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**Department of Economics and Technology Management**

**Working Paper**

n. 04 – 2010

# *The impact of airport competition on technical efficiency: a stochastic frontier analysis applied to Italian airports*

by

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[†] Il Dipartimento ottempera agli obblighi previsti dall'art. 1 del D.L.L. 31.8.1945, n. 660 e successive modificazioni.

# The impact of airport competition on technical efficiency: A Stochastic Frontier Analysis applied to Italian airports

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April, 2010

**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 their inputs less intensively than do airports with local monopoly power. Furthermore, we find that public airports are more efficient than private and mixed ones. Since public airports take into account the positive externalities created by air transportation in the local economy, they are more willing to subsidize airlines in developing the airports' connections. Hence, policy makers should provide incentives to implement airports' specialization in local systems where competition is strong. Moreover, when regulating airport charges, they should take into account the impact of the above externalities.

JEL classification: L930, L590, L110
Keywords: Airport efficiency, stochastic distance function, airport competition.

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## 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 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 slot availability.[2] 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 has signed an impressive 35% increase, from 3,410 in 1997 to 4,612 in 2008, with a Compound Annual Growth Rate (CAGR) equal to 2.78%.[3] Furthermore, 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 (the competition is *within* the airport) or at different nearby ones (the competition is *between* airports). Our aim is to investigate the impact of competition on airports' technical efficiency, which is an important factor in air transportation: airport efficiency is linked both with airport charges and with the services provided to airlines and passengers (e.g., shorter aircraft

[2]The EU liberalization process started in 1987 and, through the sequential implementation of several packages, has now formed a uniquely 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.

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

turnaround times, quicker passenger transfer, faster baggage claim times, etc.). Hence, we want to analyze whether airports with a higher intensity of competition are more technically efficient.

A further interesting feature of airport 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).[4] Hence, we want also to test whether a specific ownership type leads to greater 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 that is closer to the local monopoly model has an efficient utilization of its inputs and assets. In contrast, an airport with strong competition has a lower technical efficiency because it may lose passengers and flights (which move toward nearby facilities), while keeping the same assets.[5] This implies a reduction in its technical efficiency. In order to recover it, this airport has either to stimulate new demand (e.g., by attracting new Low Cost Carriers (LCCs) or offering new point–to–point connections not provided at nearby airports) or to divert the existing demand from other airports. However, these goals may be difficult to achieve, because of both the presence of strong airline buying power and some relevant switching costs.[6]

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

[5]Many airports cannot be easily modified. For instance, the estimated utilization period of a runway is about 50 years.

[6]In many small and medium Italian regional airports, the main LCCs have strong buyer power, because 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.

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 in the local economy. In contrast, private airports only maximize their profit and have tighter budget constraints. Hence, they may be more willing to subsidize airlines, sometimes incurring losses that are then covered by local taxation.[7] This implies that public airports have more attractive power with regard to airlines.

The above results yield the following policy implications: first, airports' specialization within the same local system (for instance, one airport may focus on LCCs and another on cargo) may be a policy recommendation to recover efficiency without requiring long–run investments in the accessibility system. Another extreme possibility is closing down some airports with very high inefficiency levels.[8] Second, airport charges should be regulated taking fully into consideration the positive externalities created in the surrounding territory, even when applied to private airports. These settings should boost private investments in airport infrastructure, including accessibility systems.

To the best of our knowledge, few previous contributions have attempted to model airport competition. Malighetti *et al.* [2007] estimate an airport's potential demand by adopting a fixed radius technique, whereby an airport's competitors are all the other airports 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

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Furthermore, switching costs may be caused by different accessibility systems among airports and by the presence of relevant transaction costs when signing up a contract with a new handler.

[7]This has created hot discussion within the sector since this practice may be considered as state aid, which is forbidden in the EU (see the well known *Charleroi–Ryanair* case (EU [2004])).

[8]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 was even larger in 2007.

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 close). 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 instead investigated airports' technical efficiency, but they do not consider the impact of airport competition on it. The majority has adopted a non parametric approach (i.e., Data Envelopment Analysis—DEA).[9] 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, volcanic eruptions, etc.). Second, as shown by Simar and Wilson [2007], this approach leads to biased estimates of the effects of some exogenous variables on the inefficiency scores.[10]

We compute airport efficiency using instead 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 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 cost stochastic frontier using accounting data,

[9] 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 U.S., 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.

[10] This analysis is usually performed with a two–stage approach, DEA in the first stage and a Tobit or truncated regression in the second stage. For instance, Gillen and Lall [1997] first estimate an 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 input and output observations; consequently the error terms in the Tobit regression are also serially correlated. Furthermore, the latter correlation does not disappear quickly enough for standard inference approaches.

a choice that involves some problems in computing input prices.[11] Finally, Chow and Fung [2009] and Tovar and Martín-Cejas [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 data set 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 introduce the stochastic distance function econometric model. Second we develop a model of an airport's potential demand. This is based on the identification of the population belonging to the catchment area that has 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 then 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 an airport system.

We implement a Stochastic Frontier Analysis (SFA), by which it is possible to disentangle random shocks from technical inefficiency, as shown by Aigner, Lovell, and Schmidt [1977] and Meeusen and van den Broeck [1977] in their

[11]These contributions have no information on unit labor costs or 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).

seminal contributions.[12] 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).

Other important issues need to be addressed when an airport's efficiency is investigated. First, our aim is to measure technical efficiency—i.e., an airport management's ability to achieve efficient input utilization. This means that we do not identify the input combination yielding the minimum cost.[13] Second, since airports are typically multi–product firms, 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 the estimation of 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 reach 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.[14]

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

[12] 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.

[13] This is due to the features of our data set that do not include monetary variables—e.g., input prices, airports' different revenues, etc.—but only physical inputs and outputs.

[14] Our approach is different from Tovar and Martín-Cejas [2009], who assume that "demand is beyond the airports' control and it has to be met", p. 254. We believe instead that airports' managers have the capacity to improve traffic movements, for instance by attracting new carriers.

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

where $\theta \leq 1$. 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 to inefficiency, as will be 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.[15]

If we assume that there are $M$ outputs and $K$ inputs, the translog distance function is defined as follows:

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

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 Eq. (2) is equal to zero.

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

As shown by Coelli and Perelman [2000], the restrictions required for homogeneity of degree 1 in outputs are the following ones:

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

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 Eq. (2) implies that $D_O(x, \omega y) = \omega D_O(x, y)$. Hence, it is 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:

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

Given Eq. (3), the translog distance function becomes:

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

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 the 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 Eq. (5), the term $-ln(D_{Oit})$ is non–observable and can be interpreted as an error term in the regression model. If we replace it with $(v_{it} - u_{it})$, we get the typical SFA composed error term: $v_{it}$ are random variables that are assumed to be *iid* as $N(0, \sigma^2_v)$ 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].[16] The technical inefficiency effect, $u_{it}$ in Eq. (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, $\sigma^2$, such that the point of truncation is -$\delta z_{it}$; i.e., $w_{it} \geq -\delta z_{it}$. Furthermore, $z_{it}$ is a $p \times 1$ vector of exogenous variables that may influence the efficiency of a firm, and $\delta$ is a $1 \times p$ column vector of parameters to be estimated. Battese and Coelli [1995] propose a method of maximum likelihood that is equivalent to the Kumbhakar *et al.* [1991] and Reifschneider and Stevenson [1991] specification, but applied to panel data.[17]

[16] 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.

[17] 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, $\delta z_{it}$, of the normal distribution, which is truncated at zero to obtain the distribution of $u_{it}$,

According to this time–varying specification of airports' inefficiency, the technical efficiency of 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 defining markets for airports assumes that an airport's relevant geographic market consists roughly of a circular area around its geographic location. A fixed–radius technique is usually implemented in order to define the airport's competitors. The latter are all the other airports located within a fixed distance around the airport. The fixed–radius technique presents some drawbacks, however. First, it is arbitrary. Second, it overstates the true size of some markets and understates others—especially, as mentioned before, in Europe. Finally, 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 traveling costs as exogenous factors affecting demand and build an airport geographic market (i.e., $CA$) based on this variable. The proxy we adopt is given by passenger traveling time to reach airports. Hence, we assume that individuals are potential passengers of any airport that they can reach in a reasonable time.

Our technique is composed of several steps.[18] First, we draw a boundary

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is not required to be positive for each observation, as in Reifschneider and Stevenson [1991]. The likelihood function is expressed in terms of the variance parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$.

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

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: $T = \{60, 75, 90, 105, 120\}$.[19] 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.[20] All the zip codes falling within the $T$–minutes defined boundary are included in the catchment area of airport $i$; i.e., $CA_i$.

Second, we define $\eta_i$ as the set of population living in airport $i$'s catchment area. The latter is the population living in all zip code towns belonging to $CA_i$. Similarly, $\eta_j$ is the set of population living in airport $j$'s catchment area, $CA_j$.[21]

Third, since in air transportation 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 a destination in different airports but located at a reasonable distance. We assume that different flights have the same destination if the arrival airports are located at a maximum distance equal to 100 kilometers.[22] The application of different methodologies to estimating the potential demand at the origin and destination airports is due to the different exogenous factors affecting them. Traveling costs are

[19]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.

[20]The driving times, influenced by the different road types, are computed using $GoogleMaps$.

[21]Hence, we assume that the value of time is the same for the entire population living a given area. Clearly, people traveling for business may have a different value of time in comparison to leisure passengers. This means that the maximum traveling distance should be lower for people with high value of time. We did not consider this issue for simplicity. Hence the share of population that may choose among alternative airports is greater in our approach, which means that we overestimate the degree of airport competition. However, the share of business travelers is small, and so this effect is rather negligible.

[22]Fuellhart [2003] shows that airports are subject to strategic interaction if they are located within a circle with 95 kilometer–150 kilometer rays.

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. 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 or he verifies whether, at a reasonable traveling distance, this region can be reached leaving from different origin airports.

Hence, if we consider all airports where route $r$ is available, we define the following expression:

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

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 $\eta_i$, 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 $r$ ($CI_{i,r}$) 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 of the routes available in that airport and also their relative importance. The latter is given, for route $r$, by the ratio between the number of Available Seats for route $r$ in airport $i$ ($AS_{i,r}$) and the total number of Available Seats ($AS_i$) in the same airport.[23]

[23] $AS_{i,r}$ and $AS_i$ are taken from the OAG database. The available seats is the variable adopted in air trasportation to measure the flight capacity.

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 $0 \leq CI_i \leq 1$ and $R$ is the total number of routes available in airport $i$. This implies that the higher is $CI_i$, the more airport $i$ is subject to competition. Figure 1 provides an example of the methodology.

Suppose we want to compute $CI_A$ by applying Eq. (11). After having fixed a given level of $T$, 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 represent the population that may, within $\overline{T}$ minutes, also reach airport $B$.

[FIGURE 1 ABOUT HERE]

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 route $B$–$E$. Routes $A$–$D$ and $B$–$E$ belong to the same market for the population $\eta_{AB}$ since airport $D$ is located 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 Eq. (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 Eq. (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 that $AS_A = 100$. Hence, from Eq. (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 over the period 2005–2008. The data sources are *Ente Nazionale Aviazione Civile* ($ENAC$)[24] 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 the airports. Information regarding exogenous variables have been collected from the Italian national institute for statistics (ISTAT) and from the airports' balance sheets. The Italian airport system is composed of 101 airports; among them only 45 are open to commercial aviation, while the others are small airports operating only for general aviation (private aircraft and air taxi). Hence, our data set covers 84% of Italian airports and 99.97% of passenger movements.[25]

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 transportation, by convention, passengers and freight are combined in a single output measure, $WLU$, such that 100 kilograms of freight corresponds to one passenger. Regarding inputs, we consider the runway capacity ($CAP$) (measured as the maximum number of authorized flights per hour),[26] 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 employees not involved in handling activities, measured in terms of Full–Time Equivalent units ($FTE$). The descriptive statistics regarding outputs and inputs are presented in Table 1.[27]

[TABLE 1 ABOUT HERE]

[24] $ENAC$ is the Italian authority in charge of air transportation regulation.

[25] In year 2008, the total number of passengers in the 7 missing airports was equal to about 41 thousand, while the total number of passengers in the whole Italian system was equal to about 133 million.

[26] This variable takes into account both the runway length and the airport's aviation technology level—e.g., some aviation infrastructure such as ground–control radars and runway lighting systems.

[27] 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.

The representative Italian airport has about 43 thousand aircraft movements per year (the smallest airport has less than 2 thousand movements), and about 3.6 million $WLU$ (the smallest has less than 8 thousand $WLU$). The average runway 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 2. The correlation between all the inputs and the two outputs is significant (at a 1% level) and positive. Moreover, the input correlation is positive, significant, and very high, as a confirmation that in managing airports, inputs are jointly dimensioned to avoid bottlenecks (Lozano and Gutiérrez [2009]).

[TABLE 2 ABOUT HERE]

We consider two types of exogenous variables. The first one influences the production frontier, and 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.[28] In principle, this has an impact on airports' production levels and not on their efficiency.[29] $SEASON$ 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 passenger flows.[30]

[28]For instance, in some Italian airports the traffic is very high during the summer, while their volume is much lower during the winter.

[29]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 characteristic of the airports' demand.

[30]We first compute the Gini index of monthly regional tourist flows (measured by

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 ($DOM$), which is a proxy of airline competition.

The airport competition index ($CI_i$) is computed from Eq. (11). Table 3 and Figure 2 show the distribution of the airport competition index as function of $T$. For instance, the first row in Table 3 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 in Table 3 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 3 ABOUT HERE]

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 does not have the same effect on all Italian airports. For some of them, this implies an increase in the competition index, while this is rather small for other airports.[31]

the recorded hotel bookings reported by ISTAT). Then, we classify a region as strongly influenced by tourist flows if the Gini coefficient is greater than the national average. Finally, we assume that the tourist flow is strongly correlated with passenger movements if the Pearson Correlation index is greater than 0.9.

[31]We have compared our measure of airport competition index with the common approaches previously adopted in the literature and we have found that they underestimate the degree of competition. For instance, the fixed–radius technique provides, on average, a measure of airport competition which is 70% lower than our index. Hence these measures reduce the impact of airport competition on technical efficiency.

[FIGURE 2 ABOUT HERE]

Regarding airports' ownership, only two Italian airports out of 38 are managed directly by the government.[32] The other 36 airports are controlled by local governments, private agents, or a combination of these. 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 a 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 majority of public airports: 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.

Finally, the variable $DOM$ 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 limit the possibility to attract new airlines. This, in turn, may reduce the airport's efficiency of asset utilization.

## 4 Econometric results

The multi–output stochastic distance function regressed is the following:

[32] Lampedusa and Pantelleria are airports located on two different Mediterranean islands south of Sicily that are directly controlled by the Italian government through $ENAC$.

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

where $WLU_{it}$ is the normalizing output—i.e., $ATM_{it}$ is expressed in $WLU_{it}$ terms, $\alpha$ is the coefficient for the $ATM_{it}/WLU_{it}$, $\beta$ is a vector of coefficients regarding inputs, and $\zeta$ is a vector of coefficients related to output–input interactions. The equation describing the impact of the exogenous variables on the inefficiency scores $u_{it}$ is the following:

$$m_{it} = \delta_0 + \delta_C C_{it} + \delta_{Priv} Priv_{it} + \delta_{Mix} Mix_{it} + \delta_{Dom} Dom_{it}, \tag{13}$$

where $m_{it}$ represents the mean of $u_{it}$.[33] Table 4 presents the econometric results.[34]

First–order coefficients are, in general, statistically significant. The first–order effect of terminal area ($TERM$) and of the number of parking positions ($PARK$) is instead not statistically significant. Concerning second–order coefficients, they are all significant with the exception of the employment level ($FTE$) and the number of parking positions ($PARK$).

Furthermore, many interaction effects are statistically significant as a confirmation of the multi–output features of airport activity.

[TABLE 4 ABOUT HERE]

As expected, seasonality has a negative impact on airports' production. Given the importance of tourism in Italy, this result confirms the difficulties encountered by airports located in tourist regions in maintaining an efficient input utilization during the entire year.

[33] Notice that not including an intercept parameter, $\delta_0$, in Eq. (13) may imply the fact that the $\delta$–parameters associated with the $z$ variables are biased and that the shape of the inefficiency effects' distributions are unnecessarily restricted (Battese and Coelli [1995]).

[34] The estimation has been performed using the package FRONTIER 4.1 (Coelli [1996]).

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 4 shows that they are statistically significant at the 1% level, with the estimated $\gamma$ equal to 0.72. Hence, the high value $\gamma$ shows that the distance between the observed output levels and the maximum feasible ones is mostly due to technical inefficiency, and not to random shocks.[35]

We can now look at the determinants of efficiency. Concerning the impact of airport competition on technical efficiency, since $CI_i$ is a function of $T$, Table 5 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. This implies that airports with higher competitive pressure are less efficient. In contrast, in the Italian system, an airport that is closer to the local monopoly model (i.e., those airports with a competition index lower than 20%—see Table 5) has an efficient utilization of its inputs.

[TABLE 5 ABOUT HERE]

We provide the following explanation for this result: airports with higher levels of competition have low technical efficiency levels because they suffer from overcapacity. In order to attract more passengers, and thus to recover efficiency, they should increase the number of routes available at their airports either by stimulating new demand (e.g., by attracting a new LCC or by offering a new point–to–point connection not provided by nearby airports) or by diverting the existing demand from other airports.[36] However, in a competitive

[35]The significance of $\gamma$ 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.

[36]Notice that in the Italian system there are no barriers to entry due to slot capacity. Milan Linate airport is the only exception because it suffers from a strong limitation in the available flights, due to the central government's plan for developing the Milan Malpensa airport.

environment, this does not seem to be an easy task for the following reasons. First, active carriers incur relevant switching costs when changing airports (e.g., different accessibility systems among airports, transaction costs when signing a new contract with different handlers, etc.). Second, the current general crisis facing airlines worldwide limits the frequency of entry (when it does not also reduce the number of existing carriers).[37]

The coefficients of $PRIV$ and $MIX$ are both statistically significant and positive, and among them the coefficient of $PRIV$ is the highest. This implies that public airports are more efficient than those with mixed ownership, whereas private airports have the lowest efficiency. This evidence confirms Curi *et al.*'s [2009] contribution for Italian airports, while it is different from the results obtained by Oum *et al.* [2008], who investigated the efficiency of the largest airports in the world.[38]

We provide the following explanation for this result. First, when planning the development of regional airports, airports controlled by local governments take into account more the positive externalities produced by air transportation on the local economy. These benefits may be tourist flows, lower firm and people transportation costs, higher standards in the quality of life, and contributions to trade and commerce with other regions and countries. For this reason, public airports are willing (*i*) to subsidize airlines when opening new routes and flights, and (*ii*) to cover the possible losses due to this practice with local taxation.[39] In contrast, private airports aim to maximize their

[37]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*.

[38]We have also considered the possibility that the decision to privatize an airport may depend on its efficiency, so that an endogeneity problem in the estimation arises. However, privatization took place much earlier than the observed period (i.e. during the 90s); hence, the possible correlation between the dummy $PRIV$ and the inefficiency component of the error term should have vanished.

[39]Subsidization in air transportation is defined as "co–marketing". It is applied especially to low–cost carriers. The recent case of Ryanair and Alghero (a regional airport in Sardinia) is a clear example. In 2009, Ryanair received subsidies of 6.4 million Euro, while the

profit and have to meet tighter budget constraints. As a result, public airports have a 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 (e.g., revenues coming from commercial activities, parking, etc.) rather than to the aviation activities which are the ones considered in this contribution.

The coefficient of the variable $DOM$ is statistically significant and positive. This means that airport efficiency is positively related to airline 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.[40]

To sum up, in the Italian airport system technical efficiency is higher in airports with low airport competition, public ownership, and high airline competition.

Concerning the dynamics of efficiency our aim is to identify which airports exhibit substantial (positive or negative) variation in their efficiency rather than small changes, exploiting the time–variant stochastic frontier model that we have implemented. Table 6 shows the airports' annual efficiency scores. The annual mean of the Italian system was equal to 87% in 2005 (see the last row of Table 6) and to 90.3% (+1.4%) in 2008. Hence, the whole Italian system has raised its technical efficiency during the period 2005–2008.

[TABLE 6 ABOUT HERE]

public company managing the airport incurred about 12 million Euro of losses. The local government of the Sardinian region, which is on the board of the company managing the airport, has covered this loss.

[40]This factor is particularly important when the main carrier is Alitalia, which has frequently implemented actions to prevent new carriers' entry (Boitani and Cambini [2007]).

The last column of Table 6 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%).

Milan Linate is the only airport with a large negative variation in technical efficiency (CAGR equal to -6%),[41] while 4 airports exhibit a substantial decrease in their efficiency (CAGR between -5% and -1%).

Hence, 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 data set regarding the period 2005–2008. The sample covers 84% of the commercial Italian airports and 99.97% of total passenger movements. Airport competition has been computed using a potential demand model, taking into account passengers' traveling times to reach an airport as an 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 air transportation has improved airport competition, and this, in turn, has stressed the importance of the management's ability concerning technical efficiency. Skillful managers have increased the utilization

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

rates of their assets. In contrast, airports with a sufficiently high degree of competitive pressure that did not exploit the opportunities coming from liberalization have still a lot of spare capacity. This is true for many small and medium–sized Italian airports not enjoying local monopoly power. In our view, there are two ways to deal with this spare capacity: one possibility is to induce airport specialization within the same territorial system (e.g., one airport may focus on LCCs and another on cargo). The other, more extreme possibility is closing down some airports that are highly inefficient.

Second, since the positive externalities created by air transportation in the local economy may justify airline subsidization, they should be considered by regulators when designing airport charges. In this way private airports may be induced to internalize these social benefits.

Our analysis has not considered airport cost efficiency, which may lead to different ownership rankings. Furthermore, we did not take into account some negative effects in airport activities, such as noise and pollution produced in the surrounding area, which may overturn our results. These issues are left for future research.

**References**


- Aigner, D.J., Lovell, C.A.K., Schmidt, P., 1977, 'Formulation and Estimation of Stochastic Frontier Production Function Models.' *Journal of Econometrics*, 6:1, 21–37.

- Barros, C.P., 2008, 'Technical Efficiency of UK Airports.' *Journal of Air Transport Management*, 14, 175–178.

- Battese, G.E., Coelli, T.J., 1992, 'Frontier Production Functions, Technical Efficiency and Panel Data: with Application to Paddy Farmers in India.' *The Journal of Productivity Analysis*, 3, 153–169.

- Battese, G.E., Coelli, T.J., 1995, 'A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data.' *Empirical Economics*, 20, 325–332.

- Boitani A., Cambini, C., 2007, La Difficile Liberalizzazione dei Cieli: Turbolenze Sulla Rotta, in Cambini, C., Giannaccari A., Pammolli, F. (eds.), 'Le Politiche di Liberalizzazione e Concorrenza in Italia.' Bologna, Il Mulino, 197-232.

- Charnes, A., Cooper, W.W., Golany, B., Seiford, L., Stutz, S., 1985, 'Foundations of Data Envelopment Analysis for Pareto–Koopmans Efficient Empirical Production Function.' *Journal of Econometrics*, 30, 91–107.

- Chow, C.K.W., Fung, M.K.Y., 2009, 'Efficiencies and Scope Economies of Chinese Airports in Moving Passengers and Cargo.' *Journal of Air Transport Management*, 15, 324-329.

- Coelli, T., 1996, ‘A guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation.’ (Centre for Efficiency and Productivity Analysis. University of New England).

- Coelli, T., Perelman, S., 1999, ‘A Comparison of Parametric and Non-Parametric Distance Functions: with Application to European Railways.’ *European Journal of Operational Research*, 117, 326–339.

- Coelli, T., Perelman, S., 2000, ‘Technical Efficiency of European Railways: A Distance Function Approach.’ *Applied Economics*, 32, 1967–1976.

- Curi, C., Gitto, S., Mancuso, P., 2009, ‘The Italian Airport Industry in Transition: A Performance Analysis.’ *Journal of Air Transport Management*, 16, 218–221.

- EU, 2004, *Commission Decision Concerning Advantages Granted by the Walloon Region and Brussels South Charleroi Airport to the airline Ryanair*, case C516.

- Fare, R., Grosskopf, S., Lovell, C. A. K., 1994, *Production Frontiers*, (Cambridge, Cambridge University Press).

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

- Gillen, D., Lall A., 1997, ‘Developing Measures of Airports Productivity and Performance: An Application of Data Envelopment Analysis.’ *Transportation Research Part E*, 33, 261–75.

- Gosling, G., 2003, *Regional Airport Demand Model: A Literature Review*, (Southern California Association Of Governments, June).

- Kumbhakar, S.C., Ghosh, S., McGuckin, J.T., 1991, 'A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in U.S. Dairy Farms.' *Journal of Business and Economic Statistics*, 9, 279–286.

- Kumbhakar, S.C., Lovell, C.A.K., 2000, *Stochastic Frontier Analysis*, (Cambridge, U.K., Cambridge University Press).

- Lovell, C.A.K., Richardson, S., Travers, P., Wood, L.L., 1994, Resources and Functionings: A New View of Inequality in Australia, in Eichhorn, W. (ed.), *Model and Measurement of Welfare and Inequality*, (Berlin, Springer–Verlag, 787–807).

- Lozano, S., Gutiérrez, E., 2009, 'Efficiency Analysis and Target Setting of Spanish Airports.' *Networks and Spatial Economics*, for–coming.

- Malighetti, P., Martini, G., Paleari, S., Redondi, R., 2007, 'An Empirical Investigation on the Efficiency, Capacity and Ownership of Italian Airports.' *Rivista di Politica Economica*, 47, 157–188.

- McClellan, M.B., Kessler, D.P., 2000, 'Is Hospital Competition Socially Wasteful?' *The Quarterly Journal of Economics*, 115, 577–615.

- Meeusen, W., van den Broeck, J., 1977, 'Efficiency Estimation for Cobb Douglas Production Functions with Composed Error.' *International Economic Review*, 18, 435-444.

- Oum, T.H., Yan, J., Yu, C., 2008, 'Ownership Forms Matter for Airport Efficiency: A Stochastic Frontier Investigation of Worldwide Airports.' *Journal of Urban Economics*, 64, 422–435.

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

- Pels, E., Nijkamp, P., Rietveld, P., 2003, 'Inefficiencies and Scale Economies of European Airport Operation.' *Transportation Research Part E*, 39, 341–61.

- Propper, C., Burgess, S., Green, K., 2004, 'Does Competition between Hospitals Improve the Quality of Care?: Hospital Death Rates and the NHS Internal Market.' *Journal of Public Economics*, 88, 1247-1272.

- Propper, C., Burgess, S., Gossage, D., 2008, 'Competition and Quality: Evidence from the NHS Internal Market 1991 - 1996.' *The Economic Journal*, 118, 138–170.

- Reifschneider, D.,Stevenson, R., 1991, 'Systematic Departures from the Frontier: A Framework for the Analysis of Firm Inefficiency.' *International Economic Review*, 32, 715–723.

- Shephard, R.W., 1970, *Theory of Cost and Production Functions*, (Princeton, NJ, Princeton University Press).

- Simar, L., Wilson, P.W., 2007, 'Estimation and Inference in Two–Stage, Semiparametric Models of Productive Efficiency.' *Journal of Econometrics*, 136, 31-64.

- Tovar, B., Martin Cejas, R.R., 2009, 'Technical Efficiency and Productivity Changes in Spanish Airports: A Parametric Distance Functions Approach.' *Transportation Research Part E: Logistics and Transportation Review*, 46, 249–260.

Table 1: 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 |

Table 2: 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 |

Table 3: 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 |
| **CI(T=120)** | 3 | 3 | 6 | 13 | 11 | 2 |

Table 4: Estimation Results

| Parameter | Estimate | Std. Error |
|---|---|---|
| Constant | -9.881754 (***) | 2.483051 |
| $ATM^*$ | -2.286812 (***) | 0.613381 |
| $TERM$ | -0.899752 | 0.737798 |
| $CHECK$ | -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 |
| $\sigma^2$ | 0.048289 (***) | 0.016498 |
| $\gamma$ | 0.722389 (***) | 0.127600 |
| $LR$ | 60.417 | |
| *log likelihood value* | 80.5802 | |

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

Table 5: 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 |

Table 6: Airports' 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% |

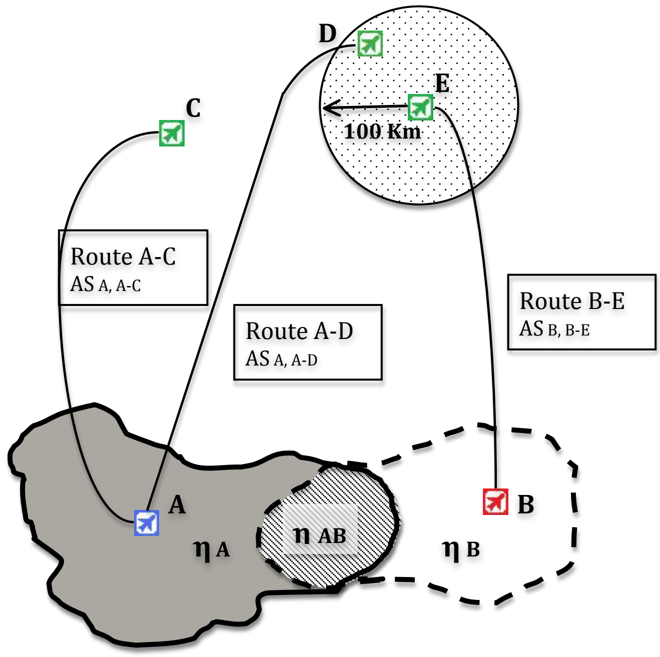


Figure 1: An example of competition between airports.

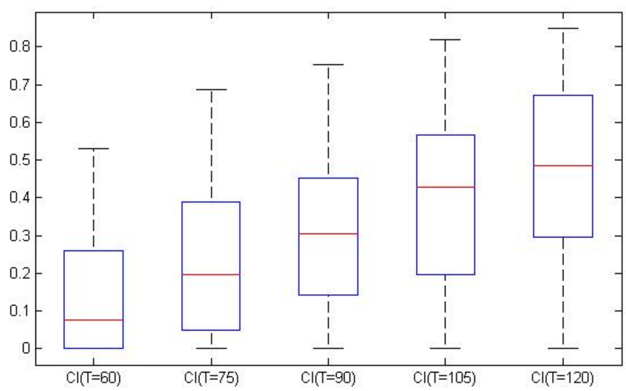


Figure 2: The dispersion of airport competition as function of $T$.