DISAGGREGATION OF PRODUCTIVITY GROWTH OF INDONESIAN AIRPORTS

Viverita
Department of Management,
Faculty of Economics and Business,
Universitas Indonesia
viverita.d@ui.ac.id

Ratih Dyah Kusumastuti
Department of Management,
Faculty of Economics and Business,
Universitas Indonesia
ratih.dyah@ui.ac.id

Abstract

This paper reports the sources of productivity growth of 23 Indonesian airports for years 2006-2010. Using input slack-based productivity index (ISP), we disaggregate total factor productivity change into each input productivity change. Apron area and terminal area are chosen as input variables while aircrafts' movement is the output. By classifying the airports based on two operators, this study finds that airports under the management of Angkasa Pura 1 (AP1) show higher productivity growth than Angkasa Pura 2 (AP2), whose growth is mainly driven by technical progress in apron areas. Moreover, the productivity decline of AP2 was mostly due to inefficient use of terminal areas.

Keywords: airports, input slack-based productivity index, productivity growth, technical change, efficiency change.

Abstrak

Studi ini menganalisis sumber pertumbuhan produktivitas 23 bandara Indonesia selama tahun 2006-2010. Dengan menggunakan indeks produktivitas berbasis slack-based (ISP). Total perubahan faktor produktivitas didisagregasi ke dalam setiap perubahan produktivitas input. Daerah apron dan terminal dipilih sebagai variabel input sedangkan pergerakan pesawat menjadi variable output. Dengan mengklasifikasikan bandara berdasarkan dua operator, studi ini menunjukkan bahwa bandara yang berada di bawah pengelolaan Angkasa Pura 1 (AP1) menunjukkan pertumbuhan produktivitas yang lebih tinggi daripada Angkasa Pura 2 (AP2), yang pertumbuhannya terutama didorong oleh kemajuan teknis di daerah apron. Selain itu, penurunan produktivitas AP2 sebagian besar disebabkan oleh penggunaan daerah terminal yang tidak efisien.

Kata kunci: bandara, indeks produktivitas berbasis slack, pertumbuhan produktivitas, teknik, efisiensi.

The Indonesian airline industry has experienced a significant growth since 2001 due to the deregulation in the industry caused by the issuance of The Decree of Minister of Transportation: Number 11, Year 2001. The decree rules an easier way for airline establishment, which caused significant growth in the number of airlines including low cost carriers (LCCs). Since 2001, at least five low LCLs have been operated through Indonesian skies. This trend brings more stiff competition in low cost carriers and application of no-frill flights. Furthermore, the revolution

Table 1. The Growth of Service Provided by the Indonesian Air Transport Industry, 2006-2010

Year	Aircraft Movement	Passenger Movement	Cargo Handled
2006			
2007	1.74%	6.94%	17.17%
2008	2.18%	2.64%	4.46%
2009	2.98%	6.76%	-2.34%
2010	15.85%	26.59%	12.52%
Average growth	**5.69%**	**10.73%**	**7.95%**
2006-2010	**24.03%**	**48.35%**	**34.49%**

Source: Angkasa Pura I (2010) and Angkasa Pura II (2010)

in the aviation industry spreads to marketing and distribution systems. As a result, every carrier is urged to operate efficiently in order to get more passengers and buyers of the service provided.

In the case of Indonesian air transport industry, the existence of LCC is suspected to influence the growth of its revenue, as it grew by 14.37% from 2002 to 2006 (Angkasa Pura 1 (2010), and Angkasa Pura II (2010)). The increased operating revenues is suspected caused by increased aircraft and passenger movement, as well as the amount of cargo handled by the airports (See Table 1). However, although airports are naturally operated as local monopolies, due to increasing competitiveness of the industry they need to enhance their ability to operate efficiently.

Airports in Indonesia are operated by two state-owned companies: PT. Angkasa Pura I (AP I) and PT. Angkasa Pura II (AP II). AP I is operating airports in the eastern part of Indonesia (in the cities of Semarang, Solo, Yogyakarta, Surabaya, Banjarmasin, Balikpapan, Makassar, Manado, Denpasar, Mataram, Kupang, Ambon, and Biak), whereas AP II is operating airports in the western part of Indonesia (in the cities of Jakarta, Bandung, Palembang, Padang, Pekanbaru, Medan, Pontianak, Banda Aceh, Tanjung Pinang, Pangkal Pinang, and Jambi).

Gillen and Hall (1997) advise that airport activities may produce two types of services: terminal services that include passenger movements and cargo handling and movements, which comprise air carrier movement and commuter movements. Furthermore, Doganis (1992) suggests that airport activities provide three types of services: operational, handling, and commercial. The operational services relate to every aeronautical activity that allows aircraft movement such as runway services, flight control duties, and aircraft parking. Handling services involve all ground activities such as processing passengers and freights in the terminal areas. Commercial services are all activities unrelated to the operational or handing services. This comprises business activities such as concession of spaces for shops, restaurants, etc.

The issue of airport efficiency received more attention and was widely studied by scholars and policy makers due to complex activities involving operating the airports and their effects on the national economy (Button and Taylor, 2000). According to Boyne (2003), two variables that most consistently influenced the performance of public service were resources and management. Furthermore, the operational performances of airports involve many aspects. For example, they provide service to air carriers, passengers, and customers who need cargo delivered. In addition, an efficient airport generally recognized as the one that can maximize its output, given input involving the production function.

To the best of our knowledge, no study is published on Indonesian airport efficiency. Considering the increasing growth of revenues, passenger movements, aircraft movements and amount of cargo handled by the Indonesian airports in the last five years, this study investigates whether the performance is due to operational efficiency or government imposed policy imposed. We also explore the productivity changes of the Indonesian airports. The sample data consist of a panel of 23 airports operating throughout the islands of Indonesia, from 2006 to 2010. The operational data was gathered from PT. Angkasa Pura I and PT. Angkasa Pura II. We use the DEA method to obtain efficiency score of each airport. The rest of the paper is organized as follows: Section 2 reviews the relevant studies on airport efficiency. Section 3 presents the proposed method and model specification. Section 4 reveals the findings. Finally, Section 5 summaries and concludes the study.

LITERATURE REVIEW

Numerous studies on airport operational efficiency applied various frontier methodologies. In general, data envelopment analysis (DEA), total factor productivity (TFP), and stochastic frontier approach (SFA) were used to measure and evaluate the efficiency of airports. Studies that used various DEA models were done by Gillen and Lall (1997), Sarkis (2000), Martin and Roman (2001), Fung et al. (2008), Barris and Weber (2008), Chi-Lok and Zhang (2009), Lam, Low and Tang (2009), Roghanian and Foroughi (2010), Yu (2010), and Lozano and Gutierrez (2011). Studies that used TFP approach, for instance, were done by Nyshadham and Rao (2000), Oum, Yu and Fu (2003), Oum, Adler and Yu (2006), Murrillo-Mechar (2006), Tovar and Martin-Cejas (2010). Studies that used SFA and other parametric approaches were done by Barros (2008), Abrate and Erbetta (2010), Tovar and Martin-Cejas (2010). Other researchers, such as Yoshida and Fujimoto (2004) used both DEA and TFP to assess the efficiency of airports in Japan while Vasigh and Haririan (2003) used Ratios analysis and regression analysis to compare the efficiency of seven privatized airports in the UK to eight government owned airports in the US.

Most studies used resources such as airport infrastructure (apron area, runway area, terminal area), labor (number of employees and labor cost), and operational costs as measures of input, whereas aircraft movements, passenger volume, and cargo volume were mostly used as measures of output. Lozano and Gutierrez (2011) included undesirable output—delayed flights, while Tovar and Martin-Cejas (2010) considered aircraft size and share of non-aeronautical revenue as output. Sarkis (2000) and Oum et al. (2003), Oum et al. (2006), Abrate and Erbetta (2010) included revenues as measure of output.

RESEARCH METHOD

One popular approach in measuring airports' production efficiency is the Data Envelopment Analysis (DEA). In order to seek the research questions, this study employs two types of the DEA approaches. First, it applies the standard DEA approach especially the efficiency measures as results of allocative and technical efficiency. Secondly, it applies the Malmquist total productivity measures to determine the efficiency gains. DEA is a non-parametric methodology that utilizes data as inputs and output quantities of a group of firms or decision-making units (DMUs) to construct a piece-wise frontier over the data points. This frontier is constructed by the solution of a sequence of linear programming problems, one for each DMU in the sample. Efficiency scores or measures are then estimated relative to this frontier, which corresponds to an efficient technology. In addition, it allows efficiency to be estimated without having to stipulate either the structure of production function or the weights for inputs and outputs used.

Charnes, Cooper and Rhodes (1978) introduced the DEA constant return to scale (CRS). It takes into account multiple inputs used in the production process to generate outputs, to estimate total factor productivity or TFP, a score including all factors of productions. DEA can be estimated either input-oriented or output-oriented. In the input-oriented, the DEA approach defines the frontier by seeking the maximum possible reduction in input usage, with output held constant, vice versa. The two results of both measures give the same technical efficiency scores when CRS is assumed, but are different when variables return to scale (VRS) are assumed. In this paper, an output-oriented measures and CRS is assumed because the DMUs want to maximize their outputs given inputs related to the production function. DEA measures are obtained by introducing a ratio of M outputs over N inputs, as follows:

$$\begin{aligned} &Max_{x,y} \quad (y'q_i / x'p_i) \\ &Subject\ to \quad y'q_j / x'p_j \le 1, \quad j = 1,2,\ldots,I, \\ &\qquad y, x \ge 0 \end{aligned} \tag{1}$$

where **y** represents an M×1 vector of output weights and **x** represents an N×1 vector of inputs weights. The N×1 input matrix, **P**, and the M×1 output matrix, **Q**, represent the data for all I DMUs.

In the second stage, the Malmquist factor productivity measure is used to identify efficiency gains/loss. In this case, we use the model proposed for the first time by Fare, Grosskopf, and Zhang (1994), and the Malmquist index of total factor productivity changes (TFPCH) over period t, and t+1 is the product of technical efficiency change (EFFCH) and technological change (TECHCH) as follows:

$$\text{TFPCH} = \text{EFFCH x TECHCH} \tag{2}$$

Fare *et al*. (1994) defined an output distance function can be defined at a time *t* as follows:

$$\begin{aligned} D_0^t(x^t, y^t) &= \min\left\{\theta : (x^t, y^t/\theta) \in S^t\right\} \\ &= \max\left\{\theta : (x^t, \theta y^t) \in S^t\right\}^{-1} \end{aligned} \tag{3}$$

This shows how much outputs (y) can be increased, given a quantity of inputs (x) used, such that x and θy remain the production set over time-1 and 1. An input distance function can similarly be defined under *constant returns to scale*: the value would be equal to the earlier distance function. In particular, the distance function $D_0^t(x^t, y^t) \le 1$ if and only if the output vector, y, is an element of the feasible set, *S (x)*. In addition, the distance functions $D_0^t(x^t, y^t) = 1$ if and only if *y* is located on the frontier technology of the feasible production set. This is likely to occur when production is technically efficient (Farrel, 1957), i.e., the production efficiency arises from employing technology that enables efficiency change over –1 to 1 period.

Following Fare et al. (1994), the Malmquist productivity change index, therefore, can be written as involving the two indices.

$$m_0(y_t, x_t y_{t+1}, x_{t+1}) = \frac{d_0^{t+1}(y_{t+1}, x_{t+1})}{d_0^t(y_t, x_t)} \left[\frac{d_0^t(y_{t+1}, x_{t+1})}{d_0^{t+1}(y_{t+1}, x_{t+1})} \times \frac{d_0^t(y_t, x_t)}{d_0^t(y_t, x_t)} \right]^{1/2} \quad (4)$$

where *y* and *x* are outputs and inputs across time *t* to *t+1*. The Malmquist indices are computed relatively to the previous period. The technical efficiency change measures the change in efficiency between period *t* and *t+1*, while the technical change captures the shift in the technology applied over time. A value greater than one in both cases indicates growth in productivity: positive factor values.

This study measures banks' total factor productivity (TFP) by applying Luenberger *multi-factor* productivity index. It assumes using a specific proportional distance function that cannot handle changes in a single productivity. Therefore, Chang et al. (2012) developed a new index model by introducing *Input Slack-based Productivity Index* (ISP), which used *directional distance function* and Färe-Lovell's efficiency measures. This index not only measures changes in TFP, but also changes in individual productivity of individual input simultaneously in the total factor productivity framework.

The I*nput Slack-based Productivity Index* assumes *M* number of *inputs* and *S* number of *outputs* for *N* objects over the period of *T*. The input i^{th} and *output* r^{th} simultaneously represented by x_{ij}^t and y_{rj}^t. Briec (2000) introduces the Färe-Lovell efficiency measures, which have an ability to choose the efficient vector toward the *frontier*. Therefore, the *input-oriented directional distance function* for observation *o* at time *t* can be written as a linear *programming* as follows:

$$\overrightarrow{D_{(t)}}(x^t, y^t) = \max \frac{1}{M}(\beta_1 + \ldots + \beta_M)$$

$$s.\ t.\ \sum_{j=1}^{N} \lambda j X_{ij}^t \leq X_{io}^t (1 - \beta_i),$$

$$\sum_{j=1}^{N} \lambda j y_{rj}^t \geq y_{ro}^t,$$

$$\lambda_j \geq 0, \beta_1 \geq 0,$$

$$j = 1, \ldots, N;\ i = 1, \ldots, M;\ r = 1, \ldots, S. \quad (5)$$

λj represents vector 1 x *n* of the positive intensity variable, which creates a convex combination of the observed *input* and *output*. *βi* is a scalar variable indicating proportional contractions of input *i* to reach the efficient level; therefore, if all values of scalar variables (*β1=β2=βM*) = 0, then observation *o* lies on the *strongly efficient frontier*. The Färe-Lovell's efficiency measures were based on the assumption of *constant return to scale* (CRS), indicating the efficiency level of *input* and *output* would be technically efficient. The other three *distance functions* in Equation (6) can be calculated based on Equation (5). The calculation of $\overrightarrow{D_{(t+1)}}(x^{t+1}, y^{t+1})$ is same as in (1), where *t* is replaced by *t+1*. It also applies for both *inter-temporal distance function*, $\overrightarrow{D_{(t)}}(x^{t+1}, y^{t+1})$ and $\overrightarrow{D_{(t+1)}}(x^t, y^t)$.

Related to the ISP, the value of *βi* form Equation (1) is defined as $\overrightarrow{D_{i(t)}}(x^t, y^t)$, which means that $\overrightarrow{D_{i(t)}}(x^t, y^t)$, is a *distance function* for the *input i* at time

t under the total factor framework. Consequently, the value of ISP for the i^{th} input is measured as follows:

$$\left[ISP = \frac{1}{2}\left[\left(\vec{D}_{i(t)}(x^t,y^t) - \vec{D}_{i(t)}(x^{t+1},y^{t+1})\right) + \left(\vec{D}_{i(t+1)}(x^t,y^t) - \vec{D}_{i(t+1)}(x^{t+1},y^{t+1})\right) \right] \right] \quad (6)$$

If the value of ISP is less than zero, it indicates the declining productivity of i^{th} *input*. In contrast, when the value of ISP is greater than zero means productivity growth. However, if the value equals to zero, then there is no change of the input productivity from time t to $t+1$.

Luenberger productivity index decomposes ISP into two components: *efficiency change* (EFFCH) and *technical change* (TECHCH). The first component (EFFCH) measures changes in relative efficiency, while the second component (TECHCH) measures changes in technology of the input i^{th}. These measures can be written as follows:

$$EFFCH_i = \vec{D}_{i(t)}(x^t,y^t) - \vec{D}_{i(t+1)}(x^{t+1},y^{t+1}) \quad (7)$$

$$TECHCH_i = \frac{1}{2}\left[\vec{D}_{i(t+1)}(x^{t+1},y^{t+1}) - \vec{D}_{i(t)}(x^{t+1},y^{t+1}) + \vec{D}_{i(t+1)}(x^t,y^t) - \vec{D}_{i(t+1)}(x^t,y^t)\right] \quad (8)$$

Since $\vec{D}_{(t)}(x^t,y^t)$ equals the average of all inputs *distance function*, therefore, change *total factor productivity* (TFPCH) can be decomposed into changes in individual input as written in equation:

$$\begin{aligned} TFPCH &= EFFCH + TECHCH \\ &= \frac{1}{M}[EFFCH_1 + \ldots + EFFCH_M] + \frac{1}{M}[TECHCH_1 + \ldots + TECHCH_M] \\ &= \frac{1}{M}[ISP_1 + \ldots + ISP_M] \end{aligned} \quad (9)$$

Equation (9) indicates that change in TFP is caused by the average change in individual input. In addition, each *efficiency change* and *technical efficiency change* of individual input can be aggregated as a *total factor efficiency change* (EFFCH) and a *total factor technical change* (TECHCH).

RESULT AND DISCUSSION

Our analysis of Indonesian airports uses annually observational data of 23 out of 25 airports, and located in 23 cities over the island nation during the period of 2006 to 2010. The airports are selected based on the data availability of each airport. This article applies non-parametric linear programming technique-based data envelopment analysis (DEA) to calculate the airports' f……. productivity (TFP) change and decomposing it to examine the contribution of each input factors on the TFP change. We measure inputs and outputs of the airport are related to parts of its infrastructure, i.e: terminal services and movements. Outputs are represented by aircraft movements (MOV), whereas inputs are apron areas (APR) and terminal areas (TMA). The number of sample airports is greater than three times the numbers of inputs and output thus satisfying the requirement of the discriminatory power (Avkiran, 2002).

Table 2 presents a summary of statistics for the input and output variables used to investigate the productivity change of Indonesian airports. Data in Table 1 show the mean value: the value of dispersion from the average as well as the maximum and minimum values of the input and output variables. The data also show the value of average growth of each variable. It exhibits that, on average, the aircraft movements grow at 5.6% while apron areas grow at around 4%, and terminal areas grow at almost 5%.

This study uses individual aggregate data from two airport operators in Indonesia: Angkasa Pura 1 (AP1) and Angkasa Pura 2 (AP2). In order to calculate the total factor productivity

Table 2. Statistical Description of Indonesian Airports

Variables	Units	Average	Maximum	Minimum	Standard Deviation	Average growth
Aircraft movements	number	36619.82	305541	2161	53049.01	5.62%
Apron areas	M^2	104358.9	818243	12400	161385.69	4.12%
Terminal areas	M^2	29199.371	312283	1280	62669.25	4.81%

Source: Airports data, processed

Table 3. Annual Productivity of Airports

Period	AP1	AP2
2006/2007	0.0039	-0.0001
2007/2008	-0.0206	-0.0105
2008/2009	-0.0272	-0.1228
2009/2010	0.0642	-0.0149
Total	0.0203	-0.1482
Average	0.0051	-0.0370

(TFP) of the airports, and their input factors as well as to decompose each of the input factors, we employed Lingo 13.0 and Microsoft Excel 2010. Results from the estimation are presented in the form of TFP change, efficiency change, and technological change. In addition, we also present the change and contribution of each input factors to the TFP change.

Productivity analysis of the airports

Table 3 presents the average annual change of TFP of all airports in AP 1 and AP 2: in terms of TFP, airports in AP 1 are more productive than those in AP2. This result may be because most of the airports under AP1 are considered big airports with the capacity to handle more aircraft and passengers than those in AP2. Furthermore, this condition may result from the increasing number of passengers after the air transport deregulation policy in 2001. In addition, data also show that, although the TFP declined from 2007 to 2009, on average, the productivity of AP1 grew, whilst AP 2 experienced TFP decline during the whole study period.

The decreasing TFP in both airports in 2007 to 2009 was mostly due to the global financial crisis that affected airports' ability to attract passengers and firms to use their cargo facilities (as indicated by the declining number of cargo handled: 2.34% from 2008 to 2009 (See Table 1).

Figure 1 presents cumulative TFP change between AP1 and AP2 during the study period. The figure shows that, although experiencing TFP decline at the beginning of the observation period until 2008, AP1 managed to increase the productivity growth. On the other hand, the TFP change of AP2 continuously deteriorated. This situation probably occurred due to the locations and different sizes of the airports in AP2. Although some

Figure 1. Cumulative TFP change of the Airports, 2006-2010

Table 4. TFP Change and Input Factor Productivity Change of AP 1

Period	TFP	APR	TMA
2006/2007	0.0039	-0.0178	0.0257
2007/2008	-0.0206	0.0017	-0.0429
2008/2009	-0.0272	-0.0094	-0.0449
2009/2010	0.0642	0.0472	0.0812
Average	**0.0051**	**0.0054**	**0.0047**

airports are large and located in big cities such as Jakarta and Medan, their frequencies and number of passengers as well as number of cargo handled by other airports were smaller than those of in the big cities.

Productivity change and input factor decomposition of AP1

The application of Input slack-based productivity index (ISP) using Färe-Lovell (1978) efficiency measure to develop Luenberger productivity make it possible to analyses the productivity change of each input factor. Table 4 reports the annual average productivity change and its factor inputs: apron area (APR) and terminal area (TMA).

Data in Table 4 indicates that on average, the TFP of AP1 growth by 0.5% during the study period. It also shows that the TFP decline by around 2.1% from 2006 to 2007, and continue to deteriorate until 2008/2009 by 2.7%. However, it bounced back by 6.4% in the last period. In terms of the input factors, on average, the apron area is the most productive input of the AP1; this input factor also contributed more to the TFP of the AP1.

Figure 2 presents cumulative change of TFP and its input factors of airports under the management of AP1. It shows that the TFP of AP1 decreased sharply during the global financial crisis 2007/2008. Although TFP of both input factors declined over that period, the unproductive terminal area (TMA) contributed more to the declining TFP. However, on average, cumulative TFP growth occurred during the study period, due mostly to more productive use of input factor apron area (APR).

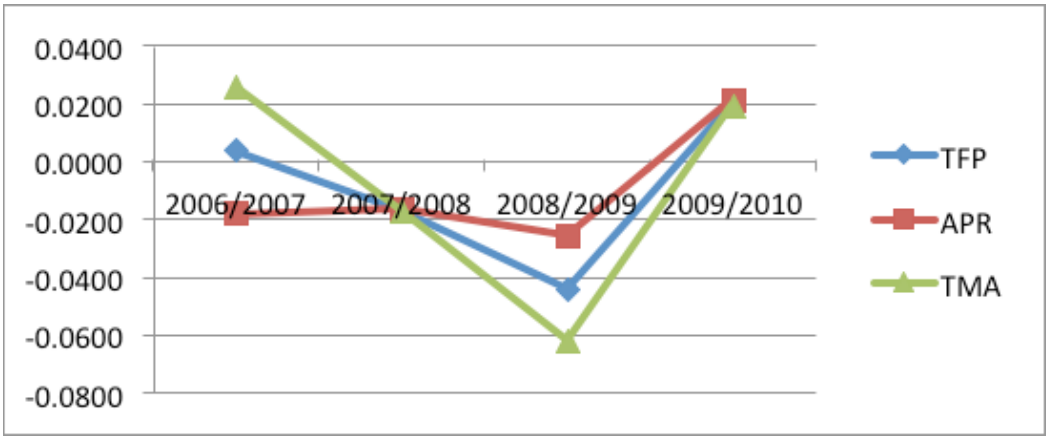

Figure 2. Cumulative Change of TFP and Its Input Factors: AP 1

Table 5. TFPCH, TECHCH, and EFFCH of AP1

Period	TFPCH	TECHCH	EFFCH
2006/2007	0.0039	-0.0704	0.0744
2007/2008	-0.0206	0.0254	-0.0461
2008/2009	-0.0272	0.2053	-0.2325
2009/2010	0.0642	0.0898	-0.0257
Average	**0.0051**	**0.0625**	**-0.0575**

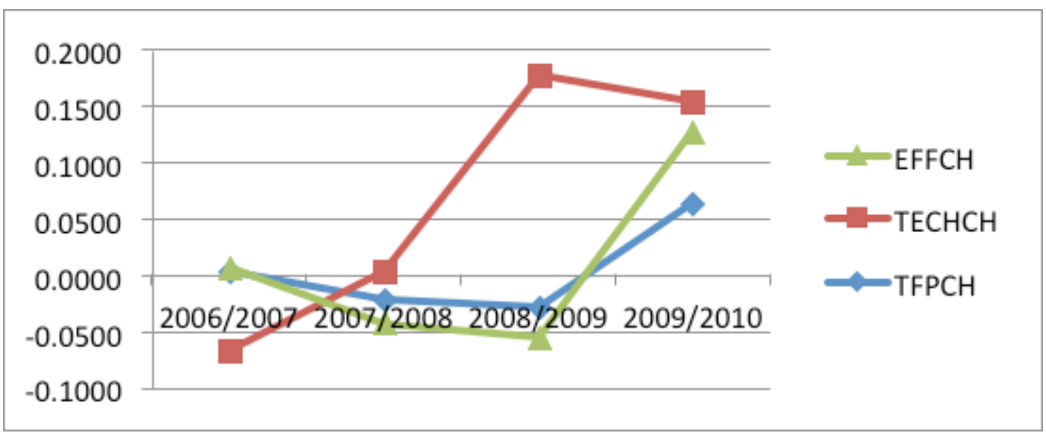

Figure 3. TFPCH, TECHCH, and EFFCH of AP1

Furthermore, TFP growth can also be decomposed into technical change (TECHCH) and efficiency change (EFFCH). As shown in Table 5, on average, TFP growth of the airports under AP1 management occurred from 2006 to 2010 and this growth was mostly due to increased innovation (TECHCH). On the other hand, AP1 experienced 5.8% decreased managerial efficiency over the period, which was probably due to inefficient mobilization of input factors (See also Figure 3).

Panel A in Table 6 describes the annual technical change of both input factors in each sub-period. It shows that, on average, both input factors increased over the study period. However, the growth of input factor APR (9.3%) is higher than input

Table 6. Decomposition of annual Technical Change and Efficiency Change of AP1

Period	TFP	APR	TMA
Panel A: Technical Change			
2006/2007	-0.0704	0.0237	-0.1646
2007/2008	0.0254	0.0314	0.0195
2008/2009	0.2053	0.2405	0.1701
2009/2010	0.0898	0.0753	0.1043
Average	**0.0625**	**0.0927**	**0.0323**
Panel B: Efficiency Change			
2006/2007	0.0744	-0.0415	0.1902
2007/2008	-0.0461	-0.0297	-0.0624
2008/2009	-0.2325	-0.2499	-0.2150
2009/2010	-0.0257	-0.0282	-0.0232
Average	**-0.0575**	**-0.0873**	**-0.0276**

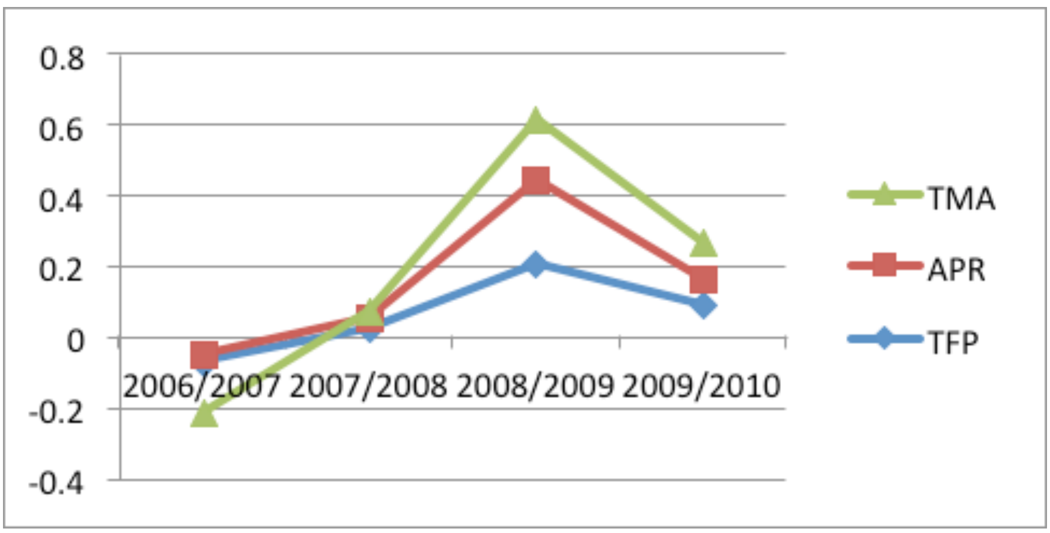

Figure 4. Decomposition of input factors of annual technical change of AP1

factor TMA (3.2%). Furthermore, results in Table 5 also indicate a negative growth of input factor TMA during 2006/2007, which contributes to the decreased productivity of technical change. Panel B presents a different story of the productivity of input factors: in general, there is productivity decline of efficiency changes and its input factors due to productivity regression of the two input factors. However, input factor APR contributed more to the decline than input factor TMA. This result indicates that the airports under AP1 management failed to maximize the use of their apron and terminal areas over the study period. If we look at each sub-period, we see that the efficiency of input factor APR declined sharply during the global financial crisis period of 2007 and 2008, which affected most economic activities (See Figures 4 and 5).

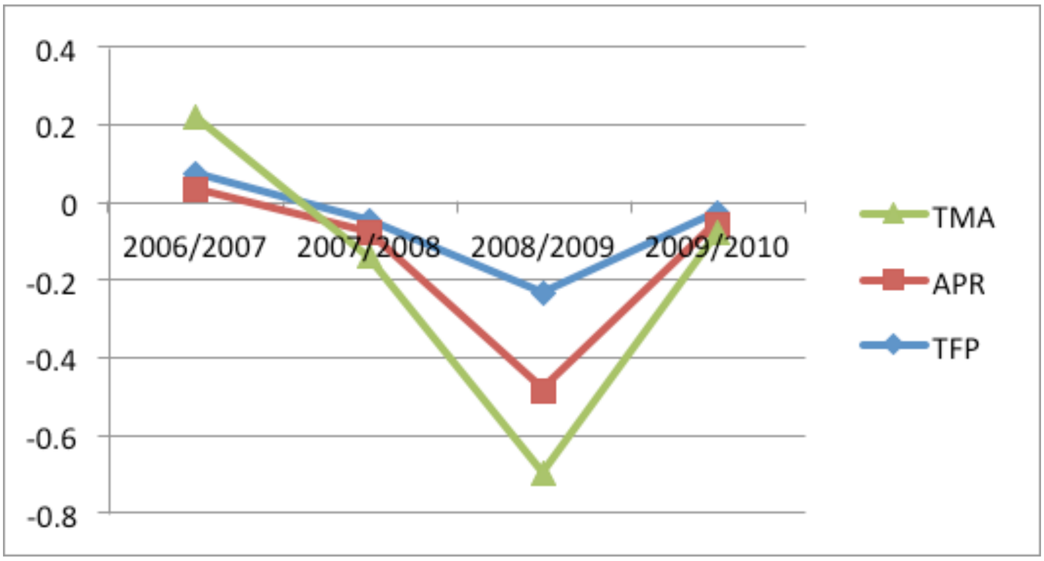

Figure 5. Decomposition of input factors of annual efficiency change of AP1

Table 7. TFP Change and Input Factor Productivity Change of AP 2

Period	TFP	APR	TMA
2006/2007	-0.0001	-0.0007	0.0006
2007/2008	-0.0105	-0.0136	-0.0074
2008/2009	-0.1333	-0.0524	-0.2142
2009/2010	-0.1482	-0.0617	-0.2346
Average	**-0.0370**	**-0.0154**	**-0.0587**

Productivity change and input factor decomposition of AP2

Table 7 reports the annual average productivity change and its factor inputs: apron area (APR) and terminal area (TMA) of airports under management of AP2.

Data in Table 7 indicate that, on average, the TFP of AP2 declined by 3.7% during the study period. Table 7 shows also that the TFP declined by around 13.3% during and after the 2008-2009 financial crisis and continued to deteriorate by 14.8% until the end of study period in 2010. In terms of the input factors, on average, terminal area declined at the higher rate (5.8%) compared to the input factor apron area (1.5%). In other words, input factor TMA contributed more to the productivity decline of AP2. Figure 6 presents cumulative change of TFP and its input factors of airports under the management of AP2. It shows that the TFP of AP2 continuously decreased during the study period, and the productivity decline of both input factors contributed to its TFP decline. However, although the TFP of both input factors declined, input factor TMA contributed more to the TFP deterioration.

Furthermore, TFP growth can also be decomposed into technical change (TECHCH) and efficiency change (EFFCH). As Table 8 shows, on average, deterioration of TFP of the airports under AP2 management during from 2006 to 2010 this decline mostly due to the declining in innovation (TECHCH).

Table 8. TFPCH, TECHCH, and EFFCH of AP2

Period	TFP	TECHCH	EFFCH
2006/2007	-0.0001	0.0492	-0.0493
2007/2008	-0.0105	0.0106	-0.0211
2008/2009	-0.1333	-0.1554	0.0221
2009/2010	-0.1482	-0.1332	-0.0149
Average	**-0.1482**	**-0.0333**	**-0.0037**

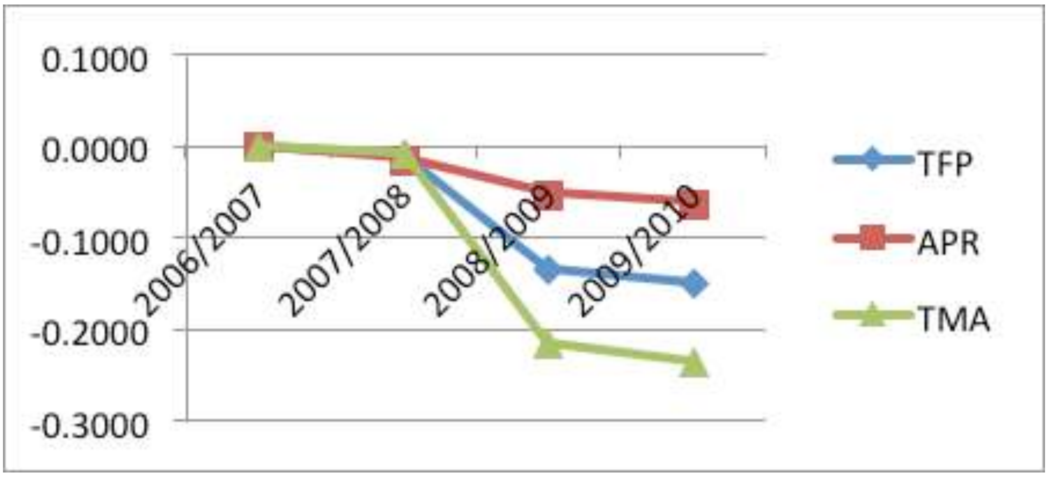

Figure 6. Cumulative Change of TFP and Its Input Factors: AP 2

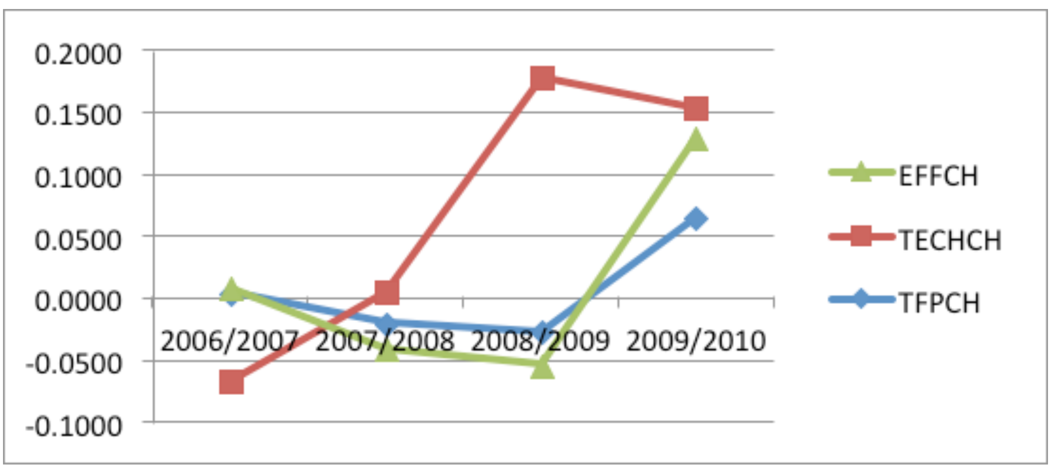

Figure 7. TFPCH, TECHCH, and EFFCH of AP2

In addition, AP2 also experienced decreasing managerial efficiency by 0.4% over the period which was probably due to inefficient mobilization of input factors (See also Figure 7).

Panel A in Table 9 describes the annual technical change of both input factors in each sub-period. It shows that, on average, input factor APR (apron area) growth by 2.9% is higher than input factor TMA (3.2%). Results in Table 5 also indicate a negative growth of input factor TMA during 2006/2007, which contributes to decreasing the productivity of technical change. Panel B presents a different story of the productivity of input factors.

Table 9. Decomposition of annual Technical Change and Efficiency Change of AP2

Period	TFP	APR	TMA
Panel A: Technical Change			
2006/2007	0.0492	0.0624	0.0360
2007/2008	-0.0386	-0.0489	-0.0282
2008/2009	-0.1660	0.0792	-0.4112
2009/2010	0.0222	0.0214	0.0230
Average	**-0.0333**	**0.0285**	**-0.0951**
Panel B: Efficiency Change			
2006/2007	-0.0493	-0.0631	-0.0354
2007/2008	0.0281	0.0360	0.0203
2008/2009	0.0432	-0.1180	0.2045
2009/2010	-0.0370	-0.0307	-0.0434
Average	**-0.0037**	**-0.0439**	**0.0365**

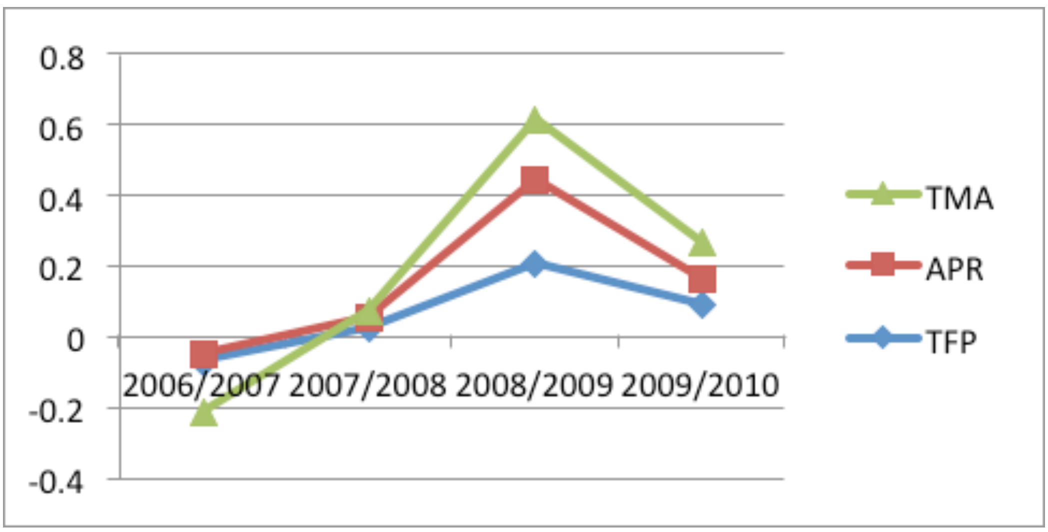

Figure 8. Decomposition of input factors of annual technical change of AP1

Table 9 shows that in general there is productivity decline of efficiency changes and input factors due to productivity regression of the two input factors. However, input factor APR contributed more to the decline than input factor TMA. This result indicates that the airports under AP1 management failed to maximize the use of their apron and terminal areas over the study period. Looking at each sub-period, we see that the efficiency of input factor APR declined sharply during the global financial crisis period of 2007 and 2008 that affected most economic activities (See also Figures 8 and 9).

CONCLUSION

This study aims to investigate the total productivity change and input productivity of the airports under the management of two operators, namely AP1 and AP2. We use a non-parametric approach of DEA output

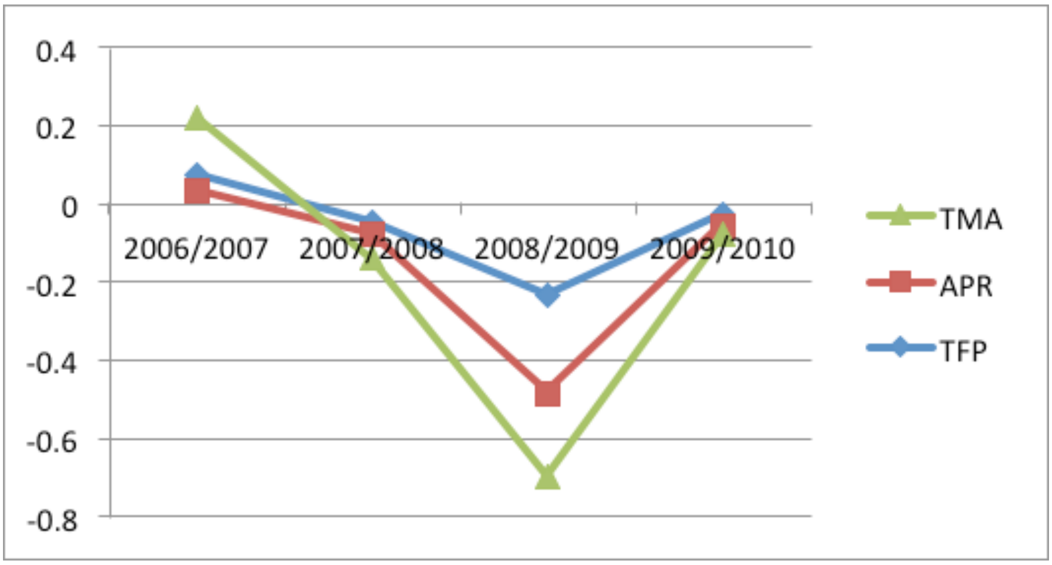

Figure 9. Decomposition of input factors of annual efficiency change of AP1

orientation to evaluate each firm's total factor productivity change, technical efficiency change, and efficiency change to examine the contribution of managerial performance and use of technology in the airports' production processes as we decompose the TFP index. In addition, we examine the productivity of each input factors to investigate the contributor to their productivity growth. In general, we found that, on average, airports under the management of AP1 are more productive than those of under the management of AP2.

Despite positive growth of TFP airports under the management of AP1, when decomposing total factor productivity change into its input factors productivity, the result shows this condition is due to the unproductive use of terminal areas (TMA). This finding is supported by further analysis of TFP change, where we found a 5.8% decrease of managerial efficiency over the period due to inefficient mobilization of input factors. In the case of AP2, we found a deterioration of TFP during the observation periods, mostly due to the high rate of decline in terminal areas compared to apron areas. In addition, the results also show that both input factors were contributed to the TFP decline.

Considering the decline TFP of AP2 and negative contribution of input factors, we suggest that the management of AP2 consider some applications to enhance airports' efficiency and productivity, especially considering the application of The Act of Minister of Transportation: Number 11, Year 2010, that made it possible for private companies to operate airports in Indonesia. Therefore, in the future, there may be more than one airport in a certain city run by different operators. To be able to compete and provide excellent service to the increasing number of customers increasing their revenues, airports in Indonesia should increase their efficiency.

This study has a limitation due to unavailability of airports' data since we were able to analyze only 23 out of 25 airports during the period of 2006-2010. Also, we could not acquire financial data of each airport; theefore, the results may not correctly depict the condition of the Indonesia airports. Furhermore, we cannot further analyze factors affecting the Indonesia airport efficiency in our study. We hope to address these limitations in our future research.

Acknowledgment

We acknowledge our gratitude to Yohanes W.S. Sudjana and Hernani W. Nugreeni from PT, Angkasa Pura, and Nur Dhani Hendranastiti for their valuable support.

References

Angkasa Pura I, 2010. Annual Reports. Retrieved from www.angkasapura1.co.id.

Angkasa Pura II, 2010. Annual Reports. Retrieved from www.angkasapura2.co.id.

Avkiran, N. K. (2002). *Productivity Analysis in the Service Sector with Data Envelopment Analysis*, 2nd Edition. Camira, Qld: N.K. Avkiran.

Button, K., & Taylor, S. (2000). International air transportation and economic development. *Journal of Air Transport Management, 6*(4), 209-222

Albretta, G., & Erbetta, F. (2010). Efficiency and patterns of service mix in airport companies: An input distance function approach. *Transportation Research Part E, 46*, 693–708.

Banker, R., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*(9), 1078–1092.

Barros, C. P. (2008). Technical efficiency of UK airports. *Journal of Air Transport Management, 14*(4), 175–178.

Barros, C. P., & Weber, W. L. (2009). Productivity growth and biased technological change in UK airports. *Transportation Research Part E, 45*, 642–653.

Boyne, G. A. (2003). Sources of public service improvement: A critical review and research agenda. *Journal of Public Administration Research and Theory, 3*(3), 367-394.

Chang, T., Hu, J., Chou, R. Y., & Sun, L. (2012). The sources of bank productivity growth in China during 2002-2009: A disaggregation view. *Journal of Banking and Finance, 36*(7), 1997-2006.

Charnes A, Cooper W. W., & Rhodes E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429-444.

Chi-Lok, A. Y., & Zhang, A. (2009). Effects of competition and policy changes on Chinese airport productivity: An empirical investigation. *Journal of Air Transport Management, 15*, 166–174.

Doganis, R. (1992). *The Airport Business*. London: Routledge.

Fare, R., Grosskopf, N. M., & Zhang, Z. (1994). Productivity growth, Technical progress, and e-ciency change in industrialized counties. *American Economic Review, 84*, 66−83.

Farell, M. J. (1957). The measurement of productive efficiency. *Journal of The Royal Statistical Society Series A (General), 120*(3), 253-290.

Forsyth, P. (2007). The impacts of emerging aviation trends on airport infrastructure. *Journal of Air Transport Management, 13*, 45–52.

Fung, M. K., Wan, K. K. H., Hui, Y. V., & Law, J. S. (2008). Productivity changes in Chinese airports 1995–2004. *Transportation Research Part E, 44*, 521–542.

Gillen, D., & Lall, A. (1997). Developing measures of airport productivity and performance: An application of Data Envelopment Analysis. *Transportation Research E, 33*(4), 261-273.

Lam, S. W., Low, J. M. W., & Tang, L. C. (2009). Operational efficiencies across Asia Pacific airports. *Transportation Research Part E, 45*, 654–665.

Lozano, S., & Gutierrez, E. (2011). Slacks-based measure of efficiency of airports with airplanes delays as undesirable outputs. *Computers & Operations Research, 38*, 131–139.

Martin, J. C., & Roman, C. (2001). An application of DEA to measure the efficiency of Spanish airports prior to privatization. *Journal of Air Transport Management, 7*, 4-157.

Oum, T. H., Yu, C., & Fu, X. (2003). A comparative analysis of productivity performance of the world's major airports: summary report of the ATRS global airport benchmarking research report-2002. *Journal of Air Transport Management, 9*, 285–297.

Oum, T., Adler, N., & Yu, C. (2006). Privatization, corporatization, ownership forms and their effects on the performance of the world's major airports. *Journal of Air Transport and Management, 12*, 109–121.

Roghanian, E., & Foroughi, A. (2010). An empirical study of Iranian regional airports using robust data envelopment analysis. *International Journal of Industrial Engineering Computations, 1*, 65-72.

Sarkis, J. (2000). An analysis of the operational efficiency of major airports in the United States. *Journal of Operations Management, 18*, 335–351.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research, 130*, 498-509.

Tovar, B., & Martin-Cejas, R. R. (2010). Technical efficiency and productivity changes in Spanish airports: A parametric distance functions approach. *Transportation Research Part E, 46,* 249–260.

Vasigh, B., & Haririan, M. (2003). An empirical investigation of financial and operational efficiency of private versus public airports. *Journal of Air Transportation, 8*(1), 91-110.

Yoshida, Y., & Fujimoto, H. (2004). Japanese-airport benchmarking with the DEA and endogenous-weight TFP methods: testing the criticism of overinvestment in Japanese regional airports. *Transportation Research Part E, 40*, 533–546.

Yu, M. (2010). Assessment of airport performance using the SBM-NDEA model. *Omega, 38*, 440-452.