Decomposition of Productivity Growth of the Malaysian Palm Oil Mill Sector

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ABSTRACT

This study investigates total factor productivity (TFP) growth in the Malaysian palm oil mill sector over the period 2005-2010, using a Stochastic Frontier Approach (SFA) model. TFP growth was decomposed into three components, namely, technical efficiency (TE), technical progress (TP) and scale components (SEC). The empirical results show that productivity growth was driven mainly by TE for all palm oil mills, followed by TP. However, a change in the scale components had a negative effect on productivity growth. Overall, the study suggests that there are opportunities to improve productivity growth in the Malaysian palm oil mill sector.

Keywords: Malaysian palm oil mill, total factor productivity, technical progress, technical efficiency, scale components.

INTRODUCTION

The concept of productivity growth has been widely used to assess the economic performance of firms, industries and countries. Productivity growth is usually calculated as the growth of output relative to the growth of input. If output grow relatively more quickly, then there is a kind of welfare improvement, as relatively more output can be produced for relatively less input.

Productivity is an important indicator for industrial enterprises to sustain long-term growth and to attain stable profitability in a competitive environment. Hence, to increase competitiveness and remain in the domestic and international markets, the industry should improve its performance, implicating two of the most important performance characteristics in the industrial sector, namely, efficiency and productivity growth (Fox, 2005).

Both productivity growth and efficiency have been widely used in literature to explain the performance of industrial organisations. They can be used to determine living standard, which means a firm can distribute more wealth to all stakeholders, including its workers, board of management, owner/s, consumers,

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suppliers and the government. With higher productivity growth, there will be lower inflation while competitiveness of the industries will be improved. In contrast, slower productivity growth limits the rate at which real income improves (Mohamad Yodfiatfinda *et al.*, 2012).

The source of economic growth can be due either to an input-driven scenario (factor accumulation) or an increase in productivity. If it is due to productivity growth, there is a further need to decompose its determinants. Once the source of economic growth is identified, decision-makers will be able to provide aids and directions in their decision-making process.

Traditionally, productivity can be mathematically defined as the relationship between a set of input values and a set of output values. This provides the basis for the concept of partial productivity, which represents the change in output produced corresponding to each input used, such as labour productivity and capital productivity (Nordin and Fatimah, 2010).

However, as technology progresses, it is observed that it is possible to produce more from less input by adopting better means and methods of production. It is therefore essential to conduct and analyse the productivity trends as well as the technological changes in order to understand the industrial situation and the productivity dynamics. Output or productivity growth is therefore not attributed only to growth in input. Improvement in input quality, efficient use of production processes, adoption of new technology and other non-physical factors do contribute to the dynamics of productivity growth. These non-physical contributions are collectively known as total factor productivity (TFP). In short, TFP addresses any effect on total output not caused by input or economies of scale, and is often found to be a significant contributor to output growth.

Improvement in TFP will enable the industry to generate a larger output from the same resources, hence shifting it to a higher frontier. The technological change component of productivity growth captures shifts in frontier technology, and can thus be interpreted as providing a measure for innovation. Technical efficiency improvement or the catching-up effect, on the other hand, is measured by the difference between the frontier output and the realised output. Thus, decomposing TFP into technological change and technical efficiency change is useful for distinguishing innovation or adoption of new technology by best practice firms from the diffusion of technology (Nordin and Fatimah, 2010).

The Malaysia Productivity Corporation (MPC) has produced a report on productivity performance in Malaysia in the last decade. According to the report, Malaysia's productivity performance grew by 2% in 2012 (MPC, 2013). The highest productivity growth was in the construction sector (15.5%), followed by manufacturing (4.5%) and services (1.8%). Sectors that exhibited a decline in productivity were agriculture (-11.2%) and mining (-4.4%) (MPC, 2013).

Malaysia recorded an average economic growth of 5.1% over 12 years, from 2000-2012, which was supported by productivity growth of 2% to the level of RM 58 874 and 1.6% employment growth. Domestic economic growth resulted from TFP growth of 1.6%, capital intensity of 2% and labour intensity of 1.5%. Over the period 2000-2012, the contribution of TFP to national economic growth was 31.6%, while capital contributed 39.3% and labour 29.1% (MPC, 2013).

On a sectoral basis, agriculture recorded a decline in productivity growth by 11.24%, dropping to RM 34 182 in 2012. For the period 2000-2012, TFP growth for the agricultural sector recorded 1.46%, leading to an output growth of 3.4%, while capital and labour contributed 1.9% and 0.05%, respectively.

Productivity of the manufacturing sector grew by 4.52% amounting to RM 83 878 in 2012. For the period 2000-2012, TFP growth for the manufacturing sector was 2.52%, resulting in an output growth of 5.12%, while capital and labour contributed 2.14% and 0.46%, respectively.

Meanwhile, productivity growth of the palm oil industry was only 0.95%, compared with an average growth rate of 4.52% by the manufacturing sector. The productivity level of the industry strengthened to RM 185 200 compared with the previous year which registered RM 183 400. The industry has also strengthened and experienced a steady increase in the level of added value at 1.32% growth in 2012 (MPC, 2013).

Despite there being extensive literature on TFP growth in the Malaysian manufacturing sector, no other studies have used a Stochastic Frontier Production model to measure and decompose TFP growth, specifically in the Malaysian palm oil mill sector. Thus, this article is the first attempt to decompose TFP growth in the Malaysian palm oil mill sector using such a production model. TFP growth was decomposed into three components, namely, technical efficiency (TE), technical progress (TP) and scale components (SEC). This article aims to provide additional insights on the productivity level of the palm oil mill sector, to enable us to examine a firm's individual TFP performance by using micro-level firm data.

DECOMPOSITION AND FUNCTIONAL FORM

Decomposition of TFP[1]

A stochastic frontier production function is defined by:

$$y_i = f(x_{it},t)\exp(-u_{it}) \quad (1)$$

where:
y_{it} is the output of the i^{th} firm ($i = 1, \ldots, N$) in the t^{th} time period ($t = 1,\ldots,T$);
f(.) is the production function;
x is an input vector;
t is a time trend index that serves as a proxy for technical change; and
$u \geq 0$ is output-oriented technical inefficiency.

Note that technical inefficiency in Equation (1) varies over time.

By totally differentiating the logarithm y in Equation (1) with respect to time, the change in production can be represented as:

$$\dot{y} = TP + \sum_j \varepsilon_j \dot{x}_j - (\partial u/\partial t) \quad (2)$$

where $\varepsilon_j = \partial in\ fl\ \partial in\ \dot{x}_j$ is the output elasticity of factor input j, while a dot over a variable indicates its rate of change. The overall productivity change is affected not only by TP and changes in input use but also by a change in technical inefficiency.

By substituting Equation (2) into TFP growth, $TFP = \dot{y} - \sum_j S_j \dot{x}_j$, where Sj is input j's share in production costs, is then rewritten as:

$$TFP = TP - (\partial u/\partial t) + (RTS - 1) \sum_j \lambda_j \dot{x}_j + \sum_j (\lambda_j - S_j)\, \dot{x}_j \quad (3)$$

where $RTS (= \sum_j \varepsilon_j)$ denotes the measurement of returns to scale, and $\lambda_j = fi\ x/\sum_j fi\ xi = \varepsilon_i = \varepsilon_i/RTS$. The last component in Equation (3) measures inefficiency in resource allocation resulting from deviations in input prices from the value of their marginal product. Thus, in Equation (3), TFP growth can be decomposed into TP, the TE change ($-\partial u/\partial t$), the scale components $[(RTS - 1) \sum_j \lambda_j x_j]$ and allocative efficiency change $\sum_j (\lambda_j - S_j)\, x_j$.

If technical inefficiency does not exist or is time-invariant, the above decomposition implies that technical inefficiency does not affect TFP growth, as in the Solow residual approach. If technology exhibits constant returns to scale, the TFP growth formula in Equation (6) is identical to the one derived by Nishimizu and Page (1982).

Functional Form

In this study, the Stochastic Production Frontier model is used but was modified from the earliest version by Coelli (1996). They proposed a time-varying model for TE effects in the Stochastic Frontier Production for panel data. In this study, the maximum-likelihood estimates of the parameters of the model and the predictors of TE were calculated using the computer program called Frontier. Details of the program are found in Coelli (1996), and the method can be outlined as follows:

$$1nV_i = X_i\beta + (v_i - u_i) \quad (4)$$

where:
$ln\ V_i$ is the log of scalar output for i^{th} firm;
X_i is the row of logs of K inputs by i^{th} firm; and
β is the column vector of K unknown coefficients.
while $(v_i - u_i)$ captures measurement error, random factors and other noise.

Two production processes that can be utilised in this study are represented by $Q = f(K, L, M)$ and $V = f(K, L)$. They will be represented by the following respective translog production functions:

$$ln\ Q_{it} = \alpha_0 + \alpha_t\, T + \alpha_K \ln K_{it} + \alpha_L \ln L_{it} + \alpha_M \ln M_{it} + 0.5\, \beta_{KK} (\ln K_{it})^2 + 0.5\, \beta_{LL} (\ln L_{it})^2 + 0.5\, \beta_{MM} (\ln M_{it})^2 + \beta_{KL} \ln K_{it} \ln L_{it} + \beta_{KM} \ln K_{it} \ln M_{it} + \beta_{LM} \ln L_{it} \ln M_{it} + \beta_{Kt} \ln K_{it}T + \beta_{Lt} \ln L_{it}T + \beta_{Mt} \ln M_{it}T + 0.5\beta_{tt}T^2 + \varepsilon_{it} \quad (5)$$

and

$$ln\ V_{it} = \alpha_0 + \alpha_t\, T + \alpha_K \ln K_{it} + \alpha_L \ln L_{it} + 0.5\, \beta_{KK} (\ln K_{it})^2 + 0.5\, \beta_{LL} (\ln L_{it})^2 + \beta_{KL} \ln K_{it} \ln L_{it} + \beta_{Kt} \ln K_{it}T + \beta_{Lt} \ln L_{it}T + 0.5\beta_{tt}T^2 + \varepsilon_{it} \quad (6)$$

where:
Q_{it} is the gross value of output for the sector i at time t;
V_{it} is the value-added for the sector i at time t;
α_x, and β_x are the coefficients of the production function;
K_{it} is the total capital input for the sector i at time t;
L_{it} is the total labour input for the sector i at time t;
M_{it} is the total material input for the sector i at time t;
T is time; and
ε_{it} is the error term.

Although gross output is generally the preferred output measure, according to Mullen and William (1994), value-added has been extensively used in empirical studies. The need to explicitly consider intermediate input and the associated data differences is avoided by using value-added. Value-added being the difference between gross value of output and material input, the high correlation between the two variables prevents the estimation from getting reasonable coefficients (Torii, 1992).

[1] The derivation in this section draws heavily on Kumbhakar (2000), Kim and Han (2001), and Kim and Mazlina (2009).

There are basically two common functional forms of production used in studying TE using Stochastic Production functions, namely, the Cobb-Douglas and the general translog functional forms. They will be represented by the following translog:

$$\ln V_u = \beta_o + \sum_j \beta_j \ln X_{jit} + \beta_t T + 0.5\sum_j\sum_k \beta_{jk} \ln X_{jit} + 0.5\ \beta_{tt} T^2 + \sum_j \beta_{jt} T \ln X_{jit} + v_{it} - u_u \qquad (7)$$

where the subscripts i and t indicate firm and time; V is the output; X_j is a vector of input and subscripts j and k the index input. The efficiency error, u, represents production loss due to firm-specific technical inefficiency. Thus, it is always greater than or equal to zero ($u \geq 0$), and it is assumed to be independent of the statistical error, v, that is assumed to be independently and identically distributed.

The Stochastic Frontier model allows for non-neutral TP. TP is input j-using (or saving) if β_{Tj} is positive (or negative); and TP is neutral if all β_{Tj}s ($j = L, K$) are equal to zero. If all βs are equal to zero ($\beta_{LL} = \beta_{KK} = \beta_{LK} = \beta_{TT} = \beta_T L = \beta_{TK} = 0$), the production function reduces to the Cobb-Douglas function with neutral TP (Kim and Han, 2001). Significance of neutral and non-neutral technical changes in the model can be tested by using a generalised likelihood test.

In this study, TFP growth was decomposed into three components, namely, rate of technical change (TP), change of SEC, and change in technical efficiency (ΔTE). Due to a limitation of data, allocative efficiency was omitted from the TFP growth Equation (3) in this study. The rate of technological progress was then estimated as follows:

$$TP = \frac{\partial \ln V_{it}}{\partial T} = \beta_t \qquad (8)$$

Meanwhile, a change in scale components is the elasticity of input contributing to TFP growth as follows:

$$SEC = (e - 1)\left(\frac{ek}{e}\Delta K + \frac{el}{e}\Delta L\right) \qquad (9)$$

where e_k and e_l are elasticities of output with respect to capital and labour.

TE change was estimated using the following equation:

$$\Delta TE = \frac{\partial u_{it}}{\partial T} = \eta \exp[-\eta(t - T)] \qquad (10)$$

where ΔTE was interpreted as the rate at which firms move from the production frontier.

Therefore, by using the decomposition method, TFP growth was equated as follows:

$$\begin{aligned}\Delta TFP &= \Delta TE + TP + SEC \\ &= \eta \exp[-\eta(t - T)] + (\beta_t + \beta_{kt} \ln K_{it} + \beta_{lt} \ln L_{it}) \\ &\quad + \left[(e - 1)\left(\frac{ek}{e}\Delta K + \frac{el}{e}\Delta L\right)\right]\end{aligned} \qquad (11)$$

DATA AND EMPIRICAL RESULTS

Data and Variables

The five-digit ISIC level balance panel data from the Manufacturing Industries Annual Survey 2010 by the Malaysian Department of Statistics were used. The data consist of annual time series for 71 palm oil mills over the period 2005-2010, totalling 426 observations. The required data for the studies were value-added (V), value of assets (K) and total number of workers (L).

The maximum likelihood estimation was used to estimate the parameters of the Stochastic Frontier Function as proposed by Coelli (1996). TE of the palm oil manufacturing sector in Malaysia was estimated using a translog production frontier as follows:

$$\ln V_{it} = \beta_0 + \beta_t T + \beta_k \ln K_{it} + \beta_l \ln L_{it} + 0.5\,[(\beta_{kk} \ln K_{it}^2) + (\beta_{ll} \ln L_{it}^2) + (\beta_{tt} T^2)] + \beta_{kl} \ln K_{it} \ln L_{it} + \beta_{Kt} \ln K_{it} T + \beta_{lt} \ln L_{it} T + (v_{it} - u_{it}) \qquad (12)$$

where the subscripts i and t indicate firm and time, respectively; V is the value-added; K is the capital; L is labour; and $(v_{it} - u_{it})$ is the error term.

The software program, Frontier 4.1C, used for the estimation of the Stochastic Frontier Production function, was made available by Professor Tim Coelli from the Centre for Efficiency and Productivity Analysis, (CEPA).

EMPIRICAL RESULTS

Hypotheses Tests

Table 1 presents the likelihood ratio test for various null hypotheses on the total sample of palm oil mills. The likelihood-ratio test statistic is $\lambda = -2[L(H_0) - L(H_1)]$, where $L(H_0)$ and $L(H_1)$ are the values of the log-likelihood function under specifications of the null and alternative hypotheses, H_0 and H_1, respectively. If the null hypothesis is true, then λ has approximately a Chi-square (or a mixed Chi-square) distribution with degrees of freedom equal to the number or restrictions. If the null hypothesis includes Y = 0, then the asymptotic distribution is a mixed Chi-square distribution (Coelli, 1996).

In *Table 1*, the first null hypothesis that represented no technical inefficiency effects (H_0: $\gamma = \mu = \eta = 0$) was rejected at the 1% significance level for the total number of samples. The result suggests that the average

TABLE 1. STATISTICS FOR TEST OF HYPOTHESES: STOCHASTIC PRODUCTION FUNCTION FOR THE PALM OIL MILL SECTOR FOR THE PERIOD 2005 - 2010

Null hypothesis	Log-likelihood function	Test statistics (λ)	Critical value	Decision
1. No technical inefficiency $H_0 : \gamma = \mu = \eta = 0$	-434.8973	259.2678	10.50	Reject H_0
2. Time-invariant $H_0 : \eta = 0$	-307.0520	3.5771	6.63	Do not reject H_0
3. No technical change $H_0 : \alpha_t = \beta_{tt} = \beta_{tl} = \beta_{tk} = 0$	-327.8669	45.20702	13.28	Reject H_0
4. Technically neutral $H_0 : \beta_{tl} = \beta_{tk} = 0$	-308.4285	6.33014	9.21	Do not reject H_0
5. Cobb Douglas function $H_0 : \beta_{ll} = \beta_{kk} = \beta_{lk} = \beta_{tt} = 0$	-310.4652	10.40358	13.28	Do not reject H_0

Note: The critical value for these tests involving $\gamma = 0$ was obtained from *Table 1* of Kodde and Palm (1986).
Every null hypothesis was rejected or accepted at the 1% of significance level.

production function or ordinary least square (OLS) was an inadequate representation of the Malaysian palm oil mill sector, and underestimated the actual frontier because of the technical inefficiency effects.

The second null hypothesis is time-invariant, obtained by imposing the restrictions of H_0: $\eta = 0$. This hypothesis was not rejected at the 1% significance level which indicated that technical inefficiency in Malaysian palm oil mill sector was time-invariant.

The third null hypothesis, *viz.* no technical change (H_0: $\alpha_t = \beta_{tt} = \beta_{tl} = \beta_{tk} = 0$), was rejected at the 1% significance level, while the fourth null hypothesis, that technical progress is neutral (H_0: $\beta_{tl} = \beta_{tk} = 0$), was not rejected at the 1% significance level. This implies the existence of non-neutral technical progress in the Malaysian palm oil mill sector.

The last null hypothesis, that technology in the Malaysian palm oil mill sector is a Cobb-Douglas production function (H_0: $\beta_{ll} = \beta_{kk} = \beta_{lk} = \beta_{tt} = 0$), was not rejected at the 1% significance level. Thus, the Cobb-Douglas production function was an adequate specification for the Malaysian palm oil mill sector with other restrictions (H_0: $\eta = 0$; H_0: $\alpha_t = \beta_{tt} = \beta_{tl} = \beta_{tk} = 0$; and H_0: $\beta_{tl} = \beta_{tl} = 0$), given the assumptions of the translog Stochastic Frontier Production function model.

Therefore, the following production function for Malaysian palm oil mill sector is appropriate for this study;

$$\ln V_{it} = \beta_0 + \beta_k \ln K_{it} + \beta_l \ln L_{it} + B_t T + (v_{it} - u_{it}) \qquad (13)$$

The parameter estimates for the palm oil mill sector are presented in *Table 2*.

Table 2 shows that all estimated coefficients were significant. Hence, the t-statistics were appropriate as the test of individual statistical significance.

DECOMPOSITION OF TOTAL FACTOR PRODUCTIVITY

Technical Efficiency

The estimated average TE for the palm oil mill sector in Malaysia for the period 2005-2010 stood at 0.3320 for the total sample of 71 palm oil mills (*Figure 1*). The top three highest estimates were 0.8421 and 0.8018 which located in Sarawak and 0.7935 located in Sabah. The least efficient palm oil mill belonged to a private limited company in Perak with TE of 0.0667.

Technical Progress

As the appropriate production function for the Malaysian palm oil mill sector was defined as in Equation (8), technical progress for the mills was as follows:

$$TP = \frac{\partial V}{\partial T} = \beta_t = 0.0699$$

Technical progress relates to effective and efficient utilisation of technology, capital, labour and management. It reflects the impact of a wide range of factors, from worker attitude to technology exploitation. Based on the experience of developed countries, technical progress should eventually be the main source of TFP growth, given the limits of economic restructuring and improvement of the educational profile of the work-force (Azman, 2012).

TABLE 2. PARAMETER ESTIMATES OF PRODUCTION FUNCTION FOR THE PALM OIL MILL SECTOR

Variable	Parameter	Coefficient	Std. error	t-ratio
Intercept	β_0	12.4679	1.1676	10.6782*
ln K	β_k	0.1833	0.0566	3.2401*
ln L	β_l	0.3811	0.1398	2.7265*
t	β_t	0.0699	0.0122	5.7339*
	σ^2	0.5303	0.0982	5.4014*
	γ	0.6902	0.0570	12.1130*
	μ	1.2100	0.2421	4.9976*
		η=0		
Log likelihood function = -311.94362				

Note: * Significant at 5% level of probability.

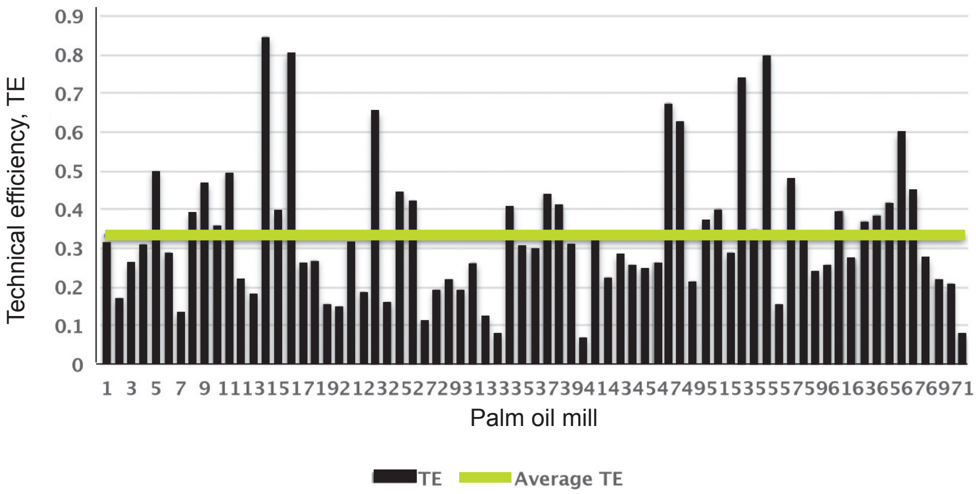

Figure 1. Estimated average technical efficiency of selected palm oil mills in Malaysia for the period 2005-2010.

Scale Components

For the period 2005-2010, the estimated average growth rate of the scale components (SEC) for the palm oil mill sector was -0.00291, and its range of variation is presented in *Figure 2*.

The SEC estimates for all the mills were very small and negative, implying that the palm oil mill sector had already reached a certain size where economies of scale no longer operate (Azman, 2012).

Total Factor Productivity

TFP growth is calculated as the sum of change in TE, TP and change in SEC. In the Malaysian palm oil mill sector, TE had been a key contributor to TFP growth (*Figure 3*).

The lowest TFP values recorded were 0.1016, 0.1395 and 0.1672. All of these were for mills which were registered as private limited companies, located in Perak and Sabah. The low TFP recorded was due mainly to low TE and SEC obtained for the period 2005-2010. It is highly recommended for these mills to enhance the efficient use of existing technology to catch up with frontier technology, and at the same time improve the quality of their workers such as by job training and optimum working hours.

CONCLUSION

Although the empirical results of this study show that productivity growth was driven mainly by change in TE, TP also had a significant positive effect on the Malaysian palm oil processing sector. However, change in scale components had a negative effect on productivity growth. Thus, the results suggest that there is opportunity to improve productivity growth in the palm oil mill sector. The less productive mills should improve their productivity by introducing a policy to induce technological innovation in order to move up the production frontier.

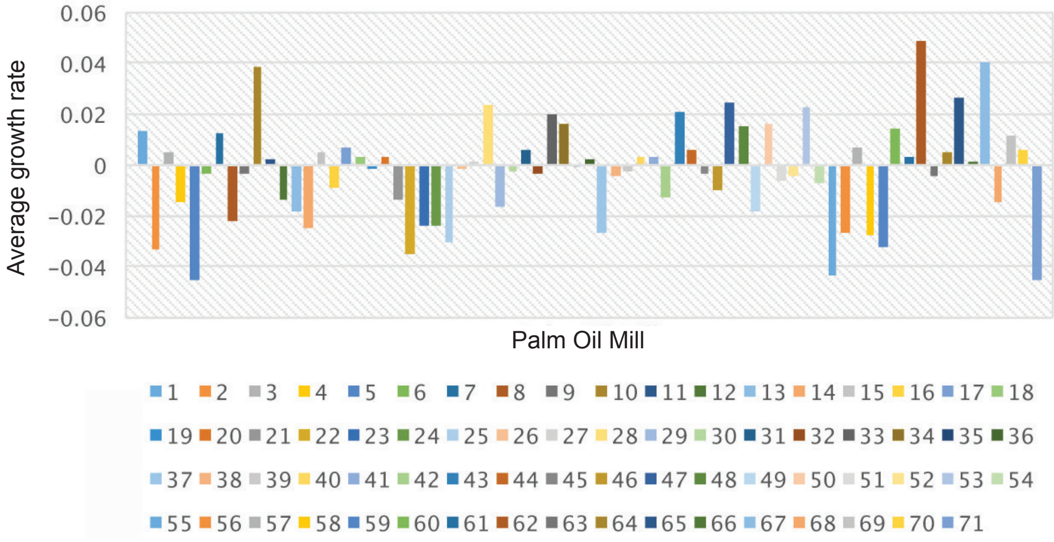

Figure 2. The average growth rate in scale components (SEC) for selected palm oil mills for the period 2005-2010.

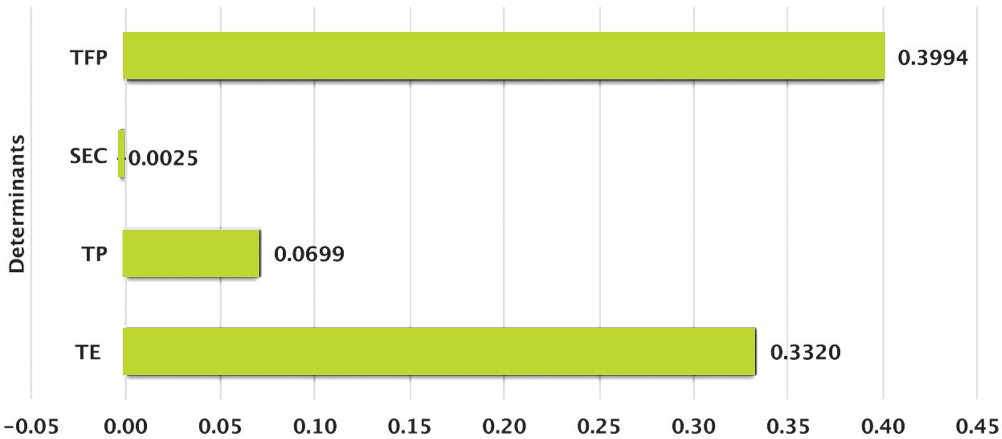

Figure 3. Decomposition of total factor productivity (TFP) growth of the Malaysian palm oil sector for the period 2005-2010.

It is also highly recommended that they apply known technology which includes improvement in learning-by-doing processes and improvement of managerial practices. The successful mills in the sector should become role models to be emulated by other palm oil mills.

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