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Operational efficiency of Asia–Pacific airports

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ABSTRACT

Airports are important drivers of economic development and thus under tremendous pressure from emerging competitors. However, few studies have analysed the operational efficiency of Asia–Pacific airports. This study therefore evaluated the operational efficiency of 21 Asia–Pacific airports between 2002 and 2011. A two-stage method was used: Data Envelopment Analysis (DEA) to assess airport efficiency, followed by the second-stage regression analysis to identify the key determinants of airport efficiency. The first-stage DEA results indicated that Adelaide, Beijing, Brisbane, Hong Kong, Melbourne, and Shenzhen are the efficient airports. The second-stage regression analysis suggested that percentage of international passengers handled by an airport, airport hinterland population size, dominant airline(s) of an airport when entering global airline strategic alliance, and an increase in GDP per capita are significant in explaining variations in airport efficiency.

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1. Introduction

Several factors have stimulated the growth in air transport demand and airport development, such as rapid economic development, privatisation of the airport industry, and the liberalisation of aviation policy in the Asia–Pacific region (e.g. Oum and Yu, 2000; Park, 2003; Williams, 2006; Yang et al., 2008; Zhang, 2003). The growth is reflected by the increasing air traffic volumes handled by Asia–Pacific airports. The Airport Council International (ACI) reported that several major Asia–Pacific airports have been frequently ranked inside the world's top 30 busiest airports between 2002 and 2011 (ACI, 2002–2011). Moreover, ACI also projects that the announced growth rates for air cargo volumes and aircraft movements in the Asia–Pacific region will reach 6.3% and 4.5%, respectively, by 2025 (ACI, 2007). The International Civil Aviation Organisation (ICAO) also estimates that the Asia–Pacific region will become the busiest and fastest growing air transportation market for international passenger traffic by 2025 (ICAO,

2008). Governments in the Asia–Pacific region have therefore invested heavily and constructed airport infrastructure and facilities to meet projected future air transport demand (O'Connor, 1995). However, airports are also under pressure from emerging competitors competing for air traffic demand. To respond to this pressure, airport efficiency has been identified as a critical issue facing airport management (Chin and Siong, 2001; Forsyth, 2003; Talley, 1983).

To investigate airport efficiency, Data Envelopment Analysis (DEA) has become the recognised method for efficiency evaluation due to its simplicity in constructing an efficiency frontier for identifying efficient or inefficient airports (Gillen and Lall, 1997). Also, the DEA model requires no assumptions for specifying production functions between airport inputs and outputs. The DEA model can also compute multiple airport inputs and outputs within a single analysis without any difficulties of aggregation, and can assess an airport's relative efficiency in a single period or in a sequence of periods as well as requiring less information for analysis (e.g. Cooper et al., 2006; Pels et al., 2001, 2003). Therefore, we first applied the DEA model to assess the operational efficiencies of Asia–Pacific airports, and then the Simar–Wilson bootstrapping regression analysis to identify which factors significantly explain variations in airport efficiency. There are three primary reasons why this study is meaningful: (i) airports operating in the Asia–Pacific region seem to be less researched compared with their counterparts in the US, Europe, and South America; (ii) this study

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contributes to the existing literature by analysing the efficiency of a large group of Asia–Pacific airports (21 airports) – the size of sampled airports in this study is a good reflection and representation of the airport industry in the Asia–Pacific region due to their roles as the international or regional hub airports in their countries; and (iii) this study extends the work of Ha et al. (2010), Lam et al. (2009), and Yang (2010a,b) in assessing the operational efficiency of Asia–Pacific airports and seeking to identify the causes of variations in airport efficiency.

The format of this study is structured as follows. Section 2 presents the literature review with regard to airport efficiency evaluations. Section 3 outlines the DEA methodology and the Simar–Wilson bootstrapping regression analysis. Section 4 presents the dataset of sampled airports, and airport input and output variables for the DEA analysis as well as the key determinants for the second-stage regression analysis. Section 5 presents the results and discussion of the first-stage DEA analysis and the second-stage regression analysis. Section 6 concludes what are the key findings of this study.

2. Literature review

DEA has become a popular method of investigating airport efficiency. Prior DEA studies showed considerable differences in the airport input and output variables used for the efficiency analysis. Three specific forms of DEA analysis were identified from the literature: (i) DEA analysis with operational variables; (ii) DEA analysis with financial variables; and (iii) DEA analysis with second-stage analysis.

Airport efficiency studies that have used DEA analysis with operational variables include Fernandes and Pacheco (2002), Fung et al. (2008), Ha et al. (2010), Lam et al. (2009), Lin and Hong (2006), Lozano and Gutierrez (2009), Roghanian and Foroughi (2010), and Yoshida and Fujimoto (2004). The reasons why DEA studies employ operational variables for benchmarking airport efficiency but then do not incorporate any financial variables are complicated and an in depth explanation is beyond the scope of the current study. However, one of the reasons may be lack of available financial data related to airport operations or because it is extremely difficult to gather relevant financial data for each airport analysed.

Most airports are currently operated as commercial organisations to maximise the profitability from aeronautical and non-aeronautical activities (Graham, 2008). Therefore the financial variables or indicators have been used in the prior studies as airport input and/or output variables in DEA analyses in order to achieve a fair evaluation of airport efficiency. DEA analysis with financial variables has been applied in such studies such as Barros and Dieke (2007), Martin and Roman (2001), Murillo-Melchor (1999), Pacheco and Fernandes (2003), Parker (1999), Sarkis (2000), Sarkis and Talluri (2004), and Yang (2010a,b).

One potential problem is that the key determinants causing variations in airport efficiency may not be clearly understood using the operational and/or financial variables in the DEA analysis, although DEA studies of airport efficiency evaluations showed the ability to evaluate airport efficiency (Gillen and Lall, 1997). A clear understanding of which factors affect airport efficiency would provide insight to airport managers and policy makers for improving airport efficiency through benchmarking; that is, it would help to compare an airport's performance with its peers in the same region and improve its operations. The approach combining a first-stage DEA analysis and a second-stage Tobit model has become a popular method to identify those significant determinants. A number of studies have used this two-stage approach to investigate airports, for example, Abbott and Wu

(2002), Barros and Sampaio (2004), Gillen and Lall (1997), Malighetti et al. (2007), Pathomsiri et al. (2006), Pels et al. (2001, 2003), Perelman and Serebrisky (2010), and Yuen and Zhang (2009).

Although adopting Tobit models in the second-stage analysis has been popular, it is considered as an invalid approach to determine the factors for explaining variations in airport efficiency, due to the presence of inherent dependence among the DEA efficiency indexes from the first-stage DEA analysis (Casu and Molyneux, 2003; Xue and Harker, 1999). Importantly, one basic assumption of regression analysis is violated – the independence within the sample. To solve this problem, Simar and Wilson (2007, 2008) introduced the bootstrapping methodology to solve this problem.

Recently, studies have begun to apply the Simar–Wilson bootstrapping approach for estimating the significant determinants of airport efficiency. For example, Barros and Dieke (2008) used the truncated bootstrapped regression to estimate the efficiency and identify the determinants of 31 Italian airports between 2001 and 2003. They found that the method to bootstrap the DEA efficiency scores with a truncated regression analysis can better explain DEA efficiency levels. Similarly, Barros (2008) employed the truncated bootstrapped regression analysis to analyse the efficiency of Argentinian airports during the period of intense economic crisis. Curi et al. (2011) also used the bootstrapping methodology to investigate 18 Italian airports. During the same year, Tsekeris (2011) used the truncated bootstrapped regression to assess the relative technical efficiency of Greek airports and investigate factors that determine airport efficiency. Merkert and Mangia (2012) also applied the bootstrapping two-stage DEA model to analyse 46 Norwegian airports' efficiency. Merkert et al. (2012) employed the input-oriented DEA model and the Simar–Wilson bootstrapping approach to analyse the efficiency of regional airports worldwide, and suggested that the more sophisticated two-stage model can deliver powerful insights into the performance of regional airports. Tsui et al. (2014b) also utilised the slack-based measure (SBM) model, the Malmquist Productivity Index (MPI), and the Simar–Wilson bootstrapping methods to investigate the efficiency and productivity changes of 11 New Zealand airports for the period of 2010–2012.

3. Methodology

3.1. Data envelopment analysis (DEA)

The DEA methodology evaluates the relative efficiency of a decision making unit (DMU) by building a ratio which consists of the maximum weighted outputs to maximum weighted inputs for each DMU subject to a set of conditions (Charnes et al., 1978). Considering a group of airports, where y_{rk} and x_{ik} are the known airport outputs and inputs of airport k . The DEA efficiency index of an airport is denoted as B_o , which represents the inputs x_{io} ($i = 1, 2, 3, \dots, n$) that produce the outputs y_{ro} ($r = 1, 2, 3, \dots, m$); u_r and v_i are the weights of aggregation (virtual multipliers), that are non-negative which are chosen to maximise the value of B_o . Thus, the fractional programming model is written as shown in Eq. (1):

$$B_o = \text{Max}_{u_r, v_i} \frac{\sum_{r=1}^m u_r y_{ro}}{\sum_{i=1}^n v_i x_{io}} \quad \text{subject to}$$

$$\frac{\sum_{r=1}^m u_r y_{rk}}{\sum_{i=1}^n v_i x_{ik}} \leq 1 \quad k = 1, 2, 3, \dots, l;$$

$$u_r, v_i \geq 0; \quad r = 1, 2, 3, \dots, m; \quad i = 1, 2, 3, \dots, n. \quad (1)$$

Later, [Banker et al. \(1984\)](#) developed the DEA-BCC model, which allows airports operating with lower airport inputs to have an increasing return to scale under the principle of Variable Return to Scale (VRS), and those operating with higher airport inputs to have a decreasing return to scale. The DEA-BCC model is written as shown in Eq. (2):

$$\begin{aligned} \theta = \max \quad & \varphi + \varepsilon \left[\sum_{r=1}^m s_{ro}^+ + \sum_{i=1}^n s_{io}^- \right] \quad \text{subject to} \\ & \sum_{r=1}^m y_{rk} \lambda_k - s_{ro}^+ = \varphi y_{ro} \quad r = 1, 2, 3, \dots, m; \\ & \sum_{i=1}^n x_{ik} \lambda_k + s_{io}^- = x_{io} \quad i = 1, 2, 3, \dots, n; \\ & \sum_{k=1}^m \lambda_k = 1; \quad \lambda_k \geq 0; \quad k = 1, 2, 3, \dots, l. \end{aligned} \quad (2)$$

where θ = airport efficiency index; ε = a constant (greater than 0)⁴; s_{ro}^+ and s_{io}^- = airport output and input slacks; λ_k = the dual variable or the scalar vector associated with each airport.

An airport is considered as a BCC-efficient airport when θ is equivalent to 1 and has zero output and input slacks ($s_{ro}^+ = 0, s_{io}^- = 0$). Otherwise, the airport is called a BCC-inefficient airport ([Cooper et al., 2006](#)).

3.2. The Simar–Wilson bootstrapping regression analysis

The DEA efficiency indexes obtained from the first-stage DEA analysis will be used to regress on the factors (e.g. the specific operating characteristics, management/ownerships, and regional locations) related to the sampled Asia–Pacific airports and identify the significant factors to explain variations in airport efficiency using the second-stage Simar–Wilson bootstrapping regression analysis⁵ (see [Simar and Wilson, 2007](#)).

The initial estimation specification can be written as shown in Eq. (3):

$$\theta_k = \alpha + z_k \beta + \varepsilon_k \quad k = 1, 2, 3, \dots, n \quad (3)$$

Eq. (3) is the first-order approximation of the unknown true relationship. Where θ_k is the DEA efficiency index of airport k . α is the constant, z_k is a vector of observation-specific variables that is expected to associate with airport k 's DEA efficiency index, β is a vector of parameters, and ε_k is the error term.

Applying the Simar–Wilson bootstrapping approach, the distribution of ε_k is limited to the condition $\varepsilon_k \geq 1 - \alpha - z_k \beta$. Thus, the distribution of ε_k becomes $\varepsilon_k \sim \text{iid}N(0, \sigma_\varepsilon^2)$. Moreover, the true and unobserved dependent variable θ_k in Eq. (3) to be replaced by θ_k^* (the DEA efficiency index of airport k after applying the Simar–Wilson bootstrapping approach), and the model specification can be written as shown in Eq. (4):

$$\theta_k^* = \alpha + z_k \beta + \varepsilon_k \quad k = 1, 2, 3, \dots, n \quad \varepsilon_k \sim \text{iid}N(0, \sigma_\varepsilon^2) \quad (4)$$

⁴ For economic reasoning, if we produce any amount of output and we must use at least a minimum quantity of every input. If any of the inputs equals zero, the total output is zero as well ([Vincová, 2005](#)).

⁵ Other studies using the same technique might include [Barros \(2008\)](#), [Barros and Dieke \(2008\)](#), [Merkert et al. \(2012\)](#), [Merkert and Mangia \(2012\)](#), and [Tsui et al. \(2014b\)](#).

Table 1
List of Asia–Pacific airports.

Airport code	Airports	Country, city	Airport status
ADL	Adelaide Airport	Australia, Adelaide	Regional hub
AKL	Auckland International Airport	New Zealand, Auckland	International hub
PEK	Beijing Capital International Airport	China, Beijing	International hub
BNE	Brisbane Airport	Australia, Brisbane	Regional hub
CHC	Christchurch International Airport	New Zealand, Christchurch	Regional hub
GMP	Gimpo International Airport	South Korea, Seoul	Regional hub
CAN	Guangzhou Baiyun International Airport	China, Guangzhou	International hub
HKG	Hong Kong International Airport	China, Hong Kong	International hub
ICN	Incheon International Airport	South Korea, Seoul	International hub
KIX	Kansai International Airport	Japan, Osaka	Regional hub
KUL	Kuala Lumpur International Airport	Malaysia, Kuala Lumpur	International hub
MEL	Melbourne Airport	Australia, Melbourne	International hub
NRT	Narita International Airport	Japan, Tokyo	International hub
MNL	Ninoy Aquino International Airport	Philippines, Manila	International hub
PER	Perth Airport	Australia, Perth	Regional hub
SXZ	Shenzhen Bao'an International Airport	China, Shenzhen	Regional hub
SIN	Singapore Changi Airport	Singapore	International hub
CGK	Soekarno-Hatta International Airport	Indonesia, Jakarta	International hub
BKK	Suvarnabhumi Airport	Thailand, Bangkok	International hub
SYD	Sydney (Kingsford Smith) Airport	Australia, Sydney	International hub
TPE	Taiwan Taoyuan International Airport	Taiwan, Taipei	International hub

Remarks: The classification of an airport's status is based on the airport's strategic role and flight connectivity network. For example, an international hub airport connects to at least 25 international destinations; a regional hub or non-hub airport flies to no more than 25 international destinations ([Matthiessen, 2004](#)).

4. Data description

4.1. The dataset

A rigid DEA convention was followed to determine the total number of airport observations in association with the total number of airport input and output variables; the minimum number of airports observed should be greater than or equal to three times the sum of airport input and output variables to ensure that satisfactory discriminating power is possible ([Banker et al., 1989](#); [Cooper et al., 2006](#); [Raab and Lichty, 2002](#)). The current study achieved this requirement with a sample size of 21 Asia–Pacific airports, and a total of seven airport input and output variables for the first-stage DEA analysis. [Table 1](#) shows the list of 21 major Asia–Pacific airports for analysis between 2002 and 2011 (Data beyond 2011 was not yet available at the time of submitting this article).

The data was collected from the following sources: International Civil Aviation Organisation (ICAO), Airport Council International (ACI), Air Transport Research Society (ATRS)–Airport Benchmarking Reports, civil aviation authority of the respective countries, airports' annual reports and websites. Individual airports were also contacted to obtain additional information.

4.2. Airport input and output variables for the first-stage DEA analysis

To select airport input and output variables for the first-stage analysis, we considered data availability, referred to extant

literature (e.g. Doganis, 1992), and sought the professional opinion from airport managers. At a result, we selected four airport input variables (i.e. number of employees, number of runways, total runway length, and passenger terminal area) and three airport output variables (i.e. air passenger numbers, air cargo volumes, and aircraft movements) for the first-stage DEA analysis.

4.3. Key determinants for the second-stage regression analysis

Three tasks were performed in this study to identify the key determinants in explaining variations in airport efficiency. First, the airport input and output variables used in the first-stage DEA analysis will not be reused as the explanatory variables in the second-stage regression analysis, avoiding the problem of double-counting and possibly obtaining misleading or biased results (Lin, 2008). Second, prior studies relating to airport efficiency were examined to identify the potential explanatory variables for the second-stage regression analysis. Lastly, an attempt was made to look at other principles applying the two-stage regression analysis that may assist in developing other relevant explanatory variables for this study (e.g. Boame, 2004; Fethi et al., 2000; Oum and Yu, 1994; Zheng et al., 1998).

Taking the literature and data availability into account, seven explanatory variables were developed for the second-stage regression analysis, which represents Asia–Pacific airports' operating characteristics, management/ownerships, and regional locations (see Table 3). Data related to the selected explanatory variables was obtained from National Yearbooks, National Statistical Departments, World Bank Data, United Nation Data, and airports' annual reports and websites.

5. Estimation of results

5.1. DEA analysis

The DEA Output-Oriented⁶ and VRS framework was selected for the first-stage DEA analysis. Table 2 shows the DEA estimation results categorising in three groups of airports with reference to changes in airport efficiency including the DEA efficiency indexes for each airport over the years and the percentage of efficient airports during each study year.

Table 2 shows that at least 52% of Asia–Pacific airports are considered as 'efficient' between 2002 and 2011. Six airports were found to be best performers over the entire study periods having consistently full DEA efficiency indexes (i.e. Adelaide, Beijing, Brisbane, Hong Kong, Melbourne, and Shenzhen). Of these, three were international hub airports (i.e. Beijing, Hong Kong, and Melbourne). This might be consistent with the concept that the international hub or gateway airports are able to attract and handle more air transport demand than the regional or non-hub airports, leading to higher efficiency. Also, their strategic roles and extensive flight connectivity networks reflect their ability to attract more international and domestic passenger traffic (i.e. origin–destination traffic and connecting traffic). The full efficiency of Beijing and Hong Kong for all ten years may be explained by their respective air traffic volumes being consistently ranked inside the world's top 30 busiest passenger airports for the period of 2002–2011. The full efficiency levels of Brisbane throughout the study period may be due to its prime location for holiday travel to

the principal Australian tourist attraction—the Gold Coast. For Shenzhen, its remarkable record may have been largely due to the rapid economic growth of the Pearl River Delta (PRD) region in Mainland China (particularly experiencing 103.4–187.8% growth for three airport outputs between 2002 and 2011).

Twelve airports were considered to be moderate performers since they were efficient in at least one of the ten years during the study periods. Overall, these airports either showed improvements (eight airports) or deteriorations (four airports) in their efficiency levels across the analysis periods, although there was no regular trend with respect to their respective efficiency levels. For the improving airports, in particular, Guangzhou deserves to be explored why its efficiency improved and it became efficient after 2007. Its rapid expansion improved the airport's flight connectivity network, covering more than 200 routes, which translated into an increase in airport traffic. In addition, Sydney was ranked as one of the world's top 30 busiest passenger airports in 2003, and its growth after 2003 could be attributable to its strategic role served as the main international gateway hub airport to and from Australasia and Oceania. In addition, Gimpo's inefficiency before 2010 was likely due to the opening of Incheon in 2000, which adversely affected its operations by attracting away international passenger and cargo traffic.⁷ However, its three airport outputs achieved a 5.4–15.0% increase between 2010 and 2011, leading to its full efficiency level in 2011. Likewise, the decline in Jakarta's efficiency was likely related to the Bali bombings that occurred in 2002 and 2005 – these disruptive events had significant negative impacts on international visitors visiting Indonesia (Hitchcock and Putra, 2005). In particular, Jakarta's positive air traffic growth after 2009 led to its full efficiency levels, with an average annual growth of air passenger numbers (10.6%), air cargo volumes (20.5%), and aircraft movements (8.9%), respectively.

The airports never achieved full efficiency levels (i.e. DEA efficiency index = 1) during the study periods (i.e. Incheon, Kuala Lumpur, and Singapore). Interestingly, these three major international hub and gateway airports were considered to be the worst performers. One explanation might be largely related to the consequences of under-utilisation or over-investment in airport resources or high capacity airports handling lower amounts of air traffic. Indeed, further investigation revealed that Incheon and Kuala Lumpur's inefficiencies across the years did not result from recent expansions but from ongoing overcapacity. Likewise, part of the explanation of Singapore's under-utilisation is the result of its passenger terminal expansion in 2007, while its international passenger traffic only increased by less than 3% between 2007 and 2008 as well as between 2009 and 2010, respectively, leaving Singapore with significant excess capacity.

Regarding the deteriorating airports, Bangkok's inefficiency after 2008 was primarily the consequence of Thailand's political unrest, which triggered negative airport traffic growth (Yin and Walsh, 2011). Moreover, Kansai became inefficient after 2006 as an additional runway came into operation in 2007,⁸ but its air traffic volumes did not respond with a significant increase accordingly. Passenger terminal expansion might contribute to the deteriorations in efficiency of Manila. Furthermore, Narita became inefficient between 2005 and 2006 as annual air passenger numbers and annual aircraft movements increased by less than 3%,

⁶ Wober (2007) indicated that the output-oriented model required a given level of inputs to achieve the maximum output levels. In this study, the DEA Output-Oriented model means that airports focus on maximising three categories of air traffic outputs (i.e. air passenger numbers, air cargo volumes, and aircraft movements), holding all of the airport inputs constant.

⁷ Comparing the average annual growth of total passenger numbers of Gimpo and Incheon between 2002 and 2011, the figures showed a 0.8% increase for Gimpo and a 6.7% increase for Incheon, respectively. In addition, after the opening of Incheon in 2000, Gimpo's air passenger number and air cargo volumes showed negative growths of 114.4% and 626.7% from 2000 to 2002, respectively (Zhang, 2003).

⁸ Kansai started to operate the second runway on August 02, 2007.

Table 2
DEA efficiency indexes of Asia–Pacific airports (2002–2011).

	Airports	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Average
Best performers ^a	Adelaide	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Brisbane	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Hong Kong	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Melbourne	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Shenzhen	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Moderate performers (improvement) ^b	Auckland	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.965	1.000	0.996
	Gimpo	0.948	0.907	0.679	0.766	0.749	0.659	0.678	0.654	0.795	1.000	0.783
	Guangzhou	0.699	0.639	0.672	0.763	0.735	1.000	1.000	1.000	1.000	1.000	0.851
	Jakarta	0.503	0.895	0.918	0.908	0.864	1.000	0.976	1.000	1.000	1.000	0.906
	Manila	0.679	0.682	0.810	0.787	0.945	1.000	0.682	0.800	0.934	0.959	0.828
	Perth	0.614	0.914	0.558	1.000	1.000	1.000	1.000	1.000	0.963	1.000	0.905
	Sydney	0.978	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.998
	Taipei	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.834	1.000	1.000	0.983
Moderate performers (deterioration) ^c	Bangkok	1.000	1.000	1.000	1.000	1.000	1.000	0.919	0.902	0.878	0.919	0.962
	Christchurch	0.956	1.000	0.952	1.000	1.000	1.000	1.000	1.000	1.000	0.753	0.966
	Kansai	1.000	1.000	1.000	1.000	1.000	0.806	0.844	0.615	0.701	0.677	0.864
	Narita	1.000	1.000	1.000	0.983	0.958	1.000	1.000	1.000	0.907	0.887	0.973
Worst performers ^d	Incheon	0.821	0.817	0.844	0.765	0.950	0.859	0.799	0.789	0.806	0.788	0.824
	Kuala Lumpur	0.660	0.734	0.677	0.591	0.502	0.677	0.707	0.784	0.779	0.779	0.689
	Singapore	0.855	0.859	0.815	0.804	0.764	0.823	0.788	0.866	0.897	0.901	0.837
	Efficient airports (%)	52	62	57	62	62	76	62	62	52	62	60.9

Remarks: Bold typefaces indicate the efficient airports.

^a Indicates an airport achieved consistently full efficiency levels.

^b Indicates an airport showed an improvement in efficiency levels.

^c Indicates an airport showed a deterioration in efficiency levels.

^d Indicates an airport never achieved full efficiency levels.

and also annual air cargo volumes experienced negative growth in 2005 and 2006. Narita's inefficiency in 2010 and 2011 resulted from negative growth of aircraft movements. In addition, Christchurch was efficient between 2005 and 2010 due to its role as one of two key international airports in New Zealand serving a significant amount of domestic and international traffic to and from South Island (New Zealand). The Christchurch Earthquake in 2011 caused significant drops in airport traffic volumes and adversely affected airport operations (Tsui et al., 2014b; Yeoman et al., 2012).

It should be noted that the DEA efficiency indexes of Asia–Pacific airports reported above were generally consistent with those reported in the extant literature. In particular, Hong Kong was claimed to be the most efficient airport during the study periods, and Incheon was also claimed to have the worst efficiency (Ha et al., 2010; Lam et al., 2009). Kuala Lumpur and Singapore were also identified as inefficient airports (Yang, 2010b), which was largely due to on-going overcapacity and the poor scale efficiency. Overall, the dissimilarity of DEA efficiency indexes (or efficiency ranking) of Asia–Pacific airports can be also seen in prior literature as the DEA efficiency indexes computed by the DEA methodology are highly dependent upon the sample size of airports and number of airport input and output variables used during the efficiency evaluation.

5.2. Average DEA efficiency index

The average performance of Asia–Pacific airports during one particular year compared to other years is very important, as this would indicate whether any year was the best performing year with respect to overall airport efficiency. This is in line with the study of Sengupta (1995), which stated that industrial competitiveness or efficiency can be evaluated through the analysis of average efficiencies.

Fig. 1 shows average DEA efficiency indexes and the number of efficient airports for the sampled Asia–Pacific airports. Over the study periods, variations in the average DEA efficiency indexes

were found among Asia–Pacific airports. In general, they showed an upward trend from 2002 to 2007, except for 2004, followed by falls in 2008 and 2009, and lastly rebounds in 2010 and 2011. The lowest and highest average DEA efficiency indexes were in 2002 (0.891) and 2007 (0.944). This situation indicated that the majority of Asia–Pacific airports did not achieve their maximum output levels throughout the study periods. It also corresponds to the fact that the smallest and largest number of efficient airports appeared during 2002 and 2007, respectively. Furthermore, the smallest average DEA efficiency index (in 2002) can be interpreted as, on average, Asia–Pacific airports were only 89.1% efficient in that year, or, on average, the airports could almost increase by an additional 10.9% of outputs to attain their maximum outputs using the same amount of inputs.

Fewer efficient airports were found during 2002, 2004, and 2010, which could largely be attributable to the impact of the September 11 terrorist attacks in 2001, the outbreak of Severe Acute Respiratory Syndrome (SARS) in late 2002 and mid-2003, and higher aviation fuel prices in 2010.⁹ These unfavourable incidents for the global aviation industry may have led to the relatively poor performance of Asia–Pacific airports, handling fewer air passenger traffic and air cargo volumes during these periods. That said, air cargo traffic was not as seriously affected as air passenger traffic during the SARS outbreak (Williams, 2006). The average airport efficiency seemed to remain stable for the periods of 2005–2006 and 2010–2011. It could be said that Asia–Pacific airports enjoyed a more favourable operating environment in these four years. More importantly, the best performing year was 2007, when the airport industry in the Asia–Pacific region seemed to benefit from a more favourable economic atmosphere for their operations. The declines in average airport efficiency that appeared in 2008 and 2009 might largely be due to aviation fuel price surges alongside the global

⁹ Crude oil prices reached the level of US\$71.21 per barrel during 2010. Data relating to crude oil prices were obtained from Illinois Oil and Gas Association.

Fig. 1. Average DEA efficiency index and number of efficient airports (2002–2011).

Table 3
Second-stage estimation results.

Dependent variable = DEA efficiency indexes				
Explanatory variables	Truncated regression with Bootstrapping		Random effect Tobit Model	
	Coefficient	t-Value	Coefficient	t-Value
Constant	0.868***	3.08	0.276	0.84
Trend	0.005	1.06	−0.001	−0.50
ln GDP per capita	0.009	0.45	0.043*	1.84
Percentage of international passengers	−0.001**	−2.17	−0.001**	−2.13
Airport hub status	0.076	1.49	0.059	1.02
Airport management	0.003	0.09	0.038	0.96
Airport operating hours	0.002	0.31	0.008	1.08
Airport hinterland population	−0.126***	−2.75	−0.004	−0.08
Alliance membership of dominant airline	0.080*	1.85	0.078**	2.32
Log-likelihood	188.710	—	214.018	—
Observations	210	—	210	—

Remarks: *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively. The truncated regression analysis with bootstrapping (Simar and Wilson, 2007) results above was derived from 5000 bootstrapped iterations.

economic downturn. These unfavourable economic factors had negative impacts for the worldwide air transport industry and, as a consequence, led to the slump in air passenger travelling and air cargo volumes across the Asia–Pacific region.¹⁰

5.3. Determinants of efficiency

To evaluate the determinants of efficiency of Asia–Pacific airports, we adopted the approach of Simar and Wilson (2007). After obtaining the DEA efficiency indexes in the first-stage, we calculated the following (truncated) regression equation through the bootstrapped procedure in the second stage (with DEA efficiency indexes bounded at both ends of the 0–1 distribution). For further details, see Simar and Wilson, 2007).

$$\theta_{i,t} = \beta_0 + \beta_1 \text{Trend}_{i,t} + \beta_2 \text{GDP}_{i,t} + \beta_3 \text{PIP}_{i,t} + \beta_4 \text{Hub}_{i,t} + \beta_5 \text{Man}_{i,t} + \beta_6 \text{OH}_{i,t} + \beta_7 \text{Pop}_{i,t} + \beta_8 \text{Alliance}_{i,t} + \varepsilon_{i,t} \quad (5)$$

where θ represents the estimated DEA efficiency score in the first-stage. ‘Trend’ is a yearly trend. ‘GDP’ represents the logarithm of GDP per capita of the country or city in which an airport is located

(in logarithm). ‘PIP’ represents the percentage of international passengers handled by an airport. The dummy value of airport hub status denoted by ‘Hub’ is 1 if an airport is an international hub airport, 0 otherwise. The dummy value of airport management denoted by ‘Man’ is 1 if an airport is government-controlled or owned, 0 otherwise. ‘OH’ represents airport’s daily operating hours. ‘Pop’ represents the dummy variable which takes 1 if an airport’s hinterland population is more than 4 million people, 0 otherwise. ‘Alliance’ represents alliance membership of dominant airline, and it is a dummy variable which takes the value 1 if the dominant airline of an airport becomes a member of a major global airline strategic alliance, 0 otherwise.

First, Im et al.’s (2003) panel unit root test was employed to check the problem of unit roots of all relevant variables. The second-stage estimation results showed the factors for explaining airport efficiency were reported in Table 3.¹¹ Four explanatory variables were found to be significant factors for explaining variations in airport efficiency: percentage of international passengers; airport’s hinterland population; alliance membership of dominant airline; and the logarithm of GDP per capita. For ‘percentage of international passengers’ the coefficient was negative; for every percentage increase in international passengers handled by an airport, its efficiency reduced by 0.001 units. Importantly, this finding appears to be consistent with Pathomsiri et al. (2006), who claimed that the handling of international passenger traffic has a negative impact on an airport’s efficiency as larger airport infrastructure and facilities (e.g. check-in counters and baggage handling areas) need to be built to serve international travellers comparing with domestic passengers.

We expected the sign of the coefficient estimation for the variable of ‘airport hinterland population’ to be positive, as a larger hinterland population may generate more airport demand, thus leading to higher airport efficiency. Surprisingly, this variable had a negative impact on airport efficiency. This may suggest that an airport that serves a larger hinterland population is less efficient than an airport that serves a smaller hinterland population; it also suggests that larger airport infrastructure or capacity need to be constructed to accommodate a larger hinterland population and the forecasted growth of air traffic demand across the Asia–Pacific region. However, air transport demand and airport operations were inevitably affected by unwanted adverse incidents or difficult operating conditions that led to lower airport efficiency (Graiss et al.,

¹⁰ The total air cargo volumes of the sampled Asia–Pacific airports showed negative growth of 3.2% between 2007 and 2008.

¹¹ To check the robustness of the Simar–Wilson bootstrapping regression analysis, the random-effects (RE) Tobit model was also computed in this study (see Merkert and Hensher, 2011). Table 3 shows both methodologies presented almost similar estimation results, therefore this study mostly discussed the estimation results of the Simar–Wilson bootstrapping regression analysis.

2003; Kozak et al., 2007; Siu and Wong, 2004). Also, it should be acknowledged that it is extremely difficult to define the exact size of an airport's hinterland size due to improvements in aircraft technology that allow longer distance to be flown, the formation of strategic alliances between airlines, the establishment of hub-and-spoke networks by many airlines, and airport overlap or congestion in multi-airport region (MAR) in which an airport competes air traffic volumes with its neighbouring airports.¹² (e.g. Graham, 1999; Graham and Guyer, 2000; Williams, 2006). The coefficient suggests that if an airport serves a larger hinterland population, its efficiency would drop by 0.126 units.

'Alliance membership of dominant airline' variable was also reported as significant in both estimations, and suggests that if an airport's dominant airline enters a global airline strategic alliance, this might positively influence its home-based airport's efficiency; when the dominant airline(s) of an airport enters a global airline strategic alliance, the airport's efficiency will increase by 0.080 units as allied airlines could share airport facilities to handle more connecting traffic. More importantly, this finding provides evidence to support the argument of Gillen and Lall (1997), who claimed that common use of airport facilities can improve efficiency by allocating passenger terminal facilities for airlines of a particular alliance so they have exclusive use of the passenger terminals. This gives airlines an incentive to use the designated passenger terminals more efficiently. Also, the current situation shows that an increasing number of large or legacy airlines have joined or intend to enter three major global airline strategic alliances (i.e. oneworld, Star Alliance, and SkyTeam) or formed their own partnerships (e.g. Qantas Airways and Emirates Airline). Importantly, allied activities between partner airlines are seen to affect airport operations in different ways such as a specific passenger terminal (e.g. Narita's Terminal One) being designated for a group of airlines associated with a particular alliance (in Narita's case, Star Alliance) (Cento, 2009).

As expected, "ln GDP per capita" has a positive and significant impact on airport efficiency when we used the Random Effect Tobit regression. This implies that there is a positive relationship between GDP per capita of a country or city with an airport's traffic demand (Abed et al., 2001; Tsui et al., 2014a), and an airport's efficiency would be improved.

The remaining variables were not statistically significant. For example, 'airport hub status' has no significant impact on the efficiency of an airport but its coefficient may imply that if an airport that serves as an international hub airport could be more efficient than those serve as regional airports or non-hub airports in the Asia-Pacific region. Prior studies (e.g. Fung et al., 2008; Gillen and Lall, 1997; Lin and Hong, 2006; Perelman and Serebrisky, 2010; Tsui et al., 2014b) also claimed that international hub airports possess size and location advantages for transporting more airport traffic and, as a consequence, improve airport efficiency.

Also, the insignificant variable of 'airport management' might imply that government-controlled/owned airports might perform better than privately-controlled/owned airports among the sampled Asia-Pacific airports. It is worthwhile to note that this finding is not consistent with the literature relating to the effect of airport management/ownership upon airport efficiency (e.g. Barros and Dieke, 2007; Muller et al., 2009; Oum et al., 2006, 2008). As many key Asian international hub airports (e.g. Beijing, Hong Kong, and Singapore) are still under government ownership and control,

since the governments consider an airport to be the strategic asset and/or an engine to contribute economic development of the country and city (Doganis, 1992). Indeed, these airports now tend to operate on a more commercial basis, rather than being guided by non-economic political objectives while facing the growth in air transport demand and other emerging competitors in the region (Hooper, 2002). Moreover, many Asia-Pacific airports have been fully or partially privatised as the benefits of airport efficiency improvement and finance support for future development (Oum et al., 2006).

In addition, the insignificant positive coefficient of 'airport operating hours' might imply that longer operating hours of an airport might positively influence its operations and increase efficiency. This finding is in line with the perspective argued by Humphreys and Francis (2000), and demonstrates that the duration of airport operating hours is a significant factor that positively affects airport operations and efficiency. However, this presumably cannot apply to Adelaide, Narita, and Sydney due to their curfew policies.

6. Conclusion

The main purpose of our paper was to investigate the operational efficiency of 21 major airports in the Asia-Pacific region, and identify the key factors to explain variations in airport efficiency. The empirical results suggested that six airports (i.e. Adelaide, Beijing, Brisbane, Hong Kong, Melbourne, and Shenzhen) are the 'efficient' airports which operated at the efficiency frontier during the period of this study. In addition, the average DEA efficiency indexes of Asia-Pacific airports suggested a varying trend throughout the study periods, and that most airports operated below their optimal output levels.

Four significant factors were found to account for the identified variations in airport efficiency among Asia-Pacific airports: (i) more international passengers handled by an airport that may reduce its efficiency level; (ii) when an airport caters to a larger hinterland population, it will become less efficient than an airport that serves a smaller hinterland population; (iii) if the dominant airline(s) of an airport enters a global airline strategic alliance, this may improve its home-based airport's efficiency; and (iv) having an increase in GDP per capita of a country or city might increase an airport's efficiency.

Airport management should also seriously pay attention to other controllable factors—factors under managerial control (e.g. outsourcing activities and concession revenues) affecting airport efficiency. Nowadays, many airports worldwide have outsourced some operational functions and services to the third parties for saving operating costs, and also made efforts to generate non-aeronautical revenues (e.g. concession revenues). Unfortunately, such important airport efficiency measurements could not be included in this study because of lack of available financial data related to most of the sampled Asia-Pacific airports. As an extension of this study, it may be meaningful to include such data (when available) that allows this study to take account of the effects of airports' strategy with regard to outsourcing activities and concession revenues on Asia-Pacific airports' efficiency.

Furthermore, it is important to consider the actual and likely impact of the global airline strategic alliance or other forms of airline partnerships on airport efficiency. For example, the recent partnership between Qantas Airways and Emirates Airline, aims to deliver the best in their respective flight networks and frequencies, lounges, loyalty programs, and customer experiences. Under this agreement, Qantas Airways will move its hub at Singapore Changi Airport to Dubai International Airport, which may reduce the amount of transit traffic to Europe via Singapore Changi Airport

¹² For example, the Pearl River Delta (PRD) region in Mainland China is considered as one of the busiest multi-airport regions, in which Hong Kong competes with four other neighbouring airports, namely Guangzhou, Macau, Shenzhen, and Xiamen Airports.

transported by Qantas Airways, thus affecting its traffic volume and efficiency.

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