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Investigating the impact of spatial dependence and heterogeneity on airport relationships: Empirical evidence from China

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This research focused on the relationships among 34 major airports in China, analyzing how these relationships are influenced by spatial dependence and heterogeneity. Using a spatial econometric model, it found that passenger traffic in China's airports displays a mutually driven aggregation effect. Furthermore, the study revealed that the airport relationship changes from complementarity to competition as the geographic distance between them decreases. The study also classified the main airports in China into three hierarchical levels and found significant complementarity and competition among those within the hub-and-spoke network structure. Specifically, this study identified a complementary relationship among regional trunk and local branch airports, as-well-as significant competition among hub airports. Crucially, the study suggests that the absence of a hub airport weakens the collaborative interactions between different types of airports, emphasizing the critical importance of hub airports for the connectivity and operational efficiency of China's airport network.

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Introduction

The relationship between airports can take many forms and is influenced by various factors, including geographical proximity (Bełej et al., 2020), air traffic patterns (Francis et al., 2003), ownership and management (Oum et al., 2008), partnerships and alliances (Peng, Lu 2022), and regulations and policies (Starkie, 2012). Airports close to each other may have a competitive relationship or form partnerships to share resources and coordinate air traffic (Cheung et al., 2020). Those with high passenger traffic may route passengers to their destinations through partnerships with other airports. Airports can be owned and operated by local, regional, or national governments or private companies, and the relationships between these entities can impact their management and operations (Oum et al., 2006). Additionally, airports may form partnerships or alliances with other airports, airlines, and aviation-related companies to increase efficiency. Furthermore, their relationship with regulatory bodies, such as the Federal Aviation Administration or the European Union Aviation Safety Agency, can impact their operations through safety, security, and environmental regulations (Giovanelli, Rotondo 2022).

Inter-airport relationships can also be explained through the concepts of spatial dependence and spatial heterogeneity in regional science and geography. Within the context of airports, spatial dependence emphasizes the mutual influences and dependencies between airports due to their geographical proximity, which may lead to competitive or cooperative relationships among neighboring airports. Their proximity to each other is a critical factor in the formation of hub-spoke networks (Alderighi et al., 2007). Airports close to each other tend to compete for the same market, while those further apart often have complementary roles, with one potentially acting as a hub for passengers headed to the other. On the other hand, fierce competition between airports close in proximity may reduce the efficiency of each one, which may encourage cooperation between them. (Bergantino et al., 2020). Spatial heterogeneity refers to the variation in characteristics or attributes of a geographic area or a set of geographic units (LeSage, Pace 2009). In the context of airports, this refers to the differences in factors such as location, size, and the services offered by different airports and how these factors impact their competitiveness and relationship with others. These differences can impact their inter-spatial relationship, as well as the broader air transportation network. Spatial heterogeneity can significantly impact the interplay between airports as either competitive or complementary (Bergantino et al., 2020; Pagliari, Graham 2020). Many airports attempt to stand out by devising specialized development strategies in areas such as marketing, route expansion, and service delivery, leading to more intense competition (Pagliari, Graham 2020). In such scenarios, airport substitution commonly occurs, where passengers choose to travel to farther airports for lower prices and improved airline services (O'Connor, Fuellhart 2016). Spatial heterogeneity significantly impacts the formation and operation of airport hub–spoke networks. For instance, a large airport equipped with advanced facilities and a wide range of international routes can serve as a hub, while a smaller airport primarily catering to local or short-haul flights can function as a spoke.

Many studies have used a spatial econometric approach to quantify the degree of competition and complementarity between airports in various geographical locations, including China (Cheung et al., 2020), the European Union (Pavlyuk, 2010), the United States (Bergantino et al., 2020) and Australia (Ke and Baker, 2022). In this regard, these studies show that the competition and complementarity between airports are influenced by several factors, such as geographic proximity, market segmentation, and the level of air traffic demand. A notable limitation of previous research is the lack of a detailed examination of how spatial dependence and heterogeneity influence airport relationships. Specifically, existing studies overlook whether the interactions between airports vary by geographical location or if these relationships differ across various hierarchical levels of airports. This oversight may restrict the applicability of findings and the validity of conclusions derived from such studies. In addition, the spatial econometric model applied in these studies only uses a single spatial weight matrix, which may not accurately capture the complex and dynamic effects of spatial dependence and spatial heterogeneity on airport relations. Therefore, this study aims to explore the following questions: First, does the spatial dependence between airports change with geographical distance, and how does this change affect their relationships? Second, how could specific indicators be used to reflect the spatial heterogeneity between airports? Third, how are the relationships between airports affected by spatial heterogeneity?

This study seeks to address these questions by establishing an analytical paradigm. Firstly, the research utilizes a spatial econometric model to ascertain the degree of competition or complementarity among airports, using spatial autoregressive coefficients as the indicator. Secondly, it examines the dynamic nature of the relationship between airports by considering the changes in the relationship as a function of geographical distance. Thirdly, the research identifies indicators capturing the spatial heterogeneity among airports and applies the entropy-weighted technique for order preference by similarity to the ideal solution (TOPSIS) method to assess the comprehensive strength of airports, subsequently classifying them into various hierarchies. Lastly, the research examines the variations in airport relationships across different hierarchies.

This study conducts empirical research using data from 34 major airports in China over 13 years. Chinese airports are selected for empirical analysis due to the multifaceted nature of their interactions, influenced by geographical proximity, traffic flow, ownership, collaborations, and regulatory environments (Wang et al., 2014; Chen et al., 2021). The diverse and complex relationships among airports in China, marked by different levels of traffic, ownership models, and strategic alliances, provide a rich context to understand the dynamics of these relationships. Moreover, the disparities in economic development and the influence of location on route layouts introduce a layer of heterogeneity, making China an exemplary case for studying the impact of these factors on airport competition. Therefore, selecting Chinese airports as research samples is more representative and provides a valuable reference for similar studies in other regions. The findings of this study are expected to provide useful insights and serve as a theoretical foundation for relevant authorities to formulate effective airport policies.

Literature review

There is a wealth of research focused on understanding inter-airport relationships and their interaction with one another. The relationship between airports can be defined as the inter-dependence or interconnection between them (Cheung et al., 2020; Wu et al., 2023). This relationship can be studied from various perspectives, including competition (Thelle and Sonne, 2018), complementarity (Mantin, 2012), market structure (Choo et al., 2018), and regional development (Tang et al., 2022). Many studies have provided comprehensive overviews of the economic, policy, and management aspects of the relationship between airports, including the competitive and complementarity dynamics between them (Wu et al., 2023), the role of airports in regional and national economic development (Tveter, 2017), and

the impact of regulatory and technological developments on airport markets (Starkie, 2002).

In previous studies, researchers have utilized an array of methodological approaches to analyze the inter-relationships among airports. Quantitative analysis models have been widely used in examining passenger or airline preferences for airport choice in a multi-airport region. For instance, Zijlstra (2020) utilized a conditional logit model to emphasize the significant impact that national borders have on airport choice. This type of analysis provides a systematic approach to understanding how various factors, such as geographical barriers, influence airport selection. In another study, Pavlyuk (2010) introduced a multi-layer model of competition and cooperation effects, elucidating how competition and cooperation between airports can have both positive and negative impacts on efficiency depending on the distance between them. The results of the study provide valuable insights into the complex relationships that exist between airports in a multi-airport region. These studies have played a critical role in advancing the understanding of the complex relationships between airports in a multi-airport region and allow researchers to gain a deeper understanding of the strategic decisions made by airports and how these decisions impact the overall performance of the airport sector.

Airport inter-relationships have been extensively studied in the literature, with several studies focusing on the correlation between these relationships and airport efficiency. One such study by Sugiyanto et al. (2018) used the Herfindahl–Hirschman Index (HHI) to examine the impact of a scheme comprising two hubs and eight spoke airports on the efficiency of cargo transportation on Sumatra Island. The study found that this scheme can improve the efficiency of cargo transportation in the region. Another study by Bergantino et al. (2020) explored the effects of competition on the technical efficiency in 2015 of 206 international airports in Europe, North America, and Pacific Asia. This study discovered that competition could have different impacts on the technical efficiency of airports, depending on the cut-off distance considered. The findings from these studies emphasize the significance of examining the inter-relationships among airports in the analysis of airport efficiency and underscore the need for additional research to gain a deeper understanding of how competition and complementarity among airports affect their efficiency and performance.

The field of applied economics has seen increasing attention given to modeling airport relationships using spatial econometric models. The spatial econometric model has obvious advantages in analyzing the spatial relationship between airports. Such models provide a flexible framework for analyzing the spatial relationships between airports and can help to account for a variety of unobservable factors that might impact these relationships. The ability to model heterogeneity is particularly important, as it allows us to capture the complexity and diversity of the relationships between airports and to account for differences across regions. Additionally, spatial econometric models can handle endogeneity, account for spatial autocorrelation, and incorporate spatial weight matrices (LeSage, Pace 2009), all of which can help to provide more accurate estimates of the relationships between the airports. For many airports, spatial econometric theory provides a convenient way to model relationships based on geographic and economic data. Once the airports' spatial attributes have been determined, multivariate regression models with various spatial dependencies can be constructed to analyze their influence on each other. Pavlyuk (2016) analyzed the spatial heterogeneity of 365 airports in Europe in 2011 using a spatial stochastic frontier model developed by Fusco and Vidoli (2013) and an inverse distances matrix. The study found that spatial heterogeneity significantly impacted airport efficiency and

productivity estimation. Bergantino et al. (2020) considered a sample of 206 airports in Europe, North America, and Pacific Asia in 2015 and used the same model to conclude that competition had an important effect on airport efficiency levels, which varied depending on the geographical distance between airports. Gudmundsson et al., (2014) conducted a survey on the congestion spillover effect of London Heathrow Airport (LHR) on other airports in the UK. The study suggested significant congestion spillover effects from LHR to other airports in London, with the extensive spatial impact of Heathrow possibly reaching the spatially more distant Manchester and Birmingham airports. Cheung et al., 2020 proposed an SDPMSE Model with an inverse travel time and distance matrix to analyze the relationship among 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 with different spillover effects between airports.

A limitation of the existing literature is its failure to shed light on the underlying mechanisms of how spatial dependence and spatial heterogeneity affect the competition or complementarity between airports. The question of how changes in distance between airports or changes in airport attributes might impact inter-airport relationships remains largely unanswered. This gap is important in the current understanding of airport relationships, as it is unclear how changes in these factors would result in shifts toward competition or complementarity. A clearer understanding of these mechanisms can facilitate more informed policy decisions for managing airport relationships and improving efficiency and productivity. Moreover, the static capture of inter-airport spatial relationships may not provide a comprehensive understanding of the dynamic nature of these relationships. Considering the dynamic changes in spatial dependence and heterogeneity is crucial to accurately reflect real airport inter-relationships and provide meaningful policy recommendations. A more nuanced and dynamic view of the relationships between airports can be obtained by continuously monitoring these elements and incorporating them into the analysis. This perspective will help to identify the specific conditions that drive changes in inter-airport relationships and inform effective policy-making for real-time responses to these changes. Based on the literature review, this study focuses on the impact mechanisms and dynamic changes of how spatial dependence and heterogeneity affect airport relationships, thereby providing a deeper and more precise revelation of airport interrelations.

Methodology

The analysis of spatial relationships is important for understanding economic growth, as it is influenced by both internal and external factors in neighboring regions, creating natural spatial externalities. Researchers often capture these effects using spatial econometric models that account for spatial dependence among variables across regions. In this context, inter-airport spatial relationships are influenced by both geographic and economic factors, which can be captured using distance weight matrix and economic weight matrix modeling in accounting for unmeasured variables. This study classifies the relationship between major airports in China as either competitive or complementary, following an approach commonly used in the literature (Cheung et al., 2020; Merkel, 2017). Specifically, this study measures competition as the strength of negative spatial dependence in passenger traffic demand between an airport and adjacent airports, indicating that they are substitutes. Conversely, complementarity is defined as the intensity of positive spatial dependence, indicating that these airports are complements.

Model specification. The spatial panel data model is an extension of the standard panel data model, which considers spatial effects among different units. The model can be represented as follows:

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

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

where, Y_{it} represents the dependent variable for a particular unit i (e.g., an airport) at time t (e.g., a year). The first term, $\delta W_{ij} Y_{it}$, represents the spatial lag of Y_{it}, where W_{ij} is a spatial weight matrix that specifies the spatial interaction structure among different units. It captures the spatial relationships between different regions and assigns weights to the neighboring regions. The second term, βX_{it}, represents the non-spatial covariates that affect Y_{it}, where X_{it} is the matrix of independent variables. The third term, $\rho W_{ij} X_{it}$, represents the spatially lagged independent variables. It captures the spatial spillover effects of the neighboring units on the independent variables. Furthermore, μ_i represents the unit-specific time-invariant fixed effects, and ε_{it} is the error term. The last equation, $\varepsilon_{it} = \lambda W_{ij} \varepsilon_{it} + \nu_{it}$, represents the spatial autoregressive structure of the error term. It shows that the error term is a function of the neighboring units' error term. The disturbance vector, ν_{it}, is of size $n \times 1$ and is assumed to follow a normal distribution $N(0, \sigma^2)$, representing a disturbance process with a mean of zero, constant variance of σ^2, and no covariance between observations.

Formulas (1) and (2) incorporate three spatial interaction effects. The first effect is captured by including a spatially lagged dependent variable term, where the parameter δ is referred to as the spatial autoregressive coefficient. This coefficient enables the identification of positive or negative spatial interactions between different airports studied in this research. The second spatial interaction effect is accounted for by incorporating spatially lagged exogenous variables, where ρ represents the spillover effects of the spatial lag of independent variables on dependent variables. These terms control for possible correlations between the dependent variable of each region and the level of explanatory variables in neighboring regions. The third spatial interaction effect is incorporated into the model by assuming that the error term, ε_{it}, is spatially correlated, with λ representing the spatial autocorrelation coefficient. This term reflects the effect of the impact of unobserved shocks that follow a spatial pattern. The inclusion of the first interaction effect in a model leads to the "spatial autoregressive model" (SAR), also known as a "spatial lag model." On the other hand, a model with only the third spatial interaction effect is called the "spatial error model" (SEM). The "spatial Durbin model" (SDM) includes both first and second interaction effects, with spatial lag for both the explained and explanatory variables. Unlike models that ignore spatial dependencies in disturbances, the SDM model provides a different specification for error dependence, as described in the literature on spatial econometrics (LeSage, Pace 2009). Furthermore, the SEM model can be derived by imposing an appropriate nonlinear restriction on the parameters of the SDM model, making the latter more general.

This study establishes the model by drawing on relevant literature to include a set of control variables at the city level. In many studies, the demand for airport services is estimated as the annual passenger flow (Chen et al., 2021). Therefore, this study considers air passenger traffic (PA) as the critical dependent variable to estimate the spatial dependence of China's airport services. Additionally, household income and gross domestic product (GDP) have been found to positively impact air travel demand (Cheung et al., 2020). This study accordingly uses per capita GDP as a control variable to measure the development

levels of the regional economy (Gong and Ling, 2017). Furthermore, this research employs the amount of aviation employment (EM) as a control variable, which corresponds to the labor variables in a production function (Chen et al., 2021). It should be noted that services such as cargo handling or transport have no value on their own and are inputs into the production of other goods (Merkel, 2017). Moreover, in the context of airport competition, the behavior of passengers is extremely relevant for leisure trips (Granados et al., 2012). From this scenario, this study assumes that the demand for passenger transport is derived from regional tourism demand. Therefore, it includes variables corresponding to regional tourism as control variables to account for the correlation in passenger traffic among airports due to increased tourism (Albayrak et al., 2020). Specifically, this study uses an airport city's foreign exchange income (FTI) from tourism to measure the tourism factor, as foreign tourists generally use air transport. Furthermore, demand for airport services may be related to the level of shipping costs, which is addressed in this study by including the price of crude petroleum (CP) in the estimation function as an approximation for shipping costs (Cheung et al., 2020). The empirical model (Formula 3) is formalized by incorporating the framework presented in Formula 1 with the control variables as follows:

$$\begin{aligned} lnPA_{it} = {}& \delta W_{ij} lnPA_{it} + \beta_1 lnGDP_{it} + \beta_2 lnEM_{it} + \beta_3 lnFTI_{it} + \beta_4 lnCP_t \\ & + \rho_1 W_{ij} lnGDP_{it} + \rho_2 W_{ij} lnEM_{it} + \rho_3 W_{ij} lnFTI_{it} + \mu_i + \varepsilon_{it} \end{aligned}$$
$$(3)$$

The spatially lagged dependent variables are distinct from the serial lags and are inherently connected to the error term, as they reflect two-directional neighbor relationships (Elhorst, 2014). Due to endogeneity problems, the ordinary least squares (OLS) estimator is biased and inconsistent. In attempting to address this issue, various estimation methods have been proposed, including the generalized method of moments (GMM), maximum likelihood (ML), and quasi-maximum likelihood (QML) (Elhorst, 2014). However, GMM estimates can result in coefficient estimates that fall outside the parameter space, and ML estimates rely on the assumption that disturbance terms follow a normal distribution. As a result, QML estimation offers clear advantages over these approaches (Elhorst, 2014). This study accounts for the structural form of endogeneity arising from the spatially lagged dependent variable by employing the QML estimate proposed by Lee (2004).

Spatial weighting matrix. Formula (1) includes a spatial weight matrix, W_{ij}, which is an $N \times N$ table that characterizes the spatial arrangement of the observed units. This weight matrix plays a crucial role in capturing spatial dependence and heterogeneity. The spatial dependence of airports was incorporated using the inverse distance matrix (W_d), given that the proximity between airports affects their spatial dependence.

$$W_d = \begin{cases} 0, & i = j \\ d_{ij}^{-2}, & i \neq j \end{cases} \qquad (4)$$

The great circle distance between airports i and j is represented by d_{ij}, while d_{ij}^{-1} represents the reciprocal of d_{ij}, which is the inverse distance between both airports.

The inverse distance matrix used to represent the spatial relationships between airports considers only the distance between adjacent airports. However, it is unrealistic to assume that adjacent airports have identical economic interrelationships, which can vary. This issue is addressed by choosing the passenger traffic difference between airports as a metric to measure the economic distance between them. This approach is justified since

Table 1 Definition of the variables.

Variable	Mean	Std. Dev.	Min	Max
PA (passenger throughput, people)	1.93×10^7	1.81×10^7	802167	1.00×10^8
GDP (GDP per capita, 10^4 yuan/person)	9.86	8.25	1.45	62.13
EM (aviation employment, people)	18148	25971.3	142	134402
FTI (international tourism receipts, 10^6 dollar)	2666.37	3814.14	3.00	20521.31
CP (price of crude petroleum, $/barrel)	79.10	23.06	44.04	111.96

spatial heterogeneity among airports is eventually reflected in the differences in passenger traffic. The economic distance matrix is defined as follows:

$$W_e = \begin{cases} 0, & i = j \\ \frac{1}{|PA_i - PA_j|}, & i \neq j \end{cases} \quad (5)$$

$$W_p = W_e \times diag\left(\frac{PA_1}{PA_a}, \dots, \frac{PA_n}{PA_a}\right), (i = 1, \dots, n) \quad (6)$$

Here, PA_i and PA_j represent the average passenger traffic of airports i and j during the sample period. A smaller difference ($|PA_i - PA_j|$) in passenger traffic indicates greater similarity in the traffic levels between both airports, implying a closer economic distance. As such, airports with smaller economic distances are assigned larger spatial weight coefficients in W_e. In this study, the economic distance matrix (W_e) is transformed into an asymmetrical matrix, where $diag(\frac{PA_1}{PA_a}, \dots, \frac{PA_n}{PA_a})$ represents a diagonal matrix, and PA_a represents the average passenger traffic of all airports during the sample period. In W_p, the mutual effects of both airports are not identical (i.e., $W_{ij} \neq W_{ji}$). The economic information contained in this asymmetric matrix is directional, reflecting the difference in mutual influence between any airport pairs (Zhang et al., 2018). Furthermore, the use of an asymmetric matrix can account for the fact that among airports with the same economic distance, those with higher passenger traffic should carry greater weight. This approach can also assign more weight to an airport that connects to a hub airport with high passenger traffic, even if there is a considerable economic distance between them.

Data description. The research targeted 34 major airports in 25 provincial capitals and nine populous cities across mainland China (2007–2019). In selecting airports for our study, we prioritized primary criteria, like passenger and cargo throughput, to focus on those with the most substantial operational volume and regional or national impact, specifically targeting airports within the top 40 rankings for passenger-cargo throughput, highlighting their importance in China's aviation network. Spatial diversity was also critical, aiming for a representation that spans mainland China's varied geographical landscapes to capture a broad spectrum of spatial interactions, including airports from all major economic regions and a variety of locations (coastal, inland, northern, and southern) to mirror the spatial hetero-geneity of the air transport network. Additionally, the selection process accounted for the availability of consistent and reliable airport data, such as operational statistics, route information, and economic indicators, and excluded airports with incomplete records during the study period to ensure the integrity of our analysis. In the case of Shanghai, the study accounted for two airports (the Pudong and Hongqiao airports). As a result, a balanced panel data set was formed, with 442 observations.

The current study draws data from multiple databanks. The passenger traffic data utilized in this study were obtained from the Civil Aviation Administration of China's (CAAC) publication of the Civil Aviation Airport Production Statistics Bulletin, covering

Table 2 Spatial correlation of the comprehensive strength of China's coastal ports.

Year	W_d		W_p	
	Moran's I	Z Value	Moran's I	Z Value
2007	0.273***	2.91	0.541***	6.309
2008	0.281***	2.99	0.534***	6.231
2009	0.272***	2.903	0.546***	6.363
2010	0.296***	3.132	0.568***	6.61
2011	0.289***	3.063	0.570***	6.632
2012	0.276***	2.937	0.582***	6.756
2013	0.274***	2.913	0.578***	6.698
2014	0.284***	3.000	0.589***	6.798
2015	0.272***	2.887	0.581***	6.719
2016	0.253***	2.708	0.574***	6.639
2017	0.257***	2.748	0.568***	6.574
2018	0.266***	2.837	0.561***	6.506
2019	0.265***	2.825	0.579***	6.696

t-statistics in parentheses, ***$p < 0.01$.

both domestic and international operations. Four control variables originate from the China Economic Net database (2007–2019). All variables underwent natural logarithm conversion to mitigate potential heteroscedasticity. The results of the descriptive statistics are displayed in Table 1.

In seeking to avoid spurious results from correlated random patterns in non-stationary variables, the panel data sets of passenger traffic series were checked for non-stationary variables using the HT test (n > t) for panel unit roots (Harris and Tzavalis, 1999). The test results show a rejection of the null hypothesis of joint non-stationary ($z = -2.102$, $p = 0.018$), indicating the reliability of the subsequent coefficient estimation.

Empirical results

Moran's I Index. This study employs the Moran's I statistic (Anselin, 1988; Moran, 1950) as a preliminary diagnostic tool to detect the spatial correlation of China's airports. Specifically, the annual passenger traffic of each airport is used to calculate Moran's I value, utilizing both the geographical distance (W_d) and economic distance (W_p) matrices. The result of Moran's I value, as presented in Table 2, reveals a significant positive spatial correlation, indicating that airports with high passenger traffic tend to cluster. This finding aligns with the geographical distribution of China's airports, whereby the ones with high passenger traffic are concentrated in the eastern coastal region, while those with low traffic are situated in central and western inland areas.

Moreover, the study demonstrates that controlling for economic proximity significantly improves the detection of spatial correlation in airport passenger traffic, as evidenced by the considerably higher Moran's I value obtained using the economic distance matrix (W_p) than the geographical distance matrix (W_d). The analysis also indicates that the spatial interaction and correlation of passenger flow are more likely to

5

Table 3 Spatial regression results for the full data model with W_d.

	SDM	SAR	SEM
lnGDP	−0.017	0.254***	0.055
	(−0.31)	(5.78)	(0.82)
lnEM	0.052***	0.071***	0.060***
	(3.00)	(4.14)	(3.19)
lnFTI	0.072***	0.082***	0.097***
	(3.44)	(3.82)	(4.60)
lnCP	−0.061**	−0.056**	−0.647***
	(−2.53)	(−2.30)	(−3.02)
W×lnGDP	0.645***		
	(7.58)		
W×lnEM	−0.023		
	(−0.59)		
W×lnFTI	−0.102**		
	(−2.08)		
δ	0.643***	0.470***	
	(17.55)	(9.60)	
λ			0.889***
			(44.72)
Log-lik	239.359	209.604	163.296
R²	0.903	0.892	0.396
N.o. obs	442	442	442
Hausman test	14.95***	26.48***	27.59***
LM-lag test		163.554***	
R-LM-lag test		66.589***	
LM-err test			108.789***
R-LM-err test			11.823***
LR-lag test	59.51***		
Wald-lag test	59.23***		
LR-err test	152.13***		
Wald-err test	96.98***		

t-statistics in parentheses, **$p < 0.05$, ***$p < 0.01$.

occur between airports with high passenger traffic and a slight economic difference. Furthermore, the study finds that Moran's I value exhibits a relatively stable spatial correlation of passenger traffic from 2007 to 2019, with only a minor fluctuation range. This outcome implies that the spatial pattern of China's airport passenger traffic remains relatively consistent over time.

Effect of geographic distance disparities on the spatial relationships of airports. Table 3 provides insight into the autoregressive coefficients of the SDM, SAR, and SEM for passenger traffic with W_d. The δ coefficient is the spatial autoregressive coefficient, and the values of δ in both the SDM and SAR models are significantly positive at a level of 1% or below. A positive δ value indicates a complementary effect, where an increase in the average level of passenger traffic in neighboring airports results in a corresponding increase in the passenger traffic of a particular airport. For instance, in the SDM, the δ value is 0.643, implying that a 1% rise in the average passenger traffic of neighboring airports will result in an increase of approximately 0.643% in the passenger traffic of the airport being analyzed. Therefore, the passenger traffic in China's airports displays a good mutually-driven aggregation effect. Additionally, the results of the analysis show that the residuals in the model are spatially correlated, indicating that unobserved factors are influencing neighboring airports, as evidenced by the positive λ value. This spatial autocorrelation of residuals may be due to the presence of omitted variables correlated across the sample region, such as factors that affect passenger demand and supply chain networks. Accounting for these unobserved spatial factors in modeling passenger traffic in China's airports is crucial for obtaining more accurate

estimates and understanding the underlying mechanisms behind passenger traffic patterns. Furthermore, this finding emphasizes the importance of considering spatial dependence when modeling passenger traffic, particularly in the presence of neighboring airports and other spatially related factors.

Moreover, various statistical tests were employed in this study to determine the most suitable model form. Firstly, the Hausmann test was utilized based on spatial panel data (Lee and Yu, 2012). Only individual fixed effects were utilized since the model included crude oil price variables that were constant across individuals. The results of the Hausmann test indicated that all three models rejected the null hypothesis of using individual random effects and preferred the individual fixed-effects model. Secondly, both the LM and robust LM tests rejected the null hypothesis that the model lacked spatial dependence and recommended using panel data models with spatial effects (SAR or SEM). Finally, the LR and Wald tests were executed for the three model forms, and the findings suggested that the simpler SAR and SEM models should be substituted with more comprehensive SDM models. Furthermore, the R-squared and log-likelihood function values also indicated that the SDM had a significantly better fit for the sample data compared to the SAR and SEM models (Elhorst, 2014). Hence, the SDM model with individual fixed effects was chosen for subsequent analysis in this study.

The positive spatial autoregressive coefficient in Table 3 represents the average spatial relationship among the 34 airports. This coefficient reflects the overall spatial relationship of the sample set rather than the specific spatial relationship between each pair of airports because a dataset with a sample size of *n* can have at most *n(n-1)* spatial autoregressive coefficients, which is beyond the sample size range. The spatial autoregressive coefficient is estimated using the quasi-maximum likelihood estimation to calculate the mean value of the spatial autoregressive coefficient. However, the inter-airport spatial relationship at different distances may vary significantly. Many studies have suggested that the impact of geographic distance on spatial relationships between airports may be subject to a threshold. Some research suggests that if the great circle distance between two locations is less than 500 km, high-speed rail transport may substitute air transport (Chen et al., 2021; Rodrigue et al., 2017). Thus, it is suggested that as the geographic distance between airports decreases, the spatial relationship between them may change, reflecting a weakening of the spatial relationship or a shift toward competition.

To better analyze the impact of geographic distance on spatial dependence between airports, this study investigates inter-airport spatial relationships at different distances and examines how these relationships change with geographic distance. Additionally, this paper tests the hypothesis that the relationship between airports has a spatial attenuation boundary, meaning that the closer the distance between airports, the weaker the complementary relationship and the more likely it is to become competitive. This study seeks to achieve these objectives by modifying the W_d, cutting off the geographical distances between airports.

$$W_d^* = \begin{cases} 0, & d_{ij} > d \\ d_{ij}^{-2}, & d_{ij} \le d \end{cases}, \ d \in \{d_{\min}, d_{\min} + m, d_{\min} + 2m, \ldots \ldots, d_{\max}\}$$

(7)

In this study, the attenuation changes of spatial dependence over short distances were observed by modifying the W_d by setting a distance interval $(d_{\min}, d_{\max})$ and progressive distance *m* from $d_{\min}$ to $d_{\max}$. For distances $d_{ij} \le d$ (*threshold distance*), the geographical unit element was set to the square of the inverse distance between two airports, while for distances $d_{ij} > d$, the geographical unit element was set to "0." This method enables the removal of airports beyond the distance *d* from the spatial weight

matrix, facilitating a more accurate observation of short-distance attenuation changes in spatial dependence. In this study, the initial threshold distance for the inverse distance spatial weight matrix was set at 100 km, with a step distance also set at 100 km. Since the farthest distance between the 34 airports is 3508.77 km (from the Urumqi airport to the Xiamen airport) and the shortest distance is 10.46 km (from the Pudong airport to the Hongqiao airport), the distance threshold was reduced from 3600 km to 100 km.

The study estimated the spatial autoregression coefficient by employing an SDM that used a spatial weight matrix based on threshold distances. Figure 1 shows that when the threshold distance is at its maximum value of 3600 km, the spatial autoregressive coefficient is positive and reaches its maximum value. As the distance threshold decreases, the spatial autoregressive coefficient shows a significant decreasing trend. This trend reflects a gradual weakening of spatial complementarity between airports as the distance between them reduces. When the threshold distance is in the range of 1500 km–3600 km, the spatial autoregressive coefficient decreases but remains positive. This outcome indicates that there is still significant spatial complementarity between airports within this distance range. Figure 2 shows that when the threshold distance is less than 1400 km, the spatial autoregressive coefficient becomes negative, and the magnitude of the negative coefficient increases as the geographic distance decreases.

This result indicates that the spatial relationship between airports changes from complementarity to competition when the geographic distance between airports is less than 1400 km. This competitive relationship gradually strengthens as the geographic distance between airports decreases further and reaches its

maximum value at a threshold distance of 100 km. Appendix 1 contains a comprehensive record of the spatial autoregressive coefficients and corresponding t-statistics across various distance thresholds. All of the spatial autocorrelation coefficients are statistically significant at a level of at least 10%. This robust result strengthens the validity of the findings.

The results validate the initial hypothesis that the spatial relationships among the 34 Chinese airports are influenced by geographic distance. This geographic influence on airport relationships manifests in several critical ways, driving both competition and complementarity within the network. Firstly, the introduction and expansion of high-speed rail networks across China have introduced a significant shift in the competitive landscape for short-haul travel. High-speed trains, offering convenience, speed, and competitive pricing, have emerged as a formidable alternative to air travel for parallel routes, particularly affecting nearby airports. This shift has not only reduced the complementarity between such airports but also heightened the competitive pressure, compelling them to innovate and diversify services to retain passenger volumes. Moreover, the substitutability phenomenon observed among neighboring airports is markedly pronounced, driven by the enhanced urban transport infrastructure. Improved road, rail, and public transport systems have made it easier for passengers to choose between airports based on factors beyond mere geographic closeness, such as flight availability, ticket prices, and service quality. This increased flexibility in airport choice amplifies the competition among nearby airports, pushing them towards strategic differentiation and specialization in services offered. The improved connectivity between cities, facilitated by China's ambitious infrastructure development initiatives, plays a pivotal role in this context. Adequate ground transport facilities linking two adjacent cities can effectively render their airports interchangeable for passengers, fostering a unique form of competition where airports vie not just on-air services but also on their accessibility and integration with ground transport networks. Conversely, the spatial complementarity observed among airports situated farther from each other illuminates the distinct advantages of air transport over long distances. These airports, serving disparate catchment areas, are less prone to direct competition and more likely to develop synergistic relationships within hub–spoke configurations. Such networks optimize the flow of air traffic, enhancing the operational efficiency and coverage of the air transport system across vast geographic expanses. This arrangement not only leverages the speed and range capabilities of air travel but also facilitates a more structured and efficient organization of air traffic, reinforcing the essential role of air transport in bridging long distances swiftly and effectively.
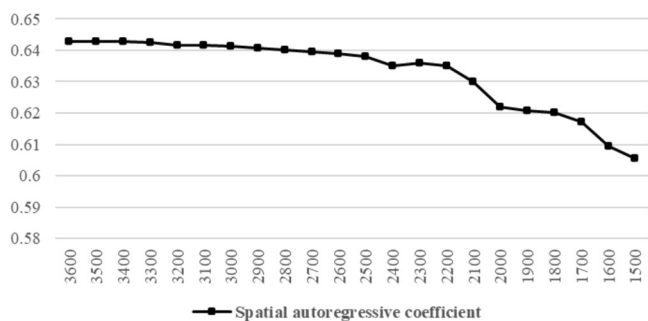

Fig. 1 Spatial dependence affected by distance (1500 km ≤ distance ≤ 3600 km). Shows that when the threshold distance is at its maximum value of 3600 km, the spatial autoregressive coefficient is positive and reaches its maximum value.
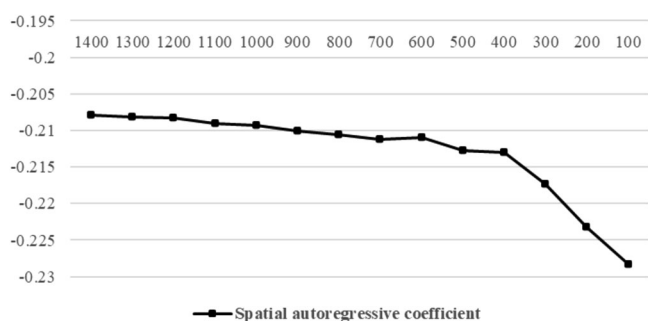

Fig. 2 Spatial dependence affected by distance (100 km ≤ distance ≤ 1400 km). Shows that when the threshold distance is less than 1400 km, the spatial autoregressive coefficient becomes negative, and the magnitude of the negative coefficient increases as the geographic distance decreases.

Effect of economic distance disparities on the spatial relationships of airports. This study also employed an asymmetric economic distance matrix to measure the spatial relationships between 34 Chinese airports. The economic distance matrix used in this study does not include geographic distance factors, which allow for a clearer understanding of the impact of heterogeneity in airport traffic, levels of economic hinterland development, policy support, and other factors on spatial relationships. Additionally, the use of this matrix can reflect the hub-spoke network structure mainly because 1) in this matrix, hub airports with high traffic have a greater spatial impact on feeder airports; 2) the spatial connections between hub airports with high traffic are closer than those between feeder airports, and 3) although the economic distance between feeder and hub airports is relatively large (smaller spatial weight), this matrix allows for larger spatial weights to be assigned when feeder airports are connected to hub airports.

Table 4 Estimated results of SDM, SAR, and SEM under W_p.

	SDM	SAR	SEM
lnGDP	0.049	0.139***	0.075
	(1.02)	(3.81)	(1.50)
lnEM	0.072***	0.075***	0.085***
	(4.78)	(5.13)	(5.66)
lnFTI	0.084***	0.080***	0.068***
	(4.61)	(4.36)	(3.89)
lnCP	−0.040*	−0.020	−0.667*
	(−1.86)	(−0.94)	(−1.82)
W×lnGDP	0.245***		
	(3.00)		
W×lnEM	−0.118***		
	(−3.34)		
W×lnFTI	0.068		
	(1.25)		
δ	0.703***	0.784***	
	(16.32)	(25.81)	
λ			0.946***
			(77.71)
Log-lik	280.608	269.531	232.937
R²	0.906	0.889	0.407
N.o. obs	442	442	442
Hausman test	28.34***	10.65*	20.15***
LM-lag test		251.28***	
R-LM-lag test		20.03***	
LM-err test			373.47***
R-LM-err test			142.23***
LR-lag test	22.15***		
Wald-lag test	21.53***		
LR-err test	95.34***		
Wald-err test	59.95***		

t-statistics in parentheses, *p < 0.10, ***p < 0.01.

Fig. 3 Airport comprehensive strength. Shows the comprehensive strength index and standardized index of the 34 airports.

Table 4 presents the estimation results of the SDM, SAR, and SEM models based on the asymmetric economic weight matrix. The spatial autoregressive coefficients of the three models are all significant and positive at a level of at least 1%, indicating a complementary spatial relationship among these airports at the overall level. This complementary spatial relationship further confirms the existence of a hub-and-spoke network structure among China's airports. Comparison with the estimation results based on the geographic matrix in the previous section reveals that the spatial autoregressive coefficients estimated based on the economic distance matrix are larger. This result is consistent across all three models. It suggests that the differences between airport hierarchical levels due to various complex spatial heterogeneities, such as the economy of the surrounding cities, policy environment, historical traditions, and other factors, have a more significant impact on inter-airport spatial relationships.

Notably, the spatial autoregressive coefficient of SEM is as high as 0.919, indicating that some unobservable factors exhibit a strong spatial correlation under the influence of the economic distance matrix. Furthermore, this outcome reflects that the asymmetric economic distance matrix can explain the influence of unobservable spatial heterogeneity on inter-airport spatial relationships. In addition, regarding the model specification, the results indicate that the individual fixed-effects model should be used, and both the LM and robust LM tests suggest that the model should include spatial lag terms. The LR and Wald tests show that the SDM model can better fit the sample data, which is also confirmed by the R-square and log-likelihood function values.

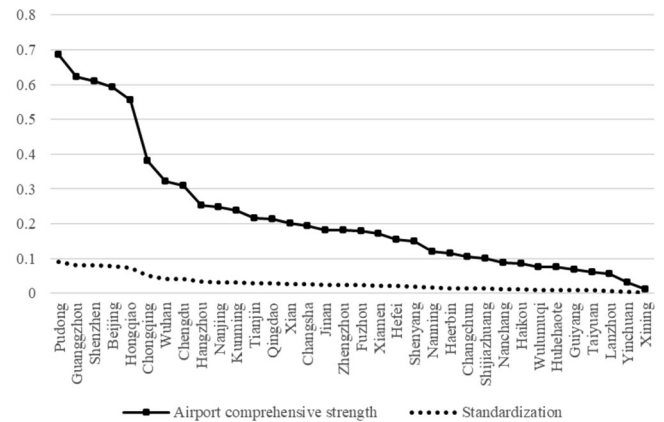The above findings suggest significant complementarity among the 34 major airports in China under the hub–spoke network structure. However, this broad conclusion cannot explain the specific spatial relationships between specific groups of airports. The significant positive spatial autoregressive coefficients in Table 4 represent the average value of all spatial relationships. Consequently, the average value might mask competitive relationships between specific airports. Due to the sample's limitations, spatial econometric models cannot provide spatial autoregressive coefficients for any two individuals. However, it is possible to study the spatial relationship between specific individuals by dividing the sample (Merkel, 2017). This study aims to classify the 34 airports into different hierarchical levels and explore the specific forms of spatial relationships between airports in these varying levels.

Traditional airport comprehensive strength rankings are measured by passenger and cargo throughput, such as the percentage of national annual passenger traffic (Chen et al., 2021). However, this factor alone cannot fully reflect the comprehensive strength of an airport, as non-airport-related factors, such as hinterland policies and resource advantages, undoubtedly influence its total strength. This study combines the ideas of systems science and uses the entropy weight TOPSIS method (Li et al., 2018; Zhao et al., 2020) to construct a comprehensive strength index system for Chinese airports. The comprehensive strength of an airport is crucial in determining its position and role within a network. It is, therefore, an essential aspect to consider when examining the airport relationship within the airport system. In this index system, the airport's comprehensive strength will be calculated based on multiple indicators and their weights. The study standardized the raw data to address the differences in dimension and the order of magnitude in each index. Subsequently, the entropy method was used to determine the index weight, and the TOPSIS evaluation model was employed to calculate the airport's comprehensive strength. Appendix 3 lists the indexes selected in this study and their corresponding weights. Figure 3 shows the comprehensive strength index and standardized index of the 34 airports. Based on the analysis of the index and assessment of common knowledge of China's airports, this study classified the 34 airports into three hierarchical levels. Those airports with a comprehensive strength index greater than 0.5 were classified as the five large-hub airports (i.e., the Pudong, Guangzhou, Shenzhen, Beijing, and Hongqiao airports); those with an index between 0.2 and 0.4 were classified as the nine regional trunk airports (i.e., the Chongqing, Wuhan, Chengdu, Hangzhou, Nanjing, Kunming, Tianjin, Qingdao, and Xian airports); and those with an index less than 0.2 were classified as the 20 local branch airports (i.e., the Changsha, Jinan, Zhengzhou, Fuzhou, Xiamen, Hefei,

Table 5 SDM estimation results of airports of different comprehensive strengths.

	Hub	Trunk	Branch
lnGDP	0.009	0.004	0.086
	(0.13)	(0.08)	(1.31)
lnEM	0.086***	0.027	0.069***
	(3.03)	(1.36)	(3.48)
lnFTI	0.389***	0.012	0.076***
	(8.27)	(0.43)	(3.29)
lnCP	−0.054***	−0.094***	−0.064**
	(−2.99)	(−2.85)	(−2.06)
W×lnGDP	0.386***	0.359***	0.282***
	(6.19)	(4.06)	(2.71)
W×lnEM	0.058*	0.030	−0.090*
	(1.95)	(0.85)	(−1.96)
W×lnFTI	0.429***	0.003	0.248***
	(7.41)	(0.05)	(3.79)
δ	−0.286***	0.536***	0.533***
	(−2.98)	(5.75)	(7.32)
Log-lik	117.871	115.134	160.469
R²	0.976	0.953	0.931
N.o. obs	65	117	260
Hausman test	32.23***	12.20**	40.70***
LR-lag test	80.22***	29.07***	29.08***
Wald-lag test	163.18***	23.69***	26.98***
LR-err test	45.48***	130.53***	79.40***
Wald-err test	83.43***	29.84***	49.58***

t-statistics in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 6 SDM estimation results of airports of different airport group.

	Hub_trunk	Hub_branch	Trunk_branch
lnGDP	−0.020	0.036	0.025
	(−0.36)	(0.60)	(0.48)
lnEM	0.012	0.065***	0.063***
	(0.60)	(3.51)	(4.09)
lnFTI	0.121***	0.107***	0.052***
	(4.47)	(4.86)	(2.78)
lnCP	−0.101***	−0.069***	0.030
	(−3.76)	(−2.61)	(1.18)
W×lnGDP	0.547***	0.423***	−0.156*
	(6.14)	(4.73)	(−1.65)
W×lnEM	−0.012	−0.159***	−0.125***
	(−0.33)	(−4.10)	(−3.25)
W×lnFTI	0.087	0.293***	0.103*
	(1.24)	(4.72)	(1.88)
δ	0.276***	0.467***	0.485***
	(2.91)	(7.44)	(6.34)
Log-lik	173.409	208.343	258.589
R²	0.940	0.924	0.935
N.o. obs	182	325	377
Hausman test	240.13***	15.47**	40.58***
LR-lag test	64.43***	64.72***	7.08*
Wald-lag test	58.24***	61.16***	6.94*
LR-err test	154.77***	140.26***	54.43***
Wald-err test	78.55***	92.82***	33.59***

t-statistics in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Shenyang, Nanning, Haerbin, Changchun, Shijiazhuang, Nanchang, Haikou, Wulumuqi, Huhehaote, Guiyang, Taiyuan, Lanzhou, Yinchuan, and Xining airports). The comprehensive strength index of the five hub airports accounted for more than 40% of the total standardized index, which could fully reflect the status of hub airports.

This study examined the spatial relationships between airports of different hierarchical levels. Based on W*p*, SDM was adopted to re-estimate the spatial autoregression coefficients of the three airport groups. Firstly, as shown in Table 5, the results of the model tests indicate that the SDM with individual fixed effects can better fit the data. Secondly, it can be seen that the spatial autoregression coefficient between the five hub airports is −0.286, which is statistically significant at the 1% level, indicating significant competition between China's five large-hub airports. This competition is manifested as a 1% increase in the passenger traffic of one hub airport, resulting in an average decrease of about 0.286% in the traffic of the other four hub airports. This result differs significantly from the estimated result (0.703) in Table 4.

It shows that, although there is an overall complementary relationship among the 34 Chinese airports, there is significant competition among the hub airports when they are specifically considered. Competition between hub airports may be reflected in the transfer of international flights. Since the majority of China's international routes are concentrated at hub airports, a considerable number of passengers using these airports are transit passengers. Passengers have the option to choose their transfer airport, which creates substitutability between hub airports and leads to competition. However, although there is complementarity between hub airports on domestic routes, the competition on international routes takes the dominant position. Secondly, the analysis shows a complementary spatial relationship between the regional trunk and local branch airports, as evidenced by the significant and positive spatial autoregression coefficients between

both groups of airports. However, it is important to note that these coefficients (0.536, 0.533) are significantly smaller than the results in Table 4 (0.703), suggesting a decrease in the strength of complementary relationships among Chinese airports without hub airports. This observation further highlights the crucial role of hub airports in China's overall airport network.

This study also explored the spatial relationships between different airport groups, the results of which are presented in Table 6. The spatial autoregression coefficient between hub and regional trunk airports is statistically significant at the 1% level, with a value of 0.276. The spatial autoregression coefficients between the hub and regional branch airports, as well as between regional trunk and regional branch airports, are also statistically significant at the 1% level, with values of 0.467 and 0.485, respectively. These findings reflect a complementary spatial relationship among the various hierarchies of airports within China's airport network. Notably, the spatial autoregression coefficient between the hub and regional trunk airports is lower than the other two coefficients, indicating a weaker complementary relationship between both types of airports. This result suggests that there may be some level of competition between them. In seeking to attract local and nearby passengers, local governments throughout China are eager to invest in expanding airports and increasing international routes, which has gradually reduced the gap between the hub and regional trunk airports, increasing their substitutability.

For example, between 2018 and 2021, the airports in Nanjing and Hangzhou, located near Shanghai Pudong Airport, expanded their international routes. This expansion inevitably resulted in a portion of passengers choosing these airports over the Shanghai Pudong Airport. In addition, the three spatial autoregressive coefficients are all smaller than the results in Table 4, indicating that the complementary effects among Chinese airports can only reach their maximum level when all airports are included in the hub-and-spoke airport network, reflecting the small-world

properties of mutual complementarity among China's airport network (Chen et al., 2020; Wang et al., 2014; Zanin and Lillo, 2013).

Robustness test. This study re-estimated the model using an inverse distance spatial weight matrix. The results show that, despite slight numerical differences, the spatial autoregression coefficient values still increase with the geographic distance and similarly turn negative for distances less than 1400 km (Appendix 2), indicating that the study's results are robust. Furthermore, the study validated the results of Section 4.3 using W_e. The outcomes revealed no significant differences among the various spatial autoregression coefficients, confirming the robustness of the results (Appendix 4).

Conclusion

This study used a spatial econometric model to examine the effect of spatial dependence and spatial heterogeneity on the spatial relationships of Chinese airports. The results showed that passenger traffic in China's airports displays a good mutually-driven aggregation effect. The study also found that the spatial relationship between airports changes from complementarity to the competition when the geographic distance between airports is less than 1400 km, and this competitive relationship gradually strengthens as the geographic distance between airports further decreases.

Additionally, the study captures the unobservable spatial heterogeneity that affects inter-airport spatial relationships by exploring the influence of disparities in economic distance on the spatial relationships of Chinese airports. Based on the research findings, it can be concluded that there is significant complementarity and competition among Chinese airports within the hub-and-spoke network structure, which is shaped by various complex spatial heterogeneities. The study classified the 34 airports in China into three hierarchies based on the comprehensive strength index and investigated the specific spatial relationships between these airport groups. The results reveal a complementary spatial relationship between the regional trunk and local branch airports and significant competition among hub airports. Moreover, the findings suggest that the absence of a hub airport weakens the strength of complementary relationships among different types of airports, highlighting the crucial role of hub airports in China's overall airport network and their impact on the relationships of other airport groups.

The study's findings suggest that policymakers should consider the competition between airports that are in close proximity when planning transportation infrastructure and investment since these airports may serve as substitutes for each other. Additionally, China's government should prioritize the development and integration of hub airports to improve the overall efficiency of the airport network. Moreover, a coordinated approach to airport development is needed. The study reveals a complementary spatial relationship among the various hierarchies of airports within China's airport network. Thus, policymakers should adopt a coordinated approach to airport development to ensure that investments in airport infrastructure are distributed to maximize the benefits of these complementary spatial relationships between different airport groups.

It is important to note that this study has several limitations that must be addressed in future research. One of the primary constraints is the lack of the possibility to extrapolate the results beyond the context of Chinese airports. The specific spatial, economic, and infrastructural contexts of these airports may limit the generalizability of the findings to other countries or regions with different airport networks and operational dynamics.

Another limitation arises from the sampling methodology. While methodologically sound, the focus on 34 major airports based on a comprehensive strength index may not fully capture the diversity and complexity of all airports within China. This selection criterion may overlook smaller or more remotely located airports, which could offer additional insights into the spatial relationships and competitive dynamics within the broader network. Moreover, the study's reliance on a spatial econometric model to examine spatial dependence and heterogeneity may not fully account for unobservable factors that could influence these relationships.

Future research should address these limitations by incorporating a broader range of airports, exploring additional models and analytical techniques to capture the complexity of airport relationships, and examining the applicability of the findings in different geographic and economic contexts. This approach would enhance the robustness of the research and provide deeper insights into the strategic development of airport networks globally.

Data availability

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

References

Albayrak MBK, Özcan İÇ, Can R, Dobruszkes F (2020) The determinants of air passenger traffic at Turkish airports. J. Air Transp. Manag. 86:101818

Alderighi M, Cento A, Nijkamp P et al. (2007) Assessment of new hub-and-spoke and point-to-point airline network configurations. Transp. Rev. 27(5):529–549

Anselin L (1988) Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. Geogr Anal 20(1):1–17

Bełej M, Cellmer R, Głuszak M (2020) The impact of airport proximity on single-family house prices—Evidence from Poland. Sustainability 12(19):7928

Bergantino AS, Intini M, Volta N (2020) Competition among airports at worldwide level: A spatial analysis. Transp. Res. Procedia 45:621–626

Chen X, Xuan C, Qiu R (2021) Understanding spatial spillover effects of airports on economic development: New evidence from China's hub airports. Transp. Res. Part A: Policy Pract. 143:48–60

Cheung TK, Wong W, Zhang A, Wu Y (2020) Spatial panel model for examining airport relationships within multi-airport regions. Transp. Res. Part A: Policy Pract. 133:148–163

Choo YY, Corbo L, Wang K (2018) Joint impact of airline market structure and airport ownership on airport market power and profit margin. Transp. Policy 72:67–78

Elhorst J (2014) Spatial Econometrics. From Cross-Sectional Data to Spatial Panels. New York: Springer

Francis G, Fidato A, Humphreys I (2003) Airport–airline interaction: The impact of low-cost carriers on two European airports. J. Air Transp. Manag. 9(4):267–273

Fusco E, Vidoli F (2013) Spatial Stochastic frontier models: Controlling spatial global and local heterogeneity. Int. Rev. Appl. Econ. 27:679–694

Giovanelli L, Rotondo F (2022) Determinants and strategies behind commercial airports' performance in general aviation. Res. Transp. Bus. Manag. 43:100795

Gong X, Lin B (2017) Forecasting the good and bad uncertainties of crude oil prices using a HAR framework. Energy Econ 67:315–327

Granados N, Gupta A, Kauffman RJ (2012) Online and offline demand and price elasticities: Evidence from the air travel industry. Inf. Syst. Res. 23:164–181

Gudmundsson S, Paleari S, Redondi R (2014) Spillover effects of the development constraints in London Heathrow Airport. J. Transp. Geogr. 35:64–74

Harris RD, Tzavalis E (1999) Inference for unit roots in dynamic panels where the time dimension is fixed. J. Econ. 91(2):201–226

Ke M, Baker D (2023) Australian Airports and Local Economic Development. J Urban Technol 30(1):71–93

Lee LF (2004) Asymptotic distributions of quasi-maximum likelihood estimators for spatial autoregressive models. Econometrica 72:1899–1925

Lee L, Yu J (2012) Spatial panels: Random components versus fixed effects. Int. Econ. Rev. 53:1369–1388

LeSage JP, Pace RK (2009) Introduction to Spatial Econometrics. Chapman &Hall/CRC, Boca Raton

Li B, Shi Z, Tian C (2018) Spatio-temporal difference and influencing factors of environmental adaptability measurement of human-sea economic system in Liaoning coastal area. Chin. Geogr. Sci. 28:313–324

Mantin B (2012) Airport complementarity: Private vs. government ownership and welfare gravitation. Transp. Res. Part B: Methodol. 46(3):381–388

Merkel A (2017) Spatial competition and complementarity in European port regions. J. Transp. Geogr. 61:40–47

Moran PA (1950) Notes on continuous stochastic phenomena. Biometrika 37(1/2):17–23

O'Connor K, Fuellhart K (2016) Airports and regional air transport markets: A new perspective. J. Transp. Geogr. 53:78–82

Oum TH, Adler N, Yu C (2006) Privatization, corporatization, ownership forms and their effects on the performance of the world's major airports. J. Air Transp. Manag. 12(3):109–121

Oum TH, Yan J, Yu C (2008) Ownership forms matter for airport efficiency: A stochastic frontier investigation of worldwide airports. J. Urban Econ. 64(2):422–435

Pagliari R, Graham A (2020) Airport competition within the Scottish Lowlands region. Res. Transp. Econ. 79:100760

Pavlyuk D (2010) Multitier spatial stochastic frontier model for competition and cooperation of European airports. Transp. Ann. Telecommun. 11:57–66

Pavlyuk D (2016) Implication of spatial heterogeneity for airports' efficiency estimation. Res. Transp. Econ. 56:15–24

Peng IC, Lu HA (2022) Coopetition effects among global airline alliances for selected Asian airports. J. Air Transp. Manag. 101:102193

Rodrigue J-P, Comtois C, Slack B (2017) The Geography of Transport Systems 4th Edition. New York: Routledge

Starkie D (2002) Airport regulation and competition. J. Air Transp. Manag. 8(1):63–72

Starkie D (2012) European airports and airlines: Evolving relationships and the regulatory implications. J. Air Transp. Manag. 21:40–49

Sugiyanto G, Santosa PB, Jajang FA and Santi MY (2018) Evaluation of hub-spoke airport networks in Sumatra Island, Indonesia, to increase efficiency of air transportation, in Proceedings of the 4th International Conference on Rehabilitation and Maintenance in Civil Engineering, Solo Baru, Indonesia, 11–12 July

Tang K, Wang HJ, Wang N (2022) The relationship between the airport economy and regional development in China. Emerg. Mark. Financ. Trade 58(3):812–822

Thelle MH, la Cour Sonne M (2018) Airport competition in Europe. J. Air Transp. Manag. 67:232–240

Tveter E (2017) The effect of airports on regional development: Evidence from the construction of regional airports in Norway. Res. Transp. Econ. 63:50–58

Wang J, Mo H, Wang F (2014) Evolution of air transport network of China 1930–2012. J. Transp. Geogr. 40:145–158

Wu Z, Lai PL, Ma F, Park KS, Nimsai S (2023) Determining spatial relationships between airports and local economy from competitiveness perspective: a case study of airports in China. Aerospace 10(2):138

Zhang JX, Chang Y, Zhang LX, Li D (2018) Do technological innovations promote urban green development? A spatial econometric analysis of 105 cities in China. J. Clean. Prod. 182:395–403

Zanin M, Lillo F (2013) Modelling the air transport with complex networks: A short review. Eur. Phys. J. Spec. Top. 215(1):5–21

Zijlstra T (2020) A border effect in airport choice: Evidence from Western Europe. J. Air Transp. Manag. 88:101874

Zhao D, Zhen-fu L, Yu-tao Z, Xiao C, Shan-shan L (2020) Measurement and spatial spillover effects of port comprehensive strength: Empirical evidence from China. Transp. Policy 99:288–298

Author contributions

Competing interests

The authors declare no competing interests.

Ethical approval

The study is exempt from review by the Ethics Committee since it is classified as non-human subject research, thereby waiving the need for informed consent.

Informed consent

This article does not contain studies involving human participants engaged by any of the authors.

Additional information

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