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A TWO-STAGE DEA- OLS METHOD FOR EVALUATING AIRPORT OPERATION EFFICIENCY

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Abstract. This paper presented a two-stage method that combines data envelopment analysis (DEA) and ordinary least squares (OLS) models to evaluate comprehensive operation efficiency of twenty-eight airports in China from 2009 to 2022. At the first stage, DEA-Malmquist model was conducted to derive operational efficiency based on a combination of peak hour sorties (PHS), departure punctuality (DP), and inbound punctuality (IP) by considering airport infrastructure, surrounding airspace, and flight volume structure. In the second stage, the OLS model was used to analyze the DEA efficiency scores from the first stage, incorporating explanatory factors associated with seven input variables across these three aspects, which provides a simple and straightforward explanation of what policies we formulate to improve airport operation efficiency. The important findings included: (1) The EC, TC, SEC, PEC, and MI efficiency scores of the twenty-eight airports produce different degrees of variability due to the variability of the different input variables considered; (2) These efficiency scores of all airports vary over time; (3) The factors affecting these efficiency scores of each airport are different.

1. Introduction

Airport operation efficiency fundamentally measures the airport's capability to manage flight schedules under normal operations and unexpected conditions. This efficiency is influenced by a range of factors related to the supply and demand of airport infrastructure, including the number of runways, airspace level, and traffic demand, etc. For policymakers and researchers, understanding the connections between these factors and the outcomes of evaluations is vital for developing optimal strategies for improvement. At present, many studies have explored airport efficiency evaluation using various input and output variables through the data envelopment analysis (DEA) approach. However, a comprehensive operation efficiency of peak hour sorties (PHS), departure punctuality (DP), and inbound punctuality (IP) in terms of airport infrastructure, surrounding airspace, and flight volume structure has not yet been evaluated.

The primary contribution was to propose a two-stage DEA-Tobit approach that combines DEA-Malmquist and OLS models to reveal the interrelationship between airport comprehensive operational efficiency and its influencing factors. The primary aims of this paper are: (1) To develop the DEA-Malmquist model in stage

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I to assess overall operational efficiency by incorporating peak hour sorties (PHS), departure punctuality (DP), and inbound punctuality (IP), while considering seven input variables linked to airport infrastructure, surrounding airspace, and flight volume structure. (2) In stage II, the OLS model was constructed to examine the regression relationship between the DEA efficiency scores and these explanatory variables. Lastly, a case study involving twenty-eight airports in China from 2009 to 2022 was conducted to demonstrate the applicability of our method. This research offers a practical tool for transit authorities to evaluate airport operational efficiency and aid in the formulation of clear and actionable management strategies for individual airports.

The structure of this study is outlined as follows. Section 1 presents an overview of the relevant literature. Section 2 outlines the data preparation process, while Section 3 details the methodology employed in the two-stage DEA-Tobit method. Section 4 presents the estimated operation efficiencies of twenty-eight airports in China from 2009 to 2022. Section 5 summarizes the main findings, draws conclusions, and offers recommendations for future research.

2. Literature review

In the process of airport operations, stakeholders primarily focus on maximizing efficiency, which intensifies competition among airports and makes the measurement of airport efficiency a focal point of research. Performance benchmarking is a crucial tool for airlines, airport operators, and regulatory bodies to assess and improve airport operational efficiency [10]. The first use of airport performance indicators as a tool allowed managers to determine and evaluate the economic status of airports, enabling more precise decision-making. As early as 1997, the Federal Aviation Administration (FAA) defined five performance indicators for the airport development system: infrastructure, environment, accessibility, capacity, and investment [2]. However, assessing airport operational efficiency is a complex task, involving the application of various models and methods.

Hensher and Waters [16] proposed three major models for efficiency evaluation: the parametric total factor productivity (TFP) model, the non-parametric TFP model, and the Data Envelopment Analysis (DEA) model. Among these, the DEA model is particularly favored because it does not require price and cost information for inputs and outputs. DEA evaluates relative efficiency through the effective combination of multiple inputs and outputs, referred to as decision-making units (DMUs) [7]. Due to its objectivity and reduced susceptibility to human bias, DEA has been widely applied in assessing airport efficiency [10]. In recent years, the CCR and BCC models within the DEA framework, along with hybrid models such as DEA combined with the Analytic Hierarchy Process (AHP) [26], have become research hotspots.

To better understand airport operational efficiency, many scholars have conducted studies on major airports across five continents, including regions such as East Asia (China, North Asia, Pakistan, Turkey), South America (Colombia), Europe (Greece, Italy), Oceania (New Zealand), and North America (the United States). These studies provide detailed summaries of samples, periods, input variables, output variables, and models, illustrating the major airports' operational efficiency across various countries.

Airport operations are typically categorized into landside and airside activities [34]. Gillen and Lall [13] were pioneers in employing two distinct DEA-Tobit models to assess the airside and landside efficiency of major U.S. airports. However, Yu [34] observed that earlier research frequently regarded the operational process as a "black box", focusing solely on initial inputs and final outputs, without analyzing the internal relationships between these stages. To address this, Yu [34] studied major airports in Taiwan, adopting free linking constraints and a two-stage DEA model, where the capacity of runways and terminals in the first stage serving as inputs for the second stage. This approach led to the finding that the airside service efficiency of Taiwan's airports was relatively high, providing valuable insights for airport managers.

Since the mid-1990s, airport privatization has become a significant trend, prompting numerous studies on how privatization affects airport operational efficiency. Oum [24], in their analysis of major airports across the Europe, Asia-Pacific and North America, demonstrated that privatized airports exhibit significantly higher operational efficiency and profitability compared to non-privately held airports. This finding is corroborated by studies conducted by Olariaga and Moreno [23], Adler and Liebert [1], and Marques and Barros [22]. Notably, factors such as airport size, runway utilization, passenger volume, and cargo volume are influential variables affecting airport operational efficiency. To analyze these characteristics more thoroughly, after assessing DEA efficiency, some scholars have used regression models in the second stage of analysis, applying techniques like Simar-Wilson bootstrapping [4], truncated regression [1,33], and Tobit regression [6,17]. Hoff [17] and Tsui et al. [6] have shown that using the Tobit model for second-stage regression analysis not only simplifies calculations but also provides more reliable estimates and more accurate predictions. As a result, the DEA-Tobit two-stage model has gradually become a mainstream approach for studying airport operational efficiency. For example, by employing the DEA-Tobit model to examine 11 major airports in Northeast Asia, Ha et al. [14] identified a significant correlation between airport operational efficiency and airline structure.Carlucci et al. [6] studied 34 major airports in Italy and demonstrated that factors such as airport size, the proportion of passengers served by low-cost carriers, and the ratio of cargo traffic to total workload units (WLUs) positively influence airport operations.

Moreover, the selection of more detailed performance indicators is critical for improving airport operational efficiency. In recent years, in addition to traditional indicators such as the number of runways, passenger volume, aircraft movements, terminal size, and cargo volume, scholars have increasingly incorporated factors such as environmental impact [34], user satisfaction [15], and airport-airline agreements [19]. These refined performance indicators provide airport managers with more precise efficiency assessments, thereby optimizing airport operations. The relationship between key elements of airport management and the policy environment is essential in impacting airport operational efficiency, highlighting the importance of detailed performance indicators under different management and policy frameworks.

Drawing on above studies, it is clear that these studies effectively identify variables for analyzing airport operation efficiency. However, several key areas require further exploration:

(1) While some literature has considered output variables such as peak hour sorties (PHS), departure punctuality (DP), and inbound punctuality (IP), they are seldom collectively used to assess the overall efficiency of airport operations (Schultz M et al, 2018; Sánchez J N et al, 2020).

(2) The input factors typically include airport infrastructure, surrounding airspace, and the structure of flight volume, etc. Most research has concentrated on how parts of these inputs affect airport operation efficiency but has overlooked the specific contributions of each factor (Tsionas et al, 2017; Lemetti A et al, 2019).

(3) As far as the authors are aware, only a few studies have looked into how supply and demand conditions at airports impact their operational efficiency. In particular, the impact of these input factors on the outputs has not been analyzed quantitatively. Such analysis is crucial for authorities to formulate optimal strategies at the appropriate times (Ngo T and Tsui, 2020).

3. Data description

To assess the operational efficiency of twenty-eight Chinese airports from 2009 to 2022, this study focused on three output variables and seven input variables. The results demonstrated the applicability of our approach. Detailed definitions of all input and output variables are provided in Table 1. The outputs were evaluated using three indicators: Peak hour sorties (PHS), Departure punctuality (DP), and Inbound punctuality (IP). The seven input variables consist of Flight Zone Rating (FZR), Number of Runways (NOR), Terminal Building (TB), Daily Average Number of Inbound Flights (DAF), Average Daily Flight Departures (ADD), Average Number of Overnight Aircraft per Day (ANO), and the Percentage of Domestic Flights (POF).

Table 1. The selected variables and their meanings of twenty-eight airports

	Variable	Abbreviations
Output Variables	Peak hour sorties	PHS
	Departure punctuality	DP
	Inbound punctuality	IP
Input Variables	Flight Zone Rating	FZR
	Number of runways	NOR
	Terminal Building	TB
	Daily average number of inbound flights	DAF
	Average daily flight departures	ADD
	Average number of overnight aircraft per day	ANO
	Percentage of domestic flights	POF

The Flight Zone Rating input variable was assigned values based on airport classification standards, with 4E set to 9 and 4F to 10. Moreover, it should be noted that the application of the OLS model will discard the TB input variable due to the correlation and heterogeneity that exists between the number of runways (NOR) and terminal building (TB) input variables.

4. Methodology

This study employed a two-stage DEA framework, combining the DEA-Malmquist and OLS models, to assess how different factors affect airport efficiency. In the first stage, the DEA-Malmquist model evaluated airport efficiencies. In the second stage, the OLS model was utilized to determine the combined dynamic impact of each input variable on efficiency, thereby confirming the influence mechanism of these variables.

4.1. **DEA-Malmquist model of the first stage.** Unlike the traditional DEA method, the DEA-Malmquist model calculates the Malmquist total factor productivity index (MI) for decision-making units (DMUs) over different periods. In the first stage, an airport's efficiency is assessed by calculating the proportion of the weighted total of its outputs to its inputs. The weights can be obtained by minimizing the bias that might arise from self-optimized weights. Using the DEA-Malmquist model, efficiency scores for the sampled airports were estimated.

In this study, the airports were the decision-making units, and their operational efficiency was measured across period t to period $t+1$. For this period, the Malmquist index, corresponding to the airports passenger and freight total factor productivity index, can be derived as:

$$\mathrm{MI}_0(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \times \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}\right]^{0.5}. \tag{4.1}$$

The (x^{t+1}, y^{t+1}) and (x^t, y^t) are the input vector (urban economic structure) and output vector (passenger and freight efficiency) at $t+1$ and t, where D_0^t and D_0^{t+1} signify the distance function at the time instants t and $t+1$, respectively, using the technology in period t as a benchmark.

The Malmquist index for output is computed using the technology from period t as a benchmark, as shown below:

$$\mathrm{MI}_0^t(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}. \tag{4.2}$$

The Malmquist index for output is computed using the technology from period $t+1$ as a benchmark, as shown below:

$$\mathrm{MI}_0^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}. \tag{4.3}$$

The index's growth rate reflects the dynamic economic growth efficiency level, and MI excludes the input contribution of results. Provided that returns to scale are constant, the Malmquist index comprises the technical efficiency change index (EC) and the technology level index (TC), following Fare's approach. The EC is primarily used to assess the level of technology acceptance. TC is mostly used to assess the level of innovation.

$$\mathrm{MI}_0(x^{t+1}, y^{t+1}, x^t, y^t) = \mathrm{EC}_0(x^{t+1}, y^{t+1}, x^t, y^t)\mathrm{TC}_0(x^{t+1}, y^{t+1}, x^t, y^t), \tag{4.4}$$

$$\mathrm{EC}_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}, \tag{4.5}$$

$$\mathrm{TC}_0(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)}\right]^{0.5}. \tag{4.6}$$

When TC > 1, the production possibility frontier expands outward, signifying an increase in efficiency; otherwise, efficiency decreases. If EC > 1, the DMU moves closer to the frontier, resulting in greater efficiency; otherwise, efficiency declines. Furthermore, the technical efficiency change index (EC) is obtained by combining the pure technical efficiency change index (PEC) with the scale efficiency change index (SEC). The purpose of PEC is to examine the input and utilization conditions, ignoring the scale reward element effect. The effective state of production scale is represented by SEC, which incorporates the factor of scale return into the analysis of input variables.

4.2. **OLS model of the second stage.** During the second stage, the DEA efficiency scores from the first stage (dependent variable) were regressed against the explanatory factors using the OLS model. Compared to the Tobit model commonly used in earlier research, the OLS model shows superior performance in both single-stage and two-stage stochastic frontier analysis, primarily due to its effectiveness in capturing the dynamic influence mechanism and reducing variability among input variables. This study structures the OLS linear regression model as follows, using panel data from the Beijing-Tianjin-Hebei region:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ki} x_{kit} + u_{it},\ i = 1, \cdots, N;\ t = 1, \ldots, T. \tag{4.7}$$

Here, y_{it} indicates the annual passenger turnover for airport i in year t; x_{kit} represents the observed value of the k explanatory variable for airport i in year t; β_{ki} denotes the estimated coefficient of the k explanatory variable for airport i; α_i is the intercept for airport i; u_{it} represents the random error term; $\{y_{it}\}_{t=1}^{T}$ comprises the panel data containing all time-series data for airport i during the period T; and $\{y_{it}\}_{t=1}^{N}$ refers to the cross-sectional data of all airports in period t within the panel data.

5. Empirical tests

5.1. **Analysis of airport operational efficiency.** In this section, the DEA-Malmquist model was utilized in the first stage using DEAP 2.1 to assess operational efficiencies. Table 2 detailed the result of MI, EC, TC, PEC and SEC of Chinese twenty-eight airports from 2009 to 2022. Under the condition that seven variables are used as input variables, results showed that:

(1) The EC, TC, SEC, PEC, and MI efficiency values for the twenty-eight airports produce different degrees of variability due to the variability of the different input variables considered.

(2) The MI for all airports averaged at a high level of 1.006, indicating that most of these twenty-eight airports operate efficiently. However, a few airports with an

TABLE 2. Result of operational efficiency of twenty-eight airports

Airport	EC	TC	PEC	SEC	MI	Airport	EC	TC	PEC	SEC	MI
PEK	1.000	0.982	1.000	1.000	0.982	TAO	1.000	0.998	1.000	1.000	0.998
CAN	1.001	0.979	1.000	1.001	0.980	CGO	1.006	1.009	1.000	1.006	1.014
SHA	1.011	0.989	1.000	1.011	1.001	URC	1.003	1.018	1.000	1.003	1.021
CTU	1.004	0.995	1.000	1.004	0.999	DLC	1.000	1.013	1.000	1.000	1.013
SZX	0.997	0.991	0.998	0.999	0.987	SYX	1.009	1.001	1.000	1.009	1.010
KMG	1.002	1.001	1.000	1.002	1.002	HAK	1.000	1.017	1.000	1.000	1.017
PVG	1.000	1.010	1.000	1.000	1.010	TNA	1.000	1.011	1.000	1.000	1.011
XIY	1.005	1.015	1.000	1.004	1.019	TSN	0.999	0.992	1.000	0.999	0.991
CKG	1.000	1.023	1.000	1.000	1.023	SHE	1.003	0.994	1.000	1.003	0.997
HGH	1.004	1.000	1.000	1.004	1.004	KWE	1.006	1.023	1.000	1.006	1.029
CSX	1.003	1.013	1.000	1.002	1.016	HRB	1.000	1.016	1.000	1.000	1.016
WUH	0.997	0.958	0.997	1.000	0.955	FOC	1.006	1.024	1.000	1.006	1.030
NKG	1.002	1.010	0.999	1.003	1.012	NNG	1.007	1.046	1.000	1.007	1.053
XMN	1.001	1.000	1.000	1.001	1.001	LHW	1.000	0.976	1.000	1.000	0.976

MI below 1 fall short of DEA effectiveness and require improvements in specific areas.

(3) The value of EC, PEC and SEC for all airports are almost equal to 1, which indicates that the twenty-eight airports in China are at a high level in terms of airport size and resource utilization.

(4) The average TC for all airports was 0.968, pointing to a low level of innovation across the twenty-eight airports. Besides, TC is the efficiency that has the most impact on the efficiency of airport operations.

Table 3 detailed the airports operational efficiency in every year from 2010 to 2022. The findings from previous years lead to the following conclusions:

(1) Input variables of the same type but with different values have different effects on airport operational efficiency, which leads to differences in operational efficiency for the same airport in different years and for different airports in the same year.

(2) There is significant variability in the change in operational efficiency from 2010 to 2022 across airports. Specifically, the operational efficiency of XIYh, HGH and TSN fluctuates around 1, while the operational efficiency of SHE exhibits a pattern of ising and then b continuously adjusting to 1.

5.2. **Results on the Factors Influencing Airport Operational Efficiency.** To assess the impact of input factors on airport operational efficiency, Eviews 9 was employed in this section. The unit root test results for the seven input variables and one output variable in the OLS model are shown in Table 4. The results show that: (1) EFF, FZR, NOR, ANO and POF satisfy the unit root test, and DAF and ADD satisfy the second order single integer test results; (2) all of the above variables are within 5% of single integer. Hence, our OLS model was explainable by analysis of autocorrelation inherent in the principal factors.

Table 5 presented the cointegration test results for the chosen series of seven variables. Seen from this table, we can concluded that the selected series satisfy the KAO test results and can be used in the OLS model.

Table 3. Result of operational efficiency of twenty-eight airports from 2010 to 2022

Airport	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
PEK	0.760	1.208	0.961	1.040	1.005	0.971	0.905	0.935	1.077	0.972	0.973	0.964	1.056
CAN	0.845	1.110	0.858	0.997	1.038	1.081	0.864	0.900	1.198	0.951	0.957	1.015	0.989
SHA	1.022	1.339	1.006	1.031	0.964	0.820	1.006	0.962	1.073	1.056	0.804	1.046	0.975
CTU	0.831	1.245	0.843	1.177	1.018	0.993	0.910	0.930	1.052	1.051	1.047	0.954	1.021
SZX	0.695	1.124	1.149	0.875	1.145	1.002	0.935	0.934	1.068	1.030	0.970	1.008	1.000
KMG	0.969	0.852	1.002	1.164	0.890	0.987	1.028	1.036	1.021	0.997	1.270	0.814	1.090
PVG	0.878	1.009	0.989	0.902	1.428	0.894	0.885	0.836	1.147	1.012	1.214	0.819	1.314
XIY	0.976	0.974	0.997	1.052	1.105	0.958	1.032	0.970	1.045	0.984	1.109	0.969	1.097
CKG	0.881	1.030	0.951	0.937	0.980	1.072	0.976	0.943	1.128	1.077	1.286	0.967	1.131
HGH	0.834	1.093	0.954	1.121	0.924	1.098	1.015	0.858	1.037	0.993	1.071	1.000	1.000
CSX	0.933	0.960	1.083	1.036	1.013	1.009	0.920	0.872	1.137	0.893	1.275	0.975	1.175
WUH	0.534	1.073	0.881	0.983	1.036	0.942	0.867	0.984	1.013	1.033	1.129	0.971	1.168
NKG	0.921	1.119	0.981	0.918	1.274	0.888	0.945	0.950	1.001	1.004	1.018	0.983	1.231
XMN	0.924	0.992	0.968	1.124	1.093	0.946	0.856	0.918	1.091	0.925	1.175	0.920	1.138
TAO	0.940	1.068	0.980	0.965	0.864	1.100	0.906	0.925	1.130	1.024	0.970	1.063	1.082
CGO	0.813	1.193	0.989	0.809	1.241	1.039	0.971	0.902	1.063	1.041	1.110	0.953	1.172
URC	1.013	1.062	1.002	0.901	1.058	0.957	1.052	1.009	1.060	0.972	1.132	0.928	1.162
DLC	0.924	1.086	1.027	0.913	0.998	0.958	1.069	0.872	1.052	1.005	1.189	0.974	1.155
SYX	1.047	1.040	0.962	1.011	0.949	0.999	0.862	0.938	1.045	0.999	1.104	1.000	1.223
HAK	0.963	0.999	0.915	0.979	1.013	1.097	0.942	0.910	1.041	1.020	1.233	0.968	1.195
TNA	0.774	1.112	0.927	0.953	0.955	1.178	0.969	0.922	1.026	1.070	1.336	0.867	1.180
TSN	0.581	1.164	0.988	0.927	1.117	0.889	1.156	0.827	1.141	0.974	1.163	0.958	1.222
SHE	0.912	0.969	0.869	0.895	1.136	0.970	0.879	0.944	1.025	1.019	1.295	0.917	1.227
KWE	0.933	1.032	1.030	1.015	1.060	0.895	0.987	0.842	1.166	1.032	1.199	0.932	1.368
HRB	0.855	0.984	0.972	0.991	0.898	1.187	0.864	0.903	0.983	1.042	1.352	0.951	1.390
FOC	0.898	1.027	1.052	0.856	0.988	1.032	0.965	0.852	1.139	1.077	1.325	0.960	1.359
NNG	0.821	1.103	1.058	0.912	1.097	1.042	0.948	0.969	1.006	0.843	2.264	0.759	1.463
LHW	0.679	1.062	0.808	1.037	0.803	0.952	0.840	0.807	1.101	1.012	1.433	0.976	1.484

Table 6 reflects estimated coefficients for the impact of FZR, NOR, DAF, ADD, ANO, and POF on airports operational efficiencies. Taking the OLS model predictions for efficiencies of the PEK and CAN in the first two rows of Table 6 as an instance, the estimated coefficients are given in the following formulas. It can been seen from the formulas that NOR and ADD harmed the EFF of PEK. Meanwhile, NOR, ADD, ANO and POF harmed the EFF of CAN.

$$\begin{aligned}\mathrm{EFF(PEK)} &= 2.265945\mathrm{FZR} - 0.813714\mathrm{NOR} + 2.479212\mathrm{DAF} - 2.462004\mathrm{ADD}\\ &\quad + 0.283641\mathrm{ANO} + 0.097712\mathrm{POF}\\ \mathrm{EFF(CAN)} &= 1.605286\mathrm{FZR} - 0.863357\mathrm{NOR} + 0.732332\mathrm{DAF} - 0.716297\mathrm{ADD}\\ &\quad - 0.722305\mathrm{ANO} - 0.755167\mathrm{POF}\end{aligned}$$

Furthermore, Table 6 indicates that identical factors exerted varying degrees of impact and significance on the operational efficiency of different airports. At the same time, each factor demonstrated consistent effects on operational efficiency across various airport types.

Table 4. The results of unit roots test

Airport	Levin, Lin & Chu t^*	Im, Pesaran and Shin W-stat	ADF - Fisher Chi-square	PP - Fisher Chi-square
EFF	−14.4941 (0.0000)	−12.866 (0.0000)	344.457 (0.0000)	432.023 (0.0000)
FZR	−4.4503 (0.0000)	−3.28468 (0.0005)	42.7098 (0.0009)	43.3603 (0.0007)
NOR	−4.09511 (0.0000)	−3.85389 (0.0005)	53.1358 (0.0009)	54.2141 (0.0007)
$D[DAF]^2$	−39.3151 (0.0000)	−29.9887 (0.0000)	474.49 (0.0000)	565.679 (0.0000)
$D[ADD]^2$	−39.2731 (0.0000)	−30.0554 (0.0000)	475.155 (0.0000)	563.531 (0.0000)
ANO	−3.33262 (0.0004)	−2.7421 (0.0031)	82.0888 (0.0131)	100.686 (0.0002)
POF	−4.56289 (0.0000)	−3.50388 (0.0002)	90.2664 (0.0025)	91.6486 (0.0019)

Table 5. The results of co-integration test

KAO test	t-statistics	Prob.
ADF statistics	−0.350107	0.0005

Table 6. Regression results of factors influencing airport operational efficiency

Airport	FZR	NOR	DAF	ADD	ANO	POF
PEK	2.265945 (0.0578)	−0.813714 (0.4426)	2.479212 (0.0423)	−2.462004 (0.0433)	0.283641 (0.7849)	0.097712 (0.9249)
CAN	1.605286 (0.1525)	−0.863357 (0.4165)	0.732332 (0.4878)	−0.716297 (0.497)	−0.722305 (0.4935)	−0.755167 (0.4748)
SHA	−0.562019 (0.5916)	1.309211 (0.2318)	2.053073 (0.0792)	−2.102218 (0.0736)	2.075467 (0.0766)	−0.13615 (0.8955)
CTU	0.605149 (0.5642)	0.861491 (0.4175)	0.389002 (0.7088)	−0.447947 (0.6677)	1.165308 (0.2821)	0.068882 (0.9470)
SZX	−0.739143 (0.4839)	2.255258 (0.0587)	−1.779105 (0.1184)	1.78728 (0.117)	−1.143628 (0.2904)	−1.50776 (0.1753)
KMG	0.588833 (0.5745)	−0.79357 (0.4535)	0.070146 (0.9460)	−0.044733 (0.9656)	−1.114935 (0.3017)	−0.198704 (0.8481)
PVG	0.536643 (0.6081)	−0.741419 (0.4826)	1.673956 (0.1381)	−1.64805 (0.1433)	0.647665 (0.5379)	0.54288 (0.6041)
XIY	0.651696 (0.5354)	0.914663 (0.3908)	−0.685899 (0.5148)	0.702009 (0.5053)	−0.451227 (0.6655)	0.654716 (0.5336)
CKG	1.509198 (0.1750)	−0.993575 (0.3535)	−1.339695 (0.2222)	1.339354 (0.2223)	0.203886 (0.8442)	0.865169 (0.4156)

Table 6. (Continued)

Airport	FZR	NOR	DAF	ADD	ANO	POF
HGH	2.415872 (0.0464)	−1.511751 (0.1744)	2.209228 (0.0629)	−2.212388 (0.0626)	−0.985626 (0.3572)	0.999566 (0.3508)
CSX	0.856093 (0.4203)	−1.418176 (0.1991)	−0.016715 (0.9871)	0.050714 (0.9610)	−1.43274 (0.1950)	1.499781 (0.1774)
WUH	−2.494349 (0.0413)	−1.230238 (0.2583)	0.179015 (0.8630)	−0.194067 (0.8516)	1.021993 (0.3408)	3.335834 (0.0125)
NKG	−0.178856 (0.8631)	−0.465921 (0.6554)	−0.120523 (0.9075)	0.148637 (0.8860)	−0.739336 (0.4838)	0.706027 (0.503)
XMN	2.941496 (0.0217)	−3.298504 (0.0131)	1.379687 (0.2101)	−1.38933 (0.2073)	1.193426 (0.2716)	−0.754507 (0.4752)
TAO	1.503586 (0.1764)	−0.643445 (0.5404)	1.352351 (0.2183)	−1.359143 (0.2163)	0.734154 (0.4867)	−0.339828 (0.7440)
CGO	−0.568843 (0.5872)	−1.298979 (0.2351)	1.097781 (0.3086)	−1.061656 (0.3236)	−1.902649 (0.0988)	1.498993 (0.1776)
URC	0.795148 (0.4526)	1.480991 (0.1822)	−1.020231 (0.3416)	1.013593 (0.3445)	−1.698037 (0.1333)	1.735576 (0.1262)
DLC	1.363373 (0.215)	−1.447181 (0.1911)	−1.225589 (0.2600)	1.206814 (0.2667)	−0.336608 (0.7463)	−0.749774 (0.4778)
SYX	−1.069664 (0.3203)	1.306562 (0.2326)	−0.741503 (0.4825)	0.701176 (0.5058)	1.396545 (0.2052)	4.219107 (0.0039)
HAK	1.567425 (0.1610)	−0.165531 (0.8732)	1.154247 (0.2863)	−1.147309 (0.2890)	−2.035478 (0.0813)	0.264391 (0.7991)
TNA	−0.382144 (0.7137)	1.024024 (0.3399)	1.562281 (0.1622)	−1.545392 (0.1662)	0.037584 (0.9711)	0.734994 (0.4862)
TSN	−0.031569 (0.9757)	0.014912 (0.9885)	−0.246722 (0.8122)	0.252622 (0.8078)	0.377602 (0.7169)	0.201205 (0.8463)
SHE	−1.028456 (0.3380)	1.41182 (0.2009)	−0.555742 (0.5957)	0.573541 (0.5842)	−1.41401 (0.2003)	1.759111 (0.1220)
KWE	1.329434 (0.2254)	−1.34411 (0.2208)	0.289955 (0.7803)	−0.296303 (0.7756)	−1.139843 (0.2918)	−0.575072 (0.5832)
HRB	1.412431 (0.2007)	−1.998757 (0.0858)	2.83241 (0.0253)	−2.853671 (0.0246)	2.497915 (0.0411)	−0.537736 (0.6074)
FOC	−1.757537 (0.1222)	1.662984 (0.1403)	−3.435883 (0.0109)	3.420653 (0.0111)	0.50477 (0.6292)	2.463022 (0.0433)
NNG	0.259295 (0.8029)	−0.601947 (0.5662)	−0.071372 (0.9451)	0.085048 (0.9346)	−1.08473 (0.3140)	0.278735 (0.7885)
LHW	1.644185 (0.1441)	0.150093 (0.8849)	−0.619109 (0.5554)	0.665424 (0.5271)	−1.758119 (0.1221)	−1.08686 (0.3131)

6. Conclusion

This paper employed a two-stage method combining DEA-Malmquist and OLS models to accurately evaluate comprehensive operation efficiency with a combination of peak hour sorties (PHS), departure punctuality (DP), inbound punctuality (IP), considering airport infrastructure, surrounding airspace, and flight volume structure, and regressed the first-stage DEA efficiency scores against explanatory factors associated with seven input variables across these three aspects. This method can also be used as an effective tool to help authorities in other countries to explain how these inputs affects DEA efficiency of a airport based on their actual data. A real-world case of twenty-eight airports in China from 2009 to 2022 was used to prove our applicability. The main findings are summarized as follows:

(1) The efficiency values for EC, TC, SEC, PEC, and MI may be differences between the same airport or across different airports. While the majority of the twenty-eight airports demonstrate high operational efficiency; however, a few airports with these efficiency values less than 1 do not achieve a DEA effective and require improvements in specific areas.

(2) The mechanisms by which different factors affect airport operational efficiency vary considerably. While some parameters showed a significant positive impact. The computed outcomes are consistent with the visual analysis.

There are two main limitations of this study. First, the input-output indicators of our model is incomplete and one-sided; Second, it is impossible to process uncertain value of these input-output indicators. Therefore, the follow-up study on airport efficiencies should consider a wider range of time serious and influencing factor with uncertain value.

First, input-output index is not comprehensive; Second, it is impossible to process uncertain indicator data

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