A comparative study of airline efficiency in China and India: A dynamic network DEA approach

Hang Yu[a], Yahua Zhang[b*], Anming Zhang[c] Kun Wang[d] and Qiang Cui[e]

[a] China Institute of FTZ Supply Chain, Shanghai Maritime University, Shanghai, China. Email: Hang Yu (yuhang@shmtu.edu.cn)

[b] School of Commerce, University of Southern Queensland, Toowoomba, Queensland, 4350 Australia. Email: Yahua Zhang (yahua.zhang@usq.edu.au)

[c] Sauder School of Business, University of British Columbia, Vancouver, BC, Canada. Email: Anming Zhang (anming.zhang@sauder.ubc.ca)

[d] School of International Trade and Economics, University of International Business and Economics, Beijing, China. Email: Kun Wang (kunwang@uibe.edu.cn)

[e] School of Economics and Management, Southeast University, Nanjing, China. Email: Qiang Cui (cuiqiang1011@163.com)

[*]Corresponding author. E-mail address: yahua.zhang@usq.edu.au Phone: +61 7 4631 2640

Abstract

Using a dynamic network DEA approach, this research examines the efficiency performance of major Chinese and Indian carriers with a consideration of the airline company's internal processes and links as well as the carry-over items that connect consecutive time periods. It has been found that three low-cost carriers (LCCs), namely, China's Spring and India's SpiceJet were the most efficient carriers during the period between 2008 and 2015. China's three state-owned airlines performed poorly in both the capacity generation and service stages, particularly the latter. The second-stage regression results confirm that the LCC model and private ownership are significantly associated with better airline efficiency performance. This paper thus calls for continual reforms in China's air transport including further privatisation and policy support for LCCs and private carriers to improve the overall efficiency of this industry.

Key words: China, India, efficiency, dynamic and network DEA, private airlines, low-cost carriers

JEL codes: L51, L93, L98

1. Introduction

Both China and India commenced the process of privatising their state-owned enterprises in the late 1980s and early 1990s. However, India had the advantage of starting the reforms from a mixed economic system where the public sector enterprises (PSEs) dominated the "core" sectors of the economy including the airline industry while the private sector enterprises played an important role in the "non-core" industries. In contrast, China had to develop a market economic system from scratch (Chai and Roy, 2006). The share of PSEs in GDP in India was 25% in the early 1990s. Due to the strong resistance of vested interest groups including trade unions (Chai and Roy, 2006), a large part of the value of PSEs have not been privatised including the government owned Air India. However, the contribution of the private sector to GDP growth has been over 80% since the 2000s. When China began its privatisation in the 1980s, the share of the private sector was less than 1% of its GDP. Three decades later, the private sector has now contributed to 60% of the nation’s GDP and 90% of the new jobs. Thus, the degree of privatisation in India has been much deeper and broader historically and currently.

In China, the government controls firms in almost all strategically important industries. The average state ownership in publicly listed companies was about 70% in 2002 and was still the case in 2017. In the case where the Chinese government is a minority shareholder in a privatised SOE, it still retains a control over the firm through appointing top managers and boards of directors (Xu and Wang, 1999). The heavy influence of Chinese government on listed companies was confirmed by a report by S&P Global Ratings in 2016 (Allirajan, 2016). The report finds that India’s top 200 companies, particularly the private companies, outperform their Chinese peers in several financial indicators despite India’s infrastructure bottlenecks. There is large difference in the size of the private sectors. The private firms account for 75% of the net debt and earnings before interest, taxes, depreciation and amortisation of the 200 companies in India, while this figure is less than 20% for the top Chinese companies.

Air transport had long been regarded as a core industry that should be regulated and protected in China and India due to its significant national security and sovereignty implications in the history. As with other industries of the two countries, deregulation and privatisation in this sector began in the 1980s. However, up to now, China’s aviation market is still dominated by state-owned carriers although all the major carriers have been partly privatised in the late 1990s and early 2000s. In 2016, Chinese carriers transported 436 million passengers with the “big three” state-owned airline groups, Air China, China Eastern and China Southern, commanding a market share of 24%, 22%, and 25%, respectively. Members of the Hainan Aviation Group (HNA), a de facto private airline group,[1] held a market share of some 14%. The share of other private airlines in the passenger market was less than 16%. In contrast, the Indian market has now been dominated by private carriers with major private carriers such as Jet Airways, SpiceJet, IndiGo, Vistara, AirAsia India, and Go Air, carrying 82 million passengers, representing a market share of 79% in the 2015-16 financial year (Wang et al, 2018). The market share of the government-owned carrier, Air India, was less than 15%. With such stunningly different governance structures in airline companies in the two countries, it is expected that the performance of airlines would be substantially different. Although research comparing the economic reforms and development between the two economies is voluminous, comparative studies into a particular industry remain rare. This research aims to fill the literature gap by investigating the efficiency performance of the airline companies in the two countries and exploring the likely determinants of the performance.

The findings of this study suggest that China's state-owned airlines are far less efficient than their Indian counterparts, in both the capacity generation stage and the service stage. Private ownership and the LCC business model are key to determine the airline efficiency performance. Next section briefly reviews the air transport sector in the two countries. Related studies are discussed in section. Section 4 presents the methodology and data, followed by the section of results and discussion. The last section contains policy implication and conclusion.

[1] Hainan Airlines was established as a state-owned carrier jointly owned by Hainan Province and the Civil Aviation Administration of China (CAAC). In the last 30 years, it has evolved from a regional airline into a global conglomerate with stakes in more than 10 Chinese carriers including Hainan Airlines, Capital Airlines, and Hong Kong airlines. HNA Group also has significant investment in the sectors of tourism, finance, logistics, real estate, etc. The evolvement of ownership structure of HNA Group was not transparent and remains a mystery. A charity organisation, Cihang Foundation, is now the largest shareholder according the HNA group website.

2. The development of China and India's air transport

In 1994, Air India and Indian Airlines were corporatized following the repeal of the Air Corporations Act 1953. Private carriers including Jet Airways was allowed to operate scheduled services. Jet Airways surpassed the state-owned Indian Airlines in 2001 and became the largest carrier in the domestic market. India's first LCC, Air Deccan, was established in 2003, and this model was quickly replicated with SpiceJet, IndiGo, GoAir and JetLite being launched between 2005 and 2007. As Air India and Indian Airlines kept losing ground to the private counterparts, the government then decided to merge the two in 2007, leading a wave of consolidations in the airline industry. For example, Jet Airways acquired the failing Air Sahara and renamed it as JetLite in 2007. Deccan was taken over by Kingfisher Airlines in 2008.[2] The Indian government has long considered privatising or at least partly privatising the national airline, but this goal has never been achieved mainly because of the political reasons and opposition from the trade union. In 2017, IndiGo was the largest domestic carrier with a market share of about 40% in terms of the number of passengers carried. Jet Airways was in the second place. The national carrier, Air India, was in the third place and only commanded a share of about 13-14%.

China's private airlines emerged in 2005 immediately after the air transport sector was opened to domestic private investors (Zhang and Round, 2008). By 2007 some 20 new private airlines had been established including Shanghai-based Spring Airlines and Juneyao Airlines, which are now the two largest private carriers in China. Spring has positioned itself as an LCC while Juneyao operates as a full service carrier (FSC). Also in 2005, several large shareholders (state-owned

[2] Kingfisher failed in 2012 due to financial problems, and subsequently its domestic and international flight entitlements were withdrawn by the government (Wang et al., 2018).

companies) sold their shares in Shenzhen Airlines to private companies and thus Shenzhen Airlines became privately owned. However, from 2007 the private airlines experienced huge setbacks. Many of the new private airlines quickly failed due to the lack of capital, experienced pilots and skilled personnel, along with the high costs and taxes associated with aircraft purchases, jet fuel and airport charges (Zhang and Zhang, 2016). Also because they brought intense competitive pressure to the domestic aviation market, which was deemed undesirable to the CAAC. In 2007 the CAAC decided to suspend the approval of new domestic entrants until 2010. This policy was not repealed until 2013. Zhang and Lu (2013) argue that China's competition policy does not favour the private carriers. For example, mergers in the air transport sector were rarely investigated and challenged, especially when private airlines were the merger target. United Eagle Airlines was taken over in 2009 by state-controlled Sichuan Airlines due to United Eagle's poor financial performance, and renamed to Chengdu Airlines. Shenzhen Airlines was taken over by Air China in 2010. In 2009 the Wuhan-based private carrier, East Star Airlines was forced to cease operation after it rejected the proposed takeover by Air China.

The volumes of passengers and freight carried by major Chinese and Indian state-owned airlines and private airlines in 2015 are reported in Figures 1 and 2. It is obvious that China's three major groups operate in a much larger scale than any of their Indian counterparts. However, China's LCC (privately-owned) carried passengers and freight less than half of those by India's largest LCC, IndiGo.

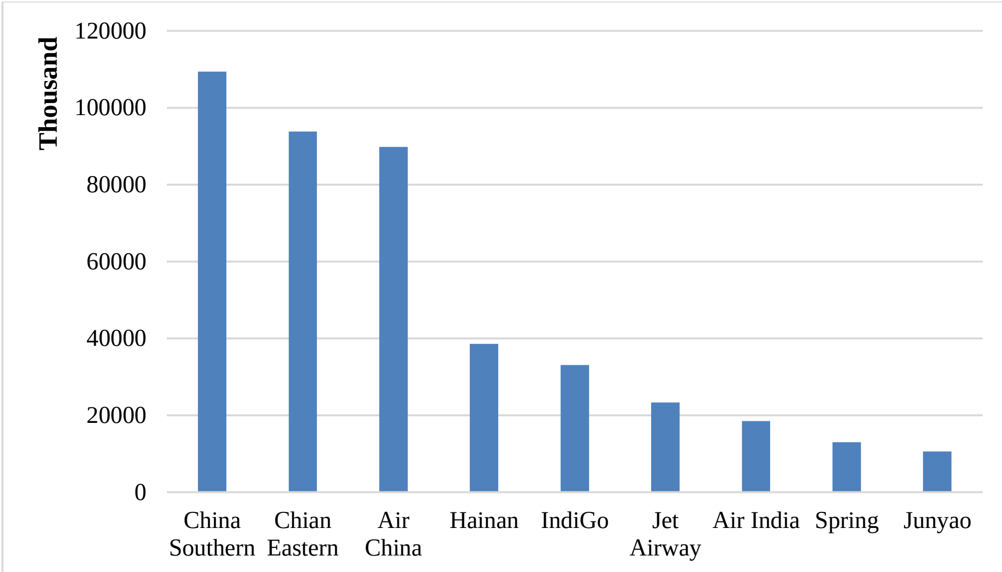

Figure 1. Passengers carried by major Chinese carriers (2015) and Indian carriers (2015-2016FY)

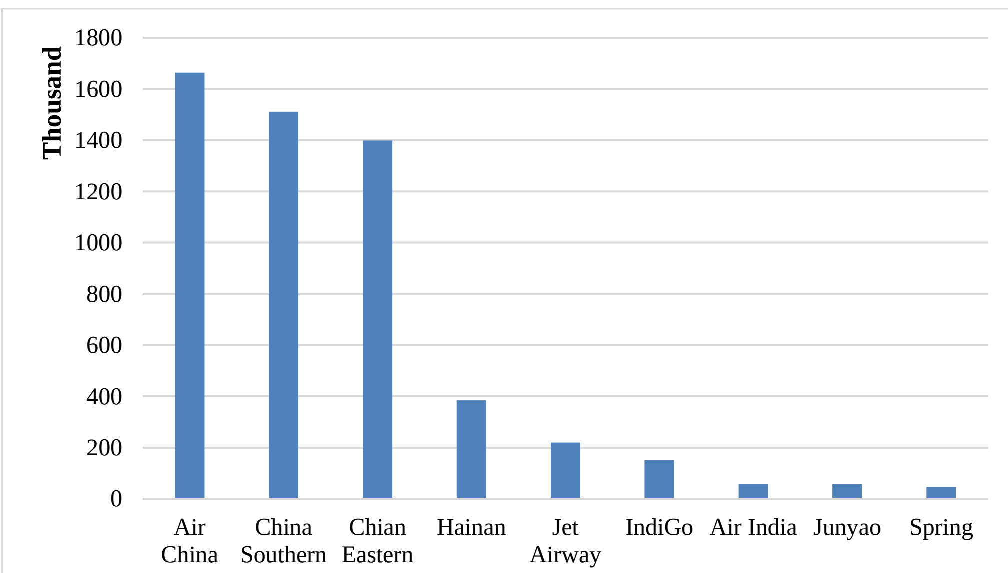

Figure 2. Freight carried by major Chinese carriers (2015) and Indian carriers (2015-2016FY)

3. Related studies

Chinese government can exert a strong influence on Chinese firms' corporate governance and performance as shown in Qian (1996) and Che and Qian (1998). One of the main channels is through direct control of the majority shares of the companies in key industries, particularly in the armaments, power generation and distribution, oil and petrochemicals, telecommunications, coal, aviation and shipping industries. Mixed results have been produced regarding the relationship between state ownership and Chinese firms' performance. Detrimental effect of state ownership on firm performance has been revealed in Xu and Wang (1999), and Sun and Tong (2003) while Le and Chizema (2011) find positive correlation between government ownership and firm performance. An inverse U-shaped relationship is reported in Sun et al. (2002) and Tian and Estrin (2008). Some studies such as Wang (2005) contends that there is no systematic relation between ownership structure and firm performance, even when different performance measures are used. Chen et al. (2017) investigated six listed Chinese airlines, and found a U-shaped relationship between state ownership and firm performance for the airline industry. Using a traditional Data Envelopment Analysis (DEA) approach, Chow (2010) shows that since the entry of private carriers in 2005, non-state-owned airlines performed better than their state-owned counterparts. It seems that strong competition brought about by the new private carriers did not help improve the efficiency performance of the state-owned carriers. Wang et al. (2014) compared the performance of leading Chinese carriers with representative foreign airlines. They concluded that Chinese airlines steadily improved their operational efficiency from 2001 to 2010 but they still lag behind leading airlines in developed markets.

For the case of India, Saranga and Nagpal (2016) used a DEA approach to evaluate the technical and cost efficiencies of major Indian airlines and in the second stage, panel data based regression models were used to identify factors driving these efficiencies. Their study finds that the national carrier Air India was among the most technically efficient airlines during 2005–2007, but both technical and cost efficiency dropped after the 2007 merger between Air India and Indian Airlines. The technical efficiency scores of the LCCs such as SpiceJet, Go Air and IndiGo were consistently high and close to the frontier, but the cost efficiency scores were comparatively low for many LCCs. Saranga and Nagpal (2016) also report that the LCC business model, participating in international air services, and pricing power are significantly associated with an airline's efficiency performance. Similar findings are reported in Jain and Natarajan (2015) using the DEA approach.

It should be noted that most of the above-mentioned studies have used DEA to measure the operating and technical efficiency. This approach and its various extensions have been widely used in the air transport literature (see e.g., Ahn and Min, 2014; Tsui et al., 2014; Georgiadis et al. 2014; Gutiérrez and Lozano, 2016),[3] to assess the efficiency of Decision-Making Units (DMUs) with multiple inputs and outputs based on the framework of Farrell (1957). The DMUs can be either airports (Lam et al., 2009; YU, 2010; Merker and Assaf, 2015; Liu, 2016; lo Storto, 2018; Lozano et al., 2013) or airlines (Tavassoli, et al., 2014). This non-parametric linear programing technique was formally developed by Charnes, Cooper, and Rhodes (1978). Compared with the parametric approach, the non-parametric approaches do not require a priori assumption on functional form specification which may restrict the frontier shape (Berger and Humphrey, 1997). A good survey of the application of the traditional DEA can be found in Yu (2016).

[3] Econometric approach such as stochastic frontiers is another commonly used approach to measure efficiency. See González and Trujillo (2009) for a good discussion of the differences between the two approaches.

The traditional DEA approach has evolved substantially in the last two decades, especially in the last 10 years. However, traditional DEA models treat the operational process of the DMU as a black box without considering the internal structure of the processes in the DMU's operation (Yu and Chen, 2017). In contrast, the network DEA considers the internal structure of a DMU as many companies comprise several stages, each of which may use its own inputs to produce its own output (Färe and Grosskopf, 2000). Readers can refer to Kao (2014) for a review of the recent development of the network DEA model. Traditional DEA models also ignore the intertemporal efficiency change as it does not consider the connecting activities or carry-overs between periods. The operation of a DMU in one period is not independent of that in another consecutive period (Yu and Chen, 2017). Therefore, dynamic DEA models have been developed (Färe and Grosskopf, 1996; Tone and Tsutsui, 2010, 2014). A comprehensive review of the dynamic and network DEA models can be found in Mariz, et al. (2018).

This research will apply the dynamic network DEA (DNDEA) model introduced in Tone and Tsutsui (2014) to measure the efficiency of major Chinese and Indian airlines by considering both the internal processes of airline companies and the existence of carry-overs that connect two consecutive periods in the airline industry. The DNDEA is the composite of network DEA and dynamic DEA. To the best of our knowledge, studies comparing airline efficiency and the underlying drivers in China and India are rare, let alone the use of the DNDEA for such comparison. This research aims to fill this gap.

4. Methodology and Data

4.1 The Dynamic network DEA model

We build our DNDEA model under the constant returns-to-scale (CRS) assumption[4] and within the slacks-based measure (SBM) framework proposed by Tone and Tsutsui (2014).[5] The operation of a transport organisation usually involves two stages: the production stage (or process) and the service stage (Yu and Chen, 2017). For a typical airline company, in the first stage, capacity is produced and in the second stage, the capacity is used as an input to generate service outputs (Zhu, 2011). In Omrani and Soltanzadeh (2016), these two interconnected stages are labelled as "production" and "consumption", respectively. In addition, some outputs produced in the production stage in the current period could be transferred into the next period (Maghbouli,et al., 2014). The two-stage structure of our research is shown as Figure 3.

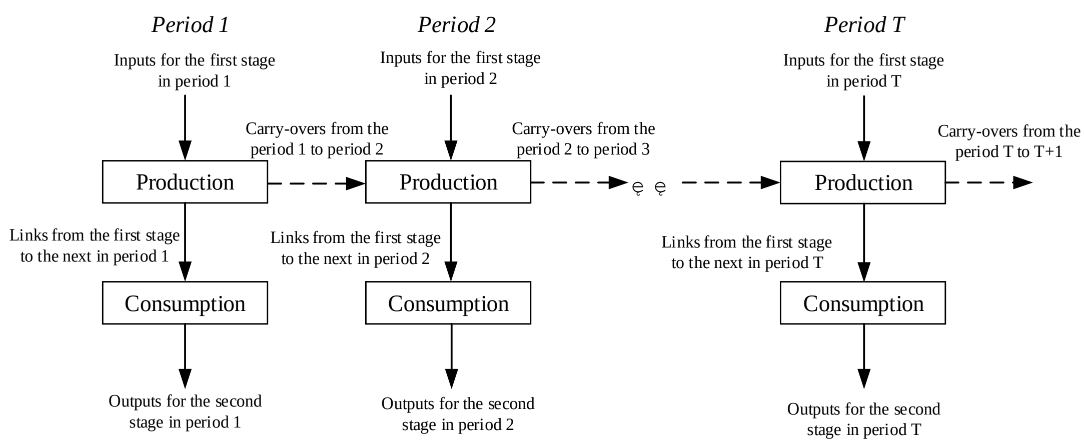

Figure 3. Two-stage structure of airline industry in this research

The indicators selected for input, output, intermediate product and carry-over are explained as follows. The input and output data for Indian airlines are from India's Directorate General of

[4] Although a DMU may operate under variable returns to scale (VRS) in the short run, in the long run, it would adjust its capacity to move to CRS (Cummins and Xie, 2013). Therefore, CRS reflects the long run situation. Yu and Chen (2017) thus argue that in a multiperiod context, it is reasonable to adopt the assumption of CRS for the efficiency calculation.

[5] The non-radial SBM models do not assume proportional changes in inputs and outputs as the radial models do (Tone and Tsutsui, 2010). See Appendix 1 for a brief description for the Tone and Tsutsui (2014) model.

Civil Aviation while the Chinese data mainly come from the Statistical Data on Civil Aviation of China.

Following previous literature (e.g., Duygun et al., 2016), two inputs, the number of employees and the number of aircraft are used in this study. The choice of the two inputs reflects the fact that the airline industry is both labour intensive and capital intensive. The non-oriented mode was chosen because airlines airlines can effectively control their inputs including employees and aircraft fleet and at the same time expand their outputs as much as possible over time. Two outputs are revenue passenger-kilometres (RPK) and revenue tonne-kilometres (RTK) that comprise the passengers, freight and mail carried multiplied by the distance flown. They are commonly used in previous literature (Yu, 2016).

The first stage of the operation uses the inputs to generate flight capacities. Therefore, the number of departures and flying hours are used as intermediate products. This is consistent with Omrani and Soltanzadeh (2016) and Li and Cui (2017) in which the number of flights and available seat kilometres (ASK) were used as intermediate outputs. In fact, the number of departures and flying hours have a close association with an airline's total capacity.

Some carry-over activities can have an impact on the airline efficiency performance between two consecutive years (Cui et al., 2016). Tone and Tsutsui (2010) and Cui et al. (2016) believe that capital stock is not only an output of the current year, but also an input of the next year. Therefore, it can be treated as a carry-over variable or a dynamic factor. In this research, we believe that the network size of an airline measured by the number of destinations served can be used as a carry-over variable which not only affects the current period but also the subsequent periods. The data for the network size variable are obtained from the airline schedule data in the IATA Airport Intelligence database.

Five major Indian airlines and eight major Chinese airlines are included in our airline efficiency study. The chosen Indian airlines include two FSCs, Air India and Jet Airways, and three other major LCCs, Spicejet, IndiGo and GoAir. Except Air India, which is the flag carrier in India, the others are all privately owned. The Chinese airlines that we chose include the state-owned “big three” airlines, namely Air China, China Eastern and China Southern, and three private airlines, Spring Airlines, Juneyao Airlines and Okay Airways. Spring Airlines is the first and the largest LCC in China, whereas Juneyao and Okay are the earliest formed private airlines in China. The remaining two carriers, namely, Sichuan Airlines and Hainan Airlines have local government ownership. The annual data for the Indian and Chinese airlines required for the DNDEA model were collected for the efficiency analysis. Due to limited data availability, we only consider a period from 2008 to 2015. The descriptive statistics of the input, output, intermediate product and the carry-over variables are reported in Table 1. In our research, all the links are treated as “outputs” from the preceding process, and all the carry-overs are desirable and treated as outputs. The DEA-Solver Pro software was used to produce the efficiency scores.

It should be noted that the weights of period and stage will have an impact on the efficiency results and that the choice of period and stage weights are kind of arbitrary. As pointed out by Li and Cui (2017), many researchers have attempted to determine the optimal stage weights including Kao and Hwang (2014) and Kao (2014), but none of them have been widely accepted as reasonable approaches. As a result, quite a few studies on airline efficiency such as Lozano and Gutiérrez (2014) and Cui and Li (2017) assume equal weights for different production stages. It is our view that for most airlines, the capacity production and service provision (consumption) are equally important and thus setting an average weight for each stage is reasonable and appropriate. This is also the case for the period weights that were set equal in previous studies using dynamic DEA models such as as Li et al. (2016) and Cui and Li (2017).

Table 1. Descriptive statistics of the input, output, intermediate product and the carry-over variables

Variable	Data source	Mean	Std. dev.	Min	Max
Number of employees (input)	India's Directorate General of Civil Aviation; Statistical Data on Civil Aviation of China (2006-2016)	21,521	27,716	763	103,228
Number of aircraft (input)		119	139	6	506
RPK (million) (output)		32,771	34,794	1,039	140,609
RTK(million) (output)		3,391	3,800	94	15,748
Number of departures (intermediate output)		154,129	151,734	9,036	611,018
Flying hours (intermediate output)		374,495	390,485	15,967	1,590,642
Number of destinations (carry-over)	Airport Intelligence database	540	472	18	1,397

4.2 The second-stage regression model

We wish to identify the drivers behind the airlines' efficiency differences in China and India. The different efficiency results may reflect the different development patterns in the two aviation markets such as the LCC penetration, the airline competition intensity and the airline ownership as discussed at the beginning of this paper. We follow previous studies (e.g., Barros and Peypoch, 2009; Yuen et al., 2013) to regress our estimated overall airline DEA efficiency scores against some explanatory variables. Many recent studies such as Kweh et al. (2015), Lee and

Worthington (2015), Pointon and Matthews (2016) and Wanke et al. (2015) have also regressed the dynamic DEA scores against possible determinant factors. Therefore, in Eq. (1), airline efficiency score $DNDEA_{it}$ is expressed as a function of several explanatory variables that we are interested in. Most of these variables are also used in previous literature such as Saranga and Nagpal (2016).

$$\widehat{DNDEA}_{it} = \beta_0 + \beta_1 LCC_{it} + \beta_2 Public_{it} + \beta_3 HHI\_Route_{it} + \beta_4 International\%_{it} + \beta_5 Stage\_length_{it} + \beta_6 HSR_{it} + \varepsilon_{it} \tag{1}$$

where the subscript i stands for the airline, t stands for the year, and $DNDEA_{it}$ is the true overall efficiency score for airline i at time t. The estimated DNDEA efficiency score $\widehat{DNDEA}_{it}$ is restricted in the interval between 0 and 1, meaning that the true efficiency score $DNDEA_{it}$ over 1 is unobservable. Therefore, a Tobit model can be used to estimate the coefficients in Eq. (1). LCC_{it} is a dummy variable which equals one if the airline is an LCC. It is expected that LCCs are more efficient in operations given their great efforts in lowering operating costs and maximising outputs. $Public_{it}$ is a dummy variable that equals one if the airline is a state-owned airline or majority-owned by government. This variable is used to capture the effect of public ownership on airlines' efficiency. HHI_Route_{it} is the average route-level HHI index, which shows how the airline competition intensity can affect airline efficiency. $International\%_{it}$ is the share of RPK on the international routes for the airline. It captures the international market involvement of an airline and has been found to have a significant impact on the technical and cost efficiency in previous studies (e.g., Saranga and Nagpal, 2016). $Stage\_length_{it}$ is the average stage length per trip for the airline. This distance measure captures the effect of route and network optimisation on airline efficiency. In the last decade, high speed rail (HSR) has emerged as a significant transport mode in China (Li and Sheng, 2016). It has been an effective substitute for air transport on short and medium haul routes, posing a serious threat to the Chinese airlines (Zhang and Zhang, 2016). Therefore, the length of HSR is included as it is expected that competition from HSR would force airlines to improve their operational efficiency.

Simar and Wilson (2007) have shown that the "naïve regression"[6] on the DEA efficiency scores can result in biased estimations. This is because the usual estimation procedures assume independently distributed error terms, which may not be valid. The second-stage regression depends on the explanatory variables, which are not considered in the first-stage efficiency estimation. Thus, there can be a correlation between the efficiency scores and the error term in the second-stage regression (Barros and Peypoch, 2009). Simar and Wilson (2007) propose a bootstrap method to address the above issues so as to produce a consistent and unbiased estimator in the second-stage regression. The method has been applied in the efficiency studies of airlines and other transport modes (e.g., Yuen et al., 2013). In this study, we also adopt the procedures proposed by Simar and Wilson (2007).[7]

The variables of the regression were collected from various sources. Airport Intelligence database of IATA provides the airline-route specific passenger volume statistics, with which we can calculate the HHI index for the major routes. India's Directorate General of Civil Aviation provides other Indian airlines statistics, including the share of international operations measured by RPK, and the average stage length. These variables for the Chinese airlines are collected from the airlines' annual reports and the yearbooks "Statistical Data on Civil Aviation of China"

[6] Naïve regression refers to the approach that directly uses the first-stage DEA scores to run the regressions in the second stage.

[7] See Appendix 2 for the details of this approach.

published by the CAAC. The data of the length of HSR were collected from the website of the Ministry of Transport of China and news media reports.

5. Results and Analysis

5.1 Results for airline efficiency

The overall and period efficiency scores for the 13 airlines are reported in Table 2. The rank column shows the ranking of the airlines based on the overall efficiency score.

Table 2. Overall DNDEA efficiency

DMU	Overall Score	Rank	2008	2009	2010	2011	2012	2013	2014	2015
Air India	0.9317	3	0.954	1	1	0.9635	0.9674	1	0.7921	0.8047
Jet Airways	0.7152	8	0.5819	0.6235	0.7399	0.5446	0.8379	0.8632	0.844	0.8776
SpiceJet	1	1	1	1	1	1	1	1	1	1
Indigo	0.8574	6	0.7125	0.8389	0.9079	0.9063	0.9162	0.925	0.898	0.8037
Goair	0.8768	5	1	0.8465	1	0.7887	0.8459	0.8795	0.8659	0.8325
Air China	0.5336	11	0.5537	0.494	0.5285	0.4479	0.5595	0.5983	0.5712	0.558
China Eastern	0.4057	13	0.3313	0.3385	0.3857	0.387	0.4704	0.4969	0.4537	0.473
China Southern	0.4404	12	0.4119	0.3683	0.4173	0.4111	0.4528	0.518	0.5053	0.5039
Hainan	0.6404	9	0.5899	0.5806	0.5747	0.5096	0.7333	0.8093	0.8052	0.6995
Sichuan	0.9078	4	0.8794	0.9093	0.8964	0.9	0.915	0.9403	0.9435	0.8829
Spring	0.9897	2	1	1	1	1	1	1	0.9641	0.9562
Juneyao	0.8409	7	0.7101	0.8454	0.8623	0.875	0.8761	0.8909	0.8439	0.8547
Okay	0.5805	10	0.5317	0.4902	0.4825	0.6469	0.6298	0.5905	0.6411	0.7163

As can be seen from Table 1, two LCCs, China's Spring and India's SpiceJet consistently ranked in the first two places from 2008 to 2015, indicating the strong competitiveness of LCCs in both countries. Air India and China' Sichuan Airlines ranked third and fourth, respectively, China's "big three", Air China, China Eastern, China Southern, are at the bottom of the ranking list. Their efficiency scores are much lower than India's national carrier, Air India that is still state-owned. This is consistent with Jain and Natarajan (2015) and Saranga and Nagpal (2016), who assessed Indian airline efficiency using the traditional DEA approach and found that Air India was among the most technically efficient airlines in the period 2005–2012. Surprisingly, Jet Airways is the least efficient airline in India. It was the largest carrier in India between 2001 and 2012 and was rated as one of the most efficient airlines in India in Saranga and Nagpal (2016). However, our research has shown that its efficiency performance was not so impressive, particularly before 2012. The different results produced in this research may be a result of the use of different estimation approaches. The DNDEA approach used here is obviously superior to the traditional model as our results can better explain the slow growth in the last decade. In fact, a recent analysis of Jet Airways' financial data by Aggarwal (2017) finds that it has failed to improve its operational efficiency, which is a worrying sign for this carrier.

Although not top-ranked, it is worth mentioning that China's Okay, a private carrier, made noticeable progress in efficiency performance after 2011. Although Wang et al. (2018) suggest that China's LCCs and private carriers have been operating in an unfriendly environment as the nation's aviation policy is overly protective of the state-owned airlines, it seems that they have managed to achieve efficiency and outperformed their state-owned counterparts. It is also worth noting that most Chinese carriers exhibited a sign of improvement in efficiency since 2008, which is consistent with Wang et al. (2014) who claimed that Chinese airlines steadily improved their operational efficiency from 2001 to 2010, but they still lagged behind leading airlines in developed markets.

Table 3 shows the airline efficiency in the production and consumption processes. E_o^1 and E_o^2 indicate the efficiency performance in the stages of production and consumption, respectively.

Consistent with the results in Table 2, SpiceJet achieved technical efficiency in both stages while China's "big three" remained to be the bottom three in the two processes. These three state-owned Chinese carriers' efficiency scores are particularly low in the consumption stage, probably implying that they have failed to attract sufficient number of passengers and tonnes of freight compared with the size of their available capacities.

Tables 4 and 5 present the efficiency changes of the 13 airlines from 2008 to 2015 in the production and consumption processes, repetitively. It can be seen that most airlines' efficiency in production remained relatively stable throughout the study period while their efficiency performance in the consumption stage exhibited wider fluctuations. SpiceJet, GoAir, and Spring were technically efficient in the production stage in all the years under study. Sichuan Airlines' efficiency score for production was one in every year from 2008 to 2014 and still close to one in 2015. Air India was technically efficient in the production stage from 2008 to 2013, but its efficiency declined substantially in 2014 and 2015. Apart from 2008 and 2015, IndiGo was also operating at the efficient level during the study period. Tables 4 and 5 also show that China's Okay followed an increasing trend after 2010. Its production stage efficiency improvement was particularly impressive. Air India was state-owned, but its efficiency performance in the consumption stage was far better than all the state-controlled Chinese carriers as shown in Table 5.

Table 3. Efficiency in different processes

No.	DMU	E_o^1	E_o^2

		Score	Rank	Score	Rank
1	Air India	0.9317	3	0.9241	7
2	Jet Airways	0.7152	8	0.8865	8
3	SpiceJet	1	1	1	1
4	Indigo	0.8574	6	0.982	5
5	Goair	0.8768	5	1	1
6	Air China	0.5336	11	0.4303	11
7	China Eastern	0.4057	13	0.3636	13
8	China Southern	0.4404	12	0.3653	12
9	Hainan	0.6404	9	0.6089	10
10	Sichuan	0.9078	4	0.9956	4
11	Spring	0.9897	2	1	1
12	Juneyao	0.8409	7	0.9503	6
13	Okay	0.5805	10	0.6822	9

Table 4. Efficiency performance in production process over time

DMU	2008	2009	2010	2011	2012	2013	2014	2015	Average	Rank
Air India	1	1	1	1	1	1	0.6892	0.7037	0.9241	7
Jet Airways	0.7827	0.7879	0.8245	0.6969	1	1	1	1	0.8865	8
SpiceJet	1	1	1	1	1	1	1	1	1	1
Indigo	0.9309	1	1	1	1	1	1	0.9255	0.982	5
Goair	1	1	1	1	1	1	1	1	1	1
Air China	0.4571	0.4525	0.4721	0.3935	0.4188	0.4361	0.4111	0.4009	0.4303	11
China Eastern	0.3243	0.3365	0.3662	0.3311	0.3759	0.4105	0.3768	0.3874	0.3636	13
China Southern	0.3725	0.3535	0.3713	0.3548	0.3568	0.3786	0.3721	0.3628	0.3653	12
Hainan	0.6366	0.5722	0.5801	0.5558	0.6094	0.6806	0.6482	0.5882	0.6089	10
Sichuan	1	1	1	1	1	1	1	0.9644	0.9956	4
Spring	1	1	1	1	1	1	1	1	1	1

Juneyao	0.8008	0.9426	0.859	1	1	1	1	1	0.9503	6
Okay	0.5307	0.558	0.5293	0.643	0.722	0.6927	0.844	0.9375	0.6822	9

Table 5. Efficiency performance in consumption process over time

DMU	2008	2009	2010	2011	2012	2013	2014	2015	Average	Rank
Air India	0.912	1	1	0.9295	0.9369	1	0.8952	0.9089	0.9478	3
Jet Airways	0.4631	0.5159	0.671	0.4469	0.7211	0.7594	0.7301	0.7819	0.6362	10
SpiceJet	1	1	1	1	1	1	1	1	1	1
Indigo	0.5771	0.7225	0.8313	0.8287	0.8454	0.8605	0.8148	0.7115	0.774	6
Goair	1	0.7339	1	0.6511	0.733	0.7849	0.7635	0.713	0.7974	5
Air China	0.6892	0.5439	0.6001	0.5115	0.781	0.8429	0.8209	0.809	0.6998	9
China Eastern	0.3387	0.3406	0.4074	0.4462	0.5972	0.6007	0.5415	0.5749	0.4809	13
China Southern	0.4606	0.3845	0.4758	0.4788	0.5896	0.7264	0.7077	0.7271	0.5688	11
Hainan	0.5496	0.5886	0.5694	0.4704	0.8696	0.9478	0.9857	0.8351	0.727	8
Sichuan	0.7847	0.8337	0.8122	0.8182	0.8433	0.8874	0.893	0.8154	0.836	4
Spring	1	1	1	1	1	1	0.9307	0.916	0.9808	2
Juneyao	0.6379	0.7668	0.8654	0.7778	0.7795	0.8032	0.7299	0.7462	0.7633	7
Okay	0.5327	0.4371	0.4445	0.6503	0.5586	0.5201	0.5216	0.581	0.5307	12

5.2 Results of second-stage regressions

Table 6 presents the descriptive statistics for the second-stage explanatory variables. Our second-stage regression results are collated in Table 7 for both the Tobit random effects and the bootstrap corrected model proposed in Simar and Wilson (2007).[8] Overall, the Tobit random effects model and the bootstrapping procedure produce similar estimations.

Table 6. Descriptive statistics for the second-stage DEA regression variables [9]

	No. of Obs.	Mean	Std. dev.	Min	Max

[8] Although widely used in the literature, this approach was criticised in Banker, Natarajan and Zhang (2019). That is why we also present the Tobit results.

[9] The public ownership dummy and LCC dummy have the same mean and standard deviation, which is a coincidence.

LCC Dummy	104	0.307	0.463	0	1
Public Ownership Dummy	104	0.307	0.463	0	1
HHI at Route Level	104	3,718	1,467	1,841	7,321
Share of International RPK (100%)	104	22.56%	26.37%	0	97.86%
Stage Length (km)	104	1,388	528	838	3,595
HSR (km)	104	6,539	7,707	0	23,600

Table 7. The Second-stage regression results of the DEA efficiency scores

	Tobit RE	Bootstrap-correction
LCC	0.215***	0.216***
	(0.076)	(0.062)
Public Ownership	-0.174**	-0.192***
	(0.083)	(0.065)
HHI at Route Level	-0.026	-0.040**
	(0.022)	(0.018)
Share of International RPK (%)	0.002*	0.0006
	(0.001)	(0.001)
Stage Length (1,000 Km)	0.008	0.167***
	(0.034)	(0.068)
HSR	2.94×10^{-6}***	2.22×10^{-6}
	(1.25×10^{-6})	(2.26×10^{-6})
Constant	0.765***	0.318
	(0.101)	(0.365)
No. of Obs	104	104
Sigma u	0.107***	0.123***
Sigma e	0.069***	-

Note: (1) Standard errors are in parentheses. * 10% significance, ** 5% significance, *** 1% significance.

(2) The “bootstrap-correction” is based on Simar and Wilson (2007). We use 500 bootstrap replications.

Our estimations suggest that LCCs are more efficient than FSCs which is consistent with the results of Barros and Peypoch (2009), and Lee and Worthington (2014). Private ownership in airlines promotes airline efficiency as suggested by both models. For the two quasi-private carriers, Sichuan and Hainan airlines,[10] a robustness estimation has also been done to categorise them as a third type ownership given their mix of public and private ownership, and the results still show that the stated owned airlines tend to be inferior in operation efficiency. Ng and Seabright (2001) find that public ownership supports higher wages and thus reduces airline efficiency. With a sample of 42 major airlines around the world, Lee and Worthington (2014) also find that private airlines are more efficient than the state-owned ones. Rajagopalan and Zhang (2008) proposed a sound explanation: when the state dominates a firm, the state may use its influence to achieve the objectives of politicians, rather than protecting the interests of investors and shareholders. Zhang and Findlay (2010) find that India's national carriers were frequently used to serve social goals in addition to commercial performance. When state-owned firms pursue other objectives, the ability to achieve efficiencies would be weakened (Martin and Parker, 1997).

Route-level competition have a significant impact on airline efficiency as shown in the bootstrap corrected model, implying lower HHI, or stronger competition can make airlines more efficient. A higher presence of international market measured by the percentage of international RPK does not necessarily lead to a higher level of efficiency as shown in Table 5. The bootstrap corrected model suggest that longer stage length is associated with higher airline efficiency. The decline in airline unit costs with increasing stage length average stage length (i.e., the distance of a flight

[10] Both airlines were established by local provincial government and other organisations but the influence from the government was much weaker compared with the state-owned "big three".

segment) is considered as an important characteristic of airline operations. This is because airport charges, ground handling costs, and take-off and landing activities become relatively smaller per passenger kilometre as stage length increases. Also, longer stage length leads to higher aircraft and crew utilisation. Finally, the Tobit model indicates a significantly positive effect of HSR on airline efficiency, but the relationship is not statistically significant in the bootstrap corrected model.

6. Policy Implication and Conclusion

The DNDEA model used in this research considers the airline's internal processes and their internal links as well as the carry-over items that connect consecutive periods. It has been found that three LCCs, namely, China's Spring and India's SpiceJet were the most efficient carriers in the period 2008-2015. China's "big three" were the least efficient carriers. These findings are consistent with S&P Global Ratings' 2016 report that India's top 200 companies, particularly the private companies, outperform their Chinese counterparts (Allirajan, 2016). To find the source of inefficiency for each airline, we use Figure 4 to highlight the relative positions of each airline in the matrix format, with efficiency scores for the consumption stage on the vertical axis and efficiency scores for production on the horizontal axis. It can be seen that China Eastern and China Southern performed poorly in both consumption and production stages. They are the only two airlines that fall within Quadrant 3. Air China lies in Quadrant 4, suggesting a relatively low efficiency in the consumption stage. Therefore, there is much room for the state-owned Chinese carriers to improve their efficiency in the service stage. For example, flight delay, a significant dimension of airline service quality, has been confirmed to have a close link with Chinese airlines' technical efficiency performance by Tsionas et al. (2017). However, Zhang and Zhang

(2016) note that frequent flight delays in China have long frustrated passengers in China, although some of the reasons causing delays are beyond the airlines' control, such as airport congestion and the lack of sufficient airspace for civil aviation flights, which should be addressed at the national level.

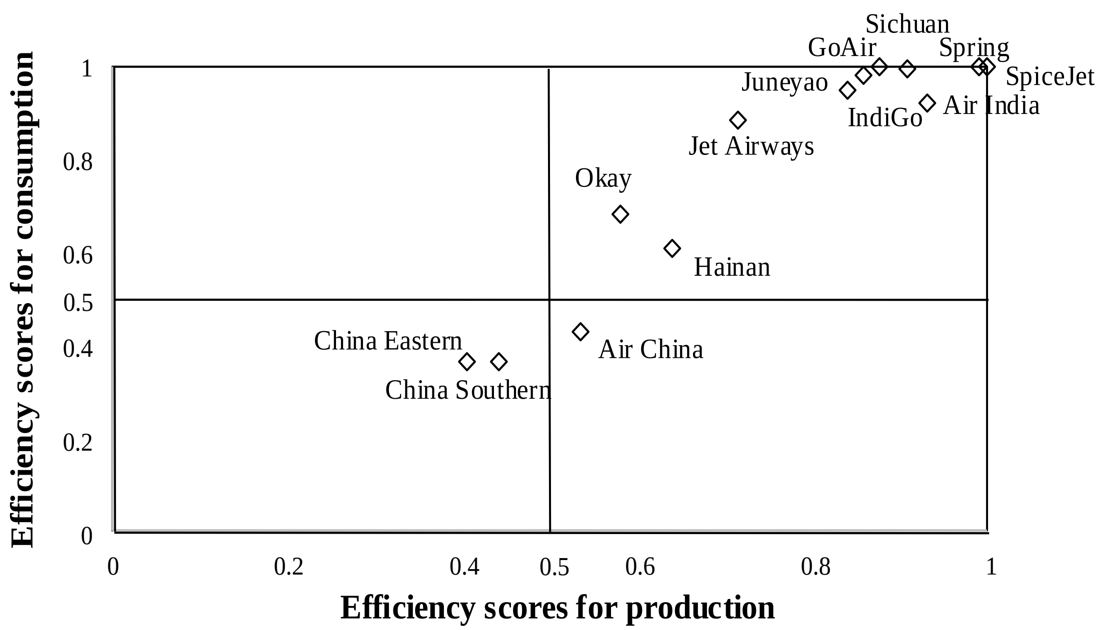

Figure 4. Airline efficiency scores in the production and consumption processes.

Airline distribution might be another area that affects airlines' efficiency in Chinese carriers' service stage. Chinese state-owned carriers use three channels to sell their tickets: online direct sales from their official website, online sales from third-party platforms such as online travel agent Ctrip, and air ticket sales agents using CAAC TravelSky Technology's booking system. In 2010, the "big three's" direct sales share was only about 10% and the airlines had to pay large amount of commission fees to the sales agents. The commission fees paid to the sale agents amounted to RMB 5 billion in 2009. However, the most important loss to the airlines for the low share of direct sales might be that they do not own the travellers purchase behaviour data and thus lose the opportunity to innovate and personalise their distribution model to attract customers and increase the load factor.[11]

The second-stage regression results confirm that the LCC model and private ownership are significantly associated with overall airline efficiency performance. Despite 100% owned by the Indian government, Air India is still much more efficient than its Chinese counterparts, probably indicating that state-owned airlines operating in an environment dominated by private and LCCs tend to become stronger in efficiency. China eased investment access to aviation industry in early 2018, allowing private capital to account for more than 50% of their equity as long as the government remains to be the largest single shareholder. This move will likely improve the efficiency of the state-owned carriers. However, what is even important is to create a level playing field for both private carriers, LCCs and state-owned airlines in China. Unlike the state-owned counterparts that have various channels to raise funds including government cash injection and bank finance for their fleet expansion, it is very difficult for a private carrier to borrow money from China's state-owned banks as airline industry is deemed as a high-risk industry. Raising money from the stock exchange market could be another possible channel, but the initial public offering (IPO) process is lengthy, unpredictable and lack of transparency in China. Spring and Juneyao were not approved to launch the IPO on the Shanghai Stock Exchange until 2015. By this time many other private carriers established at the same time with them had already failed due to the capital shortage and other reasons. In addition, China's current aviation policy on market access and airport slot allocation, and competition policy on airline mergers still favour the state-owned airlines and discriminate against the private ones. Continual

[11] In 2015, the "big three's" parent companies that represent the Chinese government required that the state-owned carriers should improve their direct sales share to 50% in the next three years.

reforms in China's air transport sector including further privatisation and policy support for LCCs and private carriers are much needed in order to improve the overall efficiency of this industry.

There are several limitations of this study. First, it is well known that in many developed economies, outsourcing is one of the strategies that can help airlines reduce costs and improve efficiency. In the developing economies like China and India, this practice is less common, but it is increasing and will become trendy in the near future. Obviously this research does not account for this issue, nor does it distinguish the full-time and part-time employees as the employee data compiled by the two nations' aviation authorities do not give any details of these issues, which may have an impact on the efficiency results. Second, it is should be acknowledged that each airline uses different airplanes models with different transport capacities and that without considering the size of the aircraft and its acquisition methods, distortion can arise in the efficiency calculation, despite the fact that for airlines, most of the production and sales activities are organised around each scheduled flight, regardless of the size of the aircraft, which may partly justify the use of the number of aircraft in many DEA studies on airline efficiency. Finally, the equal weight assumption for different stages and periods may not be realistic in some cases and can create distortion in efficiency calculations. This issue should be addressed in future research.

References:

Ahn, Y. H., Min, H. 2014. Evaluating the multi-period operating efficiency of international airports using data envelopment analysis and the Malmquist productivity index. Journal of Air Transport Management, 39, 12-22.

Aggawal, V., 2017. Jet Airways in Trouble. BBN Times. 30 September 2017. Available at https://www.bbntimes.com/en/financial/worrying-signs-for-jet-airways.

Allirajan, M. 2016. India's top companies are better placed than China's despite infrastructure gap, S&P says. The Times of India.

Banker, R., Natarajan, R., Zhang, D. (2019). Two-Stage Estimation of the Impact of Contextual Variables in Stochastic Frontier Production Function Models Using Data Envelopment Analysis: Second Stage OLS versus Bootstrap Approaches. European Journal of Operational Research. 278, 368-384.

Barros, C.P., Peypoch, N., 2009. An evaluation of European airlines' operational performance. International Journal of Production Economics 122 (2), 525-533.

Berger, A.N., Humphrey, D.B., 1997. Efficiency of financial institutions: international survey and directions for future research. European Journal of Operational Research 98, 175–212.

Chai, C.H., Roy, K.C. 2006. Economic Reform in China and India: Development Experiences in a Comparative Perspective. Edward Elgar Publishing.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research 2, 429–444.

Che, J., Qian, Y., 1998. Institutional environment, community government, and corporate governance: understanding China's township-village enterprises. Journal of Law, Economics, & Organization 14 (1), 1-23.

Chen, S.J., Chen, M.H., Wei, H.L., 2017. Financial performance of Chinese airlines: does state ownership matter?. Journal of Hospitality and Tourism Management 33, 1-10.

Chow, C.K.W., 2010. Measuring the productivity changes of Chinese airlines: The impact of the entries of non-state-owned carriers. Journal of Air Transport Management 16, 320-324.

Cui, Q., Li, Y., Yu, C.L., Wei, Y.M., 2016. Evaluating energy efficiency for airlines: an application of virtual frontier dynamic slacks based measure. Energy 113, 1231-1240.

Duygun, M., Prior, D., Shaban, M., Tortosa-Ausina, E., 2016. Disentangling the European airlines efficiency puzzle: a network data envelopment analysis approach. Omega 60, 2-14.

Färe, R., Grosskopf, S., 1996. Productivity and intermediate products: a frontier approach. Economics Letters 50 (1), 65–70.

Färe, R., Grosskopf, S., 2000. Network DEA. Social-Economics Planning Science 34, 35–49.

Farrell, M.J. 1957. The measurement of productive efficiency. Journal of the Royal Statistical Society, Series A (General) 120 (3), 253-290.

Georgiadis, G., Politis, I., Papaioannou, P. 2014. Measuring and improving the efficiency and effectiveness of bus public transport systems. Research in Transportation Economics, 48, 84-91.

González, M. M., Trujillo, L. 2009. Efficiency measurement in the port industry: A survey of the empirical evidence. Journal of Transport Economics and Policy, 43(2), 157-192.

Gutiérrez, E., Lozano, S. 2016. Efficiency assessment and output maximization possibilities of European small and medium sized airports. Research in Transportation Economics, 56, 3-14.

Jain, R.K., Natarajan, R., 2015. A DEA study of airlines in India. Asia Pacific Management Review 20, 285–292.

Kao C. 2014. Efficiency decomposition in network data envelopment analysis. Omega, 45, 1–6.

Kao C, Hwang, S.N. 2014. Multi-period efficiency and Malmquist productivity index in two-stage production systems. European Journal Operation Research, 232(3), 512–21.

Kweh, Q.L., Kuo, K.-C., Wang, W.-K., Liu, H.-M., 2015. Board independence, family control, and performance in Taiwanese listed semiconductor companies. Hitotsubashi Journal of Economics 56, 93–115.

Lam, S. W., Low, J. M., & Tang, L. C. 2009. Operational efficiencies across Asia Pacific airports. Transportation Research Part E: Logistics and Transportation Review, 45(4), 654-665.

Le, T., Chizema, A., 2011. State ownership and firm performance: evidence from Chinese listed firms. Organizations & Markets in Emerging Economies 2 (2), 72-90.

Lee, B.L., Worthington, A.C., 2014. Technical efficiency of mainstream airlines and low-cost carriers: new evidence using bootstrap data envelopment analysis truncated regression. Journal of Air Transport Management 38, 15-20.

Lee, B.L., Worthington, A.C., 2015. A network DEA quantity and quality-orientated production model: an application to Australian university research services. Omega 60, 26-33.

Li, Y., Cui, Q., 2017. Carbon neutral growth from 2020 strategy and airline environmental inefficiency: a Network Range Adjusted Environmental Data Envelopment Analysis. Applied Energy 199, 13-24.

Li, Y., Wang, Y. Z., Cui, Q. 2016. Energy efficiency measures for airlines: an application of virtual frontier dynamic range adjusted measure. Journal of Renewable and Sustainable Energy, 8(1), 015901-14.

Li, Z. C., Sheng, D. (2016). Forecasting passenger travel demand for air and high-speed rail integration service: A case study of Beijing-Guangzhou corridor, China. Transportation Research Part A: Policy and Practice, 94, 397-410.

Liu, D. 2016. Measuring aeronautical service efficiency and commercial service efficiency of East Asia airport companies: An application of Network Data Envelopment Analysis. Journal of air transport management, 52, 11-22.

lo Storto, C. 2018. The analysis of the cost-revenue production cycle efficiency of the Italian airports: A NSBM DEA approach. Journal of Air Transport Management, 72, 77-85.

Lozano, S., Gutiérrez, E. 2014. A slacks-based network DEA efficiency analysis of European airlines. Transportation Planning and Technology, 37(7), 623-637.

Lozano, S., Gutiérrez, E., Moreno, P. 2013. Network DEA approach to airports performance assessment considering undesirable outputs. Applied Mathematical Modelling, 37(4), 1665-1676.

Maghbouli, M., Amirteimoori, A., Kordrostami, S. 2014. Two-stage network structures with undesirable outputs: A DEA based approach. Measurement, 48, 109-118.

Mariz, F.B., Almeida, M.R., Aloise, D., 2018. A review of Dynamic Data Envelopment Analysis: state of the art and applications. International Transactions in Operational Research 25 (2), 469-505.

Martin, S., Parker, D., 1997. The impact of privatization: ownership and corporate performance in the UK, London: Routledge.

Merkert, R., Assaf, A. G. 2015. Using DEA models to jointly estimate service quality perception and profitability–Evidence from international airports. Transportation Research Part A: Policy and Practice, 75, 42-50.

Ng, C.K., Seabright, P., 2001. Competition, privatisation and productive efficiency: evidence from the airline industry. Economic Journal 111, 591-619.

Omrani, H., Soltanzadeh, E., 2016. Dynamic DEA models with network structure: an application for Iranian airlines. Journal of Air Transport Management 57, 52-61.

Pointon, C., Matthews, K., 2016. Dynamic efficiency in the English and Welsh water and sewerage industry. Omega 58, 86–96.

Qian, Y., 1996. Enterprise reform in China: agency problems and political control. Economics of Transition 4 (2), 427-447.

Rajagopalan, N., Zhang, Y., 2008. Corporate governance reforms in China and India: challenges and opportunities. Business Horizons 51 (1), 55-64.

Saranga, H., Nagpal, R., 2016. Drivers of operational efficiency and its impact on market performance in the Indian airline industry. Journal of Air Transport Management 53, 165–176.

Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics 136, 31-64.

Statistical Data on Civil Aviation of China. 2006-2016. China Civil Aviation Press, Beijing.

Sun, Q., Tong, W.H., 2003. China share issue privatization: the extent of its success. Journal of Financial Economics 70 (2), 183-222.

Sun, Q., Tong, W.H., Tong, J., 2002. How does government ownership affect firm performance? Evidence from China's privatization experience. Journal of Business Finance & Accounting 29, 1-27.

Tavassoli, M., Faramarzi, G. R., Saen, R. F. 2014. Efficiency and effectiveness in airline performance using a SBM-NDEA model in the presence of shared input. Journal of Air Transport Management, 34, 146-153.

Tian, L., Estrin, S., 2008. Retained state shareholding in Chinese PLCs: does government ownership always reduce corporate value?. Journal of Comparative Economics 36 (1), 74-89.

Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research 130 (3), 498-509.

Tone, K., Tsutsui, M., 2010. Dynamic DEA: a slacks-based measure approach. Omega 38, 145-156.

Tone, K., Tsutsui, M., 2014. Dynamic DEA with network structure: a slacks-based measure approach. Omega 42 (1), 124-131.

Tsionas, M.G., Chen, Z., Wanke, P., 2017. A structural vector autoregressive model of technical efficiency and delays with an application to Chinese airlines. Transportation Research Part A: Policy and Practice 101, 1-10.

Tsui, W. H. K., Balli, H. O., Gilbey, A., Gow, H. (2014). Operational efficiency of Asia–Pacific airports. Journal of Air Transport Management, 40, 16-24.

Wang, C., 2005. Ownership and operating performance of Chinese IPOs. Journal of Banking & Finance 29 (7), 1835-1856.

Wanke, P., Barros, C.P., Faria, J.R., 2015. Financial distress drivers in Brazilian banks: a dynamic slacks approach. European Journal of Operational Research 240, 258–268.

Wang, K., Fan, X., Fu, X., Zhou, Y., 2014. Benchmarking the performance of Chinese airlines: an investigation of productivity, yield and cost competitiveness. Journal of Air Transport Management 38, 3-14.

Wang, K., Zhang, A., Zhang, Y., 2018. Key determinants of airline pricing and air travel demand in China and India: policy, ownership, and LCC competition. Transport Policy 63, 80-89.

Xu, X., Wang, Y., 1999. Ownership structure and corporate governance in Chinese stock companies. China Economic Review 10(1), 75-98.

Yu, C., 2016. Airline productivity and efficiency: Concept, measurement, and applications, in: John D. Bitzan, James H. Peoples, Wesley W. Wilson (eds.), Airline Efficiency (Advances in Airline Economics, Volume 5, 11–53, Emerald Group Publishing Limited.

Yu, M. M. 2010. Assessment of airport performance using the SBM-NDEA model. Omega, 38(6), 440-452.

Yu, M.M., Chen, L.H. 2017. DEA in the transport sector. In: K. Tone (ed.) Advances in DEA Theory and Applications: With Extensions to Forecasting Models. Ch.16, pp192-215, John Wiley & Sons.

Yuen, A., Zhang, A., Cheung, W., 2013. Foreign participation and competition: a way to improve container port efficiency in China? Transportation Research Part A: Policy and Practice 49, 220-231.

Zhang, Q., Yang, H., Wang, Q. 2013. Market conduct of the three busiest airline routes in China. Journal of Transport Economics and Policy 47(3), 335-347.

Zhang, Y., Lu, Z., 2013. Low cost carriers in China and its contribution to passenger traffic flow. Journal of China Tourism Research 9, 207−217.

Zhang, Y., Zhang, A., 2016. Determinants of air passenger flows in China and gravity model: deregulation, LCCs, and high-speed rail. Journal of Transport Economics and Policy 50 (3), 287–303.

Zhu, J., 2011. Airlines performance via two-stage network DEA approach. Journal of CENTRUM Cathedra: The Business and Economics Research Journal 4 (2), 260-269.

Appendix 1: The DNDEA model description

To measure the efficiency of n DMUs (j=1,…,n) with a consideration of k stages (k=1,2) over t periods (t =1,… T) ,In our case, we talk about the period from 2008 to 2015, where T=8. We followed Tone and Tsutsui (2014) and use the following notations for the indicators used in the DNDEA model. We denote the link from stage k to stage h by (k, h) and the set of links by $l_{(k,h)}$ ($l_{(1,2)}$=2), while the carry-over set in k stage as l'_k (l'_1=1).

$x^t_{ijk} \in R_+$ (i=1,…,m_k; j=1,…,n; t=1,…, T; k=1,2) is i th input of DMU_j for stage k in period t. m_k (m_1=2) is the number of inputs for stage k.

$y^t_{rjk} \in R_+$ (r=1,…,r_k; j=1,…,n; t=1,…,T; k=1,2) is r th output of DMU_j for stage k in period t. r_k (r_2=2) is the number of outputs from stage k.

$z^t_{j(k,h)l} \in R_+$ (j=1,…,n; (k,h)=(1,2); t=1,…,T; l=1,…, $l_{(k,h)}$) is l th intermediate products of DMU_j from stage k to stage h in period t. In our research, all the links are treated as outputs from the preceding process.

$c^{(t,t+1)}_{jkl'} \in R_+$ (j=1,…,n; t=1,…,T-1; k=1,2; l'=1,…,l'_k) is l' th carry-over of DMU_j at stage k from period t to next period t+1. In our research, all the carry-overs are desirable and treated as outputs.

The production possibility set $P^t = \left\{\left(\mathbf{x}^t_k, \mathbf{y}^t_k, \mathbf{z}^t_{(kh)}, \mathbf{c}^{(t,t+1)}_k\right)\right\}$ is defined by

$$\mathbf{x}^t_k \geq \sum_{j=1}^n \mathbf{x}^t_{jk} \lambda^t_{jk} (\forall k = 1,2, t = 1,...,T) \quad \text{(A1)}$$

$$\mathbf{y}^t_k \leq \sum_{j=1}^n \mathbf{y}^t_{jk} \lambda^t_{jk} (\forall k = 1,2, t = 1,...,T) \quad \text{(A2)}$$

$$\mathbf{z}^t_{(kh)} \leq \sum_{j=1}^n \mathbf{z}^t_{j(kh)} \lambda^t_{jk} ((k,h) = (1,2), t = 1,...,T) \text{ (links as outputs from } k \text{ in period } t) \quad \text{(A3)}$$

$$\mathbf{z}^t_{(kh)} \geq \sum_{j=1}^n \mathbf{z}^t_{j(kh)} \lambda^t_{jh} ((k,h) = (1,2), t = 1,...,T) \text{ (links as inputs to } h \text{ in period } t) \quad \text{(A4)}$$

$$\mathbf{c}^{(t,t+1)}_k \leq \sum_{j=1}^n \mathbf{c}^{(t,t+1)}_{jk} \lambda^t_{jk} (k = 1,2, t = 1,...,T) \text{ (as carry-over for stage } k \text{ from } t) \quad \text{(A5)}$$

$$\mathbf{c}^{(t,t+1)}_k \geq \sum_{j=1}^n \mathbf{c}^{(t,t+1)}_{jk} \lambda^{t+1}_{jk} (\forall k = 1,2, t = 1,...,T) \text{ (as carry-over for stage } k \text{ to } t+1) \quad \text{(A6)}$$

$$\lambda^t_{jk} \geq 0 (\forall k = 1,2, j = 1,2...,n, t = 1,2...,T) \text{ (intensity of } DMU_j \text{ corresponding to stage } k \text{ at period t)} \quad \text{(A7)}$$

Inputs and outputs:

DMU$_o$(o=1,…,n)$\in P$ can be expressed as follows.

$$x^t_{iok} = \sum_{j=1}^n x^t_{ijk} \lambda^t_{jk} + s^{t-}_{iok} (\forall i, \forall k, \forall t) \quad \text{(A8)}$$

$$y^t_{iok} = \sum_{j=1}^n y^t_{ijk} \lambda^t_{jk} - s^{t+}_{iok} (\forall i, \forall k, \forall t) \quad \text{(A9)}$$

$$\sum_{j=1}^n \lambda^t_{jk} = 1 (\forall k, \forall t) \quad \text{(A10)}$$

$$\lambda^t_{jk} \geq 0 (\forall j, \forall k, \forall t), s^{t-}_{iok} \geq 0 (\forall i, \forall k, \forall t), s^{t+}_{iok} \geq 0 (\forall i, \forall k, \forall t) \quad \text{(A11)}$$

Where

s^{t-}_{iok} and s^{t+}_{iok} indicate imput and output slacks, respectively.

Links:

$$\sum_{j=1}^{n} z_{j(k,h)l}^{t}\lambda_{jk}^{t} = \sum_{j=1}^{n} z_{j(k,h)l}^{t}\lambda_{jh}^{t} (\forall(k,h), l = 1,...l(k,h), \forall t) \tag{A12}$$

$$z_{o(kh)l}^{t} = \sum_{j=1}^{n} z_{j(k,h)l}^{t}\lambda_{jk}^{t} - s_{o(k,h)l}^{t} (\forall(k,h), l = 1,..., l(k,h), \forall t) \tag{A13}$$

where $\mathbf{s}_{o(k,h)l}^{t}$ is slack for the links in our case.

Carry-overs:

$$\sum_{j=1}^{n} c_{jkl'}^{(t,t+1)}\lambda_{jk}^{t} = \sum_{j=1}^{n} c_{jkl'}^{(t,t+1)}\lambda_{jk}^{t+1} (l' = 1,...l'_{k}, \forall k, t = 1,...T-1) \tag{A14}$$

$$c_{okl'}^{(t,t+1)} = \sum_{j=1}^{n} c_{jkl'}^{(t,t+1)}\lambda_{jk}^{t} - s_{okl'}^{(t,t+1)} (l' = 1,...l'_{k}, \forall k, \forall t) \tag{A15}$$

where $s_{okl'}^{(t,t+1)}$ is slack for the carry over in our case.

Following Tone and Tsutsui (2014), the overall efficiency for the DNDEA model is:

$$E_o^{sys} = \min \frac{\sum_{t=1}^{T} W^t \left[\sum_{k=1}^{K} w_k \left[1 - \frac{1}{m_k} \sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^{t}} \right] \right]}{\sum_{t=1}^{T} W^t \left[\sum_{k=1}^{K} w_k \left[1 + \frac{1}{r_k + l_{(k,h)} + l'_k} \left(\sum_{i=1}^{r_k} \frac{s_{iok}^{t+}}{y_{iok}^{t}} + \sum_{l=1}^{l_{(k,h)}} \frac{s_{o(k,h)l}^{t}}{z_{o(k,h)l}^{t}} + \sum_{l'=1}^{l'_k} \frac{s_{okl'}^{(t,t+1)}}{c_{okl'}^{(t,t+1)}} \right) \right] \right]} \tag{A16}$$

where

$$\sum_{t=1}^{T} W^t = 1, W^t \geq 0 (\forall t = 1,...,T) \text{ and } \sum_{k=1}^{K} w_k = 1,\ w_k \geq 0 (\forall k = 1,2)$$

And the period efficiency can be defined by:

$$E_o^{(t,sys)} = \min \frac{\sum_{k=1}^{K} w_k \left[1 - \frac{1}{m_k} \sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^{t}} \right]}{\sum_{k=1}^{K} w_k \left[1 + \frac{1}{r_k + l_{(k,h)} + l'_k} \left(\sum_{i=1}^{r_k} \frac{s_{iok}^{t+}}{y_{iok}^{t}} + \sum_{l=1}^{l_{(k,h)}} \frac{s_{o(k,h)l}^{t}}{z_{o(k,h)l}^{t}} + \sum_{l'=1}^{l'_k} \frac{s_{okl'}^{(t,t+1)}}{c_{okl'}^{(t,t+1)}} \right) \right]} \forall t \tag{A17}$$

The stage efficiency can be defined by:

$$E_o^{k} = \min \frac{\sum_{t=1}^{T} W^t \left[1 - \frac{1}{m_k} \sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^{t}} \right]}{\sum_{t=1}^{T} W^t \left[1 + \frac{1}{r_k + l_{(k,h)} + l'_k} \left(\sum_{i=1}^{r_k} \frac{s_{iok}^{t+}}{y_{iok}^{t}} + \sum_{l=1}^{l_{(k,h)}} \frac{s_{o(k,h)l}^{t}}{z_{o(k,h)l}^{t}} + \sum_{l'=1}^{l'_k} \frac{s_{okl'}^{(t,t+1)}}{c_{okl'}^{(t,t+1)}} \right) \right]} \forall k \tag{A18}$$

The period-stage efficiency can be defined by:

$$E_o^{(t,k)} = \min \frac{1 - \frac{1}{m_k} \sum_{i=1}^{m_k} \frac{s_{iok}^{t-}}{x_{iok}^{t}}}{1 + \frac{1}{r_k + l_{(k,h)} + l'_k} \left(\sum_{i=1}^{r_k} \frac{s_{iok}^{t+}}{y_{iok}^{t}} + \sum_{l=1}^{l_{(k,h)}} \frac{s_{o(k,h)l}^{t}}{z_{o(k,h)l}^{t}} + \sum_{l'=1}^{l'_k} \frac{s_{okl'}^{(t,t+1)}}{c_{okl'}^{(t,t+1)}} \right)} \forall t, \forall k \tag{A19}$$

Appendix 2:

The second-stage regression is specified as follows,

$$DNDEA_{it} = \beta_0 + \beta_1 LCC_{it} + \beta_2 Public_{it} + \beta_3 HHI\_Route_{it} + \beta_4 International\%_{it} + \beta_5 Stage\_length_{it} + \beta_6 HSR + \varepsilon_{it} \quad \text{(A20)}$$

We can write it in the following matrix format as,

$$DNDEA_{it} = \boldsymbol{Z_{it}}\boldsymbol{\beta} + \varepsilon_{it} \quad \text{(A21)}$$

where $\boldsymbol{Z_{it}}$ is the vector of the control variables for DMU i at time t. $\boldsymbol{\beta}$ is the parameter vector we need to estimate. However, the true $DNDEA_{it}$ is unknown. And our obtained DNDEA in the first stage is just the estimated values, $\widehat{DNDEA}_{it}$. Thus, our second-stage regression is based on the following relationship,

$$\widehat{DNDEA}_{it} = \boldsymbol{Z_{it}}\boldsymbol{\beta} + \varepsilon_{it} \quad \text{(A22)}$$

But both the correlation among the ε_{it}, and correlation between $\boldsymbol{Z_{it}}$ and ε_{it} emerge with the use of $DNDEA_{it}$. We adopt the bootstrap algorithm proposed by Simar and Wilson (2007) as follows,

[1]. Use the original data to compute the $\widehat{DNDEA}_{it}$.

[2]. Use the maximum likelihood method to obtain an estimate $\widehat{\boldsymbol{\beta}}$ of $\boldsymbol{\beta}$ as well as an estimate of $\widehat{\sigma_\varepsilon}$ of σ_ε (the variance of ε_{it}) in the truncated regression of $\widehat{DNDEA}_{it}$ on $\boldsymbol{Z_{it}}$ in A22 using the $m < n$ observations where $\widehat{DNDEA}_{it} < 1$.

[3]. Loop over the next three steps ([3.1]- [3.3]) 500 times to obtain a set of bootstrap estimates of $\widehat{\boldsymbol{\beta}}$ and $\widehat{\sigma_\varepsilon}$:

[3.1]. For each $it = 1,2, \dots, m$, draw ε_{it} from the $\mathrm{N}(0, \widehat{\sigma_{\varepsilon}}^{2})$ distribution with right-truncation at $(1 - \boldsymbol{Z_{it}}\, \widehat{\boldsymbol{\beta}})$.

[3.2]. Again for each it, compute $DNDEA_{it}{}^{*} = \boldsymbol{Z_{it}}\, \widehat{\boldsymbol{\beta}} + \varepsilon_{it}$.

[3.3]. Use the maximum likelihood method to estimate the truncated regression of $DNDEA_{it}{}^{*}$ on $\boldsymbol{Z_{it}}$, yielding estimates ($\widehat{\boldsymbol{\beta}}^{*}$, $\widehat{\sigma_{\varepsilon}}^{*}$).

[4]. Use the bootstrap values and the original estimates $\widehat{\boldsymbol{\beta}}$ and $\widehat{\sigma_{\varepsilon}}$ to construct estimated confidence intervals for each element of $\boldsymbol{\beta}$.