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Research article

Comprehensive operating efficiency measurement of 28 Chinese airports using a two-stage DEA-Tobit method

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Abstract: This paper presents a two-stage method combining data envelopment analysis (DEA) and a Tobit model to analyze the comprehensive operating efficiency of 28 airports in China in 2016. At the first stage, the DEA-BCC (Banker-Charnes-Cooper) model was employed to obtain the comprehensive operating efficiency of the combination of flight departure punctuality, non-cancellations, landing bridge rates from the perspective of airport infrastructure, surrounding airspace, route layouts, flight volume and weather. At the second stage, a Tobit model was used to analyze the influence of nine input variables from four aspects on obtained comprehensive operating efficiency, ultimately providing a clear and straightforward basis for formulating and testing policies. The comprehensive operating efficiency with this combination was further compared with each of the three efficiencies respectively. The important findings included the following: (1) The comprehensive operation efficiencies of most airports were greater than the individual efficiency; (2) These four types of operation efficiencies for most airports did not achieved DEA validity (100% efficiency), except for six airports (i.e., Haikou, Dalian, Jinan, Fuzhou, Nanning and Lanzhou); (3) These factors affecting each of the four types of operation efficiencies were different in that the number of terminals, duration of impact and average daily inbound and outbound flights had a negative impact on airport operational efficiency, while the average number of overnight aircraft per day and peak hour sorties had positive effects.

Keywords: airport operation; comprehensive efficiency; DEA-BCC model; Tobit model

1. Introduction

Airport operating efficiency essentially reflects the airport's ability to schedule flights when operating normally and facing unforeseen conditions. It can be measured by using the data envelopment analysis (DEA) approach to calculate the efficiency frontier based on the outputs, which consider the available inputs; the goal is to answer the two main questions: (i) Are airports managing the inputs used to increase airport operating efficiency, and (ii) which are the factors that promote airport operating efficiency? Hence, it is very important for policymakers and researchers to find the relationship between inputs, outputs and evaluation results to develop the best promotion strategy [1–3].

There are many input factors influencing the DEA efficiency of airport operation. In general, they could be divided into four categories, including (1) airport infrastructure, (2) airport service conditions, (3) severe weather conditions and (4) flight operation conditions. Although some inputs (i.e., weather conditions) are difficult to adjust in quantity, they are the main reasons for the differences in the operating efficiency of different airports, and they help each airport to accurately control its adjustable inputs to achieve an effective DEA (100% efficiency). To the best of the authors' knowledge, most of the attention has been focused on two or three of them, neglecting the contributions of all input factors for the four categories to airport operating efficiency [4,5].

At present, flight departure punctuality, non-cancellations and landing bridge rates are the most common indexes of airport operation evaluation. They have different influencing factors and evaluate the operation status of airports from different perspectives. All of them are also often used as outputs for calculating airport operating efficiency when using the DEA approach. However, a comprehensive operating efficiency encompassing a combination of flight departure punctuality, non-cancellations and landing bridge rates has not been evaluated from the perspective of airport infrastructure, airport service conditions, severe weather conditions and flight operation conditions [6,7].

The main aim of this paper was to present a two-stage DEA-Tobit method by integrating the DEA-BCC [8] and Tobit models [9] to reveal a coupling relationship between an airport's comprehensive operating efficiency and influential factors. The most important tasks of this study include the following: (1) development of a DEA-BCC model in Stage I to measure the comprehensive operating efficiency in consideration of flight departure punctuality, non-cancellation rates and landing bridge rates, and under the conditions of nine variables related to airport infrastructure supply and demand, the weather environment, etc; (2) creation of the Tobit model in Stage II to analyze the regression relationship between these input and output variables. Finally, an illustrative case of 28 airports in China in 2016 was evaluated to prove the applicability of our model by comparing the difference in operating efficiency between the combination of the three factors and each of them individually. This study could be used as an effective tool for transit authorities to measure an airport's comprehensive operating efficiency, and to help them design a clear and straightforward management strategy for each airport.

The rest of this study is organized as follows. Section 1 reviews the related literature. Sections 2 and 3 describe the data preparation and methodology of the two-stage DEA-Tobit method. Section 4 estimates the operating efficiencies of 28 airports in China in 2016. Finally, the main findings, conclusions and future work are provided in Section 5.

2. Literature review

To date, many researchers have studied the influence of relevant factors on airport efficiency from the input-output perspective by using DEA approaches, which have been widely used to explore airport operations. There are a variety of DEA models, i.e., the DEA-BCC, two-stage DEA three-stage DEA models. The DEA-BCC model [2,3] seems to be better able to analyze airport efficiency at a certain time point. Two-stage DEA combining a Tobit or OLS (ordinary least squares) model [10,11] was used to evaluate the regression relationship between inputs and outputs. Three-stage DEA [12] aims to eliminate the influence of this environmental factor on it by using stochastic frontier analysis (SFA).

As for the outputs, the most frequently used variables found in the literature are aircraft movement [11] and passenger/freight throughput [1–4,13-14]. It is worth nothing that [10,15–17] considered both of the above-mentioned variables as outputs, while others suggested cancellations [6], punctuality [5,7] and flight delays [1,4,6,7,13,14,17,18] as outputs. Specifically, Schultz et al. [6] took cancellations and flight delays as outputs for analysis, and Sánchez et al. [7] considered both punctuality and flight delays.

In terms of inputs, the most used indicators for airport inputs are related to airport infrastructure and include the number of runways, number of gates, number of employees, etc. [1–4,10,11,13–17]. Considering the influence of weather conditions on flight operation, more and more studies are focusing on the weather condition and flight plan as inputs to analyze efficiencies [5,6]. Additionally, the operating costs [11,16], numbers of takeoffs and landings [14] and aircraft performance parameters [5] are all inputs which have been considered.

Table 1. Input and output perspectives of existing studies on airport operational efficiency.

	[15]	[16]	[17]	[17]	[1]	[13]	[14]	[18]	[4]	[5]	[6]	[7]	[2]	[3]	[10]	[11]
Number/Length of runways	√	√	√	√	√	√							√	√	√	√
Number of gates	√		√	√												
Number of employees	√	√	√	√			√	√	√							
Operating/Expensing costs		√												√		√
Terminal space	√				√									√	√	
Number of baggage belts			√	√	√											
Apron capacity			√	√												
Number/Performance of aircraft							√	√	√	√						
Flight plan								√		√	√	√				
Fuel (tons)							√		√							
Weather condition										√	√					
Number of passengers	√	√	√	√	√	√	√		√				√	√	√	
Cargo throughput		√	√	√	√	√	√		√					√	√	
Aircraft movement	√	√	√	√							√		√		√	√
Flight delays			√	√	√	√	√	√	√		√	√				
Air navigation service capability								√								
Punctuality										√		√				
Cancellations											√					
Revenues																√

From the perspective of input-output, some scholars have combined airport infrastructure as inputs and passenger/freight throughput as outputs to analyze operating efficiency, such as in [15] and [16]. Some others, such as the authors of [5] and [6], used weather condition as input for analysis, taking flight status as output. There are also some studies that have applied airport infrastructure and flight status as input and output, respectively, such as [17].

Using the studies mentioned in Table 1, note that the above studies clearly demonstrate variables for studying airport operating efficiency, but the following critical issues deserve further investigation.

Although some studies involved the three output variables of flight departure punctuality, non-cancellations and landing bridge rates, they are rarely taken as a whole to evaluate the comprehensive efficiency of airport operation [6,7].

The considered input factors mainly involved airport infrastructure, surrounding airspace, route layout, flight volume, weather, etc. Most studies have focused on the part of these input factors that influence airport operating efficiency, but they neglected all factor-specific contributions to it [4,5].

To the best of the authors' knowledge, a few studies have examined the effects of the supply and demand conditions of the airport on its operating efficiency. Specially, no quantitative analysis on the impact of these input factors on the output result has been reported yet. It is very important for authorities to make the best strategy at the right time and place [11].

3. Data description

Ranking	Three-character code	Airport	Passenger Throughput (2016) Unit: Passengers
1	PEK	Beijing Capital	94393454
2	PVG	Shanghai Pudong	66002414
3	CAN	Guangzhou Baiyun	59732147
4	CTU	Chengdu Shuangliu	46039037
5	KMG	Kunming Changshui	41980339
6	SZX	Shenzhen Baoan	41975090
7	SHA	Shanghai Hongqiao	40460135
8	XIY	Xi'an Xianyang	36994506
9	CKG	Chongqing Jiangbei	35888819
10	HGH	Hangzhou Xiaoshan	31594959
11	XMN	Xiamen Gaoqi	22737610
12	NKG	Nanjing Lukou	22357998
13	CSX	Changsha Huanghua	21296675
14	WUH	Wuhan Tianhe	20771564
15	CGO	Zhengzhou Xinzheng	20763217
16	TAO	Qingdao Liuting	20505038
17	URC	Urumqi Diwobao	20200767
18	HAK	Haikou Meilan	18803848
19	SYX	Sanya Phoenix	17369550
20	TSN	Tianjin Binhai	16871889
21	HRB	Harbin Taiping	16267130
22	DLC	Dalian	15258209
23	KWE	Guiyang Longdongbao	15105225
24	SHE	Shenyang Taoxian	14967228
25	TNA	Jinan Yaowang	11616914
26	FOC	Fuzhou Changle	11606446
27	NNG	Nanning Wuxu	11559860
28	LHW	Lanzhou Zhongchuan	10897025

Figure 1. Twenty-eight airports with passenger flow in 2016 in China.

For this study, there were three output variables and nine input variables under four aspects. Table 2 details the meanings of all input and output variables. The output was measured via three variables, namely, the departure punctuality (DEEF), flight non-cancellation rate (SEEF) and flight landing bridge rate (CEEF). The nine input variables included the flight zone rating (FZR), number of runways (NOR), number of terminals (TB), connectivity index (CI), weather type (WT), duration of impact (DOI), average daily inbound and outbound flights (ADF), average number of overnight aircraft per day (AAD) and peak hour sorties (PHS). All input variables could be classified into four aspects, i.e., airport infrastructure, surrounding airspace, route layout, flight volume and weather.

These three output variables are different perspectives of airport operating efficiency. Hence, it is necessary to measure the comprehensive airport operating efficiency by using a combination of them (i.e., referred to as TEEF), considering all available inputs. We are the first to quantify the impacts of all input variables from these four aspects on the comprehensive airport operating efficiency (i.e., TEEF) by considering a combination of DEEF, SEEF and CEEF.

As shown in Figure 1, the operating efficiency of 28 10 million airports in China in 2016 was estimated and analyzed to prove our applicability. The data source was VariFlight, which is one of the most well-known flight service apps in China. Table 3 details values of the input and output variables for 28 airports in 2016. For the flight zone rating input variable, according to the airport flight area classification standards, we set 4E = 9 and 4F = 10. For weather type, depending on the extent to which weather affects aircraft flight, we set thunderstorm = 3, rain and snow = 2 and fog and haze = 1.

Table 2. Selected input-output variables and their meanings for the 28 airports.

Variables	Variable selection direction	Specific variable expressions	Abbreviations	Units
Outputs/Dependent variables	Flight delays	Departure punctuality rate	DEEF	100%
	Flight termination	Flight non-cancellation rate	SEEF	100%
	Flight carrying capacity of the airport	Flight landing bridge rate	CEEF	100%
Inputs/ Independent variables	Airport infrastructure	Flight zone rating	FZR	—
		Number of runways	NOR	Uno
	Airport service conditions	Number of terminals	TB	Uno
		Connectivity index	CI	Uno
	Severe weather conditions	Weather type	WT	—
		Duration of impact	DOI	Hour
	Flight operation conditions	Average daily inbound and outbound flights	ADF	Uno
		Average number of overnight aircraft per day	AAD	Uno
		Peak hour sorties	PHS	Uno

Table 3. Original data of inputs and outputs for 28 airports in 2016.

Airport	FZR	NOR	TB	CI	WT	DOI	ADF	AAD	PHS	DEEF	SEEF	CEEF
Beijing Capital/PEK	4F	3	3	694	Fog\Thunderstorm	481	1587	240	112	0.543	0.039	0.693
Shanghai Pudong/PVG	4F	4	2	507	Thunderstorm	271	1211	124	92	0.494	0.049	0.6
Guangzhou Baiyun/CAN	4F	3	1	597	Thunderstorm	361	1170	150	85	0.665	0.04	0.687
Chengdu Shuangliu/CTU	4F	2	2	379	Fog	345	868	144	64	0.734	0.038	0.747
Kunming Changshui/KMG	4F	2	1	495	Fog\Thunderstorm	274	940	129	72	0.715	0.05	0.869
Shenzhen Baoan/SZX	4F	2	3	381	Thunderstorm	234	819	120	62	0.676	0.058	0.787

Continued on next page

Airport	FZR	NOR	TB	CI	WT	DOI	ADF	AAD	PHS	DEEF	SEEF	CEEF
Shanghai Hongqiao/SHA	4E	2	2	437	Thunderstorm	271	711	106	59	0.533	0.051	0.712
Xian Xianyang/XIY	4F	2	3	425	Fog\Snow	188	828	83	64	0.806	0.051	0.856
Chongqing Jiangbei/CKG	4E	2	2	377	Fog\Thunderstorm	138	772	98	75	0.795	0.05	0.656
Hangzhou Xiaoshan/HGH	4F	2	3	288	Fog	635	648	79	52	0.562	0.052	0.793
Xiamen Gaoqi/XMN	4E	1	2	203	Thunderstorm	219	491	57	40	0.561	0.068	0.704
Nanjing Lukou/NKG	4F	2	2	283	Fog	694	488	33	44	0.542	0.053	0.743
Changsha Huanghua/CSX	4F	2	2	205	Fog	304	453	31	39	0.701	0.053	0.772
Wuhan Tianhe/WUH	4F	2	3	225	Fog\Thunderstorm	279	478	31	45	0.727	0.052	0.707
Zhengzhou Xinzheng /CGO	4F	2	1	272	Fog\Haze	493	482	33	49	0.728	0.08	0.941
Qingdao Liuting /TAO	4E	1	2	180	Fog	276	455	46	38	0.724	0.064	0.5
Urumqi Diwobao /URC	4E	1	3	206	Fog\Snow	751	445	76	38	0.71	0.076	0.77
Haikou Meilan/HAK	4E	1	1	199	Thunderstorm	148	375	56	38	0.741	0.065	0.792
Sanya Phoenit /SYX	4E	1	3	131	Thunderstorm	24	311	42	28	0.702	0.05	0.489
Tianjin Binhai /TSN	4F	2	2	103	Fog\Haze	709	379	52	40	0.674	0.092	0.842
Harbin Taiping /HRB	4E	1	2	115	Snow\Fog	253	342	42	34	0.751	0.069	0.571
Dalian/DLC	4E	1	1	104	Fog	205	353	43	36	0.779	0.079	0.767
Guiyang Longdongbao /KWE	4E	1	2	153	Fog\Thunderstorm	134	397	32	49	0.711	0.07	0.76
Shenyang Taoxian/SHE	4E	1	3	121	Snow\Fog	191	324	43	34	0.706	0.072	0.795
Jinan Yaoqiang/TNA	4E	1	1	133	Fog	338	268	17	35	0.762	0.075	0.958
Fuzhou Changle/FOC	4E	1	1	73	Fog\Thunderstorm	157	246	42	31	0.675	0.114	0.791
Nanning Wuxu/NNG	4F	2	1	91	Fog\Thunderstorm	103	262	28	28	0.688	0.098	0.954
Lanzhou Zhongchuan /LHW	4E	1	2	121	Thunderstorm	36	254	12	31	0.801	0.074	0.826

4. Methodology

The aims of this study were to evaluate how an airport's related input variables affect the comprehensive operational efficiency of its output variables, and to find the quantitative relationship between them. Hence, a two-stage DEA approach was used to measure the TEEF, DEEF, SEEF and CEEF of airports by using the DEA-BCC model in the first stage, and to perform an empirical quantitative analysis between inputs and outputs by applying the Tobit model in the second stage.

4.1. DEA-BCC model

In this study, airport operating efficiency was measured by using the DEA approach to calculate the efficiency frontier based on the output level, as related to TEEF, DEEF, SEEF and CEEF, and in consideration of all available inputs from four aspects of airport management and development. The aim of this study was to match output and input. The DEA model contains the BCC model and the CCR model, compared with the CCR (A. Charnes, W. W. Cooper and E. Rhodes, which is the model used in the DEA method to evaluate relative effectiveness) model, the BCC model eliminates the influence of scale factors and evaluates the management and decision levels of DMUs (which represents the set of selected study objects) more accurately. Although SFA [19] considers the influence of random factors on the evaluation results, it could only deal with one output variable with a given production function form, as compared with the BCC model. Therefore, we chose the input-oriented DEA-BCC model [8], as shown in Eq (1):

$$min\,\theta - \varepsilon(\hat{e}S^{-} + e^{T}S^{+})$$
$$s.t.\begin{cases} \sum_{j=1}^{n} X_j\lambda_j + S^{-} = \theta X_0 \\ \sum_{j=1}^{n} Y_j\lambda_j - S^{+} = Y_0 \\ \sum_{j=1}^{n} \lambda_j = 1\,, j = 1,2,\ldots,n \\ \lambda_j \geq 0, S^{-} \geq 0, S^{+} \geq 0 \end{cases} \tag{1}$$

Each airport was regarded as a DMU when the efficiency was calculated, and there were n airports, denoted as $DMU_j(j = 1,2,\cdots n)$. The input vector and output vector of the DMUs are expressed as $X_j(x_{1j}, x_{2j}, \cdots x_{mj})^T$ and $Y_j(y_{1j}, y_{2j}, \cdots y_{sj})^T$. θ denotes the efficiency value of the DMU, and ε denotes the non-Archimedean, which is less than any positive number but greater than zero. S^- and S^+ represent the slack variables of inputs and outputs, respectively. λ_j represents the weight coefficient of the inputs and outputs.

4.2. Tobit model

The Tobit regression model, also known as the truncated regression model, was proposed by Tobin [20] to study dependent variables that satisfy certain constraints. Since the present paper uses the DEA result between 0 and 1 as the dependent variable, it is a truncated regression problem. The Tobit regression model based on the principle of maximum likelihood estimation can handle data with the above dependent variable and effectively avoid problems such as inconsistency and bias in parameter estimation [9]. Therefore, the Tobit regression model that follows the maximum likelihood estimation was used for regression analysis. The specific form of the model is as follows:

$$\begin{cases} y_i = x_i\beta + \varepsilon_i \\ 0 \le x_i\beta + \varepsilon_i \le 1 \\ \varepsilon_i : \ (0, \sigma^2), i = 1, 2, L \end{cases} \tag{2}$$

where y_i is the dependent variable, corresponding to the airport efficiency; x_i is the independent variable, corresponding to each influencing factor; β refers to the correlation coefficient vector; ε_i is an independent normal error term that satisfies the normal distribution.

5. Empirical analysis

5.1. Airport operational efficiency analysis

In this section, DEAP 2.1 was used to execute the DEA-BCC model in the first stage to evaluate operational efficiency. Table 4 and Figure 2 details the results for the TEEF, DEEF, SEEF and CEEF of 28 Chinese airports in 2016. As shown in Table 2, DEEF denotes flight departure punctuality, SEEF denotes non-cancellations and CEEF denotes the landing bridge rate, while TEEF is the combination of flight departure punctuality, non-cancellations and the landing bridge rate. The results showed the following:

(1) The TEEF of all airports had a high average of 0.982, which indicates that all 28 airports are at a high level of operating efficiency, but some of them still need to improve in certain areas. Sixteen airports, such as CAN, CTU, KMG, SHA and CKG, had a TEEF value of 1, achieving an effective DEA.

(2) For most airports, the TEEF was greater than their DEEF, SEEF and CEEF, and the value of TEEF for each airport was very close to that of SEEF. It led to the conclusion that SEEF played a great role in TEEF, as compared with DEEF and CEEF.

(3) There may be differences among TEEF, DEEF, SEEF and CEEF between any two airports. These four efficiency values for only five airports, such as HAK, TNA, FOC, NNG and LHW, were equal to 1. Their top five worst rankings were PVG, PEK, SZX, XIY and WUH.

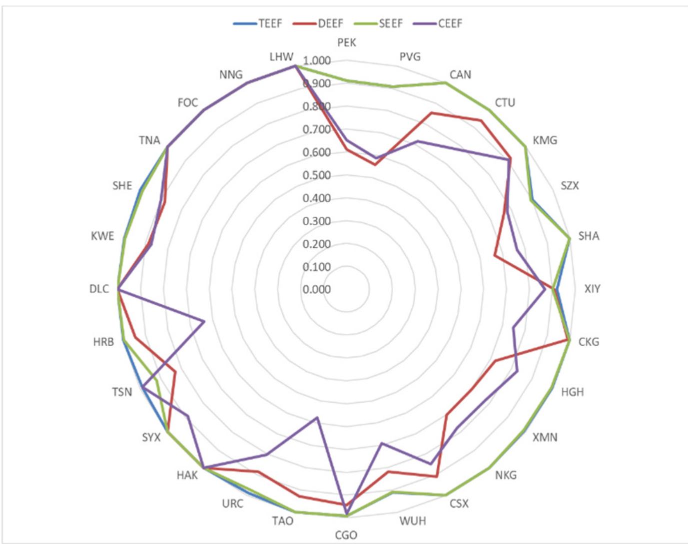

Figure 2. Overall situation operational efficiency of 28 airports.

Table 4. Results of operational efficiency for 28 airports.

Airport	TEEF	DEEF	SEEF	CEEF
PEK	0.911	0.610	0.910	0.651
PVG	0.907	0.558	0.907	0.587
CAN	1.000	0.854	1.000	0.717
CTU	1.000	0.942	1.000	0.780
KMG	1.000	0.918	1.000	0.908
SZX	0.903	0.763	0.895	0.781
SHA	1.000	0.665	1.000	0.765
XIY	0.919	0.909	0.901	0.867
CKG	1.000	0.993	1.000	0.748
HGH	0.998	0.721	0.994	0.828
XMN	0.992	0.700	0.989	0.777
NKG	1.000	0.702	1.000	0.776
CSX	1.000	0.909	1.000	0.849
WUH	0.910	0.817	0.909	0.690
CGO	0.992	0.942	0.990	0.982
TAO	1.000	0.929	1.000	0.575
URC	0.988	0.886	0.973	0.804
HAK	1.000	1.000	1.000	1.000
SYX	1.000	1.000	1.000	0.888
TSN	0.989	0.831	0.921	0.988
HRB	0.999	0.947	0.998	0.637
DLC	1.000	1.000	1.000	1.000
KWE	0.996	0.888	0.992	0.875
SHE	1.000	0.881	0.988	0.900
TNA	1.000	1.000	1.000	1.000
FOC	1.000	1.000	1.000	1.000
NNG	1.000	1.000	1.000	1.000
LHW	1.000	1.000	1.000	1.000
MEAN	0.982	0.870	0.977	0.835

5.2. Results of factors affecting the airport operating efficiency

In this section, Stata 17 was used to measure the impacts of input factors on the four indicators of airport operating efficiency. Table 5 shows the results of the Tobit regression test for 28 airports in China. It can be seen in Table 5 that the log likelihood values of TEEF, DEEF, SEEF and CEEF were 24.72995, 18.46908, 25.06807 and 15.95073, respectively, which were all greater than 1, and the Prob. values in the Table 5, which is the probability that the t-test is greater than the observed value, were all 0.0000. This indicates that the Tobit model construction is practically relevant, and that the selected variables can be used to analyze the regression relationships that exist.

Table 5. Results of Tobit regression test.

	TEEF	DEEF	SEEF	CEEF
Log likelihood	24.72995	18.46908	25.06807	15.95073
Prob > F	0.0000	0.0000	0.0000	0.0000

The regression results for the Tobit model are shown in Table 5. Taking the TEEF in the first column as an instance, the impact of the estimated coefficients of the input variables on the TEEF is described by Eq (3). It can be seen that the parameters FZR, TB, WT, DOI and ADF harmed the TEEF, in contrast to other input variables. Furthermore, FZR, TB, WT, ADF, AAD and Constant had a significant effect on TEEF.

$$\mathrm{TEEF} = -0.0531\mathrm{FZR} + 0.0255\mathrm{NOR} - 0.0313\mathrm{TB} + 0.000413\mathrm{CI} - 0.0255\mathrm{WT} - 0.0000483\mathrm{DOI} - 0.000537\mathrm{ADF} + 0.00146\mathrm{AAD} + 0.00113\mathrm{PHS} + 1.658 \quad (3)$$

Besides, it can also be seen in Table 6 that the same factors had different impacts and significance on airport operational efficiency. As an example, CI had a significant positive effect on SEEF and a non-significant negative effect on DEEF. Meanwhile, the same factor showed consistency in operational efficiency for different airports. For example, FZR and TB each had a significant impact on the operational efficiency of all four types of efficiencies of airports, while the opposite was true for NOR and PHS. In addition, TB, DOI and ADF each had a negative impact on airport operational efficiency, while AAD and PHS had the opposite effect.

Table 6. Regression results for factors influencing the efficiency of airport operations.

Factors	TEEF	DEEF	SEEF	CEEF
FZR	–0.0531**(0.0226)	0.122** (0.0606)	–0.0697**(0.0271)	0.173**(0.0688)
NOR	0.0255(0.0248)	–0.103 (0.0628)	0.0304(0.0294)	-0.0377(0.0711)
TB	–0.0313***(0.00888)	–0.0693** (0.0278)	–0.0367***(0.0108)	–0.0710**(0.0305)
CI	0.000413(0.000213)	–0.0000757 (0.000435)	0.000617**(0.000258)	0.000177(0.000485)
WT	–0.0255***(0.00839)	–0.0122 (0.0216)	–0.0266**(0.00938)	0.00262(0.0240)
DOI	–0.0000483(0.0000386)	–0.000332** (0.000116)	–0.0000761*(0.0000435)	–0.000159(0.000129)
ADF	–0.000537**(0.000244)	–0.00078 (0.000522)	–0.000527*(0.000281)	–0.00140**(0.000591)
AAD	0.00146**(0.000567)	0.00219 (0.00135)	0.00132**(0.000641)	0.00335**(0.00152)
PHS	0.00113(0.00168)	0.00591 (0.00519)	0.0000555(0.00199)	0.00844(0.00584)
Constant	1.658***(0.206)	0.202(0.552)	1.831***(0.247)	–0.434(0.622)

6. Conclusions and discussion

We employed a two-stage DEA-Tobit method to accurately measure the comprehensive operating efficiency of 28 airports in China in 2016, and we have discussed the influence of the input variables on operating efficiency. This study featured the following: (1) The input variables involve nine variables from four aspects, which describe the infrastructure, demand and external environment in a comprehensive way; (2) The output variables with a combination of DEEF, SEEF and CEEF could comprehensively evaluate the airport operation level from multiple perspectives.

The main findings are as follows: (1) There may be differences among TEEF, DEEF, SEEF and CEEF for the same airport or any two airports. For five airports, these four efficiency measures had achieved an effective DEA at the same time; for 14 airports, none had achieved an effective DEA, and, of the remaining airports, some measures had achieved an effective DEA. Besides, the TEEF and SEEF of most airports were greater than their DEEF and CEEF. (2) The action mechanism behind different influencing factors for TEEF, DEEF, SEEF and CEEF were significantly different. Some parameters harmed them, while other parameters had a significant effect on TEEF. The calculation results are in accordance with the visual analysis.

Some policy implications and suggestions for helping the airport to achieve nearly 100% efficiency include the following: (1) When the outputs of an airport do not match its inputs, the inputs of each city should be adjusted to make the best use of the outputs; (2) Increased output of airports with an efficiency of less than 100% (e.g., PEK and PVG), as well as reduced output of airports with an efficiency of more than 100%, should be achieved to realize nearly 100% efficiency; (3) When the efficiency of an airport is less 100%, decreased positive inputs (e.g., PHS and AAD) and increased negative inputs (e.g., TB and DOI) should be achieved to realize the adjustment goal.

However, this study had some shortcomings. On the one hand, one year of restricted data could not reflect the dynamic change law of airport efficiencies and their influencing factors very accurately. On the other hand, these influencing factors were incomplete. For example, the economic factors were missing. Therefore, dynamic airport efficiencies with consideration of more comprehensive factors will be our future research.

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Conflicts of interest

The authors declare no conflict of interest.

Data availability statement

Some or all data, models or code generated or used during the study are available from the corresponding author by request.

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