Journal of Air Transport Management 59 (2017) 18–25

Contents lists available at ScienceDirect

Journal of Air Transport Management

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

Multi-period efficiency and productivity changes in US domestic airlines

Kanghwa Choi [1]

Hansung University, 116 Samseongyoro 16 gil, Seongbuk-gu, Seoul, 136-792, South Korea

ARTICLE INFO

Article history:
Received 30 July 2016
Received in revised form
12 November 2016
Accepted 13 November 2016

Keywords:
US airlines
Efficiency
Bootstrapping DEA
Double bootstrap regression
M&A

ABSTRACT

This study tracked the static efficiency and dynamic productivity changes of 14 US airlines from 2006 to 2015. Moreover, we estimated the principal economic drivers of the environmental variables to increase the US domestic airlines' efficiency using the double bootstrap regression analysis. The major aspects of this study are as follows: First, network legacy carriers have the highest efficiency, whereas low-cost carriers are lowest. Nonetheless, network legacy carriers still have room to improve scale inefficiency. Second, the fluctuations in technical change, rather than in efficiency change, tended to have greater effect on the fluctuation of Malmquist productivity index for US domestic airlines. Third, M&A between US airlines have both positive and negative effects in terms of efficiency and economies of scale. Fourth, cost environmental factors have a negative effect on US airlines' efficiency, while revenue factor is a positive effect. The results of this study may help US airline industry practitioners to understand the US domestic airline environment from an operator's perspective.

1. Introduction

US airlines have experienced unprecedented turbulence over the past 15 years from the 9/11 terrorist attacks and subsequent drastic reduction in air travel volumes to the global financial crisis and skyrocketing oil prices in 2008–2009 (Belobaba et al., 2015; Jang et al., 2011). These sequences of major events have caused the efficiency and productivity of US airlines to fluctuate. This change in operational efficiency has induced mergers among US carriers in order to survive in the competitive airline industry and enhance competitiveness and efficiency (Barros et al., 2013; Lenartowicz et al., 2013; Merkert and Morrell, 2012). Indeed, over the past decade, several mergers among US airlines have occurred (e.g., *Delta–Northwest, United–Continental, and Southwest–AirTran*) to varying degrees of success.

A vast amount of previous studies employ data envelopment analysis (DEA) models to quantify the efficiency and productivity of US airlines (Assaf and Josiassen, 2012; Barros et al., 2013; Cheng, 2010; Duygun et al., 2016; Franke, 2004; Lee and Worthington, 2014; Li et al., 2015; Min and Joo, 2016). Furthermore, some of recent studies have suggested the successful implementation of mergers and acquisitions (M&A) based on annual static efficiency, while others have found dynamic productivity changes in the airline sector (Barbot et al., 2008; Barros and Couto, 2013; Belobaba et al., 2011; Pires and Fernandes, 2012).

The survival strategy of individual airlines is to respond actively to changes in the technology and market structure of the airline service industry. This study, therefore, suggests strategic operational plans to cope with the fluctuations in the internal and external environment and identify best-practice US airlines that others can emulate.

The objective of the study is threefold: First, this study investigates the efficiency and productivity of 14 US airlines from 2006 to 2015 and measures changes in the operational efficiency of each carrier in order to suggest tailored strategic initiatives. Second, this study analyzes the long-term effect of M&A between US airlines by incorporating bootstrapping efficiency scores and RTS (returns-to-scale) perspectives. Finally, we estimates the principal economic drivers of the environmental variables to increase the US domestic airlines' efficiency by double bootstrap regression analysis suggested by Simar and Wilson (2007). To reveal how external determinants impact on efficiency is essential for airline operation practitioners to identify performance improvement strategies.

This research offers quadruple main findings. First, the efficiency analysis by airline group shows that network legacy carriers (NLCs) have the highest efficiency followed by ultra low-cost

E-mail address: khchoi@hansung.ac.kr.
[1] Tel.: 82-2-760-8015; fax: 82-2-760-4442.

http://dx.doi.org/10.1016/j.jairtraman.2016.11.007
0969-6997/

carriers (ULCCs) and low-cost carriers (LCCs) under the variable returns-to-scale (VRS) assumption. Second, the comparison of the M&A performance of three merged airlines indicates that M&A have positive or negative effects on economies of scale and efficiency levels, which suggest that new service innovation is still required to enhance airline efficiency and achieve the optimum economies of scale. Third, the result of bootstrapped truncated regression suggest that environment factors have a positive or negative effect on US domestic airlines' efficiency. The cost such as fuel expense and number of full-time equivalent employee has a negative effect on efficiency, while operating revenue have a positive effect. Fourth, productivity change of US airlines mainly depends on a change of technological change (TC). Furthermore, ULCCs have the highest productivity growth, whereas LCCs have experienced a lowest efficiency change.

The remainder of this paper is organized as follows. Section 2 describes the methodologies used in our study. Section 3 defines the input/output variables necessary for DEA and explores the characteristics of the decision-making units (DMUs). Section 4 presents the empirical result, namely the analysis of annual efficiency and productivity change in US airlines as well as the M&A performance of airlines by using bootstrapping DEA And we investigate the main driver of environmental factor to increase the efficiency. Section 5 discusses and suggests managerial implications.

2. Methodology

In this study, we used output-oriented DEA to estimate and compare the contemporaneous efficiency score of US domestic airlines from 2006 to 2015 (Färe et al., 1994; Tulkens and Vanden Eeckaut, 1995). Moreover, this paper builds on a two-stage DEA to determine potential determinants of efficiency of US domestic airlines from 2006 to 2015. The first stage is concerned with bootstrapped DEA approaches to measure the efficiency of the US domestic airlines (Simar and Wilson, 2007). To measure the robustness of the data, Simar and Wilson (1998, 2000) introduced bootstrapping DEA as a tool to extract the sensitivity of DEA scores to the randomness attributed to the distribution of efficiency. Bootstrapping, a statistical method based on empirical data, employs the repeat sampling of correlation estimations in order to improve the estimates of confidence intervals and threshold accuracy (Staat, 2006). Therefore, we use an alternative bootstrapping method to improve the DEA efficiency estimates and thus evaluate the DMU, are described as follows:

- Step 1. Use DEA to calculate efficiency scores.
- Step 2. Draw with replacement from the empirical distribution of efficiency scores. Simar and Wilson (1998) suggest that smoothing the empirical distribution provides results that are more consistent.
- Step 3. Divide the original efficient input levels by the pseudo-efficiency scores drawn from the (smoothed) empirical distribution to obtain a bootstrap set of pseudo-inputs.
- Step 4. Apply DEA using the new set of pseudo-inputs and the same set of outputs and calculate the bootstrapped efficiency scores.
- Step 5. Repeat from steps 1–4 B times and use bootstrapped scores for statistical inference and hypothesis testing (B is a large number).

In the second stage of our analysis, we regress the bias-corrected efficiency scores $\widehat{\widehat{\theta}}_i$, derived from the bootstrap algorithm on a set of environmental factors using the following regression model (Barros and Peypoch, 2009; Hall, 1986; Lee and Worthington, 2014; Simar and Wilson, 2007):

$$\widehat{\widehat{\theta}}_i = \alpha + z_i\beta + \varepsilon_i \quad i = 1, \ldots, n \tag{1}$$

where $\varepsilon_i \sim N = (0, \sigma_\varepsilon^2)$ with left-truncation at $1 - z_i\beta$; α is a constant variable; z_i is a vector of environmental variables that is expected to affect bootstrapped efficiency score of US domestic airline i and β refers to a vector of parameters with some statistical noise ε_i. Simar and Wilson (2007) detail the bootstrap truncated regression algorithm, also described in a step-by-step approach in Lee and Worthington (2014) and Barros and Peypoch (2009).

While DEA measures annual efficiency by focusing on the optimal inputs and outputs, Malmquist index (MI) analysis concentrates on productivity change to investigate the input–output relationship during a specific period (Asmild and Tam, 2007). Thus, this study additionally adopts the output-oriented MI model suggested by Färe et al. (1994) to measure the change in total productivity. The reader is referred to Färe et al. (1994) and Lovell (1993) for standard conventions and details of DEA and MI.

3. Input and output data

To compare the static efficiency and dynamic productivity of the 14 US domestic airlines, financial and non-financial data were collected from the Bureau of Transportation Statistics (www.rita.dot.gov/bts) and Airline Data Project from MIT (www.web.mit.edu/airlinedata/) during 2006–2015. The air transportation industry is a large-scale service factory (Schmenner, 1986) and a service operation system generating maximum performance with limited resources for air transportation services. In airline analysis, five common industry metrics to measure the efficiency of an airline operation are the load factor, available seat miles (ASM), revenue passenger miles (RPM), cost per available seat mile (CASM), and yield per revenue passenger (Barbot et al., 2008; Barros and Peypoch, 2009; Lee and Worthington, 2014; Li et al., 2015; Mallikarjun, 2015). Based on the previous literature review and data availability, we obtain an input variable and three output variables. The CASM are significant input factor. In addition, revenue per ASM (RASM), passenger yield, and load factor (L/F) are useful indices for estimating the business competences of carriers (e.g., profitability and market share) as well as strategic importance of major service operations.

The definition of input/output variables is as follows (http://web.mit.edu/airlinedata):

- *CASM*: Measure of unit cost in the airline industry. CASM is calculated by dividing the operating expenses of an airline by ASM. In general, management uses CASM excluding fuel or transport-related expenses to better isolate and directly compare operating expenses.
- *RASM*: Also called “unit revenue,” it is obtained by dividing operating income by ASM.
- *Passenger Yield*: A measure of airline revenue derived by dividing passenger revenue by revenue passenger miles (RPMs). This measure is useful in assessing changes in fares over time.
- Load Factor (*L/F*): The percentage of available seats that are filled with revenue passengers. The load factor measures the capacity utilization of airline transport service.

Moreover, the 14 US domestic airlines can be classified into three group according to their business models, as follows:

- *NLCs* or *full service network carriers* (hub-and-spoke airlines) focus on providing a wide range of pre-flight and onboard services, including different service classes and connecting flights: American Airlines (AA), Alaska airlines (AS), Continental Air