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Applying DEA window and MPI in measuring the performance efficiency of airline industry in the Asia-Pacific region

Áp dụng DEA window và MPI trong đo lường hiệu quả hoạt động của ngành hàng không khu vực Châu Á - Thái Bình Dương

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Abstract

The aim of this study is to assess the performance and the efficiency of the aviation industry in the Asia-Pacific region through two-stage Data Envelopment Analysis (DEA). In the first stage, the relative efficiency was measured through a Window model in DEA. Then, at the second stage, the efficiency improvement was examined by the Malmquist Productivity Index (MPI).

Firstly, the selected inputs and outputs of 10 airlines in the Asia-Pacific region were analysed through a Window analysis to obtain the efficiency score over the past period 2015-2019 (year 2020 and year 2021 were skipped due to the impact of the Covid-19 pandemic). The results of the Window analysis method revealed that most airlines performed well during the observed period. In the second stage, MPI was applied to evaluate the efficiency trend during 2015-2019. The results of MPI showed a slight increase in trend.

The findings of this study contributed to the aviation industry as the results revealed real performance efficiency and also answer the question whether the aviation industry in Asia-Pacific, the region with the fastest growth in airline activity over the last decades, made any improvement.

Keywords: Aviation industry; Data Envelopment Analysis (DEA); Window analysis; Efficiency; Asia-Pacific.

Tóm tắt

Mục tiêu của nghiên cứu này là tiếp cận hiệu quả hoạt động của ngành hàng không ở khu vực Châu Á - Thái Bình Dương thông qua phân tích bao dữ liệu hai giai đoạn (DEA). Trong giai đoạn đầu, hiệu quả tương đối được đo lường thông qua mô hình Window trong DEA. Sau đó, ở giai đoạn thứ hai, việc cải thiện hiệu quả được kiểm tra bằng chỉ số năng suất Malmquist (MPI).

Thứ nhất, các yếu tố đầu vào và đầu ra của 10 hãng hàng không trong khu vực Châu Á - Thái Bình Dương đã được phân tích thông qua phân tích Window để có được điểm hiệu quả trong giai đoạn 2015-2019 vừa qua (năm 2020 và năm 2021 bị bỏ qua do ảnh hưởng của đại dịch Covid-19). Kết quả của phương pháp phân tích Window cho thấy hầu hết các

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hãng hàng không của nghiên cứu đều hoạt động tốt trong thời gian quan sát. Trong giai đoạn thứ hai, MPI được áp dụng để đánh giá xu hướng hiệu quả trong giai đoạn 2015-2019. Kết quả của MPI cho thấy xu hướng tăng nhẹ.

Những phát hiện của nghiên cứu này đã đóng góp rất nhiều cho ngành hàng không khi kết quả cho thấy hiệu quả hoạt động thật sự và cũng trả lời cho câu hỏi liệu ngành hàng không ở Châu Á - Thái Bình Dương, khu vực có tốc độ tăng trưởng nhanh về hoạt động hàng không trong những thập kỷ qua, có cải thiện được gì không.

Từ khóa: Công nghiệp hàng không; Phân tích bao dữ liệu (DEA); Phân tích Windown; Hiệu quả; Châu Á - Thái Bình Dương.

1. Introduction

Over the past decade, the Asia-Pacific region has seen the most significant growth in airline activity due to the area's substantial population and the proportion of people with sufficient disposable income to travel by air. This creates a conducive environment for well-managed airlines to succeed. Asia is projected to account for around 40% of future aircraft production [1].

In 2020, the COVID-19 pandemic led to a decrease in commercial and general aviation aircraft sales in the Asia-Pacific region, and international passenger traffic remained low in the commercial sector in 2021. However, internal passenger travel has been on the rise in several countries since late 2020, and the general aviation industry has also observed a similar trend in 2021, with aircraft traffic surpassing 2020 levels [2].

Despite the challenges brought by the pandemic, numerous airlines in the region have expressed their intention to purchase new aircraft in the next five years. This suggests that the recovery of the aviation industry in Asia-Pacific is likely to be faster than in other parts of the world in the projected period. Domestic airlines are expanding their fleets and route networks to capitalize on the growing local passenger traffic in the region. China and India are expected to be among the world's leading aviation markets by the end of the prediction period.

Thanks to the explosion in demand in the world in the past 10 years, Asia - Pacific is considered the most developed region in the world. Thus, assessing the performance of this industry is an interesting area for researchers. However, there is not much research work in this field in general as well as in the Asia-Pacific region in particular, which motivates the author to carry out this study to evaluate the operation and effectiveness of Asia-Pacific aviation industry. In order to achieve this objective, the DEA Window analysis method is employed. The paper is structured as follows: part 1 is for the introduction, then the literature is presented in the next part in which inputs and outputs are chosen. The methodology is further discussed in the third. Part 4 will present the empirical results and part 5 ends this research with the conclusion.

This section aims to review the previous relative literature on efficiency in general, then present the empirical literature and measure performance relevant to the aviation industry and provide a table of input-output indicators selected from existing studies to measure airline performance using DEA method.

One of the most important concepts in measuring performance is efficiency. There are different definitions of efficiency. However, in general, efficiency consists of two main components, namely technical efficiency and allocative efficiency [3]. Technical efficiency refers to the ability to maximize output using certain inputs or minimized inputs to produce a certain amount of output [4] while allocative efficiency is defined as the ability to use the optimal input ratio to produce the right mix of inputs and outputs for the company [5]. The combination of technical efficiency and allocative efficiency is called aggregate economic efficiency, which reflects the maximum potential profit [5].

Since allocative efficiency requires having input price information, which is limited by academic researchers, in order to estimate the cost function, technical efficiency is more widely researched. There are two methods commonly employed in measuring airline technical efficiency: (1) Data envelopment analysis (DEA) and (2) Stochastic Frontier Analysis (SFA) [6]. While DEA is a non-parametric approach, SFA is a parametric approach. These methods have their own advantages and disadvantages. However, by reviewing the recent studies in airline efficiency evaluation fields, the DEA method seems to be more widely used than SFA. Therefore, in this study we would like to employ DEA to measure the technical efficiency of the Asia-Pacific aviation industry.

Table 1: A recent DEA study samples of airlines and the indicators of inputs and outputs used.

Author	Inputs	Outputs
Lee et al. (2014) [7]	- Staff number - Total Assets - Kilometers flown	- Available ton kilometers (ATK)
Atul Rai (2013) [8]	- Staff number - Fleet number - Fuel	- Revenue passenger kilometer (RPK) - Available ton kilometers (ATK) - Number of passengers - Number of departures
Assaf and Josiassen (2012) [9]	- Staff number - Total Assets - Fuel - Operating expenses.	- Revenue passenger kilometer (RPK) - Incidental revenues - Available ton kilometers
Barros and Peypoch (2009) [10]	- Staff number - Operation cost - Fleet number	- Revenue passenger km (RPK) - Earnings before interest and taxes (EBIT)
Barbot et al. (2008) [11]	- Staff number - Fleet number - Fuel	- Available ton kilometers (ATK) - Revenue passenger kilometer (RPK) - Revenue ton kilometers

In existing studies, different input-output indicators have been chosen to analyze airlines' efficiency. Some of the most common input-output indicators are presented in Table 1.

After a closer look at each paper, it became clear that there was common ground in the selection of inputs and outputs. So, in this study, the inputs are (1) the number of fleets, (2) the total assets, and (3) the operating costs are selected. The output variables are (1) passenger kilometer revenue and (2) tons available kilometers.

2. Research Methodology

DEA is a non-parametric model that utilizes linear programming to determine the efficiency of a sample by comparing the ratio of inputs to outputs. The model has two main objectives, which are either to minimize inputs or maximize outputs. DEA is used to evaluate the efficiency of a Decision-Making Unit (DMU) by comparing its efficiency with that of the best producer's.

2.1. Window Analysis Method in DEA

The constraint of the limited DMU of DEA requiring the number of DMU should be greater than double the sum of inputs and output can be overcome by using Window analysis, which is one of the methods used to verify productivity change over time by assessing the performance of each DMU as a different entity in each time period. The unit's performance during a specific period is compared not only to its own past performance but also to the performance of other units. This comparison is achieved using the input-oriented Window analysis model, which maintains a constant return to scale. The input-oriented efficiency of DMU (represented by θ) can be determined through the use of the following dual linear programming problem. λ represents an n-dimensional vector of the model's dual variables. It is important to note that this problem must be solved n times, once for each DMU.

$$\text{Min } \theta = \theta'_{Kw\,t} \tag{1}$$

Subject to:

$$-X_{Kw}\lambda + \theta X t' \geq \theta_0 X_{K0} \tag{2}$$

$$Y_{Kw}\lambda - Yt' \geq \theta_0 Y_{K0} \tag{3}$$

$$\lambda\, n \geq 0 \ (n = 1, \ldots.., N \times W) \tag{4}$$

Let DMU_n^t refer to the n_{th} DMU during time period t, which spans from $t = 1$ to $t = T$. The input and output vectors of DMU_n^t are represented as Equations (5) and (6) and are denoted as X_n^t and Y_n^t, respectively. The total number of DMUs is denoted by N. Suppose that the window commences at time point k (where k ranges from 1 to T) and has a width of w (where w ranges from 1 to T - k). Then, the input matrix (X_{kw}) and output matrix (Y_{kw}) for each window (kw) can be expressed as:

Input Matrix

$$X_{kw} = \begin{bmatrix} x_k^1 & x_k^2 & \cdots & x_k^n \\ x_{k+1}^1 & x_{k+1}^2 & \cdots & x_{k+1}^n \\ \vdots & \vdots & \vdots & \vdots \\ x_{k+w}^1 & x_{k+w}^2 & \cdots & x_{k+w}^n \end{bmatrix} \tag{5}$$

Output Matrix

$$Y_{kw} = \begin{bmatrix} y_k^1 & y_k^2 & \cdots & y_k^n \\ y_{k+1}^1 & y_{k+1}^2 & \cdots & y_{k+1}^n \\ \vdots & \vdots & \vdots & \vdots \\ y_{k+w}^1 & y_{k+w}^2 & \cdots & y_{k+w}^n \end{bmatrix} \tag{6}$$

2.2. MPI in DEA

The output-based Malmquist productivity index is determined by the following equation [12]:

$$MPI = \left[\frac{d_o^s(x_t, y_t)}{d_o^s(x_s, y_s)} \times \frac{d_o^t(x_t, y_t)}{d_o^t(x_s, y_s)} \right]^{1/2} \tag{7}$$

The Malmquist productivity index based on output is calculated using the equation [12], where d_o^s is a distance function that evaluates how effectively inputs x_s are converted into outputs y_s during period s. The efficiency of DEA is viewed as a distance metric because it represents the proficiency of transforming inputs to outputs [13]. Whereas, if there is a technical change in period t, then:

$$d_o^t(x_s, y_s) = \text{Efficiency of conversion of input in period } s \text{ to output in period } s \neq d_o^s(x_s, y_s).$$

The Malmquist productivity index is the geometric average of the technical and efficiency changes during the two periods. As stated by Färe et al. (1994) [13], the Malmquist productivity index in Equation (7) can also be expressed as follows:

$$\text{MPI} = \frac{d_o^t(x_t, y_t)}{d_o^s(x_s, y_s)} \left[\frac{d_o^s(x_s, y_s)}{d_o^t(x_s, y_s)} \times \frac{d_o^s(x_t, y_t)}{d_o^s(x_t, y_t)} \right]^{1/2} = \text{Efficiency change} \times \text{Technical change} \tag{8}$$

The Malmquist productivity index is a tool used to evaluate the overall productivity changes of pharmaceutical companies over time. An MPI value greater than 1 indicates an increase in productivity, while an MPI value equal to 1 implies that there has been no change in productivity. An MPI value less than 1 suggests a decline in productivity.

The efficiency change, also known as the "catch-up effect," refers to the extent to which a DMU improves or worsens its efficiency over time. An efficiency change greater than 1 signifies an improvement in relative efficiency between periods *s* and *t*, whereas an efficiency change equal to 1 or less than 1 denotes no change or a decrease in efficiency, respectively.

The technical change, known as the "frontier-shift effect" or "innovation effect," illustrates the modification in the efficient frontiers between the two time periods. A technical change value greater than 1 signifies technical progress, whereas a technical change value less than 1 indicates technical regress.

3. Empirical results

To compute efficiency scores, DEA-Solver PRO 3.0 was used. The correlation results of the latest year is first present in Table 2 to make sure inputs and outputs have an equal increase/decrease. Results shown in Table 2 indicate a significant relationship between all inputs and outputs. Therefore, all five variables in this research are suitable for the further analysis step.

Table 2: Correlation results

Variables	**Fleet**	**Total Asset**	**Operating cost**	**RPK**	**ATK**
Fleet	1	0.744	0.550	0.603	0.581
Total Asset	0.744	1	0.920	0.933	0.919
Operating cost	0.550	0.920	1	0.963	0.962
RPK	0.603	0.933	0.963	1	0.998
ATK	0.581	0.919	0.962	0.998	1

Because of the limited number of DMUs in this research, Window analysis was employed to obtain efficiency results as well as identify the trends in performance of the DMUs. In this study, 3 three-year windows were selected as shown in Table 3.

Table 3: The research windows

Windows	Years
1st Window	2015-2016-2017
2nd Window	2016-2017-2018
3rd Window	2017-2018-2019

According to data in Table 4, it is clear that the efficiency scores in the first two years of the period were all greater than 0.85. However, the results changed in 2017. While all airlines remain high efficiency, Japan Airline and China Eastern Airline experienced a significant decrease and efficiency scores dropped to 0.76 and 0.89, respectively. In 2018, these two airlines continued to show a decrease in efficiency scores to 0.69 and 0.84, respectively. However, in 2019, China Eastern Airline showed a recovery and efficiency score went up to 0.87 while Japan Airline constantly dropped.

Garuda Indonesia is the most efficient airline, supported by the highest average efficiency score of 1, and this airline also showed a stable performance during the period 2015-2019, followed by Air Asia, Thai Airway, Eva Air and China Southern Airline as shown in Table 5. The scores of most airlines increased during the period of 2015-2019, except for Japan Airlines which trended in the opposite direction.

Table 4: Window Analysis Results

DMUs	2015	2016	2017	2018	2019	Average
China Southern Airline	0.98	1	1			0.99
		1	1	1		1
			0.87	0.89	1	0.92
Average	***0.98***	***1***	***0.96***	***0.95***	***1***	***0.98***
China Eastern Airline	0.91	0.92	0.92			0.92
		0.92	0.92	0.90		0.91
			0.83	0.79	0.87	0.83
Average	***0.91***	***0.92***	***0.89***	***0.84***	***0.87***	***0.89***
Air China	0.96	0.96	1			0.97
		0.93	0.98	1		0.97
			0.88	0.91	1	0.93
Average	***0.96***	***0.94***	***0.95***	***0.95***	***1.00***	***0.96***
Cathay Pacific	1	0.99	0.99			0.99
		0.99	0.97	1		0.99
			0.85	0.88	1	0.91
Average	***1.00***	***0.99***	***0.94***	***0.94***	***1***	***0.97***
Eva Air	1	1	1			1
		1	1	0.91		0.97
			1	0.92	1	0.97
Average	***1.00***	***1.00***	***1.00***	***0.91***	***1.00***	***0.98***
Garuda Indonesia	1	1	1			1
		1	1	1		1
			1	1	1	1
Average	***1***	***1***	***1***	***1***	***1***	***1***
Air Asia	1	0.96	1			0.99
		1	1	1		1
			1	0.94	1	0.98
Average	***1***	***0.98***	***1***	***0.97***	***1***	***0.99***
Japan Airline	0.88	0.82	0.77			0.83
		0.80	0.76	0.70		0.76
			0.74	0.69	0.65	0.69
Average	***0.88***	***0.81***	***0.76***	***0.69***	***0.65***	***0.76***
Thai Airway	1	1	1			1
		1	1	1		0.99
			0.89	0.88	1	0.92
Average	***1***	***1***	***0.96***	***0.92***	***1***	***0.97***
Singapore Airline	0.97	1	1			0.99
		1	1	0.99		1
			0.89	0.88	1	0.92
Average	***0.97***	***1.00***	***0.96***	***0.93***	***1.00***	***0.97***

Results in the year 2019 were divided into two groups: group 1 with an efficiency score < 0.9, group 2 with an efficiency score > 0.9. According to results in Table 5, there are two airlines in group 1 representing 20% of DMUs, including Japan Airline and Chinese Eastern Airline, while there are 8 airlines in group 2 accounting for 80% of DMUs. These results indicated that most airlines performed quite well and went up and down during the 2011-2015 period. However, at the end of the year 2019, the efficiency score of most airlines (9 DMUs) showed an increased trend. This conclusion is supported by the results of the Malmquist productivity index shown in Table 6. The average Malmquist index of most airlines is greater than 1, indicating that these airlines have improved their efficiency. According to the data presented in Table 6, the majority of airlines exhibited progress in the current year when compared to the previous year, as indicated by a Malmquist index greater than 1.

Nonetheless, the outcome of this particular stage suggested that Garuda Indonesia, Air Asia, and Japan Airline have an average index of less than 1, implying that these airlines' performance does not show any noticeable improvement from year to year.

Table 5: Summary of Window Analysis Method Results

DMUs	**2015**	**2016**	**2017**	**2018**	**2019**	**Av.**
China Southern Airline	0.98	1	0.95	0.94	1	0.98
China Eastern Airline	0.91	0.92	0.89	0.84	0.87	0.89
Air China	0.96	0.94	0.95	0.95	1	0.96
Cathay Pacific	1	0.99	0.94	0.94	1	0.97
Eva Air	1	1	1	0.91	1	0.98
Garuda Indonesia	1	1	1	1	1	1
Air Asia	1	0.98	1	0.97	1	0.99
Japan Airline	0.88	0.81	0.76	0.69	0.65	0.76
Thai Airway	1	1	0.96	0.92	1	0.98
Singapore Airline	0.97	1	0.96	0.93	1	0.97

Table 6: Malmquist Productivity Index

Malmquist	2015=>2016	2016=>2017	2017=>2018	2018=>2019	Average
China Southern Airline	0.960	0.992	0.999	1.065	1.004
China Eastern Airline	1.033	1.017	0.993	1.078	1.030
Air China	1.024	1.034	1.007	1.063	1.032
Cathay Pacific	0.942	0.993	1.105	1.165	1.051
Eva Air	1.126	1.065	0.822	1.062	1.019
Garuda Indonesia	0.944	0.940	1.030	1.328	1.061
Air Asia	0.913	0.990	0.992	1.148	1.011
Japan Airline	0.993	0.958	0.964	1.016	0.983
Thai Airway	0.983	1.054	0.925	1.084	1.011
Singapore Airline	1.139	1.075	0.937	1.420	1.143

4. Conclusion

In this study, due to the limited DMUs (only 10 DMUs including the Japanese airline), DEA Window analysis was employed in this research in order to evaluate the technical efficiency and identify the performance of the trend of major airlines in the Asia-Pacific region. All data was published and collected from these airlines' annual reports during reports 2015-2019. As indicated in part two, there is not much research on efficiency in the aviation industry because it is not easy to get the inputs and outputs of this non-regulated industry and that is why the number of DMUs in this research was limited.

The results of this showed that most airlines in Asia-Pacific performed well and experienced an uptrend. This research carries valuable insights to airlines decision makers to increase the technical efficiency.

A small sample size is one of the most serious limitations of this research. We hope to have more available data from the aviation industry to collect. Besides, it would be more useful if the time horizon could be expanded. Future work should be considered about expanding the number of DMUs as well as time periods in order to obtain more appropriate evaluation for this industry.

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