Competition and efficiency in the Italian airport system: new insights from a conditional nonparametric frontier analysis

ABSTRACT

We analyse the effect of competition on technical efficiency of Italian airports by applying, for the first time to the airport industry, a novel conditional nonparametric frontier analysis. We find that competition affects mostly the frontier of best performers, whilst airports that are lagging behind are less influenced by it. A novel two stage approach shows that, on average, competition has a negative impact on technical efficiency. We estimate a measure of *pure efficiency*, whitened from the main effect of the competition, whose distribution has a bi-modal shape, indicating the existence of two differently managed groups of airports.

Key words: Italian airports, competition, DEA, conditional efficiency, two stage analysis.

1. Introduction

The nature of the airport industry has changed over the last few decades. The deregulation process has led to increased competition among carriers, decreased average fares, increased frequency, and new route services (D'Alfonso and Nastasi, 2014; Fu and Oum, 2014; InterVISTAS, 2006). Some new entrant airlines have been exploiting the opportunities offered by secondary airports (Thompson, 2002) and the low-cost business model, which has a relevant driver in airport costs, has enabled low cost carriers to shop around airports (Dresner et al. 1996; Pels et al. 2009). In parallel, a major strategic action taken by full service carriers has involved the proliferation of alliances, both international and domestic, which is resulting in a more concentrated airline industry and new routes services (Czerny and Zhang, 2012, Jiang et al., 2015). The development of high-speed rail (HSR), interregional bus transportation and transport networks, have been additional factors influencing competition between airports (OECD, 2009). Finally, many airports have been involved in a privatization[1] and a commercialization process: non-aeronautical revenues have been growing to the point that they have become the main income source for many airports (Graham, 2009)[2]. In this context, airports, many of which have been treated in the past as public service organizations directly controlled by government administrations, have increasingly been restructured to attract private investments, search for new sources of revenues and attract (competing) full service or low cost carriers (Starkie, 2002). As a result, competition among airports has been growing and this has questioned the natural monopoly approach to regulation and led to a much more competitive outlook on the part of airport managers.

In this scenario, airports benchmarking has been of increasing concern and source of debate for both academics and practitioners (Liebert and Niemeier, 2013): the comparison of decision-making units (DMUs), such as airports, has become a popular tool to enhance their efficiency and make airports survive in a competitive environment. Most of the efficiency analysis literature has focused on the estimation of the production frontier that provides the benchmark against which airports are evaluated. There have been growing numbers of studies using Data Envelopment Analysis (DEA) to benchmark airport efficiency (Adler et al., 2013; Arocena and Oliveros, 2012; Barros and Dieke, 2007, 2008; Curi et al., 2010,2011; Fung et al., 2008; Gillen and Lall, 1997, 2001; Fernandes and

[1] According to Poole (2013), which reports data on Global Airport Privatizations happened in 2011-2012, airport privatization has taken place in Europe, Asia, Australia and New Zealand, Latin America and the Caribbean where major airports have been privatized. Several planned airport privatizations in Portugal, Spain and Greece were put on hold due to the depressed state of these European economies, still recovering from the financial crises. See Albalate and Fageda (2014) for further details on partial privatization in the European airport industry.

[2] The global airport benchmarking study by the Air Transport Research Society (ATRS, 2013) reports that non-aviation revenues account for 40 to 80 per cent of total revenues for 50 major airports around the world in 2010.

Pacheco, 2002, 2003; Gitto and Mancuso, 2012; Wanke, 2012a,b; Wanke, 2013). Some others analyse airport efficiency using stochastic frontier models (SFA) (Abrate and Erbetta, 2010; Assaf et al., 2012; Barros, 2008a, 2008b; Martin-Cejas, 2002; Oum et al., 2008; Scotti et al., 2012; Yoshida and Fujimoto, 2004; Yu et al., 2008). Other papers compare the DEA model with the SFA model (Pels et al., 2001, 2003). Some studies used total factor productivity measures (Hooper and Hensher, 1997) and others have also compared the efficiency of several international airports, such as Asia Pacific Airports, European and North American airports (Marques and Barros, 2010; Oum et al., 2003; Oum and Yu, 2004). A very important component that concerns recent studies has been the explanation of efficiency differentials by including in the analysis exogenous variables or environmental factors that, unlike the inputs and the outputs, cannot be controlled by the airport but may influence the production process. This is particularly relevant for the airport industry, characterized by regulatory constraints (Rate of Return, Price Cap, Single Till or Dual till), downstream market structure (high or low airline concentration), different type of environment (competitive vs monopolistic, HSR pressure), type of ownership (private, public, mixed) and so on. Generally speaking, these factors can be included in the analysis as exogenous variables and can help to detect and analyse possible influential factors that may affect airports' productivity patterns, explain the (in-)efficiency differentials of airports, as well as to improve policy making on the evaluated airports.

However, whilst lot of studies have analysed the impact of ownership form (e.g., Barros and Dieke, 2007; Cruz and Marques, 2011; Lin and Hong, 2006; Oum et al., 2006, 2008) on efficiency, as well as that of the regulation regime (e.g., Bel and Fageda, 2010; Marques and Brochado, 2008; Oum et al., 2004), fewer works have examined the relationship between efficiency and the level of competition from nearby airports. In fact, whether competition positively affect airports efficiency is still an open question. Dmitry (2009) builds an index of competition based on overlapping catchment areas into a SFA model and finds a positive effect of competition pressure on efficiency for a sample of European airports. Dmitry (2010) extends the results with a multi-tier model of competition and the estimates provide both positive and negative effects depending on a distance tier. Adler and Liebert (2014) investigate the combined impact of ownership form, economic regulation and competition on airport cost efficiency. They find that under relatively non-competitive conditions, public airports operate less cost efficiently than fully private airports. Furthermore, under potential regional or hub airport competition, economic regulation inhibits airports of any ownership form from operating and pricing efficiently. Ha et al. (2013) measure Chinese airports efficiency and investigate the impact of competition among airports (and from other modes of transportation, such as high-speed rail HSR), measured by means of a dummy variable to indicate whether there is another airport competing significantly with the airport in concern (whether there is HSR operation near a sample airport)[3]. They find that competition among airports and competition from substitutable transportation modes always have a positive impact on efficiency scores of an airport under examination. Scotti et al. (2012) suggest an index of competition between two airports on the base of a share of population living in the overlapped region of the airports' catchment areas. Using a multi-output SFA model in a parametric framework, the authors find that the intensity of competition has a negative impact on Italian airports' efficiency from 2005 to 2008.

The aim of this paper is to fill this gap by assessing the impact of competition on airports efficiency, that is, we evaluate whether airports where the intensity of competition is higher are more efficient than those where it is lower. We take into account the fact that airports differently located may be subject to heterogeneous environmental conditions and we ground on the recently introduced conditional efficiency measures (Daraio and Simar, 2005, Daraio and Simar, 2007a,b), which have rapidly developed into a useful tool to explore the impact of exogenous factors on the performance of DMUs in a nonparametric framework. In particular, this methodology does not rely on a separability condition between the input-output space and the space of the external factors, and hence it does not assume that these factors have no influence on the frontier of the best practice. Moreover, it is based on partial frontier non-parametric methods which are more robust than traditional full frontier non-parametric methods because they are less sensitive to extreme data and outliers and do not suffer from the problem of the curse of dimensionality, which requires big datasets to provide estimates of a reasonable precision (for more details see Daraio and Simar, 2007a).

To the best of our knowledge, Marques et al. (2014) is the only paper which has applied conditional efficiency measures for the assessment of the efficiency of the airport sector, by using the probabilistic approach proposed by Daraio and Simar (2005)[4]. In our paper, we make a methodological step further - with respect to Marques et al. (2014) - in the application of conditional efficiency measures to the airport sector. Indeed, we implement for the first time a new methodology as proposed by Badin et al. (2012) which extends the Daraio and Simar (2005) approach. On the one hand, by applying this new method, we are able to disentangle the impact of competition on the production process in its two components: impact on the efficient frontier (that is the airports which are most efficient and hence are located on the efficient boundary of the production set) and the impact

[3] See also Chi-Lok and Zhang (2009) for similar conclusions.
[4] In that paper, the influence of the operational environment on airport efficiency is examined in a sample of 141 international airports. The conclusions show that the operational environment indeed matters and that privatization, regulation, traffic transfer and the dominant carrier have a positive effect on efficiency, whereas aeronautical revenues influence it negatively. However, the impact of competition on airports efficiency is not investigated.

on the distribution of the efficiency scores. Indeed, external factors (i.e., conditional variables that cannot be controlled by the airport but may influence the production process) may either affect the efficient frontier or they may only affect the distribution of the inefficiencies (that is the probability of being more or less far from the efficient frontier), or they can affect both. We investigate these interrelationships, both from an individual and a global perspective. On the other hand, for the first time, this paper examines the impact of competition on the airport's production process by applying a new two-stage type approach - as introduced by Badin et al. (2012) and detailed in Badin et al. (2014) - which avoid the flaws of the traditional two-stage analysis. This novel approach allows us to have a measure of inefficiency whitened from the main effect of the external factor, permitting a ranking of airports according to their managerial efficiency, even when facing heterogeneous environmental conditions. Indeed, ranking airports according to the conditional measures can always be done but it is unfair, because airports face different external conditions, i.e., the different degree of competition in which they operate in, that may be easier (or harder) to handle to reach the frontier.

We focus on the Italian airport system. The Italian case has been investigated in the empirical literature. In particular, Barros and Dieke (2007, 2008) apply a Simar and Wilson (2007) two stage procedure and find that hub, private and north parameters increase efficiency. Abrate and Erbetta (2010) extend the findings by Barros and Dieke and point out the existence of low levels of efficiency among Italian airports. Curi et al. (2010), by using a Simar and Wilson (2007) two-stage approach, show that airports with a majority public holding are on average more efficient and the presence of two hubs is source of inefficiency. A bootstrapped DEA procedure is used by Curi et al. (2011) to estimate technical efficiency of Italian airports. They find that the airport dimension does not allow for operational efficiency advantages; on the other hand, it allows for financial efficiency advantages for the case of hubs and disadvantages for the case of the smallest airports. Moreover, the type(s) of concession agreement(s) might be considered as important source of technical efficiency differentials. Gitto and Mancuso (2012) find that a significant technological regress has been experienced and highlight the existence of a productivity gap between airports located in the North-central part of the country and those located in the South[5]. However, to the best of our knowledge, Scotti et al. (2012) is the only study which investigates, by using a parametric stochastic approach, how the intensity of competition among Italian airports affects their technical efficiency. Thus, research on this issue still lacks maturity.

[5] More recently, some other studies have been including quality indicators in Italian airports efficiency benchmarking: overall perception of comfort level, percentage of delayed flights, waiting time in queues at check-in, baggage reclaim time, and mishandled bags (De Nicola et al. 2013) or environmental externalities such as noise and local air pollution (Martini et al. 2013a,b). However, the impact of quality indicators on airport efficiency is out of our scope.

The paper is organized as follows. In Section 2 we present the data, the input and output variables used in the analysis. Section 3 describes the methodology, while Section 4 discusses the results. Section 5 concludes the paper.

2. Data

The Italian system consists of 45 airports open to commercial aviation[6] (ENAC, 2011). Rome Fiumicino (FCO) and Milan Malpensa (MPX) are the most important intercontinental hubs, where traffic exceeds, on average, 10 millions passengers per year. The remaining airports can be classified as medium sized airports, providing with further long haul and domestic routes, and regional airports providing a limited number of international and domestic connections.

Management companies of airports open to commercial aviation hold, in many cases, a total concession agreement: the company gets all of the airport's revenues for 40 years and is responsible for the infrastructure maintenance and development[7]. This is the case of the hub airports, Rome Fiumicino or Milano Malpensa, and some other medium sized airports like Catania Fontanarossa or Napoli Capodichino. In some other cases, mainly for medium sized airports, management companies of airports hold a partial concession agreement, where the State collects revenues from runways and parking - and is responsible for their maintenance and development - while the airport management company gets revenues from infrastructures involving passenger and freight terminals. This is the case of airports such as Brescia Montichiari, Trapani or Treviso. Finally, in some cases, mainly for regional airports like Cuneo Levaldigi or Lamezia T. Sant'Eufemia, a *precaria* concession agreement is hold by the airport companies, who manage only the passenger and freight terminals, receiving only the revenue that is related to commercial activities inside the terminals.

Data related to passengers traffic show a robust growth for Italian airports in 2010 - comparing to 2009 - driven by good results at Rome Fiumicino and Milan Malpensa, in addition to the excellent results of several medium sized airports such as Bari (+20.3%), Bologna (+15.3%), Brindisi (+47.2%), Genoa (+13.3%), Lamezia Terme (+16.4%), Trapani (+57.4%) and Treviso (+21%) (ICCSAI FactBook, 2011). In many cases, the growth has been driven by low-cost airlines: with respect to previous years, the growth has been addressed in airports other than those which have

[6] The whole Italian system consists of 113 airports - 11 exclusively open to military services and 102 to civil services.
[7] This is a form of Public–Private Partnership (PPP) where two different models can be found: institutionalized PPP or a typical contractual regime, such as the concession arrangements. See Cruz and Marques (2011) for further details on recent developments in privatizations. Through a case study approach, the authors establish a comparative analysis of different PPP arrangements models used for airport management.

historically supported the development of low-cost carriers in Italy, such as Bergamo Orio al Serio, Pisa and Rome Ciampino. The analysis of traffic statistics with respect to some socio-economic indicators (Figure 1) shows that there is a great heterogeneity among Italian airports: passengers traffic is concentrated in the North-Ovest part and in the Centre, where the most important intercontinental hubs are located. However, some differentiations arise when looking at the number of passengers per inhabitant, per GDP or per firm located in the area.

= = *Insert Figure 1*= =

Preliminary considerations about the level of competition among Italian airports arise analysing the percentage of competing Available Seats Kilometers (ASKs) and the share of competing routes (ICCSAI Factbook, 2011). The former represents the number of ASKs - related to the airport's total offer - for which there is an alternative route serving any airport in the destination catchment area, either in terms of same destination airport or in terms of same destination area. The latter considers airport routes for which at least one alternative route exists in the airport's catchment areas - within 100 km of the departure or arrival airport.

Figures 2 shows data relating to the biggest 34 Italian airports in 2010: the share of competing routes exceeds 60% in the case of Roma Fiumicino, Venezia Marco Polo, Bologna G. Marconi, among others, and 90% in the case of Catania Fontanarossa or Cagliari Elmas.

= = *Insert Figure 2* = =

The model for Italian airports is estimated using annual data on 34 airports for 2010, consisting of 16 airports located in the northern part of Italy, 7 in the centre and 12 in the southern part including islands. Small airports have been excluded due to the lack of economic data. Table 1 shows the characteristic of the airports included in the sample, with respect to the type of concession agreement and the total offer in terms of passengers, amount of cargo and movements.

= = *Insert Table 1* = =

Traffic and technical airside information have been collected from ENAC (National Civil Aviation Association) and balance sheets of airport management companies. The data have been integrated with data on direct and indirect competition provided by ICCSAI - International Center for Competitive Studies in the Aviation Industry.

Table 2 presents inputs and outputs analysed in selected previous studies on the Italian airport system.

= = *Insert Table 2* = =

According to this analysis, input variables used in this paper includes: airport area (m^2), number of runways, number of passenger terminals, number of gates, number of check-in counters and number of employees[8]. With respect to the outputs, three variables have been collected: number of passengers, amount of cargo (tons) and the number of aircraft movements. This choice is consistent with other previous studies, e.g., Curi et al. (2011), Scotti et al. (2012) on the Italian airport system, Wanke (2012a) on Brazilian airports, Martin and Roman (2001) on Spanish airports and Sarkis (2000) on US airports.

2.1 Competition factor

We include in the analysis a competition factor calculated as the share of routes in competition provided by ICCSAI (ICCSAI Factbook, 2011). The share of routes in competition considers airport routes for which at least one alternative route exists in related catchment areas (within 100 km of the departure or arrival airport). This number is expressed as a fraction of the total number of routes offered between the departure catchment area and the destination catchment area, including any offers of alternative airports that lie entirely within these areas. This index is a measure of indirect competition between airports, which is defined for a specific route offered from a specific airport, as the existence of alternative routes offered by nearby airports to nearby or identical destinations. An alternative departure airport is considered "close enough", basing on our indexes, if within 100 km of the original airport. The assumption is that distance is a good proxy for the extra travel time

[8] In some cases the cost of labor is preferred to the number of employees given the large and diversified use of part-time contracts in this sector (see Barros and Dieke, 2007,2008). However, usually the problem concerning the existence of different employment formula can be overcome by referring to the full-time equivalent number of employees (Abrate and Erbetta, 2010), which the case in this paper. See also Curi et al. (2011) and Scotti et al. (2012).

incurred by passengers (which would be the optimal driving variable, but is itself not easily measurable) and therefore of accessibility. The same criterion applies to alternative destinations[9]. We note that the problem of how to separate Origin-Destination passengers from transiting passengers might arise, since it is not a choice to fly to an airport – because it is a substitute – but rather because it links to a third airport. However, these considerations are out of concern in this paper, since Italian airports are not considered central to the international air transport network. Table 3 shows the top 20 European and Italian airports in terms of *Betweenness*.

== *Insert Table 3* ==

The *Betweenness* of an airport is defined as the number of minimal paths (any path between a pair of airports containing the minimum number of steps for that pair) passing through it. From this point of view, an airport is considered central to a network if it commonly serves as an intermediate node for routes to other airports. The second indicator, *Essential Betweenness*, counts the number of node pairs for which all (possibly the only) minimum paths pass through the airport in question. Without this airport, the destination can therefore either not be reached anymore, or only though a longer path via other intermediary airports. Figure 3 also shows the ratio between *Essential Betweenness* and *Betweenness*, an indicator of how "indispensable" an airport is for transiting paths. Rome Fiumicino is only ranked 19th, while all other Italian airport present a very low potential to serve as an intermediate stop.

Table 4 summarizes and defines all the variables used in this paper, while Table 5 provides some descriptive statistics.

9 For instance, consider a generic airline's connection between the Rome Fiumicino and London Heathrow airports. The relevant market is the Rome-London route. The Rome Ciampino airport lies less than 100 km away from Rome Fiumicino, and London Stansted is less than 100 km from London Heathrow. Hence, the Rome Fiumicino-London Heathrow connection is subject to indirect competition from the Rome Ciampino-London Stansted. The assumption related to the choice of the relevant threshold, has been used in literature: by Adler and Libert (2014) in the definition of airport regional competition (the number of commercial airports with at least 150,000 passengers per annum within a catchment area of 100 km around the airport); by Malighetti et al. (2007) and Scotti et al. (2012), in the definition of the airport competition index; by Malighetti et al. (2008) in the definition of the Betweenness and centrality of an airport within a network. Finally, the radius of the catchment area has been also defined in line with Bel and Fageda (2010). Nevertheless, this assumption may have some limits, since fixed-radius techniques do not take into account the distribution of people living in the areas around the airport and neither does it consider the real access time to reach it nor determinants of the demand for airport services in the area (Gosling, 2003).

= = *Insert Table 4* = =

= = *Insert Table 5* = =

3. Methodology

Whitin the nonparametric literature, DEA has been widely applied for efficiency estimation and benchmarking. In this framework, explaining inefficiency by looking for external or environmental factors has gained an increasing attention in recent frontier analysis studies.

The performance of economic producers is often affected by external or environmental factors that may influence the production process - being responsible for differences in the performances of the DMUs - but, unlike the inputs and the outputs, are not under the control of production units: quality indicators, regulatory constraints, type of environment (competitive versus monopolistic), type of ownership (private-public or domestic-foreign), environmental factors (conditions of the environment) and so on. Generally speaking, these factors can be included in the model as exogenous variables and can help explaining the efficiency differentials, as well as improving policy. At this aim, the nonparametric literature on this topic has focused on three main approaches: the *one-stage approach*, the *two-stage approach* (including the semi-parametric bootstrap-based approach) and the *conditional nonparametric approach*.

The one-stage approach includes in the model the external factors either as freely disposable inputs or as undesired freely available outputs. The external variables are involved in the definition of the attainable set, but without being active in the optimization for the estimation of efficiency scores.

In the two-stage approach, the nonparametric efficiency estimates obtained in a first stage are regressed in a second stage on covariates interpreted as environmental variables. Most studies using this approach employ in the second stage estimation either tobit regression or ordinary least squares. This approach has some serious inconveniences. In addition to problems related to the separability condition between the input-output space and the space of the external factors, the DEA estimates are by construction biased estimators of the true efficiency scores and they are serially correlated. Moreover, the error term in the second stage is correlated with the regressors, making standard approaches to inference invalid[10].

[10] Simar and Wilson (2007) developed a semi-parametric bootstrap-based approach to overcome these problems and also proposed two bootstrap-based algorithms to obtain valid, accurate inference in this framework.

In the nonparametric conditional approach, that is explained in details in the next section, conditional efficiency measures are defined and estimated nonparametrically. Badin et al. (2012), in particular, show that the external factors can affect the attainable set of the production process and/or may impact the distribution of the inefficiency scores. They propose a flexible regression of the conditional efficiencies on the explaining factors, which allows to estimate the residuals that may be interpreted as *pure* efficiency. This represents a technical efficiency level *purified* from the impact of the external or environmental factors and, therefore, it allows a fare ranking of units even when facing heterogeneous conditions.

In this paper, we apply a nonparametric conditional approach (Badin et al. 2012) in an output oriented framework, consistently with previous works (Barros and Dieke, 2007; 2008; Curi et al., 2010; 2011; Gitto and Mancuso, 2012; Marques et al. 2014; Scotti et al., 2012). We are concerned with technical efficiency that might be attained by exploiting physical assets that do not easily change over a span of few years - like the number of runways, passenger terminals, gates, check-in counters, number of employees - in order to maximize outputs - like movements, passengers and cargo; therefore, we decided to adopt an output-oriented approach[11]. Moreover, we assume variable returns to scale (VRS) because the sample dataset consists of airports of substantially different sizes ranging between 63.000 passengers at Bolzano airport, 1.4 million passengers at Alghero Airport, and more than 18 and 30 million passengers at Milano Malpensa and Rome Fiumicino airports. In doing so, we follow Adler and Liebert (2014).[12]

3.1 Marginal and conditional efficiency measures: local and global analysis.

DMUs transform resources (inputs) into products or services (outputs), but external or environmental conditions may affect this process. Let $X \in \mathbb{R}_{+}^{p}$ denote the vector of inputs, $Y \in \mathbb{R}_{+}^{q}$ the vector of outputs and $Z \in \mathbb{R}^{r}$ the vector of environmental factors that may influence by the process and the productivity patterns.

[11] An input orientation is consistent with the assumption that airport traffic volume is basically determined by airlines and thus it may be regarded as outside the control of managers. Nevertheless, airports now use different vertical agreements to internalize airlines' choices (Fu et al., 2011). One example is the commercial revenue sharing contract: in this case, airports usually share their revenue from commercial activities with airlines, inducing them to bring in more passengers. This mechanism is based on the existence of a positive demand externality between aviation and non aviation services: since the demand for commercial services depend greatly on the passenger throughput of an airport, the airport charge may be reduced so as to induce a higher volume of passengers and increase the demand for concessions (Fu and Zhang, 2010; Zhang et al., 2010). If airlines were unable to benefit from concession sale activities at airports, they would ignore such a demand externality in making their decisions.

[12] Similar considerations apply to the number of movement and tons of cargo. See also Table 4.

The external factors Z may either affect the boundaries of the attainable set, or it may only affect the distribution of the inefficiencies inside the production set (that is the probability of being close or far from the efficient frontier may depend on Z), or it can affect both.

Let consider a probabilistic model that generates the variables $(\mathrm{X}, \mathrm{Y}, \mathrm{Z})$, where $\mathcal{P}$ is the support of the joint distribution of $(\mathrm{X}, \mathrm{Y}, \mathrm{Z})$.The conditional distribution of (X, Y), given a particular value of Z, is described by

$$H(x,y|z) = \text{Prob } (\mathrm{X} \leq x, \mathrm{Y} \geq y | \mathrm{Z} = z), \tag{1}$$

or any equivalent variation of it (e.g., the joint conditional density function or the joint conditional cumulative distribution function). The function $H(x,y|z)$ is simply the probability for a DMU operating at level (x,y) to be dominated by DMUs facing the same environmental conditions Z, i.e., there exist DMUs that produce more outputs using less inputs with comparable levels of environmental variables. Given that $(\mathrm{Z} = \mathrm{z})$, the range of possible combinations of inputs x outputs, Ψ^z, is the support of $H(x,y|z)$:

$$\Psi^z = \{(x,y) |\, x \text{ can produce } y | \mathrm{Z} = z\}. \tag{2}$$

$H(x,y)$ denotes the unconditional probability of being dominated, defined as:

$$H(x,y) = \int_Z H(x,y|z) f_Z(z) \mathrm{d}z, \tag{3}$$

having support Ψ, that is the marginal (or unconditional) attainable set, i.e., which does not depend on Z, defined as[13]:

$$\Psi = \{(x,y) |\, x \text{ can produce } y\} = \cup_{z \in Z} \Psi^z. \tag{4}$$

As described in Daraio and Simar (2007a), the two measures $H(x,y|z)$ and $H(x,y)$ allow us to define conditional and marginal efficiency scores that can be estimated by nonparametric methods. Accordingly, the comparison of the conditional and unconditional efficiency scores can be used to investigate the impact of Z on the production process.

The literature on efficiency analysis proposes several ways for measuring the distance of a DMU operating at the level $(x_{0,}y_0)$ to the efficient boundary of the attainable set. Radial distances (Farrell, 1957) are the most popular ones and they can be input or output oriented. In particular, in this paper,

[13] Remember that the joint support of the variables (X,Y,Z) is denoted by P. It is clear that, by construction, for all z∈Z, $\Psi^z \subseteq \Psi$. If the separability condition holds, the support of (X,Y) is not dependent of Z, equivalently $\Psi^z = \Psi$ for all z∈Z.

we use the output orientation, that is we consider the maximal radial expansion of the outputs to reach the efficient boundary, given the level of the inputs. From Daraio and Simar (2005), we know that under the assumption of free disposability of the inputs and of the outputs, these measures can be characterized by an appropriate probability function $H(x, y)$, as defined above. We have, for the Farrell output measure of efficiency,

$$\lambda(x_{0,}y_0) = \sup\{\lambda > 0 | S_{Y|X}(\lambda y_0 | X \leq x_0) > 0\}, \tag{5}$$

where $S_{Y|X}(y_0|X \leq x_0) = \text{Prob}(Y \geq y_0|X \leq x_0) = H(x_{0,}y_0)/H(x_{0,}0)$ is the (nonstandard) conditional survival function of Y, nonstandard because the condition is $X \leq x_0$ and not $X = x_0$. If the DMU is facing environmental factors $Z = z_0$, then Daraio and Simar (2005) define the conditional Farrell output measure of efficiency as:

$$\lambda(x_{0,}y_0|z_0) = \sup\{\lambda > 0 | (x_{0,}\lambda y_0) \in \Psi^{z_0}\} \tag{6}$$

$$= \sup\{\lambda > 0 | S_{Y|X,Z}(\lambda y_0 | X \leq x_0, Z = z_0) > 0\} \tag{7}$$

where $S_{Y|X,Z}(y_0|X \leq x_0, Z = z_0) = \text{Prob}(Y \geq y_0|X \leq x_0, Z = z_0) = H(x_{0,}y_0|z_0)/H(x_{0,}0|z_0)$ is the conditional survival function of Y, here we condition on $X \leq x_0$ and $Z = z_0$. The individual efficiency scores $\lambda(x_{0,}y_0)$ and $\lambda(x_{0,}y_0|z_0)$ have their usual interpretation: they measure the radial feasible proportionate increase of output a DMU operating at the level (x, y) should perform to reach the efficient boundary of Ψ and Ψ^z respectively. In case the environmental factor Z has an effect on this boundary, the unconditional measure $\lambda(x_{0,}y_0)$ suffers from a lack of economic sounding, because, facing the external conditions z, this unit may not be able to reach the frontier of Ψ, that may be quite different from the relevant one that is of Ψ^z. So, the conditional measure is more appropriate to evaluate the effort a DMU must exert to be considered efficient.

In order to provide robust measures of efficiencies - robust to extreme data points or outliers - we also apply partial frontiers and the resulting partial efficiency scores[14]: while full frontiers are useful to investigate the local effect of Z on the shift of the efficient frontier, the partial frontiers are useful

[14] As extensively illustrated in Daraio and Simar (2007a), partial nonparametric frontiers have advantages and drawbacks. On the one hand, they are robust with respect to extreme values and outliers; they do not share the course of dimensionality which is common to most nonparametric estimators; they rely on a probabilistic formulation that allows us to introduce external factors in an effective way. Moreover, the value of the α can be used as a trimming parameter to make a more realistic comparison taking out the α% desired level of robustness. On the other hand, the implementation of the partial nonparametric approach requires the selection of a level of robustness (the value of α) and of a "smoothing parameter", i.e., h, which is the bandwidth, that is needed for the computation of the conditional efficiency scores.

to analyse the impact of Z on the distribution of inefficiencies. In this case, we adopt order-α quantile frontiers, as defined in Daouia and Simar (2007). For any $\alpha \in (0,1]$ the order-α output efficiency score is defined as:

$$\lambda_{\alpha}\left(x_{0,}y_{0}\right) = \sup\left\{\lambda > 0 | S_{Y|X}(\lambda y_{0} | X \leq x_{0}) > 1 - \alpha\right\}. \tag{8}$$

Similarly, by conditioning on $Z = z_0$, the conditional order-α output efficiency score of (x_0, y_0) is defined as:

$$\lambda_{\alpha}\left(x_{0,}y_{0}|z_{0}\right) = \sup\left\{\lambda > 0 | S_{Y|X,Z}(\lambda y_{0} | X \leq x_{0}, Z = z_{0}) > 1 - \alpha\right\}. \tag{9}$$

In this framework, a value of $\alpha = 0.5$, which corresponds to the median frontier, provides complementary information on the effect of Z on the distribution of the inefficiencies.

Nonparametric estimators of the conditional and unconditional efficiency scores are easy to obtain. For a DMU operating at level (x_0, y_0) the estimation of the output efficiency score, i.e., $\hat{\lambda}\left(x_{0,}y_{0}\right)$, is obtained, in the VRS case, by solving the following linear program:

$$\begin{aligned}
&\max_{\gamma,\lambda} \lambda \\
&s.t.\;\; \lambda y_0 \leq \sum_{i=1}^{n} \gamma_i y_i \\
&\qquad x_0 \geq \sum_{i=1}^{n} \gamma_i x_i \\
&\qquad \sum_{i=1}^{n} \gamma_i = 1 \\
&\qquad \lambda > 0, \gamma_i \geq 0 \;\forall i = 1 \dots n
\end{aligned} \tag{10}$$

Similarly we obtain the estimation of the output conditional efficiency score, i.e., $\hat{\lambda}\left(x_{0,}y_{0}|z_{0}\right)$, which can be computed solving the linear program[15]:

$$\begin{aligned}
&\max_{\gamma,\lambda} \lambda \\
&s.t.\;\; \lambda y_0 \leq \sum_{i|z-h \leq z_0 \leq z+h} \gamma_i y_i
\end{aligned}$$

[15] Note that this provides a local convex attainable set, local in the sense of conditional on the external factors. Concerning the computation of the bandwidth *h*, we applied the Badin et al. (2010) approach. In particular, in the Appendix of that paper the Matlab program for the implementation of the bandwidth calculation is reported.

$$x_0 \geq \sum_{i|z-h \leq z_O \leq z+h} \gamma_i x_i$$

$$\sum_{i|z-h \leq z_O \leq z+h} \gamma_i = 1$$

$$\lambda > 0, h > 0, \gamma_i \geq 0 \ \forall i = 1 \dots n \tag{11}$$

The nonparametric partial frontier efficiency estimates are obtained by plugging the estimators $\hat{S}_{Y|X}$ and $\hat{S}_{Y|X,Z}$, i.e., $\hat{S}_{Y|X}(y_0|X \leq x_0)$ and $\hat{S}_{Y|X,Z}(y_0|X \leq x_0, Z = z_0)$, in the expressions (8) and (9) defining the partial efficiency measures. For further details, the reader is referred to Badin et al. (2012).

The local analysis of the individual ratios may also be of interest: the local effect of Z on the reachable frontier for a unit (x, y) can be measured independently of the inherent inefficiency of the unit (x, y). Let consider $R_O(x, y|z) = \lambda(x, y|z)/\lambda(x, y) \leq 1$, that is the ratio of the radial distances of (x, y) to the two frontiers. The inherent level of inefficiency of the unit (x, y) is cleaned off, in the following sense:

$$R_O(x, y|z) = \frac{\lambda(x,y|z)}{\lambda(x,y)} = \frac{\|y\|\lambda(x,y|z)}{\|y\|\lambda(x,y)} = \frac{\|y_x^{\partial,z}\|}{\|y_x^{\partial}\|} \tag{12}$$

where $\|y\|$ is the modulus (Euclidean norm) of y and $\|y_x^{\partial}\|$ and $\|y_x^{\partial,z}\|$ are the projections of (x, y) on the efficient frontiers (unconditional and conditional, respectively), along the ray y and orthogonally to x. Clearly $\|y_x^{\partial}\|$ and $\|y_x^{\partial,z}\|$ are both independent from the inherent inefficiency of the unit (x, y). Hence, the ratio measures the shift of the frontier in the output direction, due to the particular value of z, along the ray y and for an input level x, whatever being the modulus of y. In the same fashion we calculate the ratios corresponding to partial score, e.g., $R_{O,\alpha}(x, y|z) = \lambda_\alpha(x, y|z)/\lambda_\alpha(x, y) \leq 1$.

Consistent estimators of the ratios are directly obtained by plugging the nonparametric estimators of the efficiency derived as described earlier, i.e., $\hat{\lambda}(x_{0,}y_0)$ and $\hat{\lambda}(x_{0,}y_0|z_0)$. So we have $\hat{R}_O(x, y|z) = \hat{\lambda}(x, y|z)/\hat{\lambda}(x, y)$.[16]

3.2 Second-stage regression and pure efficiency

[16] The reader is referred to Badin et al. (2012) for further details.

The aim of this section is to estimate the pure efficiency of DMUs through a novel two stage approach, which allows us to purify $\lambda(x, y|Z = z)$ from the impact of Z. Indeed, ranking firms according to the conditional measures $\lambda(x, y|Z = z)$ can always be done but it is unfair, because firms face different external conditions that may be easier (or harder) to handle to reach the frontier.

To avoid this problem, we analyse the average behavior of $\lambda(x, y|z)$ as a function of z, that is we analyse the expected value $\mathbb{E}(\lambda(X, Y|Z)|Z = z)$ as a function of z. We use a location scale non-parametric regression, defining $\mu(z) = \mathbb{E}(\lambda(X, Y|Z)|Z = z)$ and the variance $\sigma^2(z) = \mathbb{V}(\lambda(X, Y|Z)|Z = z)$ such that:

$$\lambda(X, Y|Z = z) = \mu(z) + \sigma(z)\varepsilon \tag{13}$$

where $\mathbb{E}(\varepsilon|Z = z) = 0$ and $\mathbb{V}(\varepsilon|Z = z) = 1$. Whereas $\mu(z)$ measures the average effect of z on the efficiency, $\sigma(z)$ provides additional information on the dispersion of the efficiency distribution as a function of z. Several flexible nonparametric estimators of $\mu(z)$ and $\sigma(z)$ could be applied; the reader is referred to Badin et al. (2012) for more details.

Analysing the residuals, for a particular given unit (x, y, z), we can define the error term ε as:

$$\varepsilon = \frac{\lambda(x,y|z) - \mu(z)}{\sigma(z)} \tag{14}$$

The error term ε can be viewed as the part of the conditional efficiency score not explained by Z. If ε and Z do not show a strong correlation, this quantity can be interpreted as a pure efficiency measure of the unit (x, y). If ε and Z show some correlation, still the quantity defined in (14) can be used as a proxy for measuring the pure efficiency, since it is the remaining part of the conditional efficiency after removing the location and scale effect due to Z. Then, ε can be used as a measure of pure efficiency because it depends only upon the managers' ability and not upon the external factors (Z). This approach allows us to purify the conditional efficiency scores from the effects of Z. In this way, we are able to compare and rank heterogeneous firms among them because the main effects of the external conditions have been eliminated. In particular, a large value of ε indicates a unit which has poor performance, even after eliminating the main effect of the environmental factors. A small value, on the contrary, indicates very good managerial performance of the firm (x, y, z). Extreme (unexpected) values of ε would also warn for potential outliers.

4. Results

DEA and conditional DEA with variable returns to scale (VRS) are applied in an output oriented framework. The model for Italian airports is estimated using annual data on 34 airports for 2010. As described in Section 4, the advantage of the partial frontier estimates and the related efficiency scores, i.e., $\lambda_\alpha(x, y|z)$, is that they are less influenced by extreme values and hence more robust to outliers. Moreover, they have the same rate of convergence as the parametric estimators, therefore they are more robust not affected by the well known "curse of dimensionality" shared by most nonparametric estimators (Daraio and Simar, 2007a). Under those circumstances, a dataset of 34 observations, although small, can be used to draw robust conclusions.

We perform a local analysis on the effect of competition on technical efficiency of Italian airports and a second stage regression of the conditional efficiencies scores on the competition factor which allows us to estimate the managerial efficiency scores[17]. In particular, we provide an illustrative analysis on the impact of competition, analysing the ratios of conditional and unconditional efficiency scores and reporting illustrative examples based on the three dimensional plots which provide useful insights. This is a descriptive empirical evidence, following other contributions which have applied the conditional efficiency analysis in this field (e.g., Marquez et al 2014)[18], as well as in other sectors (e.g., Mastromarco and Simar, 2014).

4.1. Factors on inputs, outputs and competition variables

Due to the high dimensionality of the problem (6 inputs, 3 outputs, and 1 environmental factor) with the limited sample used here (34 units), we first reduce the dimension in the input × output × external factor space by using the methodology suggested in Daraio and Simar (2007a). Indeed the curse of dimensionality implies that working in smaller dimensions tends to provide better estimates of the frontier. Moreover, if we are able to reduce the frontier estimation at the simplest situation (one input one output) it is also possible to provide graphical bi-dimensional illustrations of the estimated efficient frontier. In particular, we divide each input by its mean (to be "unit" free) and replace the 6 scaled inputs by their best (non-centered) linear combination, defined as IF, i.e., Inputs Factor. By

[17] Badin et al. (2010) report - in the Appendix - the Matlab code to perform the analysis presented in the paper. Some works are in progress for the completion of a user friendly toolbox, CONDEFF, that will be available free of charge (see Badin et al. 2014).

[18] More formal statistical based analysis could be implemented along the lines of Daraio and Simar (2014) but would require more data.

doing so, we check that: (i) we did not lose much information; and (ii) the resulting univariate input factor is highly correlated with the 6 original inputs.

From a mathematical point of view, we are looking for a vector $a \in R^{6}+$ such that the projection of the (scaled) input data matrix X on the vector a represents the data matrix X (in terms of minimizing the sum of squares of the residuals). The vector of the 6 projections is determined by the resulting input factor $IF = Xa = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6$, where X : (n × 6) is the (scaled) inputs data matrix. It can be shown that the optimal direction vector a is the first eigenvector of the matrix X^TX corresponding to its largest eigenvalue e_1. Note that, we are in a different situation than in the Principal Component Analysis (PCA)'s case: in this case, the data have not been centered, so that the eigenvalues do not represent the factors' variances. Eigenvalues are rather the "inertia" (or moment of the second order) of the factor. Therefore, the ratio $e_1/(e_1 + e_2 + e_3 + e_4 + e_5 + e_6)$ indicates the percentage of inertia which is explained by this first factor. When this ratio is high (close to 1), it indicates that most of the information contained in the original six-dimensional input data matrix X is well summarized by the first factor IF. Correlation between IF and x_1, ..., x_6 indicates also how well this new one-dimensional variable represents the original ones. We obtain:

$$IF = 0{,}34x_1 + 0{,}58x_2 + 0{,}58x_3 + 0{,}29x_4 + 0{,}24x_5 + 0{,}25x_6 \tag{15}$$

We follow the same procedure with the 3 outputs. The results are:

$$OF = 0{,}61y_1 + 0{,}47y_2 + 0{,}64y_3 \tag{16}$$

where OF stands for Outputs Factor. IF explains 87.6% of total inertia of original data, while OF explains 89.2% of total inertia of original data. To be consistent with previous notation we use, in what follows, X, Y instead of IF, OF.

4.2. Local analysis of the effect of competition on technical efficiency of Italian airports

We are in an output oriented framework. As stated in Section 4.1, the full frontier ratios $\hat{R}_O(x_i, y_i|z_i)$ are useful to investigate the local effect of competition on the shift of the efficient frontier, whilst the partial frontier ratios, $\hat{R}_{O,\alpha}(x_i, y_i|z_i)$, with $\alpha = 0{,}5$ (corresponding to the median)[19], are useful to analyse the impact of competition on the distribution of inefficiencies.

[19] Concerning the selection of the α value for the robust estimation of the full efficient frontier (that is the frontier which envelops all the data point), in this paper we computed the partial frontier ratios with $\alpha = 0.95$ to check if some outliers might mask the impact of Z (we leave out of the comparison the 5% of most extreme points). We find that even if there

Figure 3 illustrates a three dimensional plot of the full frontier ratios against inputs and competition, i.e., X and Z, whilst Figure 4 shows a three dimensional plot of the partial frontier ratios against X and Z.

= = Insert Figure 3 = =

= = Insert Figure 4 = =

Without being able to rotate the three-dimensional figures, we have an idea of what happens complementing Figures 3 and 4 with their two marginal views. Figure 5 shows the ratios $\hat{R}_O(x_i, y_i|z_i)$ as a function of the input (top panel) and the competition factor (bottom panel) respectively, i.e., the marginal effect of inputs and of competition on the efficient full frontier. Similarly, Figure 6 shows the ratios $\hat{R}_{O,\alpha}(x_i, y_i|z_i)$ as a function of X and Z respectively, i.e., the marginal effect of the input (top panel) and competition factor (bottom panel) on the distribution of inefficiency with respect to the median frontier.

= = Insert Figure 5 = =

= = Insert Figure 6 = =

By inspecting the three dimensional plots (see Figures 3 and 4), it can be easily seen that the input factor does not play any role on the full frontier levels nor on the partial frontier levels. This is also confirmed looking at the marginal effects (see top panels of Figures 5 and 6). On the contrary, the competition factor Z has a positive impact on the full frontier ratios, i.e., there is an increasing (logarithmic) pattern of the full frontier ratios when the competition factor Z increases (see Figure 5, bottom panel). The impact is heterogeneous and much less severe – showing a decreasing pattern – on the partial frontier ratios and so on the distribution of inefficiency scores (see Figure 6, bottom panel). In other words, competition can be seen as a free disposable input for best performers: when competition is taken into account in assessing technical efficiency of airports, the output that can be

are some extreme points they do not affect the detection of the impact of Z. This analysis is different with respect to that based on $\alpha = 0.5$ that is reported for providing an illustrative view on the impact on the median of the distribution.

produced given a fixed amount of inputs increases. On the contrary, the efficiency of airports that are on the median distribution (lagging behind the efficient frontier) is not affected by competition.

Analysing the Italian airport system in 2010, we conclude that competition has an impact on the efficient frontier of airports, while it has an heterogeneous and lower impact on the distribution of the inefficiencies.

4.3. Second stage analysis on the conditional efficiency scores

According to the procedure described in Section 4.2, we regress the estimated conditional efficiency scores against the competition factor, Z. We only remind here that the nonparametric model is:

$$\hat{\lambda}(X, Y|Z = z) = \hat{\mu}(z) + \hat{\sigma}(z)\varepsilon$$

where $\hat{\mu}(z)$ characterizes the average behavior of the conditional efficiency scores as a function of z, and $\hat{\sigma}(z)$ allows some heteroskedasticity. The residual ε can be interpreted as a whitened version of the conditional efficiency where the influence of Z has been eliminated from $\lambda(X, Y|Z = z)$.

Figure 8 illustrates the results for the full-conditional efficiency estimates as a function of Z.[20] We find that there is a local variable effect of competition (Z) on the average conditional scores. In particular, it appears that Z has a negative effect on $\hat{\lambda}(X, Y|Z = z)$, showing an adverse effect of competition on the technical efficiency of Italian airports.

= = *Insert Figure 7* = =

This seems to imply that airports where the competitive pressure is higher are less efficient. In contrast, in the Italian system, an airport that is closer to the local monopoly model (i.e., those airports facing a lower degree of competition) has an efficient utilization of its inputs. The results are consistent with those of Scotti et al. (2012), who find that Italian airports confronted with higher levels of competition have lower technical efficiency, and Dmitry (2010), who provides evidence on negative effects of competition on the efficiency of a sample of European airports. In fact, the debate focusing on the relationship between airport efficiency and competition is still open. Chi-Lok and Zhang (2009), Dmitry (2009) and Ha et al. (2013) show, for instance, a positive effect of competition

[20] The analysis has been done in logs but we obtained a similar shape for the picture in original units.

pressure on airport infrastructures efficiency. Adler and Liebert (2014) suggest that private, regulated airports are more efficient under monopolistic conditions whereas pure public and private airports operate equally efficiently given potential local, regional and gateway competition. Furthermore, ex-ante regulation at all airports located in a competitive environment is unnecessary and generates inefficiency of the order of 15%, which rises substantially at purely public airports.

In this direction, future research would require substantially more data to permit an improved analysis of the combined effect of competition and regulation form (Bel and Fageda, 2010; Marques and Barros, 2010; Marques and Brochado, 2008; Oum et al., 2004) as well as of the type of ownership and concession agreement, e.g., fully-private, public or public-private partnership (Barros and Dieke, 2007; Lin and Hong, 2006; Oum et al., 2006, 2008). This is extremely important if we are to be able to analyse the airport industry and provide sensible recommendations for future development.

Figure 8 shows a kernel nonparametric density distribution of estimated pure efficiencies of Italian airports, $\hat{\varepsilon}_i$. These $\hat{\varepsilon}_i$ represent pure efficiencies and have been computed eliminating the impact of the competing factor Z from the conditional efficiency score. Thus, we can compare the performance of airports, facing different competing environments, on the base of their pure attitude without the influence of the competition environment faced. Interestingly, we observe a bi-modal distribution of the pure efficiency of Italian airports and a special attention should be devoted to investigate on its generating process[21].

= = *Insert Figure 8* = =

It has to be noted that the impact of competition on the conditional efficiency scores has been nicely whitened: the Pearson correlation between z_i and $\hat{\varepsilon}_i$ is -0.03 and the Spearman rank correlation is -0.04. As shown by Figure 9, we cannot see any remaining dependence between the values of competition and of pure efficiencies of Italian airports, indicating that the location scale model has cleaned most of the effects of competition on the conditional efficiencies[22].

[21] This is beyond the scope of this work.

[22] Such a descriptive approach has been used in other papers that implement the Badin et al. (2012) approach, e.g., Mastromarco and Simar (2014). More advanced statistical investigations in this already complex context are possible (see e.g., Simar and Wilson, 2014 for an overview) but are beyond the scope of this paper.

= = *Insert Figure 9* = =

Table 6 shows the ranking of Italian airports according to $\hat{\varepsilon}_i$:

= = *Insert Table 6* = =

From a managerial point of view, the results reported in Table 6 are of great interest. *CondEff* is $\hat{\lambda}(X, Y|Z = z)$, while *PureEff* is $\hat{\varepsilon}_i$. When the conditional efficiency score, 1/*CondEff*, is one the airport is efficient given its level of competition; if it is lower than one, the airport could increase its outputs production given the inputs used and the competition environment faced. On the other hand, as the pure efficiency score, *PureEff*, increases, the airport decreases its performance, even after eliminating the main effects of competition. This depends only upon the managers' ability, since it is the remaining part of the conditional efficiency after removing the location and scale impact of competition.

Table 7 shows some descriptive statistics on 1/*CondEff* and *PureEff*, according to three characteristics of interest that are the effect of localization, type of concession agreement and size.

It appears that the airports located in the Center and in the North present, on average, the best results in terms of efficiency when taking into account their level of competition. On the contrary, those located in the South present the worst results. This means that central and northern airports have a higher level of technical efficiency since, once purified from the effect of competition, they are able to combine their inputs to obtain a higher level of outputs in terms of passengers, cargo and movements. This result is consistent with Gitto and Mancuso (2012). The explanation may rely in several reasons: the North-Central area has a higher GDP, more people travel by air in those regions, more intense domestic and international trading activities exist there and more airport facilities are built to provide better connecting services with other transport infrastructures. Moreover, regions in the North-Central area of Italy have better infrastructure than the national average, although the regions are considered to be lacking within Europe as a whole. Italy's southern regions have always been regarded as being peripheral to the core of the national and European economy.

== Insert Table 7 ==

Moreover, big airports (>5 millions of passengers), such as Catania Fontanarossa, Bergamo Orio al Serio, Roma Fiumicino or Milano Linate, result more efficient given their level of competition. On the contrary, small airports (<1 millions of passengers) tend to show the worst performance. This is consistent with some previous study on the Italian system who find that Large airport authorities are more efficient than small airport authorities (Barros and Dieke, 2007; Curi et al., 2011)

A total concession agreement also seems to produce an increase in airport productivity. This may be due to the fact that, in the case of total concession agreement, the service provider - which is often a privatized company, as Aeroporti di Roma (ADR) in the case of Rome Fiumicino and Roma Ciampino, airports or Società Esercizi Aeroportuali (SEA) in the case of Milano Malpensa and Milano Linate airports - is responsible for managing the entire airport system. As a consequence, in the vast majority of cases this has implied an increase in investments and a more efficient utilization of the inputs, in order to fully exploit the benefits of liberalization.

5. Conclusions

This paper provides new empirical evidence on the efficiency of Italian airports. We apply for the first time to the airport industry the recently developed conditional nonparametric approach proposed by Badin et al. (2012) to analyse the relationship between competition and technical efficiency.

We find that competition affects mostly the efficient frontier, whilst airports that are lagging behind are less affected by it. From the two-stage analysis, we observe that on average the impact of competition on the technical efficiency is negative. The results are consistent with those of Scotti et al. (2012), who find that airports confronted with higher levels of competition have lower technical efficiency. Moreover, when computing the *pure efficiency*, we find that the distribution of Italian airports has a bi-modal shape, pointing out on two groups of differently managed airports.

Our results show that airports located in the Center and in the North present, on average, the best results in terms of efficiency when taking into account their level of competition. On the contrary, those located in the South present the worst results. This result is consistent with Gitto and Mancuso (2012). Moreover, big airports (>5 millions of passengers), such as Catania Fontanarossa, Bergamo Orio al Serio, Roma Fiumicino or Milano Linate, result more efficient given their level of competition. On the contrary, small airports (<1 millions of passengers) tend to show the worst performance. This is consistent with some previous study on the Italian system who find that large airport authorities are more efficient than small airport authorities (Barros and Dieke, 2007). A total concession agreement also seems to produce an increase in airport productivity (see also Barros and Diecke, 2007; 2008).

Results presented in this paper are only preliminary and future research would require substantially more data to permit an improved analysis of the combined effect of competition and regulation form, ownership as well as low cost carriers' dominance, size or localization on technical efficiency of airports. The consideration of product differentiation, for instance, may render the actual degree of competition more precisely and its importance has been raised in previous literature (Adler and Liebert, 2014), as well as the that of size (Pels et al. 2003). Coto-Millàn et al. (2014), in a sample of Spanish airports, find that airport size has a positive and significant impact on overall, technical and scale efficiency and the presence of low cost carriers has produced a statistically significant impact on the overall technical efficiency. Barros (2008b) study the economic efficiency of UK airports for the period 2000–2005 and concludes that, given the heterogeneity of UK airports, medium-sized airports were more efficient than large airports. Bottasso et al. (2012), for a panel of the largest airports in the UK over the same period, find that the conspicuous entry of LCCs on European markets has facilitated airports' productivity improvements. Assaf (2009) shows that large airports are generally more technically efficient and have less operational wastage than small airports, and location could contribute to the efficiency differences. In this direction, Ha et al. (2013) show that the hinterland per capita gross domestic product and the hinterland population are positively correlated with the efficiency scores, indicating that the hinterland with strong air travel demand may help bring up the corresponding airport efficiency, which is also consistent with Chang et al. (2013)'s result.

In this paper, we have provided an illustrative analysis on the impact of competition, analysing the ratios of conditional and unconditional efficiency scores and reporting illustrative examples based on the three dimensional plots which provide useful insights. This is a descriptive empirical evidence, following other contributions which have applied the conditional efficiency analysis in this field (e.g., Marquez et al 2014). The obtained results are preliminary and have an illustrative purpose, that is to show how the newly developed condition efficiency measures may apply to the airport sector. However, a bigger dataset would be useful in order to provide more formal statistical based analysis, which could be implemented along the lines of Daraio and Simar (2014), and stronger results for median airports. Finally, extending the analysis to the evaluation of airports' performances in a period of several years would also be interesting, in order to measure the efficiency change that the industry experimented through years.

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