The spatial dimension of competition among airports at worldwide level: a spatial stochastic frontier analysis

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Abstract

In the last decade, academic literature posed a great focus on the estimation of airport efficiency and productivity. One of the main interests has been the analysis of potential impact of airport competition on cost and technical efficiency. The novelty of our research lies in applying a spatial approach which allows for the inclusion of a distance matrix and a shared destinations matrix calibrated for different distances to estimate the impact of competition on efficiencies. By analysing statistical differences between a traditional and a spatial model, it is possible to identify possible competition effects. In this study, we analyse 206 airports for the year 2015 located in Europe, North America, and Pacific Asia sourced from the ATRS database. Our results show the existence of a spatial component which is not captured by the traditional stochastic frontier analysis. We find that competition has an effect on the efficiency level of an airport, and moreover, these effects can be positive or negative depending on the distance considered in the spatial model.

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1. Introduction

Airport infrastructures strongly determine the socio-economic structure of a territory. They influence the choices of individuals, create new residential and productive settlements, and promote new job opportunities. 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 system. The ongoing 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 decades 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). According to industry analysts three major changes are influencing the competitive constraints of airports: more footloose airlines, bigger passengers' choice, and higher reactivity from other airports (ACI, 2009). Additionally, 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).

These elements have lead 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. We assist, 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 (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, we take note of increasing pressures on local authorities and airport management companies, especially when publicly owned, to subsidise, in some ways, airline companies to increase their connection supply 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 worldwide level, and by the effectiveness of the governing/regulatory bodies, given the relevant role still played in most countries by politics with respect to the infrastructural system. Finally, 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, with respect to some years ago.

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. Notwithstanding the high heterogeneity of airport governance and ownership, in general airports competition is an increasing feature of the industry, and the market power of airports has decreased as airlines increasingly pick and choose between various airports and destinations, moving aircrafts, routes and bases (ACI, 2009). The impact of these changes on the extent of economies of scale and scope are of fundamental importance. Normally, an increase in competition should be welfare enhancing, leading to greater efficiency. This, however, is not always the case. In fact, 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). A related managerial aspect concerns the airport ownership form. Many studies have focused their attention on the impact of the ownership form on efficiency, with differing outcomes (Barros and Dieke, 2007; Cruz and Marques, 2011; Lin and Hong, 2006; Oum et al., 2008; Scotti et al., 2012). Furthermore, the market power is mainly determined by the availability of proximate airports that are able to act as close substitutes (Starkie, 2002). Competition is often very strong between airports in the same country (IATA, 2013) and, moreover, international regulations (such as the *Schengen Convention* in Europe) have broadened those boundaries. The changes on 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). 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. As shown by Burghouwt (2007), most of intra-European traffic has been de-concentrated while the intracontinental flights are still concentrated in few large hub airports. To different degrees also other parts of the world are registering de-concentration toward smaller cities' airports. The restructuring of networks has relevant implications on competition conditions among various airports. For local, point-to-point connections, competition has increased, for hub and spoke networks the effect is mixed, depending on the overall effect on demand and, thus, on the possibility to exploit economies of scale.

Airport competition has been investigated in previous works both globally and locally by considering airports at different aggregation levels. The evolution of the air network takes on

particular importance for airports that face national or international competition, showing different spatial trends. Airports are usually classified as a two-sided market since revenues are generated by two different users, passengers and airlines companies (Worldwide Air Transport Conference, 2013). 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. In Europe, approximately 63 per cent of the population is within two-hours' drive of at least two airports, in 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 compare both destinations and airfares when buying a ticket. Specifically, 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. Airport competition is widely recognized for its positive pressure in the sector, leading to quality improvements and resource saving. Although this concept is clear from the micro-economic theory point of view, contradictory results and opinions emerge from empirical studies. Generally, airport efficiency has been the focus of a large body of research (see Pels et al., 2001, 2003; Oum and Yu, 2004; Yoshida, 2004; Fung, Wan, Hui and Law, 2007; Barros, 2008). However, only few studies explain competition implications on airports' efficiency levels from nearby airports and, in the available studies the evidence is mixed. For example, 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 a further research, Pavlyuk (2010) suggested a multi-tier model of competition and cooperation effects, and 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 a ten-year period. They observe that under non-competitive conditions, public airports are less cost efficient than fully private airports. 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. 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 the technical efficiency is negative, confirming the significant role of economies of scale and thus, also, of the size of demand.

In the light of these results, 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", we explicitly consider space in our efficiency analysis. Considering distances important in determining economic relations, the aim of our work is to estimate the spatial heterogeneity and the efficiency spillovers of airports at worldwide level. We base the empirical approach on the spatial model developed by Fusco and Vidoli (2013), which has been used only once for the analysis of the airport industry: Pavlyuk (2016) analysed, in fact, spatial heterogeneity among 365 European airports for the year 2011, using only a contiguity matrix, finding evidence of significant effect of spatial heterogeneity on airport's efficiency and productivity estimates. To the best of our knowledge, no one has focused the analysis at a worldwide scale. Focussing on airports located in the different continents (Europe, North America, Pacific Asia, Australia and New Zealand), we analyse the spatial effects of the airports, reflecting the territorial competitiveness, on efficiency through different matrixes. 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 destinations in sharing among airports at different distances.

The rest of the paper is structured as follow. In section 2 are presented the methodology and the econometric approach used for integrating spatial dependence into 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 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). In this work we follow 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.

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:

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

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. To consider the spatial effects, we introduce 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:

$$\log y_i = \log\big(f(x_i;\beta_i)\big) + v_i - (1 - \rho \textstyle\sum w_i)^{-1} \widetilde{u_i} \quad [2]$$

Where:

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

The spatial lag parameter ρ takes values from 0 to 1 ($\rho \in [0,1]$) and determine the correlation between two airports.

The spatial information's are incorporated into the symmetric spatial weight matrix W. Specifically, in this work, we build two different matrixes: a distance matrix and a shared destinations matrix among airports. The distance matrixes are based on the geographical distance between airports. Given the purpose of our analysis, we include different cut-off distances in estimating the stochastic frontier. We define the cut-off distances of 100, 150, 200, 250, 300 and 350 km. The spatial weights w_{ij} are

defined as the inverse standardized distance between two airports i and j. To assess the competition that may exist between two airports and consequently its effect on efficiency, in a second approach, we consider not only the distance but also the number of destinations shared between two airports i and j.

Once the estimate results of the SFA and the SSFA have been obtained and verified at average level, we analyse the effects of spatial competition on airport efficiencies by applying the equation proposed by Fusco and Vidoli (2013). 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 (d_i):

$$d_i = \frac{Eff_{SFA\,i} - Eff_{SSFA\,i}}{Eff_{SFA\,i}} * 100, \qquad \forall i = 1, \dots, n \qquad [3]$$

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

3. Data

The database analysed in this research is composed by observations coming from 206 worldwide airports in the year 2015. The airports considered in our study are the larger among the geographical areas considered. However, it is important to remark that the sample is not including all the existing airport. This leads to a possible bias in the results due to the fact that competition effect on efficiency may be underestimated. The complete list of the airports is reported in the Appendix A. The data source is the Airport Transport Research Society (ATRS) database. All airports have been geolocated in order 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 are a well-known metric in 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 (unit of measurement in squared meters), 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. The descriptive statistics of the variables used are shown in Table 1. We observe that, for the workload units (WLU) the standard deviation is higher than the mean, which indicates that the sample is quite heterogeneous.

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 Employees	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. About 85% of the WLU output measure is given by the passenger movement, while the remaining 15% by freight movement. The geographical region groups are almost balanced in terms of output, but not in terms of units. 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 presents the number of airports with at least one competitor for each of different cut-off distances. Clearly, the number of competitors increases as the distance considered increases. Indeed, we expect that the efficiency level differs among different competition interactions (in the various matrixes considered).

Table 3 - Number of Airports in competition for each distance level

	W100	**W150**	**W200**	**W250**	**W300**	**W350**
With competitors	64	91	124	140	154	164
Without competitors	142	115	82	66	52	42

4. Results and Discussion

To estimate airports' efficiency levels, a spatial stochastic frontier model has been applied. We estimate a multi-output Cobb-Douglas (CD) production function as a 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. A distance function approach is considered in the model in order to consider the airports' multi-output nature. Important properties of the 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.[4]

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

$$-\log(WLU) = \beta 1 \log\left(\frac{Movements}{WLU}\right) + \beta 2\, log(Terminal) + \beta 3\, log(Gates) + \beta 4 \log(Runway) + v_i - (1 - \rho \sum w_i)^{-1} \widetilde{u_i} \qquad [4]$$

We start our analysis applying an OLS estimation, hence not considering neither the presence of inefficiencies nor spatial interactions. Table 4 contains the results.

4 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 4 - 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.

The OLS estimation confirms the validity of the variable specifications, given the highly and significant R-squared (0.83). All the coefficients are statistically significant. Moreover, we find that 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 5.

Table 5 - SFA estimation

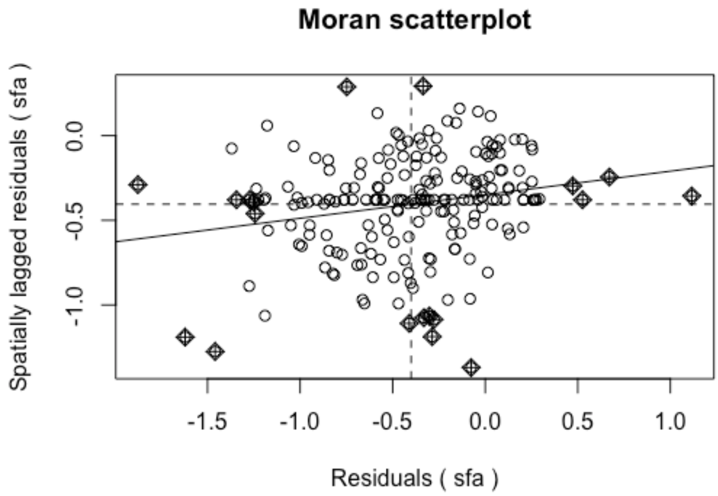
	Dependent variable: Work Load Unit
	Estimate
Intercept	-10.3468***
	(1.6004)
Movements/WLU	3.6694*
	(2.0008)
Terminal	-0.4938***
	(0.0475)
Gates	-0.4714***
	(0.0721)
Staff	-0.0930**
	(0.0417)
Runway	-0.1984
	(0.1270)
	0.2520**
	(0.1148)
σ_v^2	0.1115***
	(0.0378)
γ	0.6933
Mean efficiency	0.6986
Moran's 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 results confirm the validity of the methodological approach. 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 is due to the random variation. The coefficients remain all statistically significant, except for the runway variable. Also, the signs are compliant with our expectations being negative for the input variables and positive for the output one. The classic stochastic frontier specification shows the presence of a 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.[5] Autocorrelation among residuals can be locally displayed through the Moran's I test shown in Figure 1.

[5] The Moran's I test is statistically significant for all the cut-off distances. Results are available upon request.

Figure 1 Moran's I plot (SFA)



The horizontal axis is based on the values of the SFA residual's, while the vertical axis is based on the weighted average (or spatial lag) of the residuals on the horizontal X axis. 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 in order to account for such correlation. In this way, we are able to isolate and evaluate the territorial component separately from the individual performance of the airport. SSFA results for the different distance matrixes are shown in Table 6.

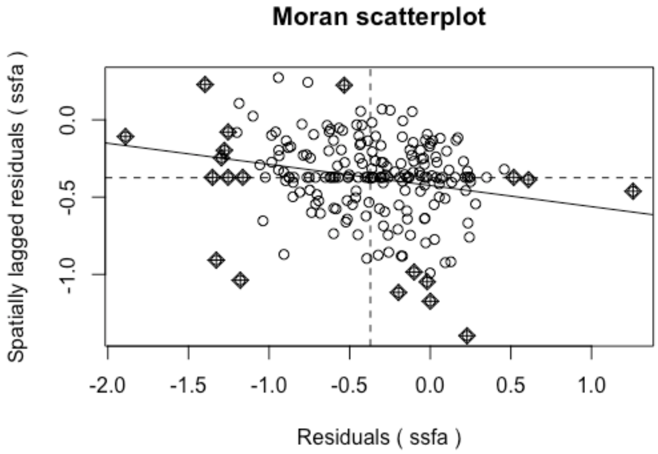
Table 6 - SSFA estimation (distance matrixes)

	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)
σ^2_{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)
σ^2_v	0.1033***	0.1113***	0.1009***	0.0974***	0.1096***	0.1125***
	(0.0348)	(0.0375)	(0.0326)	(0.0327)	(0.0382)	(0.0404)
γ	0.7257	0.6941	0.7316	0.7455	0.6797	0.6586
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
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 and show the expected signs. The SSFA model decomposes the inefficiency variance σ_u^2 into $\sigma_{u\,dmu}^2$ and $\sigma_{u\,sar}^2$, which represent respectively the part of inefficiency variance due to DMU's specificities and to spatial dependence, i.e. $\sigma_u^2 = \sigma_{u\,dmu}^2 + \sigma_{u\,sar}^2$. Consequently, the total variance is given by $\sigma^2 = \sigma_{u\,dmu}^2 + \sigma_{u\,sar}^2 + \sigma_v^2$. When checking for spatial autocorrelation, the Moran's I tests are not significant indicating the goodness of the approach. The Moran's I test scatterplot is displayed in figure 2, showing an opposite and not significant result compared to what obtained in figure 1.

Figure 2 Moran's I plot (SSFA)



The SSFA 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. It is important to notice the higher parameter as well λ in the SSFA models with respect to the classical SFA (λ=1.5034). Inefficiency levels were probably overestimated in the standard SFA model due to spatial autocorrelations. The coefficients ρ, which represent the unobserved spatial heterogeneity is significant in all the spatial estimates. In table 7 we show the results obtained from the SFA and SSFA models for different shared destinations matrix. Results are consistent with the distance matrixes estimations (table 6). 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.

Table 7 – SFA and SSFA estimation (destination matrixes)

	Dependent variable: Work Load Unit						
	SFA	***SSFA***					
		W100d	*W150d*	*W200d*	*W250d*	*W300d*	*W350d*
Intercept	-10.3468*** (1,6004)	-9,8128*** (1,6709)	-9,9493*** (1,6473)	-9,720*** (1,7314)	-9,855*** (1,5247)	-10,203*** (1,3912)	-9,9030*** (1,3345)
Mov/Pass	3,6694* (2,0008)	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	-0,4938*** (0,0475)	-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	-0,4713*** (0,0721)	-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	-0,0930** (0,0417)	-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	-0,1984 (0,1269)	-0,1772 (0,1289)	-0,1837 (0,1274)	-0,1873 (0,1275)	-0,1996 (0,1261)	-0,1968. (0,1253)	-0,2039 (0,1247)
sigma2	0,3635						
sigmau2_dmu	0,2520** (0,1148)	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	0,1115*** (0,0377)	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	0.6986	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	1,503	1,8596	2,0888	2,7308	2,4963	2,3692	2,5728
Value LR-Test	2,093*	12,927***	8,453**	4,619**	4,943**	2,359*	3,233**
Moran's I	0,1176**	-0,1094	-0,0959	-0,0728	-0,0728	-0,0328	-0,0466
Obs.	206	206	206	206	206	206	206

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

In order to estimate the effect of airport competition, we analyse the differences in terms of efficiency between the two methodologies by applying equation [3] to predict the efficiency levels.[6] Table 8 shows the descriptive statistics of the computed d_i based on the stochastic frontier estimated for different distance matrixes while table 9 consider shared destinations matrix by distance.

[6] Appendix B shows the estimated efficiency for each airport considering the SFA and the SSFA models with the distance matrix of 200 km

Table 8 - Summary statistics of d_i for each distance matrix

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

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

Table 9 - Summary statistics of d_i for each destination matrix by distance

With Competitors	*Observations*	*Mean*	*Std. Dev.*	*Min*	*Max*
d*i* (w100d)	64	1.0577 ***	2.98629	0.31775	1.79768
d*i* (w150d)	90	0.45617 ***	1.13694	0.21805	0.69430
d*i* (w200d)	120	0.71650 ***	2.92317	0.18812	1.24489
d*i* (w250d)	137	1.67744 ***	3.15374	1.14461	2.21028
d*i* (w300d)	152	-1.75265***	4.43335	-2.46313	-1.04216
d*i* (w350d)	163	-3.41570***	5.85891	-4.32191	-2.50949

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

After estimating the d_i for each distance matrix (equation [3]), we test if the efficiency distances (d_i) are statistically significant for both the models that include distance matrixes and destination matrixes by distance, for the airports that have at least one competitor. The p-values of t-test are shown in Table 8 and 9.

Moreover, the results show positive d_i values for the distances from 100 km to 250 km, while negative from 300 km to 350 km. As results suggest, we can state that competition has different effects on the efficiency levels depending on the cut off distance considered. Specifically, we find evidence of 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 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 the case of an excess of capacity, it is possible that the marginal cost of a flight is quite low, though the airport will face large sunk costs associated with its construction, for example, in building runways, parking etc. (Forsyth, P., 2003). Differently, for distance above 250km, we obtain statistically significant negative efficiency differences. This can be interpreted as positive effects of competition on the efficiency levels. This may be read as an absence of competition among

airports from 300 km to 350 km. These considerations 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 the technical efficiency. 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 matrixes. The stochastic frontier estimated considering Distance matrixes and Destination Matrixes are equivalent in terms of results. As robustness check, the effect on efficiency is captured either on a pure geographical distance and also by overlapping origins and destinations flows.

Table 10 - Summary statistics of d_i for each ownership configuration

Variable	*Observations*	*Mean*	*Std. Dev.*	*Min*	*Max*
d_i Private companies	27	2.2837	3.6570	-3.63	12.29
d_i Government Companies	15	2.112	4.1445	-2.52	12.65
d_i Public companies	26	0.6826	2.3398	-6.43	6.62

As a final check, we have investigated whether the ownership configuration might play a role in determining different efficiency level of airports, controlling for the spatial effect, by using the measure shown in [3] and grouping the airports based on their ownership configuration, as airports with private, mixed or public participations. The ownership information's for each airport are made available by the ATRS database. Three ownership's form are identified and tested: private (majority private ownership including 100% private ownership), mixed government and public. We focus our analysis on European airports in order to have greater homogeneity of definitions. In table 10 we report summary statistics of the d_i for each group of ownership considered. In appendix C the complete list of the efficiency levels and distances d_i by ownership form is reported of the European airports in the sample. We can observe that the mean of d_i manifests the largest magnitude for the group with private ownership and the lowest one for the group of publicly owned companies. These results are consistent with the findings reported by Scotti et al. (2012) where public airports are found to be more efficient, while private airports are even less efficient than those with mixed ownership. This may be due because investments in indivisible inputs may have been larger in private airports. Indeed, the difficulties involved in reaching the short run volume of traffic, essential for an efficient utilization of these indivisible inputs, private airports have lower technical efficiency than the other one.

5. Concluding Remarks

In this work we analyse 206 airports located in different continents for the year 2015. By applying a standard and a spatial stochastic frontier analysis, we observe how the spatial dependence and its effects differ among different characterization of airport neighbourhood.

Using two different forms of matrices, the first ones based on geographical distances and the second ones which consider the various number of shared destinations among two airports calibrated by each distance, our empirical results can be recapped as follows. First, positive spatial heterogeneity is discovered in the model specifications considered, as evidence of uneven distribution of airport productivity related factor over data examined. Additionally, we find that competition has an important effect on airports' efficiency levels which is varying according to the geographical distances. Specifically, comparing SFA and SSFA model, splitting the analysis among airports with and without competitors, we found a positive mean efficiency difference until 250 km distance and a negative one starting from 300 km. We retain that the negative effect could be related to higher level of competition occurring between airports that are closer to each other, while for long distance the negative efficiency differences is interpreted as positive effects of competition on the efficiency levels. Moreover, the results (table 8 and 9) are consistent for the estimates using the two different matrices.

Overall, we can confirm that the spatial stochastic frontier analysis (SSFA) is a valid instrument to estimate the levels of efficiency also in a worldwide context as we proved, that the competition dynamics are strongly dependent on the spatial distance among airports, thus requiring a detailed analysis to understand its implications on efficiency and on regulatory and competition policies. Based on our finding, the definition of the relevant market, is, in fact, a relative concept. Furthermore, policy makers when deciding on promoting the development of specific airports should consider the spillover effect on the neighbouring ones, considering the different patterns of competition.

The results obtained open interesting future research opportunities. First of all, our results can be further analysed focussing on specific aspects relevant for policy makers (i.e. public funding, ownership network, presence of airlines in the ownership; etc.) in different areas of the world. But ownership is not the only determinant of heterogeneity of the production function. A relevant aspect that could affect the airport performance could be played by management concession and airport infrastructure size. These features should be explored with more attention. Also, an additional development would be to test the robustness of the results taking into consideration time. A panel data analysis would, in fact, allow to control for seasonal or other unobserved factors that can have an influence on the results. Also, a more detailed analysis 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

Appendix C: Airports Efficiency – SSFA 200 km by ownership

Airports	*SFA*	*SSFA w200*	*di*	*Ownership*
Edinburgh Airport	0,60	0,53	12,29	1
Budapest Ferenc Liszt International Air.	0,70	0,62	11,29	1
Vienna International Airport	0,73	0,67	8,29	1
Bergamo-Orio al Serio Airport	0,63	0,59	5,54	1
London Luton Airport	0,52	0,50	4,26	1
Zurich Airport	0,72	0,70	3,57	1
Brussels Airport	0,74	0,71	3,31	1
Zagreb Airport	0,71	0,69	3,28	1
Rome Ciampino Airport	0,50	0,49	2,79	1
Bristol Airport	0,64	0,63	2,41	1
Lisbon Portela Airport	0,68	0,67	2,32	1
Bologna Airport	0,66	0,65	1,87	1
Athens International Airport	0,70	0,69	1,71	1
Düsseldorf International Airport	0,80	0,79	1,44	1
Porto Airport	0,78	0,77	1,25	1
Venice Marco Polo Airport	0,78	0,77	1,20	1
Istanbul Atatürk Airport	0,52	0,51	1,00	1
Birmingham Airport	0,75	0,74	0,74	1

Copenhagen Airport Kastrup	0,75	0,75	0,49	1
Glasgow Airport	0,85	0,84	0,24	1
Malta International Airport	0,85	0,85	0,19	1
Turin Caselle Airport	0,83	0,83	0,04	1
London Gatwick International Airport	0,67	0,67	0,00	1
London Heathrow Airport	0,68	0,68	-0,16	1
Ljubljana Jože Pučnik Airport	0,81	0,82	-0,59	1
Istanbul Sabiha Gökçen International A.	0,64	0,66	-3,48	1
Rome Fiumicino Airport	0,70	0,72	-3,63	1
Manchester Airport	0,74	0,65	12,65	2
Hamburg Airport	0,51	0,47	8,82	2
Paris Orly Airport	0,74	0,71	4,52	2
Nice Cote D’Azur Airport	0,74	0,71	3,91	2
Amsterdam Airport Schiphol	0,75	0,73	2,83	2
Milan Linate Airport	0,68	0,66	2,14	2
Frankfurt Airport	0,81	0,80	1,86	2
Cologne/Bonn Konrad Adenauer Air.	0,82	0,80	1,76	2
Paris Charles de Gaulle Airport	0,83	0,83	0,36	2
Belgrade Nikola Tesla Airport	0,75	0,75	0,23	2
Milan Malpensa Airport	0,85	0,86	-0,29	2
Naples International Airport	0,56	0,57	-0,86	2
London Stansted Airport	0,78	0,79	-1,42	2
Lyon-Saint Exupery Airport	0,81	0,83	-2,31	2
Hannover Airport	0,82	0,84	-2,52	2
Genève Aéroport	0,57	0,53	6,62	3
Helsinki Vantaa Airport	0,70	0,66	5,57	3
Oslo Airport Gardermoen	0,55	0,53	3,94	3
Berlin Tegel Airport	0,46	0,45	1,76	3
Munich Airport	0,83	0,81	1,64	3
Dublin Airport	0,68	0,67	1,55	3
Salzburg W.A. Mozart Airport	0,85	0,84	1,33	3
Palma de Mallorca Airport	0,77	0,76	1,29	3
Luxembourg Airport	0,83	0,82	1,26	3
Stuttgart Airport	0,82	0,82	0,75	3
Alicante Airport	0,83	0,82	0,71	3
Barcelona El Prat Airport	0,83	0,82	0,42	3
Gran Canaria Airport	0,82	0,82	0,41	3
Malaga-Costa del Sol Airport	0,85	0,84	0,29	3
Stockholm-Arlanda Airport	0,74	0,73	0,22	3
EuroAirport Basel-Mulhouse-Freiburg	0,79	0,78	0,20	3
Madrid Barajas Airport	0,85	0,85	0,08	3
Riga International Airport	0,73	0,73	-0,10	3
Warsaw Chopin Airport	0,82	0,82	-0,25	3
Prague International Airport	0,84	0,85	-0,32	3
Sofia Airport	0,85	0,86	-0,47	3
Bratislava Milan Rastislav Stefanik Air.	0,90	0,90	-0,48	3
Newcastle Airport	0,92	0,93	-0,56	3
Kiev Boryspil International Airport	0,88	0,89	-0,59	3
Lennart Meri Tallinn Airport	0,81	0,82	-1,09	3
Berlin Schönefeld Airport	0,63	0,67	-6,43	3

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