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Airport quality and productivity changes: A Malmquist index decomposition assessment

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ABSTRACT

This paper analyses the productivity of 20 Italian airports management companies during the period 2006–2008 using a DEA Malmquist index that includes a quality component. The proposed methodology is applied for the first time to the airport industry. In doing so, we directly assess the impact of the quality of services delivered by an airport on its productive performance. The study shows that, while Italian airports possess an acceptable level of quality in terms of their infrastructure, their managerial/administrative procedures must be strengthened in order to better deal with both technological modernization and passenger waiting time at the airports.

1. Introduction

While there is growing interest in the measurement of airport productivity world-wide (Oum et al., 2006), the literature appears to offer few studies dealing with the relationship between the level of service quality and some measure(s) of airport performance. Indeed, airports are business units engaged in the provision of a service. Clearly, then, customers' evaluation of a facility's quality of service is of fundamental importance to airport managers and related administration (Correia et al., 2008a,b).

Although airports generally benefit from a monopolistic position, it is important to understand that travelers' perceptions of airport service can be an initial indictor of the related city's 'quality' or attractiveness; and/or a parting impression for those who are leaving the area. That is to say, airports can be viewed as urban facilities essential to the city in which they are located (Caves and Gosling, 1999). Moreover, when the quality indicators involve factors having a direct bearing on airlines' operative costs, they can become important elements in a given airline's choice of hub (Adler and Berechman, 2001; Adler and Golany, 2001).

As noted, the role of service quality within an airport setting has been a focus of recent research. However, such efforts have been more concerned with the *measurement* of quality, and less so with its connection to the efficiency or productivity of facility operations. In the current paper, following the approach proposed by Fare et al. (1995) regarding the use of non-parametric Data Envelopment Analysis (DEA), we incorporate the *quality aspect* of services in the measurement of total factor productivity.

To the best of our knowledge, we thus offer the first attempt to fill this gap in the literature of performance measurement within the airport industry. As discussed below in some detail, our research suggests that the key factors explaining the deterioration of *Italian* airport productivity, in particular, are *inadequate levels of technology improvement* and*quality of service*.

The paper is structured as follows: The next section offers a brief review of the literature on airport productivity and quality analysis. In Section 3, the data set, as well the variables employed in the analysis, are presented. Section 4 discusses key

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issues in the measurement of quality, and presents the proposed Malmquist decomposition that incorporates a quality change component. Section 5 reviews the study's results, while Section 6 presents the conclusion(s) and some discussion of our findings.

2. Review of the literature

In recent years, the analysis of service quality within airports has become a mandatory element in the management of their operations. Evidence of this point is provided by the Airport Service Quality Awards (ASQ), which have been given by the Airport Council International (ACI) since 2010. The awards recognize those airports that have achieved the highest ratings of passenger satisfaction as measured by ASQ surveys.

This growing interest in quality has lead the empirical literature to focus on the measurement of level of service (LOS) in airports (Correia and Wirasinghe, 2004). Most existing studies (e.g., Omer and Khan, 1988; Seneviratne and Martel, 1991; Muller and Gosling, 1991; Yen, 1995; Magri and Alves, 2005; Yeh and Kuo, 2003; Rhoades et al., 2000) have been concerned with measuring the LOS of individual components of airport passenger terminals (check-in counter, departure lounge, etc.). Few studies, however, have sought to evaluate the *overall* LOS of an airport (Correia et al., 2008a,b; Fernandes and Pacheco, 2010).

At the same time, the literature concerned with airport performance has developed rapidly in recent years, driven mainly by the rapid changes and challenging trends that have, and continue to, face the industry. Of particular interest to us, is research on the*technical efficiency and productivity* of airports. This work has generally employed four alternative methodologies: Parametric stochastic frontiers (e.g., Abrate and Erbetta, 2010; Martín and Voltes-Dorta, 2011); non-parametric frontiers (e.g., Barros and Dieke, 2008; Barros and Weber, 2009; Assaf, 2010; Curi et al., 2011); semi-parametric stochastic frontiers (e.g., Tovar and Martín-Cejas, 2010; Assaf and Gillen, 2012); and index numbers (Yoshida and Fujimoto, 2004).

Some insights into these four metrics are warranted. Parametric frontiers, for example, require strong assumptions involving the underlying production technology. In contrast, methodologies based on both non-parametric techniques and index numbers require no specification of the functional form.

Although Hooper and Hensher (1997) stated that non-parametric techniques such as DEA, lack statistical properties (which would preclude the making of inferences on productivity measures), recent work has made this claim moot. The reason is that the statistical properties of DEA estimators are now known, and inference-making methods are available for estimators of productivity (Simar and Wilson, 2008). These tools measure an airport's economic or operational performance in relation to others. Although they suggest what action(s) may yield improvements, they fail to provide managers with a quality perspective on the services provided, and what may undermine sustainable development. Since airports are business units engaged directly in the provision of services, the question of how customers evaluate and rate the quality of such services is of fundamental importance to airport management (Fernandes and Pacheco, 2010).

Given the findings outlined above, it appears that little empirical work has sought to account for *both* airport quality and efficiency/performance. An initial effort was conducted by Adler and Berechman (2001), employing DEA and principal component analysis. However, their study relied only on quality as perceived by the airline company. Further, the quality components were added to the inputs and outputs through a principal component analysis. This implied that quality is not considered a factor in the production process.

A few other papers have dealt with the concept of "bad" outputs such as pollution/noise (Yu, 2004; Yu et al., 2008), and delay (Pathomsiri et al., 2008; Lozano and Gutierrez, 2011).

In what it follows, we adopt, for the first time, an analysis of the airport industry that applies the DEA-based approach proposed by Fare et al. (1995). It allows one to decompose the productivity index into three components: quality change, efficiency change, and technical change. We can therefore insert aspects of quality into a typical production function, thus identifying individual components of change in productivity as variations in quality, efficiency and/or technology. Such insights can have important implications for management seeking strategies for improvement in quality of service.

Given our focus on Italian airports in the current study, it is important to note that recent years have seen significant and relevant policy reforms in Italy. They have impacted both the airline industry, with the privatization of the national carrier, Alitalia, in 2009 (Bergamini et al., 2010; Beria et al., 2011), as well as the airport industry itself, which has seen institutional change since the 1990s (Abrate and Erbetta, 2010; Barros and Dieke, 2008; Curi et al., 2008, 2010, 2011; Gitto and Mancuso, 2012a,b; Scotti et al., 2012).

From the foregoing review, it is clear that an important gap exists in the productivity literature as it relates to airports in general, and those in Italy in particular.

3. Data and variables

3.1. Inputs and outputs

In the present study, we measure the global productivity of airports by employing both physical and monetary variables (Barros and Dieke, 2008; Gitto and Mancuso, 2012; Pacheco and Fernandes, 2003; Oum et al., 2003; Sarkis and Talluri, 2004).

Table 1
Summary statistics, 2006–2008.

Variables	Min	Max	Mean	Variation coef.
Output variables				
Number of movements (units × 10^5)	0.070	4.060	0.730	1.440
Work load units (units × 106)	0.346	41.740	6.485	1.620
Output factor	*0.104*	*8.505*	*1.413*	*1.535*
Input variables				
Labor cost (10^6 €)	1.970	119.542	21.072	1.460
Capital invested (10^6 €)	11.824	369.015	47.118	1.651
Soft costs (10^6 €)	4.366	186562.76	23627.01	1.64
Input factor	*0.133*	*12.686*	*1.720*	*1.737*
Quality indicators				
Overall perception of comfort level (% satisfied passengers) – *ocl*	0.710	0.987	0.906	0.067
Percentage of delayed flights (number of delayed flights on total departing flights) – *df*	0.1000	0.390	0.240	0.240
Waiting time in queues at check-in (minutes) – *wcq*	5.000	25.000	12.330	0.370
Baggage reclaim time (minutes) – *brt*	18.000	41.000	26.650	0.220
Mishandled bags (number of mishandled bags/1000 departing passengers) – *mb*	0.0001	0.0020	0.0008	0.600

Data have been collected from three sources: Airport annual statistics (ENAC, 2007-2009a,b), Assaeroporti,[1] and TELEMACO (Camere di Commercio, 2009) which provides balance sheets of the airport management companies. The airports of Rome (Ciampino and Fiumicino), Milan (Linate and Malpensa), and Puglia (Bari and Brindisi) are managed by three different management companies. As a result, they enter into the analysis as three separate units.

In the current DEA analysis, the key output variables include: work load units (given by the sum of number of passengers and amount of cargo),[2] and number of aircraft movements. The principal model inputs are seen as: labor cost, capital invested, and soft costs. Labor cost is measured as simply the cost of labor. Capital invested is expressed by book value of assets. Finally, soft costs, according to Oum et al. (2003), are measured by all those expenses not directly related to capital and personnel. All monetary variables are divided by the current GDP deflator.

Since we have a relatively small number of units, 20 airport managements companies, relative to the number of input and output variables, the DEA model loses its discriminative power. This effect, known as the ''curse of dimensionality'', can be avoid by employing the techniques proposed by Daraio and Simar (2007), which allows one to reduce the number of variables to one input and one output, referred to as factors, with minimal loss of information.[3]

3.2. Quality indicators

Measuring the services quality of an airport is indeed a difficult task given the large number of variables that must be considered. In Italy, data on the quality of services offered in an airport can be obtained through the *service charter*. The charter was created to introduce an element of transparency across all Italian airports. It contains 35 service quality indicators[4], which are measured on standardized criteria defined by the Civil Aviation Authority (ENAC). Although the charter became mandatory since 2005 (decree n. 96/2005) only recently – in 2011 – the full set of quality indicators is available for most of the nation's airports.[5] For the years considered in the current analysis, it was possible to collect data on only five indicators: overall perception of comfort level (*ocl*), percentage of delayed flights (*df*), waiting time in queues at check-in (*wcq*), baggage reclaim time (*brt*), and mishandled bags (*mb*).

The variable *ocl*, evaluated through a survey, measures the comfort level of an airport's infrastructure (perception of baggage trolley availability, perception of air-conditioning efficiency, perception of people moving efficiently, etc.). It can thus be utilized as an indicator of overall airport quality. The remaining four variables, *df*,*wcq*,*brt* and*mb*, deal with more operational aspects of airport services. It is important to note that facility's services are often not directly managed by the airport's management companies. At the same time, they have considerable influence on the overall *perception* of the airport's quality (Correia et al., 2008a,b).

The descriptive statistics for the noted inputs, outputs, and quality indicators are presented in Table 1.

4. Methodology

In this section, we first present the Malmquist index, which includes a quality component, and then discuss the measures of quality that can be obtained from the available data set.

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[1] Assaeroporti is the Italian association of airport management companies (www.assaeroporti.it).

[2] WLU is equivalent to one passenger or 100 kg of cargo.

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

[4] A subset of eight indicators involve passengers with reduced mobility.

[5] http://www.enac.gov.it/Aeroporti_e_Compagnie_Aeree/Aeroporti_italiani/Carte_dei_Servizi_dei_Gestori_Aeroportuali/index.html.

4.1. Malmquist index and its quality component

Following Fare et al. (1995), we compute the Malmquist productivity index incorporating quality attributes into the technology. This approach seeks to determine if an improvement (reduction) in productivity might be a consequence of a change in service quality. Productivity is defined in terms of distance function, estimated through DEA. This is a non-parametric estimator, where it is assumed that no specific function describes the frontier. However, the traditional DEA estimator is biased by construction and affected by the uncertainty resulting from sample variation. Fortunately, using the bootstrap procedure (Simar and Wilson, 1999), makes it possible to determine whether productivity changes are significant at established confidence levels.

So, let x represent the inputs, y the desirable outputs, and a the level of quality. Then, the production technology of each airport at time t can be characterized by the technology set defined as:

$$S^t = \{(y^t, a^t, x^t) : x^t \text{ can produce } y^t \text{ at level of quality } a^t\}. \tag{1}$$

Given (1), Shepard's distance function (Shepard, 1970) for the generic unit i ($i = 1,2,\ldots,N$), which measures the maximal feasible reduction in x^t, given the output set (y^t, a^t), is defined by:

$$D_i^t(y^t, a^t, x^t) = \sup\{\lambda : (x^t/\lambda, y^t, a^t) \in S^t\}, \tag{2}$$

where $D_i^t\,(y^t, a^t, x^t)$ is always greater or equal to one.

If an airport is efficient, its scores will be 1. Using this distance function, the input-based productivity index between the period t and $t+1$ can be expressed as:

$$M = M_i^{t,t+1}(y^{t+1}, a^{t+1}, x^{t+1}, y^t, a^t, x^t) = \sqrt{\frac{D_i^t(y^{t+1}, a^{t+1}, x^{t+1})D_i^{t+1}(y^{t+1}, a^{t+1}, x^{t+1})}{D_i^t(y^t, a^t, x^t)D_i^{t+1}(y^t, a^t, x^t)}}. \tag{3}$$

In order to highlight the components of the Malmquist, M, productivity index, Fare et al. (1995) decomposed (3) as the product of changes in quality, efficiency, and technical aspects. It is assumed that the distance functions are multiplicatively separable in both attributes and inputs/outputs. In such a case, the Malmquist index that accounts for quality aspects, M_q, can be expressed as:

$$\begin{aligned} M_q = M_i^{t,t+1}(y^{t+1}, a^{t+1}, x^{t+1}, y^t, a^t, x^t) &= \sqrt{\frac{A_i^t(a^{t+1})A_i^{t+1}(a^{t+1})}{A_i^t(a^t)A_i^{t+1}(a^t)}} \times \frac{D_i^{t+1}(y^{t+1}, x^{t+1})}{D_i^t(y^t, x^t)} \times \sqrt{\frac{D_i^t(y^{t+1}, x^{t+1})D_i^t(y^t, x^t)}{D_i^{t+1}(y^{t+1}, x^{t+1})D_i^{t+1}(y^t, x^t)}} \\ &= Qual \times Eff \times Tech = Qual \times M. \end{aligned} \tag{4}$$

In (4), *Qual*, *Eff* and *Tech* measure quality, efficiency and technical changes, respectively, between periods t and $t+1$. For the Malmquist index and each of its components, a value less than one indicates an improvement, while a value greater than one denotes a decrease; a value equal to one means no change.

As suggested earlier, computation of the Malmquist index, and of its components, does not allow us to determine whether changes in productivity, quality, efficiency or technology are real, or merely artifacts of the fact that we do not know the true production frontiers, and, thus, must estimate them from a finite sample. To overcome this problem, we use a consistent bootstrapping procedure that allows determination of associated confidence intervals for each component in (4). Now, in the next section the measurement aspects related to variable a, the level of quality, will be discussed.

4.2. Airport quality index

Specification of the productivity index in (4) requires utilization of a single variable, expressing the overall services quality of an airport. Recall that the variable *ocl* is, per se, a global indicator of airport infrastructure, while the remaining four variables concern quality levels of services related both to airside (*df*) and landside activities (*wcq*, *brt* and *mb*). A simple way to compress the five quality indicators into a single factor is to employ a factorial analysis (Rhoades et al., 2000). Importantly, however, such analysis could be meaningless if information on the four quality indicators (*df*, *wcq*, *brt* and *mb*) is summarized by the variable *ocl*. In order to evaluate this possibility, in the spirit of the work by Correia et al. (2008a,b), we perform a regression analysis given by:

$$ocl_t = a + b_1(1/df_t) + b_2(1/wcq_t) + b_3(1/brt_t) + b_4(1/mb_t) + h + y + \varepsilon_t; \quad t = 2006, 2008, \tag{5}$$

where h is a dummy variable for the hub airports, and y is a dummy variable for the year. A satisfactory regression, in terms of the coefficient of determination and statistically significant parameters, implies that *ocl* is able to measure the quality aspect represented by the four variables. In the opposite sense, a poor performance of the regression model suggests that *ocl*, and the four quality indicators, involve different aspects of the quality of services provided by an airport. We employed the statistical package R, FEAR library, to run the Malmquist index.

5. Empirical results

5.1. Airport quality index

From Section 4.2, the first step of our analysis considers the relationship between *ocl* and the four quality indicators. Due to the panel nature of our data, we estimate the Eq. (5) by employing pooled-OLS method. The results of this analysis are given in Table 2.

Note that the only regression coefficient that is significant at the 5% level, is that for the intercept. The regression analysis thus suggests that the overall perception of comfort level, *ocl*, is not statistically dependent on the other indicators of services quality, but that it may very well be influenced by other factors that are not considered in the analysis. Now, in order to summarize the four indicators in a single variable we employ the factorial analysis. The factorial analysis starts with the calculation of the correlation matrix (see Table 3).

The correlation matrix for the four quality indicators shows moderate levels of relationship, suggesting the presence of underlying common factors. The results of the subsequent factorial analysis, using the varimax rotation method (Kaiser, 1958), that better models independent spatial structures, are reported in Table 4.

Observing the values of estimated uniqueness, it is important to note that the smallest failure to explain unitary total variance occurs in the $1/wcq$ variable (0.05%), while the largest failure occurs in the $1/df$ variable (95.0%). The variable that most contributes to identification of the first factor is the waiting time in queues at check-in (*wcq*). Furthermore, the three remaining variables represent aspects related directly or indirectly to passengers' waiting time at the airport: percentage of delayed flights (*df*), baggage reclaim time (*brt*), and mishandled bags (*mb*). Accordingly, the first factor is simply named as passenger waiting time (*pwt*). *pwt* thus explains 29.7% of the variance, and oscillates between -1.812 and 2.000. Now, since DEA formulation (4) disallows to use negative values we define the following variable:

$$ipwt = \left(\frac{pwt - \min(pwt)}{\max(pwt) - \min(pwt)}\right). \tag{6}$$

Thus, airport quality increases whenever *ipwt* rises from 0 to 1.

5.2. Malmquist index

As discussed in Section 2, the main objective of the present paper is to evaluate the effect(s) of introducing a quality component within more well-known measures of productivity. We thus compare the standard Malmquist index (M) with those two measures, termed, (M_{q1}) and (M_{q2}), that include the quality indicators *ipwt* and *ocl*, respectively.

Table 2
Estimated regression model.

	Estimate	Std. error	*t* Stat	*p*-Value
(Intercept)	0.947	0.079	11.944	0.000
(1/od)	−0.022	0.040	−0.528	0.601
(1/wcq)	0.027	0.064	0.415	0.681
(1/lbrt)	0.045	0.033	1.330	0.193
(1/omb)	−0.006	0.016	−0.342	0.734
Y	0.021	0.022	0.945	0.352
H	−0.022	0.042	−0.525	0.603

Notes: R-squared: 0.121. F-statistic: 0.758 on 6 and 33 DF, p-value: 0.608.

Table 3
Correlation matrix.

	1/df	1/wcq	1/brt	1/mb
1/df	1.000			
1/wcq	0.223	1.000		
1/brt	0.019	0.266	1.000	
1/mb	0.006	0.272	−0.145	1.000

Table 4
Factorial analysis.

	Loadings	Uniquenesses
1/df	0.223	0.950
1/wcq	0.997	0.005
1/brt	0.266	0.929
1/mb	0.273	0.926

The results are shown in Tables 5 and 6.

Now, recalling that a value of $M > 1 (M \leqslant 1)$ implies a decline (increase, or no change) in productivity, it can be seen that, by comparing the geometric means of M and M_{q1}, the introduction of a quality component in the decomposition has generated a reduction of $-1.1\% = (1–1.011) \times 100$ in total factor productivity.

The impact of the quality component is even more clear when the geometric means are calculated separately for those airports that have registered a decline in their productivities vs. those that have either increased, or unchanged, productive performances. In fact, the quality component impacts negatively by $-4.7\% = (1–1.047) \times 100$ for the former, but, positively for the latter by $+6.8\% = (1–0.932) \times 100$.

In considering individual airports, Table 5 shows that the most productive facilities occur when *ipwt* is considered. Thus, observe: Rimini (+29.3%), Venezia (8.7%), Cagliari (8.4%), Olbia (3.4%), Firenze (5.4%), and Bergamo (1.5%). Cagliari and Olbia have been cited as examples of modernization and re-qualification processes of their infrastructure (ENAC, 2009).

Regarding the remaining components of the Malmquist index, the Table 5 results confirm previous findings on the performance of Italian airports (Gitto and Mancuso, 2012a,b). In particular, while these airports have improved their input and output configurations, *Eff*, by $17\% = (1–0.83) \times 100$, they have, at the same time, realized a technological regress, *Tech*, of $-31.4\% = (1–1.341) \times 100$.

In Table 6, we report our findings for the M_{q2} productivity index for Italian airports. Recall that, this index accounts for the overall perception of comfort level (*ocl*) of an airport's quality.

When the overall measure, *ocl*, is included, the results, in terms of averages, appear less interesting. In fact, the impact of quality has a marginally negative effect on airport performances: $-0.03\% = (1–1.003) \times 100$. Importantly, this finding does *not* change when the airports are grouped. Thus, we found: $-0.06\% = (1–1.006) \times 100$ for airports that have declined in productive performance, and $0.09\% = (1–0.991) \times 100$ for airports that have increased, or not changed, in overall productivity.

Unfortunately, the quality component results are statistically significant for only four airports, so it is difficult to draw a larger, more robust conclusion. Taking into consideration this limitation, the empirical evidence listed in Tables 5 and 6 highlight that, on average, Italian airports satisfy customers in terms of overall comfort. At the same time, they fail to realize an adequate level of service when the quality index involves factors related to passenger waiting time. This discrepancy does, however, seem counterintuitive. In fact, the two measures rely on different aspects of airport quality of services, as confirmed by the regression results in Section 5.1. In particular, while the overall comfort level is strictly related to services provided prior to boarding, or during flight connections, the *ipwt* index is mostly driven by variables related to passenger boarding and disembarking.

Table 5
Changes in productivity, quality (*ipwt*), efficiency, and technical elements for 20 Italian airports management companies, 2006–2008.

Airport (IATA code)	*M*	M_{q1}	*Eff*	*Tech*	*Qual*
Alghero (AHO)	1.009***	1.010***	0.768***	1.314***	1.000**
Ancona (AOI)	0.970***	1.166***	0.738***	1.314***	1.203***
Bari (BDS-BRI)	1.272***	1.309***	0.969	1.314***	1.029**
Bergamo (BGY)	0.976***	0.985***	0.743***	1.314***	1.009***
Bologna (BLQ)	1.058***	1.072***	0.806***	1.314***	1.013***
Cagliari (CAG)	0.924***	0.916***	0.704***	1.314***	0.991***
Catania (CTA)	1.113***	1.113***	0.847***	1.314***	1.001***
Firenze (FLR)	1.002***	0.976**	0.763***	1.314***	0.974**
Genova (GOA)	1.218***	1.285***	0.927*	1.314***	1.055**
Lamezia (SUF)	1.170***	1.659***	0.890**	1.314***	1.418**
Milano (LIN-MXP)	1.182***	1.182***	0.900**	1.314***	1.000
Napoli (NAP)	1.314***	1.310***	1.000	1.314***	0.998*
Olbia (OLB)	0.982***	0.961***	0.748***	1.314***	0.979***
Palermo (PMO)	1.145***	1.117***	0.872***	1.314***	0.976***
Pescara (PSR)	1.363***	1.363***	1.038	1.314***	1.000
Pisa (PSA)	1.111***	1.165***	0.845***	1.314***	1.049**
Rimini (RMI)	1.003***	0.707***	0.764***	1.314***	0.705***
Roma (CIA-FCO)	1.127***	1.127***	0.858***	1.314***	1.000
Torino (TRN)	1.052***	1.041***	0.801***	1.314***	0.990**
Venezia (VCE)	0.938***	0.913***	0.714***	1.314***	0.973***
Geom. mean	1.088(20)	1.124(20)	0.830(20)	1.314(20)	1.011(20)
Geom. mean ($M > 1$)	1.138(15)	1.199(14)	0.872(14)	1.314(14)	1.047(14)
Geom. mean ($M \leqslant 1$	0.958(5)	0.904(6)	0.739(6)	1.314(6)	0.932(6)
N. sign. obs.	20	(20)	16	20	16
Std. dev.	0.124	0.200	0.094	0.000	0.124

*** Statistically significant at 1% level.
** Statistically significant at 5% level.
* Statistically significant at 10% level according to traditional bootstrapping confidence intervals. 2000 bootstrap replications.

Table 6
Changes in productivity, quality (*ocl*), efficiency, and technical elements for 20 Italian airports management companies, 2006–2008.

Airport (IATA code)	M	M_{q2}	*Eff*	*Tech*	*Qual*
Alghero (AHO)	1.009***	1.015***	0.768***	1.314***	1.006
Ancona (AOI)	0.970***	0.949***	0.738***	1.314***	0.979
Bari (BDS-BRI)	1.272***	1.261***	0.969	1.314***	0.992*
Bergamo (BGY)	0.976***	0.976***	0.743***	1.314***	1.000
Bologna (BLQ)	1.058***	1.057***	0.806***	1.314***	0.999***
Cagliari (CAG)	0.924***	0.912***	0.704***	1.314***	0.987*
Catania (CTA)	1.113***	1.113***	0.847***	1.314***	1.000
Firenze (FLR)	1.002***	1.008**	0.763***	1.314***	1.006
Genova (GOA)	1.218***	1.217***	0.927*	1.314***	1.000
Lamezia (SUF)	1.170***	1.161***	0.890**	1.314***	0.992
Milano (LIN-MXP)	1.182***	1.182***	0.900**	1.314***	1.000
Napoli (NAP)	1.314***	1.314***	1.000	1.314***	1.001*
Olbia (OLB)	0.982***	0.982***	0.748***	1.314***	1.000
Palermo (PMO)	1.145***	1.135***	0.872***	1.314***	0.992***
Pescara (PSR)	1.363***	1.363***	1.038	1.314***	1.000
Pisa (PSA)	1.111***	1.113***	0.845***	1.314***	1.003*
Rimini (RMI)	1.003***	1.106***	0.764***	1.314***	1.102***
Roma (CIA-FCO)	1.127***	1.127***	0.858***	1.314***	1.000
Torino (TRN)	1.052***	1.052***	0.801***	1.314***	1.001**
Venezia (VCE)	0.938***	0.938***	0.714***	1.314***	1.000
Geom. mean	1.090(20)	1.092(20)	0.830(20)	1.314(20)	1.003(20)
Geom. mean ($M > 1$)	1.138(15)	1.144(15)	0.866(15)	1.314(15)	1.006(15)
Geom mean ($M \leqslant 1$)	0.963(5)	0.954(5)	0.733(5)	1.314(5)	0.991(5)
N. sign. obs.	20	20	16	19	4
Std. dev.	0.124	0.123	0.094	0.000	0.024

*** Statistically significant at 1% level.
** Statistically significant at 5% level.
* Statistically significant at 10% level according to the bootstrap confidence intervals. 2000 bootstrap replications.

We have herein found a clear decline in productivity during the period 2006–2008 for the set of considered airports while, at the same time, there was an average growth in the number of passengers (+7.4%). This finding emphasizes the importance, for the Italian airport management companies, to adopt strategies that increase innovation and improve the overall quality of services. In particular, airport strategies going forward should focus on the modernization of technological infrastructure, and the improvement of those services most related to boarding and disembarking activities.

Clearly, the two aspects are closely related. For example, the web-check-in is a technological innovation that contributes to waiting time reduction at the passenger desk.

6. Conclusions and discussion

The current paper has applied a modified Malmquist index, based on classic DEA models and methodologies, that allows to incorporate quality aspect on productivity measurement of 20 Italian airport management companies over the period 2006–2008. The advantage of the proposed approach stems directly from its underlying DEA technique, which is based on identifying the best performers in a prescribed set of units. The main contribution of the paper to the literature is that airports' quality improvements are determined in relation to the productivity evolution of the benchmarked airports, rather than in absolute terms.

The utilization of two quality indices obtained by employing data available from airports' service charters has allowed us to shed new light on those factors affecting the productivity evolution of the Italian airport industry. In Italy, the reforms that began in the 1990s have significantly, and negatively, reshaped the airport industry, in terms of the concession agreement and privatization. Based on our research, we have found that the deterioration in productivity can be ascribed to both insufficient technological improvements and, by the presence of a low level of quality of services delivered. The latter is the principal empirical novelty of the current research effort. In this framework the results thus suggest that, while Italian airport management companies have reached a satisfactory level of quality in terms of infrastructure, they must invest significantly more resources in an effort to reduce passenger waiting time at airports.

Future research in this area includes more detailed analysis of Italian airports when the full set of 35 quality indicators included in the mandatory services charter will be available. Moreover, under a methodological point of view the introduction of a classification and regression trees (De Nicola et al., 2012) on Malmquist values will let to group the airport management companies respect to the quality components and consequently it will allow to a better identification of the different sources of productive inefficiencies in the Italian airport industry.

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