

## Productivity and efficiency modeling amongst ASEAN-5 airline industries



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### ABSTRACT

This study intends to benchmark the technical efficiency and the productivity change measurement of the five national airlines in ASEAN-5 countries via Data Envelopment Analysis (DEA) and a DEA-based Malmquist Total Factor Productivity (TFP) Index approach. DEA approach uses a balanced panel data extracted from the annual report of Garuda Indonesia, Malaysia Airlines, Philippine Airlines, Singapore Airlines and Thai Airways International, covering the period of 2007 to 2013. The Tobit model is used to investigate the effect of input variables (Available Seat Kilometer (ASK) and Operating Cost) and output variables (Revenue Passenger Kilometer (RPK) and Passenger Revenue) on the efficiency scores computed by DEA. The efficiency scores of ASEAN-5 airlines computed by DEA shows that Malaysian Airlines is the least efficient airline and Philippines Airlines is the airline with the best efficiency. The result of Malmquist TFP approach reveals that there is a 1.2 percent improvement in technical efficiency, 1.2 percent deterioration in technology, 0.7 percent progression in pure technical efficiency, 0.5 percent increase in scale efficiency and a 0.1 percent decline in TFP in the airline industry in ASEAN-5 throughout the entire study period. The Malmquist TFP approach also reports that the change in TFP was mainly due to the deterioration of technology. The empirical results obtained from Tobit analysis suggest that the ASK has a significant negative impact on efficiency score, whereas both RPK and Passenger Revenue are found to have a significant positive effect on efficiency. Operating cost is the only variable that is found to have no significant impact on efficiency score.

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### 1. Introduction

Aviation industry has been a concern over the last decade because it is an important economic contributor to a country or even globally, and Association of Southeast Asian Nations (ASEAN) is no exception. The aviation industry in ASEAN has experienced a significant growth especially from 2009 to 2013. The total seat capacity of ASEAN airlines has recorded a double-digit growth within the four-year period. Today, aviation focus has turned to ASEAN's long-awaited Open Skies policy. This Open Skies policy, also known as the ASEAN Single Aviation Market (ASEAN-SAM), finally came into force on 1st January 2015. ASEAN Open Skies policy does not only aim to enhance domestic and regional connectivity, instead it targets to increase the regional trade and integrate production

networks by allowing airlines from all 10 ASEAN countries to fly freely throughout the region under a single aviation market via the liberalization of air services. The move towards such policy will boost a tremendous potential for rapid growth in ASEAN airlines. ASEAN-5 countries are Indonesia, Malaysia, Philippines, Singapore and Thailand and are home to the biggest airlines in the region. Therefore, it is not surprising that there is a recent rise of interest in the study of airline efficiency in ASEAN-5.

This paper focuses on evaluating airlines productivity and efficiency in ASEAN-5. The primary reason why this study is meaningful because the literature presently contains very little research about airline efficiency in ASEAN and ultimately none in ASEAN-5. This paper analyses 5 national airlines in ASEAN-5 as they are a good reflection and representation of the entire airline industry in the region. This paper employs annual panel data of ASEAN-5 countries during 2007-2013 to assess an airline's relative efficiency in a single period or in a sequence of periods. First, DEA approach is used to compute the efficiency scores of these 5 national airlines for each year. Second, a DEA-based

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Malmquist Total Factor Productivity (TFP) index approach is applied as to measure the relative productivity changes of these 5 national airlines over the entire study period. Third, Tobit regression analysis is conducted to investigate the effect of available seat kilometer (ASK), operating cost, revenue passenger kilometer (RPK) and passenger revenue on the efficiency scores computed by DEA in the first step.

## 2. Literature review

Open Skies policy was first introduced in the United States and Europe air transport markets since 1992. Therefore, most studies have focused on the effect of market liberalization on airline efficiency, mainly in the United States and Europe economies. Unlike United States and Europe, Asia is relatively new to aviation market liberalization, as liberalization via Open Skies policy in Asia began only after 2000. Therefore, more studies on Asian air transport market are required. Recently, in conjunction with ASEAN Open Skies policy, an additional region that deserves a great attention is the implementation of Open Skies policy in Southeast Asian economies and its effect on airline efficiency (Heshmati and Kim, 2016).

Efficiency can be defined on the assumption that output is maximized given certain inputs level and cost is minimized for a specified level of output (Kumbhakar and Lovell, 2000; Battese et al., 2000). There are three main types of efficiency based on economic theory: technical efficiency, allocative efficiency and cost efficiency. Basically, technical efficiency gives an idea on the effectiveness of a certain level of inputs used to generate an output. Allocative efficiency, on the other hand, refers to the involvement of choosing the mix of inputs in order to generate a specified level of outputs at the lowest cost (Battese et al., 2000). The combination of both technical and allocative efficiency is then known as cost efficiency (Assaf and Josiassen, 2012).

In a highly competitive air transport environment, global national airlines are in the midst of facing the challenge of enhancing effectiveness and struggle to make higher returns. The relatively high fixed costs in the aviation industry and economies of scale have left a great impact on airlines efficiency (Spurling, 2009). In order to enhance the airline efficiency, it is extremely important that the airline companies take initiatives to maximize their employment and fleet utilization as well as to serve more passengers globally as to achieve load factor at the highest possible level. Based on the reviews of the literature, the economy of density (Vasigh et al., 2008), economy of scope (Ben, 2008), economies of scale (Button, 2010) and capacity utilization (Jara-Díaz et al., 2013) could have benefited airlines significantly in term of efficiency.

The effectiveness of air transportation has been a recent spate of interest among many researchers. Many studies focused on the evaluation of airline

productivity and efficiency using Data Envelopment Analysis (DEA) approach. Most of the researchers first conducted the efficiency test, then followed by a second approach to analyze the effect of the variables of interest on the efficiency score.

Barbot et al. (2008) have measured the productivity and efficiency of 41 international airlines by classifying them into 5 regions: (1) North America and Canada, (2) Europe and Russia, (3) Middle East and Africa, (4) North Asia and China, (5) Asia Pacific. Labor (number of core business workers), fuel (in gallons consumed) and fleet (number of operating aircraft) were used as measures of inputs. RPK, ASK and revenue tonne kilometer (RTK), on the other hand, were used as measures of outputs. Productivity and efficiency comparison between low-cost carriers and full-service carriers was made in their research paper. DEA and TFP were the two methodologies used for the purpose of empirical analysis. The researchers also investigated factors that could have affected the efficiency level significantly. The result showed that full-services airlines were less efficient than low-cost airlines. It also concluded that airlines efficiency and the dispersion of both TFP and DEA indices amongst airlines varied by geographical region. The researchers were then argued that such variation was mainly caused by the different deregulation and legislation procedures based on the regions. In addition to the results, labor was seemed to be the only variable that had a significant impact on the productivity level. Meanwhile, due to the economies of scale, airlines that are larger in size were found to be more efficient than the smaller one.

Unlike previous researchers who have studied airline efficiency in a global level, Assaf and Josiassen (2011) focused solely on the efficiency of airlines in the United Kingdom that have gone through financial difficulties currently. Assaf and Josiassen (2011) investigated the technical efficiency of UK airlines by using DEA and further applying the bootstrap analysis approach. The result revealed that the airline size and load factor are correlated with technical efficiency in a positive relationship. In addition, they also found that factors such as extreme air transport market competition and higher crude oil prices were the possible causes of technical inefficiency in airlines industry.

The research by Greer (2009) examined the technical efficiencies of US airlines with the application of DEA too. Greer transformed inputs such as fuel, fleet-wide seating capacity and labor into ASK. Greer collected and analyzed the passenger data of the US airlines and applied Tobit analysis, a regression model to identify the significant factors of the efficiency score that was generated by DEA. It is common that researchers express the measures of inputs and outputs in monetary term, in order to evaluate airlines efficiency. However, unlike any other researchers, Greer defined the inputs and outputs variables in physical units instead of monetary term in this research paper. The result revealed that the average size of its aircrafts, the

average age of an airline's fleet and the average stage length were the determinants of inefficiency as they were statistically insignificant on airline efficiency.

The vast expansion in low-cost carriers, the high and volatile fuel prices have turned the air transport market into a more challenging and highly competitive environment. Such economic conditions have successfully evoked [Hensher and Merkert \(2011\)](#) interest in the study of airline efficiency. [Hensher and Merkert \(2011\)](#) intended to analyze the influencing factors that affect the efficiency and the cost of airlines in a challenging economic climate. This study targeted to evaluate the standard errors for point efficiency estimates over 58 passenger airlines. They identified the key determinants of airline efficiency by employing a two-phase DEA with partially bootstrapped random effects. Tobit regression was then used as a second stage analysis to explain variations in the efficiency level. Like any other existing literature, available tonne kilometer (ATK) as a measure of capital and full-time employment (FTE) staff as a proxy for labor were used as the inputs data in this study. Revenue tonne kilometer (RTK) and RPK are frequently used to model the output of both cargo and passenger flight operations. They are the most common output measures used in many studies that related to airlines efficiency, and this study is no exception. RTK and RPK were used widely in all DEA models in the research. Unlike DEA, ASK was used as the second-stage explanatory variable in Tobit Regression to measure the size of each airline. In addition to explanatory variables, average stage length was selected to investigate the effect of network/route optimization on airline efficiency. As discussed earlier, the average seats per aircraft as a measure of aircraft size, was also chosen to analyze whether the overall airline efficiency would be affected by the productivity measures of individual aircrafts or not. Results of the study by [Hensher and Merkert \(2011\)](#) revealed that not only the size of airlines, the fleet mixes of the size of aircrafts and the number of families of aircraft in the fleets has an impact on allocative, cost and technical efficiency too.

In a recent study, [Gramani \(2012\)](#) used a two-stage DEA to evaluate the fiscal operations and operational of airlines separately. The study is based on a set of data consists of 4 airlines (2 American and 2 Brazilian) over the period of 1997-2006. In order to evaluate airlines operational performance, an input-oriented DEA model was used and the resources optimization in producing was examined. Adversely, to evaluate airlines financial performance, an output-orientation model was used instead. Since an increase in inputs did not generate the same increase in outputs, a variable returns to scale (VRS) model instead of constant returns to scale (CRS) model was employed here. As for input variables, wages, cost per available seat mile (CASM) and aircraft fuel were used, whereas load factor and revenue passenger mile were used as output variables in the evaluation of operational

performance. When evaluating airlines financial performance, the inverse of the efficiency scores obtained from DEA was used as input, flight income and flight revenue, on the other hand, were used as output variables. It was found that airlines operational performance is much better than financial performance in an emerging market, suggesting that resource optimization is the key factor of airlines efficiency. The result revealed that in an emergent airline market, improving operational efficiency doesn't mean that the financial efficiency is improving too.

In another recent research, [Chou et al. \(2016\)](#) analyzed the efficiency of 35 airlines that were grouped into 2 regions: North America/Europe and Asia Pacific. The result from DEA approach suggested that airlines should have focusing more on input resources reduction for efficiency enhancement. Their results also revealed that carriers in the Asia Pacific regions perform better than those in North America/Europe, in term of service effectiveness and technical efficiency. [Duygun et al. \(2016\)](#), on the other hand, researched the influence of recent liberalization and deregulation of air transport in Europe. Their results revealed that cost minimization, efficient route systems and passenger satisfaction are key determinants of airlines efficiency. Unlike other researchers who examined airlines efficiency based on geographic regions, [Min and Joo \(2016\)](#) targeted to measure the effectiveness of airline alliances. Generally, airline strategic alliances are said to be a key driver in enhancing operating efficiency. However, the study did not support that hypothesis.

Instead of analyzing airline efficiency in developed countries, [Hu et al. \(2017\)](#) have turned their attention to Southeast Asia nations, the emerging markets. They measured and benchmarked the operational efficiency of 15 major airlines in ASEAN covering the period 2010-2014 and introduce a new clarification along with managerial ramifications. Number of aircraft, operating cost and ASK were used as input measures; RPK and total revenue were the output variables in their research. The researchers applied DEA models, disaggregated input efficiency measures and bootstrapping approaches to compute airline operational efficiency. The disaggregated input efficiency of ASEAN airlines is computed by comparing the actual and target inputs. Their findings reveal that available seat efficiency is the best, operating cost efficiency is better and aircraft efficiency is the lowest.

Most studies have been conducted based on the US and European airlines. In the recent years more researchers evoked their interest in Asia-based airlines as a whole. However, there is little research in the literature that was solely focusing on a region like Southeast Asia. Airlines in Southeast Asia region, ASEAN for short, deserve due attention. Research needs to be conducted to account for the substantial and growing portion of international passenger and cargo traffic in the region. Therefore, in this paper,

Southeast Asia would be the researching region, where the efficiency of flag carriers of Indonesia, Malaysia, Philippines, Singapore and Thailand will be conducted using DEA, productivity change by DEA-based Malmquist TFP Index and the factors affecting the efficiency of airlines will be examined via Tobit Regression.

**3. Methodology**

This section introduces the research methodology of the study, including DEA, Malmquist TFP Index and Tobit regression analysis.

**3.1. DEA**

Data Envelopment Analysis is a non-parametric linear programming approach used to measure the production efficiency of a decision making unit (DMU). DEA generates relative efficiency score for each unit and compares each DMU with the best practice. In short, the general concept of DEA is that if a particular DMU is able to produce a certain level of output with a given amount of inputs, theoretically other units should be able to achieve that level of production too. It always seems to be easier to identify the DMUs' efficiency performance when they only take into account of one input and one output. However, in reality, number of inputs will be injected to achieve a single output or sometimes to reach several outputs. In such cases, simple comparison is no longer works to measure their efficiency; instead, DEA should play the role as a comparative approach. DEA makes it possible to compare DMU on the levels of outputs they secure relative to their input levels.

DEA approach can further break down into input-oriented models (inputs minimization) and output-oriented models (outputs maximization). Graphically, DEA assumes the formation of a production possibility frontier and estimates the quantitative distance between the input position of a given DMU to the frontier for input-oriented model, and output position to the frontier for output-oriented model (Kourtit and Nijkamp, 2013). However, out of these two models, input-oriented DEA approach is commonly used because it is much easier to control inputs instead of outputs. If the efficiency score generated by DEA is equal to 1, this represents that 100% of the resources are fully utilized and transformed into outputs. DMU is said to be efficient and is positioned on the frontier. Meanwhile, if the efficiency score is less than 1, DMUs are inefficient and part of the inputs are being wasted or it can be said that the output is not being maximized with the given set of inputs (Suzuki et al., 2011).

The DEA model developed by Charnes et al. (1978) is as follows:

$$\text{Max } TE_k = \frac{\sum_{r=1}^s u_{rk} Y_{rk}}{\sum_{i=1}^m v_{ik} X_{ik}} \quad (1)$$

Constraints;

$$\frac{\sum_{r=1}^s u_{rk} Y_{rk}}{\sum_{i=1}^m v_{ik} X_{ij}} \leq 1 \quad (2)$$

$$u_{rk} \geq 0, v_{ik} \geq 0 \quad (3)$$

$$j = 1, \dots, n$$

$$r = 1, \dots, s; \quad i = 1, \dots, m$$

where the representations of indexes are as follow:

TE<sub>k</sub>: the technical efficiency of the DMU that is under evaluation with the use of m inputs to produce s outputs;

j: represents the DMUs and varies from 1 to n (there are n DMUs);

i: the input index and varies from 1 to m (there are m inputs);

r: the output index and varies from 1 to s (there are s outputs);

X<sub>ij</sub>: represents the value of the i<sup>th</sup> input for the j<sup>th</sup> DMU (X<sub>ik</sub> represents the value of i<sup>th</sup> input for the DMU that is under evaluation);

Y<sub>rj</sub>: represents the value of the r<sup>th</sup> output for the j<sup>th</sup> DMU (Y<sub>rk</sub> represents the value of r<sup>th</sup> output for the DMU that is under evaluation);

v<sub>ik</sub>: the weight of the i<sup>th</sup> input for the DMU that is under evaluation;

u<sub>rk</sub>: the weight of the r<sup>th</sup> output for the DMU that is under evaluation.

The equation (1) measures the ratio of weighted sum of multiple outputs to weighted sum of multiple inputs. The constraint (2) states that if the weights of a DMU are used for other DMUs, their efficiencies should not exceed 100%. The second constraint (3) provides the non-negativity of weights.

**3.2. Malmquist TFP index**

Malmquist TFP index, a DEA-based approach can deal with balanced panel data as it measures the relative productivity changes of DMUs along with time variations. It helps to understand that the TFP change is whether a result of technical efficiency change (getting close of DMUs to the production frontier) or technological change (shifting of the production frontier). The input oriented Malmquist approach according to Fare et al. (1992) for any two successive time periods t and t+1, can be expressed as:

$$M_i^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \frac{D_i^{t+1}(y^{t+1}, x^{t+1})}{D_i^t(y^t, x^t)} \times \left[ \frac{D_i^t(y^{t+1}, x^{t+1})}{D_i^{t+1}(y^{t+1}, x^{t+1})} \times \frac{D_i^t(y^t, x^t)}{D_i^{t+1}(y^t, x^t)} \right]^{\frac{1}{2}} \quad (4)$$

$$M_i^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \text{tfpch} \quad (5)$$

$$\frac{D_i^{t+1}(y^{t+1}, x^{t+1})}{D_i^t(y^t, x^t)} = \text{effch} = \text{pech} \times \text{sech} \quad (6)$$

$$\left[ \frac{D_i^t(y^{t+1}, x^{t+1})}{D_i^{t+1}(y^{t+1}, x^{t+1})} \times \frac{D_i^t(y^t, x^t)}{D_i^{t+1}(y^t, x^t)} \right]^{\frac{1}{2}} = \text{techch} \quad (7)$$

$$\text{tfpch} = (\text{pech} \times \text{sech}) \times \text{techch} \quad (8)$$

Coelli (1996) introduces "effch" as technical efficiency change, "techch" as technological change, "pech" as pure technical efficiency change, "sech" as scale efficiency change and "tfpch" as TFP change. The equation (4) represents the productivity of

production points  $(x^{t+1}, y^{t+1})$  relative to the production point  $(x^t, y^t)$ ; the value of greater than 1 implies total productivity growth from period  $t$  to the next period  $t+1$ . The ratio (6) measures the change in technical efficiency; it measures how close the DMU is to the frontier in period  $t+1$  compared with period  $t$ . If  $\text{effch} = 1$ , the DMU has the same distance from the respective production frontiers in periods  $t + 1$  and  $t$ . If  $\text{effch} > 1$ , the DMU has moved closer to the frontier in period  $t+1$  than it was in period  $t$ , and the converse occurs if  $\text{effch} < 1$ .

Index of technical efficiency change ( $\text{effch}$ ) has been further decomposed into pure technical efficiency change ( $\text{pech}$ ) and scale efficiency change ( $\text{sech}$ ).  $\text{effch}$  is the efficiency change calculated under constant returns to scale;  $\text{pech}$ , on the other hand, referred to the efficiency change calculated under variable returns to scale. The ratio of the CRS efficiency measure ( $\text{effch}$ ) to the VRS measure ( $\text{pech}$ ) will be the scale efficiency change ( $\text{sech}$ ).

Unlike ratio (6), the ratio (7) represents the index of technological change between two successive time periods. If  $\text{techch} = 1$ , it denotes no shift in technology frontier; a value of  $\text{techch} < 1$  indicates technological regress;  $\text{techch} > 1$  reflects technological progress and is considered to be a proof of innovation. In sum, the TFP change in Malmquist approach in equation (8) can be explained by either the catching-up of separate firms with the industry production frontier (technical efficiency change) or perhaps the shift of the frontier over time (technological change) (Price and Weyman-Jones, 1996).

### 3.3. Tobit regression analysis

Tobit regression analysis is known as censored regression analysis. It is designed to estimate linear relationship between a non-negative dependent variable and independent variables. The non-negative dependent variable in this research is referring to the efficiency scores generated by DEA, while the selected inputs and outputs will be the independent variables under Tobit analysis. In general, there is either left-censoring or right-censoring in the dependent variable. Left-censored which is known as censoring from below takes place when cases with values at or below the limit set. In the case of right-censored from above, values of those that fall at or above the limits are censored. There are cases where Tobit can also fit models that are censored from both sides and it is called two-limit Tobit model. The value of efficiency always lies in between 0 and 1 (Das and Ghosh, 2006; Banker et al., 2010). In this research, as the efficiency scores could not go beyond the value of 1 and have the upper limit of 1, therefore right-censored Tobit regression model will be used for analysis purpose. For interpretation part, Tobit regression coefficients are interpreted in the similar manner to OLS regression coefficients. However, the key difference is that the linear effect is on the latent variable, not on the observed outcome. For instance, the expected

efficiency score (latent variable) changes by how many units (coefficient) for each unit increase in the corresponding predictor. The Tobit model is formulated as follows:

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \dots + \hat{\beta}_n X_n$$

where:

$\hat{Y}$ : dependant variable

$\hat{\beta}_0$ : constant

$\hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_n$ : regression coefficient(s)

$X_1, X_2, \dots, X_n$ : independent variable(s)

## 4. Research framework

This section briefly explains the overall design of analysis procedure to be conducted in the entire study. Fig. 1 shows the procedure of different stages to find the determinants of efficiency.

Data that consists of two inputs (ASK and operating cost) and two outputs (PRK and passenger revenue) for each airlines will first be used to compute the efficiency scores for the five selected national airlines in ASEAN-5 by DEA approach. The same data set will then be utilized to measure the relative productivity changes of the five airlines over the year 2007-2013 via Malmquist Productivity Index approach. The research analysis will then follow by a Tobit Regression Analysis to study the effect of ASK, operating cost, RPK and passenger revenue on the efficiency scores that have computed by DEA in the first step. Note that DEA efficiency scores will be the dependent variable; ASK, operating cost, RPK and passenger revenue are the independent variables under Tobit analysis. Generally, this research framework will give a clear picture on which national airline in ASEAN-5 performs better than others in term of productivity and efficiency. This research will also give a clear insight on how significantly the variables of interest affect airline efficiency.

## 5. Data and selection of variables

The data set used in this study was obtained from the annual report of each airlines covering the period of 2007 to 2013. A balanced panel data from five national airlines including Garuda Indonesia, Malaysia Airlines, Philippine Airlines, Singapore Airlines and Thai Airways International, is used in this study. Initially, all the ten members of ASEAN were considered, but some airlines' data of the ten countries were not completed or not listed, including Brunei, Laos and Myanmar, therefore, this study ends up with only the first five core countries in ASEAN. Despite only five countries are evaluated, all the airlines in the sample are in the top 100 of passenger operations in the world's airline ranking by Skytrax.

The literature review shows that there are numerous alternative inputs and outputs that are adequate for airline efficiency analysis. Considering the data availability of ASEAN-5 airlines and the

existing literature, ASK and operating cost are used as inputs; RPK and passenger revenue are used as outputs in this study. Table 1 presents the summary of past literature that has used these input and output variables. The rule of thumb when establishing a sample size in DEA studies is that it

should be at least the product of input and output (i.e., inputs × outputs). This study satisfies the minimum requirement with a sample five airlines, from a product of two input and two output variables for the DEA model.



Fig. 1: Procedure of different stages to find the determinants of efficiency

Table 1: Input and output variables for airline efficiency evaluation

Input variables	Output variables
Operating cost: Wu et al. (2013) and Hu et al. (2017)	RPK: Barbot et al. (2008), Hensher and Merkert (2011), Wu et al. (2013), Merkert and Pearson (2015) and Hu et al. (2017)
ASK: Greer (2009), Wu et al. (2013), Merkert and Pearson (2015), Hu et al. (2017)	Passenger revenue: Barbot et al. (2008) and Merkert and Pearson (2015)

ASK measures the capacity of an airline carrying flight's passenger. It refers to the passenger capacity offered for sale expressed as number of seats multiplied by distance travelled. Operating cost, on the other hand, represents the expenses used for an airline to maintain its operation including both fixed costs and variable costs. Unlike ASK, RPK measure the traffic for an airline flight, calculated by multiplying the number of revenue-paying passengers by kilometer flown. Passenger revenue is the sale arise from revenue-paying passengers, other revenue like cargo is excluded.

Table 2 summarizes the output and input data from 2007 to 2013. The standard deviations of all variables are close to the means, denoting the structure of airlines in ASEAN-5 is close to one another in operation scale. The correlations between

each pair of input-output variables are highly positive, which is consistent with the production theory and economic intuition (Table 3).

## 6. Result and discussion

This section first present the computed efficiency scores by DEA, followed by Malmquist productivity index to measure the TFP and its corresponding changes in its components. Tobit regression analysis comes at last.

### 6.1. DEA

Table 4 presents the results of the efficiency scores of 5 national airlines during the year 2007

through 2013 using input-oriented CRS-DEA model. From 2007 to 2013, 2 to 4 national airlines achieved an efficiency score of 1. In the top rank, only one national airline reveals the best efficiency, consistent with full DEA efficiency score throughout the entire

study period, which is Philippine Airlines. The results indicate that Philippine Airlines is considered as the benchmark airline to the other four national airlines.

**Table 2:** Descriptive statistics for input and output variables (2007-2013) of the airlines in ASEAN-5 under evaluation

Inputs/Outputs	Variable	Obs	Mean	Std. Dev.	Min	Max
Inputs	ASK	35	5.99e+10	3.39e+10	2.05e+10	1.21e+11
	OC	35	5.02e+09	3.32e+09	1.41e+09	1.20e+10
Outputs	RPK	35	4.55e+10	2.67e+10	1.43e+10	9.51e+10
	PR	35	3.46e+09	2.00e+09	1.07e+09	6.71e+09

**Notes:** ASK and RPK are measured in kilometer (KM); OC and PR are measured in US dollars (USD)

**Table 3:** Correlation coefficients of input and output variables

	ASK	OC	RPK	PR
ASK	1			
OC	0.9796	1		
RPK	0.9967	0.9799	1	
PR	0.9748	0.9598	0.9719	1

**Notes:** ASK: Available seat kilometer, OC: Operating cost, RPK: Revenue passenger kilometer, PR: Passenger revenue

**Table 4:** Efficiency scores of input-oriented CRS-DEA model based on the selected ASEAN-5 airlines (2007-2013)

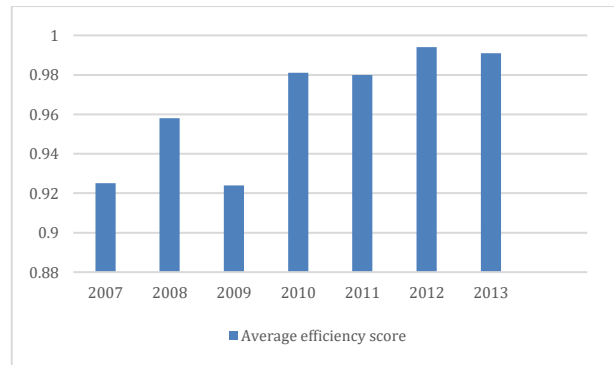
Airlines	2007	2008	2009	2010	2011	2012	2013	Average
<b>Best efficiency<sup>a</sup></b>								
Philippine Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
<b>Moderate-better efficiency<sup>b</sup></b>								
Thai Airways International	1.000	1.000	1.000	1.000	0.933	1.000	0.979	0.987
Singapore Airlines	0.954	0.962	0.870	1.000	1.000	1.000	0.978	0.966
Garuda Indonesia	0.850	0.986	0.925	0.921	1.000	1.000	1.000	0.955
Malaysia Airlines	0.823	0.842	0.827	0.983	0.965	0.968	1.000	0.915
Average efficiency score	0.925	0.958	0.924	0.981	0.980	0.994	0.991	0.965
Number of airlines with best efficiency	2	2	2	3	3	4	3	

**Notes:** <sup>a</sup>Indicates a consistently full efficiency airline; <sup>b</sup>indicate s a moderate-better efficiency airline

In the second rank of efficiency, four national airlines are efficient in at least one of the seven years during the entire study period. These four national airlines, namely Thai Airways International, Singapore Airlines, Garuda Indonesia and Malaysia Airlines are considered to have moderate-better efficiency in general. If there is any airline that never achieve full efficiency during the study period, that particular airline will fall under the third rank of low efficiency and is considered to have not good efficiency. Fortunately, among the five national airlines, all of them have achieved at least one full efficiency during the entire study period, and none of them fall under third rank in this study. However, when Philippine Airlines is considered as the best efficient national airline, there must be one to be the least efficient national airline in opposition. Therefore, for the average, Malaysia Airlines is considered to be the least efficient one among the rest. The mean efficiency score of Malaysia Airlines is 0.915, denoting 8.5 percent inefficiency. Malaysia Airlines would have to decrease its inputs by 8.5 percent in order to become efficient.

It is found that there are only two efficient airlines for 2007-2009, but the number of efficient airlines increase over the years with the highest of four airlines in 2012. This result is in line with the average efficiency scores graph that exhibits an upward trend during the study period 2007-2013 in Fig. 2. The lowest and highest DEA average efficiency scores are 0.924 in 2009 and 0.994 in 2012 respectively. The lowest average efficiency scores in 2009 are mainly attributed to the impact of global

economic downturn in 2008. Aviation as a part of the main pillars of global economy is being affected. Meanwhile for 2010 onwards, especially year 2012, the upward trend could be well-explained by air traffic growth in ASEAN as having more passengers on board to travel around.



**Fig. 2:** Average efficiency scores of ASEAN-5 airlines (2007-2013)

**6.2. Malmquist TFP index**

Table 5 shows the Malmquist index summary of the five selected national airline in ASEAN-5. According to technical efficiency change index, 60 percent of the airlines increased their average annual technical efficiency; 20 percent deteriorated; as for another 20 percent no change has been observed. Among the airlines which progressed in technical efficiency, Malaysia Airlines with a 3.3 percent change took a place on top, followed by Garuda Indonesia with a change of 2.7 percent.

Besides, due to the decay in scale efficiency, Thai Airways International is the only regressed airline in term of technical efficiency. Philippine Airlines, on the other hand, have no change in technical efficiency.

The results also reveal that there are average annual 1.2 percent decline in technology. 40 percent of the airlines improved, but 60 percent deteriorated technologically during the study period. Thai Airways International and Garuda Indonesia are the airlines that improved technologically with a minor change of 0.5 percent and 0.3 percent respectively. Among the three airlines with technology decline, Philippine Airlines is the airline with the most declines of 4 percent, whereas there are only 2.4 percent and 0.6 percent change observed in Malaysia Airlines and Singapore Airlines respectively.

The annual average TFP for the study period has a minor decline of 0.1 percent. Improvement in 60 percent and regression in 40 percent of the airlines is observed. With the highest increase in TFP during the study period, Garuda Indonesia outshone all the others with a 3 percent improvement. Nevertheless, Malaysia Airlines and Thai Airways International are observed to have an increase in TFP too with a change of 0.9 percent and 0.2 percent respectively. However, note that Garuda Indonesia's factor productivity increase is not only driven by the improvement in technical efficiency but also on innovation. While the increase in TFP for both Malaysia Airlines and Thai Airways International is solely based on the improvement in either technical efficiency or technology. Philippine Airlines - 4 percent change and Singapore Airlines - 0.2 percent change, are the two airlines declined in TFP. Note

that technology regression of Philippine Airlines and Singapore Airlines contribute to TFP reduction.

Table 6 shows the Malmquist index summary of annual means by year from 2007 to 2013. Note that technical efficiency change can be affected by pure technical efficiency change and/or scale efficiency change; TFP change can be influenced by technical efficiency change and/or technological change. Based on the results in Table 6, airlines' average annual improvement technical efficiency index is 1.012, denoting a 1.2 percent improvement throughout the study period. Besides, proceeding is observed both in pure technical efficiency and scale efficiency. As the increase in pure technical efficiency is 0.7 percent and 0.5 percent in scale efficiency, hence the average annual technical efficiency index improved. Basically, the managerial enhancement and the improvement towards required scale are the key aspects that lead to the technical efficiency growth of airline industry in ASEAN-5. However, a slight decline of 0.1 percent is spotted in TFP. The change in TFP (tfpch) was mainly due to the deterioration of 1.2 percent in technology (techch). In sum, it can be concluded that the productivity of airline industry in ASEAN-5 throughout the study period from 2007 to 2013 declines, due to technological regress.

According to the statistical line graph in Fig. 3, 2009 is the year when the technical efficiency level hit the bottom, and 2010 is the peak year. The deterioration of technical efficiency level in 2009 could be well explained by the impact of 2008 Financial Crisis, whereas the progression in 2010 symbolizes economic rebound where consumers regain their confidence towards the market.

**Table 5:** Malmquist index summary of firm means

DMU	effch	techch	pech	sech	tfpch
Garuda Indonesia	1.027	1.003	1.012	1.015	1.030
Malaysia Airlines	1.033	0.976	1.026	1.007	1.009
Thai Airways International	0.997	1.005	1.000	0.997	1.002
Singapore Airlines	1.004	0.994	1.000	1.004	0.998
Philippine Airlines	1.000	0.960	1.000	1.000	0.960
*Mean	1.012	0.988	1.007	1.005	0.999
	effch<1 = 1	techch<1 = 3	pech<1 = 0	sech<1 = 1	tfpch<1 = 2
	effch=1 = 1	techch=1 = 0	pech=1 = 3	sech=1 = 1	tfpch=1 = 0
	effch>1 = 3	techch>1 = 2	pech>1 = 2	sech>1 = 3	tfpch>1 = 3

**Notes:** Technical efficiency change (effch), Technological change (techch), Pure technical efficiency change (pech), Scale efficiency change (sech), TFP change (tfpch)

\*All Malmquist index averages are geometric means

$tfpch = effch \times techch$  and  $effch = pech \times sech$

**Table 6:** Malmquist Index Summary of Annual Means

Year	effch	techch	pech	sech	tfpch
2007/2008	1.036	0.960	1.016	1.021	0.994
2008/2009	0.964	1.008	0.997	0.967	0.972
2009/2010	1.063	0.959	1.030	1.033	1.020
2010/2011	0.999	1.029	0.996	1.003	1.028
2011/2012	1.015	0.988	1.001	1.013	1.003
2012/2013	0.998	0.984	1.005	0.992	0.982
*Mean	1.012	0.988	1.007	1.005	0.999

**Notes:** \*All Malmquist index averages are geometric means



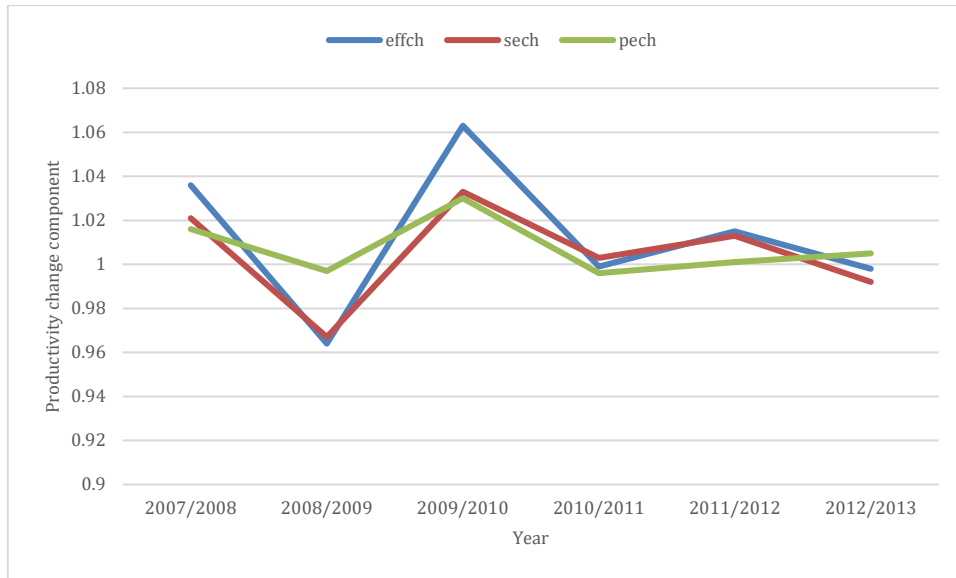


Fig. 3: Summary of annual means of ASEAN-5 airlines with effch, sech and pech components (2007-2013)

### 6.3. Tobit regression analysis

Table 7 presents the results of Tobit regression of airline efficiency score on ASK, operating cost, RPK and passenger revenue. 19 out of 35 data are observed to have full efficiency score at 1.

- effch: Technical efficiency change
- sech: Scale efficiency change
- pech: Pure technical efficiency change

(1) Estimated Tobit regression model:

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \hat{\beta}_3 X_3 + \hat{\beta}_4 X_n$$

$$ES = 1.043124 - (2.38e^{-11})ASK - (2.49e^{-12})OC + (2.13e^{-11})RPK + (1.23e^{-10})PR$$

(2) Interpretation of coefficients:

$$\hat{\beta}_0 = 1.043124 \approx 1$$

The estimated efficiency score of an airline is 1, when its ASK, OC, RPK and PR are all equals to zero. In layman's terms, all airlines are said to have achieved full efficiency level with an efficiency score of 1, without considering any of the variables: ASK, operating cost, and RPK and passenger revenue.

$$\hat{\beta}_1 = -2.23e^{-11}$$

For every increase of 1 kilometer in ASK, airline efficiency score is expected to decrease by  $2.38e^{-11}$ , while keeping other variables as constant. In other word, it also means that airline efficiency score will decrease by 0.0238 for every 1,000,000,000 kilometers increase in ASK. Note that ASK is an input. When an increase in input is not able to push the output volume higher, the efficiency will definitely become lower. Therefore, it is not surprising that ASK and efficiency score have a negative relationship.

$$\hat{\beta}_2 = -2.49e^{-12}$$

For every increase of 1 US dollar in operating cost, airline efficiency score is expected to decrease by  $2.49e^{-12}$ , while keeping other variables as constant. Like ASK, operating cost is considered as an input too. Hence, operating cost and efficiency score move in different direction.

$$\hat{\beta}_3 = -2.13e^{-11}$$

For every increase of 1 kilometer in RPK, airline efficiency score is expected to increase by  $2.13e^{-11}$ , while keeping other variables as constant. Unlike ASK, RPK is an output. When there is an increase in output level with a constant inputs level, the efficiency will be improved. Thus, it can be concluded that both RPK and efficiency score move in same direction.

$$\hat{\beta}_4 = -1.23e^{-10}$$

For every increase of 1 US dollar in passenger revenue, airline efficiency score is expected to increase by  $1.23e^{-10}$ , while keeping other variables as constant. The same output concept could be applied here, where an increase in output level could help to enhance efficiency, but with a condition that everything else should held constant. Obviously, there is a positive relationship between passenger revenue and efficiency score.

(3) Significant of parameter coefficients:

$$H_0: \beta_j = 0 \text{ (} X_j \text{ is not significant)}$$

$$H_1: \beta_j \neq 0 \text{ (} X_j \text{ is significant)}$$

where  $j = 1, 2, 3, 4$

The P-value of each independent variables presented in Table 7 reveals that ASK, RPK and passenger revenue (PR) have significant effect on airline efficiency score as their P-value is smaller than  $\alpha = 0.05$  and  $H_0$  is rejected. There is sufficient evidence to conclude that ASK has significant negative impact on efficiency score, whereas both

RPK and passenger revenue are found to have significant positive effect on efficiency at  $\alpha = 0.05$ . Concurrently, operating cost is the only variable that

is found to have no significant impact on efficiency score at  $\alpha = 0.05$ , as its P-value-0.891 is much greater than  $\alpha$  value-0.05, thus, fail to reject  $H_0$ .

**Table 7: Tobit regression analysis**

ES, $\hat{Y}$	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ASK, $X_1$	-2.38e-11	5.13e-12	-4.64	0.000*	-3.42e-11 -1.33e-11
OC, $X_2$	-2.49e-12	1.79e-11	-0.14	0.891*	-3.90e-11 3.41e-11
RPK, $X_3$	2.13e-11	5.98e-12	3.57	0.001*	9.14e-12 3.35e-11
PR, $X_4$	1.23e-10	2.79e-11	4.39	0.000*	6.57e-11 1.80e-10
_cons	1.043124	.0326543	31.94	0.000*	.9765254 1.109723
/sigma	.0564757	.0105848			.0348879 .0780635
Obs. summary:				0 left-censored observations	
				16 uncensored observations	
				19 right-censored observations at ES>=1	

Notes: \*P<0.05. ES: Efficiency score

## 7. Conclusion

This study's empirical results exhibit the following. First, the efficiency scores of ASEAN-5 airlines computed by DEA shows that Malaysia Airlines is the least efficient airline and Philippines Airlines is the airline with best efficiency. Second, the result of Malmquist TFP Index approach reveals that there is a 1.2 percent improvement in technical efficiency, 1.2 percent deterioration in technology, 0.7 percent progression in pure technical efficiency, 0.5 percent increase in scale efficiency and a 0.1 percent decline in TFP in the airline industry in ASEAN-5 throughout the period of 2007-2013. Third, the Malmquist TFP approach reports that the change in TFP was mainly due to the deterioration in technology. Fourth, the empirical result obtained from Tobit analysis suggest that ASK has significant negative impact on efficiency score, whereas both RPK and passenger revenue are found to have significant positive effect on efficiency. Fifth, operating cost is the only variable that is found to have no significant impact on efficiency score. In a nutshell, as the competition in international routes becomes more intense within ASEAN-5 region due to the emergence of low-cost carriers, a comparative airline efficiency analysis involving both full service and low-cost carriers can be a future research area.

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