Journal of Air Transport Management 40 (2014) 16–24

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Operational efficiency of Asia–Pacific airports

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ARTICLE INFO

Article history:
Available online 10 June 2014

Keywords:
Asia–Pacific airports
Operational efficiency
First-stage data envelopment analysis
Second-stage regression analysis

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.

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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http://dx.doi.org/10.1016/j.jairtraman.2014.05.003
0969-6997/

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 $x_{io}(i = 1, 2, 3, \ldots, n)$ that produce the outputs $y_{ro}(r = 1, 2, 3, \ldots, m)$; 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):

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

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

$$u_r, v_i \ge 0; \quad r = 1, 2, 3, \ldots, m; \quad i = 1, 2, 3, \ldots, n. \tag{1}$$