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The performance measurement and productivity change of agro and food industry in the stock exchange of Thailand

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Abstract: At present, the agro and food industry has a high influence to farmers in Thailand. Most of the raw materials of agriculture are sent to its manufactoring. This industry has an important role to raise the growth of the Thai economy. The main objective of the paper is to study the production trends and ability operations of the agro and food industry by using economic tools analyse two sub-industry sectors. The paper reviewed literatures on the performance measurement and productivity change of the business sector to obtain the relative variables and optimal methodology. The paper designed to use the panel data of the agro and food industry during the period 2011–2014. The Slacks-based Measure context-dependent Data Envelopment Analysis (SBM context-dependent DEA) was used to analyse the efficiency and ability in the Decision Making Units (DMUs) by employing the attractiveness and progress score. Moreover, the Malmquist index was used to demonstrate the change of the total productivity of this industry. Therefore, the empirical results of the paper can help the companies inside and outside the stock exchange of the agro and food industry to realize the performance level and benchmark leading to the improvement of their operation. Moreover, they help the government to develop its policy and to understand the character of the sub-industry sectors and the productivity trend in this industry.

Keywords: Malmquist index, SBM context-dependent DEA, sub-industry sector

The Thai agro and food industry had undergone a rapid evolution of agricultural operation in the last three decades. Meanwhile, the agricultural land used had always increased since 1970s to 1980s. At the same time, Thailand had the industrial and financial crisis, which effected the economic system and policy makers. Agriculture in Thailand was the only group that exhibited the growth in term of the Total Factor Productivity (TFP) and Gross Domestic Product (GDP). The phenomenon of this flourishing agro-economy could help the Thailand's economic to recover from the illness. Because of the agribusiness, the food and beverage sectors had responded to this chance and faced the problems of changing the output and input factors. Simultaneously, the Thai government also encountered the problems by changing agricultural and related policies of responsibility for protecting and eliminating the malaise in the Thai agricultural sector. As the result, the GDP of Thai agriculture increased during the years 1960–2009, the annual growth rate of the agricultural GDP had exhibited its average approximate more than 3%. Moreover, when considering the yield reports of the selected crops in Thailand during the years 1962–2006, the finding showed that the paddy's yield had increased from 1.75 to 3.00 tonnes/ha. The yields of maize and cassava increased from 2.125 to 3.90 tonnes/ha and from 2.40 to 3.60 tonnes/ha, respectively (Overseas Development Institute 2010). Thus, most of the agribusiness, food and beverage companies under the

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government support were successful, which had been adjusted by the production and marketing strategies. According to the economic data of Thailand, the economic system had the ability to continue as one of the world's largest producer of agricultural products, food and beverages in this decade. Thus, the agro and food industry has an important role in the structural transformation of agriculture in Thailand. Currently, regarding the agro and food industry's turnover, the agribusiness, food and beverage sectors have the ability to keep profit of their listed companies by increasing the volumes of their products (Stock exchange of Thailand 2014). According to the statistic of the Customs Department of Thailand, the increments in the volumes of exports of agricultural products were running in the opposite direction with the values of agricultural products which had been declining since year 2009 (The Customs Department of Thailand 2014). This problem is becoming a major challenging issue in the sub-industry sectors of agro and food industry of Thailand. The problem of this industry concerns both in the term of internal restriction and external challenges.

This paper has the purpose to analyse the benchmark of reference sets for referring the improvement target of the sub-industry sectors by using the SBM context-dependent DEA. The performance of the sub-industry sectors in the agro and food industry is grouped on the performance level. At the same time, the advantage and disadvantage of the sub-industry sectors in this industry are indicated by the attractive and progress score. Moreover, the productivity change of agro and food industry is demonstrated by using Malmquist productivity index. The technical efficiency change, pure technical efficiency change and scale efficiency change are overviewed as the outcomes in this paper. According to the previous studies of the SBM context-dependent DEA, Cheng et al. (2009) applied the performance measurement model by improving the slack-based measure context-dependent DEA model to be optimal measurement tool in the hotel industry of Taiwan. This method can create benefit to the hotel industry as follows. Firstly, this method can analyse the performance of the organization operation of the hotel. Secondly, this method can provide reference sets for the hotel competitor. In addition, Soltane (2014) applied the Malmquist productivity index (MPI) and a balanced panel dataset of 198 observations to analyse the productivity changes of 33 Middle East and North Africa microfinance institutions during the years 2006–2011. The results indicate that the microfinance industry has reported an overall productivity regress even though all the MENA MFIs which have positive TFP in this period.

LITERATURE REVIEW

In 1957, the DEA was first time to develop the method and model for evaluating productivity by Farrell (1957) proposed the activity analysis for solving the problem that he failed to combine multiple inputs into any satisfaction. After one decade, the DEA was developed to be the faultless DEA approach by Charnes et al. in 1978. At this time, the CCR model of the DEA approach was launched and used to measure efficiency. The CCR model was radial and oriented frontier under the restriction of the constant return scale. After several years, the DEA approach was extended, the model from CCR model became the BBC model by Banker et al. (1984), then the BBC model was used. Thus, the DEA is a non-parametric method and mathematical programming technique. It is an analytical technique base on linear programming. This method has been broadly used to measure the efficiency performance of each of decision making units (DMUs). The performance of this method is simply used for generating operation model. Moreover, Seiford and Zhu (2003) applied the DEA model to make a number of spreadsheet models that can be used in the organization evaluation in term of the performance and benchmarking. Thus, each DEA model has provided various DMU forms to define the performance of the organization such as school, hospital, university, city, business and others. According to the concept of the DEA method in the previous studies, the step of the DEA will start from considering input and output of each DMU and then all DMUs are evaluated by a more holistic evaluation solution when it decides to use different inputs to make several outputs.

As the previous literature review of Färe and Lovell (1978) shows, there was the Russell measure model, which was introduced as a non-oriented model and also used the slacks to measure the input or output variables by considering their proportion at different rates. After several years, Tone (2001) had introduced the original slacks-base measure (SBM) DEA approach. This model is used to compute the ratio of production and yield by adjusting the average of inputs reduction with the output increase. The SBM model has implied

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the improvement of the simultaneous implementation between input and output variables. Moreover, Lozano and Gutiérrez (2011) applied the SBM model measure the efficiency DMUs of 39 Spanish airports during of 2006 to 2007. The SBM model has been used to demonstrate more the discriminating power than the mutual directional distance function. The findings show that during two years of airports operation, they have the technical efficiency of more than fifty percentages of all airports.

The context-dependent data envelopment analysis model (context-dependent DEA) was established by Seiford and Zhu (2003). The original model is designed by using the radial efficiency measure, where the evaluation context is generated as a set of DMUs into difference levels of efficient frontiers. The overall DMU in different performance level can provide an evaluation context for estimating own assessment background of DMUs. This model has been used to measure the performance by considering the relative attractiveness and progress score of the Decision Making Unit (DMU). Tomas and Alvydas (2014) studied the context-dependent DEA approach in Lithuanian family farms. This study is used to identify and quantify the discrepancies in efficiency levels. The results show that the mixed and livestock farms were specific by certain strata featuring inflated values of the progress scores. According to the empirical study of the context-dependent DEA, the concept of this model can summarize that the relative attractiveness with higher value can generate more competitive advantage. In contrast, the relatively progressive development with a higher value can indicate that the relative efficiency is worse.

Morita et al. (2005) established a Slack-based Measure with the context-dependent DEA. It has integrated two models, the SBM model of Tone (2001) and the context-dependent DEA which introduced by Seiford and Zhu (2003). This new concept of the DEA approach has only used the supper-efficiency DEA in the attractiveness model but it does not mention the application of supper-efficiency in the progressiveness model. Cheng et al. (2009) improved the weakness of the Slack-base Measure context-dependent DEA model (SBM context-dependent DEA) of Morita et al. (2005) introduced. This study has modified the equation of attractiveness model and changed it to the progressiveness model, then this model was used to measure the international tourism in Taiwan. The results show that the differentiations of the tourist market have five performance levels under the benchmarks structure form. The higher attractiveness has served as the learning target. The leading level can use the lower progress to analyse the potential competitor in the lagging levels. Particularly, Ouenniche et al. (2014) studied the previous research of perfect SBM context-dependent DEA model. They applied this model into the forecasting of the oil prices' volatility. This model is designed on the efficient frontier and has property of zero slacks to maintain their ranks.

As the original productivity index, Malmquist (1953) had presented a quantity index by using it to measure the standard of living of consumption analysis, the Malmquist index and its variations had mainly been used in the production analysis field. Later on, Fare et al. (1994) combined two ideas of the efficiency measurement and productivity by constructing a DEA Malmquist Productivity Index to measure the productivity change over time. The DEA Malmquist Productivity Index is considered a decent tool for measuring the productivity change of the overall DMUs. The productivity index has defined to calculate in measuring of the DMUs, when all data are exact and definite. Čechura et al. (2016) studied the determining changes in the total factor productivity (TFP) in the agriculture sector of Czech Republic. They focus on three important sectors which consist of cereals, dairy and pork. This paper studied the period (2004–2011) after the Czech Republic accession to the EU. The results show that the TFP development was significantly determined by the technological change (TCH).

In addition, financial statements and market ratios are used there to be the variables for evaluating the operational efficiency. The financial statements are used to report financial results, financial conditions and cash flows of the company's operation. They can help the company to consider the capability of the business to generate cash, the uses of that cash and also to identify the capability to pay back its debts. Meanwhile, they can help the company to analyse the financial ratios from these statements, which can indicate the critical factors of the business. Moreover, this paper also considers the market ratio, which is the ratio of the current market. This ratio measures the relationship between the price of a share of the common stock and an indicator of the company's ability. This ratio can be used to indicate the profits or assets held by the company. As regards the literature review of Fang et al. (2009), they compared the operational performance of the listed coal mining companies between the Mainland China and the United States. This

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study focuses on operating costs, the total assets and numbers of employees were the input variables, and the output variables consisted of earnings per share, operating revenue and the net profit before tax. Thus, the DEA approach has been used to measure the efficiency from input and output variables. Similarly, the research of Liu (2011) used the variables in financial statements and evaluated the performance of Taiwan financial holding companies. There are five variables that consist of employee, assets and shareholders' equity as the inputs and they also use revenues and profit as outputs. In addition, Vukoje and Dobrenov (2011) studied the main indicators of the economic position within companies of the food industry in Serbia. This paper focused on the transition, profit rates and net working capital. The findings showed that this industry achieved a positive financial result for most of the years but the increasing of business activity was not accompanied by the appropriate financial effects during the nine-year period.

Thus, this paper has focused on the elements of financial statements for identifying the input and output variables. According to the literature review of the previous DEA studies, the input variables in this paper can be defined as follows; the input variables consist of assets, liabilities and shareholders' equity, the output variables are chosen as revenue and profit. The definitions of input and output variables are exhibited in Table 1.

METHODOLOGY

SBM context-dependent DEA models

The context-dependent DEA is a radial efficiency measure, which is generated as a set of DMUs divided into difference levels of efficient frontiers. Each performance level can provide an evaluation context to examine own operation of DMUs. In the original concept of SBM, it uses to evaluate the efficiency together with the slack value. The slack value has the value between 0 and 1. As the integration of two models, it can be summarized into the concept of a new model as follows

Based on the restrictions of the original context-dependent DEA model, there are J^l = {DMUj = 1, …, n} be the set of all n DMUs and $J^{l+1} = J^l - E^{l,}$ where E^l = {DMU$_0$ ∈ J^l| = 1}. As the integration of SBM context-dependent DEA model of Marita et al. (2005), it can state that the set of efficiency E^l was defined from the slack-based efficiency score p_k^l between 0 and 1. Thus, this paper can define the SBM model by following linear program.

$$\text{Min } p_k^l = \left[1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}\right] / \left[1 + \frac{1}{S}\sum_{r=1}^{S}\frac{s_r^+}{y_{rk}}\right]$$

Subject to

$$\sum_{j \in J^l} \lambda_j x_{ij} + s_i^- = x_{ik} \quad i = 1, \dots, m \tag{1}$$

$$\sum_{j \in J^l} \lambda_j y_{rj} - s_r^+ = y_{rk} \; r = 1, \dots, s$$

$$\lambda_j \geq 0, j \in J^l;\; s_i^- \geq 0, i = 1, \dots, m, s_r^+ \geq 0, r = 1, \dots s$$

where i^{th} replaces input and r^{th} replaces output of DMU$_j$ (j = 1,…, n) which are denoted by $x_{i,j}$ (i =1,…, m) and $y_{r,j}$ (r = 1,…, s), respectively. Let λ_j replace the weight assigned to DMU$_j$ in constructing its ideal benchmark, which defines s_i^- and s_r^+ replace slack variables associated with the first and second sets of constraints. Then, p_k^l will replace the SBM context-

Table 1. Definition of input and output variables

Variable	Definition	Author/year
Asset	Asset is real property or movable property of business. It is business's resource that it may be tangible or intangible. It also helps own control the produce value and hold business's position.	
Liability	Liabilities are legal debts or obligations that company obtains from business partners or debtors during business operations.	
Shareholders' equity	Shareholders' equity is capital which is first invested in the company. After business run, it will come from retained earnings of company during its operations.	Fang et al. (2009), Liu (2011), Vukoje and Dobrenov (2011)
Revenue	Revenue is income of the company, it receives achievement activities from the sale of goods and services.	
Profit	Profit is the money of business makes after calculation income with all the expenses and taxation.	

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dependent score of DMU_k which has the achievement at performance level l, if the optimal value of $p_k^l = 1$.

As the steps of the SBM context-dependent DEA model, there are 4 steps, which have been used to reach the best practice.

Step 1: Let $l = 1$ and assess the overall DMUs sets J^l, by using model (2) calculate the first-level frontier DMUs, for generating set E^1.

Step 2: Separate the inefficient DMUs from future DEA runs. $J^{l+1} = J^l - E^l$.

Step 3: Assessment of a new subset of DMUs, J^{l+1}, by using the same model to obtain the new set of DMUs E^{l+1}, it will reach to be the new best-practice frontier.

Step 4: Let $l = l + 1$and go to step 2.

Stop rule: $J^{l+1} = \varnothing$, the algorithm will be stopped.

According to the reference set of DMU_o under the SBM context-dependent DEA model, it can generate the performance level "*n*" which upon the context "*l*" when it appears that $l < n$, n is presented by a specific model as below

$$R_n^{SBM}(l) = \{ j \in J^l \mid \lambda_j > 0 \text{ in } (2) \} \tag{2}$$

As the identification of Morita et al. (2005), the evaluation context E^l is measured with respect to the DMUs in the subset J^l. Thus, the attractiveness for DMU_o base on the evaluation context E^l is obtained from the following programming problem.

$$\min \delta = \frac{1/m \sum_{i=1}^{m} \bar{x}_i / x_{ik}}{1/s \sum_{r=1}^{s} \bar{y}_r / y_{rk}}$$

Subject to

$$\bar{x}_i \geq \sum_{j \in E^l} \lambda_i x_{ij} \quad i = 1, \dots, m \tag{3}$$

$$\bar{y}_r \leq \sum_{j \in E^l} \lambda_i y_{rj} \quad r = 1, \dots, s$$

$$\lambda_j \geq 0, j \in E^l, \bar{x}_i \geq x_{ik}, i = 1, \dots, m, 0 \leq \bar{y}_r \leq y_{rk}, r = 1, \dots, s$$

To compute the relative attractiveness score, this research applies the super-efficiency model which was proposed by Tone (2002). This model has calculation of the distance between the efficient DMU_k and those at the lagging performance level (E^l). Therefore, the attractiveness index can be obtained by following linear programming.

$$\text{Min } \tau(A) = 1 / m \sum_{i=1}^{m} \bar{x}_i / x_{ik}$$

Subject to

$$1 = \frac{1}{s} \sum_{r=1}^{s} \bar{y}_r / y_{rk} \tag{4}$$

$$\bar{x}_i \geq \sum_{j \in E^l} \lambda_j x_{ij} \; i = 1, \dots, m$$

$$\bar{y}_r \leq \sum_{j \in E^l} \lambda_j y_{rj} \; r = 1, \dots, s$$

$$\lambda_j \geq 0, t > o, \bar{x}_i \geq t x_{ik}, 0 \leq \bar{y}_r \leq y_{rk}, j \in E^l$$

As for computing the attractiveness score in model (4), the finding of this model can summarize that the score must be more than 1. Thus, a large score of $\tau(A)$ can indicate that if there is a DMU that has the score of $\tau(A)$ more than other DMUs, it means that this DMU has a better efficiency than other in same performance level.

Based on the calculation of distance between the inefficient DMU_k, and those at the leading performance level (E^1), the relative progress is measured by the follow linear programming problem.

$$\text{Min } \tau(P) = 1 / s \sum_{r=1}^{s} \bar{y}_r / y_{rk}$$

Subject to

$$1 = \frac{1}{m} \sum_{i=1}^{m} \bar{x}_i / x_{ik} \tag{5}$$

$$\bar{x}_i \leq \sum_{j \in E^l} \lambda_j x_{ij} \quad i = 1, \dots, m$$

$$\bar{y}_r \geq \sum_{j \in E^l} \lambda_j y_{rj} \quad r = 1, \dots, s$$

$$\lambda_j \geq 0, t > 0, \bar{y}_r \geq t y_{rk}, 0 \leq \bar{x}_i \leq x_{ik}, j \in E^l$$

This model was designed to overturn the property of super-efficiency of model (4). Thus, the progress score in the model (5) must be less than 1. In addition, a small score of $\tau(P)$ can indicate that if there is a DMU has score of $\tau(P)$ less than other DMUs, it means that this DMU has a better improvement than other DMUs on the same performance level.

Malmquist index

Currently, there are several different methods that can be employed to assess the productivity change including the Fisher index, the Tornqvist index and the Malmquist index. Based on the productivity

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change in this paper, the Malmquist productivity index has been used to analyse data from one period time to another period time. This method can be used to demonstrate the reason for the research problem, without doubt. According to the previous studies, the Malmquist productivity index was often used to measure the total factor productivity (TFP) between two data points by considering the ratio of the distance of each data point from one can period time to be merged with the technology of another period time. Moreover, the Malmquist productivity index can be defined as the product of the Catch-up and Frontier-shift term. In term of the Catch-up, it is related to the degree of a DMU, which can enhance or worsens its efficiency. Meanwhile, the frontier shift (Technology) will reflect the changing efficiency of its frontiers.

The Malmquist productivity index has many advantages, which are decomposed as follows; the total factor productivity (TFP) of technical efficiency change and technological change. The technical efficiency change (TEC) is the effectiveness of the production process by the given set of inputs use to produce an output during one period time. The technological change (TC) is any shift in the production frontier and it also is the technology of production, which affects the relationship between inputs and outputs of the production process during one period of time to another period of time. Further, the technical efficiency change is decomposed into the pure technical efficiency change (PEC) and the scale efficiency change (SEC). Sunil and Rachita (2008) mentioned that the pure technical efficiency change (PEC) was an efficiency measurement in term of managerial performance by organizing the inputs in the production process during one period time. The scale efficiency change (SEC) is the ratio of average productivity of any level of input used in the optimal point from one period time to another period time.

The Malmquist productivity index can be defined according to the previous studies. Wilmsmeier et al. (2013) defined the Malmquist index and distance functions by considering two different intervals.

Suppose $x^t = (x_1^t, \dots, x_n^t)$ mean a vector of "n" inputs and let $y^t = (y_1^t, \dots, y_m^t)$ mean a vector of "m" outputs at time t, t,...,T from t to t + 1. The input distance function at time t can be defined as follows:

$$D_i^t(y^t, x^t) = \sup\{\lambda: (x^t/\lambda, y^t) \epsilon\, S^t\} \tag{6}$$

To define the Malmquist index, the input distance functions at time t + 1 is defined as follows:

$$D_i^t(y^{t+1}, x^{t+1}) = \sup\{\lambda: (x^{t+1}/\lambda, y^{t+1}) \epsilon\, S^t\} \tag{7}$$

Each of the distance functions can measure the maximum proportional change as input-oriented and is a complete characterization of the technology T.

The concept of input distance function at time t, Malmquist productivity index is defined by the following function;

$$M_i^t(y^t, x^t, y^{t+1}, x^{t+1}) = \frac{D_i^t(y^{t+1}, x^{t+1})}{D_i^t(y^t, x^t)} \tag{8}$$

Similarly, the input distance function at time t + 1, it can be determined by taking the technology, which can be show as follows:

$$M_i^{t+1}(y^t, x^t, y^{t+1}, x^{t+1}) = \frac{D_i^{t+1}(y^{t+1}, x^{t+1})}{D_i^{t+1}(y^t, x^t)} \tag{9}$$

As the expressions of (8) and (9) are assumed that they have the technology remains the same time at time t and t + 1. In this context, the changes of technology can be defined by calculating the geometric mean. Thus, the input-based Malmquist productivity change index can be show as follows:

$$M_i^t(y^t, x^t, y^{t+1}, x^{t+1}) = $$

$$= \left[\frac{D_i^t(y^{t+1}, x^{t+1})}{D_i^t(y^t, x^t)} \frac{D_i^{t+1}(y^{t+1}, x^{t+1})}{D_i^{t+1}(y^t, x^t)}\right]^{1/2} \tag{10}$$

Based on the production change between the periods t and t + 1, there can be indicated the significant indicator by the Malmquist productivity index. If $M_i^t > 1$ the productivity will be improved, if $M_i^t < 1$ the productivity will be declined, and if $M_i^t = 1$ the productivity is stable.

An equivalent way of writing this Malmquist productivity change index is:

$$M_i^t(y^t, x^t, y^{t+1}, x^{t+1}) = $$

$$= \frac{D_i^{t+1}(y^{t+1}, x^{t+1})}{D_i^t(y^t, x^t)} \left[\frac{D_i^t(y^{t+1}, x^{t+1})}{D_i^{t+1}(y^{t+1}, x^{t+1})} \frac{D_i^t(y^t, x^t)}{D_i^{t+1}(y^t, x^t)}\right]^{1/2} \tag{11}$$

According to the expression of (11), the Malmquist productivity change can clarify two components. The first component on the left hand side measures the efficiency changes between the period t and t + 1. The second component on the right hand side measures the technical change by capturing the shift in the frontier technology between the period t and t + 1.

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Table 2. Descriptive statistics for eight DMUs of two sub-industry sectors

Variable	Maximum	Minimum	Mean	Std. dev.
Input items				
Asset	762 798.80	87 149.76	349 973.4	274 410.3
Liabilities	299 728.20	19 107.10	96 306.94	88 436.15
Shareholders' equity	131 714.00	2 815.90	52 713.45	45 194.40
Output items				
Revenue	728 280.90	3 774.12	174 604.20	227 815.80
Profit	12 458.03	198.89	4 714.00	4 445.99

Source: Author's calculation

Data description

This paper uses secondary data of financial statements and operation's statistic from agribusiness, food and beverage sectors in stock exchange of Thailand during the years 2011–2014. The screening procedures of input and output variables are used to consider in this paper. As the previous studies of input and output selection of Dyson et al. (2001), it can be summarized that there are two screening steps can exhibit as following. The first step was to establish a list of inputs and outputs related to this paper. In the second step, the list of inputs and outputs will be examined by the statistics analysis in term of the correlation. The descriptive statistics of input and output items are demonstrated in Table 2. The results exhibit the distributions of the data selection, which are ensured by the arithmetic mean and standard division.

In addition, Table 3 shows the correlation coefficients among the input and output variables are conducted to test the relationship. The results show that the input and output variables have positive correlations with the independent variables. More than half of all correlation matrixes have the correlation index higher than 0.70. Moreover, a strong correlation was discovered among all variables, which means that there exist significant relationships between the input and output variables.

EMPIRICAL RESULTS AND ANALYSIS

This section collects the panel data of two sub-industry sectors during the years 2011–2014, which were analysed by the SBM context-dependent DEA method and Malmquist productivity index. Numbers of DMUs can be calculated from two sub-industry sectors multiplied by four years. Thus, as the calculation in this paper, the numbers of DMUs are equal to 8 DMUs. This paper employs the DEA software to group the performance level of the overall DMUs. The reference sets of sub-industry sectors in agro and food industry under the standard performance are determined by the SBM concept. The measurements of attractiveness and progress score in each performance level are demonstrated by the SBM context-dependent DEA concept. Moreover, the productivity changes during 4 years of the agro and food industry in the stock exchange are investigated by the Malmquist productivity index in this section.

Performance level

Based on the identified return to scale, the SBM context-dependent DEA has the Constant Return to Scale (CRS) and Variable Return to Scale (VRS) for choosing to calculate the optimal result. This paper chooses the SBM context-dependent DEA under the constant return to scale (CRS) to analyse the panel

Table 3. Correlation coefficients among input and output variables

	Asset	Liabilities	Shareholders' equity	Revenue	Profit
Asset	1				
Liabilities	0.7014	1			
Shareholders' equity	0.9301	0.6195	1		
Revenue	0.8145	0.5037	0.8950	1	
Profit	0.8181	0.4226	0.6644	0.7274	1

Source: Author's calculation

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Table 4. The grouping of eight DMUs in four performance levels

Performance level	Group of DMUs
First – DMUs (E^1)	DMU01, DMU06, DMU08
Second – DMUs (E^2)	DMU02, DMU05
Third – DMUs (E^3)	DMU04
Fourth – DMUs (E^4)	DMU03, DMU07

Source: Author's calculation

data set. By using Model (1) based on the CRS, it can distinguish 8 DMUs of 2 sub-industry sectors into 4 performance levels in Table 4.

Reference set

This section presents the reference sets of two sub-industry sectors in the agro and food industry under the standard performance which are analysed by the benchmark structure (Table 5).

Attractiveness and progress score

Table 6 shows the attractiveness and progress scores of two sub-industry sectors of the agro and food industry during the years 2011–2014. In this paper, 8 DMUs of two sub-industry sectors are distinguished performance levels in the context-dependent DEA concept. The higher attractiveness score of the overall DMUs will represent a long distance of the efficient DMUs from the lagging performance level. This concept can explain that the sub-industry sector shows a higher attractiveness score, which has a better performance than the other. Meanwhile, the lower progress score will represent a short distance of the inefficient DMUs from leading level. It means that the sub-industry sector has a need to improve its inputs and has the best chance to be the leader of the industry at the same level.

For the results of attractiveness and progress scores by analysing of SBM context- dependent DEA method, see Table 6. Based on the attractiveness score of the sub-industry sector in level E^1, the DMU01 and DMU08 show a higher attractiveness score when the level 2, 3 and 4 are used to consider the score as an evaluation context. In level E^2, the DMU05 hasa higher attractiveness score when level 3 is used to consider the score. Also, the DMU02 shows a higher progress when level 1 is used to consider the score at the same level E^2. Similarly, in level E^3, DMU04 has a higher progress score when level 1 and 2 are used to consider the score. In level E^4, the DMU03 shows a higher progress when level 1, 2 and 3 are used to consider the score.

Regarding the results in Tables 4, 5 and 6, DMU01 is the best performance both in level E^1 and other performance levels. This DMU does not need to improve any input and output variables. In level E^2, the DMU05 has a higher score of both the attractiveness and progress and is followed by DMU02. In this performance level, the DMU05 and DMU02 should improve some variables a little by the reference from the DMU01and DMU08, respectively. In level E^3, the DMU04 has a high score of both attractiveness and progress. The DMU04 should improve some variables a little by reference to the DMU01and and DMU08. In level E^4, the DMU03 and DMU07 show the worst performance of the sub-industry sectors in the agro and food industry when compared with the other performance levels. The DMU03 and DMU07 must improve all variable by the reference to the DMU01 and DMU08, respectively. Therefore, according to the observation of 2 sub-industry sectors during 4 years, it can be summarized that the agribusiness

Table 5. The reference sets of eight DMUs of agro and food industry

Sector code	Sub-industry sector	Level	RTS	$R_k^{SBM}(1)$	$R_k^{SBM}(2)$
DMU01	Agribusiness*	1	Constant	DMU01	
DMU02	Food and Beverage*	2	Increasing	DMU08	
DMU 03	Agribusiness**	4	Increasing	DMU01	DMU08
DMU04	Food and Beverage**	3	Increasing	DMU01	DMU08
DMU05	Agribusiness***	2	Increasing	DMU01	DMU08
DMU06	Food and Beverage***	1	Constant	DMU06	
DMU07	Agribusiness****	4	Increasing	DMU01	DMU08
DMU08	Food and Beverage****	1	Constant	DMU08	

*year 2011, **year 2012, ***year 2013, **** year 2014; RTS is return to scale and R_k^{SBM} is benchmark target of DMU_k

Source: Author's calculation

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Table 6. The attractiveness and progress scores of eight DMUs in agro and food industry

Performance level	Sub-industry sector	Level 1	Level 2	Level 3	Level 4
			#	#	#
E1	DMU01 Agribusiness*		6.701 (1)	19.950 (1)	31.668 (1)
	DMU06 Food and Beverage***		2.025 (3)	6.521 (3)	12.626 (2)
	DMU08 Food and Beverage****		2.696 (2)	6.982 (2)	8.698 (3)
E2		##		#	#
	DMU02 Food and Beverage*	0.601 (1)		3.221 (2)	5.227 (2)
	DMU05 Agribusiness***	0.801 (2)		3.870 (1)	12.71 (1)
E3		##	##		#
	DMU04 Food and Beverage**	0.512 (1)	0.950 (1)		4.326 (1)
		##			
E4	DMU03 Agribusiness**	0.082 (1)	0.109 (1)	0.372 (1)	
	DMU07 Agribusiness****	0.491 (2)	0.932 (2)	0.984 (2)	

*year 2011, **year 2012, ***year 2013, **** year 2014, # = attractiveness score, ## = progress score and numbers in parenthesis () explain the ranking of performance which is considered by high efficiency score start from 1 to low efficiency score *n*

Source: Author's calculation

sub-industry sector shows the performance decrease. The government should improve and support some policies that affect the operation of the listed company. Meanwhile, the listed companies should improve and develop the input and output variables by using technology. On the other hand, the food and beverage sub-industry sector shows the performance increase. The government should support some policies that help the listed company to reduce their operational cost and support their efficiency. Also, the listed companies should look for the new technologies to create their competitive advantage.

Decomposition results of the Malmquist productivity index

Table 7 exhibits the total factor productivity change (TFPC) and explains the component of this method, namely the technical efficiency change (TEC), the technical change (TC), the pure technical change (PEC) and the scale efficiency change (SEC) (see Table 7). The findings of empirical results can indicate that during the years 2011 to 2013, the agro and food industry showed an increase in the productivity by 96.6%. It indicated that there was an apparent trend of the catch-up term, which led to earning more income. During of the years 2013 to 2014, the productivity of this industry declined by 84.01%, its values were very close to one, which hinted that the efficiency of this industry was constant.

In addition, the results of the productivity change of this industry showed fluctuation, they can indicate the frontier shift that there is no continuous progress for the technology. Moreover, the technical change (TC) exhibits the fluctuation of its value, and the same for the value of the total factor productivity change (TFPC). Thus, the analytical results of this paper show that there are large ranges between the min and max values of the TFPC and it implies that the agro and food industry has the variation of productivity and efficiency change. According to the empirical results of technical efficiency change (TEC), there are values that are very close to one and the values of pure technical change are equal one. Thus, these values indicate the scale efficiency change (SEC) in Table 7. In this table, there was the value less than 1 during the years of 2011and 2012. It means that the combination of inputs and outputs of the agro and food should increase

Table 7. The summary of Malmquist productivity index

Time period	Technical Efficiency Change (TEC)	Technical Change (TC)	Pure Technical Change (PEC)	Scale Efficiency Change (SEC)	Total factor Productivity Change (TFPC)
2011–2012	0.610	0.273	1.000	0.610	0.167
2012–2013	1.638	2.998	1.000	1.638	4.910
2013–2014	0.745	1.055	1.000	0.745	0.785
Mean	0.906	0.952	1.000	0.906	0.863

Source: Author's calculation

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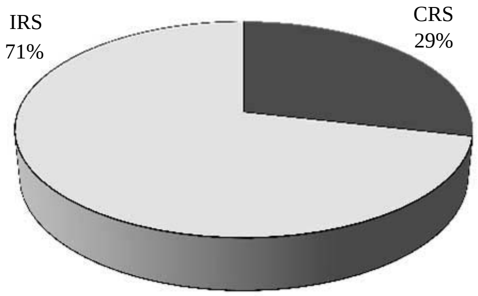

Figure 1. Return to scale of the agro and food industry

IRS = increasing returns to scale, CRS = constant returns to scale

Source: Author's calculation

efficiency for obtaining the scale efficiency. During the years of 2012 and 2013, the value was more than 1. It means that the combination of variables of this industry should be decreased. In addition, during the years of 2013 and 2014, the scale showed inefficiency because the values were lower than 1.

As the empirical results in Table 7 and Figure 1, the findings are used to explain the trend and direction in term of industry scale. The sums of return to scale during the years 2011–2014, they can explain the majority of this industry as follows; there are 71% of the total sample, operates under increasing returns to scale and 29% exhibit constant returns to scale. Therefore, they can indicate that the majority of the agro and food industry in Thailand was operated under small scale. These findings can hint that two sub-industry sectors can increase the performance by increasing their size.

CONCLUSIONS

The agro and food industry in the stock exchange of Thailand is an important industry as the large producer of agricultural products. This industry is one of the main players driving the economy system of Thailand. The performance measurements and productivity indexes of two sub-industry sectors are the indicators for identifying the performance, trend and yield of agro and food industry. This paper uses secondary data of financial statements and operational statistics of two sub-industry sectors. A panel data of 8 DMUs is considered and employed for the analysis. Based on the consistency of input and output variables, the correlation coefficients among the input and output variables are considered.

Regarding the empirical results of this paper, the findings of positive correlation of both of input and output variables can indicate that when some inputs increase, it will lead to an increase in some outputs. This paper proposes the SBM context-dependent DEA method to group the performance level and benchmark of two sub-industry sectors. The reference sets are used to be the benchmarks of inefficiency of the sub-industry sector by proposing the improvement target referring to optimal efficiency. Moreover, the SBM context-dependent DEA method is applied to measure the performance of each sub-industry sector by calculation of the attractiveness and progress score. Based on the concept of attractiveness and progress score, the higher attractiveness score represents a long distance between the efficient DMUs and the lower progress score represents a short distance between the inefficient DMUs. This concept can demonstrate that if the sub-industry sector has a higher attractiveness and lower progress score, it will have a better performance than other sub-industry sectors and does not need to improve its efficiency. In addition, the Malmquist productivity index is used to demonstrate the changes of the total productivity of the agro and food industry from one time period to another time period Regarding the basic element of the total factor productivity (TFP) in the Malmquist productivity index, this paper has used the technical efficiency change (TEC), which explains the effectiveness of production process, and it also used the technological change (TC), which shows any shift in the production frontier and explains the technology production which affects the relationship between input and output of production process. Moreover, this paper has used the scale efficiency change (SEC) explains average productivity ratio of any level of input used in the optimal point.

Therefore, as the empirical results of this paper, they can be summarized that the situation of the agro and food industry regarding the performance level and benchmark should lead to improving their inefficiency. Moreover, they can help the companies and the government to develop strategic planning and to understand the character of two sub-industry sectors and the trend of productivity in this industry.

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