MEASURING THE IMPACT OF AIRLINES' DOMINANCE, INTER - AIRPORT COMPETITION AND LOCAL GOVERNMENTS ON THE EFFICIENCY OF ITALIAN AIRPORTS

Davide Scotti, University of Bergamo, Italy, email: davide.scotti@unibg.it

Paolo Malighetti, University of Bergamo, Italy, email: paolo.malighetti@unibg.it

Gianmaria Martini, University of Bergamo, Italy, email: gianmaria.martini@unibg.it

Nicola Volta, University of Bergamo, Italy, email: nicola.volta@unibg.it

ABSTRACT

We investigate how the intensity of competition among airports affects their technical efficiency by computing airports' markets on the basis of a potential demand approach. We find that the intensity of competition has a negative impact on airports efficiency in Italy during the 2005-2008 period. This implies that airports belonging to a local air transportation system where competition is strong exploit less intensively their inputs than those ones with local monopoly power. Furthermore, we find that public airports are more efficient than private and mixed ones. A possible explanation is that this is due to a distortion effect driven by the different value assigned (by public and private agents) to the positive externalities created by air transportation in the local economy. Hence polices should provide incentives to implement airports specialization in local systems where competition is strong. Moreover, when designing airport charges, regulators should take the impact of the above externalities into account, even when the airport has been privatized.

Keywords: airports efficiency, stochastic distance function, airports competition.

1 INTRODUCTION

An important effect of the liberalization process implemented in the EU air transportation market has been the exponential growth in the European network. Today every European airline (i.e. belonging to European citizens) can provide new European connections (i.e. flights having origin and destination in airports belonging to the EU 25) without any further restrictions than that regarding slots availability.[1] As a consequence, if we consider all 460 airports of the 18 countries belonging to the European Common Aviation Area (ECAA) in 1997 (i.e. the 15 EU members plus Iceland, Norway and Switzerland), the total number of airport pairs connections (i.e. point-to-point flights) has marked an impressive 35% increase, from 3,410 in 1997 to 4,612 in 2008, with a CAGR equal to 2.78%.[2] Furthermore also the total number of connecting flights has increased from 4,102,484 in 1997 to 5,228,688 in 2008, with a CAGR for the period equal to 2.23%.

The network expansion has increased the intensity of competition between airports, given that travelers may now choose the same origin-destination route using alternative flights. The latter may be available at the same airport (i.e. the competition is *within* the airport) or at different nearby ones (i.e. the competition is *between* airports). Our aim is to investigate which is the impact of airport competition on their technical efficiency, which is an important factor in air transportation: airports efficiency is linked both with airport charges and with the services provided to airlines and passengers (e.g. shorter aircraft's turnaround times, quicker passengers transfers, faster baggage claim times, etc.). Hence we want to analyze whether airports with higher intensity of competition are more technically efficient.

A further interesting feature of airports competition in Europe is the presence of different ownership types. The large majority of European airports are controlled either by local governments (e.g. municipalities, regional governments, etc.) or by private agents. Furthermore some airports have a mixed ownership (local governments and private agents).[3] Hence we want also to test whether a specific ownership type leads to higher efficiency. This paper deals with these issues by developing a potential demand approach to compute an airport competition index and a multi-output stochastic frontier econometric model to estimate technical efficiency. These techniques are applied to a sample of 38 Italian airports for the period 2005-2008.

We find a statistically significant negative relation between airport competition and technical efficiency. This implies that an airport which is closer to the local monopoly model has a more efficient utilization of its inputs and assets then those facilities having a high intensity of competition. On the contrary, an airport with strong competition, may lose passengers and flights (which move toward nearby facilities), while keeping, for instance, the same runway

[1]The EU liberalization process started in 1987 and, through the sequential implementation of several packages has now formed a unique large internal market. The set of measures adopted in December 1987 led to the approval of the "first package" of the integrated European rules on air transportation. Two other packages (1990 and 1992) led up to the creation of the European common market. However the complete liberalization entered into force in April 1997, 15 years after the start of the process.

[2]Data extracted from the OAG (Official Airline Guide) database; information regarding the total number of operating flights connecting airports belonging to the European Common Aviation Area (ECAA) during a year. Operating flights mean that co-sharing connections are considered as a single flight, to avoid useless replications.

[3]Spain is a relevant exception since all Spanish airports are controlled by the same central government authority, AENA.

capacity and terminal area. This leads to a reduction in its technical efficiency. In order to recover it, this airport has either to stimulate new demand (e.g. by attracting a new LCC or offering a new point-to-point connection not provided by nearby airports) or to divert the existing demand from other airports. However, these goals may be difficult to achieve, both for the presence of a strong airline's buyer power and of some relevant switching costs.[4]

Second, we find that public airports are the most efficient ones, while private facilities are even less efficient than mixed airports. A possible explanation is that public airports take into account the positive externalities produced by air transportation on the local economy, while private airports only maximize their profit. For this reason public airports may be more willing to subsidize airlines, sometimes incurring in losses which are then covered by local taxation.[5] As a consequence, they have more attractive power towards airlines and reach higher utilization levels of their inputs.

The above results yield the following policy implications: first, airports' specialization within the same local system (e.g. one airport may focus on LCCs and another one on cargo) may be a policy recommendation to recover efficiency without requiring long-run investments. Another extreme possibility is closing down some airports with very high inefficiency levels.[6] Second, airport charges should be regulated taking fully into consideration the positive externalities created in the surrounding territory, even for private agents. The latter may also boost private investments in airport infrastructure, including accessibility systems.

To the best of our knowledge, few previous contributions have attempted to model airports competition. Malighetti *et al*. (2007) estimate an airport's potential demand by adopting a fixed radius technique, where airport's competitors are all the other facilities located within a fixed distance around the airport. Oum *et al*. (2008) assume that airports are in competition if they belong to the same metropolitan area. These arbitrary approaches may overstate the true size of some markets and understate others, especially in Europe where urbanization is different than in the U.S. (many towns and airports are relatively closed). Furthermore they do not take into account the determinants of the demand for airport services in a geographic area. Our model instead considers travelers' costs as exogenous factors affecting demand and builds an airport geographic market (i.e. its Catchment Area, CA) based on this variable.

Many papers have investigated airports' technical efficiency, but they did not consider the impact of airports competition on it. The majority has adopted a non parametric approach (i.e. Data Envelopment Analysis-DEA).[7] The latter presents some drawbacks: first, it does not take into account the impact of random shocks on production (e.g. weather conditions, epidemic diseases, etc.). Second, the effects of some variables (e.g. the airports

[4]In many small and medium Italian regional airports the main Low Costs Carriers (LCC) have strong buyer power, since they account for a large share of the airport's traffic. Under these circumstances, airports frequently subsidize LCCs for the flights provided (the so called co-marketing strategy). The subsidy is usually equal to a fixed rebate per passenger. Furthermore, switching costs may be due to different accessibility systems among airports and to presence of relevant transaction cost when signing up a contract with a new handler.

[5]This has created hot discussion within the sector since this practice may be considered as state aid, which is forbidden in EU (see the well known *Charleroi-Ryanair* case.

[6]For instance, we find that Parma airport, a small regional facility, is constantly at about 60% distance from the estimated production frontier; furthermore the 2008 annual report of the company managing the airport presents a loss of 4.2 million euros. The loss has been even larger in 2007.

[7]See Gillen and Lall's seminal contribution (1997), and the comprehensive survey provided by Lozano and Gutiérrez (2009). These studies usually deal with a single country (e.g. the US, Brazil, Taiwan, Japan, Australia, Italy and Spain), but there are also some studies at a European level and a few that benchmark airports from different countries.

competition) on the estimated inefficiency scores is usually performed with a two-stage analysis: DEA in the first stage and a Tobit (or truncated) regression in the second stage using the estimated inefficiency scores. However, as shown by Simar and Wilson (2007), this approach leads to biased estimates.[8]

We compute airports efficiency using a parametric approach: in doing so, we have links with a limited number of previous contributions. Pels *et al.* (2001, 2003) adopt a stochastic frontier model but without taking into account the multi-output features of airports' activities (i.e. aircraft, passenger and cargo movements); Barros (2008), Oum *et al.* (2008) and Martín *et al.* (2009) estimate a costs stochastic frontier but using accounting data, a choice which involves some problems in computing inputs' prices.[9]. Last, Chow and Fung (2009) and Martín-Cejas and Tovar (2009), which adopt a multi-output approach, did not investigate the determinants of airports' estimated inefficiency scores.

The paper proceeds as follows. In Section 2 we present the multi-output stochastic distance function adopted to estimate the airports technical efficiency and the model of potential demand developed to compute the airport competition index. The dataset is described in Section 3, while empirical results are reported in Section 4. Concluding comments are highlighted in Section 5.

2 METHODOLOGY

This Section is split into two parts: first we develop the stochastic distance function econometric model, which is used to estimate the airports efficiency scores. Second we develop a model of airport's potential demand based on the identification of the population belonging to its catchment area which have the possibility (measured in terms of "reasonable" traveling times) to choose between alternative airports. Building on the estimated potential demand and on the connections available in nearby airports, we compute an index of airport competition.

2.1 The stochastic distance function econometric model

In order to analyze the determinants of airports efficiency, a crucial step is the estimation of a production frontier for the Italian airport system. In doing so, we can choose between two approaches: parametric (i.e. the estimation of a stochastic frontier) and non-parametric (i.e. DEA). As already mentioned, DEA has been frequently adopted in previous contributions on airports' efficiency, but presents some drawbacks.

On the contrary, with a Stochastic Frontier Analysis (SFA) it is possible to disentangle random shocks from technical inefficiency, as shown by Aigner, Lovell and Schmidt (1977)

[8]For instance, Gillen and Lall (1997) first estimated a output oriented DEA model and then use the estimated inefficiency scores as a dependent variable in a Tobit regression with yearly and territorial dummies as explanatory variables. Simar and Wilson (2007) show that the inefficiency scores are serially correlated since they depend on all inputs and outputs observations; consequently the error terms in the Tobit regression are also serially correlated. Furthermore, the latter correlation does not disapper enough quickly for standard inference approaches.

[9]These contributions have not information on unit labor costs and unit capital costs; they are obtained from balance sheet data. The latter may lead to biased estimates, since, for instance, the assets values are not updated (e.g. the historical value of a runway is registered in the balance sheet and not its substitution value).

and Meeusen and van den Broeck (1977) in their seminal contributions.[10] Furthermore, SFA may involve "the incorporation of exogenous variables, which are neither inputs to the production process nor outputs of it, but which nonetheless exert an influence on producers' performance" (Kumbhakar and Lovell (2000), p. 261). This implies that SFA allows to obtain consistent and unbiased estimates of the coefficients regarding the determinants of technical inefficiency. Both these features make SFA more suitable for our empirical investigation.

Other important issues need to be addressed when an airports efficiency is investigated. First, we measure technical efficiency, i.e. airports' management ability to get an efficient inputs utilization. This means that we do not identify the input combination yielding the minimum cost).[11] Second, since airports are tipically multi-product firms (they provide aircraft, passengers and cargo movements) an appropriate multi-output framework for estimating technical efficiency is required. As shown by Coelli and Perelman (1999, 2000) and Kumbhakar and Lovell (2000), this implies to estimate a stochastic distance function. Third, we need to choose between input and output orientation. The former (the latter) identifies the inputs' reduction (the output improvements) required to achieve the efficient frontier. Given that in airport operation many inputs are indivisible (at least in the short run) an output oriented stochastic distance function seems to be more appropriate, especially in a context where airports are in competition.[12]

In this framework we define $P(x)$ as the airports' production possibility set, i.e. the output vectors $y \in R_+^M$ that can be obtained using the input vector $x \in R_+^K$. That is: $P(x) = \{y \in R_+^M : x\ can\ produce\ y\}$. By assuming that $P(x)$ satisfies the axioms listed in Fare *et al.* (1994), we introduce Shepard's (1970) output oriented distance function:

$$D_O(x, y) = min\{\theta : (y/\theta) \in P(x)\} \tag{1}$$

where θ is $\leq$ 1. Lovell *et al.* (1994) show that the distance function (1) is nondecreasing, positively linearly homogeneous and convex in y and decreasing in x. $D_O(x, y) = 1$ means that y is located on the outer boundary of the production possibility set, i.e. $D_O(x, y) = 1$ if $y \in IsoqP(x) = \{y : y \in P(x), \omega y \notin P(x), \omega > 1\}$. If instead $D_O(x, y) < 1$, y is located below the frontier; in this case the distance represents the gap between the observed output and the maximum feasible output. This gap may be due both to random shocks and inefficiency, as shown later.

We adopt a translog distance function for its nice properties: (i) it is flexible, (ii) it is easy to calculate and (iii) it allows the imposition of homogeneity.[13] If we assume that there are M outputs and K inputs, the translog distance function is defined as follows:

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[10]They were the first to develop SFA, where the error term of the usual regression model is equal to the sum of two components. The first one is typically assumed to be normally distributed and represents the usual statistical noise (i.e. the random shocks). The second component is non negative and represents technical inefficiency.

[11]This is due to the features of our dataset which do not include monetary variables, e.g. input prices, airports different revenues, etc., but only physical inputs and outputs.

[12]Our approach is different from Martín-Cejas and Tovar (2009), which assume that "demand is beyond the airports' control and it has to be met". We believe instead that airports' managers have the capacity to improve traffic movements, for instance by attracting new carriers.

[13]Notice that a Cobb - Douglas distance function requires a constant elasticity of substitution, which is unlikely to be fulfilled.

$$\begin{aligned} lnD_{Oit} &= \alpha_0 + \sum_{m=1}^{M}\alpha_m \ ln\ y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ ln\ y_{mit}\ ln\ y_{nit} \\ &+ \sum_{k=1}^{K}\beta_k\ ln\ x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ ln\ x_{kit}\ ln\ x_{lit} \\ &+ \frac{1}{2}\sum_{k=1}^{K}\sum_{m=1}^{M}\zeta_{km}\ ln\ x_{kit}\ ln\ y_{mit} \\ i &= 1,2,...,N \quad t = 1,2,...,T \end{aligned} \tag{2}$$

where N is the total number of airports in the sample and T represents the total periods (years) of observation. Hence lnD_{Oit} is the distance from the frontier of airport i in year t. Notice that being on the frontier yields $D_{Oit} = 1$, so that the left hand side of (2) is equal to zero. As shown by Coelli and Perelman (2000), the restrictions required for homogeneity of degree 1 in outputs are the following ones:

$$\sum_{m=1}^{M}\alpha_m = 1;\ \sum_{n=1}^{M}\alpha_{mn} = 0,\ m = 1,2,...,M;\ \sum_{m=1}^{M}\zeta_{km} = 0,\ k = 1,2,...,K$$

Furthermore the restrictions required for symmetry of the interaction terms are: $\alpha_{mn} = \alpha_{nm}$ ($m,n = 1,2,...,M$), $beta_{kl} = \beta_{lk}$ ($k,l = 1,2,...,K$). The homogeneity condition upon Equation (2) implies that $D_O(x,\omega y) = \omega D_O(x,y)$. Hence it possible to choose arbitrarily one of the outputs (e.g. output M), so that we define $\omega = 1/y_M$ and obtain the following expression:

$$D_O(x, y/y_M) = \omega D_O(x,y)/y_M \tag{3}$$

Given (3), the translog distance function becomes:

$$\begin{aligned} ln(D_{Oit}/y_{Mit}) &= \alpha_0 + \sum_{m=1}^{M-1}\alpha_m\ ln\ y^*_{mit} + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1}\alpha_{mn}\ ln\ y^*_{mit}\ lny^*_{nit} \\ &+ \sum_{k=1}^{K}\beta_k\ ln\ x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl}\ ln\ x_{kit}\ ln\ x_{lit} \\ &+ \frac{1}{2}\sum_{k=1}^{K}\sum_{m=1}^{M-1}\zeta_{km}\ ln\ x_{kit}\ lny^*_{mit} \end{aligned} \tag{4}$$

where $y^*_{mit} = y_{mit}/y_{Mit}$. Equation (4) can be written as $ln(D_{Oit}/y_{Mit}) = TL(x_{it}, y_{it}/y_{Mit}, \alpha, \beta, \zeta)$, where TL stands for translog function.
Hence we can write:

$$-ln(y_{Mit}) = TL(x_{it}, y_{it}/y_{Mit}, \alpha, \beta, \zeta) - ln(D_{Oit}) \tag{5}$$

In Equation (5), the term $-ln(D_{Oit})$ is non observable and can be interpreted as an error term in the regression model. If we replace the term it with $(v_{it} - u_{it})$, we get the typical SFA composed error term: v_{it} are random variables which are assumed to be iid as $N(0,\sigma_v^2)$

and independent of the u_{it}; the latter are non negative random variables distributed as $N(m_{it}, \sigma_u^2)$. v_{it} represent the random shocks, while the inefficiency scores are given by u_{it}. Hence we can now write the translog output oriented stochastic distance function that we are going to regress later:

$$\begin{aligned} -ln(y_{Mit}) &= \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \; ln \; y^*_{mit} + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{n=1}^{M-1} \alpha_{mn} \; ln \; y^*_{mit} \; ln \; y^*_{nit} \\ &+ \sum_{k=1}^{K} \beta_k \; ln \; x_{kit} + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \; ln \; x_{kit} \; ln \; x_{lit} \\ &+ \frac{1}{2} \sum_{k=1}^{K} \sum_{m=1}^{M-1} \zeta_{km} \; ln \; x_{kit} \; ln \; y^*_{mit} + v_{it} - u_{it} \end{aligned} \tag{6}$$

In order to investigate the determinants of inefficiency, we apply a single-stage estimation procedure following Coelli (1996).[14] The technical inefficiency effect, u_{it} in Equation (6) can be specified as follows:

$$u_{it} = \delta z_{it} + w_{it} \tag{7}$$

where the random variable w_{it} is defined by the truncation of the normal distribution with zero mean and variance, σ^2, such that the point of truncation is -δz_{it}, i.e. $w_{it} \geq -\delta z_{it}$. Furthermore z_{it} is a $p \times 1$ vector of exogenous variables which may influence the efficiency of a firm and δ is an 1 x p column vector of parameters to be estimated. Battese and Coelli (1995) propose a method of maximum likelihood which is equivalent to the Kumbhakar *et al.* (1991) and Reifschneider and Stevenson (1991) specification, but applied to panel data.[15] According to this time-varying specification of airports' inefficiency, the technical efficiency of production for airport i at period t is defined as follows:

$$TE_{it} = e^{-u_{it}} \tag{8}$$

2.2 The airport Competition Index

The common approach to define markets for airports assumes that an airport's relevant geographic market consists roughly of a circular area around its geographic location. A fixed

[14] This issue was addressed by Kumbhakar *et al.* (1991) and Reifschneider and Stevenson (1991) who propose stochastic frontier models in which the inefficiency effects are expressed as an explicit function of a vector of firm specific variables and a random error.

[15] The model proposed by Battese and Coelli (1995) differs from that of Kumbhakar *et al.* (1991) and Reifschneider and Stevenson (1991) in that the w_{it} random variables are not identically distributed nor are they required to be non negative. Furthermore the mean, δz_{it} of the normal distribution, which is truncated at zero to obtain the distribution of u_{it}, is not required to be positive for each observation, as in Reifschneider and Stevenson (1991). The likelihood function is expressed in term of the variance parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$.

radius technique is implemented in order to define an airport's competitors. The latter are all the other airports located within a fixed distance around the airport. The fixed radius technique presents some major drawbacks: first it is arbitrary. Second it will overstate the true size of some markets and understate others, especially, as mentioned before, in Europe. Last it does not depend on the determinants of the demand for airport services in a geographic area (Gosling (2003)).

In dealing with these issues, we have to take into account that any measure based on the determinants of demand cannot be implemented using actual realized airport choices taken by passengers (or by firms shipping freights). Observed choices may be influenced by unobservable airport heterogeneity regarding the quality and the cheapness of their available supply (Kessler and McClellan (2000)). This, in turn, is likely to produce biased estimates of demand determinants. For this reason it is necessary to compute predicted travelers choices based on exogenous factors. We consider travelers' costs as exogenous factors affecting demand and build an airport geographic market (i.e. CA) based on this variable: potential passenger traveling times to reach each airport, i.e. we assume that individuals are potential passengers of any airport that they can reach in a reasonable time.

Our technique is composed by several steps.[16] First, we draw a boundary around airport i that defines all the zip codes within T minutes drive from that airport. We will consider the following specifications of the maximum traveling time: $T = \{60, 75, 90, 105, 120\}$.[17] We compute the traveling time from zip code j to airport i driving a car on three different road types: urban roads, extra-urban roads and motorways.[18] All the zip codes falling within the T-minutes defined boundary are included in the catchment area of airport i, CA_i.

Second, we define η_i as the set of population living in airport i's catchment area, given by all people living in all zip code towns belonging to CA_i. Similarly, η_j is the set of population leaving in airport j's catchment area, CA_j.

Third, since in the air transportation sector each O-D route defines a separate market, airport i is subject to competition coming from airport j only if the same route is available at both airports. This means that airport i and airport j must have either the same airport destination, or destination in different airports but with a maximum distance equal to 100 kilometers.[19] The different techniques applied in order to estimate the potential demand of origin and destination airport is due to the different exogenous factors affecting it for a specific route. We assume that traveling cost are the main determinant of the origin airport's potential demand; while the region where the travel is directed is instead the main factor influencing the destination airport's potential demand.[20] Hence if we consider all airports where route r is available, we define the following expression:

[16] A similar technique has been implemented by Propper *et al*. (2004, 2008) for hospitals.

[17] The analyses performed by many airports and national aviation authorities (for instance the British CAA) show that almost all passengers choosing a given airport leave in an area where it is possible to reach the airport within 90 minutes.

[18] The driving times, influenced by the different road types are computed using *Google Maps*.

[19] Fuellhart (2003) shows that airports are subject to strategic interaction if they are located within a circle with 95 kilometers-150 kilometers ray.

[20] The intuition is the following: a traveler when choosing a flight considers first the region that needs to be reached (not necessarily the town but also the surrounding region), then she/he verifies if at a reasonable traveling distance this region can be reached leaving from different origin airports.

$$\eta_{ij,r} = \{(\eta_i \cap \eta_j) \setminus \eta_k,\ for\ all\ k \neq i, j\}$$
$$\eta_{ijk,r} = \{(\eta_i \cap \eta_j \cap \eta_k) \setminus \eta_h, \forall h \neq i, j, k\}$$
$$\ldots$$

where $\eta_{ij,r}$ is the subset of population leaving in CA_i which has only the possibility to reach also airport j within T minutes traveling time for the route r; $\eta_{ijk,r}$ is the subset of η_i which has only the possibility to reach also airport j and airport k within T minutes traveling time always for the route r.

Fourth, if we denote $\hat{\eta}_{i,r}$ as the potential demand of airport i on the route r, this is given by:

$$\hat{\eta}_{i,r} = \eta_i - \sum_j \frac{1}{2}\eta_{ij,r} - \sum_k \frac{1}{3}\eta_{ijk,r} - \sum_h \frac{1}{4}\eta_{ijkh,r} + \ldots \tag{9}$$

Fifth, the Competition Index for airport i on route r is:

$$CI_{i,r} = 1 - \frac{\hat{\eta}_{i,r}}{\eta_i},\ 0 \leq CI_{i,r} \leq 1 \tag{10}$$

We need an aggregate index of competition for airport i, i.e. a measure that takes into account all the routes available in that airport and also their relative importance i.e. their weights. The latter is given, for route r, by the ratio between the number of Available Seat for the route r in airport i ($AS_{i,r}$) and the total number of Available Seat (AS_i) in the same airport.[21] Hence the aggregate index of competition for airport i is defined as follows:

$$CI_i = \sum_{r=1}^{R} \frac{AS_{i,r}}{AS_i} \times CI_{i,r} \tag{11}$$

where $0 \leq CI_i \leq 1$. This implies that the higher is CI_i, the more airport i is subject to competition. Figure 1 provides an example.

Suppose we want to compute CI_A by applying (11). After having fixed a given level of $\overline{T}$, the procedure draws the boundary of its catchment area, given by the grey area. Suppose that airport B is the unique nearby airport, and that people living in the dashed area are those which may, within $\overline{T}$ minutes, reach also airport B.

[21] $AS_{i,r}$ and AS_i are taken from the OAG database (Official Airline Guide)

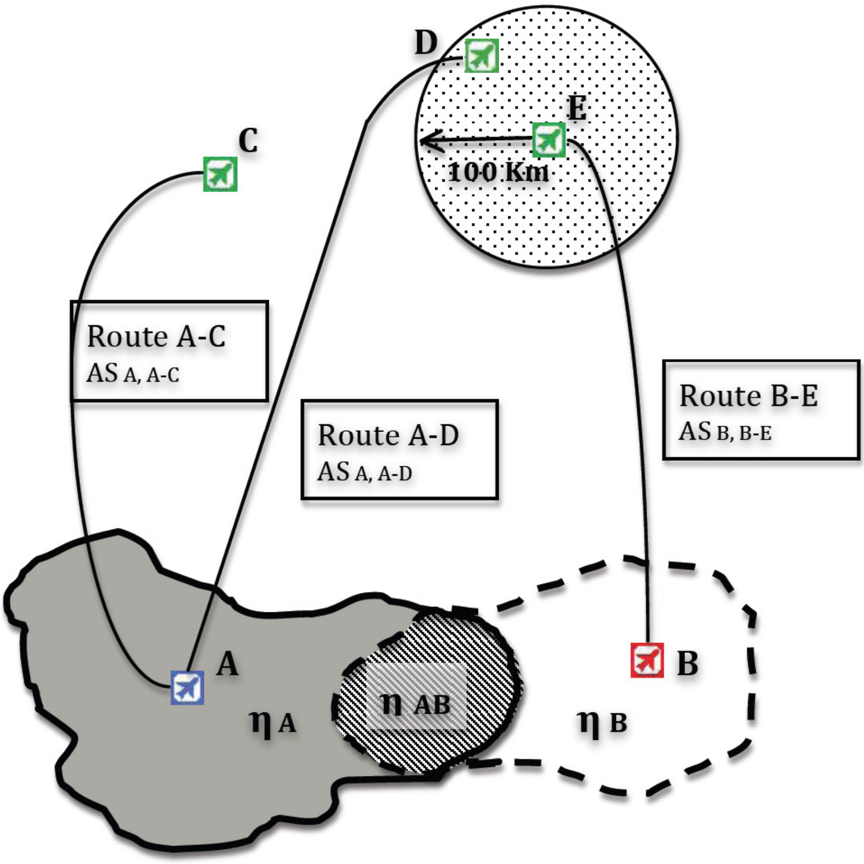

Figure 1 – Example of computation of airport competition index

The next step is to consider the available routes at the two airports. Airport A has two routes: A-C and A-D. Airport B has only. A-D and B-E belong to the same market for the population η_{AB} since airport D is at less than 100 kilometers distance from airport E. Clearly, on route A-C airport A is not subject to any competition coming from airport B. Hence $\eta_{AB,A--C} = 0$ while $\eta_{AB,A--D} = \eta_{AB}$. Consequently from (9) we get that $\hat{\eta}_{A,A--C} = \eta_A$ while $\hat{\eta}_{A,A--D} = \eta_A - \frac{1}{2}\eta_{AB}$. Then from (10) we get: $CI_{A,A--C} = 0$, while $CI_{A,A--D} = 1 - \frac{\eta_A - \frac{1}{2}\eta_{AB}}{\eta_A} = \frac{\eta_{AB}}{2\eta_A}$. Now suppose that $AS_{A,A--D} = 50$ (i.e. during a year the total number of available seats for the route A-D is equal to 50) and $AS_A = 100$. Hence from (11) we obtain $CI_A = 0 + \frac{50}{100} \times \frac{\eta_{AB}}{\eta_A} = \frac{\eta_{AB}}{4\eta_A}$, which is airport A's competition index.

3 DATA

The multi-output/multi-input production frontier for Italian airports is estimated using annual data on 38 airports observed over the four-year period from 2005 to 2008. The data sources are $ENAC$ for outputs (i.e. aircraft, passenger and freight movements) and, the technical information provided by the airports' official documents for inputs. The latter have been integrated by a direct investigation with the managing boards of 38 Italian airports. Information regarding exogenous variables have been collected from the Italian national institute for statistics (ISTAT) and from the airports' balance sheets. Italian airport-system is composed by 101 airports; among them only 45 airports are open to commercial aviation, while the other ones are small airports operating only for general aviation (private aircrafts and air taxi). Hence our dataset covers 84% of Italian airports but 99.97% of passenger movements.[22]

For each airport we compute two output variables: the yearly number of aircraft movements (ATM) and of work load units movements (WLU), i.e. a combination of passenger and freight movements. In air trasportation, by convention, passengers and freights are combined in a single output measure, WLU, such that 100 kilograms correspond to one passenger. Regarding inputs, we consider the runways capacity (CAP) (measured as the maximum number of authorized flights per hour)[23], the total number of aircraft parking positions ($PARK$), the terminal surface area ($TERM$), the number of check-in desks ($CHECK$), the number of baggage claims (BAG) and the number of not handling employees, measured in terms of full time equivalent units (FTE). The descriptive statistics regarding outputs and inputs are presented in Table I.[24]

Table I – Descriptive statistics of input (I) and output (O) variables

	Average	**Median**	**Std. Dev.**	**Max**	**Min**
ATM (O) (number)	43,024	18,919	63,881	346,650	1,748
WLU (O) (number)	3,600,544	1,343,857	6,618,747	36,758,411	7,709
CHECK (I) (number)	37	17	62	358	3
FTE (I) (number)	208	74	387	2,186	1
BAG (I) (number)	4	3	3	15	1
PARK (I) (number)	24	16	25	142	2
CAP (I) (flights per hour)	17	12	17	90	2
TERM (I) (sqm)	33,326	11,600	69,630	350,000	256

The representative Italian airport has about 43 thousand aircraft movements per year (the smallest airport has less then 2 thousand movements), and about 3.6 million WLU (the smallest has less then 8 thousand WLU). The average runways capacity is equal to 17 movements per hour, with 24 aircraft parking positions, a terminal area of about 33 thousand sqm, 37 check-in desks, 4 baggage claims and 208 FTE workers.

It is possible to check the validity of the chosen inputs and outputs by testing for their isotonicity, i.e. outputs should be significantly and positively correlated with inputs (Charnes *et al*. (1985)). Pearson correlation coefficients are shown in (Table II). The correlation between all the inputs and the two outputs is significant (at a 1% level) and positive. Moreover, the inputs correlation is positive, significant and very high, as a confirmation that in

[22]In year 2008 the total number of passengers in the 7 missing airports was equal to about 41 thousands while the total number of passengers in the whole Italian system was equal to about 133 million.
[23]This variable takes into account both the runways length and the airport's aviation technology level, e.g. some aviation infrastructures such as ground-control radars and runway lighting systems.
[24]Notice that we have not included in our inputs the total surface area because this may lead to biased estimation, since in many Italian airports a relevant portion of the surface is dedicated to military activities.

managing airports, resources and facilities are jointly dimensioned to avoid bottlenecks (Lozano and Gutiérrez, (2009)).

Table II – Pearson correlations of input (I) and output (O) variables

	CHECK (I)	FTE (I)	BAG (I)	PARK (I)	CAP (I)	TERM (I)
ATM (O)	0.969	0.958	0.878	0.890	0.944	0.936
WLU (O)	0.976	0.948	0.860	0.889	0.946	0.952
CHECK (I)	1	0.928	0.903	0.923	0.943	0.979
FTE (I)	0.928	1	0.836	0.859	0.932	0.895
BAG (I)	0.903	0.836	1	0.858	0.875	0.875
PARK (I)	0.923	0.859	0.858	1	0.904	0.927
CAP (I)	0.943	0.932	0.875	0.904	1	0.920
TERM (I)	0.979	0.895	0.875	0.927	0.920	1

We consider two types of exogenous variables: the first one influences the production frontier; the other type of exogenous variables has an impact on the airports' inefficiency scores. Seasonality ($SEASON$) is the only variable influencing the frontier: airports more affected by tourist flows may have a high traffic variation across the different months.[25] This has an impact on airports production levels but not necessarily on their inefficiency scores.[26] $SEASON$ is a dummy variable equal to 1 if the airport belongs to a region whose monthly tourist flows are strongly seasonal and correlated with airports' monthly passengers flows.[27]
Four variables are instead considered as determinants of airports' inefficiency scores: the airport competition index (CI_i), two dummies regarding ownership ($PRIV$ for private ownership and MIX for mixed public-private ownership) and the degree of dominance of the main airline in a specific airport (DOM).
The airport competition index (CI_i) is computed from (11). Table III and Figure 2 show the distribution of the airport competition index as function of T . For instance the first row of Table III shows that if $T = 60$, then 10 Italian airports have no competition at all. Furthermore, for the same maximum traveling time, the degree of competition is rather small (i.e. $CI \leq 20\%$) in 16 airports, while only 4 airports have a competition index between 40% and 60%. No airports have a degree of competition higher than 60%. If instead $T = 90$, row 3 of Table III shows that only 4 airports have no competition, 8 airports have a rather high competition index (between 40% and 60%), while competition is very high in 3 airports (60%$\leq CI_i \leq$ 80%).

Table III – Distribution of airport competition index as function of *T*

%	**0**	**(0,20]**	**(20,40]**	**(40,60]**	**(60,80]**	**(80,100]**
CI(T=60)	10	16	8	4	0	0
CI(T=75)	5	13	11	8	1	0
CI(T=90)	4	7	16	8	3	0
CI(T=105)	4	5	8	14	7	0

[25]For instance, in some Italian airports the traffic is very high during the summer, while its volume is much lower during the winter.
[26]Airports subject to seasonality must have enough capacity to deal with the summer peaks, even if this implies the existence of spare capacity during the winter. The latter assets' underutilization is not due to inefficiency but to a characteristics of airports' demand.
[27]We first compute the Gini index of monthly regional tourist flows (measured by the recorded hotel bookings reported by ISTAT). Then we classify a region as strongly influenced by tourist flows if the Gini coefficient is greater then the national average. Last, we assume that the tourist flow is strongly correlated with passenger movements if the Pearson Correlation index is greater than 0.9.

CI(T=120)	3	3	6	13	11	2

Figure 2 confirms the positive correlation between the competition index and T as well as the increase in its variance as the maximum traveling time grows. The latter implies that an enlargement of the airport's catchment area has not the same effect on all Italian airports. For some of them this implies an increase in the competition index. This effect is instead small for other airports.

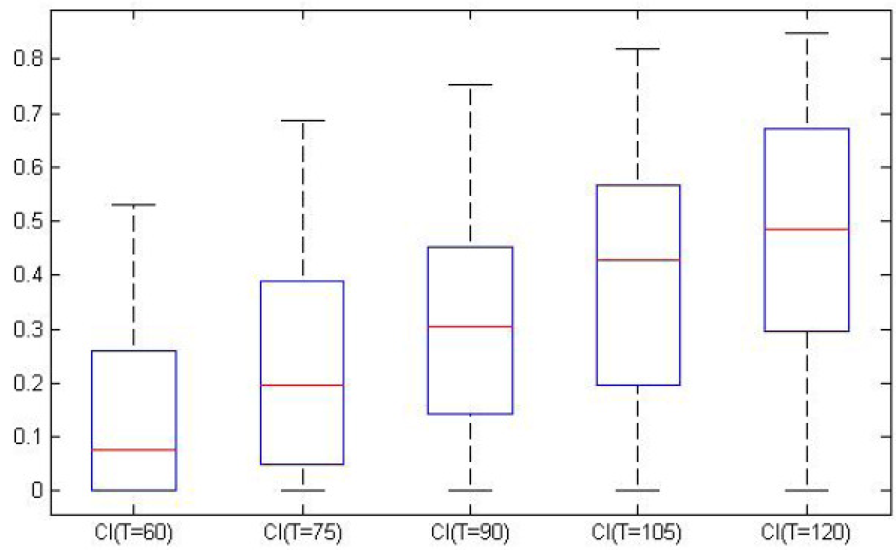

Figure 2 – Airport Competition Index. Box–plots for different T levels.

Regarding airports' ownership, only two Italian airports out of 38 are managed directly by the government.[28] The other 36 airports are controlled by local governments, private agents or a combination of them. As mentioned before we consider two ownership dummies: $PRIV$ means that private agents are the main shareholders of the company managing the airport. $PRIV$ is equal to 1 if the stake of private agents is higher than 50% of the capital stock. MIX is instead the dummy variable characterizing those airports with mixed public-private ownership. MIX is equal to 1 when the stake of private agents is greater than 25% but lower than 50% of the capital stock. Hence public airports are those where private agents have less than 25% of the shares.

The distribution of airports' ownership during the period 2005-2008 is characterized by a public airports' majority: 28 out of 38 (74%) both in 2005 and in 2008. Private airports have slightly increased during the observed period: from 5 in 2005 (13%) to 7 in 2008 (18%). Mixed ownership airports were 13% in 2005 and 8% in 2008.

Last, to consider the impact of airlines competition on airports' efficiency, we have included the variable DOM , which is given by the percentage of AS offered by the main airline in a specific airport (i.e. its market share). The higher is this percentage the lower is the competition among airlines in airport i . In terms of airports' efficiency, this variable may also show the impact of incumbent carriers' strategy to block entrance, which may deny to airports' managers the possibility to attract new airlines. This, in turn, may reduce the airport efficient assets' utilization.

[28] Lampedusa and Pantelleria are airports located in two different mediterranean islands South of Sicily directly controlled by the Italian government through the public authority ENAC.

4 RESULTS

In this Section we present the results of the empirical analysis divided into two parts. First (4.1), we present the estimates[29] of the production frontier and the impact of competition and ownership on the estimated inefficiency scores[30] Second (4.2), we analyze the dynamics of the estimated efficiency scores over the observed period, to check if Italian airports are improving their efficiency over time.

4.1 Econometric results

Estimation results for our model are given in Table IV. The estimated multi-output stochastic distance function is

$$\begin{aligned} -ln(WLU_{it}) = TL(\quad & ATM_{it}/WLU_{it}, TERM_{it}, CHECK_{it}, BAG_{it}, FTE_{it}, \\ & PARK_{it}, CAP_{it}, \alpha, \beta, \zeta) + \lambda SEASON + v_{it} - u_{it} \end{aligned} \qquad (12)$$

where WLU_{it} is the normalizing output i.e. ATM_{it} is expressed in WLU_{it} terms, α is the coefficient for ATM_{it}/WLU_{it}, β is a vector of coefficient regarding inputs and ζ is a vector of coefficient related to output-input interactions. The equation describing the impact of the exogenous variables on the inefficiency scores u_{it} is the following:

$$m_{it} = \delta_0 + \delta_C C_{it} + \delta_{Priv} Priv_{it} + \delta_{Mix} Mix_{it} + \delta_{Dom} Dom_{it} \qquad (13)$$

where m_{it} represents the mean of u_{it}.[31] Table IV presents the results.

First order coefficients are, in general, statistically significant. The first order effect of terminal area (i.e. $TERM$) and of the number of parking positions (i.e. $PARK$) is instead not statistically significant. Concerning second order coefficients, they are all significant with the exception of the employment level (FTE^2) and of the number of parking positions ($PARK^2$). Furthermore, many interaction effects are statistically significant as a confirmation of the multi-output features of airport activity.

Table IV – Final maximum likelihood estimates

Parameter	Estimate	Std. Error
Constant	-9.881754 (***)	2.483051
ATM^*	-2.286812 (***)	0.613381
$TERM$	-0.899752	0.737798

[29]The estimation has been performed using the package FRONTIER 4.1 (Coelli, 1996) of the econometric software R.

[30]By inefficiency score we mean $u_{it} = -ln(TE_{it})$, where TE_{it} is the efficiency of airport i in period t. Clearly the higher is u_{it}, the greater is the inefficiency score and so the lower is the airport's efficiency.

[31]Notice that not including an intercept parameter, δ_0, in Equation (17) may imply the fact that the δ-parameters associated with the z-variables are biased and that the shape of the inefficiency effects' distributions are unnecessarily restricted (Battese and Coelli, 1995).

Parameter	Estimate	Std. Error
$CHECK$	-3.801795 (***)	1.006785
FTE	-4.251388 (***)	0.617905
$PARK$	-0.780825	0.693384
CAP	9.171560 (***)	0.923990
BAG	6.500563 (***)	0.990672
ATM^{*2}	0.340078 (***)	0.074918
$ATM^{*} \times TER$	0.402892 (***)	0.105747
$ATM^{*} \times CHECK$	-0.168535	0.145686
$ATM^{*} \times FTE$	-0.062048	0.053111
$ATM^{*} \times PARK$	0.210768	0.130186
$ATM^{*} \times CAP$	0.444732 (***)	0.126395
$ATM^{*} \times BAG$	0.013127	0.149691
$TERM^{*2}$	0.218052 (*)	0.111932
$TERM \times CHECK$	0.532163 (***)	0.153986
$TERM \times FTE$	0.599155 (***)	0.088966
$TERM \times PARK$	0.079273	0.137026
$TERM \times CAP$	-1.066190 (***)	0.127544
$TERM \times BAG$	-1.122393 (***)	0.135864
$CHECK^2$	-2.194695 (***)	0.363926
$CHECK \times FTE$	-0.510896 (***)	0.097889
$CHECK \times PARK$	0.393199 (*)	0.206071
$CHECK \times CAP$	1.236659 (***)	0.197873
$CHECK \times BAG$	1.758001 (***)	0.256612
FTE^2	0.049934	0.060052
$FTE \times PARK$	0.201071 (*)	0.105133
$FTE \times CAP$	-0.380414 (***)	0.103624
$FTE \times BAG$	-0.149992	0.120087
$PARK^2$	0.130238	0.199227
$PARK \times CAP$	0.310167 (*)	0.159670
$PARK \times BAG$	-0.588757 (***)	0.170502
CAP^2	0.551847 (**)	0.255853
$CAP \times BAG$	0.97988	0.212633
BAG^2	0.609049 (*)	0.338145
$SEASON$	0.177293 (***)	0.047231
$Constant_Z$	-2.160487 (***)	0.499319
$CI(T=90)$	3.086832 (***)	0.587989
$PRIV$	0.836423 (***)	0.192170
MIX	0.608078 (***)	0.193079
DOM	0.846379 (***)	0.258419
σ^2	0.048289 (***)	0.016498
γ	0.722389 (***)	0.127600
LR	60.417	
$log\ likelihood\ value$	80.5802	

Note that *,**,*** denote significance at 10%, 5% and 1% respectively.

As expected, seasonality has a negative impact on airports' production. Given the importance of tourism in Italy, this result confirms the difficulties encountered by managers of airports located in tourist regions in setting an efficient inputs' utilization during all the year.
The likelihood function is expressed in terms of the variance parameters, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$. Table IV shows that they are statistical significant at 1% level with the estimated γ equal to 0.72. Hence technical inefficiency explians a lot of airports' distances from the frontier (i.e. the variance of the inefficiency term is large compared to the variance of the disturbance term).[32]
We can now look at our main research questions. Concerning the impact of airport competition on technical efficiency, since CI_i is function of T, Table V shows the estimated coefficients for different specifications of the maximum traveling time. They are always positive and statistically significant. Moreover their magnitude is the largest among the determinants of the inefficiency scores. This implies that airports with higher competitive pressure are less efficient. On the contrary, in the Italian system, an airport which is closer to the local monopoly model (i.e. those airports with a competition index lower than 20%-see Table II) has a more efficient utilization of its inputs then those structures which have a high intensity of competition coming from nearby airports.

Table V – Airport competition index sensitivity

Parameter	Estimate	Std. Error
$CI(T=60)$	3.118810 (***)	0.984361
$CI(T=75)$	3.265859 (***)	0.741844
$CI(T=90)$	3.086832 (***)	0.587989
$CI(T=105)$	3.155377 (***)	0.748179
$CI(T=120)$	2.7760532 (**)	1.3604814

We provide the following explanation for this result: airports with higher levels of competition are not able to attract a share of traffic sufficiently high to induce an efficient inputs' utilization (i.e. they suffer of overinvestment) due to the presence of many nearby airports. In order to attract more passengers, and so to recover efficiency, managers should increase the number of routes available at their airports either by stimulating new demand (e.g. by attracting a new LCC or offering a new point-to-point connection not provided by nearby airports) or by diverting the existent demand from other airports. Since many inefficient Italian airports have spare slots capacity, there are no technical barriers in doing this.[33] However, in a competitive environment, attracting more passengers does not seem to be an easy task. First active carriers incur in relevant switching costs when changing airports (e.g. different accessibility systems among airports and transaction costs when signing up a new contract with different handlers, etc.).

[32]The significance of γ is also confirmed by the generalized likelihood-ratio (LR) test. In our case the LR statistic is greater than 60 and this confirms that most of the variance of the estimated residual is then attributed to variations in the degree of efficiency, rather than to a stochastic disturbance.
[33]Milan Linate airport is the only exception because it suffers from a strong limitation in the available flights, due to the central government plan for developing Milan Malpensa.

Furthermore, the current general crisis investing airlines worlwide limits the frequency of entry (when does not even reduce the number of existing carriers).[34] and economic troubles have forced Alitalia to shrink its network. This implies that many inefficient airports suffer of a second mover disadvantage, i.e. it is difficult to recover the lost opportunity to attract a carrier.
As shown in Table IV, the coefficients of the variables $PRIV$ and MIX are both statistically significant and positive; among them the coefficient of $PRIV$ is the highest. This implies that public airports are more efficient then those with mixed ownership, whereas private airports have the lowest efficiency. This evidence confirms Curi *et al.* (2009) previous contribution for Italian airports, while it is different from the results obtained by Oum *et al.* (2008), that investigated the efficiency of the largest airports in the world.

We provide the following explanation for this result. First, when planning the development of regional airports, public airports controlled by local governments take more into account the positive externalities produced by air transportation on the local economy. These benefits are tourist flows, lower firms and people transportation costs, higher standards in the quality of life and contribution to the trade and commerce with other regions and countries. For this reason they are willing (i) to subsidize airlines when opening new routes and flights, (ii) to cover the possible losses due to this practice with local taxation. Subsidization in air transportation is defined as “co-marketing”. It is applied especially to low costs carriers. [35]
On the contrary private airports aim to maximize their profit, and have only to match their budget constraints. As a result public airports have an higher attractive power and so they obtain higher utilization rates of their assets. For the same reason mixed airports are more efficient than private ones.
Second, private agents managing airports may pay more attention to the more profitable non aviation activities rather than to the aviation ones which are instead considered in this contribution.
Last, the coefficient of the variable *DOM* is statistically significant and positive. This means that airports efficiency is positively related with airlines competition: when the latter is strong the airport has a high efficiency. This negative dominance effect may be explained in terms of entry deterrence adopted by incumbent airlines. As a consequence the airport's capacity to attract new routes is limited, and, in turn, its utilization of assets.[36]

4.2 The dynamics of the estimated efficiency scores

[34]Note that, between 2008 and 2009, the Italian authority suspended the license to fly to several airlines: *Air Vallee*, *Airbee*, *Alpi Eagles*, *Clubair*, *Italian Tour Airlines*, *Myair.com* and *Ocean Airlines*.
[35] The recent case of Ryanair and Alghero (a regional airport in Sardinia) is a clear example. In 2009 the Raynair received subsidies for 6.4 million Euro while the public company managing the airport has incurred in about 12 million Euro of losses. The local government of the Sardinian region, which is in the board of the company managing the airport, has covered this loss.
[36] This factor is particularly important when the main carrier is Alitalia, which has frequently implemented conducts to prevent new carriers' entry (Boitani and Cambini (2007)).

In this Section we analyze the dynamics of the Italian airports' efficiency, exploiting the time-variant stochastic frontier model that we have implemented. Our aim is to identify which airports exhibit substantial (positive or negative) variation in their efficiency rather then small changes.

Table VI shows the airports' annual efficiency scores. The annual mean of the Italian system has been equal to 87% in 2005 (see the last row of Table VI); it raises to 89.4% in 2006, decreases a little to 88,8% in 2007 and then improves by +1.4% in 2008. Hence the whole Italian system has raised its technical efficiency during the period 2005-2008.

Table VI – Technical efficiency scores

	Airport	**IATA**	**2005**	**2006**	**2007**	**2008**	**CAGR**
1	Alghero	AHO	0.9836415	0.9842496	0.9770360	0.9707992	-0,44%
2	Ancona	AOI	0.9425376	0.9616924	0.9735283	0.9577992	0,54%
3	Bari	BRI	0.9860810	0.9819029	0.9763722	0.9740863	-0,41%
4	Bergamo	BGY	0.9352280	0.9244395	0.8870738	0.8454589	-3,31%
5	Bologna	BLQ	0.9708243	0.9604578	0.9482653	0.9059992	-2,28%
6	Bolzano	BZO	0.9824226	0.9189067	0.8990231	0.9403304	-1,45%
7	Brescia	VBS	0.3907214	0.5011971	0.5707491	0.5858690	14,46%
8	Brindisi	BDS	0.9701730	0.9692220	0.9766164	0.9740494	0,13%
9	Cagliari	CAG	0.9772717	0.9825461	0.9758782	0.9741006	-0,11%
10	Catania	CAT	0.9792962	0.9810636	0.9789461	0.9807305	0,05%
11	Crotone	CRV	0.8851390	0.7458056	0.9296510	0.9623955	2,83%
12	Cuneo	CUF	0.9653214	0.9801301	0.9480145	0.9453068	-0,70%
13	Florence	FLR	0.5272279	0.7742315	0.6868216	0.7354824	11,74%
14	Foggia	FOG	0.9844493	0.9824432	0.9835212	0.9810433	-0,12%
15	Forlì	FRL	0.8204561	0.8110829	0.6466028	0.9625694	5,47%
16	Genoa	GOA	0.9710718	0.9685230	0.9602479	0.9694018	-0,06%
17	Lamezia	SUF	0.9699381	0.9779079	0.9781033	0.9795399	0,33%
18	Lampedusa	LMP	0.9808781	0.9802290	0.9802518	0.9761944	-0,16%
19	Milan Linate	LIN	0.8162571	0.7920055	0.8050826	0.6876792	-5,55%
20	Milan Malpensa	MXP	0.9648632	0.9592233	0.9429037	0.9599671	-0,17%
21	Naples	NAP	0.9678935	0.9515858	0.9575563	0.9773567	0,32%
22	Olbia	OLB	0.9648301	0.9639634	0.8302374	0.9672304	0,08%
23	Palermo	PMO	0.9793438	0.9780920	0.9689187	0.9762111	-0,11%
24	Pantelleria	PNL	0.9760933	0.9845797	0.9744702	0.9744702	-0,06%
25	Parma	PMF	0.2628253	0.3655662	0.4034930	0.3225401	7,06%
26	Perugia	PEG	0.9662135	0.9726140	0.9602774	0.9647310	-0,05%
27	Pescara	PSR	0.9761582	0.9708395	0.9729135	0.9770956	0,03%
28	Pisa	PSA	0.9266374	0.8993993	0.7868844	0.8546060	-2,66%
29	Reggio Calabria	REG	0.9704143	0.9579598	0.9679713	0.9748475	0,15%
30	Rimini	RMI	0.9717582	0.9741712	0.9633711	0.9743450	0,09%
31	Rome Ciampino	CIA	0.4495883	0.4415360	0.6621204	0.6358238	12,25%
32	Rome Fiumicino	FCO	0.9402595	0.9455571	0.9244329	0.9506459	0,37%
33	Turin	TRN	0.8956007	0.9491515	0.9588245	0.9673853	2,60%
34	Trapani	TPS	0.9149201	0.9243414	0.8575312	0.9234287	0,31%
35	Treviso	TSF	0.6152299	0.8227256	0.7336250	0.7523407	6,94%
36	Trieste	TRS	0.8929918	0.9055847	0.9507476	0.9432263	1,84%
37	Venice	VCE	0.9132553	0.9276772	0.8728349	0.9305756	0,63%
38	Verona	VRN	0.6092241	0.9080349	0.9560596	0.9602381	16,38%
	Mean		0.8736062	0.8942273	0.8875515	0.9025237	1,09%

The last column of Table VI shows that the CAGR of technical efficiency is positive for 22 airports (58%). A large improvement has taken place in 4 airports (CAGR greater than +10%, i.e. a 2,5% annual productivity increase), while 3 airports exhibit a substantial efficiency growth (CAGR between +5% and +10%). A moderate increase is observed in 3 airports (i.e. CAGR between +1% and +5%), while a small or negligible positive variation is observed in 12 airports (CAGR lower then +1%, i.e. the maximum average annual productivity growth is equal to +0.25%).

Milan Linate is the only airport with a large negative variation in technical efficiency (CAGR equal to -6%)[37], while 4 airports exhibit a substantial decrease in their efficiency (CAGR between -5% and -1%). The remaining 11 airports have small or negligible negative variations.

Hence we can argue that 61% of Italian airports have not substantially changed their technical efficiency. Strong improvements have been identified for 10 airports (26%) while only 5 airports (13%) exhibit of a substantial shortfall in technical efficiency.

5 CONCLUSION

This paper has investigated the impact of airport competition on the efficiency of 38 Italian airports, by applying a stochastic distance function model with time-dependent inefficiency components to a panel dataset regarding the period 2005-2008. The sample covers the 84% of the commercial Italian airports, but more than the 95% of total movements and passengers. Airports competition has been computed using a potential demand model, taking into account passengers traveling times to reach an airport as exogenous factor affecting demand.

We find that airports with higher intensity of competition are less efficient than those which benefit from local monopoly power. Furthermore, we show that public airports are more efficient, while private airports are even less efficient than those with mixed ownership.

These results yield the following policy recommendations. First, the European liberalization of the air transportation sector has improved airports competition and this, in turn, has created spare capacity in many small and medium airports subject to a sufficient large degree of competitive pressure. There are ways to deal with this spare capacity: one possibility is to adopt air transportation policies inducing specialization among airports belonging to the same territorial system (e.g. one airport may focus on LCCs and another one on cargo). The other one is closing down some airports which are highly inefficient (we observed that some airports are always at a 65% distance front the efficient frontier during the period 2005-2008).

Second, when dealing with the competitive consequences of co-marketing practices adopted by regional airports, antitrust authorities may not consider it a state aid (as in the well known European Charleroi-Ryanair case). The positive externalities created by air transportation in the local economy may justify subsidization. Furthermore these externalities should be considered by regulators when designing airport charges even for private airports, which may in this way internalize this social benefits.

Our analysis has not considered airports costs efficiency, which may lead to different ownership ranking. Furthermore we did not take into account some negative effects in

[37] This is partially explained by the strong limitations in the maximum flights per hour imposed to Milan Linate by the Italian government in order to transfer flights to Milan Malpensa.

airports activities, such as noise and pollution produced in the surrounding area. The latter may provide different inefficiency rankings. These issues are left for future research.

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