, then it is considered technically inefficient since with the available input, the firm should be able to produce output at point B. Another way of looking at this is the firm at point C produces the same amount of output as the firm operating at point A but with a lesser input used.

To measure technical efficiency, we must first estimate the unknown production frontier. Methods for estimating the frontier can be categorized into two approaches, parametric approach and non-parametric approach. These approaches can either be deterministic or stochastic as shown in Table 2.1.

Table 2.1: The taxonomy of efficiency measurement. Source: Bogetoft & Otto (2011).

Approach	Deterministic	Stochastic
Parametric	Corrected Ordinary Least Squares (COLS)	Stochastic Frontier Analysis (SFA) Thick Frontier Approach (TFA) Distribution Free Approach (DFA)
Non-Parametric	Data Envelopment Analysis (DEA) Free Disposal Hull (FDH)	Stochastic Data Envelopment Analysis (SDEA)

Corrected Ordinary Least Squares (COLS)

Aigner and Chu (1968) proposed the corrected ordinary least squares (COLS), an extension of the ordinary least squares (OLS) estimation. The COLS method adjusts the OLS frontier upward with the maximum error term to ensure that all observations are below the estimated frontier. This creates a frontier that represents the maximum possible production. The advantage of the COLS method compared to a mathematical programming method is that COLS permits the testing of hypotheses (Coelli & Perelman, 1999).

Data Envelopment Analysis (DEA)

The core of the data envelopment analysis (DEA) technique is deterministic and involves the use of linear programming methods. Farrell (1957) proposed a non-parametric piece-wise-linear convex hull approach over the data for frontier estimation. To accomplish this Boles (1966) and Afriat (1972) proposed mathematical programming methods. The term 'data envelopment analysis' (DEA) was first used in the work by Charnes et al. (1978). They suggested a model assuming constant returns to scale (CRS). The frontier is a piece-wise linear isoquant determined by all the firms in the sample. All deviations from the frontier are considered to be cause by inefficiency. An efficiency score below 1 would indicate an inefficient firm while a value of 1 represents a point on the frontier indicating a technically efficient firm. Banker et al. (1984) proposed a model for variable returns to scale (VRS) situations. This method yields technical efficiency (TE) scores greater than or equal to the CRS TE because this approach forms a convex hull of intersecting planes that envelop the data points more tightly than the CRS conical hull (Coelli et al., 2005).

If the CRS TE and VRS TE are known, the scale efficiency (SE) of the firm can be calculated. Even if a firm is technically efficient, there is still a possibility of it being scale inefficient which means that the firm is not operating at optimal scale size, resulting in lower productivity. Figure 2.2 shows the effect of scale on productivity with a single input, single output production.

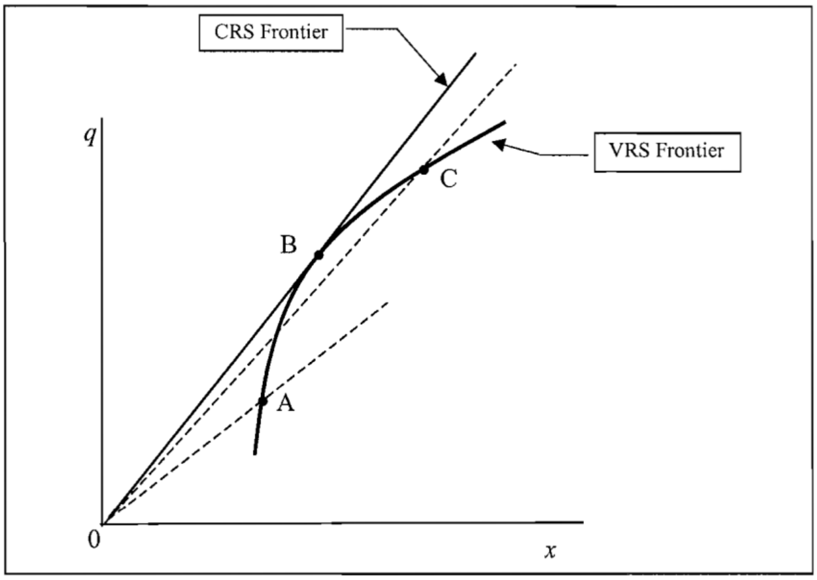

Figure 2.2: The effect of scale on productivity. Source: Coelli et al. (2005).

Firms operating at point A, B and C are all fully efficient firms scoring TE of 1 under the VRS DEA function, producing the maximum output respective to their input. However, their productivity varied. The slopes of the lines 0A, 0B and 0C represent the productivity measurement of *q*/*x*. Point B has the highest productivity measurement and is the point of optimal scale being the most productive scale size since it is on the CRS frontier. Firms operating at A and C are said to have scale inefficiency and can increase their productivity and CRS TE (overall efficiency) values by adjusting their operation to move closer to point B. Scale efficiency value shows how close a firm is to optimal scale and can be calculated by the ratio of the CRS TE to the VRS TE of a firm (Färe et al., 1998).

Some other extensions of the DEA technique includes super efficiency (Andersen & Petersen, 1993), bootstrap methods (Simar & Wilson, 1998), the additive model (Charnes et al., 1985) and the flexible disposable hull (FDH) approach (Deprins & Simar, 1984).

Free Disposal Hull (FDH)

The non-parametric free disposal hull (FDH) method is considered as an alternative to the DEA approach in measuring efficiency. The model was developed by Deprins, Simar, and Tulkens (1984) and later extended by Lovell et al. (1994). The FDH model assumes the free disposability relaxing the convexity assumption of basic DEA models, in defining the production possibility set from the observations.

Stochastic Frontier Analysis (SFA)

The specification of the stochastic frontier production model was originally independently proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) for cross-sectional data on *I* firms:

$$\ln q_i = \boldsymbol{x}_i'\boldsymbol{\beta} + v_i - u_i \qquad i = 1, \ldots, I, \tag{2.1}$$

where q_i is the ouput of the i-th firm, $\boldsymbol{x}_i$ is a vector (K x 1) containing the logarithms of the inputs, $\boldsymbol{\beta}$ is a vector of unknown parameters, v_i is a symmetric random error which represents statistical noise and u_i is a non-negative random variable accounting for technical inefficiency assumed to follow a half-normal distribution. The observed output values are bounded from above by the stochastic frontier outputs, $\exp(\boldsymbol{x}_i'\boldsymbol{\beta} + v_i)$. The stochastic frontier output is where outputs level are with no inefficiency effects representing the potential output that could be produced by a fully efficient firm given the same set of inputs. Since the v_i term can take positive or negative values, therefore the stochastic frontier outputs can be above or below the deterministic component of the frontier model, $\exp(\boldsymbol{x}_i'\boldsymbol{\beta})$. The measurement of technical efficiency is the ratio of the observed output value to the corresponding stochastic frontier output. Coelli et al. (2005) illustrated this concept of the stochastic frontier production model by a single output (q_i), single input (x_i) production with a Cobb-Douglas functional form shown in Figure 2.3:

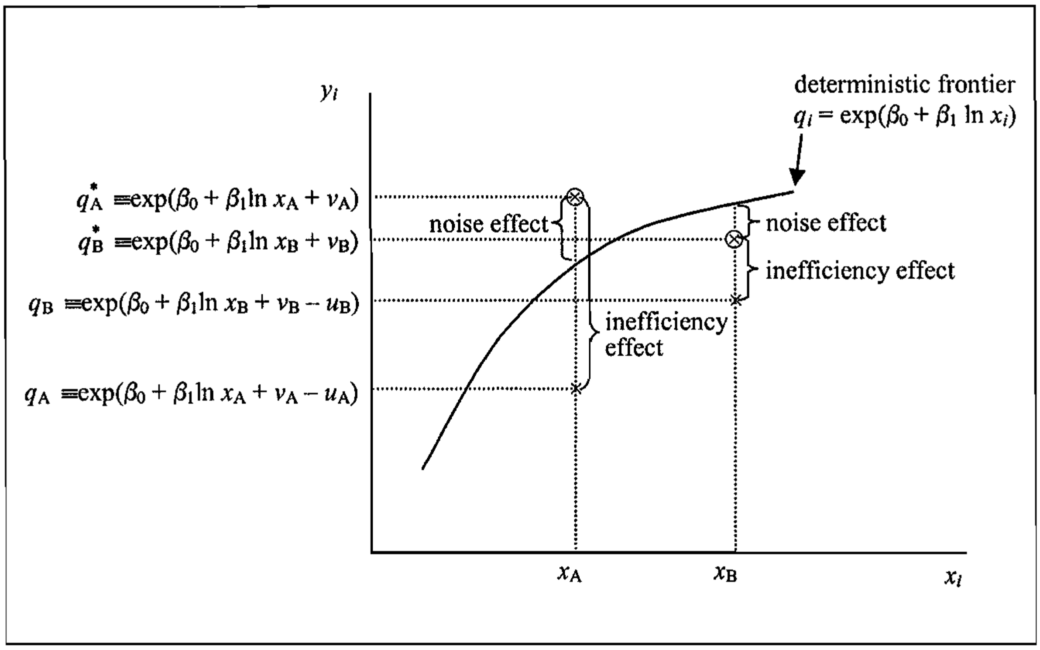

Figure 2.3: The stochastic production frontier. Source: Coelli et al. (2005).

Firms A and B produce output at q_A and q_B using the input at x_A and x_B, respectively. q_A* and q_B* are the stochastic frontier outputs for firm A and B, respectively, where $u_A = 0$ and $u_B = 0$. The stochastic frontier output, q_A* is above the deterministic frontier because $v_A > 0$ while q_B* is below the deterministic frontier due to $v_B < 0$. The technical efficiency of firm A and B would be q_A / q_A* and q_B / q_B* respectively.

The Cobb-Douglas function and the transcendental logarithmic (Translog) function are the two most commonly applied functional forms in SFA (Mustapha, 2011). The selection of the functional form for the model in an analysis is crucial because it can significantly affect the results (Ferdushi, 2013). For the inefficiency effects model, a half-normal or truncated normal distribution are often considered due to the simplicity of estimation and interpretation (Kirkley et al., 1995).

Many studies have been done, extending and altering the original SFA model to accommodate different types of data set and production situations. The most common applied include the works by Battese and Coelli (1992) and Battese and Coelli (1995). Battese and Coelli (1992) extended the stochastic frontier model to accommodate panel data where the inefficiencies are assumed to follow a truncated normal distribution and are allowed to be time-variant. There has been interest to identify factors causing inefficiency between firms in an industry. Battese and Coelli (1995) proposed a stochastic frontier model permitting panel data, where the inefficiency term (u_i) is in the form of a function containing a vector of firm-specific variables and a random error.

Thick Frontier Approach (TFA)

The thick frontier approach (TFA) of Berger and Humphrey (1992) sorts the data based on average production. Two "thick-frontiers" are estimated, one for the lowest and one for the highest average production quartile of firms. Average inefficiency of the highest quartile firms is then computed by comparison of the two thick frontiers. No assumptions are made regarding the random error and inefficiency terms distributions. The disadvantage of TFA is in the case of increasing returns to scale, the approach tends to omit small efficient firms, while large efficient firms tend to be omitted in the case of decreasing returns to scale (Wagenvoort & Schure, 2006).

Distribution Free Approach (DFA)

Berger (1993) introduced the distribution-free approach (DFA) where it is called "distribution free" since no specific distribution for the inefficiency component is chosen. This approach is used when both cross-sections and time-series data are available. Berger assumed that the managerial inefficiency is stable over time, meaning inefficiency is constant over time. Besides that, it is presumed that the random noise will cancel out over the years.

Stochastic Data Envelopment Analysis (SDEA)

Various studies have been done to incorporate statistical noise in the DEA method. Among some of these work includes chance-constrained DEA, fuzzy DEA and interval DEA. Banker (1986) allows the possibility of random errors in deviations in the traditional DEA by adding a symmetric two-sided error component to the model. The result is a non-parametric stochastic approach that includes both the VRS DEA model and the minimum absolute deviation (MAD) regression model. Banker et al. (1991) extended this method to allow the simultaneous consideration of inputs, outputs and other factors so that the impact of factors influencing productivity can be examined.

Chance-constrained programming was developed by Charnes and Cooper (1963) and Kall et al. (1976). This programming method was designed to allow violation of constraints, but not too frequently (Land et al., 1993). Land et al. (1993) and Olesen and Petersen (1995) applied the chance-constrained programming into the estimation of efficient frontiers where some of the decision making unit (DMUs) are allowed to cross outside of the frontier with a certain probability.

A fuzzy systems approach in DEA was first proposed by Sengupta (1992). Fuzzy DEA models deal with situations where measuring the efficiency of DMUs involves imprecise or vague input and output data. The precise data may not be available due to unquantifiable, incomplete or non-obtainable information (Hatami-Marbini et al., 2011). Fuzzy DEA methods can be classified into four categories; the tolerance approach (Kahraman & Tolga, 1998; Sengupta, 1992), α-level based approach (Girod, 1996; Kao & Liu, 2000; Saati et al., 2002), the fuzzy ranking approach (Guo & Tanaka, 2001, 2008) and the possibility approach (Guo et al., 2000; Lertworasirikul et al., 2003; Ramezanzadeh et al., 2005).

Interval DEA or imprecise DEA was also developed to cope with uncertain input or output data. The method was first introduced by Cooper et al. (1999) where the method proposed allows the mixtures of imprecise with exactly known data, transforming it into an ordinary linear programming forms. Despotis and Smirlis (2002) transform a non-linear DEA to an equivalent linear programming without applying scale transformation on the data first. Transformations are only applied on the variables made on the basis of the original data.

Total Factor Productivity (TFP)

Productivity of a firm can be displayed by the ratio of output(s) that it produces to the input(s) used:

$$\text{productivity} = \frac{\text{outputs}}{\text{inputs}} \tag{2.2}$$

The larger the value of this ratio, the better the performance of the firm. The above ratio is easy to measure in single output and single input cases, but becomes complex for multiple outputs or multiple inputs situations (Coelli et al., 2005). Total factor productivity (TFP) is a productivity measurement involving all factors of production. It is the ratio of the aggregate output to the aggregate input. TFP change is associated with the movement in the productivity performance of a firm over time. The techniques for calculating productivity include the Malmquist approach to productivity measurement, the Hicks-Moorsteen approach (Diewert, 1992), profitability ratios and the component-based approach (Balk, 2001).

In this study, we applied the Malmquist TFP change index using DEA approach. The Malmquist TFP index was introduced by Caves et al. (1982) where TFP change was measured by comparing the observed outputs in period t and t+1 with the maximum feasible level of outputs (keeping the output mix constant) that can be produced given inputs x_t and x_{t+1}, operating under the reference technology. The productivity change could be due to efficiency change and/or technological change.

2.2 Background of the Malaysian Palm Oil Industry

The oil palm tree, which originated from West Africa, was first brought to Malaya by the British in 1870s. Henri Fauconnier was the first to establish a commercial oil palm plantation in Tennamaram Estate, Selangor. In the early 1960s, the cultivation of oil palm increased significantly due to the government's programme to promote the crop so that dependency of the country's economy on rubber and tin can be reduced. The government introduced land settlement schemes for oil palm cultivation among the rural poor and landless. Currently, only a quarter of the total oil palm plantation areas are under Government land schemes, for example, the Federal Land Development Authority (FELDA). The remaining plantation areas are owned by private companies.

Malaysian Palm Oil Board (MPOB) is the main regulator of the Malaysian oil palm industry. It was established in year 2000 from the mergers of the Palm Oil Research Institute of Malaysia (PORIM) and the Palm Oil Registration and Licensing Authority (PORLA). Its main function is to develop programmes, implement policies, regulate and promote all matters relating to Malaysian oil palm industry (MPOB, 2013). MPOB also conducts research and development in the field and becomes the resource centre for information regarding the oil palm industry.

The largest importer of Malaysian palm oil products is China while Netherlands is the main importer of crude palm oil (CPO) from Malaysia. Other markets include India, the EU, Japan and Iran.

There are two types of oil produced from the fruits of the oil palm tree; crude palm oil (CPO) and crude palm kernel oil (CPKO). While palm kernel oil is mainly saturated fatty acid, palm oil is more balance in terms of the ratio between saturated and unsaturated fatty acid. They are used in food products such as cooking oil, margarine, ice cream and non-diary creamers. These two oils are also used in an array of non-food products including soaps, fragrance, candles, in cosmetic products and in rubber products.

2.3 Previous Research

Krasachat (2001) had studied the technical efficiency of Thai oil palm farms in the year 2000 by using the data envelopment analysis (DEA) approach. He found that scale inefficiency made a greater contribution to the overall inefficiency.

Hasnah et al. (2004) studied the performance of a nucleus estate and smallholder scheme for oil palm production in West Sumatra, Indonesia. They measured their technical efficiency by using a stochastic frontier analysis. Their results indicated a mean technical efficiency of 66%.

Ramasamy et al. (2005) analysed the effects of market structure components and other performance measures, particularly the effects of firm size and firm ownership on profitability, within the Malaysian palm oil sector. They found that size is negatively related to performance while privately owned plantation companies are more profitably managed.

Iwala et al. (2006) investigated the productivity and technical efficiency of oil palm production among oil palm farmers in Nigeria using the Cobb-Douglas stochastic frontier production function analysis. The data were collected from 241 oil palm farms from six local government areas of Edo and Ondo states. The results showed that the predicted technical efficiencies varied widely across the farms, ranging between 0.403 and 0.999.

Basiron (2007) highlighted the development of oil palm cultivation and responsible farming practices in Malaysia. R&D activities and technological advances have raised yields and reduce inputs, maximizing oil production from a smaller land area. Palm oil is now a major source of sustainable and renewable raw material for the world’s food, oleochemical and biofuel industries. Downstream activities have uplifted the quality of life of people on a sustainability platform.

Bushara and Mohayidin (2007) reported the application of the frontier analysis based on deterministic data envelopment analysis (DEA) on the economic performance and competitiveness of Malaysian oil and fat industry in the years 1985 to 1996. The study was able to determine the technical efficiency, scale efficiency and productivity changes. Innovation was improving in a gradual and slow increment of technological change (TC) over time. Scale inefficiency due to operating on increasing return to scale (IRS) was proven. Efficiency change was contributing substantially to the total factor productivity progress and technical change.

Wadud (2008) estimated the productivity growth in Malaysian manufacturing over the period 1983-1999 by computing Malmquist productivity indices (MPI) using non-parametric data envelopment analysis (DEA) type linear programming. Results indicated that a high majority of the industries operated with low levels of technical efficiency with little or no improvement over time. Two-third of the industries experienced average annual productivity improvement ranging from 0.1% to 7.8%. Ninety-five industrial categories recorded average annual technical progress while technical efficiency improvement was achieved by 53 industries.

Mohamad and Said (2010) used data envelopment analysis (DEA) to compute and analyse the decomposition of Malmquist index of total factor productivity (TFP) into technological change, technical efficiency change and scale efficiency change for selected Malaysian food manufacturing sub-industries for the period 2002 to 2007. The results suggested that the TFP growth was largely due to positive technological change rather than technical efficiency change.

Lee (2011) tried to identify factors causing low production efficiency for the last 20 years in Malaysia's palm oil production. He used the system dynamics method. He found that the problem was due to low fresh fruit branch yield and low oil extraction rate. Production efficiency had weak relationship to labour.

Man and Baharum (2011) applied a qualitative approach to identify the major cost influencing factors in the production of crude palm oil (CPO) from two palm oil mills in Sabah, Malaysia for the year 2009. They concluded that palm oil mills with higher production capacity were efficient in producing CPO than lower production capacity palm oil mills.

Ong et al. (2012) assesses several limiting factors which impede the development of biodiesel by undertaking a techno-economic and sensitivity analysis of biodiesel production in Malaysia, the second largest producer of crude palm oil feedstock. It was found that the life cycle cost for a 50 kilotons palm biodiesel production plant with an operating period of 20 years was $665 million, yielding a payback period of 3.52 years. The largest share was the feedstock cost which accounted for 79% of total production cost. Sensitivity analysis results indicated that the variation in feedstock price would significantly affect the life cycle cost for biodiesel production. One of the most important findings of this study was that biodiesel price was compatible with diesel fuel when a fiscal incentive and subsidy policy were implemented.

Emokaro and Ugbekile (2014) focused on the economics of oil palm processing in Ovia North East and Ikpoba-Okha Local Government Areas of Edo State, Nigeria, in order to identify gaps that could be exploited. Primary data used were collected through questionnaire, administered on 120 randomly selected oil palm processors in the study area. Descriptive statistics, budgetary analysis and the Stochastic Frontier Production Function were used in analysing the data. Results of the Stochastic Frontier Production Function analysis indicated that the major factors that influenced the output of oil palm processing enterprise were palm fruits, water and labour. Major factors which influenced the technical efficiency were processing experience and membership of cooperative society.

Azman (2014) set out to evaluate the technical efficiency of palm oil mills in Malaysia. He wanted to see whether large mills are more efficient than small mills and also wanted to compare the technical efficiency between integrated and non-integrated mills. Econometric approach was used whereby crude palm oil production function in a Cobb-Douglas model form was estimated by using OLS technique. It was found that large mills which have processing capacity of more than 20 t/hr are more efficient than small mills. Integrated mills are also more efficient compared to non-integrated mills.

Euler et al. (2016) explores yield gaps and production constraints in smallholder oil palm production systems based on crop modeling analysis and farm household survey data from Sumatra, Indonesia. The results showed that only around 50% of the cumulative exploitable yield over a 20-year plantation life cycle were obtained by the farmers. Furthermore, the yield gaps were the largest during the most productive phase of oil palm. Significant determinants of yield gaps are found to be management practices such as fertilizer dosage, length of harvesting intervals and plant mortality. They concluded that farmers' awareness about the changing management requirements of oil palm over the plantation life cycle needs to be enhanced.

Afzal et al. (2018) evaluated the performance and change in the technical as well as technological efficiency in the total factor productivity of the 34 food processing industries in Malaysia. The study investigates the changes in their efficiency from 2009 to 2010 by applying two recent methods of data analysis, namely order-m and Malmquist productivity index. The Manufacturer of Crude Palm Oil was shown to be one of the best performing industries, having an efficiency score of 1 in both years. The CPO manufacturing industry also achieved a 95.1% change in TFP.

CHAPTER THREE

MATERIALS AND METHODS OF ANALYSIS

3.1 Materials

For the purpose of analysis, a set of secondary data from different sources was chosen to be the sample data. The characteristics of the data set and the variables used are explained in this section.

3.1.1 Data Sources and Types

The data set used for the analysis is a panel data on the annual production of crude palm oil in Malaysia. This information was collected from the Malaysian Oil Palm Statistics report published annually by the Economics and Industry Development Division, which is a division under Malaysian Palm Oil Board (MPOB, 1999-2016). The Economics and Industry Development Division's main role is to collect, monitor and publish data regarding the performance of the palm oil industry in Malaysia. Besides that, all of the inputs concerning the labour data were obtained from the Malaysia Economics Statistics-Time Series 2016 report (DOSM, 2017) and the Labour Force Survey Time Series Statistics by State, 1982-2017 (DOSM, 2018) that were published by the Department of Statistics Malaysia. The department delivers Malaysia's official statistics covering everything from population to economics.