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# Determining Spatial Relationships between Airports and Local Economy from Competitiveness Perspective: A Case Study of Airports in China

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**Abstract:** The intent of this research is to present an investigation into whether spatial relationships in China's airports are primarily characterised by competition or complementarity; accordingly, this is approached from the perspectives of passenger and cargo traffic. This research also focused on two issues: The first is the spatial Durbin model (SDM), which is used to judge the competition or complementarity among airports with spatial dependence as an indicator. Second, considering that airport activities may be affected by neighbouring cities due to the externality of economic development, the spillover effects of different geo-economic factors at the city level are calculated. Through the utilisation of a spatial Durbin model and yearly airport traffic data for 34 Chinese airports between 2007 and 2019, it was found that the nature of spatial relationships tends to differ regarding passengers and cargo traffic. Concerning passenger traffic, airports in China are mainly characterised by complementarity and are competitive regarding cargo traffic. This study also indicates that the geo-economic factors of central cities (Beijing, Shanghai, and Guangzhou) can affect the spatial relationship between China's airports. China's airports are more dependent on the economic development of central cities, and therefore more dependent on the traffic replenishment at China's hub airports. In addition, the validity of the asymmetrical economic weight matrix illustrates that after controlling the exogenous interaction effects between the independent variables and dependent variables, the difference of regional economic development and airport traffic does lead to endogenous interaction effects among China's airports.

**Keywords:** airports; China; spatial Durbin model; spillover effect analysis; urban economics

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## 1. Introduction

Decision-makers choosing a particular airport from a group of viable alternatives depends on whether air transport is more efficient than other modes of transport. This process also includes other airports being considered as relevant alternatives. The airport choice for the decision-makers is affected by some restrictions, such as time distance [1], number of connections offered [2,3], and the ticket price [4]. These restrictions, combined with high barriers to entry in the airline industry, may have dampened fierce competition between airports. However, as many airports have developed a wide range of business development competencies—particularly in marketing, route development, and delivering service quality [5]—this limitation is gradually being weakened, and competition among airports is becoming increasingly fierce. In such cases, airport substitution often occurs. For example, passengers may travel to more distant airports to enjoy lower fares and sometimes better airline service [6]. Moreover, the development of intermodal logistics chains and well-developed public transport systems allows airports to interact or compete to achieve wider network coverage while preventing market share leakage to neighbouring airports.

The relationship between airports is likely to be complex and may not always be defined by competition. One reason for the low level of competition is that airports may prefer to be motivated by cooperation rather than competition. Airports are part of a larger system, and each airport is a node connected by an airline to another node. The airport provides supplementary services to all airports to which it is connected [7]. The reasons for this cooperation between airports might be from objective conditions, such as the economic scale of the airport's hinterlands, the location of the airport, and so on. Within an area, some international routes may be concentrated in a limited number of hub airports, and frequent transfer promotes complementarity between airports. Simultaneously, efforts have been made to form a hub-and-spoke network between airports of different sizes to reduce the overall costs of air travel, increase travel demand, and improve transport efficiency [8]. Moreover, fierce competition between airports in close proximity may reduce the efficiency of each one [9], which may promote cooperation between them.

Many empirical models have been used to examine the competition and complementarity between airports, including the conditional logit model, multinomial logit (MNL) model, Ramsey Regression Equation Specification Error Test (RESET), ordinary least squares (OLS), demand functions, stochastic frontier analysis (SFA), gravity equation, decision-making model, Herfindahl–Hirschmann Index (HHI), cumulative prospect theory model, Nash equilibrium, cost function, efficiency model, and an airline network model. These models assist in the analysis of the competition and complementarity between airports from the perspectives of cost, demand, customer psychology, efficiency, and ownership. In addition, spatial characteristics are considered as a key to understanding airport relationships [8–10]. Furthermore, [11] revealed the obvious interaction between spatially adjacent airports, which depends on the competition and cooperation mechanisms between airports, and this influence varies in the short and long term. Notably, some recent studies also pay attention to airport relationships via spatial econometrics—but the number is limited. Another study [1] proposed a spatial econometric model and found that there was a competitive relationship between airports in China's PRD areas, which is represented by the presence of negative spatial dependence in airport capacity.

According to statistics from the World Bank open data, China's airport system has made significant progress in terms of passenger traffic over the past decades [12]. As more and more people travel by air, China's airport network presents an obvious hub-and-spoke structure, gradually developing into a national airport network with Beijing, Shanghai, and Guangzhou as large hub airports, other provincial capitals and developed city airports as regional trunk airports, and other small- and medium-sized city airports as branch airports. In recent years, the China regional trunk airports have added domestic and international routes to attract transit passenger traffic. This may lead to increased competition between these particular hub-and-spoke airports. Therefore, it is necessary to evaluate the relationship between Chinese airports from different perspectives and the promotion of coordinated development among airports. So far, there have been few studies on the relationships among the major airports in China, and all the existing studies only focused on a specific region. The study that comes close is [1], which explored the competition between airports in the Pearl River Delta region using a spatial econometric model. On the other hand, in the existing studies, the relationships between Chinese airports were mostly measured with a single index, such as airport capacity and passenger throughput. Since the factors influencing the passenger and cargo traffic of airports are very different [13–16], the relationships between airports reflected in passenger and cargo traffic are also different. Therefore, this study presents an analysis of the relationships among Chinese airports from the perspective of passenger and cargo traffic, respectively.

This study is based on data derived from 34 major airports and their host cities in China. There was an investigation into the relationships among Chinese airports from the perspectives of passenger and cargo traffic. It also focused on two issues, the first of which is the spatial dependence model, which is used to judge the competition or complementarity among airports with spatial dependence as an indicator. Second, considering that airport activities may be affected by neighbouring cities due to the externality of economic development, the spillover effect of different geo-economic factors at the city level was analysed using the spatial Durbin model. Furthermore, different spatial weight matrices—especially the asymmetrical spatial weight matrices—were used to test the robustness of the results. This study makes an empirical contribution by providing a reasonable explanation of the interrelationship of airports in China, thereby assisting in the formation of rational airport operation plans and perfecting the corresponding policy of coordinated development of China's airports. The rest of this paper is organised as follows: Section 2 presents a literature review of the status quo; Section 3 discusses the data and main methodological issues; and Section 4 presents the main empirical results. Finally, Section 5 concludes the paper, together with policy implications.

## 2. Literature Review

There has been considerable research on the relationship between airports. In previous studies, a variety of methodological approaches have been used in the analysis of interrelationships in the airport sector.

In many cases, the quantitative analysis models were used to explore the passenger's or the airline's preference of airport choice in a multiairport region. A study using a conditional logit model stressed the importance of the barrier effect of national borders on airport choice [17]. In another research study, [18] proposed a multilayer model of competition and cooperation effects. The estimated results showed that competition and cooperation have both positive and negative effects as per the distance among airports. Game theory has also been used to study the inter-relationships among airports. In another study, [19] used game theory to simulate the setting of landing fees for airports in the hub-and-spoke network, and the results showed that in order to maximise its welfare, airports in the network should set joint profits, thus maximising landing fees instead of landing fees that maximise profits at each airport.

Following a large volume of literature on the inter-relationships among airports, several contributions have also studied the possible correlations between airport relationships and airport efficiency. Using the HHI, [8] found that the scheme with two hub airports and eight spoke airports can improve the efficiency of cargo transportation on Sumatra Island. Other researchers, [9], discovered competition has different effects on the technical efficiency level of airports depending on the cut-off distance considered—accordingly, 250 km was a turning point.

Some studies explained the airport relationships from the perspective of spatial linkage and heterogeneity. Airports are a typical point infrastructure that can exist in point-to-point or hub-and-spoke transportation networks [20]. Even though airports are far apart, they are very close to each other if there are a substantial number of air flights connecting them. So, an airport can produce network externalities to all other connected airports, even though they are not close to each other [21]. In this context, spatial linkages take into account the interaction and diffusion effects between local and nearby airports. Changes to an attribute in a given airport city can jointly affect the airport activities of the city and also its neighbouring cities through its spatial linkages. When the traffic demand of an airport depends on the traffic demand of its nearby airports, there is spatial interaction between them [1]. Spatial linkages also reveal some alliance or partnership between airlines and airports that will generate positive passenger growth.

Spatial heterogeneity is the main reason for the difference of attributes of cities where airports are located. It can be seen as a function of geo-economic factors and service-related factors [1]. The tendency for an airport to be regarded by a user (e.g., airline, passenger, or shipper) as a best choice among a set of alternative options is likely determined by the distance separating them and the ease of access to the airport [5]. Furthermore, not only geographical distance, but also socio-economic distance affects the options of airport users, which is why some international airlines are mainly concentrated in central cities with large economies of scale. Another researcher, [1], noted in his research that in the Pearl River Delta region, the competition between airports is influenced by Hong Kong's immigration control policies. Therefore, spatial heterogeneity factors associated with airport characteristics and airport cities need to be taken into account when analysing the possible interdependence among airports. Moreover, spatial heterogeneity is also closely related to competition between airports. Competition reflects people's choices of different airports in the face of the heterogeneity of airport attributes and promotes passenger flow in a multiairport area [1].

For a large set of airports, spatial econometric theory provides convenient ways to model relationships based on geographic and economic data. In general, when the spatial attributes of airports have been determined, the multivariate regression models with various spatial dependences can be constructed to analyse the mutual influences they have on each other. However, only limited research has attempted to model airport relationships using spatial econometric models, a field that has garnered an increasing amount of attention in applied economics [22]. Based on spatial stochastic frontier models developed by [23,24] used an inverse distances matrix to analyse the spatial heterogeneity of 365 airports in Europe in 2011 and found that spatial heterogeneity had significant influence on airport efficiency and productivity estimation. Using the same model, [9], for the year 2015, considered a sample of 206 airports located in Europe, North America, and Pacific Asia. Competition has an important effect on airport efficiency levels, which vary depending on the geographical distance among airports. A survey was conducted by [10] involving the congestion spillover effect of London Heathrow Airport (LHR) on other airports in the UK. It suggested significant congestion spillover effects from LHR to other airports located in London, and the extensive spatial impact of Heathrow can even reach the spatially more distant Manchester and Birmingham airports. In another study, [1] proposed a SDPMSE model with inverse travel time and distance matrix to analyse the relationship among the four major airports in the Pearl River Delta region from the perspective of airport capacity. This study found a significant competitive relationship between airports in the Pearl River Delta region, and the spillover effects between airports are different. In previous studies, all the models used a relatively simple symmetrical spatial weight matrix, which could not reflect the strength gap between airports in the model construction. Specifically, in the hub-and-spoke network, although the distance between two airports is the same, the hub airports have obviously stronger spillover effect on the spoke ones. Therefore, the application of the asymmetric economic geographic weight matrix [25,26] may more accurately reflect the interdependence of spatial elements.

Most of the past research on airport relationships is limited to two airports or within a multiairport region, and the research indices are mostly single ones, such as passenger traffic and airport capacity. Moreover, most of the studies analysing the relationship between airports focus on airport passenger traffic and its derived variables, without considering the impact of cargo traffic. In recent years, more and more studies have been conducted on the economic impact of air cargo traffic. Many of these have shown that worldwide air cargo traffic growth is rapid, and its relationship with urban economic development is very close. Another study, [13], found a strong relationship between air cargo traffic and a city's service and manufacturing industries in California; moreover, the total volume of air cargo at California's airports is growing faster than the population. Yet other researchers, [16], noted that Chinese air freight currently mainly flows through a relatively small network compared to passenger traffic. However, China's air freight industry is set to grow faster than the overall economy with major airports in the economic zone being well positioned to develop into major cargo gateways hubs. In view of the rapid development of airport freight in China, this study also considers the spatial relationship between airports from the perspective of cargo traffic.

This study uses the spatial econometric model in accordance with the theoretical basis and airport relationship background of different studies. Additionally, the relationship between China's airports is analysed from the perspective of passenger and cargo traffic, respectively. This study aims to examine the spatial relationships between China's airports at a country level. Considering the differences of regional geo-economic factors (spatial heterogeneity), this study also constructs an asymmetric spatial weight matrix to estimate the spatial relationship and the spillover effects of each geo-economic factor.

## 3. Methodology

There may be several reasons to include spatial parameters in economic models. For example, the economic growth of a country or region depends not only on income levels, population, technology levels, and other factors within an economy, but also on these variables in neighbouring economies, which indicates a natural spatial externality. Another reason spatial econometric models are used is that there are unobservable effects that cannot be directly included in the model but which can be approximated using geographic data in conjunction with economic data. Accordingly, this is the main reason for using the spatial model in this paper: it is assumed that the alternative airports in the vicinity are better able to serve the target hinterland than those in the remote areas, and the hub airports may have a greater spillover effect on the branch airports.

The spatial econometric model mainly determines the attributes of spatial relations through the spatial dependence of dependent variables in different regions. This is mainly due to two reasons. First, there is direct interaction between dependent variables. In addition, the spatial model can consider the omitted variable in the model. Therefore, if we consider the spatial dependencies (i.e., spatial lag terms) between airport traffic, we can capture these omitted variables. The use of distance weight matrix and economic weight matrix modelling can consider the spatial heterogeneity and economic differences of geographical units, which contain many immeasurable omitted variables. Of course, spatial econometric models cannot consider all influencing factors.

The spatial relationship between airports and the local economy are likely to be determined by the geographic distance or economic distance between them. Therefore, distance can be used to describe the strength of the relationship [21]. On the other hand, economic growth depends not only on the income level, population, technology level, and other factors within an economy, but also on these variables in neighbouring economies, which indicates a natural spatial externality [21]. This is perhaps the most important reason for researchers to use spatial econometric models when studying the impact of infrastructure on regional economies.

The spatial relationship between major airports in China is classified as competitive or complementary, which is also the most used way to describe the relationship between airports in the literature. In this paper, the term competition or complementarity between airports is operationalized in terms of spatial dependency of demand for passenger and cargo traffic. The level of complementarity is defined as the strength of the positive spatial dependence of demand for air traffic between an airport and its adjacent airports—in which case, airports are interdependent. In contrast, competition is defined as the opposite of complementarity. So, the level of competition is defined as the intensity of negative spatial dependence. The basic assumption of this approach is that spatial dependence captures the extent to which airports are considered as alternatives.

### *3.1. Model Specification*

The panel data model can be enriched to account for possible spatial effects among different units. When such spatial interaction effects are included, the panel data model becomes:

$$Y_{it} = \delta W_{ij} Y_{it} + \beta X_{it} + \rho W_{ij} X_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

$$\varepsilon_{it} = \lambda W_{ij} \varepsilon_{it} + \nu_{it} \quad (2)$$

where $t$ is the time dimension, and $i$ denotes the index for cross-section. $Y_{it}$ is the dependent variable (airport traffic) at $i$ and $t$. $X_{it}$ is an $it \times k$ vector of observations on independent variables. $\beta$ is a $k \times 1$ vector of unknown parameters, and $W$ is the spatial weight matrix with each element $W_{ij}$ ($I \neq j$), which explains the interaction between different airport cities. $\varepsilon_{it}$ is an error term with *0* mean and variance $\sigma^2$, and $\mu_i$ denotes regional effect (time invariant factor), indicating the regional heterogeneity of macroeconomic variables.

According to Equations (1) and (2), the $\delta$ is called the spatial autoregressive coefficient with which the positive or negative spatial interaction between different airports can be identified—namely, complementarity or competition. $\rho$ represents the spillover effects of the spatially lagged independent variables to dependent variables. These terms control for possible correlation between dependent variables in one region and independent variables in adjacent regions. $\lambda$ denotes the spatial autocorrelation coefficient of the error term. This term can reflect the unobserved shocks following a spatial pattern. The spatial Durbin model (SDM) contains spatial lagged terms of dependent variables and independent variables. Rather than ignore spatial dependencies in disturbances, SDM provides a different type of specification for error dependence [27]. Hence, it was decided that SDM be considered to analyse the spatial spillover effect.

When the equation contains a spatial lag of the dependent variable, parameter estimation cannot be regarded as a marginal effect. Therefore, to solve this problem, [27] proposed the decomposition of the influence coefficient and further explored the influence and its mechanism by using the spatial regression model partial differential method. They computed three different marginal effects: the direct effect, which measures the impact of independent variables on local dependent variables. Such an effect is akin to the regression coefficient; the indirect effect refers to the spillover effect of independent variables of one region on the dependent variables of other regions; and the total effect, which is the sum of direct and indirect effects [28]. To calculate the spillover effects, we can rewrite the reduced form of Model 1:

$$Y_{it} = \left(I - \delta W_{ij}\right)^{-1}\left(\beta X_{it} + \rho W_{ij} X_{it}\right) + \left(I - \delta W_{ij}\right)^{-1}\left(\mu_i + \varepsilon_{it}\right) \tag{3}$$

According to Formula (3), the partial derivative matrix of $N$ space units of dependent variable $Y_{it}$ with respect to explanatory variable $x_k$ can be solved using the following formula:

$$\begin{pmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdots & \frac{\partial y_1}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial x_{1k}} & \cdots & \frac{\partial y_N}{\partial x_{Nk}} \end{pmatrix} = \left(I - \delta W_{ij}\right)^{-1} \begin{pmatrix} \beta_k & \cdots & \rho_k W_{1N} \\ \vdots & \ddots & \vdots \\ \rho_k W_{N1} & \cdots & \beta_k \end{pmatrix} \tag{4}$$

According to Formula (4), the mean value of diagonal elements in the matrix is the direct effect, and the mean value of off-diagonal elements is the indirect effect (spillover effect). In particular, the sum of nondiagonal elements in each column of the matrix represents the average influence of the change of independent variable ($x_k$) in one region on the dependent variable in other regions.

Referring to relevant literature, we propose the following variables to establish our model. All the data are defined at the city level.

First, many studies estimated the demand for airport services, approximated as the yearly flow of passenger and cargo such as [29]. This study applied two measures of airport activity, including air passenger traffic (PA) and air cargo traffic (CA), which serve as the critical dependent variables to estimate the spatial dependence of China's airport services. Several control variables are also applied in this research. Household income and gross domestic product (GDP) were found to have a positive impact on air travel demand [1]. In this study, per capita GDP (GDP) is presented as a control variable to quantify the development levels of the regional economy [16]. Furthermore, the amount of aviation employment (AE) of each city is employed as the control variable in our analysis; principally, this corresponds to the labour variables in a production function [29].

When analysing the demand relationships between airports, it must be kept in mind that services such as handling cargo or transport have no value of their own; instead, they are inputs to production of other things [30]. The study [31] found that in the case of leisure trips, the behaviour of passengers is extremely relevant in the context of airport competition. Based on this scenario, we can assume that the demand for passenger transport is derived from regional tourism demand. In this paper, in order to account for the correlation in passenger traffic among airports that is due to increases in tourism, variables corresponding to regional tourism are included as control variables [32]. Since foreign tourists generally use air transport, we use an airport city's tourism foreign exchange income (FTI) to measure the tourism factor. Furthermore, the total retail sales of social consumer goods (CO) can reflect the living standard and consumption ability of residents in a region and have a great impact on the airport traffic [33]. In this study, the total retail sales of social consumer goods is used as the control variable to reveal the impact of residents' consumption level on airport cargo traffic. In addition, demand for airport services may be related to the level of shipping costs. To illustrate this, the price of crude petroleum (OIL) is included in the estimation function as an approximation for shipping cost [1]. Combining the framework outlined in Equation (1) with the variables, the empirical model is formalised as:

$$\begin{aligned} lnPA_{it} = \delta W_{ij} lnPA_{it} + \beta_1 lnGDP_{it} + \beta_2 lnAE_{it} + \beta_3 lnFTI_{it} + \beta_4 lnOIL_t \\ + \rho_1 W_{ij} lnGDP_{it} + \rho_2 W_{ij} lnAE_{it} + \rho_3 W_{ij} lnFTI_{it} + \mu_i + \varepsilon_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} lnCA_{it} = \delta W_{ij} lnCA_{it} + \beta_1 lnGDP_{it} + \beta_2 lnAE_{it} + \beta_3 lnCO_{it} + \beta_4 lnOIL_t \\ + \rho_1 W_{ij} lnGDP_{it} + \rho_2 W_{ij} lnAE_{it} + \rho_3 W_{ij} lnCO_{it} + \mu_i + \varepsilon_{it} \end{aligned} \tag{6}$$

Models 5 and 6 represent the SDM of airport passenger and cargo traffic, respectively. Where *i, j* represents different airports, and $W_{ij}$ means the 34 × 34 spatial weights matrix. The dependent variable is the log of passenger and cargo traffic. The spatial lag of the dependent variable can be interpreted as proximity weighted value of the passenger and cargo traffic in neighbouring airports to airport *i*. $\delta$ is the spatial autocorrelation coefficient, and its coefficient and significance will directly affect the existence of spatial interactions among different Chinese airports. In Models 5 and 6, $\beta$ and $\rho$ explain the main effect and the spillover effect of each control variable to the dependent variable.

The spatially lagged dependent variables are different from the serial lags and are, by definition, related to the error term [28]; this is because neighbour relationships are two-directional. This leads to endogeneity problems, rendering the OLS biased and inconsistent. Suggested estimation approaches are based on generalised method of moments (GMM), maximum likelihood (ML), and Quasi maximum likelihood (QML) [28]. GMM estimates may cause coefficient estimates to fall outside the parameter space, while ML estimates rely on the assumption that disturbance terms obey a normal distribution. Therefore, QML estimation has obvious advantages in comparison [28]. This study utilises a quasi-maximum likelihood estimate (QML) proposed by [34], which explicitly takes the structural form of the endogeneity of the spatially lagged dependent variable into account.

### 3.2. Spatial Weighting Matrix

In Models 5 and 6, $W_{ij}$ represents an $N \times N$ table spatial weight matrix, which describes the spatial organisation of observed units. The robustness of the results is checked by different weighting matrices. When analysing regional units such as provinces and cities, $d_{ij}$ between adjacent units can be set to 1 or 0 if it is not adjacent. However, regional units such as airports are not suitable for the above construction methods, because airports are discrete points. This peculiar geographic structural element of airports may lead to an unreliable weights matrix when either contiguity or *k*-nearest criteria is applied. In this paper, therefore, we first chose to employ a spatial weight matrix ($W_1$) of the inverse of squared distances between every two airports, given that the correlation between two spatial units should converge to zero as the distance separating them infinitely increases. Here, $d_{ij}$ represents the distance between ports *i* and *j*, and ${d_{ij}}^{-1}$ is the reciprocal of $d_{ij}$—that is, the inverse distance between two regions. Considering the competitive impact of high-speed rail on the aviation network and the impact of China's high-speed rail speeding up, the threshold distance of the route network is set at 800 km [35]. For ease of interpretation, it is a common practice to row normalise the weight matrix, which ensures that the weighting operation can be interpreted as an averaging of adjacent values [28].

$$W_1 = \begin{cases} 0, & d_{ij} \leq 800 \\ d_{ij}^{-2}, & d_{ij} > 800 \end{cases} \tag{7}$$

In the distance matrix, only the distance between adjacent regions is used to construct the matrix. If the distance is the same, the relationship between adjacent regions is simply regarded as the same. In fact, despite the same distances, the economic inter-relationships between adjacent regions cannot be exactly the same. In order to solve this problem, an asymmetrical matrix is still considered in this study to reflect the differences between different airports. The economic scale of the airport hinterland has an important influence on the airport. China's large hub airports are located near the central cities. Therefore, based on the inverse distance matrix, the economic weight matrix ($W_2$) is constructed to reflect the difference of geo-economic factors of airport hinterland. This matrix contains not only distance information but also economic information, and economic information also has directivity.

$$W_2 = W_1 \times diag\left(\frac{GDP_1}{GDP_a}, \ldots, \frac{GDP_n}{GDP_a}\right) \tag{8}$$

where $diag\ (GDP_i/GDP_a)$ represents a diagonal matrix, and $GDP_a$ represents the average GDP of all airport hinterlands. In $W_2$, the mutual effects of two regions are not identical (i.e., $W_{ij} \neq W_{ji}$). The economic information contained in this asymmetric matrix is directional, which reflects the difference of mutual influence between any two airports [25].

When the passenger or cargo traffic of airport $i$ is larger than that of airport $j$, the spatial spillovers of airport $i$ should also be relatively larger. This asymmetry can reflect the difference of mutual influence between any two airports. Therefore, Matrices 3 and 4 are established in this study to reflect the hub-and-spoke structure between airports. In this asymmetric matrix, it is assumed that central hub airports with large passenger and cargo traffic have stronger spillover effects on branch airports.

$$W_3 = W_1 \times diag\left(\frac{PA_1}{PA_a}, \ldots, \frac{PA_n}{PA_a}\right) \tag{9}$$

$$W_4 = W_1 \times diag\left(\frac{CA_1}{CA_a}, \ldots, \frac{CA_n}{CA_a}\right) \tag{10}$$

In the modelling of the spatial panel model, it has become a common practice to investigate whether the estimation results are sensitive to the choice of a different spatial weight matrix [36]. In this study, we tested different spatial weight matrices in the SDM. Unlike previous studies, this study addresses the presence of the spatial interaction effect by accounting for both symmetric and asymmetric matrices.

### 3.3. Data Description

The data used in this study were derived from several databanks. The data of five control variables come from the database of the China Economic Net (2007–2019). The descriptive statistical results are shown in Table 1.

The PA and CA data are obtained from the Civil Aviation Administration of China (CAAC) publication of the Civil Aviation Airport Production Statistics Bulletin. The PA and CA data used in this study included both domestic and international operations. The CA includes air cargo using aircraft belly space or lower-hold and air freight using special cargo aircraft. All variables were converted to a natural logarithm form to reduce possible heteroscedasticity. Based on the availability and integrity of the data, this research intercepted 34 airports that were located in 25 provincial capitals and 9 populous cities in mainland China. The airports of interest are ranked among the top 40 in China in terms of passenger-cargo throughput. In addition, because of the incomplete data, Lhasa, the capital city of Tibet, is taken out of the analysis. In the case of Shanghai, two airports are considered. Therefore, a balanced panel data set is constructed with 442 observations.

**Table 1.** Definition of the variables.

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| *PA* (passenger throughput, people) | $1.93 \times 10^7$ | $1.81 \times 10^7$ | 802,167 | $1.00 \times 10^8$ |
| *CA* (cargo and mail throughput, ton) | 352,219 | 624,724 | 5219 | 3,824,280 |
| *GDP* (GDP per capita, $10^4$ yuan/person) | 9.86 | 8.25 | 1.45 | 62.13 |
| *AE* (aviation employment, people) | 18,148 | 25,971.3 | 142 | 134,402 |
| *FTI* (international tourism receipts, $10^6$ dollar) | 2666.37 | 3814.14 | 3.00 | 20,521.31 |
| *CON* (total retail sales of consumer goods, $10^8$ yuan) | 3016.21 | 2778.34 | 128.10 | 15,847.60 |
| *OIL* (price of crude petroleum, \$/barrel) | 79.10 | 23.06 | 44.04 | 111.96 |

## 4. Empirical Analysis

### *4.1. Moran's I Index*

At first, a Moran's I index was used to determine whether there is overall spatial dependence among the observed airports. Table 2 shows that the Moran's I values of passenger traffic based on $W_1$, $W_2$, and $W_3$ are 0.652, 0.651, and 0.664, respectively, with $p$-values significant at 10% level for the whole panel period. The Moran's I values of passenger traffic show significant positive spatial correlation; that is, the airports with high passenger flow are bound to gather with a large number of airports with high passenger flow. Specifically, Table 2 shows that the Moran's I value in $W_3$ perform significantly larger spatial correlations than that of the other two matrices. Therefore, spatial dependence of passenger traffic has a significant improvement after controlling the traffic imbalance. For cargo traffic, the Moran's I values using $W_1$, $W_2$, and $W_4$ are 0.805, 0.825, and 0.843, respectively, with $p$-values significant at 10% level for the whole panel period. The Moran's I value of cargo traffic reflects the same agglomeration effect as that of passenger traffic.

**Table 2.** Panel of the global Moran's I values of passenger and cargo traffic.

| 2007–2019 | Passenger | | Cargo | | | |
|---|---|---|---|---|---|---|
| | $W_1$ | $W_2$ | $W_3$ | $W_1$ | $W_2$ | $W_4$ |
| Moran's I values | 0.652 (<0.001) | 0.651 (<0.001) | 0.664 (<0.001) | 0.805 (<0.001) | 0.825 (<0.001) | 0.843 (<0.001) |
| Observations | 442 | 442 | 442 | 442 | 442 | 442 |

Notes: $p$-values in parentheses.

The Moran's I index shows a significant positive value, thus leading to a rejection of the null hypothesis of no spatial dependence in favour of a spatial panel data model that considers the spatial dependence among the outcome variables.

### *4.2. Identification of Spatial Econometric Estimation Methods*

In panel data analysis, the Hausman test is used for model selection, and the null hypothesis of the test is that the preferred model is a random effect rather than a fixed effect [37]. In [38], researchers extended the Hausman test to the spatial panel model. Therefore, in this research, the form of the model is first determined using the Hausman test. In all model specifications, the Hausman test results (Table 3) showed which $p$-values are at least significant at 10% level. The Hausman test reflected the assumption that treats specific effects ($\mu_i$) as random variables as being too restrictive. Therefore, a fixed-effects model was selected for use instead of a random-effects model. Fixed effects may account for time-invariant regional heterogeneity affecting airport traffic, such as that associated with socio-economic conditions and geographical aspects.

**Table 3.** Spatial econometric model test under $W_1$, $W_2$, $W_3$, and $W_4$.

| Contents | Methods | Passenger | | | Cargo | | |
|---|---|---|---|---|---|---|---|
| | | $W_1$ | $W_2$ | $W_3$ | $W_1$ | $W_2$ | $W_4$ |
| SAR and SEM test | LM-lag test | 90.0643 (<0.001) | 79.8795 (<0.001) | 79.0945 (<0.001) | 0.0965 (0.756) | 1.8820 (0.170) | 3.8684 (0.049) |
| | R-LM-lag test | 82.5354 (<0.001) | 115.5380 (<0.001) | 115.0205 (<0.001) | 12.6650 (<0.001) | 6.3369 (0.012) | 6.6095 (0.010) |
| | LM-err test | 11.5006 (0.001) | 0.0068 (0.934) | 0.0551 (0.814) | 39.8250 (<0.001) | 51.8969 (<0.001) | 46.3007 (<0.001) |
| | R-LM-err test | 3.9717 (0.046) | 35.6654 (<0.001) | 35.9811 (<0.001) | 52.3935 (<0.001) | 56.3518 (<0.001) | 49.0418 (<0.001) |
| Hausman test | | 200.99 (<0.001) | 280.11 (<0.001) | 2747.80 (<0.001) | 1473.15 (<0.001) | 45.09 (<0.001) | 174.96 (<0.001) |
| Simplified test of SDM | LR-lag test | 26.74 (<0.001) | 45.00 (<0.001) | 43.92 (<0.001) | 13.64 (0.003) | 26.04 (<0.001) | 29.25 (0.004) |
| | Wald-lag test | 25.84 (<0.001) | 39.80 (<0.001) | 37.53 (<0.001) | 13.78 (0.003) | 26.84 (<0.001) | 30.36 (0.003) |
| | LR-err test | 58.29 (<0.001) | 230.27 (<0.001) | 232.95 (<0.001) | 15.19 (0.002) | 23.70 (<0.001) | 24.12 (0.002) |
| | Wald-err test | 37.80 (<0.001) | 64.37 (<0.001) | 55.66 (<0.001) | 14.58 (0.002) | 23.96 (<0.001) | 24.58 (0.002) |

Notes: *p*-values in parentheses.

The Moran's I test indicates that it is necessary in this analysis to consider an appropriate spatial econometric model. Before the multiple regression analysis, it is necessary to select an appropriate spatial econometric model to accurately reflect the causes of spatial dependence. When choosing the exact form of spatial panel model, the LM test and robust LM test are usually used to first check the model form [28,39]. Table 3 shows that the LM and robust LM statistics of the SAR model have passed the 10% significance test in passenger with different matrices. Robust LM statistics of the SEM also passed the 10% significance test with different matrices, but the LM statistics did not pass the significance test with $W_2$ and $W_3$. This shows that the SAR model may be better than the SEM, and it furthermore confirms that the influence of these factors is spatially dependent. On the contrary, LM and robust LM statistics of the SEM model have passed the 10% significance test in cargo with 3 spatial matrices. However, the LM statistics of the SAR did not pass the significance test with $W_1$ and $W_2$. This result shows that the SEM model may be better than the SAR.

Although the LM and robust LM test statistics confirm that the SAR is better in passenger and SEM is better in cargo, a more generalised SDM needs to be further established [28], and a better model type should be selected through the Wald and LR tests. Wald and LR tests are used to test the hypotheses $H_0$: $\rho = 0$ and $H_0$: $\rho + \delta\beta = 0$. Table 3 shows that in passenger and cargo with different matrices, the Wald and LR statistics of the SDM simplified to the SAR model passed the significance test of the 10% level, and the Wald and LR statistics of the SDM, simplified to the SEM, passed the significance test of 10% level, indicating that the SDM cannot be simplified to the SAR model or the SEM. Accordingly, the SDM must be adopted instead of the SAR and SEM.

### 4.3. Spatial Regression Analysis

Table 4 presents the autoregressive coefficients of the SDM for passenger and cargo traffic with a different spatial weight matrix.

The values of the spatial autoregressive coefficient $\delta$ of passenger with $W_1$, $W_2$, and $W_3$ are all significantly positive below the level of 10%. A positive $\delta$ can be interpreted as a complementary effect. For instance, under $W_1$, the $\delta$ in the SDM is 0.538, which indicates that the passenger traffic of a particular airport is increased by 1%, which will drive the average level of passenger traffic in the neighbouring airports to increase by about 0.538%. Therefore, the passenger traffic of China's airports shows a good mutually driven aggregation effect. In terms of cargo traffic, the parameter estimate, $\delta$, of the spatially lagged cargo traffic, is negative and statistically significant with $W_2$, and $W_4$. A negative spatial dependence would imply that the cargo traffic of an airport is negatively related to the cargo traffic level of its neighbouring airports. For instance, under the $W_1$, the delta coefficient is −0.125, which indicates that the passenger traffic of a particular airport has increased by 1%, which will drive the average level of passenger traffic in the neighbouring airports to decrease by about 0.125%.

**Table 4.** Spatial regression results for the full data model with $W_1$, $W_2$, $W_3$, and $W_4$.

| **Variables** | **Passenger** | | | **Cargo** | | |
|---|---|---|---|---|---|---|
| | $W_1$ | $W_2$ | $W_3$ | $W_1$ | $W_2$ | $W_4$ |
| ln*GDP* | 0.089 * | 0.131 ** | 0.110 ** | 0.221 *** | 0.234 *** | 0.224 *** |
| | (1.67) | (2.45) | (2.08) | (3.42) | (3.66) | (3.58) |
| ln*AE* | 0.050 *** | 0.047 *** | 0.045 ** | 0.123 *** | 0.125 *** | 0.125 *** |
| | (2.77) | (2.60) | (2.54) | (6.29) | (6.47) | (6.54) |
| ln*OIL* | −0.056 ** | −0.057 ** | −0.061 ** | −0.022 | −0.004 | 0.001 |
| | (−2.14) | (−2.16) | (−2.29) | (−0.67) | (−0.17) | (−0.06) |
| ln*FTI* | 0.095 *** | 0.093 *** | 0.092 *** | - | - | - |
| | (4.36) | (4.25) | (4.24) | | | |
| ln*CON* | - | - | - | 0.261 *** | 0.292 *** | 0.260 *** |
| | | | | (3.64) | (4.03) | (3.67) |
| $W \times$ ln*GDP* | 0.620 *** | 0.900 *** | 0.893 *** | 0.544 | 0.529 | 0.632 ** |
| | (5.05) | (6.27) | (6.03) | (1.36) | (1.53) | (2.44) |
| $W \times$ ln*AE* | −0.078 | −0.085 | −0.092 * | −0.143 ** | −0.233 *** | −0.223 *** |
| | (−1.50) | (−1.41) | (−1.71) | (−2.51) | (−3.52) | (−3.41) |
| $W \times$ ln*FTI* | −0.268 *** | −0.380 *** | −0.336 *** | - | - | - |
| | (−2.80) | (−3.64) | (−3.29) | | | |
| $W \times$ ln*CON* | - | - | - | −0.116 | 0.025 | −0.002 |
| | | | | (−0.33) | (0.08) | (−0.01) |
| $\delta$ | 0.538 *** | 0.414 *** | 0.426 *** | −0.125 | −0.292 ** | −0.298 ** |
| | (6.40) | (3.97) | (3.48) | (−0.91) | (−2.15) | (−2.29) |
| $R^2$ | 0.899 | 0.906 | 0.907 | 0.807 | 0.810 | 0.811 |
| *log-lik* | 226.119 | 226.711 | 227.921 | 196.481 | 202.0717 | 203.525 |

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Notably, the values of $\delta$ with different matrices are generally approximate. It means that the $\delta$ coefficient of the spatially lagged outcome variable (passenger and cargo traffic) under the effects of the endogenous spatial interaction is robust for different spatial weight matrices. In addition, as argued by [40], we can select the spatial weight matrix that exhibits the highest log-likelihood and goodness of fit. In Table 4, the goodness of fit and log-likelihood value corresponding to the asymmetrical spatial weight matrix ($W_2$, $W_3$ and $W_4$) is greater than that of the symmetrical inverse distance matrix ($W_1$). This indicates that the asymmetrical weight matrix may better reflect the spatial heterogeneity. The validity of the asymmetrical economic weight matrix illustrates that after controlling the exogenous interaction effects between the independent variables and dependent variables, the difference of regional economic factor ($W_2$) and airport traffic ($W_3$ and $W_4$) does lead to endogenous interaction effects among China's airports.

The spatial dependence parameters show that there appears to be a difference in interairport relationship characteristics from the perspectives of passenger and cargo traffic. Regarding the passenger traffic, significantly positive spatial dependence is found; in contrast, the cargo traffic exhibits negative spatial dependence. There may be several explanations for such a finding. For passenger traffic, the hub-and-spoke airline network has been basically formed between China's airports since international flights are mainly concentrated at hub airports in large cities, and there are frequent transfers between these airports. Furthermore, Chinese hub airports have more obvious spillover effects on surrounding spoke airports because they are located in central cities. For cargo traffic, the hub-and-spoke airline network between China's airports is not well defined or has yet to be developed. This result is consistent with previous research that suggests that Chinese domestic air freight flows through a relatively small point-to-point network, and the leading airports located in metropolitan regions are yet to become gateway hubs [16]. Therefore, the imperfect freight network is not really providing the cargo traffic for the hub airports in central cities. This result is also partly because airport cargo operations typically have much larger catchments than passenger traffic [16], giving users a wider choice of airports.

However, rising cost levels in central cities have led many companies to move to peripheral cities for lower cost of land, labour, and energy. A lead firm's relocation decision may promote many firms in the same global production network to follow [41]. In this case, spoke airports may significantly increase their air freight, thus intensifying the competition with hub airports. Simultaneously, as Chinese airports are actively building airport economic zones and developing airport-related industries, it also intensifies the competition of Chinese airports in cargo traffic. Moreover, because of the shift of China's economic development focus from the eastern coast to the western inland, the growth rate of cargo traffic of airports in the central and western regions is significantly faster than that of airports in the eastern regions. This trend of economic development makes China's airports competitive with each other in terms of cargo transportation.

### *4.4. Spillover Effect Analysis*

Table 5 reports the estimated direct, indirect, and total effects of each independent variable on passenger and cargo traffic.

**Table 5.** Estimated direct and spillover effects on airport passenger and cargo traffic.

| Variables | Passenger | | | Cargo | | |
|---|---|---|---|---|---|---|
| | $W_1$ | $W_2$ | $W_3$ | $W_1$ | $W_2$ | $W_4$ |
| Direct effect (ln*GDP*) | 0.122 ** (2.28) | 0.162 *** (3.07) | 0.141 *** (2.67) | 0.220 *** (3.37) | 0.230 *** (3.57) | 0.218 *** (3.43) |
| Indirect effect (ln*GDP*) | 1.429 *** (6.02) | 1.618 *** (6.79) | 1.646 *** (5.62) | 0.452 (1.29) | 0.359 (1.38) | 0.446 ** (2.31) |
| Total effect (ln*GDP*) | 1.552 *** (6.42) | 1.780 *** (7.46) | 1.788 *** (6.04) | 0.673 * (1.81) | 0.589 ** (2.11) | 0.665 *** (3.23) |
| Direct effect (ln*AE*) | 0.047 *** (2.69) | 0.045 ** (3.34) | 0.043 ** (2.46) | 0.123 *** (6.29) | 0.128 *** (6.78) | 0.128 *** (6.81) |
| Indirect effect (ln*AE*) | −0.106 (−0.95) | −0.107 (−1.05) | −0.123 (−1.29) | −0.138 *** (−2.69) | −0.210 *** (−3.96) | −0.202 *** (−3.81) |
| Total effect (ln*AE*) | −0.058 (−0.51) | 0.061 (−0.60) | −0.080 (−0.82) | −0.015 (−0.30) | −0.082 (−1.62) | −0.073 (−1.47) |
| Direct effect (ln*OIL*) | −0.058 ** (−2.21) | −0.058 ** (−2.24) | −0.063 ** (−2.38) | −0.019 (−0.60) | −0.002 (−0.08) | 0.0008 (0.03) |
| Indirect effect (ln*OIL*) | −0.064 ** (−1.98) | −0.039 * (−1.83) | −0.045 * (−1.81) | 0.001 (0.29) | 0.0005 (0.08) | −0.0001 (−0.00) |
| Total effect (ln*OIL*) | −0.122 ** (−2.23) | −0.097 ** (−2.29) | −0.108 ** (−2.44) | −0.018 (−0.60) | −0.002 (−0.08) | 0.0007 (0.04) |
| Direct effect (ln*FTI*) | 0.086 *** (4.00) | 0.084 *** (3.93) | 0.084 *** (3.92) | - | - | - |
| Indirect effect (ln*FTI*) | −0.483 ** (−2.00) | −0.592 *** (−2.78) | −0.540 ** (−2.23) | - | - | - |
| Total effect (ln*FTI*) | −0.396 (−1.60) | −0.508 ** (−2.33) | −0.456 ** (−1.83) | - | - | - |
| Direct effect (ln*CON*) | - | - | - | 0.259 *** (3.61) | 0.291 *** (3.95) | 0.260 *** (3.60) |
| Indirect effect (ln*CON*) | - | - | - | −0.128 (−0.42) | −0.044 (−0.18) | −0.066 (−0.39) |
| Total effect (ln*CON*) | - | - | - | −0.131 (0.43) | 0.246 (1.07) | 0.194 (1.20) |

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

The direct and indirect effect of GDP per capita (GDP) on passenger and cargo traffic is significantly positive at 10% level, indicating that the increase in GDP per capita of the city increases the passenger and cargo traffic of local airports. It also increases the passengers and cargo traffic of the airports in surrounding cities. The reason that the direct effect differs from its coefficient estimates in Table 4 is due to the feedback effects (impacts passing through neighbouring regions and back to the regions themselves). Furthermore, the spillover effects tend to dominate the direct impact, as they account for more than 50% of the total effect, thus suggesting that the spillover effect is the main source of regional economic development's contribution to airport traffic growth. In particular, the total effect of per capita GDP on passenger traffic is greater than that of cargo, which reflects that passenger traffic is more closely related to the regional economy. This also reflects the fact that the development of China's airports is dominated by passenger traffic. Furthermore, the total effects are greater than 1, suggesting air passenger growth will outpace the overall economy. This reflects the government's strong support for the aviation industry in China.

The direct effects of AE on airport traffic are significantly positive at 10% level in all results, but indirect effects are significantly negative only on cargo traffic. This means that AE in most cases does have a significant impact on passenger and cargo traffic of local airports. Additionally, from the larger direct effect coefficient, it can be seen that airport cargo traffic is more greatly affected by labour force factors. This can be understood by the fact that air cargo transport is more complex than passenger, and air transport cargo is mostly fresh goods and valuables, so it is more dependent on professional logistics personnel. The negative indirect effect also reflects the importance of professional logistics manpower to airport cargo traffic and reflects the fact that there is competition among China's airports to attract professional logistics manpower.

In terms of passenger traffic, the direct, indirect, and total effect of crude oil price is negative and significant at 10% level, reflecting the opposite relationship with the passenger traffic, which is consistent with previous research [1]. However, in terms of cargo traffic, this factor is not significant. This is probably because cargo transports have largely been an add-on service using aircraft belly space/lower-holds and are less affected by freight rates.

The impact of international tourism receipts of cities (FTI) on airport passenger traffic is also considered in this research. Under each spatial weight matrix, the direct effects of FTI are significantly positive at 10% level, indicating the promotion effect of local tourism development on the increase of airport passenger traffic. The negative indirect effect of this control variable reflects the wide competition among China's cities to attract tourists, which affects passenger traffic in each airport. In other words, the development of tourism in a local city not only promotes the significant growth of passenger traffic in local airports, but also has a negative impact on tourism in neighbouring cities, thus producing a negative spillover effect on the passenger traffic demand of airports in neighbouring cities.

This study considers the impact of total retail sales of consumer goods (CON) on airport cargo traffic. The direct effect of CON is significantly positive at the level of 10% under $W_1$, $W_2$, and $W_4$, while the spillover effects are all insignificantly negative. The direct effect of CON is larger than that of the other two control variables (GDP and AE). This indicates that the increase of consumer demand is a key player in promoting the cargo traffic in local airport.

Table 5 shows the average of direct and indirect effects of each control variable on airport passenger and cargo traffic corresponding to 34 airports. This average value can reflect the overall situation of direct and indirect effects of each control variable but cannot reflect the regional differences that exist in direct and indirect effect. In order to compare the possible differences between direct and indirect effects in different regions, this study calculated the direct and indirect effects corresponding to each region for each control variable, that is, the diagonal element and the column sum of nondiagonal elements in Formula (4). Since the goodness of fit and log-likelihood value of asymmetrical economic weight matrices is greater than the other spatial weight matrix, the direct and indirect effects of each region are calculated based on asymmetrical economic weight matrices

($W_3$ and $W_4$). Since per capita GDP can most comprehensively reflect the macroeconomic operation of a country or region, and it can be seen from Table 5 that the direct and indirect effects of per capita GDP on passenger and cargo traffic are all statistically significant and greater than other control variables, this study focuses on comparing and analysing the direct and indirect effects of per capita GDP in different regions.

Figures 1 and 2 illustrate the direct impact of a one log-unit change of per capita GDP on a specific airport's passenger traffic, as well as the average indirect effect (spillover effect) on other airports' passenger traffic. From the perspective of direct effect, the impact of per capita GDP on airport passenger traffic in China's first-tier cities (Beijing, Shanghai, and Guangzhou) is significantly higher than that of other regions, which indicates that the airport passenger traffic in China's first-tier cities is more strongly correlated with local economic development level. However, in the western region (Yinchuan, Wulumuqi, Xining, etc.), airport passenger traffic is less dependent on local economy than in other parts of China. From the perspective of indirect effect, a one log-unit change of Beijing's per capita GDP has the largest spillover effect on airports' passenger traffic in other regions. The economic growth of Shanghai and Guangzhou, both first-tier cities, also has an obvious spillover effect on airport passenger traffic in other regions. This shows that the economic growth of regional central cities has the most obvious spillover effect on airport passenger traffic, while the economically underdeveloped cities in the central and western regions has difficulty exerting obvious spillover effects on airport passenger traffic.

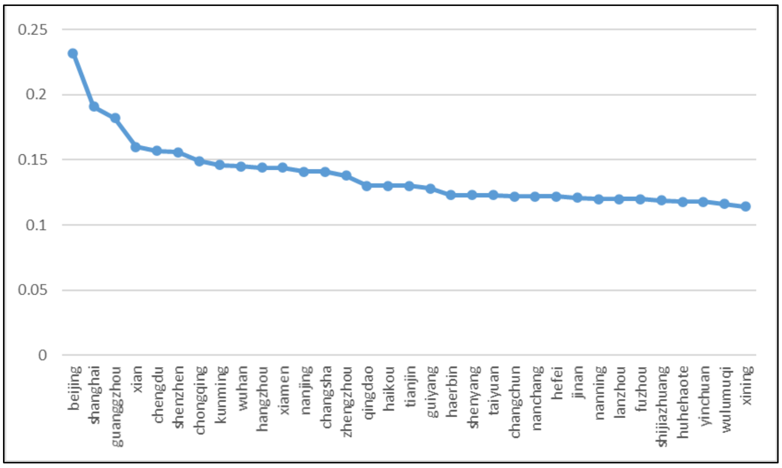


**Figure 1.** The direct effect of per capita GDP on passenger traffic in different regions.

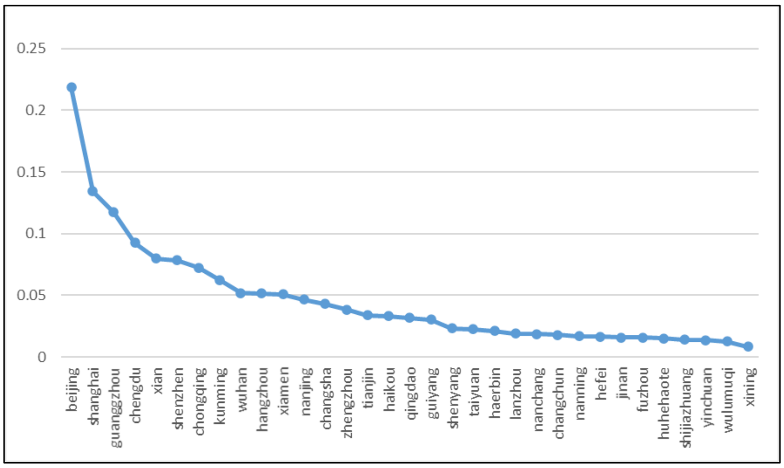


**Figure 2.** The indirect effect of per capita GDP on passenger traffic in different regions.

Figures 3 and 4 show the direct impact of a one log-unit change of per capita GDP on a specific airport's cargo traffic, as well as the average spillover effect on other airports' cargo traffic. Firstly, the economic development of the second- and third-tier cities (Wulumuqi, Lanzhou, Taiyuan, Yinchuan, Xining, etc.) has an obvious impact on the local airport cargo traffic; on the contrary, the economic growth of the first-tier cities (Beijing, Shanghai, Guangzhou) has no obvious driving effect on local airport cargo traffic. This result reflects the fact that second- and third-tier cities in central and western China are more dependent on air transport. The possible reason is that due to the impact of natural factors such as terrain and distance; these cities located in inland mountains rely more on air transport to realize cargo turnover. In terms of indirect effects, Shanghai's economic growth has the most obvious spillover effect on the airport cargo traffic in other regions, which also confirms Shanghai's status as the leader of the Chinese economy. Beijing and Guangzhou, as first-tier cities, also have significant spillover effects on airport cargo traffic in other regions. It is worth noting that although the economic growth of the second- and third-tier cities in central and western China (Wulumuqi, Lanzhou, Taiyuan, Yinchuan, Xining, etc.) has obvious impact on local airports' cargo traffic, the spillover effect on other airports' cargo traffic is not obvious. This may prove that the spillover effect exactly depends on economic development level.

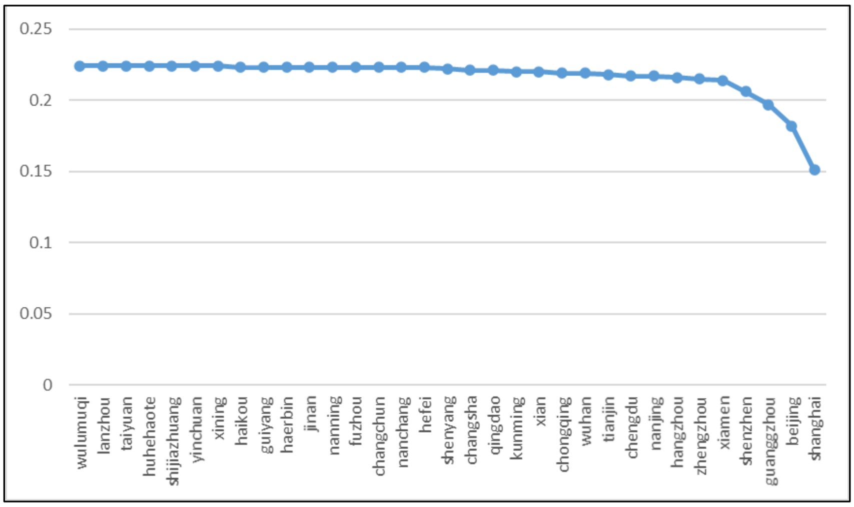


**Figure 3.** The direct effect of per capita GDP on cargo traffic in different regions.

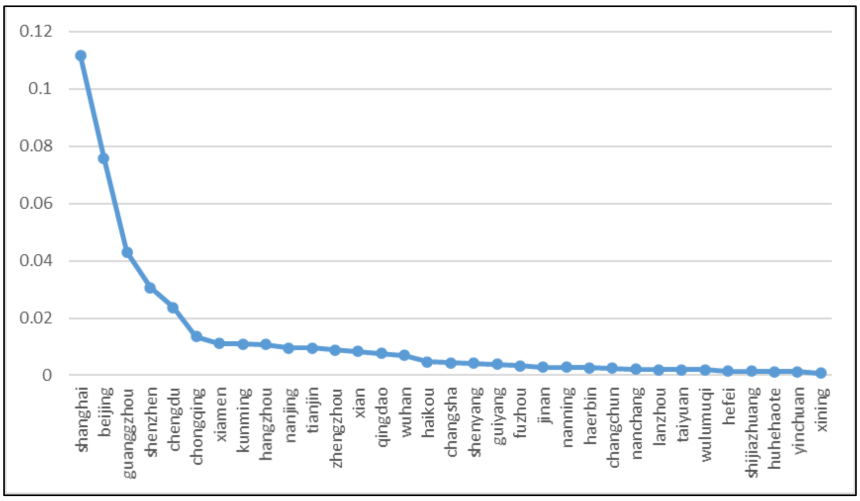


**Figure 4.** The indirect effect of per capita GDP on cargo traffic in different regions.

This study also calculates the spillover effects of per capita GDP on airport passenger and cargo traffic between individual cities. Due to the length of the thesis, this study lists the details of the spillover effects between Beijing, Shanghai, Guangzhou, and Chengdu (the three major hub airports in China and the important hub airports in western China).

The spillover effects of per capita GDP have an effect on airport passenger and cargo traffic between individual cities. The relationship between the four regional hub airports in China is listed in Table 6. The diagonal elements (0.232, 0.191, 0.182, 0.157) represent the impact of local per capita GDP on the passenger traffic of the local airport. For example, 0.232 means that a 1% increase in Beijing's per capita GDP will increase the passenger traffic of Beijing Airport by 0.232%.

**Table 6.** Spillover effects of per capita GDP on airport passenger/cargo traffic (Beijing, Shanghai, Guangzhou, and Chengdu).

| **Spillover Effects of per Capita GDP on Airport Passenger Traffic** | | | | |
|---|---|---|---|---|
| | Beijing | Shanghai | Guangzhou | Chengdu |
| Beijing | 0.232 | 0.190 | 0.105 | 0.083 |
| Shanghai | 0.292 | 0.191 | 0.149 | 0.077 |
| Guangzhou | 0.181 | 0.167 | 0.182 | 0.112 |
| Chengdu | 0.211 | 0.128 | 0.165 | 0.157 |
| **Spillover Effects of per Capita GDP on Airport Cargo Traffic** | | | | |
| | Beijing | Shanghai | Guangzhou | Chengdu |
| Beijing | 0.182 | 0.269 | 0.013 | 0.017 |
| Shanghai | 0.170 | 0.151 | 0.098 | 0.014 |
| Guangzhou | 0.020 | 0.231 | 0.197 | 0.032 |
| Chengdu | 0.066 | 0.091 | 0.087 | 0.217 |

In Table 6, each column represents the impact of a region's per capita GDP on passenger traffic at other airports. For example, 0.292 means that a 1% increase in Beijing's per capita GDP will increase the passenger traffic of Pudong Airport by 0.292%. As can be seen from Table 6, the spillover effects of Beijing's per capita GDP on passenger traffic derived from Shanghai's, Guangzhou's, and Chengdu's airports are 0.292, 0.181, and 0.211, respectively. The spillover effect of Beijing to the other three regions is obviously greater than the spillover effect of the three regions to Beijing (e.g., the spillover effect from Beijing to Shanghai is 0.292, but the spillover effect from Shanghai to Beijing is 0.190.) Therefore, the rank of spillover effect of per capita GDP on airport passenger traffic is Beijing, Shanghai, Guangzhou, and Chengdu. In addition, it can be seen from Table 6 that the passenger traffic of one airport may be more dependent on the economic development of other regions. For example, the passenger traffic of Chengdu Airport is influenced more by the per capita GDP of Beijing (0.211) and Guangzhou (0.165) than by the per capita GDP of itself (0.157). Per capita GDP can indirectly affect passenger traffic of other airports by influencing local airport passenger traffic (i.e., local per capita GDP $\rightarrow$ local airport passenger traffic $\rightarrow$ passenger traffic of other airports). This indicates that the geo-economic factors of central cities (Beijing, Shanghai, and Guangzhou) can affect the spatial relationship between China's airports. China's airports are more dependent on the economic growth of central cities, and therefore more dependent on the traffic replenishment at China's hub airports. It also reflects that China's major hub airports have irreplaceable competitive advantages in geo-economy aspects.

The second part of Table 6 lists spillover effects of per capita GDP on airport cargo traffic between four cities. It can be seen that the per capita GDP of Shanghai has the largest spillover effect on the cargo traffic of other three regional airports, followed by Beijing, Guangzhou, and Chengdu. On the other hand, whether from the perspective of passenger or cargo traffic, the spillover effect between Beijing and Shanghai is much larger than other types of spillover effects. The above results show that although the four representative airports are far apart and do not belong to the same multiairport region, the spatial interactions between them are still obvious. Considering these results, the measurement of the spatial relationship between airports should not be confined to multiairport regions adjacent to each other. With the expansion of air transport networks, the spatial relationships between airports should be captured from a wider range than ever before.

## 5. Conclusions

This study investigated whether China's airports are primarily characterised by competition or complementarity from the perspective of passenger and cargo traffic, respectively. The results show that there appears to be a difference in relationship characteristics from the perspective of passenger and cargo traffic. Based on spatial econometric methods under a different spatial weight matrix, we found that passenger traffic of Chinese airports appears to be primarily distinguished by complementarity. The complementarity results of passenger traffic show that the hub-and-spoke network structure between China's airports is obvious as hub airports and spoke airports present mutual supply cooperation in passenger traffic. Subsequently, the cargo traffic of China's airports appears to be mostly competitive. This result suggests that the network structure of China's airports in cargo traffic is not obvious, and there is no mutual supply relationship between airports. Additionally, because of the influence of macroeconomic factors such as the outward relocation of manufacturing industries and the shift of economic development centres to inland areas, China's airports present competition in cargo transportation.

In the analysis of the main influencing factors of airport passenger and cargo traffic, this study found that GDP per capita has the most obvious impact. According to the results of the SDM model, per capita GDP of a city not only promotes the passenger and cargo traffic of the local airport, but also has a positive spillover effect on the passenger and cargo traffic of other cities' airports. In addition, through the decomposition of the overall spillover effects, this study analyses the differences of spillover effects in different regions. The results show that the spillover effects of economic growth in Beijing, Shanghai, and Guangzhou on other cities' airport traffic are significantly higher than that of other second- and third-tier cities.

This finding may motivate the airport authorities to give full consideration to the relationship with neighbouring airports when formulating development strategies, so as to diversify airport business and formulate different strategies according to different businesses. In addition, these findings may provide important managerial implications to airports' authorities. When deciding to add international routes, hub airports should also pay attention to maintaining a certain number of domestic routes, especially routes to central and western airports, to connect the entire hub-and-spoke network and maximize spillover effects. On the other hand, the results of this study indicate that there is competition in air freight traffic at Chinese airports. It is a reminder that airport authorities should consider interaction with neighbouring airports when opening new air freight routes so as to avoid unnecessary vicious competition. China's airports (especially small and medium airports) should take full account of local industry conditions when investing in dedicated cargo terminals, so as to ensure adequate supply of cargo.

Our study is among the first to estimate a SDM model with an asymmetric spatial weight matrix to analyse the spatial spillover effects of regional economic development on airport traffic, and specifically list the average spillover effects of economic development in major Chinese central cities on airport traffic. More specifically, this study also analyses the impact of economic growth on airport traffic between two specific regions. This allows us to determine spillover effect between any individual, rather than just giving an average value of spillover effect. Limitations within this analysis need to be recognised. First, although the spatial econometric model used in this paper makes it possible to discover inter-relationships between airports, it does not indicate what factors will affect the intensity of competition or complementarity. Second, airport rivalries may manifest in other forms than simply competition for transport services provided, such as airport duty-free shop operations, airport industrial base construction, and so on. Third, this study considers the inter-relationship between airports in China as a whole, and the inter-relationship between airports in specific regions can also be considered in future studies (e.g., the relationship between airports in the eastern region). Finally, it is also worth studying which relationship (competition or complementation) can produce positive effects on the improvement of airport operation efficiency and airport profits.

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