



## ANALYSING AIRPORT EFFICIENCY IN EAST CHINA USING A THREE-STAGE DATA ENVELOPMENT ANALYSIS

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**Abstract.** This paper evaluates the Technical Efficiencies (TEs) of a group of airports in East China by applying a three-stage Data Envelopment Analysis (DEA) method. The merit of this method allows us to consider the impact of the environmental factors on measuring airport efficiencies. Three variables, i.e. per capita Gross Domestic Product (GDP), the proportion of the tertiary industry, and the number of tourists, are used to represent the environmental factors. The results show that the environmental factors have airport-specific impacts on the value of the efficiencies. Additionally, airport TE are dominated by both Pure Technical Efficiency (PTE) and Scale Efficiency (SE). Based on empirical results, airport specific strategies can be provided to enhance airport efficiency, such as taking the effects of environmental variables and the statistical noise into consideration when analysing the airport efficiency, improving airport efficiencies according to their own conditions and improving the PTE or SE according to their categorizations.

**Keywords:** air transport, airport, technical efficiency, scale efficiency, three-stage DEA, East China.

### Notations

#### Abbreviations:

AE – allocative efficiency;  
 AHP – analytic hierarchy process;  
 BCC – acronym from R. D. Banker, A. Charnes and W. W. Cooper (Banker *et al.* 1984);  
 CCR – acronym from A. Charnes, W. W. Cooper and E. Rhodes (Charnes *et al.* 1978);  
 CRS – constant returns to scale;  
 CV – coefficient of variation;  
 DEA – data envelopment analysis;  
 DEA-AR – DEA assurance region;  
 DMU – decision-making unit;  
 GDP – gross domestic product;  
 IATA – international air transport association;  
 LR – likelihood ratio;  
 OLS – ordinary least squares;  
 PTE – pure technical efficiency;  
 RS – returns to scale;  
 SD – standard deviation;  
 SE – scale efficiency;  
 SFA – stochastic frontier analysis;

TE – technical efficiency;  
 TFP – total factor productivity;  
 VRS – variable returns to scale;  
 WLU – work load units;  
*irs* – increasing returns to scale;  
*drs* – decreasing returns to scale.

#### Variables and functions:

$e$  – coefficient matrix of slack variables for outputs of  $DMU_{i_0}$ ;  
 $\hat{e}$  – coefficient matrix of slack variables for inputs of  $DMU_{i_0}$ ;  
 $\hat{E}$  – conditional estimators;  
 $f^n$  – stochastic frontier function;  
 $N^+$  – truncated normal distribution;  
 $S^-$  – slack variables for inputs of  $DMU_{i_0}$ ;  
 $S^+$  – slack variables for outputs of  $DMU_{i_0}$ ;  
 $s_{ni}$  – the stage 1 slack in the usage of the  $n$ th input for  $DMU_i$ ;  
 $u_{ni}$  – managerial inefficiency;  
 $v_{ni}$  – statistical noise;

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- $X_i$  – the input value of  $DMU_i$ ;  
 $X_0$  – the input of  $DMU_{i_0}$ ;  
 $x_{ni}$  – the original  $n$ th input of  $DMU_i$ ;  
 $x_{ni}^A$  – the adjusted  $n$ th input of  $DMU_i$ ;  
 $Y_i$  – the output value of  $DMU_i$ ;  
 $Y_0$  – the output of  $DMU_{i_0}$ ;  
 $z_i$  – environmental variables;  
 $\beta^n$  – the parameter to be estimated for the environmental variables;  
 $\hat{\beta}^n$  – evaluated values of  $\beta^n$  via the SFA model;  
 $\gamma_n$  – the variance of managerial inefficiency divided by the variance of managerial inefficiency plus the variance of statistical noise;  
 $\varepsilon$  – a small positive real number (usually, in empirical calculations,  $10^{-6}$ );  
 $\varepsilon_{ni}$  – the sum of managerial inefficiency and the statistical noise;  
 $\phi(\cdot)$  – the probability density function for standard normal distribution;  
 $\Phi(\cdot)$  – the cumulative distribution function for standard normal distribution;  
 $\lambda_i$  – weight coefficient;  
 $\lambda_n$  – the ratio of  $\sigma_{un}$  to  $\sigma_{vn}$ ;  
 $\theta$  – the value of the PTE;  
 $\sigma_n$  – the standard deviation of  $\sigma_n^2$ ;  
 $\sigma_n^2$  – the variance of managerial inefficiency plus the variance of statistical noise;  
 $\sigma_{un}^2$  – the variance of managerial inefficiency;  
 $\sigma_{vn}^2$  – the variance of statistical noise.

## Introduction

In China, air transport is growing at a very fast rate. To illustrate, according to the *Statistical Bulletins of Civil Aviation Industry Development* (CAAC 2014, 2018), growth rates over all commercial airports between 2013 and 2017 for passenger transport equals 52.2% and 28.5% for the transport of cargo. The question that follows from this strong increase in air travel is whether the air transport sector (airports and airlines) can uphold this trend, and related to that, what measures are necessary to (further) accommodate such a growth. Part of the answer can be found in the 13th five-year plan (ranging from 2016 to 2020) the Chinese government has put forward for the development of the civil aviation in China (CAAC 2017b). This plan proposes to develop six airport clusters and to study and evaluate the differences in airport efficiency in these airport clusters.

The current paper focuses specially on the airport efficiency in East China (one of the six airport clusters) during the period from 2013 to 2017. The aim is to evaluate the airport efficiency and make suggestions to improve airport efficiency. The common technique used is DEA.

DEA has been widely used to analyse efficiency in diverse areas since the study of Charnes *et al.* (1978). DEA is a data planning method to evaluate the relative efficiency of a DMU with multi-inputs and multi-outputs (Cui, Li 2014). DEA has become one of the most frequently used methods for analysing efficiency. There exist several DEA approaches. The methodology selected here deals with three-stages as initially developed by Fried *et al.* (2002). This three-stage DEA model has the following built-up. First, the classical DEA model as proposed by Banker *et al.* (1984) is applied (referred to as the BCC-DEA model). Second, a SFA regression equation is used to eliminate the effects of environmental variables (i.e. referring to the external factors that affect airport efficiency) and the statistical noise (i.e. referring to the impact of omitted variables, and other related phenomena, which are represented in a random error term); the outcome of which is used to adjust the original inputs. Third, and finally, the standard BCC-DEA model is re-used to recalculate the efficiency, but then with the adjusted inputs. This latter stage is often not applied.

This paper is organized as follows: Section 1 presents a brief literature review to support the selection of the analysis model and the related variables. Section 2 formally introduces the three-stage DEA method. Section 3 introduces the data and main results. Discussions are presented in Section 4, whereas the final section draws conclusions and suggests avenues for further research.

## 1. Literature review

DEA has many different forms and has been applied in various fields. To illustrate, Graham (2005) reviews the situation of airport benchmarking and points that DEA is a more attractive technique than the other methods for its less demanding data requirements. Radonjić *et al.* (2011) employ DEA method in deciding the most favourable container line from Serbian ports to the near East ports. Jaržemskienė (2012) draws the conclusion that DEA proves to be most suitable for measuring the productivity of airports as complex systems. Charles and Zegarra (2014) develop a methodology based on DEA to measure and rank the competitiveness of different regions of Peru. Wanke and Barros (2014) use a two-stage DEA model to measure the cost efficiency and productive efficiency of Brazilian banks. Cui and Li (2014) propose a new three-stage virtual frontier DEA model, which can distinguish the DEA efficient DMUs to estimate the transportation energy efficiency. In addition, Lozano (2015) formulates a parallel-processes network DEA approach to assess the efficiency of a production process and a pollution generation process. Hence, many different applications, and also many different DEA varieties. In terms of methodological improvements, the three-stage DEA seems most promising, but little evidence has been put forward to support this claim.

The three-stage DEA method has been developed and applied in recent years. Fried *et al.* (2002) propose a

three-stage DEA to eliminate the effects of environmental variables and the statistical noise with a sample of 990 US hospital-affiliated nursing homes. Cui *et al.* (2015) employ a three-stage DEA and Bootstrap DEA to estimate regional coal resource efficiency in China, taking environmental influences, managerial inefficiencies, and statistical noise into consideration. Li and Lin (2016) combine the rationale of a sequential DEA and super efficiency DEA models to improve the estimation method, thereby obtaining an improved three-stage DEA method, which measures the actual, environmentally-sensitive TFP, or green productivity growth. Fuentes *et al.* (2016) combine the three-stage DEA and super-efficiency DEA model to evaluate the TE of the learning-teaching process in higher education, which eliminate the effects of contextual variables when making the calculation of values of efficiency.

Since Gillen and Lall (1997) firstly apply a DEA to measure the performance of 21 airports in the US, the approach has been more frequently used to analyse airport efficiencies. There are examples of national studies: Gillen and Lall (1997) for the US; Yoshida and Fujimoto (2004) for Japan; Curi *et al.* (2011) for Italy; Fragoudaki *et al.* (2016) for Greece; Wanke and Barros (2017) for Senegal, and Fernandes and Pacheco (2018) for Brazil. In addition, comparative studies between countries exist, e.g. Adler, Liebert (2014); Lai *et al.* (2015); Ferreira *et al.* (2016); Chen *et al.* (2017), Button *et al.* (2018). Nearly all reviewed contributions analyse airport efficiencies within one country or between countries, but do not focus on the airport efficiency within an airport cluster or a multi-airport system. This paper focuses on East China, considering that the developments of airports in East China are not balanced and the development disparity among these airports is becoming larger.

As for the study period, there are studies that use annual data: Lozano *et al.* (2013) assess the performance of 39 individual Italian airports in 2008, whereas Liu (2017) uses a sample of 24 individual global airports in 2010. Oth-

ers opt for relatively longer periods, such as 3 years from 2007 to 2009 by Merkert and Mangia (2014), 5 years from 2000 to 2004 by Curi *et al.* (2011), 6 years from 2009 to 2014 by Örkücü *et al.* (2016), or even 10 years from 1998 to 2007 by Adler and Liebert (2014). We opt for 5 years from 2013 to 2017 considering that on the one hand, this period covers 12th and 13th five-year plans for the development of the civil aviation in China; on the other hand, in this time frame, some airports expanded or relocated which may have an effect on the airport efficiency.

As for inputs, the most frequently used variables found in the literature are terminal area, apron area, number of runways, total runway length, number of employees, number of gates, and number of aircraft parking spaces (Gillen, Lall 1997; Wanke 2012; Lozano *et al.* 2013; Merkert, Mangia 2014; D’Alfonso *et al.* 2015; Chen *et al.* 2017). Barros and Weber (2009) also use capital cost, labour cost and airport operating cost as inputs. Other input indicators have been considered such as number of baggage collection belts (Lozano *et al.* 2013), number of check-in counters (D’Alfonso *et al.* 2015). Specially, Yoshida and Fujimoto (2004) adopt time access cost as the input to study Japanese airport efficiency.

In respect to outputs, the most used indicators for airport outputs are the number of aircraft movements, the number of passengers, and the amount of cargo (Curi *et al.* 2011; Gitto, Mancuso 2012; Lozano *et al.* 2013; Merkert, Mangia 2014; D’Alfonso *et al.* 2015; Örkücü *et al.* 2016; Wanke, Barros 2017). Others have suggested aeronautical revenues, and non-aeronautical revenues as outputs (Adler, Liebert 2014; Lai *et al.* 2015; Liu 2017; Fernandes, Pacheco 2018).

Note also that some studies have included the effects of environmental variables, but none recalculate the airport efficiency. We employ a three-stage DEA to analyse the airport efficiency in East China during the period from 2013 to 2017 using the studies mentioned in Table 1 as a reference.

Table 1. Review of the methodology and indicators analysing airport efficiency

| Author(s)                | Methodology                       | Inputs   | Outputs   |
|--------------------------|-----------------------------------|--|---|
| Gillen, Lall (1997)      | – two-stage DEA                   | – number of runways;<br>– number of gates;<br>– terminal area;<br>– number of employees;<br>– number of baggage collection belts;<br>– number of public parking spots;<br>– airport area;<br>– runway area | – number of passengers;<br>– pounds of cargo;<br>– air carrier movements;<br>– commuter movements |
| Yoshida, Fujimoto (2004) | – DEA;<br>– endogenous-weight TFP | – total length of runways;<br>– total floor area of terminal buildings;<br>– monetary access cost;<br>– time access cost;<br>– number of employees in terminal building                                    | – passenger loading;<br>– cargo handling;<br>– aircraft movement                                  |
| Barros, Weber (2009)     | – DEA;<br>– Malmquist index       | – labour;<br>– capital;<br>– other cost  | – passengers;<br>– cargo shipments;<br>– aircraft movements                                       |

Continue of Table 1

| Author(s)                       | Methodology                                  | Inputs  | Outputs   |
|---------------------------------|--|---|---|
| Curi <i>et al.</i> (2011)       | – bootstrapped DEA                           | – employees;<br>– number of runways;<br>– apron size  | – number of movements;<br>– number of passengers;<br>– amount of cargo                                |
| Gitto, Mancuso (2012)           | – DEA  | – number of workers;<br>– runway area;<br>– airport area  | – number of movements;<br>– number of passengers;<br>– amount of cargo                                |
| Wanke (2012)                    | – bootstrapped DEA                           | – airport area;<br>– apron area;<br>– number of runways;<br>– total runway length;<br>– number of aircraft parking spaces;<br>– terminal area;<br>– number of parking places                  | – number of landings and take offs;<br>– number of passengers;<br>– cargo throughput                  |
| Lozano <i>et al.</i> (2013)     | – network DEA                                | – square meters;<br>– number of stands;<br>– number of gates;<br>– number of belts;<br>– number of counters   | – aircraft traffic movements;<br>– annual passenger movements;<br>– cargo handled                     |
| Wanke (2013)                    | – two-stage network DEA                      | – terminal area;<br>– aircraft parking spaces;<br>– runways   | – passengers;<br>– cargo throughput   |
| Adler, Liebert (2014)           | – DEA;<br>– regression analysis              | – staff costs;<br>– other operating costs;<br>– declared runway capacity  | – passengers;<br>– cargo;<br>– air transport movements;<br>– non-aeronautical revenues                |
| Merkert, Mangia (2014)          | – two-stage DEA                              | – terminal area;<br>– apron area;<br>– number of runway;<br>– runway length;<br>– runway area;<br>– total area;<br>– number of employees;<br>– operating cost, staff cost;<br>– material cost | – air traffic movements;<br>– passengers;<br>– cargo  |
| D'Alfonso <i>et al.</i> (2015)  | – DEA;<br>– two-stage approach               | – airport area;<br>– number of runways;<br>– number of passenger terminals;<br>– number of gates;<br>– number of check-in;<br>– number of employees   | – number of passengers;<br>– amount of cargo;<br>– number of movements                                |
| Lai <i>et al.</i> (2015)        | – AHP;<br>– DEA-AR model                     | – number of employees;<br>– number of gates;<br>– number of runways;<br>– size of terminal area;<br>– length of runway;<br>– operational expenditure  | – number of passengers;<br>– amount of freight and mail;<br>– aircraft movements;<br>– total revenues |
| Ferreira <i>et al.</i> (2016)   | – DEA;<br>– Malmquist index                  | – number of boarding gates;<br>– number of employees;<br>– total length of runways;<br>– other operational costs  | – number of flights;<br>– number of equivalent passengers   |
| Fragoudaki <i>et al.</i> (2016) | – DEA;<br>– Malmquist index                  | – runway length;<br>– apron size in square meters;<br>– passenger terminal size   | – total aircraft movements;<br>– WLUs   |
| Örkcü <i>et al.</i> (2016)      | – DEA;<br>– bootstrapping<br>Malmquist index | – number of runway;<br>– dimension of runway units;<br>– passenger terminal area  | – annual number of flights;<br>– annual passenger throughputs;<br>– annual cargo throughputs          |

End of Table 1

| Author(s)                   | Methodology   | Inputs   | Outputs  |
|-----------------------------|---|--|--|
| Chen <i>et al.</i> (2017)   | – non-concave metafrontier DEA approach                     | – number of full-time-equivalent employees;<br>– number of gates;<br>– number of runways;<br>– total area of all passenger terminals;<br>– average length of runways at each airport | – number of passengers;<br>– weight of cargo and mail;<br>– aircraft movements;<br>– total revenues              |
| Liu (2017)                  | – multi-period DEA;<br>– Malmquist index                    | – runway area;<br>– staff cost;<br>– other operating cost  | – passengers and cargo;<br>– non-aeronautical revenues   |
| Wanke, Barros (2017)        | – two-stage satisficing DEA-support vector machine approach | – number of employees;<br>– runway length in feet  | – cargo movement per year;<br>– number of aircraft movements per year;<br>– number of passengers per year        |
| Button <i>et al.</i> (2018) | – DEA;<br>– tobit-regression                                | – number of airlines;<br>– car park capacity;<br>– distance to city center;<br>– passenger terminals;<br>– gates;<br>– runways;<br>– length of the longest runway;<br>– destinations | – passenger throughput;<br>– aircraft movements  |
| Fernandes, Pacheco (2018)   | – bootstrapped DEA;<br>– Malmquist index                    | – average number of employees;<br>– payroll (including direct and indirect benefits);<br>– operating expenses  | – total passengers;<br>– freight plus mail;<br>– operating revenue;<br>– commercial revenue;<br>– other revenues |

## 2. Methodology

DEA is one of the most frequently used method for analysing the (airport) efficiency since the approach does not need a formal definition of a functional relationship between inputs and outputs. In that sense, it is a non-parametric method (Fuentes *et al.* 2016). The method uses linear programming in determining the efficiency of companies where natural prices for specific inputs are lacking, which is ideal for situations where it is impossible to calculate prices, as is the case in airport efficiency analysis. DEA provides a scalar measure of relative efficiency by comparing the efficiency achieved by a DMU with the efficiency obtained by similar DMUs (Gillen, Lall 1997), which is an appropriate way to analyse relative efficiency of the airport in the same airport cluster.

As with any other method, DEA also has a number of disadvantages. The approach rules out any possibility of random influences since it is a deterministic model, which assumes that any resulting inefficiency is solely and exclusively due to the inappropriate management of the DMU (Fuentes *et al.* 2016). To partly solve this, Fried *et al.* (2002) propose a three-stage DEA that can eliminate the effect of environmental variables and the statistical noise. This study selects a three-stage DEA since its advantages are greater and more significant than any potential disadvantage.

In short, DEA is a method to obtain an efficient frontier based on a set of observations. The frontier is calculated by a linear optimization program in which the measurement of efficiency is defined as a ratio between the weighted sum of the outputs and inputs in each DMU (Fuentes

*et al.* 2016). The weights for the inputs and outputs are not pre-determined but instead are the result of the linear programming procedure (Graham 2005). Efficiency is the result of the product of the TE and the AE. Since the latter considers information provided by the prices of the resources, the most common-used type of efficiency in airport analysis is the TE. The TE is a reflection of the efficiency obtained by the DMUs in terms of the quantities of outputs produced in comparison to the inputs used (Fuentes *et al.* 2016), which can be calculated through the CCR-DEA model as proposed by Charnes *et al.* (1978).

RS refers to the variation of outputs caused by the variation of all inputs in the same proportion when other conditions remain unchanged. The CCR-DEA model is under the assumption of CRS, meaning that if all inputs are increased in the same proportion, then outputs will be increased in the same proportion, which can calculate the TE. The BCC-DEA model deals with efficiency of DMUs under the assumption of VRS given that outputs do not always vary in the same proportion as inputs, which can obtain the PTE. The PTE excludes the effect of economic scale, which demonstrates how effectively generation techniques are applied to obtain maximum output. The SE is equal to TE divided by PTE, which indicates that the degree to which scale economy effect is realized. Airport managers are typically evaluated in terms of their ability to minimize input usage in the production of given outputs (input-oriented model), or to maximize output production with given inputs (output-oriented model). This paper considers the first type of orientation (inputs) according to the conditions in China.

## 2.1. The first stage: BCC model

The BCC-DEA model is based on the characteristics of the airports (DMUs) under analysis. The linear programming model used to obtain the efficiency of  $DMU_{i_0}$  is defined as follows:

$$\begin{aligned} & \min(\theta - \varepsilon \cdot (\hat{e}^T \cdot S^- + e^T \cdot S^+)) \\ & \text{subject to:} \\ & \sum_{i=1}^I X_i \cdot \lambda_i + S^- = \theta \cdot X_0; \\ & \sum_{i=1}^I Y_i \cdot \lambda_i - S^+ = Y_0; \\ & \sum_{i=1}^I \lambda_i = 1; \\ & \hat{e} = (1, 1, \dots, 1)^T \in E^N; \\ & e = (1, 1, \dots, 1)^T \in E^M; \\ & \lambda_i \geq 0, \quad i = 1, \dots, I; \\ & S^- \geq 0; \quad S^+ \geq 0, \end{aligned} \quad (1)$$

where:  $I$  is the number of DMUs;  $N$  is the number of inputs;  $M$  is the number of outputs;  $X_i = [x_{1i}, x_{2i}, \dots, x_{Ni}]^T$ ,  $i = 1, \dots, I$ ;  $Y_i = [y_{1i}, y_{2i}, \dots, y_{Mi}]^T$ ,  $i = 1, \dots, I$ ;  $\lambda_i$  is defined  $\sum_{i=1}^I \lambda_i = 1$ ;  $S^- = [S_1^-, S_2^-, \dots, S_N^-]^T$  are slack variables for inputs of  $DMU_{i_0}$ ;  $S^+ = [S_1^+, S_2^+, \dots, S_M^+]^T$  are slack variables for outputs of  $DMU_{i_0}$ .

In this stage we can obtain the PTE and SE since we assumed VRS. The  $DMU_{i_0}$  is efficient when  $TE = PTE = SE = 1$  and  $S^- = S^+ = 0$ , at the stage of CRS. Meanwhile, the input slacks of all DMUs can be calculated, which demonstrate the disparities between the actual and targeted input values.

## 2.2. The second stage: obtain the adjusted input values

Fuentes *et al.* (2016) use a linear programming model to minimize the slack variables, so that they can modify the value of inputs and outputs. Fried *et al.* (2002) attribute the input slacks (radial plus non-radial) to managerial inefficiency (it means that managers do not achieve the expected goals during the organization of various resources for the company), environmental variables and the statistical noise, which all lead to the pure technical inefficiency. Our goal is to eliminate the effects of environmental variables and the statistical noise, and then if the PTE is less than 1, we can ascertain that the managerial inefficiency leads to the pure technical inefficiency. In order to capture the effect of the statistical noise on efficiency, the model must be stochastic, so we apply a SFA in the second stage as Fried *et al.* (2002) did. The similar SFA model of  $n$ th

input can be structured with slacks of inputs obtained in the first stage as dependent variables while environmental variables as independent variables as follows:

$$\begin{aligned} s_{ni} &= f^n(z_i; \beta^n) + v_{ni} + u_{ni}; \\ n &= 1, \dots, N; \quad i = 1, \dots, I, \end{aligned} \quad (2)$$

where:  $f^n(Z; \beta^n)$  is stochastic frontier function representing the effects of environmental variables to input slacks;  $z_i = [z_{1i}, z_{2i}, \dots, z_{ki}]^T$ ,  $i = 1, \dots, I$ ;  $v_{ni} + u_{ni}$  denotes mixed error term;  $v_{ni} \sim N^+(0, \sigma_{vn}^2)$ ;  $u_{ni} \sim N^+(0, \sigma_{un}^2)$ ;  $v_{ni}$ ,  $u_{ni}$  distribute independently of each other and each of the  $N$  regressions (2) may be estimated by maximum likelihood techniques. In each regression, the parameters to be estimated are  $(\beta^n, \sigma_{vn}^2, \sigma_{un}^2)$ . All parameters vary across the  $N$  input slack regressions, which allows the environmental variables, statistical noise and managerial inefficiency to exert different impacts across inputs (Fried *et al.* 2002).

Set  $\gamma_n = \frac{\sigma_{un}^2}{\sigma_{vn}^2 + \sigma_{un}^2}$ , and the value of  $\gamma_n$  close to 1 indicates that the effect of managerial inefficiency dominate

the airport inefficiency, and the SFA method can be used for estimation. If  $\gamma_n$  near to 0 means that the airport inefficiency is mainly derived from the statistical noise, and thus the OLS approach should be applied. The value of  $\gamma_n$  is utilized to identify the feasibility and applicability of the SFA regression.

It is necessary to separate the statistical noise from managerial inefficiency in the residuals of the SFA regression models (2) in order to obtain estimates of  $v_{ni}$  as follows:

$$\begin{aligned} \hat{E}(u_{ni} | v_{ni} + u_{ni}) &= \\ \frac{\lambda_n \cdot \sigma_n}{1 + \lambda_n^2} \cdot \left( \frac{\phi\left(\frac{\varepsilon_{ni} \cdot \lambda_n}{\sigma_n}\right)}{\Phi\left(\frac{\varepsilon_{ni} \cdot \lambda_n}{\sigma_n}\right)} + \frac{\varepsilon_{ni} \cdot \lambda_n}{\sigma_n} \right); \end{aligned} \quad (3)$$

$$\hat{E}(v_{ni} | v_{ni} + u_{ni}) = s_{ni} - z_i \cdot \hat{\beta}^n - \hat{E}(u_{ni} | v_{ni} + u_{ni}), \quad (4)$$

where:  $\hat{E}(u_{ni} | v_{ni} + u_{ni})$  denote the conditional estimators for managerial inefficiency;  $\hat{E}(v_{ni} | v_{ni} + u_{ni})$  denote the conditional estimators for statistical noise. For easy calculation, Luo (2012) defines that  $\lambda_n = \frac{\sigma_{un}}{\sigma_{vn}}$ ,  $\sigma_n^2 = \sigma_{vn}^2 + \sigma_{un}^2$  and  $\varepsilon_{ni} = v_{ni} + u_{ni}$ .

Using the regression results, we further adjust inputs after eliminating the effect of environmental variables and statistical noise. The adjustment formula for  $DMU_{i_0}$  is as follows:

$$\begin{aligned} x_{ni}^A &= x_{ni} + \left( \max_i(z_i \cdot \hat{\beta}^n) - z_i \cdot \hat{\beta}^n \right) + \\ & \left( \max_i(\hat{v}_{ni}) - \hat{v}_{ni} \right), \end{aligned} \quad (5)$$

where: the first bracket adjusts  $DMU_{i_0}$  to a common operating environment; the second one puts it into a common state of nature and the worst situation encountered in the sample. These adjustments vary across DMUs and inputs. Such adjustments can make all DMUs in the same exterior condition.

### 2.3. The third stage: reuse BCC model

The BCC-DEA model is used again with the input  $x_{ni}^A$  obtained from the second stage and the efficiency can reflect the real operation status after eliminating external environmental variables and statistical noise.

## 3. Data and results

### 3.1. Variables and data sources

We select the terminal area –  $I_1$ , the number of gate positions –  $I_2$  and total length of runways –  $I_3$  as inputs. The terminal area is a significant input in the landside of airports that decides the ability of accommodating passengers. The number of gate positions and total length of runways are both typical inputs in the airside of airports, which limit the number and type of aircrafts that airports can handle at the same time. We also take the number of destinations –  $I_4$  into consideration because it reflects the service scope of airports in a degree.

For outputs, we select the passenger throughput –  $O_1$ , the cargo and mail throughput –  $O_2$ , and the number of aircraft movements –  $O_3$ .

Another important decision is the choice of environmental variables. Environmental variables are factors that affect airport efficiency but that are objective and uncontrollable, such as social and economic factors. We select per capita GDP –  $Z_1$ , the proportion of the tertiary industry in the GDP –  $Z_2$ , and the number of tourists travelling to the city where the airport is located –  $Z_3$ . Per capita GDP determines the purchasing power of consumers and the level of economic development in the city. The proportion of the tertiary industry in the GDP is a proxy for the economic structure of the city. The bigger the proportion,

the better market environment for the development of air transport. Finally, the larger the number of tourists, the more flights will be arranged which is good for airports.

Data required for the analysis were collected from the airports official websites, *Issues the Statistics Bulletin of Civil Airports in China* (CAAC 2017a), OAG (2018) database and other Internet resources. The time span ranges from 2013 to 2017. In addition, we selected the top 20 airports in East China as DMUs ranked by passenger throughputs in 2017 (as shown in Appendix A Table A). Table 2 shows the descriptive statistics of the collected data of all variables, while Table 3 shows that, the results of the Pearson correlation test are significant, indicating a high correlation level and fulfilling the principle of the indicator selection required by DEA.

Table 3. Pearson correlation coefficients between inputs and outputs

| Outputs | Years | Inputs   |          |          |          |
|---------|-------|----------|----------|----------|----------|
|         |       | $I_1$    | $I_2$    | $I_3$    | $I_4$    |
| $O_1$   | 2013  | 0.955*** | 0.983*** | 0.911*** | 0.949*** |
|         | 2014  | 0.949*** | 0.955*** | 0.895*** | 0.953*** |
|         | 2015  | 0.957*** | 0.956*** | 0.907*** | 0.952*** |
|         | 2016  | 0.964*** | 0.947*** | 0.918*** | 0.955*** |
|         | 2017  | 0.968*** | 0.951*** | 0.919*** | 0.949*** |
| $O_2$   | 2013  | 0.885*** | 0.830*** | 0.900*** | 0.901*** |
|         | 2014  | 0.833*** | 0.778*** | 0.852*** | 0.897*** |
|         | 2015  | 0.838*** | 0.775*** | 0.936*** | 0.893*** |
|         | 2016  | 0.863*** | 0.747*** | 0.936*** | 0.889*** |
|         | 2017  | 0.845*** | 0.730*** | 0.936*** | 0.852*** |
| $O_3$   | 2013  | 0.951*** | 0.981*** | 0.919*** | 0.964*** |
|         | 2014  | 0.956*** | 0.958*** | 0.908*** | 0.971*** |
|         | 2015  | 0.960*** | 0.959*** | 0.915*** | 0.966*** |
|         | 2016  | 0.965*** | 0.953*** | 0.921*** | 0.968*** |
|         | 2017  | 0.965*** | 0.952*** | 0.927*** | 0.959*** |

Note: \*\*\* indicates the 1% significance level.

Table 2. Descriptive statistics of the collected data of all variables

| Variables                             | Min        | Max          | Mean         | SD           | CV    |
|---------------------------------------|------------|--------------|--------------|--------------|-------|
| $I_1$ [ $\cdot 10^4$ m <sup>2</sup> ] | 1.400      | 83.200       | 15.946       | 19.490       | 1.222 |
| $I_2$ [No]                            | 9.000      | 224.000      | 58.500       | 58.391       | 0.998 |
| $I_3$ [m]                             | 2400.000   | 15000.000    | 4253.000     | 2547.506     | 0.599 |
| $I_4$ [No]                            | 13.000     | 273.000      | 73.750       | 53.737       | 0.729 |
| $O_1$ [person]                        | 548306.000 | 70001237.000 | 12909898.620 | 14846125.706 | 1.150 |
| $O_2$ [ton]                           | 2655.970   | 3824279.946  | 288828.852   | 718050.924   | 2.486 |
| $O_3$ [sortie]                        | 6231.000   | 496774.000   | 106135.520   | 105164.025   | 0.991 |
| $Z_1$ [CNY]                           | 49817.000  | 160706.000   | 94543.450    | 23380.655    | 0.247 |
| $Z_2$ [-]                             | 0.349      | 0.698        | 0.499        | 0.085        | 0.170 |
| $Z_3$ [ $\cdot 10^4$ person]          | 2737.693   | 32718.010    | 8900.013     | 7296.782     | 0.820 |

### 3.2. Results of the first stage

We use MaxDEA8.0 (<http://maxdea.com/MaxDEA.htm>) and Frontier 4.1 (<http://frontier.r-forge.r-project.org/front41.html>) software to obtain the results shown in Table 4. The first column reflects the airports (DMUs). Column 2, 3 and 4 indicate TE, the PTE and the SE of each airport respectively in 2013 (followed by the same order in other years). Columns 5, 9, 13, 17 and 21 indicate the stage of returns to scale; *irs* means increasing returns to scale (if all inputs are increased in the same proportion, then outputs will be increased in the higher proportion); *drs* means decreasing returns to scale (if all inputs are increased in the same proportion, then outputs will be increased in the lower proportion); others show CRS. We can increase or decrease inputs properly according to the stage of *irs* or *drs* if the airport is scale inefficient. Since the DEA model is input-oriented, all the values in columns 2, 6, 10, 14, 18 and 22 may be equal to 1 (efficient) or less than 1 (inefficient). The lower the value is, the more inefficient the airport will become.

Airports abbreviations (IATA codes) is available in Appendix A. PVG, SHA, XMN, WNZ and NGB are superior to other airports because their average TEs of the five years from 2013 to 2017 are equal to 1, as shown in Figure 1. Ten airports (NKG, TNA, FOC, KHN, HFE, WUX, YNT, JJN, CZX and WEH) do not have a good performance because their average TEs are all less than 0.849 (the average value of 20 airports). Taking CZX as an example, TEs from 2013 to 2017 are equal to 0.472, 0.506, 0.541, 0.511, 0.771, respectively, and the average TE of the five years is 0.560, which is the lowest average TE within 20 airports.

The average TE of all the 20 airports decreases first and then increases as shown in Figure 2. Average PTEs are always above 0.9, and the tendency of which is the same as the tendency of average TEs. Average SEs nearly has a rising tendency in the five years, while the values are always lower, than which of average PTEs. Airport inefficiency is dominated by both pure technical inefficiency and scale inefficiency. Almost all airports are at the stage of *irs* except HGH from 2013 to 2017, NKG in 2017 and FOC in 2014, which are at the stage of *drs* as shown in Table 4, which means airports at the stage of *irs* can achieve more outputs by increasing their inputs properly.

### 3.3. Results of the second stage

The SFA approach is applied to analyse the slack of inputs, embodying the terminal area, the number of gate position, total length of runways, and the number of destinations. Three environmental variables, which are per capita GDP, the proportion of the tertiary industry in the GDP and the number of tourists travelling to the city where the airport is located, are regarded as the independent variables of the input slacks.

Table 5 demonstrates the SFA estimation results in 2017 as an example, others are shown in Appendix B. The LR test results of the one-side error of SFA regressions for four input slacks with three environmental variables are all under 1% significance level, which indicates the robustness of the SFA model. The values of  $\gamma_n$  are all near 1, which shows that managerial inefficiencies dominates the pure technical inefficiencies. The separation of managerial inefficiency and the statistical noise by employing the SFA model is effective.

Table 4. Efficiency of the first stage

| Year<br>Airport | 2013  |       |       |            | 2014  |       |       |            | 2015  |       |       |            | 2016  |       |       |            | 2017  |       |       |            | Average |       |       |
|-----------------|-------|-------|-------|------------|-------|-------|-------|------------|-------|-------|-------|------------|-------|-------|-------|------------|-------|-------|-------|------------|---------|-------|-------|
|                 | TE    | PTE   | SE    | RS         | TE      | PTE   | SE    |
| PVG             | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1       | 1     | 1     |
| SHA             | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1       | 1     | 1     |
| HGH             | 0.915 | 0.919 | 0.996 | <i>drs</i> | 0.985 | 1     | 0.985 | <i>drs</i> | 0.932 | 0.937 | 0.994 | <i>drs</i> | 0.856 | 0.914 | 0.936 | <i>drs</i> | 0.943 | 0.975 | 0.967 | <i>drs</i> | 0.926   | 0.949 | 0.976 |
| XMN             | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1       | 1     | 1     |
| NKG             | 0.961 | 0.975 | 0.986 | <i>irs</i> | 0.724 | 0.776 | 0.933 | <i>irs</i> | 0.764 | 0.804 | 0.950 | <i>irs</i> | 0.852 | 0.897 | 0.950 | <i>irs</i> | 0.832 | 0.839 | 0.992 | <i>drs</i> | 0.827   | 0.858 | 0.962 |
| TAO             | 0.984 | 1     | 0.984 | <i>irs</i> | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 0.997   | 1     | 0.997 |
| TNA             | 0.767 | 0.827 | 0.927 | <i>irs</i> | 0.830 | 0.863 | 0.961 | <i>irs</i> | 0.777 | 0.826 | 0.941 | <i>irs</i> | 0.828 | 0.847 | 0.977 | <i>irs</i> | 0.932 | 0.939 | 0.992 | <i>irs</i> | 0.827   | 0.860 | 0.960 |
| FOC             | 0.852 | 0.889 | 0.958 | <i>irs</i> | 0.941 | 0.944 | 0.998 | <i>drs</i> | 0.745 | 0.82  | 0.908 | <i>irs</i> | 0.689 | 0.810 | 0.851 | <i>irs</i> | 0.607 | 0.800 | 0.759 | <i>irs</i> | 0.767   | 0.853 | 0.895 |
| WNZ             | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1       | 1     | 1     |
| KHN             | 0.643 | 0.801 | 0.803 | <i>irs</i> | 0.628 | 0.803 | 0.782 | <i>irs</i> | 0.647 | 0.825 | 0.784 | <i>irs</i> | 0.636 | 0.848 | 0.75  | <i>irs</i> | 0.710 | 0.847 | 0.839 | <i>irs</i> | 0.653   | 0.825 | 0.792 |
| NGB             | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1       | 1     | 1     |
| HFE             | 0.713 | 0.848 | 0.841 | <i>irs</i> | 0.746 | 0.858 | 0.869 | <i>irs</i> | 0.813 | 0.888 | 0.916 | <i>irs</i> | 0.847 | 0.919 | 0.921 | <i>irs</i> | 0.949 | 0.993 | 0.955 | <i>irs</i> | 0.814   | 0.901 | 0.900 |
| WUX             | 0.846 | 1     | 0.846 | <i>irs</i> | 0.854 | 1     | 0.854 | <i>irs</i> | 0.608 | 0.866 | 0.701 | <i>irs</i> | 0.652 | 0.872 | 0.748 | <i>irs</i> | 0.744 | 0.888 | 0.838 | <i>irs</i> | 0.741   | 0.925 | 0.797 |
| YNT             | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 0.498 | 0.753 | 0.662 | <i>irs</i> | 0.539 | 0.762 | 0.708 | <i>irs</i> | 0.563 | 0.767 | 0.733 | <i>irs</i> | 0.720   | 0.856 | 0.821 |
| JJN             | 0.596 | 1     | 0.596 | <i>irs</i> | 0.648 | 1     | 0.648 | <i>irs</i> | 0.786 | 1     | 0.786 | <i>irs</i> | 0.738 | 1     | 0.738 | <i>irs</i> | 0.875 | 1     | 0.875 | <i>irs</i> | 0.729   | 1     | 0.729 |
| CZX             | 0.472 | 0.882 | 0.536 | <i>irs</i> | 0.506 | 0.794 | 0.637 | <i>irs</i> | 0.541 | 0.750 | 0.721 | <i>irs</i> | 0.511 | 0.756 | 0.677 | <i>irs</i> | 0.771 | 0.938 | 0.822 | <i>irs</i> | 0.560   | 0.824 | 0.679 |
| WEH             | 0.602 | 1     | 0.602 | <i>irs</i> | 0.318 | 1     | 0.318 | <i>irs</i> | 0.602 | 1     | 0.602 | <i>irs</i> | 0.681 | 1     | 0.681 | <i>irs</i> | 0.717 | 1     | 0.717 | <i>irs</i> | 0.584   | 1     | 0.584 |
| NTG             | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 0.966 | 1     | 0.966 | <i>irs</i> | 0.908 | 1     | 0.908 | <i>irs</i> | 1     | 1     | 1     | -          | 0.975   | 1     | 0.975 |
| XUZ             | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 0.983 | 1     | 0.983 | <i>irs</i> | 0.997   | 1     | 0.997 |
| YTY             | 0.629 | 1     | 0.629 | <i>irs</i> | 0.755 | 1     | 0.755 | <i>irs</i> | 0.950 | 1     | 0.950 | <i>irs</i> | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 0.867   | 1     | 0.867 |
| Average         | 0.849 | 0.957 | 0.885 | -          | 0.847 | 0.952 | 0.887 | -          | 0.831 | 0.923 | 0.894 | -          | 0.837 | 0.931 | 0.892 | -          | 0.881 | 0.949 | 0.924 | -          | 0.849   | 0.943 | 0.896 |

Table 5. SFA estimation results in 2017

| Independent variables  | Slacks | Terminal area                | Number of gate positions   | Number of runways            | Number of destinations     |
|--|--------|------------------------------|----------------------------|------------------------------|----------------------------|
| Constant term  |        | -1.4412** (-2.2869)          | -14.6630*** (-5.8031)      | -393.1780*** (-9.5587)       | -2.7204*** (-6.0124)       |
| Per capita GDP   |        | 1.7125** (2.2674)            | 11.5758*** (7.8775)        | 545.8718*** (32.2813)        | 3.7584*** (25.5233)        |
| The proportion of the tertiary industry in the GDP                         |        | 1.2281** (2.2017)            | 16.7610*** (10.5880)       | 172.4547*** (7.4710)         | 1.2258*** (3.7472)         |
| The number of tourists travelling to the city where the airport is located |        | -1.2381* (-1.9588)           | -10.9842*** (-14.3993)     | -393.6742*** (-22.1047)      | -3.0897*** (-4.0139)       |
| $\sigma_n^2$   |        | 9.9259*** (7.5302)           | 374.9131*** (409.1222)     | 399593.8000*** (399551.8500) | 145.3205*** (153.0928)     |
| $\gamma_n$   |        | 0.99999999*** (4372298.6000) | 0.99999999*** (24268.9450) | 0.99999999*** (188263.4900)  | 0.99999999*** (89680.0330) |
| LR test  |        | 15.6823***                   | 15.2384***                 | 12.1738***                   | 16.7473***                 |

Notes: \*\*\*, \*\*, \* indicates the 1, 5, 10% significance level; data in brackets demonstrate *t*-statistics of the coefficients.

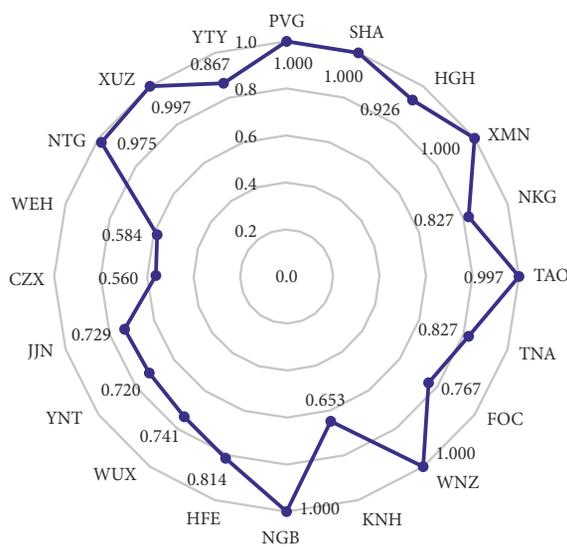


Figure 1. Average TEIs of five years of 20 airports in the first stage

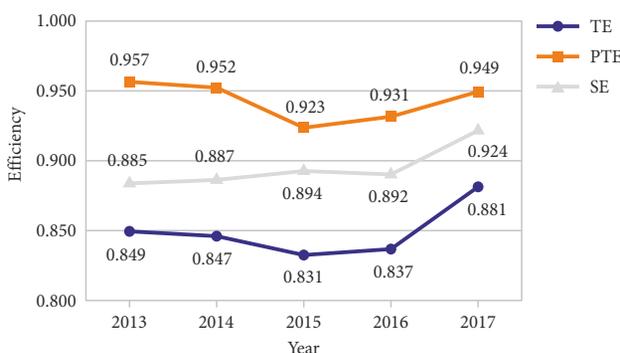


Figure 2. Average efficiencies of 20 airports from 2013 to 2017 in the first stage

For the evaluated coefficients, in accordance with the *t*-statistics in brackets, all coefficients are significant at 1 or 5% significance level, which demonstrates that three environmental variables do exert critical effects on airport efficiencies. It is essential to remove the effects of environmental variables and the statistical noise on airport efficiencies to obtain the “real” airport efficiencies. Different coefficients represent different relationships between environmental variables and input slacks. The negative coefficient implies the favourable effects brought by environmental variables on the improvement of airport efficiencies, and the positive coefficient demonstrates the unfavourable effects.

For per capita GDP, all the coefficients are positive and significant. This indicates that per capita GDP will lead to the input increase of the terminal area, the number of gate positions, total length of runways and the number of destinations, which can bring unfavourable impacts on airport efficiencies. The city where the airport is located will expand the airport scale ahead of time to meet the growing demand for travel as the increase of per capita GDP, which leads to the input slacks of airports and causes the airport inefficiency.

For the proportion of the tertiary industry in the GDP, the coefficients are all positive and significant, which means that the increase of the proportion will not be good for the decrease of input slacks. This result means, the continuous increase in the proportion of the tertiary industry in the GDP has led to economic transformation and triggered new demand, which promotes the development of the air transport market, further expanding the airport scale and increasing airport inputs. While at these recent years, the actual demand cannot fully satisfy the supply, which means that the advanced construction of airports

will lead to airport input slacks and be unfavourable for the increase of airport efficiencies.

For the number of tourists travelling to the city where the airport is located, coefficients of the terminal area, the number of gate positions, total length of runways and the number of destinations are all negative and significant. As more and more tourists come to the city where the airport is located, the airport's inputs will be utilized adequately, and outputs will be increased significantly, which can bring favourable effects on the improvement of airport efficiencies.

In accordance with the regression results from 2013 to 2017, the selected three environmental variables exert effects on different input slacks for airport efficiencies. It is necessary to measure airport efficiencies by eliminating effects of environmental variables and the statistical noise. According to the regression results obtained by the SFA model, the adjusted inputs can be obtained according to Equations (2)–(5) to evaluate the real airport efficiencies.

**3.4. Results of the third stage**

Airport efficiencies are evaluated again using the adjusted inputs and original outputs, as shown in Table 6. PVG, SHA, XMN are still superior to other airports after eliminating the effect of environmental variables and the statistical noise as implied in Figure 3. Eleven airports (FOC, KHN, HFE, WUX, YNT, JJN, CZX, WEH, NTG, XUZ and YTY) do not have a good performance, considering that the average TE of 20 airports is 0.775. WEH has the lowest average TE (0.434) within 20 airports, of which TEs are equal to 0.384, 0.195, 0.432, 0.528 and 0.629 respec-

tively from 2013 to 2017. The average TE of 20 airports decreases first and then increases as shown in Figure 4, and the biggest efficiency emerges in 2017. Average PTEs are still above 0.9, and the tendency of which is near to the tendency of average TEs. Average SEs also has a similar tendency with average TEs, while the values are still always lower, than which of average PTEs. Pure technical inefficiency and scale inefficiency both lead to the technical inefficiency. Other airports are at the stage of *irs* from 2013 to 2017 except HGH from 2015 to 2017 and NKG in 2017 after eliminating the effects of environmental variables and the statistical noise, as shown in Table 6.

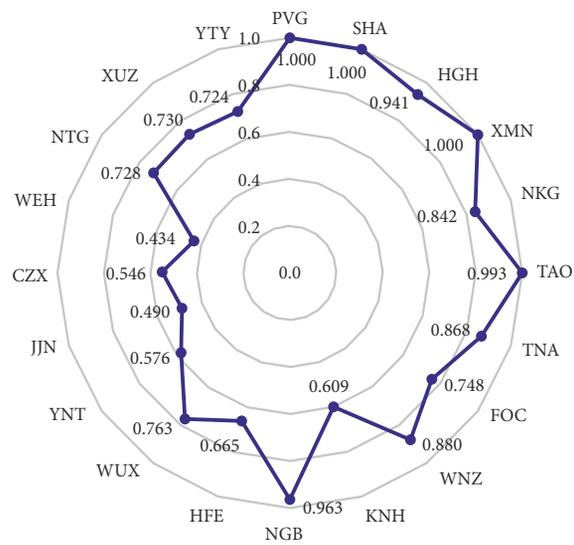


Figure 3. Average TEs of five years of 20 airports in the third stage

Table 6. Efficiency of the third stage

| Year    | 2013  |       |       |            | 2014  |       |       |            | 2015  |       |       |            | 2016  |       |       |            | 2017  |       |       |            | Average |       |       |
|---------|-------|-------|-------|------------|-------|-------|-------|------------|-------|-------|-------|------------|-------|-------|-------|------------|-------|-------|-------|------------|---------|-------|-------|
|         | TE    | PTE   | SE    | RS         | TE      | PTE   | SE    |
| PVG     | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1       | 1     | 1     |
| SHA     | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1       | 1     | 1     |
| HGH     | 0.924 | 0.925 | 0.999 | <i>irs</i> | 1     | 1     | 1     | -          | 0.951 | 0.956 | 0.995 | <i>drs</i> | 0.872 | 0.935 | 0.933 | <i>drs</i> | 0.957 | 0.986 | 0.971 | <i>drs</i> | 0.941   | 0.960 | 0.980 |
| XMN     | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1       | 1     | 1     |
| NKG     | 0.946 | 0.972 | 0.973 | <i>irs</i> | 0.746 | 0.816 | 0.914 | <i>irs</i> | 0.806 | 0.852 | 0.946 | <i>irs</i> | 0.852 | 0.900 | 0.946 | <i>irs</i> | 0.859 | 0.860 | 0.999 | <i>drs</i> | 0.842   | 0.880 | 0.956 |
| TAO     | 0.967 | 0.994 | 0.973 | <i>irs</i> | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 1     | 1     | 1     | -          | 0.993   | 0.999 | 0.995 |
| TNA     | 0.807 | 0.911 | 0.886 | <i>irs</i> | 0.949 | 1     | 0.949 | <i>irs</i> | 0.778 | 0.852 | 0.913 | <i>irs</i> | 0.808 | 0.876 | 0.922 | <i>irs</i> | 1     | 1     | 1     | -          | 0.868   | 0.928 | 0.934 |
| FOC     | 0.866 | 0.913 | 0.948 | <i>irs</i> | 0.906 | 0.918 | 0.987 | <i>irs</i> | 0.711 | 0.792 | 0.898 | <i>irs</i> | 0.654 | 0.793 | 0.825 | <i>irs</i> | 0.601 | 0.792 | 0.759 | <i>irs</i> | 0.748   | 0.842 | 0.883 |
| WNZ     | 1     | 1     | 1     | -          | 0.932 | 1     | 0.932 | <i>irs</i> | 0.686 | 0.811 | 0.845 | <i>irs</i> | 0.782 | 0.885 | 0.884 | <i>irs</i> | 1     | 1     | 1     | -          | 0.880   | 0.939 | 0.932 |
| KHN     | 0.626 | 0.797 | 0.785 | <i>irs</i> | 0.566 | 0.776 | 0.73  | <i>irs</i> | 0.593 | 0.779 | 0.761 | <i>irs</i> | 0.586 | 0.790 | 0.741 | <i>irs</i> | 0.673 | 0.808 | 0.833 | <i>irs</i> | 0.609   | 0.790 | 0.770 |
| NGB     | 0.930 | 1     | 0.930 | <i>irs</i> | 1     | 1     | 1     | -          | 0.956 | 1     | 0.956 | <i>irs</i> | 0.930 | 1     | 0.930 | <i>irs</i> | 1     | 1     | 1     | -          | 0.963   | 1     | 0.963 |
| HFE     | 0.675 | 0.844 | 0.800 | <i>irs</i> | 0.582 | 0.777 | 0.749 | <i>irs</i> | 0.640 | 0.764 | 0.838 | <i>irs</i> | 0.647 | 0.785 | 0.825 | <i>irs</i> | 0.780 | 0.880 | 0.887 | <i>irs</i> | 0.665   | 0.810 | 0.820 |
| WUX     | 0.645 | 0.952 | 0.677 | <i>irs</i> | 0.984 | 1     | 0.984 | <i>irs</i> | 0.648 | 0.958 | 0.676 | <i>irs</i> | 0.726 | 1     | 0.726 | <i>irs</i> | 0.813 | 1     | 0.813 | <i>irs</i> | 0.763   | 0.982 | 0.775 |
| YNT     | 0.699 | 0.935 | 0.747 | <i>irs</i> | 0.684 | 0.923 | 0.741 | <i>irs</i> | 0.459 | 0.754 | 0.608 | <i>irs</i> | 0.500 | 0.764 | 0.654 | <i>irs</i> | 0.539 | 0.766 | 0.705 | <i>irs</i> | 0.576   | 0.828 | 0.691 |
| JJN     | 0.503 | 0.978 | 0.514 | <i>irs</i> | 0.405 | 0.880 | 0.460 | <i>irs</i> | 0.514 | 0.863 | 0.596 | <i>irs</i> | 0.427 | 0.902 | 0.474 | <i>irs</i> | 0.602 | 0.954 | 0.631 | <i>irs</i> | 0.490   | 0.915 | 0.535 |
| CZX     | 0.409 | 0.912 | 0.448 | <i>irs</i> | 0.467 | 0.898 | 0.519 | <i>irs</i> | 0.539 | 0.867 | 0.622 | <i>irs</i> | 0.498 | 0.840 | 0.593 | <i>irs</i> | 0.817 | 0.987 | 0.827 | <i>irs</i> | 0.546   | 0.901 | 0.602 |
| WEH     | 0.384 | 1     | 0.384 | <i>irs</i> | 0.195 | 1     | 0.195 | <i>irs</i> | 0.432 | 1     | 0.432 | <i>irs</i> | 0.528 | 1     | 0.528 | <i>irs</i> | 0.629 | 1     | 0.629 | <i>irs</i> | 0.434   | 1     | 0.434 |
| NTG     | 0.941 | 1     | 0.941 | <i>irs</i> | 0.668 | 1     | 0.668 | <i>irs</i> | 0.590 | 1     | 0.590 | <i>irs</i> | 0.581 | 0.998 | 0.582 | <i>irs</i> | 0.860 | 1     | 0.860 | <i>irs</i> | 0.728   | 1.000 | 0.728 |
| XUZ     | 1     | 1     | 1     | -          | 0.727 | 1     | 0.727 | <i>irs</i> | 0.710 | 1     | 0.710 | <i>irs</i> | 0.517 | 0.782 | 0.662 | <i>irs</i> | 0.694 | 0.907 | 0.766 | <i>irs</i> | 0.730   | 0.938 | 0.773 |
| YTY     | 0.527 | 1     | 0.527 | <i>irs</i> | 0.549 | 1     | 0.549 | <i>irs</i> | 0.768 | 1     | 0.768 | <i>irs</i> | 0.774 | 1     | 0.774 | <i>irs</i> | 1     | 1     | 1     | -          | 0.724   | 1     | 0.724 |
| Average | 0.792 | 0.957 | 0.827 | -          | 0.768 | 0.949 | 0.805 | -          | 0.739 | 0.912 | 0.808 | -          | 0.734 | 0.913 | 0.800 | -          | 0.841 | 0.947 | 0.884 | -          | 0.775   | 0.936 | 0.825 |

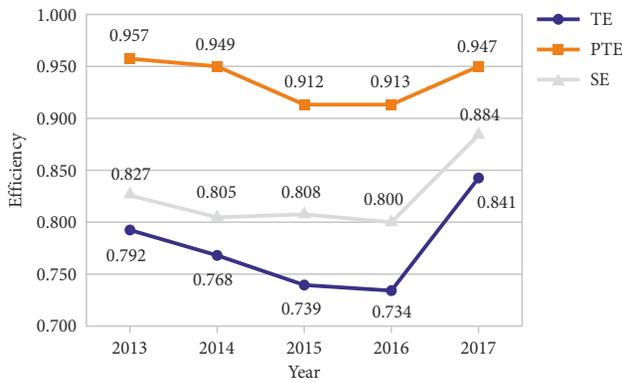


Figure 4. Average efficiencies of 20 airports from 2013 to 2017 in the third stage

#### 4. Discussions

##### 4.1. Discussion on airport TEs

Through comparing airport efficiencies (Table 4 and Table 6), we discover that PVG, SHA and XMN are always efficient in the first and third stage for the period under analysis. The average TE of these 20 airports decreases from 0.849 to 0.775, the average PTE decreases from 0.943 to 0.936, and the average SE decreases from 0.896 to 0.825 after eliminating environmental variables and the statistical noise, which indicates that exterior environmental variables and the statistical noise may result in the underestimation of airport efficiencies in East China, and it is necessary to measure “real” efficiencies. For airports, after eliminating environmental variables and statistical noise, average TEs of three airports (PVG, SHA and XMN) are equal to 1, while at the first stage, which of five airports (PVG, SHA, XMN, WNZ and NGB) are equal to 1, which indicate that exterior environmental variables and statistical noise of WNZ and NGB have exerted fa-

vourable influences on airport efficiencies. Average TEs of 13 airports (TAO, FOC, WNZ, KHN, NGB, HFE, YNT, JJN, CZX, WEH, NTG, XUZ and YTY) decrease in the third stage compared with the first stage. The result means that exterior environmental variables of these airports are conducive to the improvement of efficiencies and airport efficiencies will decrease when adjusting these airports to the most unfavourable environments. Average TEs of 4 airports (HGH, NKG, TNA and WUX) increase in the third stage compared with the first stage, which means the exterior environmental variables will lead to relatively low airport efficiencies of these airports. Considering that the economic level of the region where these four airports are located respectively is relatively high, these airports have the problem of advanced construction, which may cause low airport efficiency.

Relating our findings to the 12th and 13th five-year plans for the development of the civil aviation in China, results indicate that the average TE from 2013 to 2015 (in the 12th five-year period) is 0.842 in the first stage and 0.767 in the third stage, while the average TE between 2016 and 2017 (in the 13th five-year period) is 0.859 in the first stage and 0.788 in the third stage. After eliminating effects of environmental variables and statistical noise, the average TE decrease both in the two periods, and which of the period 2016–2017 is higher than the period 2013–2015 both in the first and third stage. Figure 5 shows that the number of efficient airports during the period 2016–2017 is larger than that in the period 2013–2015, which are separately equal to 7 and 6, and TAO and YTY become more efficient between 2016 and 2017 compared to the period 2013–2015 in the first stage. In the third stage, the number of efficient airports during the period 2016–2017 is still larger than that in the period 2013–2015, which are separately equal to 4 and 3. Average TE of XUZ is not equal to 1 between

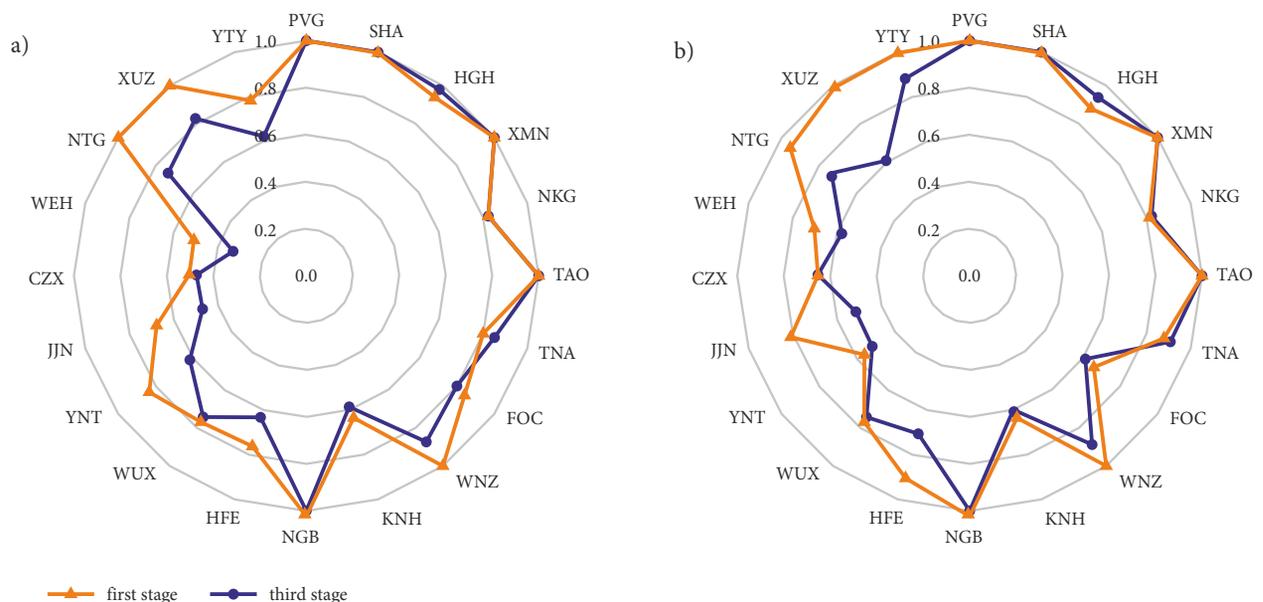


Figure 5. Average TE of two periods: a – from 2013 to 2015; b – from 2016 to 2017



equal to 1 in 2017 in the third stage, slacks of inputs and outputs are all equal to 0. Other inefficient airports have different degree of redundancy in four inputs and output deficiency in three outputs. WUX has the most redundancy in terms of terminal area, which is equal to 62995 m<sup>2</sup>, FOC has the most redundancy in terms of gate positions and number of destinations, while as for total length of runway, NTG has the most redundancy. Although the relevant inputs of airports (terminal area, number of gate positions, runway length and number of destinations) cannot be changed in a short time, input slacks reflect the unreasonable allocation of airport resources and have important reference value for the improvement of efficiency. In order to reduce input slacks, the terminal area can be fully utilized by increasing flights or arranging flight schedule reasonably; airports had better attract more airlines to deploy more different types of aircraft to reduce the slacks of gate positions and total runway length; and reducing the number of destinations moderately to improve the route network will be also helpful to make intensive use of resources. HGH, NKG, WEH and NTG have different degree of output deficiency in passenger throughput; NKG, KHN, HFE, YNT, CZX, WEH and XUZ have different degree of output deficiency in cargo and mail throughput. It would be better for these airports to increase outputs to improve efficiency.

#### 4.2. Discussion on the decomposition of airport TEs

To better understand variations of the 20 airports' TEs, we decompose the TE into the PTE and the SE. Figures 6 and 7 illustrate the categorization of PTE and SE of 20 airports separately in the first and third stage. We categorize the airports into four different groups on the basis of high–low PTE and high–low SE.

For the high–high group, the amount of airports categorized to this group in the first stage is more than that in the third stage because TEs may be overestimated when we do not consider the effects of environmental variables and the statistical noise. PVG, SHA, HGH, XMN, TAO, WNZ and NGB are all categorized into the high–high

group no matter the effects of environmental variables and the statistical noise are eliminated or not. These airports can play a role model for other airport managers to improve the airport efficiency. NTG and XUZ drop from the high–high group to the high–low group after eliminating environmental variables and the statistical noise. The PTEs in this group are close to each other, while their SEs vary significantly, which means that their SEs have great improvement potential.

For the low–high group, airports in this group have low PTEs and high SEs. In the first stage, NKG, TNA and HFE locate in this group, with lower PTE than the average efficiency of 20 airports and higher SE than the average. When eliminating environmental variables and the statistical noise in the third stage, HFE moves from the low–high group to the low–low group, and FOC moves from the low–low group to the low–high group. Optimizing the check-in process, improving transit connection process, enhancing the employee cohesion, allocating the parking position reasonably and accelerating technological innovation are the common effective ways to improve PTEs of these airports. Additionally, the SE improvement in these airports should not be ignored.

For the low–low group, KHN, YNT and CZX are always in this group no matter considering environmental variables and the statistical noise or not. HFE drops from the low–high group to the low–low group, which means the SE gets smaller after eliminating environmental variables and the statistical noise. JJN drops from the high–low group to the low–low group, while WUX moves from this group to the high–low group in the third stage. Both the PTE and the SE of airports in the low–low group are lower than the average point. PTEs and SEs of these airports are required to be improved to accelerate the improvement of TEs. What these airports can do are improving the management level and adjusting the production scale for getting higher TEs.

For the high–low group, it represents the airports with high PTE and low SE. WEH and YTY are all categorized into the high–low group whether effects of environmental variables and the statistical noise are eliminated or not.

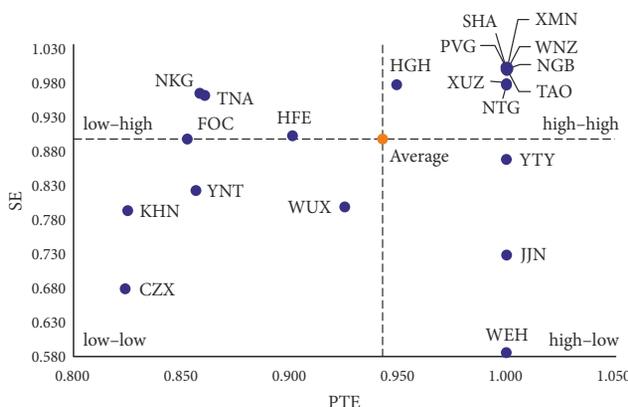


Figure 6. Categorizations of PTE and SE of 20 airports in the first stage

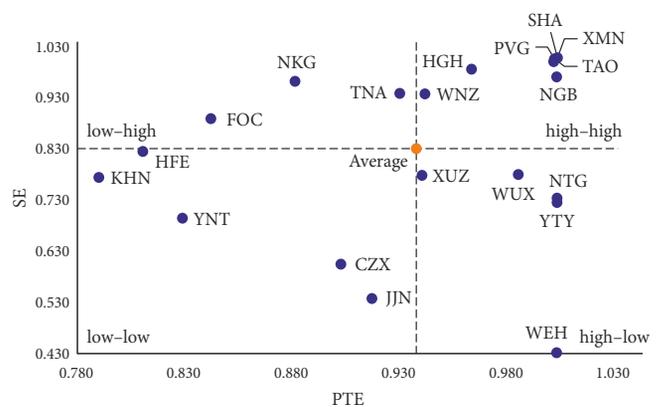


Figure 7. Categorizations of PTE and SE of 20 airports in the third stage

NTG and XUZ drop from the high–high group to the high–low group, and WUX moves from the low–low group to this group in the third stage. Airports in the high–low group need to focus on improving the SE, especially WEH, who's SEs rank the lowest among all airports.

20 airports are divided into four categories according to the PTE and SE, and different groups have different efficiency characteristics. The high–high group has higher PTE and Higher SE than the average level, which makes them to be the benchmark of other airports. The low–high group, low–low group and high–low group all need to take different actions to improve corresponding efficiencies. Airports in the same group share the similar characteristic, but are also slightly different. For example, SEs of HGH and XMN, which are both in the high–high group are nearly the same, but PTE of HGH is lower, than which of XMN, hence HGH needs to focus on the improvement of PTE. It is also necessary to compare the efficiency between different groups. Such as CZX, which have the same output scale with YTY in 2017, is always in low–low group, while YTY is always in the high–low group. The PTE and SE of CZX are lower than YTY. According to Table 7, CZX have a different degree of slacks of inputs and outputs, which indicate that CZX need to adjust the input scale with the reference of YTY. Similarly, NKG and XMN, which handled almost 25 million passengers in 2017, have different efficiency performance. XMN is always efficient from 2013 to 2017 both in the first and third stage, while NKG is in the low–high group. NKG has two runways but XMN has only one runway, there are input redundancies and output deficiencies in NKG according to Table 7. Compared with XMN, inputs of NKG do not match with the existing demand, so it is necessary to allocate the existing resources reasonably or stimulate the demand to improve the efficiency.

### 4.3. Policy recommendations for airport efficiency improvement in East China

To improve the airport efficiency, several policy recommendations are proposed as below.

Firstly, airport managers had better not only consider the airport efficiency calculated in the first stage, but also refer to real airport efficiency obtained in the third stage. Since the traditional DEA model neglect the effects of environmental variables and statistical noise, the airport efficiency will be misestimated. The real airport efficiency eliminating the effects of environmental variables and statistical noise has much more significant reference values for improving the airport efficiency.

Secondly, airports had better improve their efficiencies according to their own conditions. Different airports are located in different environments, which have various effects on airport efficiencies. HGH, NKG, TNA and WUX are located in regions with high level of economies, which may cause the inappropriate advanced construction of airports so that lead to input redundancies and output

deficiencies. If exterior environments are conducive to the improvement of the efficiency, airports should make full use of the market environment to expand output so that improving efficiencies; otherwise, take actions to avoid the impact of the market environment on airports, such as not rebuilding or expanding the airport scale blindly, allocating existing inputs reasonably and stimulating the increase of demand to improve airport efficiencies.

Thirdly, airports should take different measures to improve the PTE or SE so that the airport TE can be increased. According to four categories of airports based on the decomposition results of airport efficiencies, airports attributed to the low–high group, such as NKG and TNA, should improve PTEs so that TEs can be improved. Airports belong to the low–low group, such as KHN, YNT and CZX, both PTEs and SEs should be improved to guarantee the improvement of TEs. These airports had better improve the management level and adjust the production scale for getting higher TEs. WEH and YTY, attributed to the high–low group, should focus on improving the SE to obtain high TEs.

## Conclusions

This paper calculated the efficiency of 20 airports in East China from 2013 to 2017 using a three-stage DEA methodology. The terminal area, the number of gate positions, total length of runways and the number of destinations are taken as input variables. The passenger throughput, the cargo and mail throughput and the number of aircraft movements are taken as output variables. Meanwhile, the effects of environmental variables and the statistical noise are also considered. First, we obtained the real airport efficiency by eliminating the effect of environmental variables and the statistical noise. Second, we analysed the cause of inefficient airports and explored differences between inefficient and efficient airports for offering suggestions for airport managers to promote the regional development.

We find that firstly, PVG, SHA and XMN are always superior to other airports because their TEs are equal to 1 from 2013 to 2017 no matter eliminating effects of environmental variables and the statistical noise or not. The number of efficient airports between 2016 and 2017 is more, than which in the period 2013–2015 both in the first and third stage. The number of efficient airports in the third stage is less, than which in the first stage no matter in the period 2013–2015 of the period 2016–2017. Secondly, at the second stage, three environmental variables containing per capita GDP, the proportion of the tertiary industry in the GDP and the number of tourists travelling to the city where the airport is located, are regarded as the independent variables of the input slacks. In accordance with the regression results of the SFA method in 2017, all coefficients are significant. The coefficients of per capita GDP and the proportion of the tertiary industry in the GDP are positive, which indicates these environmental variables

do exert unfavourable effects on the improvement of the airport efficiency. The coefficients of the number of tourists travelling to the city where the airport is located are all negative, which imply that it exerts favourable effects on the airport efficiency improvement. Thirdly, the exclusion of environmental variables and the statistical noise has airport-specific effects. Except for PVG, SHA and XMN, efficiencies of HGH, NKG, TNA and WUX will increase while which of other airports will decrease after eliminating the effects of environmental variables and the statistical noise. Generally, environmental variables and the statistical noise do exert effects on the evaluation of airport efficiencies. Finally, airport TE can be decomposed into PTE and SE. In accordance with the average level of PTE and SE, 20 airports are categorized into four groups, and each group has airport-specific strategies to improve airport efficiency.

According to the empirical results, several policy recommendations can be proposed: firstly, airport managers had better not only consider the airport efficiency calculated in the first stage, but also refer to real airport efficiency obtained in the third stage; secondly, airports had better improve their efficiencies according to their own conditions; finally, airports should take different measures to improve the PTE or SE so that the airport TE can be increased.

Our paper obviously also has certain limitations. For one, we did not use a dynamic model, despite including information from various years. A possible solution is to calculate the productivities of airports for successive years such as 2013–2015, 2014–2016 and 2015–2017. Second, we cannot further distinguish between efficient airports, although there are also differences among those airports that have been denoted as efficient. Third, input, output and environmental variables we selected are the most representative indicators, but limited by the availability of data and the requirements of sample size, other input and output variables that can reflect airport characteristics or environmental factors that may affect the airport efficiency evaluation are not included. Future studies should seek to prevent these limitations, treating the information in a dynamic manner by specific models such as DEA-Malmquist method to obtain the changes of airport productivities, and/or considering the differences between efficient airports through specific algorithms such as a super-efficiency DEA model. Finally, other input or output variables can be included, such as inputs of an airport in technology, labour or finance, outputs in finance or even undesirable outputs. The effects of overlapping catchments, airport type (hub or non-hub), or dynamic economic growth rates on the airport efficiency can also be considered.

Finally, we are convinced that this paper is of value to governments and public bodies, and airport managers to take actions to improve the airport efficiency according to

the efficiency values such as increasing inputs, raising the management level and so on, which are beneficial to the development of the region.

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**Author contributions**

Zhuxuan Zeng wrote the first draft of the paper and were responsible for data collection and analysis.

Wendong Yang conceived the study and were responsible for the design of the data analysis.

Shengrun Zhang and Frank Witlox were responsible for data interpretation and reviewing the paper.

**Disclosure statement**

The authors declare that there are no conflicts of interest.

**Appendix A**

See Table A, Figure A.

Table A. Airports selected as DMUs

| IATA code | Airport                                 |
|-----------|---|
| CZX       | Changzhou Benniu International Airport  |
| FOC       | Fuzhou Changle International Airport    |
| HFE       | Hefei Xinqiao International Airport     |
| HGH       | Hangzhou Xiaoshan International Airport |
| JJN       | Quanzhou Jinjiang International Airport |
| KHN       | Nanchang Changbei International Airport |
| NGB       | Ningbo Lishe International Airport      |
| NKG       | Nanjing Lukou International Airport     |
| NTG       | Nantong Xingdong International Airport  |
| PVG       | Shanghai Pudong International Airport   |
| SHA       | Shanghai Hongqiao International Airport |
| TAO       | Qingdao Liuting International Airport   |
| TNA       | Jinan Yaoqiang International Airport    |
| WEH       | Weihai International Airport            |
| WNZ       | Wenzhou Longwan International Airport   |
| WUX       | Sunan Shuofang International Airport    |
| XMN       | Xiamen Gaoqi International Airport      |
| XUZ       | Xuzhou Guanyin International Airport    |
| YNT       | Yantai Penglai International Airport    |
| YTY       | Yangzhou Taizhou International Airport  |

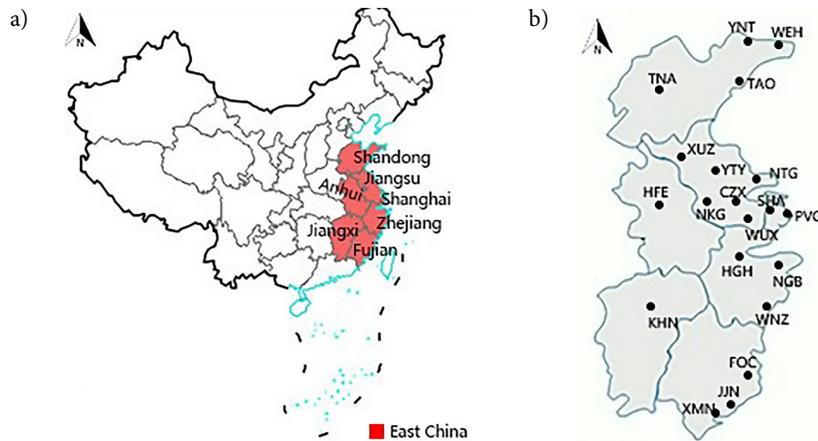


Figure A. Map of East China (a) and top 20 airports in East China (b)

## Appendix B

See Table B.1, Table B.2, Table B.3 and Table B.4.

Table B.1. SFA estimation results in 2013

| Independent variables  | Slacks | Terminal area                  | Number of gate positions       | Number of runways               | Number of destinations  |
|--|--------|--------------------------------|--------------------------------|---------------------------------|-------------------------|
| Constant term  |        | -1.0070***<br>(-6.1812)        | -2.3279***<br>(-4.6197)        | -371.1345<br>(-1.4122)          | -2.1440**<br>(-2.6003)  |
| Per capita GDP   |        | -1.2802***<br>(-8.9992)        | -5.4659***<br>(-11.5311)       | -110.4701<br>(-0.3742)          | -4.3973***<br>(-4.4004) |
| The proportion of the tertiary industry in the GDP                         |        | 2.8974***<br>(3.6977)          | 6.5073***<br>(4.1420)          | 803.7622***<br>(2.9147)         | 7.6798***<br>(8.0578)   |
| The number of tourists travelling to the city where the airport is located |        | -2.0991***<br>(-12.0354)       | -3.5988*<br>(-1.8581)          | -770.8934***<br>(-4.1698)       | -7.5126***<br>(-7.5169) |
| $\sigma_n^2$   |        | 22.2348***<br>(451.7510)       | 144.5792***<br>(140.3985)      | 545885.8900***<br>(543832.4600) | 42.0041***<br>(42.0084) |
| $\gamma_n$   |        | 0.99999999***<br>(146600.4400) | 0.99999999***<br>(754035.3600) | 0.99999999***<br>(66330.7980)   | 0.9958***<br>(9.1050)   |
| LR test  |        | 16.6867***                     | 13.0505***                     | 13.5464***                      | 5.0492**                |

Notes: \*\*\*, \*\*, \* indicates the 1, 5, 10% significance level;  
data in brackets demonstrate *t*-statistics of the coefficients.

Table B.2. SFA estimation results in 2014

| Independent variables  | Slacks | Terminal area                | Number of gate positions      | Number of runways               | Number of destinations        |
|--|--------|------------------------------|-------------------------------|---------------------------------|-------------------------------|
| Constant term  |        | -3.9785***<br>(-5.9440)      | -15.5733***<br>(-5.5419)      | -686.3853***<br>(-5.6792)       | -5.2602***<br>(-4.4777)       |
| Per capita GDP   |        | 1.6071*<br>(2.0212)          | 9.8961***<br>(6.9507)         | 406.8541***<br>(9.5798)         | 0.5922*<br>(1.8607)           |
| The proportion of the tertiary industry in the GDP                         |        | 5.8280***<br>(7.3159)        | 20.0725***<br>(13.7393)       | 926.7358***<br>(19.5295)        | 9.2195***<br>(116.1619)       |
| The number of tourists travelling to the city where the airport is located |        | -4.4453***<br>(-4.5788)      | -16.1098***<br>(-14.3039)     | -854.6575***<br>(-32.5575)      | -8.7637***<br>(-10.9775)      |
| $\sigma_n^2$   |        | 38.4690***<br>(38.6078)      | 340.1350***<br>(340.5488)     | 710473.1800***<br>(710400.8200) | 69.0693***<br>(70.5585)       |
| $\gamma_n$   |        | 0.99999999***<br>(2630.2330) | 0.99999999***<br>(27971.5970) | 0.99999999***<br>(94657.8350)   | 0.99999999***<br>(60952.7320) |
| LR test  |        | 15.9270***                   | 15.7871***                    | 13.8195***                      | 12.1071***                    |

Notes: \*\*\*, \*\*, \* indicates the 1, 5, 10% significance level;  
data in brackets demonstrate *t*-statistics of the coefficients.

Table B.3. SFA estimation results in 2015

| Independent variables  | Slacks | Terminal area              | Number of gate positions      | Number of runways               | Number of destinations       |
|--|--------|----------------------------|-------------------------------|---------------------------------|------------------------------|
| Constant term  |        | -4.1935**<br>(-2.3675)     | -11.9367***<br>(-4.9358)      | -716.6093***<br>(-148.9640)     | -4.8651***<br>(-3.1736)      |
| Per capita GDP   |        | 4.5397***<br>(4.0280)      | 12.8174***<br>(5.6379)        | 806.1141***<br>(244.0888)       | 5.5462***<br>(4.9200)        |
| The proportion of the tertiary industry in the GDP                         |        | 3.7526***<br>(3.0201)      | 10.9723***<br>(4.1039)        | 587.2965***<br>(416.9624)       | 3.8815***<br>(3.4847)        |
| The number of tourists travelling to the city where the airport is located |        | -4.1680***<br>(-3.9507)    | -12.0508***<br>(-6.2569)      | -815.1276***<br>(-817.1051)     | -7.9574***<br>(-7.6759)      |
| $\sigma_n^2$   |        | 26.4252***<br>(26.1977)    | 238.7421***<br>(238.7541)     | 542952.0700***<br>(542952.0700) | 89.7683***<br>(90.2293)      |
| $\gamma_n$   |        | 0.9999999***<br>(349.7115) | 0.9999999***<br>(684349.6300) | 0.9999999***<br>(170294.2800)   | 0.9999999***<br>(83974.6480) |
| LR test  |        | 13.1003***                 | 14.9998***                    | 8.7611***                       | 10.4098***                   |

Notes: \*\*\*, \*\*, \* indicates the 1, 5, 10% significance level; data in brackets demonstrate *t*-statistics of the coefficients.

Table B.4. SFA estimation results in 2016

| Independent variables  | Slacks | Terminal area                | Number of gate positions    | Number of runways               | Number of destinations          |
|--|--------|------------------------------|-----------------------------|---------------------------------|---------------------------------|
| Constant term  |        | -2.2805**<br>(-2.9136)       | -17.5641**<br>(-2.4454)     | -547.2226***<br>(-229.6595)     | -4.3531***<br>(-31.8705)        |
| Per capita GDP   |        | 3.1841***<br>(3.6710)        | 17.3864***<br>(3.9945)      | 684.7692***<br>(625.1071)       | 3.6751***<br>(4.3358)           |
| The proportion of the tertiary industry in the GDP                         |        | 0.6055<br>(0.6126)           | 13.2306***<br>(3.2090)      | 335.1967***<br>(221.2449)       | 3.5532***<br>(82.8724)          |
| The number of tourists travelling to the city where the airport is located |        | -1.6965*<br>(-1.8293)        | -10.5707***<br>(-4.4796)    | -613.7995***<br>(-341.2435)     | -1.7424***<br>(-3.8436)         |
| $\sigma_n^2$   |        | 23.6010***<br>(27.2364)      | 490.0769***<br>(489.1801)   | 448358.8800***<br>(448358.7100) | 73.9776***<br>(76.1967)         |
| $\gamma_n$   |        | 0.9999999***<br>(27344.4750) | 0.9999999***<br>(1197.1118) | 0.9999999***<br>(10.7367)       | 0.9999999***<br>(26420086.0000) |
| LR test  |        | 13.6035***                   | 13.9710***                  | 9.2392***                       | 11.2976***                      |

Notes: \*\*\*, \*\*, \* indicates the 1, 5, 10% significance level; data in brackets demonstrate *t*-statistics of the coefficients.

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