Productivity change in Italian airports

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31 August 2009

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Abstract

This paper examines the total factor productivity of 28 Italian airports during 2000–2006 using non-parametric estimation methods. Moreover, non-parametric inference and hypothesis test on the Malmquist index and its two main components, efficiency and technological change, have been carried out. All the airports have been characterized by technological regress and only a minority of airports experienced an increase in productivity lead by the improvement of efficiency.

Keywords: Airport efficiency, bootstrap, Malmquist index, DEA.

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1. Introduction

This paper contributes to debate on the evolution of the productive performance in the European airport industry. In particular, we analyze the evolution of productivity and efficiency of the Italian airport industry over the period 2000-2006. During this time period European and national directives have produced relevant impacts on the operations and the organisation of the airport services in Italy.

Over the last decades three alternative methodologies to measure productivity and technical efficiency in the airport industry have been employed: the parametric stochastic frontier, the non-parametric stochastic frontier and the index numbers. Table 1 highlights the main contributes for each methodology.

Insert table 1 approximately here

In what it follows we employ the Malmquist index obtained through the well know parametric technique, Data Envelopment Analysis (DEA). But, departing from most of the above literature, we use it in a inferential setting. In fact, the traditional determistic way to compute the Malmquist index does not allow to ascertain whether indicated changes in productivity, efficiency, or technology are real, or merely artefacts of the fact that we do not know the true production frontiers and must estimate them from a finite samples (Simar and Wilson, 1999). In other words, the aim of this research is to investigate total factor productivity changes of the Italian airports using a bootstrap methodology which allows to evaluate if changes are statistically significant. Finally, departing from the previous studies on the Italian airports (Barros and Dieke, 2007, 2008; Curi et al., 2008) we analyze, for the first time, the evolution of the Malmquist index and its components: efficiency change and technological change.

The next section briefly describes the Italian airport industry. Section 2 illustrates the institutional setting and the data. Section 3 presents empirical evidence. Section 4 concludes.

2. Institutional setting and data

2.1 Institutional setting

The privatization of the airports in Italy has started in the middle of 90s by laws n. 537/93 and 351/95. Even if the privatization process has involved most of the Italian airports we can observe generally the constitution of stock companies owned by local councils rather than new companies operated and owned by private operators. Starting from 90s the national legislators has began to change the concessions agreement assigning the right to use and manage the airport land and infrastructures for a maximum of forty years. With this type of concession agreement, called total, the management companies collect revenues derived from all airport operations and services and they are responsible for the whole infrastructural development (landside and airside). The previous concession agreements restricted the operations and services which can operated by the management companies and have a duration of twenty years. Finally, the European directive on handling liberalisation (EU 96/67) has forced airports management companies, with more than 2 million passengers, to open the market to other handling providers. But, the European directive has been implemented by the Italian law n. 18/99 which imposed, at the new incoming, to hire the workers, previously employed by the incumbent airport management company. Thus from 2000, in Italy handling services can be operated directly by the airport management company and/or by independent companies. Table 2 presents, for the twenty-eight airports, some characteristics in term of concession agreement, capital composition and handling services.

Insert table 2 approximately here

2.2. Data

Our sample covers on average 96%, 99% and 99% of total number of passengers, movements and cargos registered in Italy from 2000 to 2006. In the present paper the variables, to measure the airport performances, are standard in the literature (for a survey, see Barros and Dieke, 2008). In particular, outputs include: number of passengers, amount of cargo, number of aircraft movements, aeronautical and non aeronautical revenues Three inputs are used: labor cost, capital invested and soft costs. Data has been collected from the two following sources: airport annual statistics (ENAC, 2001-2007) and balance sheets of airport management companies[2]. The above sources have to be carefully employed for the airports managed by the same management company. In such cases, since it is not possible to obtain from ENAC or from company balance sheet disaggregates financial data, we have aggregate their airports physical data. The problem arises for the following airports: Rome Ciampino and Fiumicino, Milano Linate and Malpensa, and Bari, Brindisi, Foggia and Taranto. All the monetary variables have been divided by the GDP deflator: table 3 reports the descriptive statistics. In Italy there are a total of 42 airports, managed by 37 companies (ENAC, 2007).

Insert table 3 approximately here

3. Methodology

[2] Balance sheets are taken from Italian Chambers of Commerce.

To examine the issues raised in the previous sections we employ DEA (Charnes et al., 1978) to compute the Malmquist productivity index (Färe et al., 1992). We use an output-orientated model as it ensures to account the objective of exploiting the facilities to satisfy the steady growth demand in aviation market (Martìn and Romàn, 2001). However, following the papers by Simar and Wilson (1998, 1999), we analyze airports productivity evolution in a inferential setting. In fact, as noted by the two authors, the traditional DEA-estimator is biased by construction (downward for output orientation) and is affected by the uncertainty due to sample variation.

Now in a deterministic setting the Malmquist index for each airport, or Decision Making Unit (DMU), is obtained by solving four DEA problems[3]. The DEA basic model, which assume constant returns to scale everywhere, measures the Shepard (1970) distance $\square_{it}$ of DMU *i,* at time *t,* relatively to technology existing at same period. Its mathematical formulation is given by:

$$
\begin{aligned}
\Delta_{i,t}\left(\mathrm{y}_{i,t},\mathrm{x}_{i,t}\right) = \left[D_{i,t}\left(\mathrm{y}_{i,t},\mathrm{x}_{i,t}\right)\right]^{-1} &= \max_{\theta,\lambda}\theta \\
s.t. \quad \mathrm{x}_{\mathrm{i,t}} &\geq X_t\lambda \qquad i=1,2...,n; \qquad t=1,2...,T \qquad (1) \\
\theta y_{i,t} &\leq Y_t\lambda \\
\lambda &\geq 0
\end{aligned}
$$

where $D_{i,t}(y_{i,t}, x_{i,t})$ is Debreu's distance function (Debreu, 1951), $\mathbf{Y_t}$ is a *sxn* matrix of observed output, $\mathbf{X_t}$ is a *rxn* matrix of observed input and λ represent a *nx1* vector of weights which allow to obtain a convex combinations of inputs and outputs; $\Delta_{i,t}$ is always less than one. The above linear programming model allows to compute the Malmquist ouput-oriented index (Färe et al. 1992):

$$
\mathrm{M}_{\mathrm{i,t}} = \frac{\Delta_{\mathrm{i,t}}\left(\mathrm{x}_{\mathrm{i,t}},\mathrm{y}_{\mathrm{i,t}}\right)}{\Delta_{\mathrm{i,t}}\left(\mathrm{x}_{\mathrm{i,t-1}},\mathrm{y}_{\mathrm{i,t-1}}\right)} \times \left(\frac{\Delta_{\mathrm{i,t-1}}\left(\mathrm{x}_{\mathrm{i,t-1}},\mathrm{y}_{\mathrm{i,t-1}}\right)}{\Delta_{\mathrm{i,t}}\left(\mathrm{x}_{\mathrm{i,t-1}},\mathrm{y}_{\mathrm{i,t-1}}\right)} \times \frac{\Delta_{\mathrm{i,t-1}}\left(\mathrm{x}_{\mathrm{i,t}},\mathrm{y}_{\mathrm{i,t}}\right)}{\Delta_{\mathrm{i,t}}\left(\mathrm{x}_{\mathrm{i,t}},\mathrm{y}_{\mathrm{i,t}}\right)}\right)^{0.5} = \mathrm{EC}_{\mathrm{i,t}} \times \mathrm{TC}_{\mathrm{i,t}}
$$

$$
t = 2,\ldots, T \qquad (2)
$$

[3] For more details see Cooper et al. (2007), Thanassoulis et al. (2008), Simar and Wilson (2008).

where $EC_{i,t}$ and $TC_{i,t}$ represent the efficiency change and technical change, respectively. Values of $M_{i,t}$, $EC_{i,t}$, or $TC_{i,t}$ greater (less) than one indicate productivity growth (decline) for the DMU *i (i=1,2,…,n)* between period *t-1* and *t (t=2,…,T)*. However, relation (2) does not allow to determine whether changes in productivity, efficiency, or technology are real, or merely artifact of the fact that we do not know the true production frontiers and must estimate them from a finite samples (Simar and Wilson, 1998). Thus, following the papers by Simar and Wilson (1998, 1999) we employ a consistent bootstrap estimation procedure for correcting and obtaining confidence intervals for the Malmquist index, M_t, and its components EC_t and TC_t. The idea underlying the bootstrap is to approximate the sampling distributions of the Malmquist indexes, $\hat{M}_t$, by simulating the data generating process (DGP). In other terms, given the estimates $\hat{M}_t$ of the unknown true values of M_t we generate through the DGP process a series of pseudo datasets to obtain bootstrap estimate $\hat{M}_t^*$. If the bootstrap is consistent, then:

$$\left(\hat{M}_t - M_t\right)\Big| S \overset{\text{approx}}{\sim} \left(\hat{M}_t^* - \hat{M}_t\right)\Big| S^* \qquad t = 2,\dots, T \qquad (3)$$

where S and S^* denotes the observed and the bootstrap sample. To gain consistence on the empirical distribution for efficiencies, Simar and Wilson (1998, 1999) use a smooth bootstrap procedure. Relation (3) implies the original estimates, $\hat{M}_t$, to the true values, M_t, can be approximated by the relation between the bootstrapped estimates, $\hat{M}_t^*$, and original estimates, $\hat{M}_t$ At this point the bias of the Malmquist estimates are estimated by their bootstrap approximations $\widehat{\text{bias}}_{S^*,t} = E_{S^*}(\hat{M}_t^*) - \hat{M}_t$.

Thus a bias-corrected estimates of the Malmquist index, $\tilde{M}_t$, can be obtained as follows:

$$\tilde{M}_t = \hat{M}_t - \hat{b}ias_t = 2\hat{M}_t - B^{-1}\sum_{i=1}^{B}\hat{M}_t^* \qquad t = 2,\ldots, T \qquad (4)$$

where *B* is the number of the bootstrap replications. However, the correction of the bias introduce additional noise which increase the variance of the estimator. Thus, as rule of thumb, Simar and Wilson (2000) recommended not to correct for the bias unless $\left|\hat{b}ias_t\right| > \hat{s}td(\hat{M}_t^*)$.

The construction of confidence intervals is obtained in a similar manner determining the quantile of the sampling distribution of $\left(\hat{M}_t - M_t\right)$ through the bootstrap technique. Practically, the procedure sorts the values of $\left\{\left(\hat{M}_t^* - \hat{M}_t\right)\right\}_{b=1}^{B}$ in increasing order and deletes the $\left(\frac{\alpha}{2}\cdot 100\right)$-percent of the elements at either end of the sorted list. Then, setting $\hat{a}_\alpha^*$ and $\hat{b}_\alpha^*$ (with $\hat{a}_\alpha^* < \hat{b}_\alpha^*$) equal to the endpoints of the sorted array. So, the bootstrap quantile approximation of $\left(\hat{M}_t - M_t\right)$ is given by:

$$\Pr ob\left(-\hat{b}_\alpha^* < \hat{M}_t - M_t < -\hat{a}_\alpha^* \mid S\right) = 1 - \alpha \qquad t = 2,\ldots, T \qquad (5)$$

And, thus, the estimated $\left((1-\alpha)\cdot 100\right)$-percent confidence interval for the estimates M_t is:

$$\hat{M}_t + \hat{a}_\alpha < M_t < \hat{b}_\alpha + \hat{M}_t \qquad t = 2,\ldots, T \qquad (6)$$

Relations (4), (5) and (6) are similarly computed for the two components of the Malmquist index: EC_t and TC_t. With the obtained confidence interval for Malmquist index and its components, it is possible to check whether productivity growth (or decline) is significant at the established confidence level. The smooth bootstrap procedure for efficiency measures was implemented using FEAR package (Wilson, 2008).

4. Empirical results

4.1 Preliminary analysis

As pointed out by the literature on DEA, an excessive number of inputs and/or outputs respect to the number of observations, causes in a large number of efficient units (Daraio and Simar, 2007, Simar and Wilson, 2008). So, in what it follows we first analyze the relation among inputs (outputs) and then we reduce the number of variables by employing the methodology proposed by Daraio and Simar (2007). In figure 1 the scatter plots among variables is reported.

Insert figure 1 approximately here

How it can be noticed from the above figures there is a clear linear dependence among variables. This allows, applying the methodology proposed by Daraio and Simar (2007), to reduce the number of variables by aggregating them in factors with minimum loss of information. The factor input (output) variable is obtained as weight sum of the original variables with weight represented by the values of the first eigenvalue of the input (output) matrix[4]. The output and inputs factors, and their relative inertia[5], are shown in table 4.

Insert table 4 approximately here

The percentage of inertia explained by the two factors is high: about 97%. Therefore it is certainly appropriate to summarize the information of the full data matrix by these factors.

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[4] Mathematically the factor variable, **F**, is obtained as follows: **F= Xa**, where **X** is the matrix of the input (output) variables and **a** is the first eigenvector of the matrix **XX**'.

[5] It measures the capacity of the aggregate variable to summarize the information contained in the original variables. The inertia is computed by dividing the first eigenvalue by the sum of all eigenvalues of the matrix **XX**'. Value close to 1 indicates an accurate representation.

4.2 Productivity, efficiency and technological change

In tables 5 and 6 the empirical results are shown.

Insert tables 5 and 6 approximately here

Looking at the bias corrected Malmquist index, $\tilde{M}$, we have six airports which show significant increasing in productivity and fifteen which sign a significant decrease; for two airports, Treviso and Bologna, changes are not statistically significants. The geometric mean of bias corrected Malmquist index reveals that the global performance of the industry is characterized by a decrease ((1-0.837)x100 = -16.3%). But, the Italian airport industry appears as a polarized structure where few airports, Genova, Lamezia, Milano (Linate and Malpensa), Roma (Ciampino e Fiumicino), Torino and Venezia increase (+41.0%), and the remaining decline in their productivity performances ((1-0.659)x100 = -34.1%). The well performers airports are placed, with the exception of Lamezia, in the third quartile of airports' ranking (see table 6) and are located in the north (Genova, Milano, Torino and Venezia) and in the middle (Roma) of Italy. Valuable is the performance of Lamezia (+10.5%), located in the south of Italy, which in 2001, has expanded its aerostation. All the above airports hold a complete concession agreement and only two, Roma and Venezia, are controlled by a private majority. Unfortunately, as pointed out in section 2, data does not allow to asses the performance of the two hubs of Rome Fiumicino and Milano Malpensa. However, the two airports system of Rome and Milano have increased their productivity. In particular, the rapid growth of Roma airports has been triggered by low-cost carrier activity in the Ciampino airport where, from 2001 to 2006, the movements and the passengers have been increased by 317% and 717% respectively. For Milano metropolitan area, most of low cost traffic has been absorbed by Bergamo which has decreased its productivity: (1-0.839)x100 = -15.1%.

The airports in the first quartile (Alghero, Bari, Brindisi, Catania, Foggia, Olbia, Rimini, Taranto), located in the south of Italy with the exception of Rimini, show an high decline of their productivity rate, (1-0.514)x100 = -48.6%; excluding Catania, Alghero, and Olbia they are all small regional airports. Alghero and Olbia are close each other (about 100 km) and they face strong seasonal demand due to the tourist vocation of the Sardinia Island which can cause a non optimal input utilisation. Now, in order to better asses the source of productivity gain, or loss, let us consider the two main components of the Malmquist indexes. The bias-correct efficiency change, $\tilde{EC}$, is statistically significant for just 11 airports. The average value, +22.1%, denotes a catch-up in their efficiencies. However, seven airports have substantially increased (+71.7%) and four have decreased ((1-0.672)x100 = -32.8%) their efficiencies. The airports of Roma (Ciampino and Fiumicino), Genova and Venezia are in the third quartile and have signed the highest values in approaching (+110%) the best practise frontier (catch-up). The airports in the first quartile (Alghero, Bari, Brindisi, Catania, Foggia, Rimini and Taranto) characterized by a decline in their efficiencies are all small regional airport, with the exclusion of Alghero and Catania. However, the poor performances of Alghero and Catania could be attributed to the infrastructural development started in 2000.

The change in the technical efficiency score, measures the diffusion of best-practice technology in the management of the activity and is attributed to investment planning, technical experience, management and organization in the airports. In other terms, technological change is a consequence of innovation, i.e. the adoption of new technologies by best-practice airports. The bias corrected technological change index, $\tilde{TC}$, is less than one for all airports and it has statistically significant at twenty-one of the twenty-three airports. The average value of ((1-0.744)x100 = -25.6%) indicates technological regress. The airports of Lamezia and Milano (Linate and Malpensa) experienced the lowest technological regress: ((1-0.820)x100 = -18.0%) and ((1-0.856)x100 = -14.4%) respectively. Therefore, in the future a gain in frontier shift, that is innovation, will be the most important source of productivity progress in the Italian airport industry. We re-estimated the components of the Malmquist index over three sub-periods for each airport and report the results in table 7.

Insert table 7 approximately here

From the above tables some relevant aspects regarding the Italian airport industry and the employed methodology can be obtained. We first note that most of the airports that defined the frontier in 2000-2006 are the same that individuate the frontier in each of the three sub-periods (2000-2002; 2002-2004; 2004-2006). But focussing on innovation, we note that nineteen of the twenty-three airports experienced technological regress during the first period. The period 2000-2001 has been characterized by important factors: the tragedy of the 11th September, changed in the concession agreements and liberalisation of the handling services. While the first factor was transitory the remaining produced permanent impacts on the organisation and operation of airports. Thus, after six years the Italian airport industry seem to be far in individuating the best-practice technology to manage in a efficient way the airports in the new institutional setting.

As far as the methodological aspects, the results in the last period, 2004-2006, highlight the importance to employ a bootstrap technique. In fact, the confidence intervals are essential in interpreting estimates of Malmquist index. Without any inferences, it is not sufficient to know whether the Malmquist index estimator indicates increases or decreases in productivity, but whether the changes are significant in a statistical sense. Moreover the methodology overcomes distribution problems due to the presence of outliers. All bias-corrected indexes are includes between the inner lower fence and the inner upper fence (see tables 5 and 6)

4. Conclusion

In this paper we analyze the productive evolution of the Italian airport industry over the period 2000-2006. We apply the consistent bootstrap procedure (Simar and Wilson, 1998, 1999) for correcting and obtaining confidence intervals for Malmquist index and its two main components: efficiency change and the technological change. Throughout the period, Italian airports globally experienced average decreases in productivity. The Italian airport industry appears as a polarized structure where few airports (Genova, Lamezia, Milano Linate, Milano Malpensa, Roma Ciampino, Roma Fiumicino, Torino and Venezia) experienced a productivity growth and the remaining a steadily decline. Only one airport (Lamezia) is located in the south: the less developed area of the country. We also found that all the examined airports experienced technological regress during the considered time period. In particular, we note that technological regress appears during the period 2000-2002 when important institutional change occurred in the Italian airport industry: new concession agreement and the liberalisation of the handling services. These factors, changing the organisation and the operation of the airports activities, have not allowed to the airport management companies to individuate the best-practice technology. Moreover, we observe that the airports which have improved their productivity hold a complete concession agreement. Finally our empirical analysis highlights the importance of bootstrapping Malmquist index in the airport industry in order to drawn correct implications, in a statistical sense, on productivity changes.

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FIGURE.

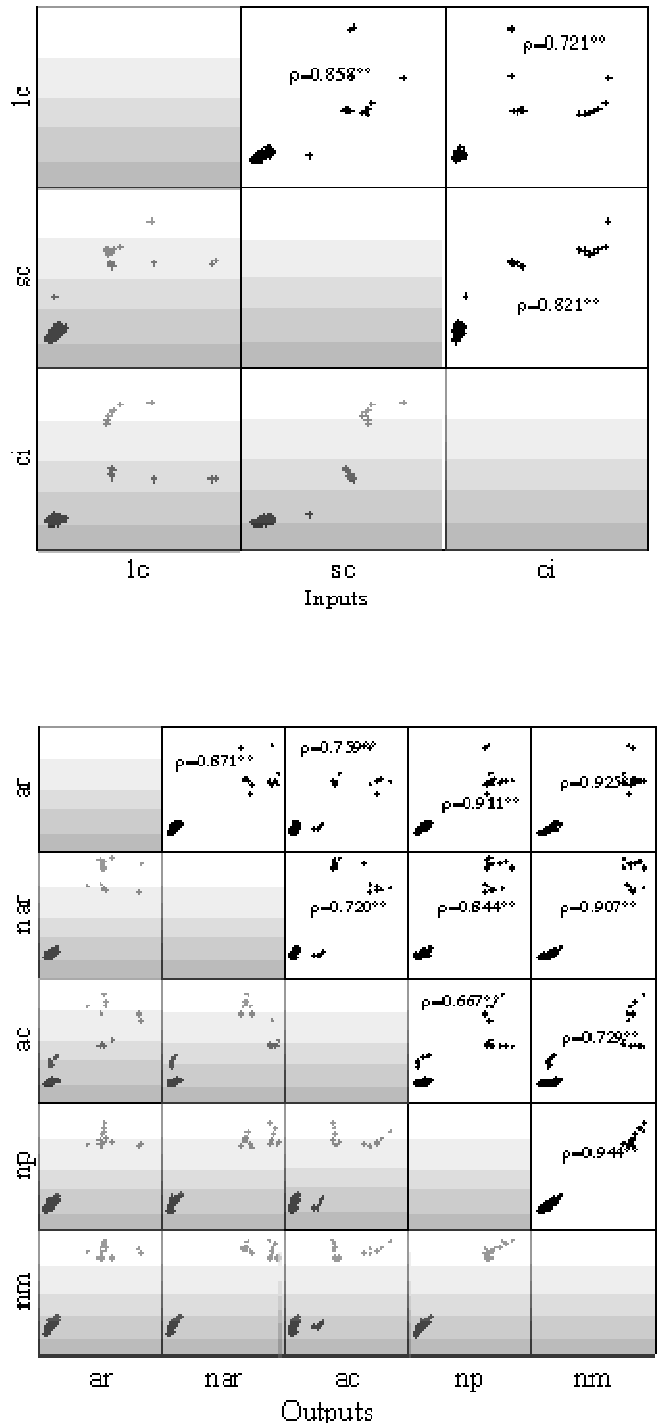

Figure 1. Variables scatter plot. *lc* = labour cost, *sc* = soft cost, *ci* = capital invested, *ae* = aeronautical revenues, *nar* = non aeronautical revenues; *ac* = amount of cargo; *np* = number of passengers, *nm*=number of movement. Sperman's correlation coefficient ρ; °° correlation is significant at the 0.01 level (2-tailed).

Tables.

methods	papers
parametric stocastic frontier	
	Pels et al.[1]
	Pels et al. [2]
	Martin-Cejas [3]
	Barros [4]
	Barros [5]
non-parametric stocastic frontier(DEA)	
	Gillen and Lall [6]
	Murillo-Melchor [7]
	Sarkis [8]
	Adler and Berechman [9].
	Gillen and Lall [10]
	Martín and Román [11]
	Pels et al. [1]
	Fernandes and Pacheco [12]
	Fernandes and Pacheco [13]
	Sarkis and Talluri [14]
	Yoshida and Fujimoto [15]
	Barros and Dieke [16]
	Barros and Dieke [17]
	Fung et al. [18]
	Curi et al. [19]
	Barros and Weber [20]
index numbers (Tornqvist)	
	Douganis et al. [21]
	Hooper and Hensher [22]
	Oum et al. [23]
	Coelli et al. [24]
	Yoshida and Fujimoto [25]

Table 1. Methods to measure efficiency in the airport industry.

Airports (IATA CODE)	Airport Company	Majority shareholders (1= private, 0=public)§	Concession agreement (1=total, 0=others)	Handling°
Alghero (AHO)	SOGEAAL SpA	0	0	0
Ancona (AOI)	AERDORICA S.p.A	0	0	0
Bari(BRI)	SEAP S.p.A.	0	1	0
Bergamo(BGY)	SACBO SpA	0	1	1
Bologna(BLQ)	SAB SpA	0	0	1
Brindisi(BDS)	SEAP S.p.A.	0	1	0
Cagliari(CAG)	SOGAER S.p.A.	0	0	1
Catania(CTA)	SAC SpA	1	1	1
Firenze(FLR)	Aerop.Firenze S.p.A.	1	1	0
Foggia(FOG)	SEAP S.p.A.	0	1	0
Genova(GOA)	Aer. Gen. SpA	0	1	0
Lamezia(SUF)	SACAL SpA	0	1	0
Milano Linate(LIN)	SEA SpA	0	1	1
Milano Malpensa(MXP)	SEA SpA	0	1	1
Napoli(NAP)	GESAC SpA	1	1	1
Olbia(OLB)	GEASAR S.p.A.	0	0	0
Palermo(PMO)	GESAC SpA	0	0	1
Pescara(PSR)	SAT SpA	0	0	0
Pisa(PSA)	SAGA SpA	0	0	1
Rimini(RMI)	AERADRIA S.p.A.	0	0	0
Roma Ciampino(CIA)	ADR SpA	1	1	1
Roma Fiumicino(FCO)	ADR SpA	1	1	1
Taranto(TAR)	SEAP S.p.A.	0	1	0
Torino(TRN)	SAGAT SpA	0	1	1
Treviso(TSF)	AER TRE S.p.A.	1	0	0
Trieste(TRS)	Aerop. Fr. Ven. Giu. S.p.A.	0	0	1
Venezia(VCE)	SAVE SpA	1	1	1
Verona(VRN)	Aer. Cat. SpA	0	0	1

Table 2. Italian airports and airport management companies (Note. ° 1 if there are two or more handling services operators. We exclude airline self-handling).

Variables	Definition	Min	Max	Mean	Variation coef.
Outputs					
number of movements *(nm)*	number of plans that lands and takes-off from the airport;	5076.00	379542.00	60088.68	1.48
number of passengers *(np)*	number of passengers arriving, or departing and passengers stopping temporarily;	114024.00	35121826.00	4402276.66	1.73
amount of cargo *(ac)*	number of the amount of cargos expressed in tons;	489.00	446596.00	37474.63	2.29
aeronautical revenues *(ar)*	sales to planes in billion of euro (constant €);	1544	394360	41542.04	1.78
non aeronautical revenues *(nar)*	sales to passengers in billion of euro (constant €);	297.3543814	245767	24622.11	2.30
Inputs					
labour cost *(lc)*	labour cost in billion of euro (constant €);	969.12	263458	19888.32	1.99
capital invested *(ci)*	book value of fixed asset in billion of euro (constant €);	1481.13	2375682.24	171888.59	2.89
soft costs *(sc)*	operation cost excluding labour and capital costs (constant €);	966.76	186562.76	23627.01	1.64

Table 3. Descriptive statistics

Factors	Original variables	Inertia
Outputs		
o_1	aeronautical revenues *(ar)*, non aeronautical revenues *(nar)*, number of passengers *(nm)* and number of movements *(nm);*	0.976
o_2	amount of cargo *(ac)*	
Inputs		
i_1	capital invested *(ci)* and soft cost *(sc;)*	0.972
i_2	labour cost *(lc)*	

Table 4. Inputs and outputs inertia.

Airports (IATA CODE)	M	$\widetilde{M}$	EC	$\widetilde{EC}$	TC	$\widetilde{TC}$
Alghero(AHO)	0.350	0.348°°	0.502	0.514°°	0.697	0.672°°
Ancona(AOI)	0.734	0.727°°	0.933	0.931	0.786	0.777°°
Bergamo(BGY)	0.839	0.849°°	1.000	0.909	0.839	0.861
Bologna(BLQ)	0.984	0.984	1.304	1.328°°	0.755	0.737°°
Bindisi, Bari, Foggia and Taranto(BRI, BDS, FOG and TAR)	0.472	0.484°°	0.665	0.706°°	0.709	0.680°°
Cagliari(CAG)	0.665	0.679°°	0.877	0.900	0.759	0.749°°
Catania(CTA)	0.587	0.588°°	0.785	0.773°°	0.747	0.759°°
Firenze(FLR)	0.678	0.678°°	0.960	0.984	0.707	0.685°°
Genova(GOA)	1.683	1.654°°	2.243	2.134°°	0.751	0.766°°
Lamezia(SUF)	1.100	1.105°°	1.403	1.327	0.784	0.820°°
Milano Linate and Malpensa(LIN and MXP)	1.340	1.344°°	1.599	1.560°°	0.838	0.856°°
Napoli(NAP)	0.767	0.743°°	1.091	1.081	0.703	0.683°°
Olbia(OLB)	0.605	0.622°°	0.873	0.921	0.693	0.668°°
Palermo(PMO)	0.667	0.685°°	0.931	0.958	0.717	0.712°°
Pisa(PSA)	0.781	0.793°°	1.023	0.994	0.763	0.793°°
Pescara(PSR)	0.931	0.931	1.196	1.167	0.778	0.793°°
Rimini(RMI)	0.556	0.581°°	0.722	0.729°°	0.770	0.793°°
Roma Ciampino and Fiumicino(CIA and FCO)	1.774	1.800°°	2.224	2.275°°	0.798	0.787°°
Torino(TRN)	1.224	1.252°°	1.628	1.668°°	0.752	0.748°°
Treviso(TSF)	0.970	1.000	1.068	1.041	0.908	0.946
Trieste(TRS)	0.705	0.722°°	0.961	0.979	0.734	0.734°°
Venezia(VCE)	1.404	1.417°°	1.892	1.920°°	0.742	0.735°°
Verona(VRN)	0.974	0.977°°	1.344	1.367°°	0.724	0.709°°
Total (increasing)	6	6	12	7	0	0
Total (decreasing)	17	15	11	4	23	21
Total	23	21	23	11	23	21
geometric mean	0.837	0.827	1.105	1.221	0.757	0.743

Table 5. Total factor productivity change for the Italian airports: 2000-2006. M = Malmquist index, EC = efficiency change, TEC = technical change; ~ = bias correction. °° Significant at 5% level. B = 5000 (Bootstrap replications).

Parameters	M	$\widetilde{M}$	EC	$\widetilde{EC}$	TC	$\widetilde{TC}$
ouf	2.170	2.575	2.782	4.923	0.963	1.021
iuf	1.606	1.858	2.078	3.359	0.872	0.904
maximum	1.774	1.800	2.243	2.275	0.908	0.856
q3	1.042	1.142	1.374	1.794	0.781	0.787
median	0.781	0.735	1.023	1.367	0.752	0.748
q1	0.666	0.664	0.904	0.751	0.721	0.709
minimum	0.350	0.348	0.502	0.514	0.693	0.668
ilf	0.102	-0.053	0.200	-0.814	0.630	0.592
olf	-0.462	-0.769	-0.505	-2.378	0.539	0.475
ir	0.376	0.478	0.470	1.043	0.061	0.078
Total	23	21	23	11	23	21

Table 6. Boxplot parameters: q1 = first quartile; q3 = third quartile; ir = interquartile range; ouf (outer upper fence) = q3+3×ir; iuf (inner upper fence) = q3+1.5×ir; olf (outer lower fence) = q1+3×ir; ilf (inner lower fence) = q1+1.5×ir.

	2000-2002						2002-2004						2004-2006					
Airports(IATA CODE)	M	$\widetilde{M}$	EC	$\widetilde{EC}$	TC	$\widetilde{TC}$	M	$\widetilde{M}$	EC	$\widetilde{EC}$	TC	$\widetilde{TC}$	M	$\widetilde{M}$	EC	$\widetilde{EC}$	TC	$\widetilde{TC}$
Alghero(AHO)	0.505	0.508°°	0.705	0.749°°	0.716	0.667°°	0.874	0.874°°	0.897	0.886°°	0.974	0.984	0.782	0.775°°	0.897	0.886°°	0.974	0.984
Ancona(AOI)	0.728	0.732°°	0.852	0.847°°	0.855	0.861°°	1.047	1.060°°	0.974	0.978	1.074	1.081	1.024	1.034°°	0.974	0.978	1.074	1.081
Bergamo(BGY)	1.051	1.046	1.000	0.991	1.051	1.038	0.885	0.899°°	1.000	1.019	0.885	0.861	0.894	0.896°°	1.000	1.019	0.885	0.861
Bologna(BLQ)	0.793	0.790°°	1.055	1.102	0.752	0.709°°	1.035	1.035	1.021	1.022	1.014	1.011	1.087	1.056	1.021	1.022	1.014	1.011
Bindisi, Bari, Foggia and Taranto(BRI, BDS, FOG and TAR)	0.669	0.672°°	0.920	0.976	0.728	0.681°°	0.916	0.933	0.858	0.858°°	1.069	1.084	0.778	0.791°°	0.858	0.858°°	1.069	1.084
Cagliari(CAG)	0.887	0.849°°	1.000	0.922	0.887	0.908	0.725	0.736°°	0.857	0.947	0.846	0.748°°	0.944	0.942°°	0.857	0.947	0.846	0.748°°
Catania(CTA)	0.698	0.692°°	0.938	0.943	0.745	0.732°°	1.108	1.111°°	1.148	1.157°°	0.965	0.958	0.724	0.716°°	1.148	1.157°°	0.965	0.958
Firenze(FLR)	0.808	0.810°°	1.102	1.143°	0.734	0.703°°	1.003	1.001	1.038	1.042	0.967	0.959	0.837	0.838°°	1.038	1.042	0.967	0.959
Genova(GOA)	0.818	0.817°°	1.101	1.157	0.742	0.697°°	1.507	1.510°°	1.550	1.539°°	0.972	0.978	1.373	1.296°°	1.550	1.539°°	0.972	0.978
Lamezia(SUF)	1.145	1.130°°	1.546	1.524°	0.740	0.738°°	1.032	1.026°°	1.038	1.004	0.994	1.010	0.899	0.900°°	1.038	1.004	0.994	1.010
Milano Linate and Malpensa(LIN and MXP)	0.893	0.879°°	1.106	1.117	0.808	0.785°°	1.238	1.204°°	1.203	1.165	1.029	1.030	1.056	1.054°°	1.203	1.165	1.029	1.030
Napoli(NAP)	0.852	0.844°°	1.165	1.219°	0.732	0.684°°	0.958	0.962°°	0.980	0.963	0.978	0.995	0.924	0.906°°	0.980	0.963	0.978	0.995
Olbia(OLB)	0.709	0.712°°	1.000	1.080	0.709	0.643°°	0.944	0.963	0.912	0.905	1.035	1.062	0.952	0.949°°	0.912	0.905	1.035	1.062
Palermo(PMO)	0.744	0.742°°	1.000	0.998	0.744	0.739°°	0.584	0.606°°	0.607	0.627°°	0.963	0.964	1.519	1.528°°	0.607	0.627°°	0.963	0.964
Pisa(PSA)	0.846	0.841°°	1.087	1.076	0.779	0.778°°	0.977	0.985	1.015	1.009	0.963	0.972	0.938	0.953°°	1.015	1.009	0.963	0.972
Pescara(PSR)	0.692	0.691°°	0.875	0.908	0.791	0.757°°	0.889	0.897°°	0.835	0.820°°	1.065	1.089	1.548	1.509°°	0.835	0.820°°	1.065	1.089
Rimini(RMI)	0.823	0.830°°	0.942	0.950	0.873	0.870°°	0.791	0.806°°	0.813	0.821°°	0.972	0.980	0.934	0.945°°	0.813	0.821°°	0.972	0.980
Roma Ciampino and Fiumicino(CIA and FCO)	1.414	1.394°°	1.540	1.455°	0.918	0.948	1.127	1.126°°	1.244	1.339°°	0.906	0.822°°	1.059	1.060°°	1.244	1.339°°	0.906	0.822°°
Torino(TRN)	1.268	1.249°°	1.628	1.658°	0.779	0.749°°	1.042	1.041	1.000	0.961	1.042	1.073	0.904	0.942	1.000	0.961	1.042	1.073
Treviso(TSF)	1.003	0.969	1.068	1.042	0.939	0.921	1.038	1.034	1.000	0.996	1.038	1.027	0.869	0.884°°	1.000	0.996	1.038	1.027
Trieste(TRS)	0.675	0.681°°	0.922	0.948	0.732	0.715°°	1.079	1.070°°	1.120	1.116	0.963	0.957	0.933	0.938°°	1.120	1.116	0.963	0.957
Venezia(VCE)	0.946	0.954	1.273	1.342°	0.743	0.705°°	1.411	1.429°°	1.289	1.254°°	1.095	1.131	1.055	1.049°°	1.289	1.254°°	1.095	1.131
Verona(VRN)	0.983	0.979	1.308	1.375°	0.752	0.703°°	1.105	1.106°°	1.135	1.120	0.984	0.984	0.892	0.893°°	1.135	1.120	0.974	0.984
Total (increasing)	5	3	12	7	1	0	13	9	13	9	9	0	8	7	11	4	9	0
Total (decreasing)	18	13	11	2	22	19	10	7	10	7	14	2	15	14	12	5	14	2
Total	23	16	23	9	23	19	23	16	23	16	23	2	23	21	23	9	23	2

Table 7. Total factor productivity change for the Italian airports: 2000-2006. M = Malmquist index, EC = efficiency change, TEC = technical change; ~ =bias correction. °° Significant at 5% level. B = 5000 (Bootstrap replications).