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Estimate Spatial Spillover of Airport Operational Efficiency in the YRD Region

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Abstract: Accurate measurement of airport operational efficiency and the analysis of key influencing factors can provide theoretical references for regional airport planning and air traffic management. Many studies are conducted on the operational efficiency of airports in the region, but little attention is paid to their interactions. To fill this gap, this paper measures the operational efficiency of airports in four major cities in the Yangtze River Delta (YRD) region, and on this basis, the spatial Durbin model is used to explore the influencing factors and spillover effects of airport operational efficiency based on two aspects: airport physical characteristics and regional characteristics. The study demonstrates that the efficiency of airport operations has a significant negative spillover effect, indicating that the efficiency of neighboring airports evolves in a competitive interaction. In terms of direct effects, the number of flights, the number of destinations, airport capacity utilization and *GDP* are important factors affecting airport efficiency. In terms of spillover effects, this paper found that the population and income positively affect the efficiency of local airport operations, while the number of flights and airport capacity utilization effects have negative effects.

Keywords: multi-airport region; airport efficiency; spatial Durbin model; direct effects; spillover effects

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1. Introduction

For years, with the increasing demand for transport services, the civil aviation transport industry rapidly developed world-wide. Competition has been fierce in both domestic and global markets in the last few decades. In a multi-airport region (MAR), where airports are close to each other, multiple factors are considered by passengers in the common catchment area, for example, which airport to choose, flight frequency, travel time, and fares [1–3], and these factors always interact and compete with each other. In order to meet the increasing tourism-related activities of future air transport growth within MAR, the regional airport authority needs to improve airport efficiency and competitiveness and needs to consider its interdependence with nearby airports on its own airport traffic to achieve better air traffic management.

Under the pressure of competition for air traffic demand, the measurement of airport efficiency has become the focus of a large number of studies. There also is a greater interest in improving the effectiveness of regional airports [4,5]. However, to improve the overall efficiency of the MAR, it is necessary to rely on the coordination and cooperation among the airports within the MAR. Whether the input and output of the airports within the MAR are appropriate or not will not only affect air transport efficiency of each individual airport, but it will also affect the overall efficiency of the MAR. Previous studies on airport efficiency were compiled based on two main aspects. Firstly, to assess the performance of the airport, data-envelopment analysis was the most commonly used tool for the performance measurement of airports [6,7]. Then, on the basis of these measurements, Tobit regression analysis was implemented to measure the effects of multiple factors on airport efficiency. Previous studies show that the most common variables comprise airport capacity utilization [8], size [9,10], transport movements [11], population [12,13], location [14], etc. Better knowledge of the variables affecting airport efficiency can provide airport operators and decision-makers with insight on how to improve airport efficiency. However, the operational efficiency of airports within the MAR is affected not only by factors related to the one airport city, but it is also affected by spillover effects from neighboring airport cities. Due to airport size, flights and airlines, the airport located nearby within the MAR can compete for passengers resulting in passenger diversion and changes in airport efficiency [11]. Conversely, airport efficiency is also affected by the level of income of the population and the number of persons in the catchment area of the airport. Population and income growth may encourage traffic volumes at the region′s airports [12]. However, little research has been conducted to investigate the spatial variation of airport operational efficiency from the perspective of the MAR as a whole.

The motivation of this paper is to investigate the uneven development level and operational efficiency of the airports in the YRD region by combining spatial effects in order to promote the coordinated development of the MAR. First, the slack-based measure (SBM) was used in this paper to analyze the operational efficiency of major airports, examine the individual airport performances and compare the changes in the YRD region between 2009 and 2018. Then, a spatial weight matrix was established, and Moran′s I index was used to analyze the spatial correlation of airport operational efficiency. This paper also explored the influencing factors of airport operational efficiency from two dimensions: airport operational characteristics and airport regional characteristics. Then, the spatial econometric models were introduced into the analysis of efficiency by influencing factors to study their spatial spillover effects. Some results show that there are spatial interactions between the local and alternative nearby airports. Airport operational efficiency has a negative spillover effect, indicating that there is a competitive relationship between neighboring airports within the MAR. Airports within the MAR should focus on different development strategies according to their own positioning and their market characteristics in order to improve the overall aviation operation capacity of the MAR and meet the fast-growing demand for air transportation.

The rest of the paper is organized as follows. The second section reviews the earlier studies that are subjected to the multi-airport region and efficiency analysis; the third section proposes the theoretical model of SBM-DEA and Durbin and analyzes spatial weight of the airport; the fourth section introduces the data used in this research; the fifth section discusses the empirical results and findings; the sixth section summarizes the full text, and the implications will be drawn from the results obtained from the analysis which suggest some efficient governance mechanisms for the decision maker.

2. Literature Review

2.1. Multi-Airport Region

The relationship between airports in a multi-airport region is of considerable interest to policymakers, academic researchers and many others. Although many multi-airport regions around the world are properly developed, the development in China is still poor. The growth of multi-airport regions needs to develop rapidly, especially with the increasing demand for air transport services in China. Historically, commercial traffic consisting of multiple airports serving a common area was defined as a multi-airport region and was independent of attributes such as airport ownership, operator, manager or administrative region to which they belonged [15]. Based on the concept of a multi-airport region, some scholars further studied the progress of multi-airport regions and focused on two main aspects: the operational status and the travel behaviors of individuals.

In terms of the operational status of a multi-airport region, the authors of [16] studied the San Francisco Bay Area region and found that most of the time, the operational patterns of airports within a multi-airport region do not change easily and that competition among airports for shared airspace resources is more pronounced, which can further reduce airport capacity and efficiency. The authors of [17] summarized three major problems that exist in operations within a multi-airport region that share the same departure points, shared airspace and neighboring airport configurations. In addition, the high degree of interdependence of operations in each multi-airport region makes it quite difficult to manage them effectively. The authors of [18] proposed a framework for the design of dynamic arrival and departure routes in a multi-airport region, which fundamentally changed the operation in MAR airspaces for a much improved efficiency. In addition, other aspects such as terminals and runways in a multi-airport region were also investigated in various studies (e.g., [19–21]).

Previous research focuses on what people have chosen across airports in the face of the heterogeneity of airport attributes, which was seen as a form of airport competition, and provides the forces that drive the passenger movement patterns within a multi-airport region. First, the impact of air fares on a multi-airport region was repeatedly shown. When choosing an airport, air fares ware the dominant predictor ([3,22,23]). The authors of [24] found that 60% of leisure passengers and 45% of business passengers rated ticket fare as the most important factor when choosing a flight. The authors of [25,26] found that passengers were willing to travel further and/or longer in exchange for a better air fare. Second, there are a number of airport connectivity characteristics that influence airport choice such as travel time, flight frequency and market served. The authors of [2] used a nested logit model (NL) to analyze airports in the San Francisco Bay area and concluded that travel time to an airport was the dominant predictor for airport choice. The authors of [27] found that passengers prefer non-stop or fewer-stop routes when choosing a flight. The authors of [28] drew the analogy with Huff models to calculate airport attractiveness to passengers and showed that airport connectivity and different elements of airport utility are key drivers of airport choice.

2.2. Airport Efficiency

The evaluation of airport efficiency is an important tool to be used for measuring the development and competitiveness of airports. There are a number of methods of airport performance measurements in the previous literature, with the most preferred and cited one being the data envelopment analysis (DEA). DEA is a non-parametric approach that can handle multiple inputs and outputs, and there are many DEA applications to assess airport efficiency [29–32]. The main drawback of what constitutes traditional DEA models is that they neglect intermediate products of linking activities or fail to identify the sources that lead to airport inefficiency [33]. In recent years, the SBM-DEA model was also designed to evaluate airport efficiency. For example, [31] made use of the SBM-CRS model to access the major Asia-Pacific airports performances from 1987 to 2005. The authors of [34,35] also utilized the SBM-NDEA model with the VRS framework to investigate the efficiency of 15 Taiwanese airports in 2006. This study split airport efficiency into production and service efficiency and estimated the input excesses and output shortfalls in the production and service processes, respectively. The authors of [36] considered undesirable outputs and employed the SBM model to analyze the Spanish airports' efficiency. The authors of [37] used the SBM model and MPI to investigate productivity changes and the efficiency of New Zealand's major airports between 2010 and 2012 and further analyzed the efficiency of eleven New Zealand airports between 2006 and 2006 [38]. In a similar vein, [39] estimated the efficiency of the Italian airport system using the SBM model, and [40] used SBM-DEA to measure the efficiency of nine major airports in Southeast Asia and evaluated their strengths and weaknesses.

Based on the measurements of airport efficiency, there is a wide range of variables that are used to explain the variations in efficiency scores in airports. Some of these physical variables were also used as inputs and outputs, such as airport size, aircraft movements, cargo traffic, location connected and regular flight [41–44]. In addition, regional characteristics of the airport are also important. For example, the location of the airport plays a critical role in its performance. The authors of [12] found that hub airports possess the location advantages, and airport location may explain the productive efficiency. Typically, airports located in big cities, metropolitan areas and coastal areas tend to have higher efficiency [14,45,46]. The authors of [47] also studied the efficiency of small remote airports and found that most of these airports do not achieve positive economic benefits. In addition, the hinterland population also affected airport efficiency, which can be evaluated in two ways, number of persons in the catchment area of the airport (hinterland population) or the level of income of the city (*GDP*). The authors of [48] found a positive and significant effect of population on airport efficiency, and *GDP* always has been taken into account as an explanatory variable in the regression model [10,37]. Other scholars studied the efficiency variables of airport operations in Spain and Greece and found that airports with increased population density and *GDP* per capita are likely to have higher levels of efficiency [49,50], while similar circumstances were observed in New Zealand [38].

It is clear that while there are many studies on the evaluation of airport operational efficiency in a multi-airport region, few paid attention to the spatial variation of airport operational efficiency in multi-airport regions, especially the spillover effects of changes in airport attributes on the efficiency of individual airports and the interaction and diffusion effects between the local and nearby airports within a multi-airport region. To the best of our knowledge, the only study that came close to this variation is [51], which proposed a spatial panel regression model as a way to discuss this type of simultaneous interaction between different airports. Incidentally, they also conducted a case study in the Pearl River Delta region (PRD region) with their proposed model. In their study, the findings showed that airport degree, flight frequency, income, population and *GDP* are significant factors affecting the airport's capacity, and the spatial panel analysis showed that competition across the four airports in the PRD region is intensifying.

Based on a review of the relevant literature, the existing studies are important insights and implications for understanding the efficiency of airport operations. However, to date, there are still relatively few assessments of the efficiency of the entire system of multi airports. In addition, to our knowledge, there is no study so far that has used the spatial analysis approach to estimate impacts of regional competition on airport efficiency in a multi-airport region. To fill this gap, this paper attempts to consider the spatial linkage to measure the effects of some of these factors on airport operational efficiency in a multi-airport region. Through theoretical model analysis, efficiency measurement and influence factor analysis, this paper aims to explore the correlation characteristics among a multi-airport region from the perspective of airport operational efficiency and provide a theoretical reference for the construction and development of a multi-airport region in China.

3. Methodology

At the core of this study is the estimation of spillover effects between each airport in a multi-airport region. To this end, firstly, the SBM-DEA model was used to evaluate the operational efficiency of each airport in the MAR, and a spatial Durbin model was employed and gauged spillover effects by the spatial correlation in the airport performance. In this paper, the main contribution actually concerns the measurement of a dynamic spatial model that assesses the factors associated with the airport efficiency in a multi-airport region and how neighboring airports affect the airport efficiency to a given airport in the region.

3.1. Data Envelopment Analysis-Slack-Based Measurement

Many studies used DEA with operational variables to analyze airport efficiency [52]. Since the pioneering work of [53], DEA was demonstrated to be an effective technique for measuring the relative efficiency of a set of DMUs that utilize the same inputs to produce the same outputs, such as airports under consideration, and the efficiency score has a value between 0 and 1. DMUs with an efficiency score of 1 are situated on the frontier as the best practices. The DEA method has numerous advantages that contribute to its prominence in airport performance evaluation. Compared to other approaches, DEA does not need any assumption about either the technology or behaviors of actors and can be performed without detailed financial data. However, the traditional DEA model does not consider the redundancy and slackness of the input and output, which implies that an efficient DMU with an equivalent efficiency score of 1 could be inefficient. To solve the issue, [54] proposed a direct slack-based efficiency measure to assess a DMU's performance in terms of input and output slacks. A DMU with an efficiency score equal to 1 is highly proficient with SBM. The SBM efficiency score is obtained from Equation (1). The SBM efficiency index of an airport is denoted as ρ, which represents the inputs x_{ik} that produce the outputs $y_{rk}(r = 1, \ldots, s)$; m and s are the number of inputs and outputs, respectively. Meanwhile, k can be regarded as the number of DMUs. The vector S_i^- and S_r^+ are slacks, which represent the input excess and output shortfall. In addition, the λ_j is the dual variable or the scalar vector associated with each airport.

$$Minimise\ \rho = 1 - \frac{1}{m}\sum\nolimits_{i=1}^{m}\frac{S_i^-}{x_{ik}}/1 + \frac{1}{s}\sum\nolimits_{r=1}^{s}\frac{S_r^+}{y_{rk}} \tag{1}$$

subject to

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{ik},\ i = 1, \ldots,\ m;$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - S_r^+ = y_{rk},\ r = 1, \ldots, s;$$

$$\lambda_j \geq 0,\ j = 1, \ldots, n$$

$$S_i^- \geq 0, i = 1, \ldots, m;$$

$$S_r^+ \geq 0, r = 1, \ldots, s$$

In the SBM model, the efficiency score in different DMUs is 1, and it is not possible to differentiate and compare these DMUs further. In order to differentiate efficient DMUs from a radial efficiency assessment, Ref. [55] proposed the Super SBM model based on the SBM model to rank efficient DMUs by giving the efficiency score of the strongly efficient DMUs an efficiency score of larger than 1 in order to differentiate efficient DMUs under the slacks-based measure. The super-efficient SBM model is as follows in Equation (2):

$$Minimise\ \rho = \frac{1}{m}\sum\nolimits_{i=1}^{m}\frac{\overline{x_i}}{x_{ik}}/\frac{1}{s}\sum\nolimits_{r=1}^{s}\frac{\overline{y_r}}{y_{rk}} \tag{2}$$

subject to

$$\overline{x_i} \geq \sum_{j=1,\ j\neq k}^{n} x_{ij}\lambda_j,\ i = 1, \ldots,\ m;$$

$$\overline{y_r} \geq \sum_{j=1,\ j\neq k}^{n} x_{rj}\lambda_j,\ r = 1, \ldots, s;$$

$$\lambda_j \geq 0,\ j = 1, \ldots, n,\ j \neq k;$$

$$\overline{x_i} \geq x_{ik}, i = 1, \ldots, m;$$

$$\overline{y_r} \geq 0, \overline{y_r} \leq y_{rk}, r = 1, \ldots, s$$

From the above model, minimizing the ratio implies the simultaneous pursuit of improvements in both airport inputs and outputs [36]. However, we should know that the super-efficiency model always contains an efficiency score greater than or equal to 1. Even an inefficient DMU always has an efficiency score achieved by the super efficiency model. Therefore, to measure the efficiency and super efficiency scores for all DMUs, this paper first applies the SBM model to all DMUs and then applies the super-efficiency model to the efficient DMUs filtered out in the first step for their super-efficiency scores.

3.2. Spatial Durbin Model

Spatial analysis is used to measure and explain the spatial interaction between an economic attribute in one region and the same economic attribute in another region. In general, when locations such as airports are characterized, and the types of spatial attributes are determined, the relationship between the attributes and the mutual influences they have on each other are analyzed. In a regional area, several notable models have been used; Ref. [56] first defined the concept of spatial correlation in traditional panel models. On this basis, Ref. [57] introduced the spatially lagged error term into the traditional panel model. In addition, Ref. [58] refined the spatial lag model (which is known as the spatial autoregressive model or *SAR*) and the spatial error model (*SEM*). The *SAR* only incorporates the neighboring effect of the dependent variable (efficiency output) which is introduced in Equation (3).

$$SAR : Y_t = \rho W Y_t + X_t \beta + \varepsilon_t \quad (3)$$

In addition, the *SEM* only contains the interactions among error terms which are introduced in Equation (4).

$$SEM : Y_t = X_t \beta + (1 - \gamma W)\varepsilon_t \quad (4)$$

However, the spatial durbin model (*SDM*) contains both interactions between the outcome and independent correlations. This paper uses the *SDM* to measure the spillover effects of airport operational efficiency. The general form of this model is as shown in Equation (5).

$$SDM : Y_t = \rho W Y_t + X_t \beta + W X_t \theta + \varepsilon_t \quad (5)$$

where the outcome variable Y_t can be regarded as an n-dimensional vector of efficiency measurement values for the n airport in MAR; $t = 1, \cdots, T$ is an index for the T time periods; ρ is the auto-regressive parameter that measures the strength of dependence between airports; W is a $n \times n$ spatial weight matrix that describes the neighbor relationships among the MAR airports; X_t is an $n \times m$ matrix containing m covariance that measures the operational and regional related factors for each of the n MAR airports over the time period t; β is an associated parameter contained in a m-dimensional vector; θ are vectors of response parameters for the spatial lags of covariance; and ε_t is the overall disturbance term, which also specifies the potential spatial auto-correlation within the error terms.

3.3. Spatial Weight Matrix

Determining the appropriate spatial weight matrix is an important step in applying spatial econometrics to measure spillover effects. However, there is no unique definition for a spatial weight matrix. Scholars construct spatial weight matrices based on specific forms of spatial associations corresponding to their study context [59]. Commonly used matrices include the adjacency weight matrix, geographic distance weight matrix and economic distance weight matrix. Based on the purpose of this research paper, the weight should be placed at the travel time between airports. In a MAR, when making a choice, passengers will choose between airports with lower travel time costs in mind, rather than overflowing demand to closer airports. Hence, the travel time is set as the spatial weight of the airport. The spatial weight matrix was defined in Equation (6):

$$w_{ij} = \frac{1}{d_{ij}} \quad (6)$$

$$w = \begin{bmatrix} 0 & \cdots & w_{1j} \\ \vdots & \ddots & \vdots \\ w_{i1} & \cdots & 0 \end{bmatrix}$$

In the above equation, w_{ij}, $i, j = 1, \cdots, n$ is the inverse square travel time between airport i and airport j. By definition, the diagonal elements of W are set to zero to exclude self-dependence. In addition, this paper assumes W to be row normalized; that is, the sum of each row in the matrix is 1.

4. Data and Selection of Variables

4.1. Data

The data employed in this study are derived from several databanks. The data of aviation such as air passenger traffic and air cargo shipment were obtained from the website of VariFlight and the International Air Transport Association (IATA). The data of control variables of airport regional characteristic come from the China Statistic Yearbook (2008–2018) compiled by the National Bureau of Statistics of China. In the analysis of the spatial model, all variables are transformed into a natural logarithm form to reduce possible heteroscedasticity. Note that when a city is served by more than one airport, such as Shanghai, all airports in the same city are combined together to calculate the traffic volume to facilitate comparison.

The YRD region is the part of leading economic development zones in China (see Figure 1). Including the two airports in Shanghai, altogether there are sixteen airports in this region. In 2018, airports in the YRD region completed air passenger traffic of 230 million passengers and air cargo shipment of 5.59 million tons, with the total scale of passenger transportation accounting for about 18% of the total passenger traffic of domestic airports and the scale of air cargo accounting for about 33% of the total cargo shipment of domestic airports. With the large volume of handled passengers and cargoes, Shanghai Pudong International Airport (PVG) has been considered as a leading hub in this region. Traditionally, the classification of airports in a MAR is based on a certain distance from the hub [60], or on a legally defined locale (city/country) in which the airports are situated. Here, this paper defines airports in the city as within a two-hour-public transport time to Shanghai as air passengers' target airports within the same MAR [51]. Therefore, the airports belonging to the YRD region in this study include Hangzhou Xiaoshan International Airport (HGH), Nanjing Lukou International Airport (NKG), Ningbo Lishe International Airport (NGB), Wuxi International Airport (WUX) and Changzhou Airport (CZX). However, because the total travel demand of WUX and CZX did not exceed 10 million passengers, so they were not included in our study.

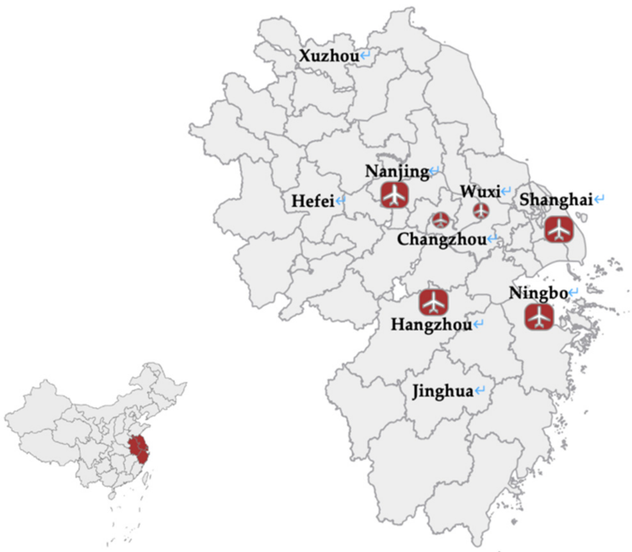

Figure 1. Airports in the YRD region.

4.2. Selection of Variables

To measure the airport efficiency score by DEA, the first step is to define the inputs and outputs generated by the airport. Considering the units of measurement, inputs and outputs are divided into two types, physical and financial. On the physical side, the length of runways and terminal area were always used as input in the studies [29,46]. Physical outputs always include aircraft movements, number of passengers and tons of cargo [11]. Many other studies also used financial variables. In the study about Taiwan airport's performance, [35] used labor (employees) as an input. Operational expenses and revenues were also used as the input and output in the studies of [37]. However, considering the data for these financial inputs or outputs, measures are not available for most Chinese airports. Therefore, length of runways and terminal area were used as airport inputs, and aircraft movements, number of passengers and tons of cargo were used as airport outputs in this study. A summary of the descriptive statistics relating to the airport inputs and outputs for five major YRD region airports is presented in Table 1.

Table 1. Descriptive statistics of airport input and outputs.

	Mean	Standard Deviation	Minimum	Maximum
Terminal Area ('000)	32.4188	20.09249	4.35	62.2
Runway Area ('000)	37.08	21.86176	15.3	90
Passenger ('000)	2782.28	1788.292	403.1	7405.4
Cargo ('000)	88.5808	119.9764	4.7	382.4
Flight ('000)	21.13	12.43348	3.8	50.4

In order to explore the spatiality of airport operational performance, a clear understanding of the factors influencing airport operational efficiency is an important prerequisite for the optimal development of a MAR. There are a number of factors impacting performance of an airport. Based on the research results of many scholars, this paper summarized the previous research on the factors influencing the efficiency of the airport. The independent variables were selected from two aspects: airport operational characteristics and regional characteristics. On the operational side, regular flights [31], airport capacity utilization [8] and airport destinations connected [41] were used in this paper. On the other side, this paper used the most influential factors, including hinterland population [37], income and *GDP* [10,13] to measure airport regional characteristics, which can potentially affect air travel demand of an airport in a multi-airport region. The definitions of variables are shown in Table 2, and the descriptive statistic results of variables are shown in Table 3.

Table 2. Definition of variables.

	Independent Variables	Definition
operational characteristics	$ln(Fli)$	Number of regular flights
	$ln(Cap)$	Number of seats on scheduled flights
	$ln(Des)$	Number of air destination
regional characteristics	$ln(GDP)$	Gross domestic production
	$ln(Pop)$	Number of hinterland population
	$ln(Inc)$	Per capita income

Table 3. Descriptive statistic results of variables.

	Mean	Standard Deviation	Minimum	Maximum
$ln(Fli)$	5.9532	0.8535	4.4886	7.4776
$ln(Cap)$	11.0517	0.9295	9.4042	12.7375
$ln(Des)$	4.7596	0.7172	3.4657	5.9889
$ln(GDP)$	9.2485	0.5544	8.3634	10.3945
$ln(Pop)$	6.8828	0.5376	6.3474	7.7938
$ln(Inc)$	10.6049	0.2747	10.1253	11.0694

5. Empirical Study

5.1. Airport Efficiency Scores and Comparative Analysis

Based on the panel data of major airports in the YRD region from 2009–2018, this paper measures the operational efficiency of each airport in the Yangtze River Delta using the SBM-DEA super-efficiency model as shown in the following Table 4:

Table 4. 2009–2018 DEA-SBM super efficiency scores for 4 urban airports.

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Shanghai	1.60	1.90	1.86	1.94	1.92	2.00	1.98	1.96	2.04	2.12
Hangzhou	0.77	0.84	0.93	1.03	1.00	1.00	1.02	1.05	1.23	1.34
Nanjing	0.85	0.92	1.00	1.03	1.07	1.03	1.17	1.21	1.36	1.45
Ningbo	1.07	1.07	1.10	1.07	1.11	1.19	1.24	1.27	1.33	1.37

An examination of Table 4 revealed that the SBM efficiency scores of airports in the YRD region did not show a single upward or downward trend during 2009–2018; the growth rate is staggered positively and negatively. Because there are two airports in Shanghai, the traffic volumes of both airports were combined here to facilitate comparison. As expected, Shanghai′s airport efficiency was the most efficient throughout the study period. This is mainly due to its status as an international hub, which allows it to take advantage of more advanced airport equipment and advanced management. The efficiency values of the remaining three cities′ airports (HGH, NKG and NGB) fluctuate over the decade but are almost all above 0.80 and play a dominant role in the YRD region.

In addition, the industrial competitiveness or efficiency can be evaluated through the analysis of average efficiencies [37]. Figure 2 demonstrated the growth of efficiency of the average and each airport with the DEA-SBM super-efficiency model. The mean SBM efficiency scores of YRD airports increased from 1.075 in 2009 to 1.570 in 2018, indicating that in general, YRD airports improved their operational efficiency during the study period. However, as seen in Figure 1, the growth rate of average efficiency in the YRD region declined significantly in 2013 and 2014, and the growth rate in Shanghai in 2013 is negative. Among these four airports, Shanghai airport is the traffic leader; therefore, the declined efficiency scores of Shanghai airport further affected the efficiency scores of the YRD region. Presumably the main reason for its declining efficiency level in Shanghai was that its capacity is gradually becoming over-saturated. It is worth mentioning that the growth rates of efficiency scores in Hangzhou and Nanjing airports are huge, and at these rates, these two airports will surpass Shanghai airport in a few years.

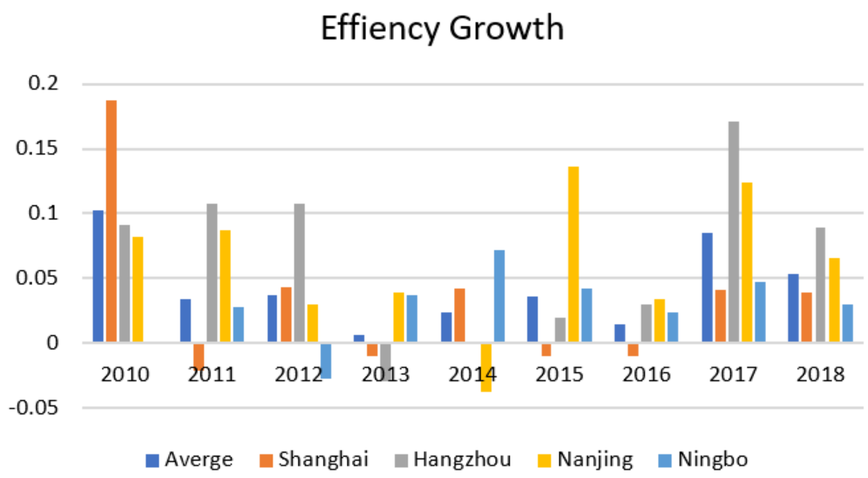

Figure 2. The growth of efficiency of all airports and the average.

5.2. Spatial Autocorrelation Test

As a preliminary diagnostic test, Moran's I statistic [61], a commonly used measure of spatial autocorrelation [56,62], was employed to detect the spatial association across the airports in the YRD region. The corresponding formula is shown in Equation (7):

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n} \sum_{j=1}^{1} w_{ij} \sum_{i=1}^{n} (x_i - \overline{x})^2} \tag{7}$$

The results of Moran's I statistic from 2009–2018 are illustrated in Table 5. The value of the statistic shows a significant negative value for the whole panel period, thus leading to a rejection of the null hypothesis of no spatial dependence in favor of negative spatial dependence across the regions. The results give a clear indication of the spatial model, which is capable of taking spatial dependence among the outcome variables (the observed efficiencies of all airports) into account.

Table 5. Moran′s I of airport operational efficiency in the YRD region.

Year	Moran′s	p	Year	Moran′s	p
2009	−0.213	0.005	2014	−0.200	0.007
2010	−0.225	0.003	2015	−0.189	0.001
2011	−0.306	0.000	2016	−0.213	0.000
2012	−0.393	0.000	2017	−0.145	0.000
2013	−0.232	0.010	2018	−0.100	0.000

5.3. Spatial Regression Analysis

Based on the spatial correlation of airports' operational efficiency in the YRD region, it is necessary to choose the right model to consider the interactions between neighboring airports when analyzing the influencing factors. Based on LM-lag and LM-err tests, the hypothesis $\theta = 0$ is rejected at the 1% or 5% significance level. This paper further conducted LR and Wald tests; the hypothesis $\theta + \lambda\beta = 0$ cannot be supported; this implies that *SDM* cannot be simplified to either *SAR* or *SEM* and suggests that *SDM* can be safely adopted as an appropriate model specification.

As in many other studies, this paper selected six indicators affecting airport efficiency, including *GDP* (*GDP*), income (*Inc*), hinterland population (*Pop*), number of regular flights (*Fli*), number of airport destinations (*Des*) and airport capacity utilization (*Cap*), as key explanatory variables from the regional side and airport operational side. Replacing the corresponding items in Equation (5) with the above variables, then the final model specifications can be written as Equation (8).

$$\begin{aligned} lnEFFI_t = {} & \rho WlnEFFI_t + \beta_{gdp}lnGDP_t + \beta_{pop}lnPopulation_t + \beta_{inc}lnIncome \\ & + \beta_{fli}lnFlight + \beta_{des}lnDestination \\ & + \beta_{cap}lnCapacity\ utilization_t + \theta_{gdp}W(lnGDP_t) \\ & + \theta_{pop}W(lnPopulation_t) + \theta_{inc}W(lnIncome_t) \\ & + \theta_{fli}W(lnFlight_t) + \theta_{des}W(lnDestination_t) \\ & + \theta_{cap}W(lnCapacity\ utilization_t) + u + \varepsilon_t \end{aligned} \tag{8}$$

Based on the above spatial model, the estimation results explaining the efficiency changes of our spatial panel regression model are reported in Table 6. The parameter estimate, *Rho*, of the spatially lagged outcome variable ($W \times lnEfficiency$) is negative and statistically significant. It indicates the existence of negative effects in airport efficiency among YRD airports, and it can be interpreted as an "airport competition" effect in the YRD region. Furthermore, the value of *Rho* is -0.1667, which mean that each 1% increase in the efficiency of neighboring airports leads to a 0.1667% decrease in the efficiency of local airports. In addition, among all the factors being considered, the estimates of explanatory variables, except for population and income, are significant and have expected signs showing positive impacts on airport efficiency. It appears that the sampled YRD region airports with increasing *GDP* are likely to have high efficiency levels and outperform their counterparts during the study period. The value is 0.1450, suggesting that an increase in *GDP* would lead to a 0.1450% improvement in airport efficiency. Similar circumstances were observed in Greece [49], Spain [50] and New Zealand [38]. In addition, having more regular flights, destinations and capacity positively affected airport efficiencies, which could be caused by more airport characteristics being available to attract more passengers to bring more air traffic volumes.

Table 6. Estimation results of spatial panel regression.

Coefficients	Estimated Value	Standard Error	*p*-Value	
$ln(GDP)$	0.1450	0.0502	0.060	*
$ln(Pop)$	0.0490	0.0313	0.214	
$ln(Inc)$	0.0169	0.0167	0.296	
$ln(Fli)$	0.2996	0.0430	0.002	***
$ln(Des)$	0.0869	0.0181	0.038	**
$ln(Cap)$	0.3975	0.0320	0.000	***
$W \times \ln(GDP)$	0.0532	0.0154	0.304	
$W \times \ln(Pop)$	0.0657	0.0304	0.007	***
$W \times \ln(Inc)$	0.0234	0.0163	0.092	*
$W \times \ln(Fli)$	−0.1574	0.0269	0.05	*
$W \times \ln(Des)$	−0.0505	0.0308	0.450	
$W \times \ln(Cap)$	−0.2536	0.0188	0.016	**
Rho	−0.1667	0.0549	0.009	***
$sigma^2$	0.1458			
$Log - likelihood$	268			

* Significance level: $p < 0.01$ (***); $p < 0.05$ (**); $p < 0.1$ (*).

Due to the presence of a spatial lag term, the spillover measures cannot be obtained easily by estimated parameters. As the total, direct and indirect effects of each explanatory variable need to be calculated and decomposed based on the variance covariance matrix of the *SDM* estimation results [62]. The equation is as follows:

$$y_t = (I_n - \rho W)^{-1}(X_t\beta + WX_t\theta + \mu + \varepsilon_t) \tag{9}$$

Then, the effects of a change in any of the explanatory variables X_t on the value of Y are measured by the partial derivative in Equation (10):

$$\left[\begin{array}{ccc}\frac{\partial_{y_t}}{\partial_{x_{1kt}}}, & \cdots & \frac{\partial_{y_t}}{\partial_{x_{nkt}}}\end{array}\right] = \begin{pmatrix} \frac{\partial_{y_{1t}}}{\partial_{x_{1kt}}} & \cdots & \frac{\partial_{y_{1t}}}{\partial_{x_{nkt}}} \\ \vdots & \ddots & \vdots \\ \frac{\partial_{y_{nt}}}{\partial_{x_{1kt}}} & \cdots & \frac{\partial_{y_{nt}}}{\partial_{x_{nkt}}} \end{pmatrix} = (I_n - \rho W)^{-1}(\beta_k I_n + W\theta_n) \quad (10)$$

Here, following the definitions in [58], the direct effect is measured by the average of the diagonal elements in the matrix of Equation (8), which measures the effects that a change in an independent variable in airport i has on efficiency variations in the airport itself, while the spillover effect is calculated by the average of the off-diagonal elements of the matrix, which measures the effects of a change in an independent variable x_k in airport i on efficiency variations in all the other airports in the YRD region. The direct, spillover and total effects computations are reported in Table 7:

Table 7. Direct, spillover and total effects.

	Direct Effects	Spillover Effects	Total Effects
ln(*GDP*)	0.1433 (∗)	0.0746	0.2179
ln(*Pop*)	0.0458	0.0881 (∗∗∗)	0.1339 (∗∗)
ln(*Inc*)	0.0186	0.0457 (∗)	0.0643 (∗∗)
ln(*Fli*)	0.2992 (∗∗∗)	−0.1367 (∗)	0.1625 (∗∗∗)
ln(*Des*)	0.0918 (∗∗)	−0.0631	0.0287
ln(*Cap*)	0.3830 (∗∗∗)	−0.2632 (∗∗)	0.1198 (∗∗∗)

* Significance level: $p < 0.01$ (***); $p < 0.05$ (**); $p < 0.1$ (*).

Firstly, from the results of the direct effects, the coefficients of the variables of the number of regular flights and capacity utilization are 0.2992 and 0.3830, respectively, and are significant at the 1% level. In addition, the coefficient of the variable number of destinations is 0.0918 and is significant at the 5% level. This suggests that variables of airport characteristics have a positive impact on airport operational efficiency. For this, this paper argues that airports with more destinations usually attract more passengers, which results in more passenger loads. In addition, the more frequently visited the airport is, the wider the range of options available to passengers. The capacity utilization of an airport indicates the amount of passenger traffic that the airport can handle, and typically an increase in airport traffic will lead to an increase in airport efficiency, which is similar to the findings of [43]. In addition, in terms of regional characteristics, it can be demonstrated from Table 7 that among the three variables of *GDP*, population and income, only the variable *GDP* is significant at the 10% level, and the coefficients is 0.1433. These results may probably be due to the expansion in economic level, which may encourage the concentration of high-quality resources to the one-airport city, and which may further lead to an increase in airport traffic demand which will improve the operational efficiency of the airport. The positive effect of regional *GDP* on an airport's efficiency was also reported in the study of [12,38].

In terms of spillover effects, the coefficient of the hinterland population is 0.0881 at the 1% significant level. The coefficient of income is 0.0457 at the 10% significant level. This indicates that an increase in population and income of neighboring airports also drives the operational efficiency of regional airports. A reasonable explanation for this is due to the proximity of airports in the multi-airport region, the existence of the hinterland crossover phenomenon and the mobility of passengers between airports. Thus, the increase in the number of people and income in the hinterland will not only increase the traffic of the local airport; it will also spill over to other airports in the region, which is conducive to the synergistic improvement in the efficiency of the whole multi-airport region. In addition, from Table 7, it can be seen that the coefficient of the number of regular flights and the capacity utilization is negative, which means that a one log unit increase in the number of regular flights, or in the capacity utilization, leads to statistically significant negative spillover effects on airport efficiency. Airports with multiple flight options to the same destination within the multi-airport region generally attract more passengers. In addition, the airport capacity utilization may be considered as a proxy for demand level, and high utilization implies the situation of high passenger demand. Thus, the concentration of passengers to one airport in the region will inevitably have a negative impact on neighboring airports, which also will lead to an increase in the competitive relationship between airports in the multi-airport region. This is similar to the previous study that different elements of airport utility such as airport destination, capacity and flight are key drivers of airport choice [28].

6. Conclusions and Implications

6.1. Conclusions

Airports are commonly regarded as an important infrastructure for the local municipality to promote regional economic development, while the improvements in airport efficiency and competitiveness are considered critical for airport management. This paper uses the super-SBM method to measure the operational efficiency of airports in four major cities in the Yangtze River Delta region during 2009–2018. The results were then analyzed for different periods and regions, and finally, the spatial Durbin model was applied to explore the factors influencing the operational efficiency of the airports in two dimensions: airport physical characteristics and regional characteristics. The conclusions are as follows.

During the examination period, the mean super-SBM efficiency score of the YRD region airports will increase from 1.075 in 2009 to 1.570 in 2018; thus, the overall operational efficiency of airports in the YRD region is on the rise. Among them, the Shanghai airport has the highest efficiency value, which indicates its key role played in the YRD region. However, as its capacity gradually became over-saturated, its efficiency value declined after 2013, which further led to a decline in the average efficiency growth rate in the YRD region. In addition, the efficiency values of Hangzhou and Nanjing airports are less than Shanghai, but they showed a steady upward trend and had different degrees of operating space. In terms of the efficiency growth rate, the growth rates of efficiency scores in the Hangzhou and Nanjing airports were huge, and at these rates, these two airports will surpass Shanghai airport in a few years.

The global Moran′s I of airport operational efficiency in the YRD region is generally in the range of -0.2 to -0.4 ($p \leq 0.01$), indicating that the overall efficiency shows negative spatial autocorrelation and a strong spatial aggregation effect. The global Moran′s I fluctuates and decreases over time, indicating that the spatial correlation gradually decreases over time.

The airport operational efficiency of the YRD region has a negative spatial spillover effect, indicating that the airport operational efficiency among neighboring airports has an evolutionary characteristic of competitive interaction. In terms of the direct effects of the influencing factors, the number of regular flights, the number of airport destinations and the capacity utilization of the local airports have significant positive effects on the operational efficiency of this airport. In terms of regional characteristics, local *GDP* also appears as a significant positive effect on airport operational efficiency. In terms of spillover effects, the number of regular flights and capacity utilization of neighboring airports negatively affect the operational efficiency of regional airports, while the population and income of the hinterland show a positive effect.

6.2. Implications

In the context of the new national airport master plan, which has just been implemented, this paper argues that a sustainable development plans for a multi-airport region should be developed, and different airports in the region should be positioned differently. Shanghai airport, as an international hub airport, is the most efficient airport in the sample. In fact, Shanghai airport is the biggest passenger and cargo hub of the YRD region as its passenger and cargo volume per year outnumbered other rivals. The leading position of Shanghai airport is thanks to its strategic geographic location, superb connectivity, highly developed facilities, adequate passenger and cargo handling capacity and free port status. However, the efficiency scores of Shanghai airport declined since 2013 as its airport capacity gradually saturated. Facing the growing air demand in the YRD region, increasing traffic will not significantly improve Shanghai airport's efficiency but will greatly improve the efficiency of other small airports [63]. In addition, the efficiency growth rates of Nanjing airport and Hangzhou airport are at the high level, which means these airports still have potentials of producing more outcomes. Thus, to improve the overall efficiency of a multi-airport region, the single airport policy is not practical; it should be developing collaboration between these airports in the region to achieve sustainable development.

In addition, the spatial spillover effect is fully utilized by focusing on the key factors influencing the operational efficiency of the airports that could help airport managers and policy makers better understand ways for improving their efficiencies [37,38]. For example, airport authorities and regional operators in the YRD region should further recognize the important role of airport hinterland populations and the differences in their behavioral choices. As people′s living standards improve, aviation demand is growing, with a large percentage of travelers traveling for leisure; fare is key factor of their travel choices. Nanjing Airport, Hangzhou Airport and Ningbo Airport should make great efforts to introduce low-cost airlines to reduce airport operating costs, tap more potential aviation demand and increase their market share. Considering that time is important for business travelers, they should also make an effort to promote air-rail patterns to maintain more seamless air connectivity to air travels, especially in smaller regions or remote aeras. The convenience of access to the airport not only saves travelers time, but also enhances the role of airports in supporting regional economic development. In addition, the number of regular airport flights and airport capacity utilization have a greater impact on airport operational efficiency than other independent variables. However, the share of international traffic has a negative impact on airport efficiency as it calls for sophisticated infrastructure and operational complexity [32,64]. Thus, increasing the frequency of busy short-haul routes and expanding the capacity available for flights of Nanjing and Hangzhou airports while maintaining the international share of Shanghai airport are important strategies for the development of the YRD multi-airport region. This will not only relieve the pressure on the operation of large airports, but also alleviate flight delays of passengers′ concerns by increasing the frequency of flights from smaller airports. This is useful and instructive for the development of airport management and aviation services.

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