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Competition among airports at worldwide level: a spatial analysis

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Abstract

Academic literature posed a great focus on the estimation of airport efficiency and productivity in the last decade. Using a spatial approach, which allows for the inclusion of a distance matrix and a shared destinations matrix calibrated for different distances, we 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 that is not captured by the traditional stochastic frontier analysis. We find that competition has a positive or negative effect on the efficiency level of an airport, depending on the distance considered in the spatial model.

Keywords: Competition; Efficiency Analysis; Airports; Spatial Stochastic Analysis.

1. Introduction

Airport infrastructures deeply determine the socio-economic structure of a territory. 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. According to ACI (2009) airports are characterized by more footloose airlines, bigger passengers' choice, and higher reactivity from other airports. For these reasons, there is an increasing interest in the transport-related literature on the potential interaction effects among airports. Strategies of a given airport may

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not be unresponsive to those of other neighbouring airports. 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 aircraft, routes and bases (ACI, 2009). 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 (Oum et al., 2008; Scotti et al., 2012). Furthermore, 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.

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). 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 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 compare both destinations and airfares when buying a ticket. Specifically, in the case of leisure trips, this behavior 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. Generally, airport efficiency has been the focus of a large body of research (see Pels et al., 2001, 2003; Oum and Yu, 2004). However, only a 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) 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, and the estimates point to both positive and negative effects, depending on the distance among airports. Consistently, 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. 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 has a positive impact on efficiency scores of airports. D'Alfonso et al. (2015), assess the impact of higher competition on airport efficiency. 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.

In light of these results, we explicitly consider space in our efficiency analysis. Considering distances important in determining economic relations, our work aims to estimate the spatial heterogeneity and the efficiency spillovers of airports at a 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 on 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 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 main conclusions.

2. Methodology

Stochastic Frontier Analysis (SFA) is a well-known methodology estimating observations' inefficiency and separating it from the stochastic noise. If spatial effects are significant, the traditional SFA estimation techniques generate biased results and inconsistent estimators (Vidoli et al. 2016; Fusco and Vidoli, 2013). In Spatial Stochastic Frontier Analysis (SSFA) the spatial dependence is incorporated in technical efficiency analysis by using an autoregressive specification of the inefficiency (1):

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

Where:

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

The spatial lag parameter ρ takes values from -1 to 1 ($\rho \in [0,1]$) and determine the correlation between two airports. The spatial information is 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. We include different cut-off distances in estimating the stochastic frontier: 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.

In the end, 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 (di):

$$d_i = \frac{Eff_{SFA\,i} - Eff_{SSFA\,i}}{Eff_{SFA\,i}} * 100, \qquad \forall i = 1,\dots,n \tag{2}$$

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 (Fusco and Vidoli, 2013).

3. Data

The ATRS database used in this research is composed of observations coming from 206 worldwide airports in the year 2015. The airports considered in our study are the larger among the geographical areas considered (Europe, North America, and Pacific Asia). 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 Work Load Unit (WLU). 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 square meters), the number of gates, the number of staff 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.

Table 1 - Summary statistics

Variable	Mean	Std. Dev.	Min	Max
WLU	24,200,000	24,500,000	861,982	113,000,000
Air Movements	189,759	154,616	6,800	867,860
Terminal size	222,986	281,157	6,450	1,972,474
N. of Gates	59	47	5.00	226.00
N. of Employees	1,053	1,634	23.00	15,929
N. of Runways	2	1	1.00	8.00
N. of Staff	1,053	1,634	23.00	15,929

Table 2 presents the number of airports with at least one competitor for each of the different cut-off distances. 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 2 - 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 Conclusions

Efficiency, in economics, is quite extensive and it covers different aspects. Efficiency measures how well a firm performs relative to the best practice or the most output obtainable from a given input level with the given production. We refer to this work as the joint effect of two factors: technical and allocative efficiency (Coelli et al., 2005). To estimate airports' efficiency levels, we estimate a multi-output Cobb-Douglas (CD) production function as a functional form of the frontier specified in equation 1. A distance function approach is considered in the model to consider the airports' multi-output nature (homogeneity restriction is imposed)†. The econometric model specification can be expressed in the following form:

$$-\log(WLU) = \beta 1 \log\left(\frac{Movements}{WLU}\right) + \beta 2\, log(Terminal) + \beta 3\, log(Gates) + \beta 4 \log(Runway) + \beta 5 \log(Staff) + v_i - (1-\rho\sum w_i)^{-1}\tilde{u_i} \quad (3)$$

Where:

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

† For a detailed analysis look Coelli et al. (2005).

The classic stochastic frontier specification shows the presence of a strong spatial autocorrelation. Indeed, the Moran's I statistic is highly significant and equal to 0.1390 witnessing how the use of spatial methodologies are appropriate for the analysed data (Anselin, 1988, 1995, 1996)‡. For this reason, we apply the Spatial Stochastic Frontier model to account for such correlation. 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. Results obtained for different shared destinations matrix are consistent with the distance matrixes estimations.

To estimate the effect of airport competition, we analyse the differences in terms of efficiency between the two methodologies (for both approaches) by applying equation (2) to predict the efficiency levels.

Our results show positive di values for the distances above 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 the negative pressure of competition on the technical efficiency level for distances below 250 km. In other words, airports in a 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). Differently, for distance above 250km, we obtain statistically significant negative efficiency differences. This can be interpreted as the 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). Similarly, Scotti et al. (2012), using a 100 km radius to define the catchment area, find a negative effect of competition on technical efficiency.

In conclusion, 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, we find the same results: competition has an important effect on airports' efficiency levels which is varying according to the geographical distances and shared destinations among airports. 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 a higher level of competition occurring between airports that are closer to each other, while for long-distance the negative efficiency differences are interpreted as positive effects of competition on the efficiency levels.

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

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