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Spatial competition and efficiency: an investigation in the airport sector

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Abstract

This paper analyses the potential impact of airport competition on technical efficiency by applying the spatial stochastic frontier approach (SSFA) rather than traditional model (SFA). The SSFA allows to isolate the cross-sectional spatial dependence and to evaluate the role of intangible factors in influencing the airport economic performance, through the inclusion of the distance matrix and the shared destinations matrix, calibrated for different distances. By analysing statistical differences between the traditional and the spatial model, it is possible to identify the competition effects. This study includes 206 airports at worldwide level. First, the results show the existence of the spatial component, that could not be otherwise captured by the traditional SFA. Moreover, airport competition is found to affect the efficiency level with either a positive or a negative effect, depending on the distance considered in the spatial model.

Keywords: Transportation; Major Airports; Efficiency Analysis; Spatial Interaction; Airport Competition.

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1. Introduction

Airport infrastructures strongly affect the socio-economic structure of a territory. They create new residential and productive settlements, promote new job opportunities and influence the choices of individuals. These infrastructures contribute to the local development of the area in which they are located, by integrating the regional economy with the rest of the national and international economic systems. In this context, the globalization process has extended the national borders, and, for this reason, air accessibility is one of the essential factors for the development of any advanced economy. The last decade registered a striking +214% increase in the worldwide number of passengers (World Bank, 2015). The trend is expected to speed up in the future with the demand for air travel forecasted to grow at an average annual rate of 4.1%, reaching 7.3 billion/year passengers by 2034 (IATA, 2015). In this scenario, according to industry analysts, three major changes are influencing the competitive constraints and productivity of airports: more footloose airlines, greater passengers' choice, and higher reactivity of airports[4] (ACI, 2009). Furthermore, the changes in the aviation industry, shifting from a point-to-point system to a hub-and-spoke network, have redefined the industry globally by creating patterns of traffic concentration: in the early 2000s, the hubbing network strategies have emerged in US, Europe and Southeast Asia (Goetz and Sutton, 1997; Button, 2002; Reynolds-Feighan, 2001; Bowen, 2000). After the deregulation period, airlines developed Hub-and-spoke networks allowing them to aggregate demand, increase frequency, decrease airfares and preclude entry into the marketplace (Adler, 2001). Later de-concentration tendencies have emerged again, especially among regional and low-cost carriers, which has involved a shift of passenger traffic volume away from the largest cities, toward airports of those next in rank (O'Connor, 2003). This phenomenon is quite evident in Europe[5]. To different degrees also other parts of the world are registering de-concentration toward smaller cities' airports.

Airports are usually classified as a two-sided market since revenues are generated by two different users, passengers and airline companies (Worldwide Air Transport Conference, 2013[6]). In this view airports define their position in the market based on their ability to generate new demand and, at the same time, to attract airlines and passengers from other airports. For this reason, focussing on airports located in three different continents (Europe, North America, and Pacific Asia), we analyse the spatial effects of the airports, reflecting the territorial competitiveness, on efficiency through different matrices that capture in different and precise ways the competition patterns. For instance, in Europe, approximately 63 percent of the population is within two hours' drive of at least two airports, in the USA and in ASIA the rate is lower but still relevant (IATA, 2013). Moreover, digital innovations and the widespread use of online platforms allow passengers to

[4] The growing attention by local authorities to the potential benefits from airport connectivity complicates the scene as incentive programs, investments, or benefits are put into place to either maintain demand, increase it, or reverse passenger losses (Ryerson, 2016; Sharkey, 2014).

[5] As shown by Burghouwt (2007), most of the intra-European traffic has been de-concentrated while the intracontinental flights are still concentrated in a few large hub airports.

[6] For details: Worldwide Air Transport Conference (ATCONF) ATConf/6-WP/90 4/3/13.

compare both destinations and airfares when buying a ticket. In fact, internet allows consumers to increase their trading power choosing different airlines and the most competitive flights, while companies can easily check the behaviours of consumers to adapt their pricing tactics using internal information (Moreno-Izquierdo et al., 2015). In the case of leisure trips, this behaviour is extremely relevant in the context of airport competition (Granados et al., 2012). Airports need to attract passengers and airlines by strategically acting on marketing and route development and trying to differentiate their offer. These elements have led to an increasing interest in the transport-related literature on the potential interaction effects among airports. The underlying idea is that the strategies of a given airport may not be indifferent to those of other neighbouring airports. This is particularly true when the catchment areas physically overlap or when the airports compete for hub and spoke connections and, although physically distant, might have an overlapping market. It assists, on the one hand, to phenomena of airport passenger leakage - when passengers choose to travel longer distances to access more extensive air services offered by airlines at an out-of-region hub[7] (or, substitute) airport (Qian Fu, Amy M. Kim, 2015; Elwakil et al., 2013; Fuellhart, 2007; Suzuki and Audino, 2003; Suzuki et al., 2004). In this case, airports with different natural catchment areas might become competitors, or, even, might decide to cooperate. On the other hand, there are increasing pressures on local authorities and airport management companies, especially when publicly owned, to subsidise, in some ways, airline companies to increase their connections or to establish themselves on the territory.

Increasingly airports located nearby are placed in the conditions to compete to acquire airlines and, consequently, potential demand. Airports' level of dynamism is often influenced by the ownership form, which is still very heterogeneous at a worldwide level, and by the effectiveness of the governing/regulatory bodies, given the relevant role still played in most countries by politics for the infrastructural system. Also, HSR connections have strongly influenced, especially in Europe, the scene of competing airports either within the same country (i.e. Florence and Bologna in Italy) or among different countries (i.e. Paris, Brussels, Amsterdam). More generally, all over the world the airport sector has become much more strategically oriented, respect to some years ago.

1.1 Literature review

Airport efficiency has been the focus of a large body of research (see Barros, 2008; Fung, Wan, Hui and Law, 2007; Martin et al., 2009; Oum and Yu, 2004; Pels et al., 2001, 2003; Suzuki et al., 2010; Yoshida, 2004). Different aspects have been analysed. For instance, Suzuki et al. (2010), using a distance friction minimization approach in a DEA analysis, generate an appropriate efficiency-improving projection model for input reduction and output increase considering thirty European airports. Assaf and Gillen (2012), using a DEA and a semi-parametric Bayesian approach, examine the joint impact on airport efficiency of governance

[7] Hub networks arise when passengers, goods or data flows are to be routed from origins to destinations (OD). Instead of connecting each OD pair directly in a network, flows are routed through hub infrastructure. Additionally, it is expected that the transfer cost between hubs is cheaper than the collection/distribution costs between hubs and non-hubs due to the economies of scale (Soylu and Katip, 2019).

structure and economic regulation, finding that the latter affects more the efficiency than the governance structure. Adler and Golany (2001), using a DEA-PCA formulation in the European market, select the most efficient networks configurations that are desirable to choose for an airline. Differently, other studies focus on the number of runways and their effect on the landing procedure of aircraft at an airport (Bäuerle et al., 2007) or on reducing operational queueing delays at busy airports, formulating the optimal dynamic control of service facilities model (Shone et al., 2019). Airport slot scheduling problem is further analysed by Androutsopoulos et al. (2020) using a bi-objective resource-constrained project scheduling problem with partially renewable resources and non-regular objective functions.

Frohlich and Niemeier (2011) state that the presence of spatial competition among airports lies within one market, although sometimes, overlapping competition circles are observed within common areas. However, only a few studies explain competition implications on airports’ efficiency levels from nearby airports and, in the available studies the evidence is mixed[8]. Specifically, Pavlyuk (2009) using an index of competition based on overlapping catchment areas into the stochastic frontier model, discovered a positive effect of competitive pressure on efficiency for a sample of European airports. In further research, Pavlyuk (2010) suggested a multi-tier model of competition and cooperation effects. The estimates point to both positive and negative effects, depending on the distance among airports. Malighetti et al. (2009), considering a sample of 57 European airports, conclude that the intensity of competition between airports has, on average, a positive effect on efficiency. By analysing the relationship between efficiency and the degree of competition within the same country (a sample of Italian airports between 2005 and 2008), Scotti et al. (2012), however, find the opposite result. They explain it considering the less intensive use of the inputs in the airports belonging to a local air transport system in which competition is stronger than in airports with local monopoly power. Adler and Liebert (2014), investigate the combined impact of economic regulation, ownership form, and competition on airport cost efficiency for 48 European airports and 3 Australian airports over ten years. They observe that under non-competitive conditions, public airports are less cost-efficient than fully private airports. D'Alfonso et al. (2015), assess the impact of competition on airport efficiency, to evaluate whether airports are more efficient when the intensity of competition is higher. They find that on average the impact of competition on technical efficiency is negative, confirming the significant role of economies of scale and thus, also, of the size of demand.

Different studies detected the importance of spatial effects on the efficiency of Chinese airports (Chi-Lok and Zhang, 2009; Chang et al., 2013). They just consider dummy variables as a spatial proxy that could measure the observed spatial heterogeneity (Pavlyuk, 2016). However, Barros (2008) and Pavlyuk (2016) argue that

[8] The assumption that airports act as monopolists in the market, stemming from the situation prior to the deregulation wave in the airline industry, is no longer undisputed (Thelle and la Cour Sonne, 2018). Airports cannot be considered as isolated entities any longer since they compete and decide their strategic behaviour considering other airports' strategies. Normally, an increase in competition should be welfare-enhancing, leading to greater efficiency. This, however, is not always the case. When additional airports come into an oligopolistic market, they may lead to greater competition, but overall welfare can fall because of the loss of economies of scale, given the high level of fixed costs in the sector (Forsyth et al., 2010). Furthermore, market power is mainly determined by the availability of proximate airports that can act as close substitutes (Starkie, 2002).

unobserved spatial heterogeneity is also crucial for affecting airport performance. Ha et al. (2013), measuring the Chinese airport efficiency and competition among airports and other modes of transportation, find that competition among airports and competition from substitutable transportation modes have a positive impact on efficiency scores of airports. Chen et al. (2017) show that spatial effects are present in a hub and spoke Chinese services and as certain airports serve as origins or destinations of point-to-point services. Authors state that any public policy focusing on airports must take the spatial effect into consideration since it indicates that traffic among Chinese airports produces autocorrelation or spatial dependency.

1.2 Contributions and outline

In the light of the results illustrated by the literature and following Starkie (2002), which stated that the appropriate framework of analysis should consider the airport industry "as an imperfect or monopolistic competition sector in a spatial setting", in this work we explicitly consider the space in the efficiency analysis. Specifically, by considering the distance between airports as crucial for determining economic relations, we estimate the spatial heterogeneity and the efficiency spillovers across airports at a worldwide level. Ignoring spatial autocorrelation among residuals limits the strength of the empirical investigation for several reasons: it causes serious consequences to statistical inference, reducing both efficiency and the consistency of the estimations. Furthermore, it generates a negative impact on the validity of testing procedures and the predicting capability of the model (Vidoli et al., 2016).

The principal models accounting for spatial dependence in frontier analysis can be divided into two main groups. First, those that analyse efficiency/inefficiency in terms of exogenous determinants investigating heterogeneity. The others consider the spatial dependence, including in the model a spatial autoregressive specification (Vidoli et al., 2016). Different researchers (Lavado and Barrios, 2010; Hughes et al., 2011; Jeleskovic and Schwanebeck, 2012; Brem, 2013) focused on heterogeneity by including contextual factors as regressors or by modeling the inefficiency term. However, these methodologies tend to introduce a substantial quantity of bias in the estimated values of technical efficiency (Simar and Wilson, 2007). Differently, the second stream of research (Affusso, 2010; Glass et al., 2013, 2014, 2016; Adetutu et al., 2015; Skevas, 2020; Vidoli and Canello, 2016), trying to deal with these problems focuses on approaches that account for spatial dependence in the data adding a spatial autoregressive specification in the stochastic frontier model. Specifically, Areal et al. (2010), through a Bayesian procedure, suggested to include a spatial lag directly into inefficiency, enable to split the inefficiency into a spatial component and a specific term for every observation. The empirical approach is based on the spatial model developed by Fusco and Vidoli (2013), which measure the global effect of spatial factors through a spatial lag in the inefficiency term of the stochastic frontier specification. This method has been used only once for the analysis of the airport industry by Pavlyuk (2016). He found, in fact, a spatial heterogeneity among 365 European airports for the year 2011, using only a contiguity matrix, proving the necessity of incorporation of spatial heterogeneity into airport benchmarking procedures. No study so far has focused on a worldwide scale.

Analysing the 206 airports located in Europe, North America, and Pacific Asia, we focus on the spatial effects of the airports on efficiency through different matrices that capture in different and precise ways the competition patterns. For this purpose, for the first time, two types of matrices are considered: the first one that reflects the distance among airports and the second one the number of sharing destinations among airports at different distances.

The rest of the paper is structured as follows. In section 2 are presented the methodology and the econometric approach used for integrating spatial dependence into the stochastic frontier analysis. Section 3 is dedicated to the description of the data and the variables used. In Section 4 we show the results and provide the discussion. Finally, the main findings, some concluding remarks, and suggestions for possible future research are summarized in Section 5.

2. Methodology

Stochastic Frontier Analysis (SFA) is a well-known methodology estimating observations' inefficiency and separating it from the stochastic noise. SFA assumes a homogeneous underlying technology and independence between observations. However, the latter hypothesis is violated in the presence of spatially auto-correlated observations. When spatial effects are significant, the traditional SFA estimation techniques generate biased results and inconsistent estimators (Vidoli et al. 2016; Fusco and Vidoli, 2013). This work follows the approach implemented by Fusco and Vidoli (2013). Spatial dependence is incorporated in technical efficiency analysis by using an autoregressive specification of the inefficiency. The inclusion of spatial autocorrelation into stochastic frontier production framework, as proposed by Fusco and Vidoli (2013), is suitable since (i) it limits the analysis of the spatial dependence to the inefficiency term, excluding the need to choose exogenous determinants and to implement two-stage approaches that have proved to introduce bias in the estimates, (ii) it reduces the amount of complexity in the model and, (iii) it is comparable with the classical SFA model. This specification allows to isolate the local intangible factors, often statistically and economically difficult to capture through specific proxies, that nonetheless are determinant in influencing the airport productivity, since contextual variables would have not been sufficient to explain the spatial heterogeneity existing among the airports in the sample (Vidoli et al., 2016).

Denoting y_i the output of the observation i, x_i the inputs vector and f a generic parametric function, the standard cross-sectional production frontier model can be specified as:

$$\log y_i = \log(f(x_i;\beta_i)) + v_i - u_i \qquad [1]$$

where:

1) $v_i \sim iid\ N(0,\sigma_v^2)$ is the random term;
2) $u_i \sim iid\ N^+(0,\sigma_u^2)$ is the inefficiency term;
3) v and u are assumed to be independently and identically distributed.

The traditional SFA model presented in the equation [1] estimates airport-level efficiency from the residuals, assuming that all the airports in the sample are independent. However, this assumption is violated if we consider the spatial effects in the theoretical model. When spatial effects are significant, the traditional approaches used to estimate SFA or MLE (or its variants) generate biased results: indeed, if the disturbances are spatially correlated, the assumption of a spherical error covariance matrix is violated, leading to biased and inconsistent estimators (Lesage, 1997).

To consider the spatial effects, is introduced a spatial lag in the efficiency term u_i by reformulating the SFA density function with a spatial error autoregressive specification. Rewriting the equation [1] by specifying the u_i term, the spatial stochastic frontier (SSFA) model can be defined as:

$$\log y_i = \log\left(\mathrm{f}(x_i;\beta_i)\right) + v_i - u_i = \log\left(f(x_i;\beta_i)\right) + v_i - (1-\rho\sum w_{i.})^{-1}\widetilde{u_i}$$

[2]

where:

1) $v_i \sim iid\ N(0, \sigma_v^2)$ is the random term;
2) $u_i \sim iid\ N^+\left(0, (1-\rho\sum_i w_{i.})^{-2}\sigma_{\tilde{u}}^2\right)$ is the inefficiency spatial autoregressive term;
3) $\widetilde{u_i} \sim iid\ N\left(0, \sigma_{\tilde{u}}^2\right)$;
4) v and u are independent of each other and of the regressors.

The spatial lag parameter ρ takes values from -1 to 1 and determine the correlation between two airports. This technique does not rely on Bayesian method, but it reformulates the SFA density function with a spatial error autoregressive specification (SEM) using a maximum likelihood function (Fusco and Vidoli, 2013). The idea is that spatial dependence refers to how much the level of technical 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 neighbour DMU *j*'s performances (Fusco and Vidoli, 2013; Glass et al., 2016). This is consistent with previous research in SFA literature: indeed, all the main stochastic estimation models focused on *u* and *v* terms being equal the deterministic part of the production function, given that the compounded residuals are the main motivation of the investigation. It needs to be considered that frontier estimations techniques considering the spatial dependence also in the deterministic part (like Simultaneous Autoregression or the Spatial Durbin models) have not been yet completely developed in this field of research (Vidoli et al., 2016).

The spatial information is incorporated into the symmetric spatial weight matrix w^k. The spatial weight matrices are generated from the latitude and longitude of the airport. Specifically, in this work, we build two different kinds of matrices: the distance matrix and a shared destinations matrix among airports. The distance matrices are based on the geographical distance between airports (eq. n.3). Given the purpose of our analysis, we include different cut-off distances in estimating the stochastic frontier.

We define the cut-off distances (k) of 100, 150, 200, 250, 300 and 350 km. Each generic element of $\mathbf{w^k}$ is defined as:

$$w_{ij}^{k} = \begin{cases} \frac{1}{d_{ij}} \;\; if \; d_{ij} \;\; \leq \mathrm{k} \\ 0 \; otherwise \end{cases} \qquad [3]$$

where d_{ij} is the distance between airport *i* and airport *j* and k is the cut off established. The spatial weights w_{ij} are defined as the inverse standardized distance between two airports i and j. The matrices are row-standardized (i.e. the weights are standardized such that $\sum \;\; w_{i.} = 1, \forall i$) to ensure that $|\rho| < 1$ (i.e. stability condition) is satisfied.

To further investigate and to verify the results obtained regarding the competition that may exist between two airports and consequently its effect on efficiency, in the second approach, we consider the number of common destinations between two airports i and j at a different cut off distances (eq. n.4). The shared destinations matrix $\hat{\mathrm{w}}^{\mathbf{k}}$ is defined as:

$$\hat{\mathrm{w}}_{ij}^{k} = \begin{cases} n_{ij} \; if \; n_{ij} \;\; \leq \mathrm{k} \\ 0 \; otherwise \end{cases} \qquad [4]$$

where n_{ij} is the number of shared destinations between airport *i* and airport *j* and k is the cut off considered.

Once the estimate results of the SFA and the SSFA have been obtained and verified at the average level, we analyse the effects of spatial competition on airport efficiencies by applying the equation proposed by Fusco and Vidoli (2013)[9]. To test local perturbations, we consider the differences in terms of efficiency estimated among the SFA models with and without spatial interactions (i.e. $Eff_{SFA}, \; Eff_{SSFA}$), calculating the following distance of efficiencies index (x^*):

$$x^* = \frac{Eff_{SFA\,i} - Eff_{SSFA\,i}}{Eff_{SFA\,i}} * 100, \qquad \forall i = 1, \dots, n \qquad [5]$$

The term x^*shows the absolute magnitude of the effect of the airport endowment of the area k on the efficiency of each unit and the signs observe if the interdependencies among airports are positive or not. Moreover, a negative x^* indicates a positive local effect on the catchment area (and vice versa). This is because even in the presence of the global index of high spatial dependence, dependencies do not occur uniformly over the whole territory examined (Fusco and Vidoli, 2013).

[9] For software details: Fusco, E., Vidoli, F., (2015a) Spatial Stochastic frontier models: Instruction for use. Vignette r Package Version 1.1.

Fusco, E., Vidoli, F., (2015b). Ssfa: Spatial Stochastic Frontier Analysis. R Package Version 1.1.

3. Data

The database employed in this research is composed by observations coming from 206 worldwide airports in the year 2015. The airports considered in our study are larger among the geographical areas considered. However, it is important to remark that the sample is not including all the existing airports. This leads to a potential bias in the results since the competition effect on efficiency may be underestimated. The complete list of the airports is reported in Appendix A. The data source is the Airport Transport Research Society (ATRS) database. All airports have been geolocated to use spatial techniques. The choice of inputs and outputs for our research is consistent with the extensive efficiency analysis literature. As outputs, we included the number of passengers and the cargo transported combined in the Work Load Unit (WLU). The WLUs is a well-known metric in the aviation industry and it is equivalent to one passenger or 100 kg of freight. The second output considered in our analysis is the number of aircraft movements at the airport. On the input side, we consider the terminal size measured in square meters (Yoshida, 2004; Yoshida and Fujimoto, 2004; Fung et al., 2008a, 2008b), the number of gates, the number of staffs employed at the airport (average number of full-time equivalent employees employed at the airport during the year), and the number of runways (Fan et al., 2014; Fragoudaki et al., 2016). The descriptive statistics of the variables used are shown in Table 1.

Table 1 - Summary statistics

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
WLU	206	24,200,000	24,500,000	861,982	113,000,000
Air Movements	206	189,759	154,616	6,800	867,860
Terminal size	206	222,986	281,157	6,450	1,972,474
N. of Gates	206	59.47	47.93	5.00	226.00
N. of Staff	206	1,053	1,634	23.00	15,929
N. of Runways	206	2.45	1.25	1.00	8.00

The sample composition by geographical region is shown in Table 2. While Europe and North America are self-explaining groupings, a clarification is needed for the Pacific Asia group. The latter includes airports located in the Asian, Australian and New Zealand areas. About 85% of the WLU output measure is given by the passenger movement, while the remaining 15% by freight movement. The European airports considered in the dataset show, on average, less WLU output in comparison to the other macro-areas.

Table 2 - Sample composition by geographical region

	Obs.	*WLU*	*Passengers(n.)*	*Cargo (100 kg)*	*% of total WLU*
Pacific Asia	55	1,680,267,541	1,363,551,357	316,716,184	34.06
Europe	68	1,437,116,630	1,275,848,196	161,268,434	29.13
North America	83	1,815,845,014	1,530,459,544	285,385,470	36.81
	206	4,933,229,185	4,169,859,097	763,370,088	100.00

Table 3 reports the number of airports with at least one competitor for each different cut-off distance. The number of competitors increases as the distance considered increases. Indeed, the efficiency level could differ among different competition interactions (in the various matrices considered).

Table 3 - Number of Airports in competition for each cut-off distance (k)

	100	**150**	**200**	**250**	**300**	**350**
With competitors	64	91	124	141	155	165
Without competitors	142	115	82	65	51	41

Table 4 shows the number of competing airports for each geographical area. It should be noted that the airports for each cut-off compete only with other airports located in the same geographical area. The number of airports is constantly increasing for the three areas analysed. Considering the cut-off of 300 and 350km the number of competing airports increases slightly. We believe that 350km is a valid maximum measure to monitor competition among airports and that monitoring longer distances may not correspond to reality. In fact, increasing by 50 km the cut-off distance (i.e. from 350 to 400km), the airports with competitors increase only by 4 units (from 165 to 169).

Table 4 - Number of Airports in competition for geographical area for each cut-off distance (k)

	100	**150**	**200**	**250**	**300**	**350**
Pacific Asia	12	13	21	24	32	37
Europe	26	38	46	49	55	58
North America	26	40	57	68	68	70

4. Results and Discussion

To estimate airports' efficiency levels, the spatial stochastic frontier model has been applied. A multi-output Cobb-Douglas (CD) production function has been estimated as the functional form of the frontier specified in equation [4]. Despite being less flexible than other functional forms, the CD specification ensures the convergence of the estimates considering the relative low number of observations in our sample. The distance function approach is included in the model to account for the airports' multi-output nature. The important properties of this function are to be non-decreasing, linearly homogeneous and concave in inputs, and non-increasing and quasi-concave in outputs (Coelli et al. 2005). This function can be estimated when the homogeneity restriction is imposed. A convenient method of imposing the homogeneity constraint on the distance function is to follow Lovell et al. (1994). Specifically, we choose one output and rewrite the constant regress and the other output using the output selected as a numeraire. The arbitrary choice of the output and the resulting estimates will be invariant to the normalization.[10]

The econometric model specification can be expressed by the following form:

$$-\log(WLU) = \beta 1 \log\left(\frac{Movements}{WLU}\right) + \beta 2\ log(Terminal) + \beta 3\ log(Gates) + \beta 4 \log(Staff) + \beta 5 \log(Runway) + v_i - (1 - \rho \sum w_{i}.)^{-1} \tilde{u}_i \quad [4]$$

This research starts with the classical approach (OLS estimation) and, then, moves up to more complex specifications. OLS model does not consider either the presence of inefficiencies nor spatial interactions. Table 5 contains the results. The OLS estimation confirms the validity of the model specifications, given the high and significant R-squared (0.83). All the coefficients are statistically significant. Moreover, the multioutput coefficient has a positive sign, while the four input coefficients present negative coefficients. Using the OLS as a starting point model for the analysis, we further consider a more complexed analysis by introducing the inefficiency term in the error component. The estimated SFA results are shown in Table 6. The appropriateness of the methodological approach is confirmed: the values of the coefficients are similar to the OLS case, except for the intercept that decreases in absolute term. This expected trend can be explained by a shift in the production function from the average values to efficient ones without producing effects in the relationship between inputs and outputs.

10 Homogeneity implies that

$D_{0(x,\mu y)=\mu D_{0(x,y),\mu>0}}$ and by arbitrarily choosing one of the outputs, such as the Mth output, we can set $\mu = {}^{1}/_{yM}$:

$D_0\left(x, \frac{y}{yM}\right) = \frac{D_0\ (x,y)}{yM}$ which yields a regression of the general form

$\frac{1}{yNit} = D_0\left(y_{it,x_{it},}\beta\right) * h\ (\varepsilon_{it})$ where $Y_{it}^{*} = (y1it/yNit\ , y2it/yNit\ , \dots , yN - 1it/yNit)$ (Cuesta and Orea, 2001)

Table 5 - OLS estimation

	Dependent variable: Work Load Unit
	Estimate
Intercept	-11.8645***
	(1.3834)
Movements/WLU	4.8798***
	(1.8305)
Terminal	-0.4700***
	(0.0459)
Gates	-0.4810***
	(0.0737)
Staff	-0.0866**
	(0.0435)
Runway	-0.2276*
	(0.1301)
Observations	206
R^2	0.8306
Adjusted R^2	0.8264

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10.

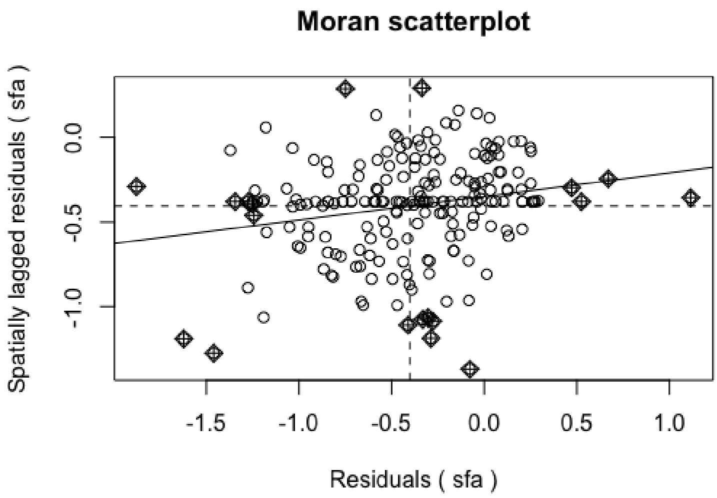
Table 6 - SFA estimation

	Dependent variable: Work Load Unit
	Estimate
Intercept	-10.3468***
	(1.6004)
Movements/WLU	3.6694*
	(2.0008)
Terminal	-0.4938***
	(0.0475)
Gates	-0.4714***
	(0.0721)
Staff	-0.0930**
	(0.0417)
Runway	-0.1984
	(0.1270)
σ_u^2	0.2520**
	(0.1148)
σ_v^2	0.1115***
	(0.0378)
γ	0.6933
Mean efficiency	0.6986
Moran's I	0.1390**
	(0.0145)
LR-Test	2.093*
Observations	206

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10.

The inefficiency standard deviation ($\sigma_u^2 = 0.252$) is statistically significant. Similarly, the parameter λ suggests that 69% of the variation is due to inefficiency, while the remaining part to the random variation. All coefficients remain statistically significant, except for the runway variable. Also, the signs are as expected, being negative for the input variables and positive for the output ones. The traditional stochastic frontier specification shows the presence of strong spatial autocorrelation. Indeed, the Moran's I statistic is significant and equal to 0.1390 witnessing how the use of spatial methodologies are appropriate for the analysed data. Autocorrelation among residuals can be locally displayed through the Moran's I test shown in Figure 1.

Figure 1 Moran's I plot (SFA)



The scatterplot assesses that SFA results hide the presence of a high spatial correlation. Given the presence of spatial autocorrelation in the SFA residuals, we apply the Spatial Stochastic Frontier (SSFA) model to account for such correlation. In this way, we can isolate and evaluate the territorial component separately from the individual performance of the airport. SSFA results for the different distance matrices are shown in Table 7.

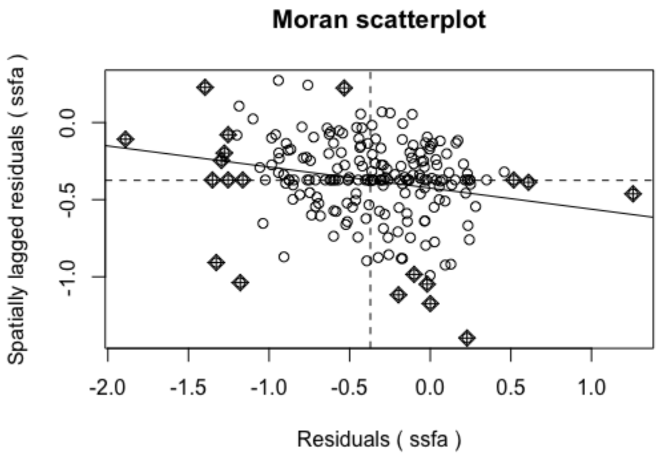
Table 7 - SSFA estimation (distance matrices)

	Dependent variable: Work Load Unit					
	W100	*W150*	*W200*	*W250*	*W300*	*W350*
	Estimate	*Estimate*	*Estimate*	*Estimate*	*Estimate*	*Estimate*
Intercept	-9.8426***	-10.3288***	-9.6961***	-9.5482***	-9.7136***	-9.7011***
	(1.6407)	(1.4863)	(1.4377)	(1.7347)	(1.4617)	(1.5585)
Movements/WLU	3.1808	3.6470**	2.7913	2.5865	2.4825	2.3922
	(2.0142)	(1.8241)	(1.7969)	(2.1541)	(1.7853)	(1.8523)
Terminal	-0.4982***	-0.4935***	-0.4822***	-0.4836***	-0.4468***	-0.4388***
	(0.0473)	(0.0479)	(0.0473)	(0.0489)	(0.0517)	(0.0531)
Gates	-0.4408***	-0.4704***	-0.4697***	-0.4701***	-0.5053***	-0.5159***
	(0.0760)	(0.0732)	(0.0698)	(0.0711)	(0.0705)	(0.0709)
Staff	-0.1087**	-0.0939**	-0.1045**	-0.1011**	-0.1032**	-0.0972**
	(0.0437)	(0.0429)	(0.0417)	(0.0428)	(0.0428)	(0.0436)
Runway	-0.2029	-0.1981	-0.1857	-0.1754	-0.1749	-0.1787
	(0.1265)	(0.1252)	(0.1252)	(0.1279)	(0.1256)	(0.1283)
sigmau2_dmu	0.2731**	0.2526**	0.2741***	0.2846***	0.2297**	0.2137*
	(0.1089)	(0.1141)	(0.1028)	(0.1048)	(0.1143)	(0.1194)
sigmav2	0.1033***	0.1113***	0.1009***	0.0974***	0.1096***	0.1125***
	(0.0348)	(0.0375)	(0.0326)	(0.0327)	(0.0382)	(0.0404)
Mean efficiency	0.6896	0.6984	0.6893	0.6850	0.7083	0.7160
Spatial parameter ρ	0.1799	0.0088	0.1772	0.1867	0.3138	0.3791
Ineff. parameter λ	2.6440	2.2690	2.7180	2.9222	2.0970	1.8993
Moran's I	-0.0512	-0.0131	-0.0879	-0.0930	-0.1270	-0.1369
Value LR-Test	3.413**	2.098*	5.493***	5.642***	11.129***	13.581***
Observations	206	206	206	206	206	206

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Most of the coefficients are significant with expected signs. When introducing the spatial autocorrelation, the Moran's I tests are no more significant, implying the goodness of SSFA. The Moran's I test scatterplot is displayed in figure 2, showing the opposite and not significant result compared to figure 1.

Figure 2 Moran's I plot (SSFA)



The results show that the SSFA approach implemented is able to neutralize the high spatial correlation present in the residuals. The increase of the likelihood ratio test in all the SSFA estimations, respect to the SFA estimation, confirms the better fit of the data analysed by introducing spatial specifications. The coefficients ρ, which represent the unobserved spatial heterogeneity, are positive and significant in all the spatial estimates. In table 8 we show the results obtained from the SSFA models for different shared destinations matrix (see specification n.4).

Table 8 – SSFA estimation (destination matrices)

	Dependent variable: Work Load Unit					
	W100d	*W150d*	*W200d*	*W250d*	*W300d*	*W350d*
Intercept	-9.8128*** (1.6709)	-9.9493*** (1.6473)	-9.720*** (1.7314)	-9.855*** (1.5247)	-10.203*** (1.3912)	-9.9030*** (1.3345)
Movements/WLU	2.5832 (1.9858)	2.8187 (1.9956)	2.7964 (2.1369)	2.9452 (1.887)	3.5041** (1.7172)	3.2384* (1.6636)
Terminal	-0.4362*** (0.0541)	-0.4483*** (0.0535)	-0.482*** (0.0493)	-0.477*** (0.0489)	-0.491*** (0.0479)	-0.4972*** (0.0466)
Gates	-0.5294*** (0.0717)	-0.5075*** (0.0721)	-0.473*** (0.0718)	-0.474*** (0.0710)	-0.464*** (0.0728)	-0.443*** (0.0746)
Staff	-0.0940** (0.0443)	-0.1022** (0.0436)	-0.0984** (0.0430)	-0.1015** (0.0422)	-0.0995** (0.0431)	-0.1078** (0.0419)
Runway	-0.1772 (0.1289)	-0.1837 (0.1274)	-0.1873 (0.1275)	-0.1996 (0.1261)	-0.1968 (0.1253)	-0.2039 (0.1247)
sigmau2_dmu	0.2119* (0.1170)	0.2326** (0.1169)	0.2761** (0.1081)	0.2625** (0.1069)	0.2585** (0.1109)	0.2694** (0.1064)
sigmav2	0.1139*** (0.0396)	0.1113** (0.0390)	0.101*** (0.03426)	0.105*** (0.0345)	0.1091*** (0.0361)	0.1047*** (0.0341)
Mean efficiency	0.7172	0.7072	0.6884	0.6941	0.6958	0.6911
Spatial parameter ρ	0.4118	0.2813	0.1680	0.1816	0.0608	0.1687
Ineff. parameter λ	1.8596	2.0888	2.7308	2.4963	2.3692	2.5728
Moran's I	-0.1094	-0.0959	-0.0728	-0.0728	-0.0328	-0.0466
Value LR-Test	12.927***	8.453**	4.619**	4.943**	2.359*	3.233**
Observations	206	206	206	206	206	206

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, *p<0.10.

Results are consistent with the distance matrices estimations (Table 7). Specifically, the same signs and statistically significant values are found for all the variables, except for the multioutput variable that is significant for the destination matrix 300 and 350. Consistently with table 7, the spatial parameter is positive and significant in all the specifications.

To estimate the effect of airport competition and to predict the related efficiency levels, the differences in terms of efficiency between the two methodologies are analysed by applying equation [5][11]. Table 9 shows the descriptive statistics of the computed x^*based on the stochastic frontier estimated for different distance matrices, while table 10 consider shared destinations matrix by distance.

[11] After estimating the $x^*$for each distance matrix (equation [3]), the efficiency distances (x^*) are tested to detect if they are statistically significant for both the models that include distance matrices and destination matrices by distance, for the airports that have at least one competitor. The p-values of the t-test are shown in tables 9 and 10. Appendix B shows the estimated efficiency for each airport considering the SFA and the SSFA models with the distance matrix of 200 km.

Table 9 - Summary statistics of x^* for each distance matrix

With Competitors	*Observations*	*Mean*	*Std. Dev.*	*Min*	*Max*
x^* (w100)	64	1.2681 ***	3.2916	-4.4304	9.7844
x^* (w150)	91	0.0309 *	0.1504	-0.3352	0.5115
x^* (w200)	124	1.6098 ***	3.6443	-6.4329	12.6472
x^* (w250)	140	2.2327 ***	4.0205	-9.0128	14.4847
x^* (w300)	154	-1.9555 ***	5.3279	-30.4801	10.2485
x^* (w350)	164	-3.2151 ***	6.0261	-28.5844	8.1975

Note: *** p<0.01, ** p<0.05, * p<0.10

Table 10 - Summary statistics of x^* for each destination matrix by distance

With Competitors	*Observations*	*Mean*	*Std. Dev.*	*Min*	*Max*
x^* ($\hat{w}$100)	64	1.0577 ***	2.9862	0.3177	1.7976
x^* ($\hat{w}$150)	91	0.4561 ***	1.1369	0.2180	0.6943
x^* ($\hat{w}$200)	124	0.7165 ***	2.9231	0.1881	1.2448
x^*($\hat{w}$250)	140	1.6774 ***	3.1537	1.1446	2.2102
x^* ($\hat{w}$300)	154	-1.7526 ***	4.4333	-2.4631	-1.0421
x^* ($\hat{w}$350)	164	-3.4157 ***	5.8589	-4.3219	-2.5094

Note: *** p<0.01, ** p<0.05, * p<0.10

The results show positive x^* values for the distances from 100 km to 250 km, while negative values from 300 km to 350 km. Our estimates suggest that competition has different effects on the efficiency levels depending on the cut-off distance considered. Specifically, we find evidence of the negative pressure of competition on the technical efficiency level for distances below 250 km. In other words, airports in competition show a lower level of efficiency. A possible explanation may be related to a higher level of competition occurring between airports that are closer to each other, possibly due to their overcapacity not exploited (i.e. competition for passengers and cargo within the same catchment area). Indeed, in case of capacity excess, the marginal cost of a flight may be quite low, though the airport will face large sunk costs associated with its construction, for example, in building runways, parking, etc. (Forsyth, 2003). Differently, for cut-off greater than 250km, we obtain statistically significant negative efficiency differences. This can be interpreted as a positive effect of competition on efficiency levels. This may be read as an absence of competition among airports from 300 km to 350 km. These results are consistent with Fuellhart (2003) which finds that airports are subject to strategic interaction if they are located within a circle with 95 km -150 km rays. Similarly, Scotti et al. (2012), using a 100 km radius to define the catchment area, find a negative effect of competition on technical efficiency. As well as Bottasso et al. (2017) adopt a standard approach to identify an airport catchment area as defined by a circle of 90 km around each airport. Furthermore, these positive and negative effects (tables 9 and 10) are also consistent for the three areas considered using both matrices (tables 11 and 12).

Table 11 – Summary statistics of x^* for each distance matrix and area

	w100	**w150**	**w200**	**w250**	**w300**	**w350**
Pacific Asia	1.98	0.05	2.25	3.26	-2.59	-4.36
Europe	1.26	0.04	1.62	2.13	-0.52	-1.35
North America	1.58	0.04	1.34	2.05	-2.08	-3.58

Table 12 – Summary statistics of x^* for each destination matrix by distance and area

	ŵ100	**ŵ150**	**ŵ200**	**ŵ250**	**ŵ300**	**ŵ350**
Pacific Asia	1.57	0.57	1.27	2.56	-2.02	-4.37
Europe	1.08	0.40	0.82	1.58	-0.71	-1.76
North America	1.31	0.51	0.46	1.46	-1.82	-3.72

In conclusion, we observe that the spatial effects are important in competition analysis to estimate unbiased efficiency levels in the airports' sector, as found by Pavluk (2016), also confirmed, through a different methodology approach, by D'Alfonso et al. (2015) for the Italian airport sector. Moreover, it's important to compare the results obtained from the two models that consider different matrices. The stochastic frontier estimated considering distance matrices and destination matrices are equivalent in terms of results. As a robustness check, the effect on efficiency is captured either on a pure geographical distance and also by overlapping origins and destination flows.

5. Concluding Remarks

In this paper, we analyse 206 airports located in different continents for the year 2015. By applying a traditional SFA and a SSFA, and comparing results, we observe how the spatial dependence and its effects differ among different characterizations of the airport neighbourhood. The SSFA allows us to isolate the local intangible factors, often statistically and economically difficult to capture through specific proxies, that nonetheless are determinant in influencing the airport productivity. This method, in fact, is able to disentangle the observed spatial effect by isolating a particular component that is erroneously attributed to the error term in the traditional SFA approach.

Our empirical results can be summarised as follows. First, positive spatial heterogeneity is discovered in the model specifications considered, as evidence of uneven distribution of airport productivity-related factors over the data examined. Additionally, the effect of competition on airports' efficiency levels, which varies according to the geographical distances, is detected. This paper, for the first time, uses two different specifications of matrices, one based on geographical distances and the other one based on the number of shared destinations among two airports calibrated by each distance cut-off. This latter measure is considered an indicator of the degree of overlapping markets among the airports. Specifically, comparing SFA and SSFA model, splitting the analysis among airports with and without competitors, we find a positive mean efficiency difference until 250 km cut-off and a negative one starting from 300 km. This paper is the first in discovering and analysing these effects. We argue that the negative effect could be related to a higher level of competition occurring between airports that are closer to each other, while for larger distances the negative efficiency differences are interpreted as positive effects of competition on the efficiency levels. Moreover, the resulting estimates (tables 8 and 9) are consistent using the two different matrices.

Overall, we can confirm that the SSFA is a valid instrument to estimate the levels of efficiency at worldwide level. We prove that the dynamics of competition are strongly dependent on the spatial distance among airports. This finding requires further analysis in order to understand the implications on efficiency and on regulation and competition policies. Based on our findings, the definition of the relevant market, is, in fact, a relative concept. Furthermore, policymakers when deciding on promoting the development of specific airports should consider the spillover effects on the neighbouring ones, considering the different patterns of competition. This is extremely relevant since distance matters for international policy regulation. For instance, the EU developed in the last years, policy related to "state aid for airports and airlines", excluding however those airports located close to existing airports that provide scheduled air services. An airport is defined close to another one if it is located within 100 km of distance or 60 minutes of travel by car, bus, train or high-speed train from an existing airport that manages scheduled air services. Our results open interesting future research opportunities with regards to state aid and level playing field among airports. First of all, the attention can be devoted to relevant aspects for policymakers (i.e. public funding, ownership network, presence of airlines in the ownership; etc.) across different areas of the world. But ownership is not the only determinant of heterogeneity of the production function. A further aspect that could affect the airport performance could be the management concession and airport infrastructure size. Also, additional development would be to test the robustness of the results taking into consideration the time dimension. The panel data analysis would allow controlling for seasonal or other unobserved factors that can influence the results. Finally, the introduction of territorial and contextual variables could yield additional insights to calibrate policy measures and investment decisions.

Appendix A: Airports considered in the study

Number	*Airport Name*	*Continent*
1	Adelaide International Airport	Asia Pacific
2	Antonio B. Won Pat International Airport	Asia Pacific
3	Auckland International Airport	Asia Pacific
4	Bai Yun Airport	Asia Pacific
5	Bandaranaike International Airport	Asia Pacific
6	Beijing Capital International Airport	Asia Pacific
7	Brisbane Airport	Asia Pacific
8	Cairns International Airport	Asia Pacific
9	Central Japan International Airport	Asia Pacific
10	Chennai International Airport	Asia Pacific
11	Chhatarpati Shivaji International Airport	Asia Pacific
12	Chiang Mai International Airport	Asia Pacific
13	Christchurch International Airport	Asia Pacific
14	Darwin International Airport	Asia Pacific
15	Dubai International Airport	Asia Pacific
16	Dunedin International Airport	Asia Pacific
17	Gimhae International Airport	Asia Pacific
18	Gold Coast Airport	Asia Pacific
19	Haneda Airport	Asia Pacific
20	Hat Yai International Airport	Asia Pacific
21	Hong Kong International Airport	Asia Pacific
22	Incheon International Airport	Asia Pacific
23	Indira Gandhi International Airport	Asia Pacific
24	Jakarta Soekarno-Hatta International Airport	Asia Pacific
25	Jeju International Airport	Asia Pacific
26	Juanda International Airport	Asia Pacific
27	Kansai International Airport	Asia Pacific
28	Kuala Lumpur International Airport	Asia Pacific
29	Macau International Airport	Asia Pacific
30	Mae Fah Luang-Chiang Rai Int. Apt.	Asia Pacific
31	Meilan International Airport	Asia Pacific
32	Melbourne Airport	Asia Pacific
33	Nadi International Airport	Asia Pacific
34	Newcastle Airport	Asia Pacific
35	Ninoy Aquino International Airport	Asia Pacific
36	Penang International Airport	Asia Pacific
37	Perth International Airport	Asia Pacific
38	Phnom Penh International Airport	Asia Pacific
39	Phuket International Airport	Asia Pacific
40	Queenstown Airport	Asia Pacific
41	Seoul Gimpo International Airport	Asia Pacific
42	Shanghai Hongqiao International Airport	Asia Pacific
43	Shanghai Pudong International Airport	Asia Pacific
44	Shenzhen Bao'an International Airport	Asia Pacific
45	Siem Reap International Airport	Asia Pacific
46	Singapore Changi International Airport	Asia Pacific
47	Suvarnabhumi Airport	Asia Pacific
48	Sydney Airport	Asia Pacific
49	Taiwan Taoyuan International Airport	Asia Pacific
50	Tokyo Narita International Airport	Asia Pacific
51	Townsville Airport	Asia Pacific
52	Wellington International Airport	Asia Pacific
53	Xiamen Gaoqi International Airport	Asia Pacific

Number	Airport Name	Continent
54	Alicante Airport	Europe
55	Amsterdam Airport Schiphol	Europe
56	Athens International Airport	Europe
57	Barcelona El Prat Airport	Europe
58	Belgrade Nikola Tesla Airport	Europe
59	Ben Gurion International Airport	Europe
60	Bergamo-Orio al Serio Airport	Europe
61	Berlin Schönefeld Airport	Europe
62	Berlin Tegel Airport	Europe
63	Birmingham Airport	Europe
64	Bologna Airport	Europe
65	Bratislava Milan Rastislav Stefanik Airport	Europe
66	Bristol Airport	Europe
67	Brussels Airport	Europe
68	Budapest Ferenc Liszt International Airport	Europe
69	Cologne/Bonn Konrad Adenauer Airport	Europe
70	Copenhagen Airport Kastrup	Europe
71	Dublin Airport	Europe
72	Düsseldorf International Airport	Europe
73	Edinburgh Airport	Europe
74	EuroAirport Basel-Mulhouse-Freiburg	Europe
75	Frankfurt Airport	Europe
76	Genève Aéroport	Europe
77	Glasgow Airport	Europe
78	Gran Canaria Airport	Europe
79	Hamburg Airport	Europe
80	Hannover Airport	Europe
81	Helsinki Vantaa Airport	Europe
82	Istanbul Atatürk Airport	Europe
83	Istanbul Sabiha Gökçen International Apt	Europe
84	Keflavik International Airport	Europe
85	Kiev Boryspil International Airport	Europe
86	Lennart Meri Tallinn Airport	Europe
87	Lisbon Portela Airport	Europe
88	Ljubljana Jože Pucnik Airport	Europe
89	London Gatwick International Airport	Europe
90	London Heathrow Airport	Europe
91	London Luton Airport	Europe
92	London Stansted Airport	Europe
93	Luxembourg Airport	Europe
94	Lyon-Saint Exupery Airport	Europe
95	Madrid Barajas Airport	Europe
96	Malaga-Costa del Sol Airport	Europe
97	Malta International Airport	Europe
98	Manchester Airport	Europe
99	Milan Linate Airport	Europe
100	Milan Malpensa Airport	Europe
101	Munich Airport	Europe
102	Naples International Airport	Europe
103	Nice Cote D'Azur Airport	Europe
104	Oslo Airport Gardermoen	Europe
105	Palma de Mallorca Airport	Europe
106	Paris Charles de Gaulle Airport	Europe
107	Paris Orly Airport	Europe
108	Porto Airport	Europe
109	Prague International Airport	Europe
110	Pulkovo Airport	Europe
111	Riga International Airport	Europe
112	Rome Ciampino Airport	Europe
113	Rome Leonardo Da Vinci/Fiumicino Airport	Europe
114	Salzburg W.A. Mozart Airport	Europe
115	Sheremetyevo International Airport	Europe
116	Sofia Airport	Europe
117	Stockholm-Arlanda Airport	Europe
118	Stuttgart Airport	Europe
119	Turin Caselle Airport	Europe
120	Venice Marco Polo Airport	Europe
121	Vienna International Airport	Europe
122	Warsaw Chopin Airport	Europe
123	Zagreb Airport	Europe
124	Zurich Airport	Europe

Number	Airport Name	Continent
125	Albany International Airport	North America
126	Albuquerque International Sunport	North America
127	Austin Bergstrom International Airport	North America
128	Baltimore Washington International Airport	North America
129	Bob Hope Airport	North America
130	Boston Logan International Airport	North America
131	Bradley International Airport	North America
132	Buffalo Niagara International Airport	North America
133	Calgary International Airport	North America
134	Charlotte Douglas International Airport	North America
135	Chicago Midway Airport	North America
136	Chicago O'Hare International Airport	North America
137	Cincinnati/Northern Kentucky International A	North America
138	Cleveland-Hopkins International Airport	North America
139	Dallas Forth Worth International Airport	North America
140	Dallas Love Field Airport	North America
141	Denver International Airport	North America
142	Detroit Metropolitan Wayne County Airport	North America
143	Edmonton International Airport	North America
144	Eppley Airfield	North America
145	Fort Lauderdale Hollywood International Air	North America
146	General Mitchell International Airport	North America
147	George Bush Intercontinental Airport	North America
148	Halifax Stanfield International Airport	North America
149	Hartsfield-Jackson Atlanta International Airpo	North America
150	Honolulu International Airport	North America
151	Indianapolis International Airport	North America
152	Jacksonville International Airport	North America
153	John Wayne Orange County Airport	North America
154	Kahului Airport	North America
155	Kansas City International Airport	North America
156	LA/Ontario International Airport	North America
157	LaGuardia International Airport	North America
158	Las Vegas McCarran International Airport	North America
159	Los Angeles International Airport	North America
160	Louis Armstrong New Orleans Iint. Apt	North America
161	Louisville International-Standiford Field	North America
162	Memphis International Airport	North America
163	Miami International Airport	North America
164	Minneapolis/St. Paul International Airport	North America
165	Montréal-Pierre Elliott Trudeau Int. Apt	North America
166	Nashville International Airport	North America
167	New York-John F. Kennedy International Air	North America
168	Newark Liberty International Airport	North America
169	Norman Y. Mineta San José International Air	North America
170	Oakland International Airport	North America
171	Orlando International Airport	North America
172	Ottawa Macdonald-Cartier International Airpo	North America
173	Palm Beach International Airport	North America
174	Philadelphia International Airport	North America
175	Phoenix Sky Harbor International Airport	North America
176	Pittsburgh International Airport	North America
177	Port Columbus International Airport	North America
178	Portland International Airport	North America
179	Québec City Jean Lesage International Apt	North America
180	Raleigh-Durham International Airport	North America
181	Regina International Airport	North America
182	Reno/Tahoe International Airport	North America
183	Richmond International Airport	North America
184	Ronald Reagan Washington National Apt	North America
185	Sacramento International Airport	North America
186	Salt Lake City International Airport	North America
187	San Antonio International Airport	North America
188	San Diego International Airport	North America
189	San Francisco International Airport	North America
190	San Juan Luis Muñoz Marín International Air	North America
191	Seattle-Tacoma International Airport	North America
192	Southwest Florida International Airport	North America
193	St. John's International Airport	North America
194	St. Louis-Lambert International Airport	North America
195	Tampa International Airport	North America
196	Ted Stevens Anchorage International Apt	North America
197	Theodore Francis Green State Airport	North America
198	Toronto Lester B. Pearson International Apt	North America
199	Tucson International Airport	North America
200	Tulsa International Airport	North America
201	Vancouver International Airport	North America
202	Victoria International Airport	North America
203	Washington Dulles International Airport	North America
204	Will Rogers World Airport	North America
205	William P. Hobby Airport	North America
206	Winnipeg James Armstrong Richardson Int.	North America

Appendix B: Airports Efficiency – SSFA 200 km

Airports	*eff. SFA*	*eff. SSFA*	*eff. Diff %*	*Comp.*	*Airports*	*eff. SFA*	*eff. SSFA*	*eff. Diff %*	*Comp.*
Berlin Schönefeld Airport	0,63	0,67	-6,43	1	Bandaranaike Int. Airport	0,73	0,72	1,09	0
Penang Int. Airport	0,69	0,73	-5,76	1	Las Vegas McCarran Int. Airport	0,69	0,69	1,13	0
Tokyo Narita Int. Airport	0,71	0,74	-3,69	1	Orlando Int. Airport	0,81	0,80	1,19	1
Rome Leonardo Da Vinci/Fiumicino Airport	0,70	0,72	-3,63	1	Venice Marco Polo Airport	0,78	0,77	1,20	1
Istanbul Sabiha Gökçen Int. Airport	0,64	0,66	-3,48	1	San Diego Int. Airport	0,51	0,51	1,21	1
Toronto Lester B. Pearson Int. Airport	0,80	0,82	-3,45	1	Porto Airport	0,78	0,77	1,25	0
Mae Fah Luang-Chiang Rai Int. Airport	0,80	0,82	-3,44	1	Luxembourg Airport	0,83	0,82	1,26	1
Incheon Int. Airport	0,75	0,77	-3,31	1	Palma de Mallorca Airport	0,77	0,76	1,29	0
Dallas Forth Worth Int. Airport	0,72	0,74	-3,18	1	Minneapolis/St. Paul Int. Airport	0,72	0,71	1,32	0
Honolulu Int. Airport	0,74	0,77	-3,15	1	Salzburg W.A. Mozart Airport	0,85	0,84	1,33	1
Macau Int. Airport	0,77	0,79	-3,15	1	Wellington Int. Airport	0,69	0,68	1,42	0
San Antonio Int. Airport	0,66	0,68	-2,61	1	Düsseldorf Int. Airport	0,80	0,79	1,44	1
Hannover Airport	0,82	0,84	-2,52	1	Port Columbus Int. Airport	0,80	0,79	1,48	1
Brisbane Airport	0,72	0,73	-2,42	1	Dublin Airport	0,68	0,67	1,55	0
Lyon-Saint Exupery Airport	0,81	0,83	-2,31	1	Southwest Florida Int. Airport	0,73	0,72	1,56	1
Shenzhen Bao'an Int. Airport	0,65	0,67	-2,25	1	Portland Int. Airport	0,71	0,70	1,58	0
Cincinnati/Northern Kentucky Int. Airport	0,80	0,81	-2,24	1	Austin Bergstrom Int. Airport	0,57	0,56	1,60	1
San Francisco Int. Airport	0,71	0,73	-2,11	1	Auckland Int. Airport	0,74	0,73	1,62	0
George Bush Intercontinental Airport	0,74	0,76	-2,08	1	Dubai Int. Airport	0,77	0,75	1,63	0
Indianapolis Int. Airport	0,63	0,64	-1,98	1	Munich Airport	0,83	0,81	1,64	1
General Mitchell Int. Airport	0,81	0,83	-1,81	1	Baltimore Washington Int. Airport	0,71	0,70	1,68	1
Québec City Jean Lesage Int. Airport	0,78	0,80	-1,77	0	Athens Int. Airport	0,70	0,69	1,71	0
Philadelphia Int. Airport	0,76	0,77	-1,70	1	Theodore Francis Green State Airport	0,80	0,79	1,74	1
London Stansted Airport	0,78	0,79	-1,42	1	Berlin Tegel Airport	0,46	0,45	1,76	1
Chicago O'Hare Int. Airport	0,62	0,63	-1,36	1	Cologne/Bonn Konrad Adenauer Airport	0,82	0,80	1,76	1
Lennart Meri Tallinn Airport	0,81	0,82	-1,09	1	Queenstown Airport	0,84	0,83	1,80	1
Washington Dulles Int. Airport	0,85	0,85	-1,08	1	Ottawa Macdonald-Cartier Int. Airport	0,82	0,80	1,83	1
Nadi Int. Airport	0,69	0,70	-1,06	0	Salt Lake City Int. Airport	0,66	0,64	1,84	0
Tucson Int. Airport	0,83	0,84	-0,94	1	Frankfurt Airport	0,81	0,80	1,86	1
Naples Int. Airport	0,56	0,57	-0,86	1	Bologna Airport	0,66	0,65	1,87	1
Regina Int. Airport	0,83	0,84	-0,86	0	Calgary Int. Airport	0,66	0,65	1,88	0
Victoria Int. Airport	0,73	0,74	-0,77	1	Cleveland-Hopkins Int. Airport	0,82	0,80	1,93	1
Shanghai Hongqiao Int. Airport	0,78	0,78	-0,67	1	Jakarta Soekarno-Hatta Int. Airport	0,64	0,63	1,99	0
Halifax Stanfield Int. Airport	0,86	0,86	-0,64	0	Milan Linate Airport	0,68	0,66	2,14	1
Bob Hope Airport	0,59	0,60	-0,61	1	Lisbon Portela Airport	0,68	0,67	2,32	0
Winnipeg James Armstrong R. Int. A.	0,75	0,75	-0,61	0	Bristol Airport	0,64	0,63	2,41	1
Ljubljana Jože Pučnik Airport	0,81	0,82	-0,59	1	Tampa Int. Airport	0,75	0,74	2,43	1

Kiev Boryspil Int. Airport	0,88	0,89	-0,59	0	Suvarnabhumi Airport	0,69	0,68	2,44	0
Norman Y. Mineta San José Int. Airport	0,69	0,69	-0,57	1	Meilan Int. Airport	0,67	0,65	2,53	0
Newcastle Airport	0,92	0,93	-0,56	1	Albany Int. Airport	0,82	0,79	2,68	1
Bratislava Milan Rastislav Stefanik Airport	0,90	0,90	-0,48	1	Xiamen Gaoqi Int. Airport	0,58	0,56	2,78	0
Sofia Airport	0,85	0,86	-0,47	0	Rome Ciampino Airport	0,50	0,49	2,79	1
LA/Ontario Int. Airport	0,71	0,71	-0,45	1	Amsterdam Airport Schiphol	0,75	0,73	2,83	1
Antonio B. Won Pat Int. Airport	0,85	0,85	-0,39	0	Dunedin Int. Airport	0,80	0,78	2,85	1
Edmonton Int. Airport	0,78	0,79	-0,39	0	Singapore Changi Int. Airport	0,70	0,68	2,87	0
Miami Int. Airport	0,77	0,78	-0,37	1	Louis Armstrong New Orleans Int. Airport	0,66	0,64	2,94	0
Prague Int. Airport	0,84	0,85	-0,32	0	Chicago Midway Airport	0,53	0,52	2,98	1
Milan Malpensa Airport	0,85	0,86	-0,29	1	Chennai Int. Airport	0,66	0,64	2,99	0
Warsaw Chopin Airport	0,82	0,82	-0,25	0	Detroit Metropolitan Wayne County Airport	0,78	0,76	2,99	1
St. John's Int. Airport	0,76	0,77	-0,25	0	Ninoy Aquino Int. Airport	0,66	0,63	3,23	0
London Heathrow Airport	0,68	0,68	-0,16	1	Zagreb Airport	0,71	0,69	3,28	1
Palm Beach Int. Airport	0,76	0,76	-0,15	1	Hartsfield-Jackson Atlanta Int. Airport	0,62	0,60	3,31	0
Richmond Int. Airport	0,82	0,82	-0,14	1	Brussels Airport	0,74	0,71	3,31	1
Newark Liberty Int. Airport	0,65	0,65	-0,11	1	Sheremetyevo Int. Airport	0,60	0,58	3,35	0
Riga Int. Airport	0,73	0,73	-0,10	0	Adelaide Int. Airport	0,61	0,59	3,35	0
Bai Yun Airport	0,57	0,57	-0,08	1	Ben Gurion Int. Airport	0,60	0,58	3,43	0
Los Angeles Int. Airport	0,58	0,58	-0,07	1	Zurich Airport	0,72	0,70	3,57	1
Reno/Tahoe Int. Airport	0,83	0,83	-0,06	1	San Juan Luis Muñoz Marín Int. Airport	0,45	0,44	3,57	0
Albuquerque Int. Sunport	0,79	0,79	-0,03	0	Beijing Capital Int. Airport	0,66	0,63	3,58	0
Christchurch Int. Airport	0,81	0,82	-0,03	0	Nice Cote D'Azur Airport	0,74	0,71	3,91	1
John Wayne Orange County Airport	0,65	0,65	-0,02	1	Will Rogers World Airport	0,80	0,76	3,93	1
London Gatwick Int. Airport	0,67	0,67	0,00	1	Oslo Airport Gardermoen	0,55	0,53	3,94	0
Turin Caselle Airport	0,83	0,83	0,04	1	Indira Gandhi Int. Airport	0,67	0,64	4,02	0
Raleigh-Durham Int. Airport	0,80	0,80	0,06	0	London Luton Airport	0,52	0,50	4,26	1
Bradley Int. Airport	0,86	0,86	0,07	1	Charlotte Douglas Int. Airport	0,50	0,48	4,29	0
Madrid Barajas Airport	0,85	0,85	0,08	0	William P. Hobby Airport	0,58	0,56	4,35	1
Malta Int. Airport	0,85	0,85	0,19	0	Seattle-Tacoma Int. Airport	0,60	0,57	4,39	1
EuroAirport Basel-Mulhouse-Freiburg	0,79	0,78	0,20	1	Kahului Airport	0,49	0,47	4,41	1
St. Louis-Lambert Int. Airport	0,77	0,77	0,21	0	Paris Orly Airport	0,74	0,71	4,52	1
Stockholm-Arlanda Airport	0,74	0,73	0,22	0	Dallas Love Field Airport	0,53	0,51	4,59	1
Belgrade Nikola Tesla Airport	0,75	0,75	0,23	0	Kansai Int. Airport	0,66	0,63	4,68	1
Kansas City Int. Airport	0,80	0,80	0,23	0	Boston Logan Int. Airport	0,72	0,69	4,83	1
Glasgow Airport	0,85	0,84	0,24	1	Gimhae Int. Airport	0,45	0,43	4,90	0
Malaga-Costa del Sol Airport	0,85	0,84	0,29	0	Oakland Int. Airport	0,51	0,48	5,15	1
Central Japan Int. Airport	0,74	0,74	0,35	1	Chhatrapati Shivaji Int. Airport	0,44	0,42	5,28	0
Paris Charles de Gaulle Airport	0,83	0,83	0,36	1	Sydney Airport	0,57	0,54	5,42	0
Gran Canaria Airport	0,82	0,82	0,41	0	Shanghai Pudong Int. Airport	0,63	0,60	5,42	1
Pittsburgh Int. Airport	0,88	0,87	0,41	1	Bergamo-Orio al Serio Airport	0,63	0,59	5,54	1
Barcelona El Prat Airport	0,83	0,82	0,42	0	Helsinki Vantaa Airport	0,70	0,66	5,57	1

Siem Reap Int. Airport	0,70	0,70	0,42	0	Fort Lauderdale Hollywood Int. Airport	0,57	0,54	5,59	1
Sacramento Int. Airport	0,73	0,72	0,44	1	Hat Yai Int. Airport	0,43	0,40	5,62	1
Copenhagen Airport Kastrup	0,75	0,75	0,49	0	Melbourne Airport	0,57	0,54	5,65	0
Kuala Lumpur Int. Airport	0,80	0,80	0,53	0	Juanda Int. Airport	0,43	0,40	5,75	0
Tulsa Int. Airport	0,85	0,85	0,60	1	Taiwan Taoyuan Int. Airport	0,58	0,54	6,11	0
Phnom Penh Int. Airport	0,74	0,73	0,61	0	Gold Coast Airport	0,56	0,52	6,34	1
Darwin Int. Airport	0,80	0,80	0,65	0	Ronald Reagan Washington Nat. A.	0,54	0,51	6,60	1
Jacksonville Int. Airport	0,76	0,75	0,70	0	Genève Aéroport	0,57	0,53	6,62	1
Alicante Airport	0,83	0,82	0,71	0	Hong Kong Int. Airport	0,44	0,41	6,95	1
Vancouver Int. Airport	0,78	0,77	0,73	1	Phoenix Sky Harbor Int. Airport	0,66	0,61	7,33	1
Birmingham Airport	0,75	0,74	0,74	0	Seoul Gimpo Int. Airport	0,46	0,42	7,35	1
Stuttgart Airport	0,82	0,82	0,75	1	Phuket Int. Airport	0,38	0,35	7,38	0
Keflavik Int. Airport	0,79	0,78	0,76	0	Buffalo Niagara Int. Airport	0,46	0,42	7,47	1
Townsville Airport	0,75	0,75	0,79	0	Ted Stevens Anchorage Int. Airport	0,41	0,38	7,64	0
Perth Int. Airport	0,73	0,72	0,80	0	Haneda Airport	0,44	0,40	8,08	1
Cairns Int. Airport	0,81	0,80	0,87	0	Vienna Int. Airport	0,73	0,67	8,29	1
Pulkovo Airport	0,71	0,70	0,89	0	Jeju Int. Airport	0,34	0,31	8,30	0
Nashville Int. Airport	0,74	0,73	0,93	0	Memphis Int. Airport	0,44	0,40	8,35	0
New York-John F. Kennedy Int. Airport	0,63	0,62	0,94	1	Hamburg Airport	0,51	0,47	8,82	1
Denver Int. Airport	0,74	0,73	0,97	0	Chiang Mai Int. Airport	0,40	0,36	9,64	1
Eppley Airfield	0,73	0,73	0,98	0	Louisville Int.-Standiford Field	0,28	0,25	10,05	1
Istanbul Atatürk Airport	0,52	0,51	1,00	1	Budapest Ferenc Liszt Int. Airport	0,70	0,62	11,29	1
Montréal-Pierre Elliott Trudeau Int. A.	0,84	0,83	1,08	1	Edinburgh Airport	0,60	0,53	12,29	1
LaGuardia Int. Airport	0,53	0,53	1,09	1	Manchester Airport	0,74	0,65	12,65	1

References

ACI Policy and Recommended Practices Handbook. Seventh Edition. November 2009.

Adler, N. (2001). Competition in a deregulated air transportation market. *European Journal of Operational Research*, 129(2), 337-345.

Adler, N., & Golany, B. (2001). Evaluation of deregulated airline networks using data envelopment analysis combined with principal component analysis with an application to Western Europe. *European Journal of Operational Research*, 132(2), 260-273.

Adler, N., & Liebert, V. (2014). Joint impact of competition, ownership form and economic regulation on airport performance and pricing. *Transportation Research Part A: Policy and Practice*, 64, 92-109.

Affuso, E., 2010. Spatial autoregressive stochastic frontier analysis: An application to an impact evaluation study, Auburn University Working Papers. (Available at SSRN

Androutsopoulos, K. N., Manousakis, E. G., & Madas, M. A. (2020). Modeling and solving a bi-objective airport slot scheduling problem. *European Journal of Operational Research*, 284, 135-151.

Areal, F.J., Balcombe, K., Tiffin, R., 2010. Integrating Spatial Dependence into Stochastic Frontier Analysis. MPRA Paper 24961, University Library of Munich, Germany.

Assaf, A. G., & Gillen, D. (2012). Measuring the joint impact of governance form and economic regulation on airport efficiency. *European journal of operational research*, 220(1), 187-198.

Barros, C.P. and Dieke, P.U.C., (2008). Measuring the Economic Efficiency of Airports: A Simar-Wilson Methodology Analysis. *Transportation Research, Part E*

Barros, C.P., 2008. Technical efficiency of UK airports. *Journal of Air Transport Management*. 14 (4), 175-178.

Bäuerle, N., Engelhardt-Funke, O., & Kolonko, M. (2007). On the waiting time of arriving aircrafts and the capacity of airports with one or two runways. *European Journal of Operational Research*, 177(2), 1180-1196.

Bottasso, A., Bruno, M., Conti, M., & Piga, C. (2017). Competition, vertical relationship and countervailing power in the UK airport industry. *Journal of Regulatory Economics*, 52(1), 37-62.

Brehm, S., 2013. Fiscal incentives, public spending, and productivity: county-level evidence from a Chinese province. *World Dev*. 46, 92–103.

Bowen, J., 2000. Airline hubs in Southeast Asia: national economic development and nodal accessibility. *Journal of Transport Geography*, 8 (1), pp. 25-41.

Burghouwt, G., 2007. Airline Network Development in Europe and its Implications for Airport Planning. *Ashgate Publishing, Ltd*.

Button, K., 2002. Debunking some common myths about airport hubs. *Journal of Air Transport Management*, 8 (3), pp. 177-188.

Chang, Y.C., Yu, M.M., Chen, P.C., 2013. Evaluating the performance of Chinese airports. *Journal of Air Transport Management*. 31, 19-21.

Chen, Z., Barros, C., & Yu, Y. (2017). Spatial distribution characteristic of Chinese airports: A spatial cost function approach. *Journal of Air Transport Management*, 59, 63-70.

Chi-Lok, A.Y., Zhang, A., 2009. Effects of competition and policy changes on Chinese airport productivity: an empirical investigation. *Journal of Air Transport Management* 15 (4), 166-174.

Coelli, T.J., Prasada, R., D.S., O'Donnell, D.J., Battese, G.E., (2005). An Introduction to Efficiency and Productivity Analysis. Springer Science, New-York, USA.

Cuesta, R. A., & Orea, L. (2002). Mergers and technical efficiency in Spanish savings banks: A stochastic distance function approach. *Journal of Banking & Finance,* 26(12), 2231-2247.

D'Alfonso, T., Daraio, C., & Nastasi, A. (2015). Competition and efficiency in the Italian airport system: new insights from a conditional nonparametric frontier analysis. *Transportation Research Part E: Logistics and Transportation Review*, 80, 20-38.

Elwakil, O. S., Windle, R. J., & Dresner, M. E. (2013). Transborder demand leakage and the US–Canadian air passenger market. *Transportation Research Part E: Logistics and Transportation Review*, 57, 45-57.

Fan, L.W., Wu, F., Zhou, P., 2014. Efficiency measurement of Chinese airports with flight delays by directional distance function. *Journal of Air Transport Management* 34, 140e145.

Forsyth, P. (2003). Airport competition and the efficiency of price structures at major airports. In GARS Research Seminar, Leipzig.

Forsyth, P., Gillen, D., Muller, J. Niemeier, H. M., 2010. Airport Competition: The European Experience. *Ashgate Publishing Ltd.*

Fragoudaki, A., Giokas, D., Glyptou, K., 2016. Efficiency and productivity changes in Greek airports during the crisis years 2010e2014. *Journal of Air Transport Management*. 57, 306-315.

Fröhlich, K., & Niemeier, H. M. (2011). The importance of spatial economics for assessing airport competition. *Journal of Air Transport Management*, 17(1), 44-48.

Fu, Q., & Kim, A. M. (2016). Supply-and-demand models for exploring relationships between smaller airports and neighbouring hub airports in the US. *Journal of Air Transport Management*, 52, 67-79.

Fuellhart, K., 2003, 'Inter-metropolitan Airport Substitution by Consumers in an Asymmetrical Airfare Environment: Harrisburg, Philadelphia and Baltimore.' *Journal of Transport Geography*, 11, 285-296.

Fuellhart, K. (2007). Airport catchment and leakage in a multi-airport region: The case of Harrisburg International. *Journal of Transport Geography*, 15(4), 231-244.

Fung, M.K.Y., Wan, K.K. H., Hui, Y.V., Law, J.S., 2007. Productivity Changes in Chinese Airports 1995-2004. *Transportation Research, Part E*.

Fung, M.K.Y.,Wan, K.K.H., Hui, Y.V., Law, J.S., 2008a. Productivity changes in Chinese airports 1995-2004. *Transportation Research, Part E*. 44, 521e542.

Fung, M.K.Y., Wan, K.K.H., Hui, Y.V., Law, J.S., 2008b. Measuring the efficiency of airports in China with the DEA and endogenous-weigh TFP methods. *International Journal of Transport Economics* 35 (1), 45-73.

Fusco, E., Vidoli, F., (2013) Spatial Stochastic frontier models: controlling spatial global and local heterogeneity. *International Review of Applied Economics* 27, 679-694.

Glass, A., Kenjegalieva, K., Paez-Farrell, J., 2013. Productivity growth decomposition using a spatial autoregressive frontier model. *Economics Letters* 119 (3), 291–295.

Glass, A., Kenjegalieva, K., Sickles, R.C., 2014. Estimating efficiency spillovers with state level evidence for manufacturing in the {US}. *Economics Letters* 123 (2), 154–159.

Glass, A.J., Kenjegalieva, K., Sickles, R.C., 2016. A spatial autoregressive stochastic frontier model for panel data with asymmetric efficiency spillovers. *J. Econom*. 190 (2), 289–300.

Goetz, A.R., Sutton, C.J., The geography of deregulation in the US airline industry, 1997. *Annals of the Association of American Geographers*, Volume 87, Issue 2, Pages 238-263.

Granados, N., Gupta, A., Kauffman. R., 2012. Online and offline demand and price elasticities: evidence from the air travel industry. *Information System Research* 23, 164-181

Hughes, N., Lawson, K., Davidson, A., Jackson, T., Sheng, Y., 2011. Productivity Pathways: Climate-Adjusted Production Frontiers for the Australian Broadacre Cropping Industry. Technical Report, ABARES Research Report 11.5.

Jeleskovic, V., Schwanebeck, B., 2012. Assessment of a Spatial Panel Model for the Efficiency Analysis of the Heterogonous Healthcare Systems in the World. MAGKS Papers on Economics 201248, Philipps-Universität Marburg, Faculty of Business Administration and Economics, Department of Economics.

Lavado, R.F. Barrios, E.B., 2010. Spatial Stochastic Frontier Models. Discussion Papers DP 2010-08, Philippine Institute for Development Studies.

LeSage, J., 1997. Regression analysis of spatial data. *J. Region. Anal. Policy* 27 (2), 83–94.

Lovell, C.A.K., Richardson, S., Travers, P., Wood, L.L., (1994). Resources and functionings: A new view of inequality in Australia. In: Eichhorn, W. (Ed.), Models and Measurement of Welfare and Inequality. Springer, Berlin.

Malighetti, P., Martini, G., Paleari, S., Redondi, R. (2009). The Impacts of Airport Centrality in the EU Network and Inter-Airport Competition on Airport Efficiency. Paper 17673. Munich, Germany: MPRA.

Martín, J. C., Román, C., & Voltes-Dorta, A. (2009). A stochastic frontier analysis to estimate the relative efficiency of Spanish airports. *Journal of Productivity Analysis*, 31(3), 163-176.

Moreno-Izquierdo, L., Ramón-Rodríguez, A., & Ribes, J. P. (2015). The impact of the internet on the pricing strategies of the European low cost airlines. *European Journal of Operational Research*, 246(2), 651-660.

O'Connor, K. (2003). Global air travel: toward concentration or dispersal? *Journal of Transport Geography*, 11(2), 83-92.

Oum, T. H., & Yu, C. (2004). Measuring airports' operating efficiency: a summary of the 2003 ATRS global airport benchmarking report. *Transportation Research Part E: Logistics and Transportation Review*, 40(6), 515-532.

Oum, T. H., Yan, J., Yu, C., (2008). Ownership forms matter for airport efficiency: A stochastic frontier investigation of worldwide airports. *Journal of Urban Economics* 64, 422-435.

Pavlyuk, D. (2009). Spatial competition pressure as a factor of European airports' efficiency. *Transport and Telecommunication*, 10(4), 8–17.

Pavlyuk, D. (2010). Multitier spatial stochastic frontier model for competition and cooperation of European airports. *Transport and Telecommunication*, 11(3), 57-66.

Pavlyuk, D. (2016). Implication of spatial heterogeneity for airports' efficiency estimation. *Research in Transportation Economics* 56, 15-24.

Pels, E., Nijkamp, P. Rietveld, P., (2001). Relative Efficiency of European Airports. *Transport Policy* 8, 183-192.

Pels, E., P. Nijkamp, P. Rietveld, (2003). “Inefficiencies and Scale Economies of European Airports Operations.” *Transportation Research Part E* 39 (5): 341–61.

Reynolds-Feighan, A., 2001. Traffic distribution in low-cost and full-service Carrier networks in the US air transportation market. *Journal of Air Transport Management*, 7 (5), pp. 265-275.

Ryerson, M. S. (2016). Building Air Service Sustainability: Analytical Approach to Documenting Air Carrier Incentive Programs in Airport Sustainability Plans. Transportation Research Record: *Journal of the Transportation Research Board*, (2569), 1-15.

Scotti, D., Malighetti, P., Martini, G., Volta, N., (2012). The impact of airport competition on technical efficiency: a stochastic frontier analysis applied to Italian airport. *Journal of Air Transport Management* 22, 9-15.

Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. *J. Economet.* 136 (1), 31–64.

Sharkey, J., 2014. Losses at Smaller Airports are Unlikely to be Reversed. New York Times, New York, NY, United States. Retrieved June 2015, from New York Times: http://www.nytimes.com/2014/04/01/business/efforts-by-smaller-airports-tolure-new-service-largely-lost-causes.html.

Shone, R., Glazebrook, K., & Zografos, K. G. (2019). Resource allocation in congested queueing systems with time-varying demand: An application to airport operations. *European Journal of Operational Research*, 276(2), 566-581.

Skevas, I. (2020). Inference in the spatial autoregressive efficiency model with an application to Dutch dairy farms. *European Journal of Operational Research*, 283(1), 356-364.

Soylu, B., & Katip, H. (2019). A multiobjective hub-airport location problem for an airline network design. *European Journal of Operational Research*, 277(2), 412-425.

Starkie, D., (2002). Airport regulation and competition. *Journal of Air Transport Management* 8, 63-72.

Suzuki, Y., Crum, M. R., & Audino, M. J. (2003). Airport choice, leakage, and experience in single-airport regions. *Journal of transportation engineering*, 129(2), 212-218.

Suzuki, Y., Crum, M. R., & Audino, M. J. (2004). Airport leakage and airline pricing strategy in single-airport regions. *Transportation Research Part E: Logistics and Transportation Review*, 40(1), 19-37.

Suzuki, S., Nijkamp, P., Rietveld, P., & Pels, E. (2010). A distance friction minimization approach in data envelopment analysis: a comparative study on airport efficiency. *European journal of operational research*, 207(2), 1104-1115.

Thelle, H. M., la Cour Sonne, M., (2018). Airport Competition in Europe. *Journal of Air Transport Management* 67, 232-240.

Vidoli, F., & Canello, J. (2016). Controlling for spatial heterogeneity in nonparametric efficiency models: an empirical proposal. *European Journal of Operational Research*, 249(2), 771-783.

Vidoli, F., Cardillo, C., Fusco, E., Canello, J., (2016). Spatial nonstationarity in the stochastic frontier model: An application to the Italian wine Industry. *Regional Science and Urban Economics* 61, 153-164.

World Bank, (2015). “Air transport, passengers carried”, available at http://data.worldbank.org/indicator/IS.AIR.PSGR

Yoshida, Y., 2004. Endogenous-Weight TFP Measurement: Methodology and its Application to Japanese-Airport Benchmarking. *Transportation Research, Part E.* 40,151- 182.

Yoshida, Y., Fujimoto, H., 2004. Japanese-airport benchmarking with DEA and endogenous-weight TFP methods: testing the criticism of over-investment in Japanese regional airports. *Transportation Research, Part E.* 40, 533e546.

Yu, M. M. 2004. “Measuring Physical Efficiency of Domestic Airports in Taiwan with Undesirable Outputs and Environmental Factors.” *Journal of Air Transport Management* 10 (5): 295–303.