Full length article

Energy efficiency of airlines and its influencing factors: A comparison between China and the United States

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\textbf{A R T I C L E  I N F O}

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\textbf{A B S T R A C T}

The development of Chinese and American airlines evidences the rise of the global aviation industry. Improving energy efficiency of airlines is critical to realize the targets of energy conservation and emissions mitigation in this industry. However, the gap of energy efficiency between Chinese and American airlines and its influencing factors has not been revealed. This study measures and compares the energy efficiency and productivity of Chinese and American airlines during 2011−2014. The results show that the average energy efficiencies of Chinese airlines lagged behind those of American airlines, and the gap of energy efficiency between these two countries’ airlines was enlarging over the period of 2011−2014. Differences in fleet age, passengers per flight, share of freight traffic, firm size, and ownership of airlines are the main factors that influence the gap between energy efficiency of Chinese and American airlines. Moreover, the comparison between environmentally sensitive measurement and conventional measurement of productivity shows that the growth of total factor productivity will be underestimated without considering undesirable outputs. And technical progress contributes most to productivity growth of Chinese and American airlines.

1. Introduction

With improvement in living standards and reduction in cost of air transportation, the demand for airline services has increased steadily in the past ten years. The number of passengers transported by airlines increased from 2.0 billion in 2004 to 3.3 billion in 2015 (IATA, 2016). And it’s forecasted to be 2.6 times the 2014 level in the coming 20 years (COMAC, 2014). The value of goods delivered by air transportation increased by 32% compared to 2004, accounting for 35% of total international trade in 2014 (ATAG, 2016). With the rapid increase in demand for airline services, the total number of global airlines increased by 56% compared with 2004, amounting to 1402 in 2015 (ATAG, 2016). As an energy-intensive industry, increasing demand for air transportation will lead to more energy consumption and carbon emissions. The annual growth rate of fuel consumption in airline industry is more than 6% in the past ten years (Cui et al., 2016). And the CO\textsubscript{2} emissions of airline industry account for approximately 2% of global CO\textsubscript{2} emissions in 2015 (ATAG, 2016). This proportion is estimated to grow to 2.4% − 4.1% by 2050 (Owen et al., 2010).

The airline industry in the United States and China ranks the first and second in the world, contributing to 28% (US$207.7 billion) and 14% (US$100.8 billion) of global airline revenues in 2014, respectively (IATA, 2014). These two countries look forward to reducing energy consumption and emissions from airlines through increasing the productivity and efficiency of airlines. And they have issued numerous environmental policies and laws to regulate the carbon emissions of the airline industry. According to the statistical data of U.S. Government Accountability Office, the Legislation of Clean Air Act (CAA) of the United States was established as early as 1973, regulating the emissions of civil aircraft (section B of chapter two). The American congress passed the Next Generation Air Transportation System Implementation Plan in 2011, with a target to mitigate the total carbon dioxide emissions of American airlines by 1600 million tons, and to reduce the total fuel consumption by 1.6 billion gallons by 2020 compared to the 2004 levels (GAO, 2011). Compared with the U.S., the issuance of air emission legislation in China is relative late. The Civil Aviation Administration of China (CAAC) released the first law and regulation of aircraft carbon emissions in 2002, the regulations on fuel discharge and exhaust emissions of turbine-engine aircraft (CAAC, 2002). In 2011, the CAAC issued the Guidance of promoting energy conservation and emissions...
2. Methods and data

The framework of methodology adopted in this study is shown in Fig. 1. First, we adopt a SBM-DEA model to evaluate and compare the energy efficiency of airlines from China and the United States during 2011–2014 with Slacks-based measurement (SBM) model. In SBM model, undesirable outputs are taken into account. And this study firstly investigates differences between energy efficiency of Chinese and American airlines. In addition, we use Malmquist-Luenberger (ML) index to measure the evolution of productivity and efficiency and compare with conventional measurement. Factors that influence energy efficiency are explored using a Tobit regression model as well. These results are beneficial to the sustainable development of Chinese and American aviation enterprises.

2.1. Slacks-based measurement model

The traditional DEA method suggests proportionally reduction in all inputs and maximizes all outputs to be efficient (Charnes et al., 1978; Cooper et al., 2000). It ignores the undesirable outputs, which are the by-products of desirable outputs during the production process (Chang et al., 2013). To solve this problem, undesirable outputs are proposed to be integrated into traditional DEA model by changing the form of data (Seiford and Zhu, 2002). It is based on strong disposability of outputs (i.e., non-proportional reduction in undesirable or desirable outputs is feasible) (Fare and Grosskopf, 2004). Another approach is taking undesirable outputs as input variables and using traditional DEA model based on the weak disposability reference technology (i.e., reducing undesirable outputs in proportion to desirable outputs) (Fare and Grosskopf, 2004; Hailu and Veeman, 2001; Zhou et al., 2007). These two methods have been critically debated among scholars (Cui and Li, 2016; Hailu, 2003; Hailu and Veeman, 2001; Li et al., 2012; Sueyoshi and Goto, 2012). Most recent approach to cope with this problem is the SBM-DEA model. It utilizes non-radial and non-oriented evaluation methods to solve the problem of efficiency evaluation with undesirable output (Li et al., 2013; Liu et al., 2016a; Tone, 2001). And it has been adopted in many studies of efficiency evaluation (Apergis et al., 2015; Chang et al., 2014; Liu et al., 2016b; Song et al., 2013).

The basic SBM-DEA model is described as follow. Let n represent the number of decision making units (DMUs); Matrices X, Y, and B stand for m inputs, s1 desirable outputs, and s2 undesirable outputs of n DMUs, respectively. Then the matrices X, Y, and B can be written as

\[ X = [x_{ij}] = [x_1, \ldots, x_n] \in \mathbb{R}^{m \times n}, \quad Y = [y_i] = [y_1, \ldots, y_n] \in \mathbb{R}^{s_1 \times n}, \quad B = [b_j] = [b_1, \ldots, b_n] \in \mathbb{R}^{s_2 \times n}. \]

\( \lambda \) is the intensity vector and its non-negative (Chang et al., 2013). Eq. (1) shows the production possibility set, and Eq. (2) indicates the SBM-DEA model (Tone, 2001).

\[
P(x) = \{ (x, y, b) | x \geq X, y \leq Y, b \geq B, \lambda \geq 0 \}
\]

\[
\beta_0^\ast = \min \left\{ \frac{1 - \frac{1}{n} \sum_{i=1}^{n} s_{0i}^u}{1 + \frac{1}{n} \sum_{i=1}^{n} s_{0i}^d + \frac{1}{n} \sum_{i=1}^{n} b_{0i}^d} \right\}
\]

S.T.

\[
x_0 = x_i + s_{0i}^u
\]

\[
y_0 = y_i - s_{0i}^d
\]

\[
b_0 = b_i + b_{0i}^b
\]

\[
s_{0i}^d \geq 0, s_{0i}^u \geq 0, s_{0i}^b \geq 0, \lambda \geq 0
\]

In Eq. (2), the vector \( s_{0i}^u \) and \( b_{0i}^b \) stands for inputs and undesirable outputs excesses, respectively; the vector \( s_{0i}^d \) indicates the shortage of good outputs. The subscript 0 represents the DMU being estimated. If \( \beta^\ast = 1 \), the DMU is relatively efficient, and all the slack variables are zero (\( s_{0i}^u = s_{0i}^d = b_{0i}^b = 0 \)). If \( \beta^\ast < 1 \), the DMU is inefficient and it can become efficient through optimizing its inputs or outputs (Chang et al., 2013; Tone, 2001).

Input and output variables selected usually have significant influences on the results of SBM-DEA model. Labour, capital, and energy are major types of inputs of enterprises, and outputs include both financial income and environmental impacts (Lin and Zheng, 2017; Qin et al., 2017). In this paper, we select the number of aircraft, labour, and fuel...

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**Fig. 1.** The framework of methodology.
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