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Spatial distribution characteristic of Chinese airports: A spatial cost function approach

Zhongfei Chen [a], Carlos Barros [b], Yanni Yu [c, *]

[a] School of Economics, China Center for Economic Development and Innovation Strategy Research, Jinan University, Guangzhou, Guangdong 510632, China
[b] Instituto Superior de Economia e Gestão, University of Lisbon, Rua Miguel Lupi, 20, 1249-078 Lisbon, Portugal
[c] Institute of Resource, Environment and Sustainable Development, Jinan University, Guangzhou, Guangdong 510632, China

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A B S T R A C T

This paper uses spatial econometric models to analyze the spatial distribution of Chinese airports from 2002 to 2012, taking into consideration the factors that explain the distribution of airports around the country. A cost function allowing for latitude and longitude is estimated based on spatial location, which leads us to advise the implementation of policies that take into account the spatial distribution of the airports. Results show that the development of airports in China needs to consider the spatial relationship among the many different regions of China. To improve the cost efficiency, airports should be located in more economically developed areas. Meanwhile, it also helps to reduce the cost when listing on the stock market.

1. Introduction

Airports located in specific locations serve China's transportation network as feeders of a hub-and-spoke system and as origins or destinations of point-to-point services (Button, 2002). The airport network service contributes to China's economic growth and regional development (Wells and Young, 2004). Research conducted on China's airports has generally focused on efficiency and productivity, while neglecting the role of space in the study of airport activity (Fung, 2008; Fung et al., 2008a, 2008b; Fan et al., 2014). Therefore, the locations of airports and its spatial effects are needed to be included into consideration to study airport benchmarking and policy review (Lian and Rønnevik, 2010; Fröhlich and Niemeier, 2011; Fan et al., 2014; Pavlyuk, 2016). The present research aims at filling this gap and analyze Chinese airports using spatial models; a cost function is estimated for the period from 2002 to 2012 that takes into account the spatial effects measured by latitude and longitude of the airports analyzed.

The motivations behind the present research are the following. First, China is an extensive country, and airports are a core asset for connecting the country and regions; therefore, an understanding of the spatial distribution of airports around the country is important. As the connectivity of China's airports is complementary rather than competitive in nature, establishing a balance of competition and cooperation (Derudder et al., 2010), it is important to understand the spatial correlations that may exist on airports (Miller, 1999). Second, China's airports have recently undergone several reforms since Deng Xiaoping's policy changes. In this context, an analysis of the cost of China's airports, as well as of their observed spatial characteristics, is justified, as it may help clarify the role that transportation networks play in cost, and thus allow for analysis that proposes optimal cost controls. Third, built on the deregulation of China's air transportation, the hub airports also faced increasing competition for hub passengers because of the adoption of hub-and-spoke models for organizing route structures (Button, 2002). This factor justifies the focus on cost efficiency and the adoption of spatial analysis to identify spatial correlations. Finally, while research has noted the significant effects of location on an airport's performance or productivity, no study has used spatial models in its methodology. Rather, the existing literature mainly focuses on the technical efficiency or productivity of Chinese civil airports with traditional SFA (Stochastic Frontier Analysis), which ignore independence between observations. This paper is innovative and make use of the spatial models found in the SFA to examine the cost efficiency of Chinese airports.

* Corresponding author.
E-mail addresses: hongyeczf@163.com (Z. Chen), yayabaobei@naver.com (Y. Yu).

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0969-6997/

The present research analyzes the cost functions of Chinese airports during the period from 2002 to 2012 using five alternative spatial models, which (to reiterate) no study on Chinese airports had done before. It also provides certain policy implications for improving cost efficiency that should be considered before a new round of construction of civil airports begins (Hyard, 2013). This research is of particular interest at this time (Chang et al., 2013; Fan et al., 2014; Jiang and Zhang, 2014; Wang et al., 2015).

The remainder of paper is organized as follows: Section 2 describes the background of Chinese civil airports; Section 3 surveys the literature on the topic; Section 4 presents the methodology framework and the data; Section 5 presents the results, and finally Section 6 presents the discussion and conclusion.

2. Background of Chinese civil airports

With the rapid development of China's economy in the last three decades, more people and cargo than ever now moves from one place to another (see Fig. 1), causing China's civil airports to become increasingly important in the national infrastructure. The number of civil airports has been doubled, increasing from 83 in 1987 to 180 in 2012 (See Fig. 1). However, the overall progress of civil airports in China may create some problems. According to the government reports, the majority of Chinese airports still lost money, the demand for airport services still outweighs supply, and many civil airports are overloaded at present (Wang et al., 2014)[1]. Therefore, more research is needed in order to study how to enhance the management and the planning of airports investment in China. Therefore, according to “the National Civil Airports Scheme” that was approved by the State Council of China, there will be 244 civil airports established in total by the year 2020.

Reform of Chinese airports is kept in pace with development and transition of Chinese Economy. The regulator of civil aviation, the Civil Aviation Administration of China (CAAC), was founded in 1949 and was simultaneously in charge of airline companies, airports and traffic control, which are the three main businesses in the civil aviation industry. Between 1980 and 1986, the industry still operated under a planned economy, and the CAAC was the single institute that ran all of the business. Beginning in early 1987, the government divided business within the airline companies from business within the airports, in order to decrease the monopoly power of the CAAC. None of the civil airports was managed by the provincial government[2] until 2002, when the State Council ordered the CAAC to transfer administrative authority of airports over to the relevant provincial governments,[3] accompanied by their assets, liability and personnel. The main reason for this was that the CAAC, with its limited funds, could not afford the tremendous investments required to improve the airports. The principal airport hubs in China are Beijing Capital International Airport, Baiyun International Airport and Shanghai Pudong International Airport, each of which has started IPO (Initial Public Offering) proceedings and been listed on the stock market since 1998. This should help to attract private funds to increase investment in airports and also improve corporate governance.

Fig. 2 shows the location of all airports in China.

3. Literature survey

The present paper contributes to airport research by analyzing the cost function of airports with a spatial regression model. Some research has analyzed airports' regional characteristics (Barros and Sampaio, 2004; Barros, 2008a, 2008b; Barros and Dieke, 2007, 2008; Derudder et al., 2010; Papatheodorou and Arvanitis, 2009), but it has not analyzed the cost functions according to spatial distribution. Derudder et al. (2010) present a detailed empirical description of airport connectivity in four multiple airport cities (London, New York, Los Angeles, and San Francisco), taking into account the transnational routes that are flown; this study allows for a thorough assessment of the chief connectivity characteristics of specific airports. Using information derived from a number of sources, the study points to functional divisions among airports, both in terms of their geographical scale (e.g., national, regional and international airports) and their specific role in the airline network (e.g., origin/destination versus hub airports). Papatheodorou and Arvanitis (2009) explore the evolution of airport passenger traffic in Greece during the period from 1978 to 2006 and find that despite air transport liberalization, spatial concentration of traffic and asymmetry remains high and has not decreased significantly over time. Moreover, Greece is still short of traffic generated by low-cost carriers especially outside the main metropolitan airports, restricting the regional development. Martin and Voltes-Dorta (2008) analyze airline hubs in relation to spatial concentration indexes and conclude that the spatial concentration does not explain by itself the main features of the network hubs; in other words, this study distinguishes between connection and concentration. More related to the present research, Novak et al. (2008) apply a spatial linear regression to predict outbound freight generation in the United States. Fu and Kim (2016) also complete similar work. Meanwhile, Pavlyuk (2016) pays attentions to the implication of spatial heterogeneity in European airports. In a word, from the existing research on airport efficiency or performance, the spatial factors are widely recognized in the airport industry and should be not ignored in studies.

Until recent years, more research began to focus on the civil airports of China and their performance or productivity (Fung et al., 2008a, 2008b; Chi-Lok and Zhang, 2009; Chang et al., 2013; Fan et al., 2014; Jiang and Zhang, 2014; Wanke et al., 2015; Wang et al., 2015). Several studies have noticed the importance of locational or spatial effects on the performance or efficiency of airports (Chi-Lok and Zhang, 2009; Chang et al., 2013). They just introduced dummy variables or polytomous variables as spatial proxy, which can be considered as observed spatial heterogeneity (Pavlyuk, 2016). However, Barros (2008b) and Pavlyuk (2016) argue that the unobserved spatial heterogeneity is also essential for affecting airport performance. As we know, even the careful selection of these observed factors will still leave unobserved spatial heterogeneity out of a model. The spatial econometrics explicitly deals with spatial dependence and is able to fully take account of unobserved spatial heterogeneity (Pavlyuk, 2016). However, it is rarely applied to analyze the airports performance or efficiency.

Moreover, while much research has concentrated on the management of airport efficiency, no literature has analyzed the cost efficiency of Chinese airports with SFA (Stochastic Frontier Analysis) model. Fan et al. (2014) employs a directional distance function to evaluate the technical efficiency of twenty major Chinese airports during the period from 2006 to 2009 within a joint production framework of desirable and undesirable outputs (i.e., flight delays). Fung (2008), Chow and Fung (2009), Chi-Lok and Zhang (2009) and Zhang et al. (2012) also use the traditional DEA (Data Envelopment Analysis) method to estimate the technical efficiency of Chinese airports in different periods. They compare the difference in efficiency relative to the different characteristics of Chinese airports. However, comparing to the cost efficiency, the technical just takes account of the productivity ignoring the information of

[1] http://www.chinanews.com/cj/2015/05-17/7281640.shtml.

[2] It also can be a municipal government that is equal to a provincial government in China.

[3] It was also called the airport localization program (Chi-Lok and Zhang, 2009).

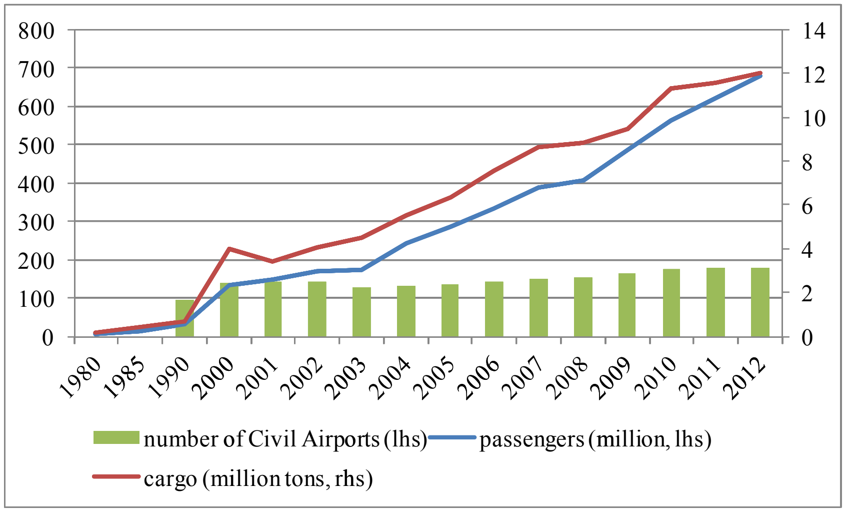

Fig. 1. The passenger, cargo throughput and number of civil airports in China.
Sources: The reports of the Civil Aviation Administration of China (CAAC); Statistical Data on the Civil Aviation of China

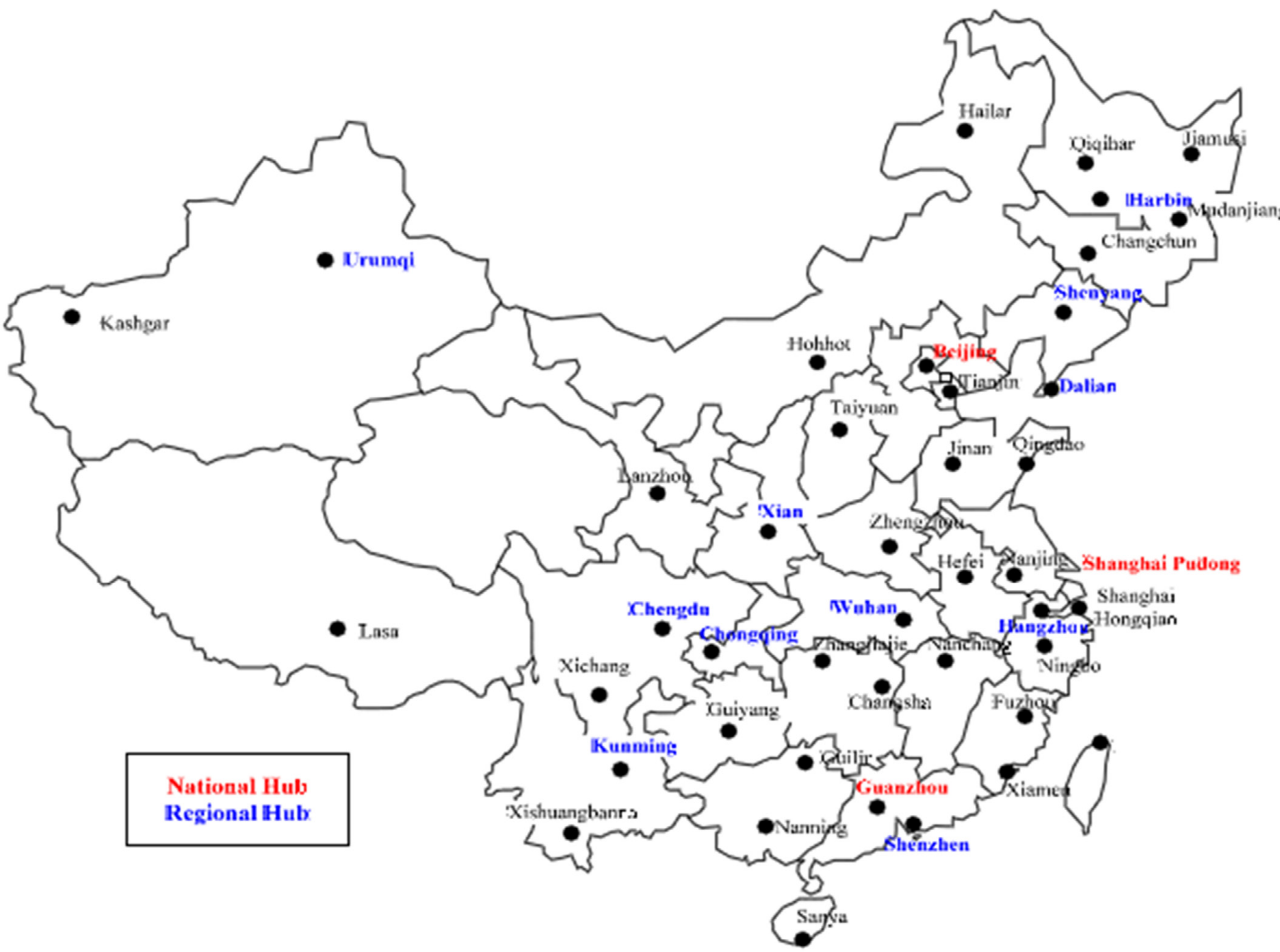

Fig. 2. A map of the airports in China (cited from the paper "Geographical characteristics, service strategy and operating performance in Chinese airports").

price and related allocation efficiency. It is highly significant for the Chinese airports management as they are all modern profit-making companies after the stock-reforms. Nowadays, China has already switched from the traditional central-planned economy to the market-driven economy.

Hence, from the arguments above, this paper fills the gap in the literature and takes advantage of the spatial econometric models when analyzing the cost efficiency of Chinese airports with SFA.

4. Econometric models

To understand the differing implications of spatial and temporal autocorrelation, it is helpful to consider Anselin's (1988) general spatial model for panel data:

$$y_{it} = \rho W y_{it} + \mathrm{X}_{it}\beta + \mu_i + \varepsilon_{it} \tag{1}$$

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + \xi \tag{2}$$

where y_{it} is an N^*T vector of observation on the dependent variable (in this paper, the dependent variable y is labeled as airport costs); Wy_{it} is a spatially lagged dependent variable with spatial weights matrix W; ρ is the spatial autoregressive parameter for the spatially lagged dependent variable; X are exogenous explanatory variables with β as the associate parameter; μ_{i} is the individual fixed effect; ε is an N by T vector of error terms; ε is a spatially lagged error term with spatial weights matrix W; λ is the spatial autoregressive parameter for the spatially lagged error term; and $\xi \sim N(0,\Omega)$, where $\Omega ii = hi(\mathbf{z}\alpha)$. When $\alpha = 0$, $h = \sigma_2$, the errors are homoscedastic. The spatial lag model consistent with a diffusion process in the DGP (Data Generation Process) results from setting λ equal to zero. The spatial error model consistent with attributional dependence results from setting ρ equal to zero. The main idea is that spatial dependence refers to how much the level of cost efficiency of airport i depends on the levels set by other airports (j = 1, …, n) under the assumption that part of the airport i efficiency is linked to the neighbor DMU j's performances (Fusco and Vidoli, 2013, 2015; Glass et al., 2016). In contrast to the traditional SFA models, it splits the spatial heterogeneity into three terms: the first one related to spatial peculiarities of the territory in which each DMU operates, the second one related to the specific production features and the third one representing the error term (Fusco and Vidoli, 2013, 2015).

The data generating process (DGP) that produced the sample data determines the type of spatial dependence (LeSage and Pace, 2010). As we do not know the true DGP, alternative approaches to applied modeling situations have been always advocated. In this paper, we choose five basic spatial models, which are popular in the main literature and consider different kinds of spatial dependence, to the empirical research of Chinese airports. After regression, we will further test which spatial model is most appropriate or best for Chinese airports (LeSage and Pace, 2010). Let us first consider the spatial auto regression model (SAR). This bears some similarity to a time series model with a lagged dependent variable:

$$y_{it} = \rho W y_{it} + \mathrm{X}_{it}\beta + \mu_i + \varepsilon_{it} \tag{3}$$

where the lag in (3) is temporal rather than spatial, as it is in (2). The parameter ρ is a coefficient on the spatially lagged dependent variable, Wy_{it}. W and M *are spatial weight matrix.* The Spatial lag implies spatial externalities in both modeled and unmodeled effects, i.e. the systematic and stochastic components (Franzese and Hays, 2008). Moreover, spatial lag and spatial error models are two workhorse regression models in the Spatial Econometrics.

Second, consider the Durbin model (SDM), which takes account of spatial lags of both dependent variable and explanatory variables. It is motivated by concern over omitted variables, while is highly criticized by the potential identification problem.

$$y_{it} = \rho W y_{it} + \mathrm{X}_{it}\beta + W\mathrm{X}_{it}\vartheta + \mu_i + \varepsilon_{it} \tag{4}$$

Third, the spatial autocorrelation model (SAC) that simultaneously includes spatial lags of dependent variable and disturbance process. It is a more general model comparing to SAR and SEM.

$$y_{it} = \rho W y_{it} + \mathrm{X}_{it}\beta + \mu_i + \upsilon_{it} \text{ with } \mathrm{v}_{it} = \lambda \mathrm{M} \mathrm{v}_{it} + \varepsilon_{it} \tag{5}$$

Fourth, the spatial error model (SEM), in which the spatial dependence arises only in the disturbance process. Meanwhile, the spatial error part implies that the pattern of spatial dependence is only attributable to unmeasured covariates, i.e., the stochastic component (Franzese and Hays, 2008).

$$y_{it} = \mathrm{X}_{it}\beta + \mu_i + \upsilon_{it} \text{ with } \mathrm{v}_{it} = \lambda \mathrm{M} \mathrm{v}_{it} + \varepsilon_{it} \tag{6}$$

And finally, the generalized spatial random errors model (GSPRE) that assumes the spatial correlation occurs not only in the residual error term, but also in the individual effect (Anselin, 1988; Baltagi et al., 2013). It implies a different spatial spillover mechanisms and assumes the spillovers to be time-invariant as well as time-variant (Baltagi et al., 2013). The other four models do not take account of this time-invariant spillovers.

$$y_{it} = \mathrm{X}_{it}\beta + \mu_i + \upsilon_{it} \text{ with } \mu_i = \rho W \mu_i + \eta_i \text{ and } \upsilon_{it} = \lambda \mathrm{M} \upsilon_{it} + \varepsilon_{it} \tag{7}$$

4.1. Research design

According to the present study on cost efficiency (Papatheodorou and Arvanitis, 2009; Scotti et al., 2012; Kutlu and McCarthy, 2016; Pavlyuk, 2016) as well as the accessibility of data on Chinese airports, the following variables are considered in the empirical estimations of our model: airport operational cost; price of labor, price of capital, terminal size, passengers, cargo, planes, airports quoted, airports in the Yangtze River Delta, airports in the Bohai Gulf Region, latitude and longitude. The data is a panel data from a sample of Chinese airports in the period from 2002 to 2012 obtained from a series of records known as the Statistical Data on Civil Aviation in China and financial reports of different airports that obtained from Shanghai Stock Exchange (http://www.sse.com.cn/) and Shenzhen Stock Exchange (http://www.szse.cn/).

The endogenous variable is the airport's operational cost. According to the theoretical model and the contextual setting of Chinese airports, the following hypotheses are presented below.

H1 (Hub): Chinese airports that are hubs decrease operational costs. This is based on the economies of scale derived from hub activities (Button, 2002; Yang and Chen, 2016). Chang et al. (2013) note that Chinese airports located in cities with populations of more than two million are more efficient than those located in smaller cities. They come to this conclusion by looking at the efficiency of airports in various sizes of city and also looking at how far an airport is from its local business district.

H2 (quoted): Quoted Chinese airports decrease the operational cost. This effect is based on the disciplinary role of the stock exchange on the quoted companies (Hooper, 2002; Lyon and Francis, 2006; Yang et al., 2008). Chi-Lok and Zhang (2009), and Fan et al. (2014), also find that Chinese airports that are listed on the stock exchange have higher technical efficiency than non-listed ones.

H3 (Yangtze River Delta): The location of the Yangtze River delta improve the cost efficiency of airports. Yangtze River delta airports are the airports of Shanghai Pudong, Shanghai Hongqiao, Nanjing and Hangzhou. These airports, based in densely populated areas and one of the economic centers in China, obtain economies of scale that decrease costs (Zhang, 1998; Yang et al., 2008).

H4 (Bohai Gulf Region): The location of the Bohai Gulf region improves the cost efficiency of airports. Sample airports located in the Bohai Gulf region are Dalian, Jinan and Beijing (Fung, 2008; Fung et al., 2008a, 2008b). It is also another densely populated area and one of economic centers in China, obtain economies of scale that reduce costs (Zhang, 1998; Yang et al., 2008; Chi-Lok and Zhang, 2009; Fan et al., 2014).

In the adopted five spatial models above, i.e. model [3–7], we will further test the hypotheses outlined; see Anselin (1988) and LeSage and Pace (2010). The motivation to use the spatial models is derived from the fact that geographical effects may not be independent and may tend to generalize.

$$\log\frac{Cost_{it}}{PK2_{it}} = \beta_0 + \sum_i \beta_p \log\left(\frac{P_{it}}{PK2_{it}}\right) + \beta_k \log\left(\frac{K_{it}}{PK2_{it}}\right) + \beta_y \log Y_{it} + \frac{1}{2}\sum_l \beta_{pp}\log\left(\frac{P_{it}}{PK2_{it}}\right)^2 + \frac{1}{2}\beta_{kk}\log\left(\frac{K_{it}}{PK2_{it}}\right)^2 + \frac{1}{2}\sum_i \beta_{yy}\log(Y_{it})^2 + \sum_l \beta_{pk}\log\left(\frac{P_{it}}{PK2_{it}}\right)\log\left(\frac{K_{it}}{PK2_{it}}\right) + \sum_l \beta_{py}\log\left(\frac{P_{ilt}}{PK2_{it}}\right)\log Y_{it} + \sum_l \beta_{ky} Log\left(\frac{K_{it}}{PK2_{it}}\right)\log Y_{it} + \beta_1 Hub + \beta_2 Quoted + \beta_3 Yangtze + \beta_4 Bohai + \mu_i + \varepsilon_{it} \tag{8}$$

4.2. Data

To estimate the spatial cost function, we used balanced panel data on 41 Chinese airports for the years from 2002 to 2012 (11 years*41 units = 451 observations). The data was obtained from the Statistical Data on Civil Aviation in China (i.e. From the Statistical View of Civil Aviation, which has been published every year), which is an official publication of the Civil Aviation Administration of China, as well as from the financial reports of different airports through their websites or stock market information disclosure (Shanghai Stock Exchange (www.sse.com.cn); Shenzhen Stock Exchange (www.szse.cn)). These 41 airports represent the majority of Chinese civil airports, and the passengers who use these 41 airports account for approximately 89% of all passengers flying from Chinese airports during the study period.

The variables were transformed as described in Table 2, where monetary figures are expressed in Yuan, deflated by the GDP deflator and denoted at 2006 prices. The outputs are measured by three metrics, which describe the operational activity of airports: number of passengers, total cargo and aircrafts. We measured inputs using three indicators: price of labor, measured by dividing total wages by the number of employees; price of capital-premises, measured dividing amortizations by the fixed asset (Kutlu and McCarthy, 2016) and the area of passenger terminals (Yoshida, 2004; Yoshida and Fujimoto, 2004; Fung et al., 2008a, 2008b). Many studies also use runway length as an additional input as it determines the nature of airline traffic which can be handled by an airport in a specific time (Fan et al., 2014; Fragoudaki et al., 2016). However, the variation in this variable in each year was quite stable over time for Chinese airports (Fung et al., 2008a, 2008b). It would be captured by the individual fixed effect in the panel models. Moreover, much of runway length data is unavailable for many Chinese airports. Therefore, we have not used this input like some other paper. We specify the capital variable as a quasi-fixed factor (Caves and Christensen, 1980; Kaparakis et al., 1994). The spatial weights matrix W is generated from the latitude and longitude of the airport. The characteristics of the variables are shown in Table 1.

5. Empirical results and discussion

The specification of the cost function follows microeconomic theory (Varian, 1987). The costs are regressed in the input prices and output descriptors. Each explanatory variable is divided by its geometric mean. In this way, the translog function can be considered as an approximation of an unknown function, and the first-order coefficients can be interpreted as the production elasticities that are evaluated at the sample geometric mean. The baseline SFA equation to be estimated as follows:

where cost is the logarithm of the variable cost of a Chinese airport; PK_2 is the price of capital-funding; P denotes input price (labor and capital-premises); K is the capital variable defined as a quasi-fixed factor (Caves and Christensen, 1980), which in the present context is the terminal area; Y is the airport's output (passengers, cargo and aircraft); μ_i is the individual fixed effect; ε is a random error which reflects statistical noise and is assumed to follow a normal distribution centered at zero. Meanwhile, *Hub*, *Qutoed*, *Yangtze* and *Bohai* are dummy variables used to verify the hypothesis mentioned above.

Table 2 presents the estimation results for the five alternative estimations. First, we consider the SAR-a model with spatial lags and autocorrelations. The spatial lag model relaxes the assumption of independence between the explanatory variables by including the spatial matrix W, defined in the methodology and the spatial model with a spatial matrix with a lag (Pisati, 2001; Huang and Xia, 2016; Liu et al., 2016). The SAC-a model simultaneously with a spatial lag and spatial error autocorrelation that combines the two aspects of the SAR and SEM models presented above (Franzese and Hays, 2008). This model is estimated using a generalized spatial 2SLS-two stages least squares method. The fourth column presents the results of the SEM-a model with spatial error autocorrelation. The error spatial model relaxes the assumption of independence between the explanatory variables by including the spatial matrix W defined in the methodology. These two spatial models are estimated as having maximum likelihood. Finally, we use the generalized spatial random errors model.

As shown in Table 2, consistency of results among the different estimated model specifications can be found. Meanwhile, the results of the SAC model, a model with a spatial lag autocorrelation, reveal that the estimated coefficient on the spatial lag (rho) is positive and statistically significant. It suggests that there is spatial lag in the costs of Chinese airports. The results reveal that the SEM-a model with spatial error autocorrelation presents a good fit with the spatial error parameter effect (lambda) being negative and statistically significant (Cliff and Ord, 1981). This further suggests that spatial autocorrelation exists among Chinese airport costs, and that this autocorrelation is negative. This result is reinforced with

Table 1
Descriptive statistics of the data.

Variable	Unit	Description	Minimum	Maximum	Mean	Standard Deviation
Cost	Yuan	operational cost in Yuan at constant price 2006 = 100	787,552	4.29e+09	2.95e+08	4.58e+08
PK1	–	Price of capital-premises, measured dividing amortizations by the fixed asset value at constant price of 2006	0.01	0.46	0.10	0.24
PK2	–	Price of capital-funding, measured dividing financial costs by total debt	0.01	0.15	0.22	0.32
PL	Yuan	Price of workers, measured by dividing total wages between the number of workers	3183	480,206	83,984.35	80,812.10
Terminal	m^2	Terminal size area in square meters (10,000)	0.14	141.40	8.61	16.28
Passengers	person	Number of passengers at each airport	15,307	5.59e+07	6,118,615	8,450,646
Cargo	ton	Tons of cargo	19.70	2,603,027	150,551	342,363
Aircraft	–	Number of aircraft movements at each airport	337	429,649	59,918	70,547
Hub	–	Dummy variable which is one for national hub airports and zero elsewhere	0	1	0.22	0.41
Quoted	–	Dummy variable which is one for quoted airports and zero elsewhere	0	1	0.07	0.26
Yangtze	–	Dummy variable which is one for airports located in Yangtze River delta and zero elsewhere	0	1	0.10	0.30
Bohai	–	Dummy variable which is one for airports located in Bohai Gulf region and zero elsewhere	0	1	0.07	0.26
Longitude	degree	The longitude of the airport	76	130	112.78	10.95
Latitude	degree	The latitude of airport	13	22	18.53	1.64

Moran I statistics of 0.215 with a z value of 5.12, indicating the operation of Chinese airports has high spatial agglomeration. This may be the results from the facts that the economic centers all lies in the eastern area of China, which is much developed than the middle and west of China and attracts more passengers and trade. Moreover, this spatial agglomeration helps to reduce the operational cost of Chinese airports, implying the economies of scale in China. In other words, it is the spillover effect of the local economy. The link and interchange between the neighbor areas benefits the development as well as operation of neighbor airports. According to Anselin (1988), we can reject the null hypothesis that there is zero spatial autocorrelation present in the costs of Chinese airports. Furthermore, these results also validate the use of spatial models in the analysis of Chinese airport costs. The results of the SAR model, a model with spatial lag autocorrelation, reveals that the estimated coefficient of the spatial lag (rho) is positive and statistically significant; this means that there is spatial lag in Chinese airport costs. This result is reinforced by the results of the SAC model, in which the spatial lag (rho) is also statistically significant. However, the standard error of the regression (i.e., the estimated standard deviation of the stochastic component, the error term, of the model) sigma is positive and therefore the model fit is highly statistically significant. A clear view of the spatial effect of Chinese airport costs emerges from these spatial models, fitted as described. The GSPRE model validates these results.

From the empirical results for these five different spatial models, the presence of statistically significant spatial heterogeneity can be found. Based on the absolute value of log likelihood, the SAC model has the largest one and is more appropriate and chosen in order to interpret the results (LeSage and Pace, 2010).

Furthermore, we also observe that almost all signs of variables are maintained throughout the various spatial models, despite some of them being not significant at 10% level. Moreover, given the estimated model, it is verified that the estimated cost functions verify the homogeneity in prices.

Chinese airport costs are partially explained by spatial effects that may result from their interaction in traffic management as well as the spillover effects of local economy. Further, the majority of airports analyzed are supervised by the Civil Aviation Administration of China, which can help to explain the spatial effects.

Moreover, according the empirical results of the SAC model, hub airports and listing of airports on the stock exchange seems to have an effect of decreasing the airports' costs, and therefore these factors are statistically significant. These results validate hypothesis 1 and 2. It is also compatible with the results of Chi-Lok and Zhang (2009) and Fan et al. (2014). Hub airports and listed airports are all big airports with more rigorous management under supervision of government and the market. Airports situated in the Yangtze River Delta and the Bohai Gulf Region have lower costs but their estimated parameters are statistically insignificant. Therefore hypothesis 3 and 4 are not validated, suggesting that the Yangtze River Delta and Bohai Gulf Region location does not significantly help to improve cost efficiency. The Yangtze River Delta and Bohai Gulf Region location stands for the spatial aspects of observed heterogeneity related to airports' geographical location (Pavlyuk, 2016). However, as we also have taken account of the spatial spillover effect through spatial econometric model specification (i.e. SAR, SDM, SAC, SEM and GSPRE), it may undermine the significance of these regional characteristic variables.

This research suggests that spatial effects are present in hub-and-spoke services, and as certain airports serve as origins or destinations of point-to-point services, any public policy focusing on airports must take this effect into consideration, since it signifies that traffic among Chinese airports generates autocorrelation or spatial dependency. Moreover, because the Chinese government plans to build many more civil airports in the next decade, the location of these new airports should take into account the spatial effects noted in this research, so as to reduce operational cost.

Compared with earlier research on Chinese airports, this paper considers data from the entire country and uses an estimation method that considers spatial effects in the cost function, enabling a more accurate view of Chinese airports.

6. Conclusion

Airports have been in rapid development across different regions of China during recent decades. The existing literature focuses mainly on the technical efficiency or productivity of airports with traditional SFA, which ignore independence between observations. This paper fills this gap by using the cost function and considering the spatial effects. It analyzes 41 Chinese airports costs during the period from 2002 to 2012. This is the first study to be undertaken at the national level, with a contemporary data span, using spatial analysis. The empirical results show that there are five

Table 2
Estimation Results (dependent variable: Log Operational cost).

	SAR model	SDM model	SAC model	SEM model	GSPRE model
Cost(t-1)		0.833***			
		(11.41)			
W*Cost		0.217***	0.124***		
		(18.08)	(124.00)		
Log PK_1	0.010***	0.010***	0.009***	0.011***	0.012***
	(3.62)	(3.90)	(3.83)	(3.94)	(3.71)
Log PL	0.651	1.155	0.626	1.375	0.162
	(0.37)	(0.70)	(0.38)	(1.17)	(0.09)
Terminal	−0.110	−0.089	−0.115	−0.111	−0.133
	(-0.74)	(-0.65)	(-0.81)	(-0.94)	(-0.87)
Log Passengers	1.189	1.281***	1.194	1.274***	1.152
	(1.34)	(3.79)	(1.43)	(8.55)	(1.27)
Log Cargo	−0.568**	−0.542***	−0.575**	−0.546***	−0.487*
	(-2.02)	(-2.97)	(-2.15)	(-5.65)	(-1.69)
Log Aircraft	0.260	0.995	2.591	0.810	1.998
	(0.29)	(0.31)	(0.30)	(0.46)	(0.21)
1/2 logPK_1^2	−1.997	−0.834***	−2.013	−2.084*	−1.181
	(-1.53)	(-3.33)	(-1.63)	(-1.81)	(-0.89)
1/2 logPL^2	−0.750***	−2.006*	−0.762***	−0.924***	−0.662**
	(-2.96)	(-1.66)	(-3.14)	(-4.45)	(-2.56)
1/2 log$Terminal^2$	−0.0004**	−0.0004**	−0.0004**	−0.0004**	−0.0004**
	(-2.31)	(-2.29)	(-2.47)	(-2.56)	(-2.43)
1/2 log$Passengers^2$	0.515	−0.963	−0.627	−1.246***	−0.185
	(-0.12)	(-1.02)	(-0.16)	(-3.76)	(0.04)
1/2 log $Cargo^2$	−0.243***	−0.257***	−0.245***	−0.268***	−0.204**
	(-2.72)	(-4.52)	(-2.90)	(-9.74)	(-2.25)
1/2 log $Aircraft^2$	0.682*	0.589***	0.668*	0.511***	0.683*
	(1.90)	(4.86)	(1.95)	(8.23)	(1.86)
logPK_1*LogPL	−0.805	−0.920	−0.813	−1.007	0.183
	(-0.74)	(-0.90)	(-0.79)	(-1.03)	(0.17)
logPK_1*LogTerminals	−0.042	−0.041	−0.042	−0.040	−0.017
	(-0.52)	(-0.57)	(-0.59)	(-0.56)	(-0.23)
LogPK_1*LogPassengers	−0.284	−2.498	−2.853	−0.238	−0.386
	(-0.90)	(-0.85)	(-0.96)	(-0.87)	(-0.07)
LogPK_1*LogCargo	−0.675	−0.685***	−0.679***	−0.708***	−0.407
	(-1.251)	(-2.76)	(-2.67)	(-2.98)	(-1.44)
LogPK_1*LogAircraft	1.072*	1.043**	1.078**	1.058**	0.596
	(1.95)	(2.07)	(2.08)	(2.27)	(0.94)
Log PL*logTerminal	0.041***	0.042***	0.041***	0.042***	0.041***
	(4.06)	(4.36)	(4.31)	(4.55)	(3.98)
LogPL*LogPassengers	0.664	0.515	0.697	0.564**	0.577
	(0.76)	(0.82)	(0.83)	(2.37)	(0.64)
logPL*Log Cargo	−1.113***	−1.237***	−1.117***	−1.280***	−1.065***
	(-2.85)	(-3.20)	(-3.03)	(-6.59)	(-2.66)
LogPL*LogAircraft	0.692	1.008	0.666	1.026***	0.765
	(0.67)	(1.52)	(0.68)	(3.30)	(0.72)
LogTerminal*Log Passengers	−0.0014	−0.011	−0.0004	−0.011	−0.003
	(-0.02)	(-0.15)	(-0.01)	(-0.20)	(-0.04)
LogTerminal*Log Cargo	−0.010	−0.008	−0.010	−0.008	−0.015
	(0.85)	(-0.71)	(-0.92)	(-0.83)	(-1.22)
Log terminal*Log Aircraft	0.002	0.009	0.002	0.012	0.014
	(0.03)	(0.11)	(0.03)	(0.20)	(0.14)
Log Passengers* Log Cargo	0.327***	0.332***	0.329***	0.332***	0.280**
	(2.95)	(5.82)	(3.14)	(18.54)	(2.49)
Log Passengers* Log Aircraft	−0.577	−0.521***	−0.567	−0.481***	−0.568
	(-1.51)	(-7.46)	(-1.57)	(-16.65)	(-1.45)
Log Cargo* Log Aircrafts	0.342	0.468	0.352	0.649	0.355
	(0.23)	(0.66)	(0.25)	(2.05)	(0.23)
Hub	−0.152	−0.136	−0.143**	−0.087***	−0.106
	(-1.58)	(-1.46)	(-2.48)	(-2.90)	(-1.08)
Quoted	−0.161	−0.130*	−0.167***	−0.188***	−0.106
	(-0.90)	(-1.82)	(-2.98)	(-2.82)	(-0.58)
Yangtze River Delta	−0.051	−0.030	−0.062	−0.101	−0.0006
	(-0.40)	(-0.27)	(-0.49)	(-0.79)	(-0.05)
Bohai Gulf Region	−0.040	−0.083	−0.049	−0.105	−0.033
	(-0.33)	(-0.74)	(-1.41)	(-1.04)	(-0.26)
Log Likelihood Function	−155.024	−155.723	−156.244	−155.234	−155.102
R-square		0.927			0.932
Lambda			−0.019**	−0.012***	
			(-**3.01**)	(-**2.62**)	
Rho	0.0002**		0.008***		
	(**2.27**)		(**3.27**)		
Observations	451	451	451	451	451

Note: * Denotes statistical significance at the 10% level. ** Denotes statistical significance at the 5% level. *** Denotes statistical significance at the 1% level. T value are shown in parentheses.

kinds of different spatial dependence (i.e. SAR, SDM, SAC, SEM and GSPRE) among Chinese airports (Vega and Elhorst, 2012; Glass et al., 2016), signifying that neglecting these effects may result in bias in the estimated models. Moreover, we further investigate whether these four distinctive characteristics affect the costs of Chinese airports using different spatial cost functions. The status of an airport as a hub and the listing of an airport on the stock exchange both decrease an airport's costs, while the location (i.e., whether the airport is located in the Yangtze River Delta or the Bohai Gulf Region) does not significantly decrease the costs. This implies that the development of airports in China should consider the spatial relationship among different regions of China, especially the relationship with China's hub airports. Moreover, in general, population does not decrease operational costs, while the status of hub airports, which are located in economic centers of China, does decrease the operational costs, implying that the development of airports should be consistent with economic development, rather than occurring ahead of the demand for infrastructure. Finally, the airports of China need to strengthen their management. Most Chinese airports are still SOEs (State-owned Enterprise) and present many opportunities to improve management and efficiency. The quoted or listed airports could help reduce the cost through increasing supervision from shareholders.

This is the first paper to analyze the cost efficiency of Chinese airports taking account of the spatial effects. More research is needed to confirm the present research.

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