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On the Relationship between efficiency and Competition: Evidence from Italian Airports

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Abstract. This paper provides new empirical evidence on the efficiency of Italian airports. Analysing data on 2010 trough conditional efficiency measures, we find that competition affects mostly the frontier of best performers, whilst airports that are lagging behind are less influenced by it. By applying a novel two stage approach, we show that competition has an inverse U-shape impact. Finally, the bi-modal shape of the distribution of pure efficiency indicates the existence of two differently managed groups of airports.

Keywords: Italian Airports, Competition, DEA, Conditional Efficiency, Two Stage Analysis.

1. Introduction

Deregulation of airlines, privatizations of airports and the recent phenomenon of low cost air transport have questioned the non-competitive nature of the airport business and the natural monopoly approach to airport regulation ([1]). Actually, the EU liberalization process – completed in 1997 – has formed a unique market where cabotage has been allowed ([2]): every European airline can provide a new route in the European network, i.e. a route having a European airport both as origin and destination. This has increased the available routes in the network and, therefore, the numbers of competing routes and competing airports. This is particularly true in the case of airports located in different metropolitan areas sharing - at least in part - the same catchment area (e.g. the case of major hub-and-spoke airports as Fiumicino in Rome and Malpensa in Milan, the airports of Barcelona and Madrid, Brussels and Amsterdam or Brussels and Paris). Nevertheless, even if they are located in the same metropolitan area and are managed by the same company (notably, Paris ADP airports, London BAA airports, Rome ADR airports, Milan SEA Airports), some competitive issues may arise due to possible cross-subsidies and the ensuing distortions ([3]).

Running in parallel to the airline deregulation, many airports were involved into a privatization process, starting in Europe in 1987 with the privatization of the seven major British airports - including London Heathrow, Gatwick, and Stansted - sold to the British Airports Authority plc. (BAA). Meanwhile, non-aeronautical revenues have been growing significantly to the point that they have become the main income source for many airports ([4]): encouraged by the privatization process, has been also the commercialization of the airport industry.

A positive influence of low-cost carriers' (LCCs) activity on airport competition is even well researched ([5]): an increasing number of small-medium secondary and regional airports relies on the operations of LCCs which use a business model that has a relevant cost driver in airport costs and enables LCCs to shop around airports.

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Finally, besides these institutional changes, other sources of increasing competition pressure, as the development of high-speed rails, interregional bus transportation and transport networks, have been constituting additional factors influencing competition between airports ([6], [7]).

These changes, in turn, have led to a much more competitive outlook on the part of airport managers: 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 the competing full service or low cost carriers ([1]). In this scenario, it is essential for airport managers to improve daily operations and upgrade operational efficiency relative to other players in the market, enhancing their standing in a competitive environment ([8]). Moreover, it is crucial both for airport managers and the government to identify the best practices in a range of airport operations to provide the best services in the most efficient manner ([9]; [10]). Efficiency benchmarking constitute, in this sense, a fundamental issue because of its implications for the operation of a competitive industry and the ensuing regulatory requirements. For these reasons, the impact of competition on airports efficiency is of increasing concern for airports management, policy makers and even municipalities, who require efficient airports for attracting businesses and tourists into a region ([11]).

In this paper we aim at assessing the impact of competition on airport efficiency, which is we aim at evaluating whether airports where the intensity of competition is higher are more efficient than those where it is lower. We focus on 35 Italian airports observed in 2010. Specifically, departing from previous studies on the Italian airport system ([10]; [11]; [12]; [13]; [14]; [15]; [16]), we use the recently introduced conditional efficiency measures ([17]; [18]; [19]; [20]) which have rapidly developed into a useful tool to explore the impact of exogenous factors on the performance of Decision Making Units (DMUs) in a nonparametric framework. This novel approach also provides a measure of inefficiency whitened from the main effect of the environmental factors, such as competition. This allows a ranking of units according to their pure efficiency, even when facing heterogeneous environmental conditions.

Hence, the contribution of the paper is twofold. On the one hand, we apply for the first time to the airport industry the recently developed conditional nonparametric approach to evaluate the impact of competition on efficiency. On the other hand, we provide new empirical evidence on the relation between competition and efficiency with respect to Italian airports. Indeed, to the best of our knowledge, Scotti et al. (2012) ([11]) is the only study which investigates how the intensity of competition among Italian airports affects their technical efficiency. Using a parametric stochastic approach, they find that a negative impact of competition exists on technical efficiency of Italian airports. Thus, research on this issue still seems to lack maturity.

The paper is organized as follows. Section 2 reviews the literature addressing the evaluation of airport performance and efficiency. In Section 3 we present the data as well as the input and output variables used in the analysis. Section 4 describes the methodology applied while Section 5 discusses the results. Section 6 contains some concluding remarks.

2. Literature survey

Airports efficiency is of increasing concern and source of debate for both academics and practitioners. There have been growing numbers of studies using Data Envelopment Analysis (DEA) to benchmark airport efficiency ([10]; [13]; [14]; [15]; [16]; [21]; [22]; [23]; [24]; [25]). Still others focus on stochastic frontier models (SFA) to analyze airport efficiency ([11]; [12]; [26]; [27]; [28]).

The Italian case has been investigated in the empirical literature. In particular, Barros and Dieke (2007, 2008) ([13]; [14]) applied a Simar and Wilson (2007) ([29]) two stage procedure and find that hub, private and north parameters increase efficiency. Abrate and Erbetta (2010) ([12]) extended the findings by Barros and Dieke and pointed out the existence of low levels of efficiency among Italian airports. Curi et al. (2010) ([15]) by using a Simar and Wilson (2007) ([29]) 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) ([16]) to estimate technical efficiency of Italian airports and 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) ([10]) 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.

In this framework, attention to empirical researches of competition as a factor affecting airport efficiency has not been sufficiently paid. Pavlyuk (2012) ([7]) provides a critical review of different approaches to airport benchmarking, focusing on the relationship between spatial competition and efficiency of airports: despite the fact of a well-developed theory of spatial competition and signs of its growing effects in the airport industry, he finds a lack of studies devoted to this issue.

Pavlyuk (2009) ([30])includes an index of competition based on overlapping catchment areas into a stochastic frontier model and finds a positive effect of competition pressure on efficiency for a sample of European airports. Pavlyuk (2010) ([31]) 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 (2010) ([32]) investigate the influence of competition on airport efficiency using a two stage DEA model. The level of competition is measured as the number of significant airports within a catchment area and it is found the find competition is a significant factor for results of different regulation forms.

Scotti et al. (2012) ([11]) investigate how the intensity of competition affects the technical efficiency of Italian airports. They 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. Competition is calculated separately for every destination point and combined into a general competition index using available seats shares as weights. Moreover, they use dummies regarding ownership and the degree of dominance of the main airline in a specific airport proxies for competition. Using a multi-output stochastic frontier analysis in a parametric framework, the authors find that the intensity of competition has a negative impact on airports' efficiency from 2005 to 2008.

Departing from previous studies on the Italian airport system, this paper adds to literature as we use, for the first time, non parametric conditional efficiency measures ([17]; [18]; [19]; [20]) to evaluate the impact of competing factors on airports' performance.

3. Data

The Italian system consists of 45 airports open to commercial aviation[1]. Rome Fiumicino (FCO) and Milan Malpensa (MPX) are the most important intercontinental hubs, where traffic exceeds, on average, 10 million 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. This is the case of the hub airports, Rome Fiumicino or Milano Malpensa, and some other medium sized airports like Catania Fantanarossa 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

[1] The whole Italian system consists of 113 airports - 11 exclusively open to military services and 102 to civil services.

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) ([33]). 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 historically supported the development of low-cost carriers in Italy, such as Bergamo Orio al Serio, Pisa and Rome Ciampino.

Preliminary considerations about the level of competition among Italian airports arise analyzing the percentage of competing Available Seats Kilometers (ASKs) and the share of competing routes (ICCSAI Factbook, 2011) ([33]). 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, served by an alternative airport. 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. 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.

Figures 1 shows data relating to the biggest 35 Italian airports in 2010: the share of competing routes exceeds 60% in the case of Roma Fiumicino, Venezia Marco Polo, Bologna Marco Polo, among others, and 90% in the case of Catania Fontanarossa or Cagliari Elmas.

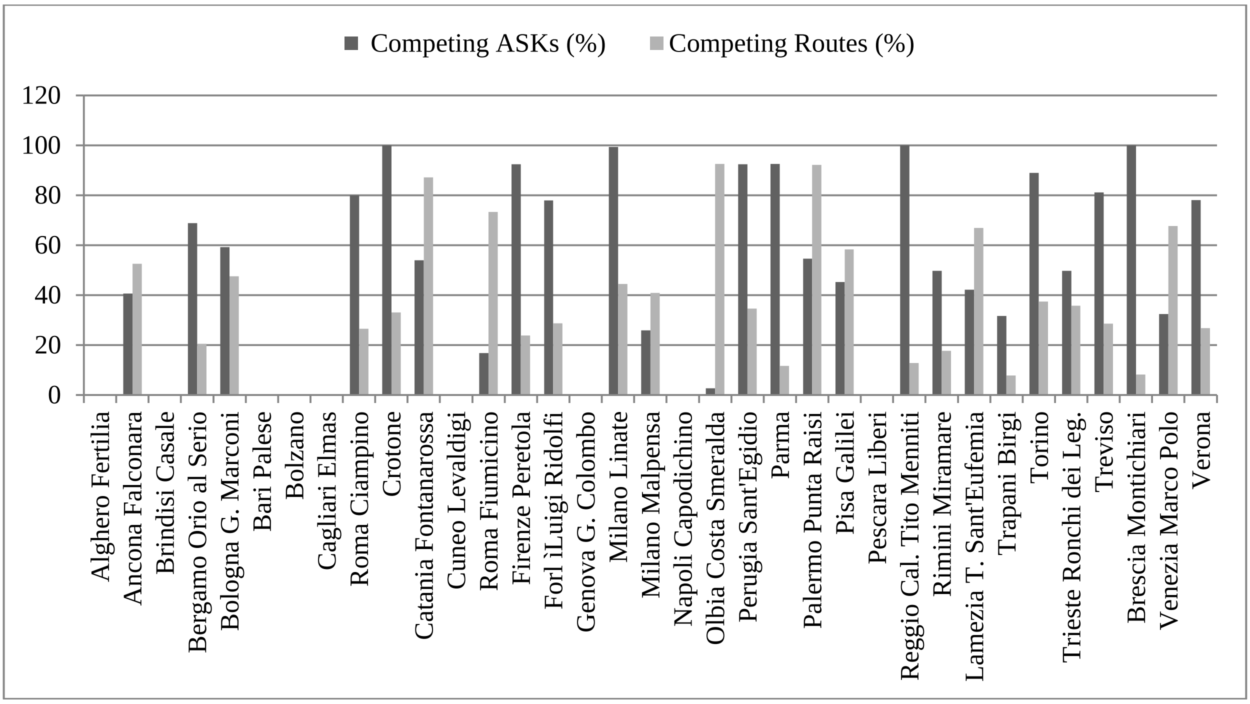

Fig. 1. Percentage of competing ASKs and routes. Source: our elaboration on data from ICCSAI - International Center for Competitive Studies in the aviation industry.

Table 1: Characteristics of Italian airports included in the sample, with respect to traffic, amount of cargo and number of movements

Total Passengers	**Amount of cargo (tons)**	**Number of movements**
Total Concession		
4259197.56	34066.61	50775.22
Partial Concession		
1665773.25	2918.38	19515.38
Precaria Concession		
370958.44	702.67	7256.44

Source: Our elaborations on data provided by ICCSAI – International Center for Competitive Studies in the Aviation Industry.

Table 2: Inputs and outputs used in previous literature

Selected previous studies	Input	Output
Abrate and Erbetta (2010)	Labour costs	Number of passengers
	Soft cost	Handling revenues
	Runway lenght	Commercial revenues
	Apron size	
	Total airport area	
Barros and Dieke (2007)	Labour costs	Number of planes
	Operational costs excluding labour costs	Number of passengers
	Capital invested	Commercial sales
		Amount of cargo
		Aeronautical sales
		Handling receipts
Barros and Dieke (2008)	Labour costs	Number of planes
	Operational costs excluding labour costs	Number of passengers
	Capital invested	Commercial sales
		Amount of cargo
		Aeronautical sales
		Handling receipts
Curi et al. (2010)	Labour costs	Number of planes
	Operational costs excluding labour costs	Number of passengers
	Capital invested	Commercial sales
		Amount of cargo
		Aeronautical sales
		Handling receipts
Curi et al. (2011)	Employees	Number of movements
	Apron size	Number of passengers
	Number of runway	Amount of cargo
Gitto and Mancuso (2012)	Number of movements	Labor costs
	Number of passengers	Soft costs
	Amount of cargo	Capital invested
	Aeronautical revenues	
	Non-aeronautical revenues	
Scotti et al. (2012)	Runway capacity	Yearly numbers of aircraft movements
	Number of aircraft parking positions	Passengers movements
	Terminal area	Amount of cargo
	Number of check-in desks	
	Number of baggage claims	
	Number of employees	
Wanke (2012)	Airport area	Number of landings and take-offs
	Apron area	Number of passengers
	Number of runways	Cargo throughput
	Total runway length	
	Number of aircraft parking spaces	
	Terminal Area	
	Number of parking places	

Table 3: List of inputs, outputs and competition variables

Variables	Code	Definition
Inputs		
Airport area (m^2)	SED	Total airport surface
Number of runways	NPI	Number of runways dedicated to the landing and taking-off of planes
Total runways area (m^2)	API	Total runways surface
Number of passenger terminals	NTP	Number of terminals excluding those dedicated to cargo handling
Total terminal area (m^2)	ATE	Total terminal surface
Terminal area for passengers (m^2)	APA	Share of terminal area dedicated to passengers movements
Terminal area for concessions (m^2)	ACO	Share of terminal area dedicated to concession activities
Number of gates	NGA	Number of gates in all passengers terminals
Number of check – in	NCI	Number of check-in counter desks in all passengers temrinals
Outputs		
Number of passengers	APM	Number of passengers arriving or departing and passengers stopping temporarily
Amount of cargo (tons)	CAR	Amount of cargo in tons
Number of movements	ATM	Number of plans that lands and takes-off from the airport
Competition variables		
% of EU GDP in a 100 km range	PKM	This indicator measures the GDP generated in all European administrative areas defined at the NUT3 level (*Nomenclature of Territorial Units for Statistics: Local Areas)* whose centers lie within 100 km of the airport, as a share of total European GDP.
% of EU GDP accessible in one step	PI1	The indicator measures the total GDP of NUT3 administrative areas whose centers lie within 100 km of any destination airport reachable by a non-stop route departing from the airport.
% of EU population accessible in one step	POP	This indicator measures the total European resident population of NUT3 administrative areas whose centers lie within 100 km of any destination airport reachable by a non-stop route departing from the airport.
1/ Average number of steps necessary to reach any European airport	ISE	For a given airport, this index expresses the inverse of the average number of flights necessary to reach any other European airport (considered separately even when serving the same area).
1/ Average number of steps necessary to reach any airport worldwide	ISM	For a given airport, this index expresses the average number of flights necessary to reach any other airport worldwide (considered separately even when serving the same area).
Airports in the catchment area	ABU	This is defined as the number of airports within 100 km as the crow flies from the airport in question
% of ASK in competition	ASK	Number of ASK in an 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, served by an alternative airport)
Share of routes in competition	QRC	This indicator 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.

The model for Italian airports is estimated using annual data on 35 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 and the total offer in terms of passengers, amount of cargo and movements.

Table 4: Descriptive statistics on inputs, outputs and competition variables

Variables	Range	Minimum	Maximum	Mean	Std. Deviation
Inputs					
SED	15,736,00	164,000	15,900,000	3,101,828.57	3,012,989.42
NPI	3	1	4	1.37	0.65
API	701,400	50,100	751,500	162,390.66	126,647.13
NTP	3	1	4	1.11	0.53
ATE	317,400	800	318,200	40,269.71	71,554.39
APA	152,216	520	152,736	18,238.31	31,481.25
ACO	47,592	138	47,730	5,369.77	9,619.75
NGA	89	2	91	14.77	19.17
NCI	428	2	430	44.29	82.58
Outputs					
APM	36,275,264	62,259	36,337,523	3,899,824.14	6,725,579.64
CAR	432,674	0	432,674	26,238.69	77,968.00
ATM	326,362	2,907	329,269	44,670.43	62,283.49
Conditional variables					
PKM	4,3	,2	4.5	1.75	1.29
PI1	88.30	1.80	90.10	44.84	23.79
POP	90.70	1.70	92.40	41.69	23.89
ABU	4	0	4	1.49	1.29
ASK	100.0	0.00	100.00	50.78	34.19
QRC	99.60	0.00	99.60	34.37	30.55
ISE	0.17	0.34	0.51	0.41	0.04
ISM	0.13	0.25	0.38	0.30	0.02

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

We consider some physical inputs and outputs according to the current literature: Table 2 presents inputs and outputs analysed in selected previous studies. Input variables used in this paper includes: airport area (m2), number of runways, total runway area (m2), number of passenger terminals, total terminal area (m2), terminal area dedicated to passengers (m2), terminal area dedicated to concession activities (m2), number of gates and number of check-in counters. With respect to the outputs, three variables have been collected: number of passengers, amount of cargo (tons) and the number of aircraft movements.

In addition, we include in the analysis a competition factor built on some conditional variables calculated as competition indices provided by ICCSAI (ICCSAI Factbook, 2011) ([33]): the percentage of European GDP in a 100 km range, the percentage of European GDP accessible in one step, the percentage of European population accessible in one step, the inverse average number of steps necessary to reach any European airport, the inverse average number of steps necessary to reach any European airport worldwide, the number of airports in the catchment area, the percentage of competing ASKs and the share of routes in competition. Table 3 summarizes and defines all the variables used in this paper, while Table 4 provides some descriptive statistics.

4. Methodology

Within the nonparametric literature, Data Envelopment Analysis (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 Decision

Making Units (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 pure policy of the evaluated units.

Generally speaking, the nonparametric literature on this topic has been 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 defining 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 employed in the second stage estimation either tobit regression or ordinary least squares[2].

In the nonparametric conditional approach, conditional efficiency measures are defined and estimated nonparametrically. The traditional Debreu Farrell efficiency scores are defined in terms of a nonstandard conditional survival function, therefore smoothing procedures and the estimation of a bandwidth parameter are required; the nonparametric estimators of conditional efficiency measures are further defined by a plug-in rule, providing conditional FDH estimators as in Daraio and Simar (2005) ([17]) or conditional DEA estimators, as in Daraio and Simar (2007b) ([19]). Recently, Badin et al. (2012) ([20]) analyze further the conditional efficiency scores, showing 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. It 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 DEA and conditional DEA (Daraio and Simar, 2007b) ([19]), with variable returns to scale (VRS) in an output oriented framework, to assess the efficiency of Italian airports. After that, the analysis of conditional efficiency scores is carried out for the first time to the airport industry to assess the impact of competition on airport performance.

4.1. Marginal and Conditional Efficiency Measures: Local and Global Analysis

Decisions Makings Units (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 the process and the productivity patterns.

The effect of Z on the production may either affect the range of achievable values for the couples (X,Y), including the shape of the boundaries of the attainable set, or it may only affect the distribution of the inefficiencies inside a set with boundaries not depending on Z (only the probability of being more or less far from the efficient frontier may depend on Z), or it can affect both. Finally, the environmental factors Z may also be completely independent of (X,Y).

[2] The traditional two-stage approach has some serious inconveniences. First, it relies on a separability condition between the input-output space and the space of the external factors, assuming that these factors have no influence on the attainable set, affecting only the probability of being more or less efficient, which may not hold in some situations. Second, the regression in the second stage relies on strong parametric assumptions (e.g., linear model and truncated normal error term). Moreover, the DEA estimates are by construction biased estimators of the true efficiency scores and they are serially correlated. Finally, the error term in the second stage is correlated with the regressors, making standard approaches to inference invalid. Simar and Wilson (2007) ([29]) 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.

Let consider a probability model that generates the variables$(\mathrm{X}, \mathrm{Y}, \mathrm{Z})$, where 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

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

or any equivalent variation of it (the joint conditional density function or the joint conditional cumulative distribution function, etc.). The function $\mathrm{H}(\mathrm{x}, \mathrm{y}|\mathrm{z})$ 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 $\mathrm{H}(\mathrm{x}, \mathrm{y}|\mathrm{z})$:

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

$H(x, y)$ 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[3]:

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

As described in Daraio and Simar (2007a), the two measures $\mathrm{H}(\mathrm{x}, \mathrm{y}|\mathrm{z})$ and $\mathrm{H}(\mathrm{x}, \mathrm{y})$ 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 $(\mathrm{x}_{0,} \mathrm{y}_0)$ to the efficient boundary of the attainable set. Radial distances are the most popular ones and they can be input or output oriented. In particular, in this paper, 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) ([17]), 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 $\mathrm{H}(\mathrm{x}, \mathrm{y})$, 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 $S_{Y|X}(\lambda y_0 | X \leq x_0) = \mathrm{Prob}(Y \geq y_0 | X \leq x_0) = H(x_{0,} y_0)/H(x_{0,} 0)$ is the (nonstandard) conditional survival function of Y, nonstandard because the condition is $\mathrm{X} \leq \mathrm{x}_0$ and not $\mathrm{X} = \mathrm{x}_0$. If the DMU is facing environmental factors $\mathrm{Z} = \mathrm{z}_0$, then Daraio and Simar (2005) ([17]) 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 $S_{Y|X,Z}(\lambda y_0 | X \leq x_0, Z = z_0) = \mathrm{Prob}(Y \geq y_0 | X \leq x_0, Z = z_0) = H(x_{0,} y_0 | z_0)/H(x_{0,} 0 | z_0)$ is the conditional survival function of Y, here we condition on $\mathrm{X} \leq \mathrm{x}_0$ and $\mathrm{Z} = \mathrm{z}_0$. The individual efficiency scores $\lambda(\mathrm{x}_{0,} \mathrm{y}_0)$ and $\lambda(\mathrm{x}_{0,} \mathrm{y}_0 | \mathrm{z}_0)$ 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 $\lambda(\mathrm{x}_{0,} \mathrm{y}_0)$ 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.

[3] 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.

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: while full frontiers are useful to investigate the local effect of Z on the shift of the efficient frontier, the partial frontiers are useful to analyse the impact of Z on the distribution of inefficiencies. In this case, we adopt order-α quantile frontiers. For any $\alpha \in (0,1]$ the order-α output efficiency score is defined as:

$$\lambda_\alpha(x_{0,}y_0) = \sup\{\lambda > 0 | S_{Y|X}(\lambda y_0 | X \leq x_0) > 1 - \alpha\}. \tag{8}$$

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

$$\lambda_\alpha(x_{0,}y_0|z_0) = \sup\{\lambda > 0 | S_{Y|X,Z}(\lambda y_0 | X \leq x_0, Z = z_0) > 1 - \alpha\}. \tag{9}$$

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. $\hat{\lambda}(x_{0,}y_0)$, is obtained, in the (Variable Return to Scale) VRS case, by solving the following linear program:

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

Similarly we obtain the estimation of the output condtional efficiency score, i.e., $\hat{\lambda}(x_{0,}y_0|z_0)$, which can be computed solving the linear program[4]:

$$\begin{aligned} &\max_{\gamma,\lambda} \lambda \\ s.t.\ \ &\lambda y_0 \leq \sum_{i|z-h \leq z_0 \leq z+h} \gamma_i y_i \\ &x_0 \geq \sum_{i|z-h \leq z_0 \leq z+h} \gamma_i x_i \\ &\sum_{i|z-h \leq z_0 \leq z+h} \gamma_i = 1 \\ &\lambda > 0, h > 0, \gamma_i \geq 0\ \forall i = 1 \dots n \end{aligned} \tag{11}$$

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. (2012a) for details on all the formulae and their statistical properties.

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). Indeed, $R_O(x, y|z) = \lambda(x, y|z)/\lambda(x, y) \leq 1$ is the ratio of the radial distances of (x, y) to the two frontiers. The inherent level of inefficiency of the unit (x, y) has been cleaned off, in the following sense:

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

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[4] Note that this provides a local convex attainable set, local in the sense of conditional on the external factors.

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 of 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 $\hat{R}_O(x, y|z) = \hat{\lambda}(x, y|z)/\hat{\lambda}(x, y)$. 5

4.2. Second-stage Regression and Pure Efficiency

The aim of this section is to estimate the pure efficiency of DMUs through a novel two stage approach, which allows 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 analyze the average behavior of $\lambda(x, y|z)$ as a function of z, that is we want to capture the marginal effect of Z on the efficiency scores analyzing the expected value $\mathbb{E}(\lambda(X, Y|Z)|Z = z)$ as a function of z. Then, we use a flexible regression model 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. (2012a) for more details.

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

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

It 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). Indeed, 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 environmental 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.

5. 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 35 airports for 2010. As described in Section 3, Table 4 summarizes and defines all the variables used in this paper while Table 5 provides some descriptive statistics. We then perform a local analysis of competition on technical efficiency of Italian airports and a local linear regression of the conditional efficiencies scores on the competition factor which allows us to estimate the residuals.

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

5.1. Factors on Inputs, Outputs and Competition Variables

Due the dimensionality of the problem (9 inputs, 3 outputs, and 8 environmental factors) with the limited sample used here (35 units), we first reduce the dimension in the input × output × environmental factors space by using the methodology suggested in Daraio and Simar (2007a) ([18]). In particular, we divide each input by its mean (to be "unit" free) and replace the 9 scaled inputs by their best (non-centered) linear combination, defined as IF, i.e. Inputs Factor. By doing so, we check that: (i) we did not lose much information; and (ii) the resulting univariate input factor is highly correlated with the 9 original inputs. We follow the same procedure with the 3 outputs and the 8 environmental factors. The results are:

$$IF = 0{,}31x_1 + 0{,}49x_2 + 0{,}36x_3 + 0{,}51x_4 + 0{,}23x_5 + 0{,}23x_6 + 0{,}23x_7 + 0{,}26x_8 + 0{,}29x_9 \quad (15)$$
$$OF = 0{,}6y_1 + 0{,}47y_2 + 0{,}64y_3 \quad (16)$$
$$CF = 0{,}08z_1 + 0{,}12z_2 + 0{,}11z_3 + 0{,}07z_4 + 0{,}09z_5 + 0{,}07z_6 + 0{,}62z_7 + 0{,}75z_8 \quad (17)$$

where OF and CF stand, respectively, for Outputs Factor and Competition Factor. IF explains 88.7% of total inertia of original data, OF explains 88.9% of total inertia of original data, while CF explains 98.1% of total inertia of original data. To be consistent with previous notation we use, in what follows, X, Y and Z instead of IF, OF and CF respectively.

5.2. Local analysis of competition on technical efficiency of Italian airports

We are here in an output oriented framework. As stated in Section 4.1 of D'alfonso et al (2013) ([34]), 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)[6], are useful to analyse the impact of competition on the distribution of inefficiencies.

Figure 2 illustrates a three dimensional plot of the full frontier ratios against inputs and competition, i.e. X and Z, whilst Figure 3 shows a three dimensional plot of the partial frontier ratios against X and Z.

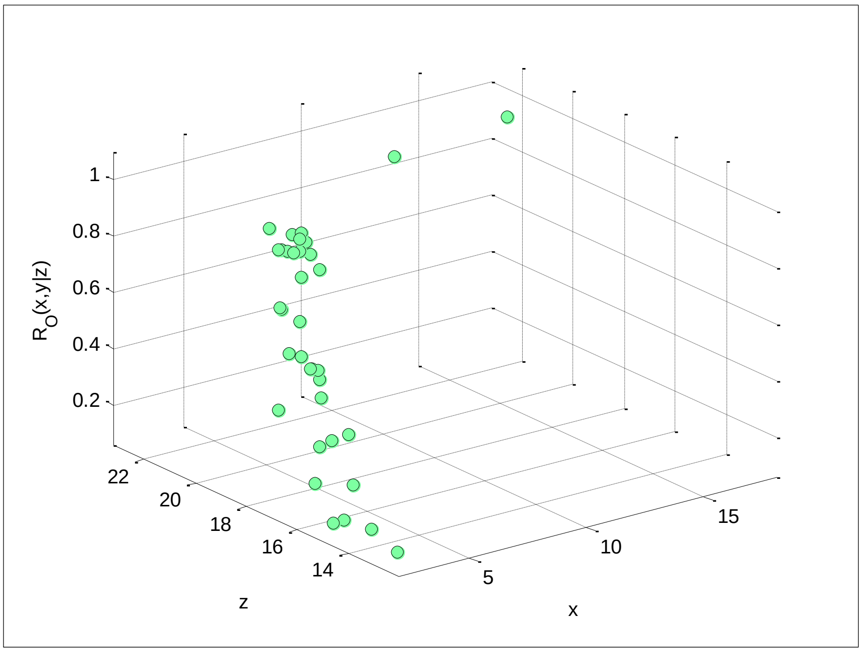

Fig. 2: Full frontier ratios against Input Factor (X) and Competition Factor (Z)

Without being able to rotate the three-dimensional figures, we have an idea of what happens complementing Figures 2 and 3 with their two marginal views. Figure 4 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, that is they show the marginal effect of inputs and of competition on the efficient full frontier. Similarly, Figure 5 shows the ratios

[6] We computed also the partial frontier ratios with $\alpha = 0{,}95$ to check if some outliers might mask the impact of Z, and found that even if there are some extreme points they do not affect the detection of the impact of Z.

$\hat{R}_{O,\alpha}(x_i, y_i|z_i)$ as a function of X and Z respectively, that is they show the marginal effect of the input (top panel) and competition factor (bottom panel) on the distribution of inefficiency with respect to the median frontier.

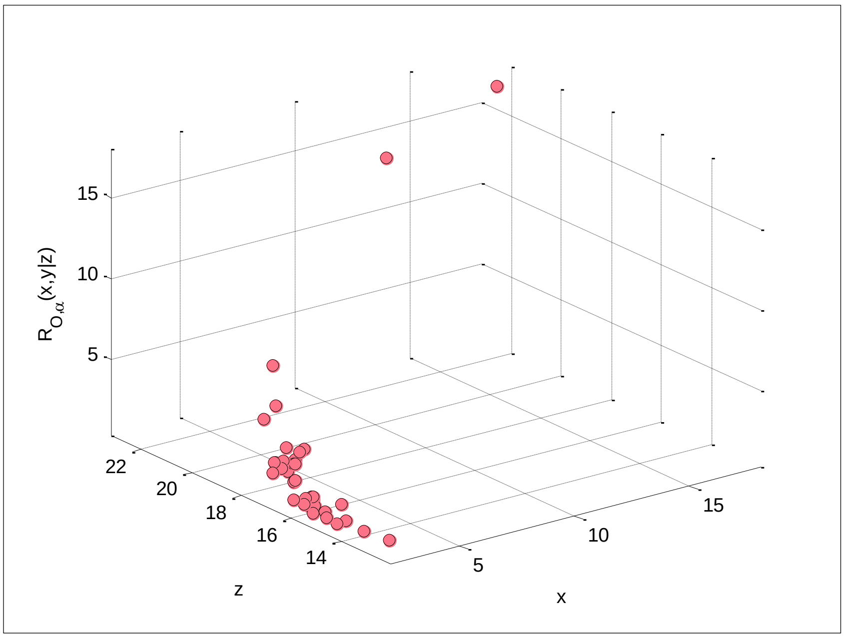

Fig. 3: Partial frontier ratios against Input Factor (X) and Competition Factor (Z). ($\alpha = 0.5$, i.e. median of the distribution of efficiencies)

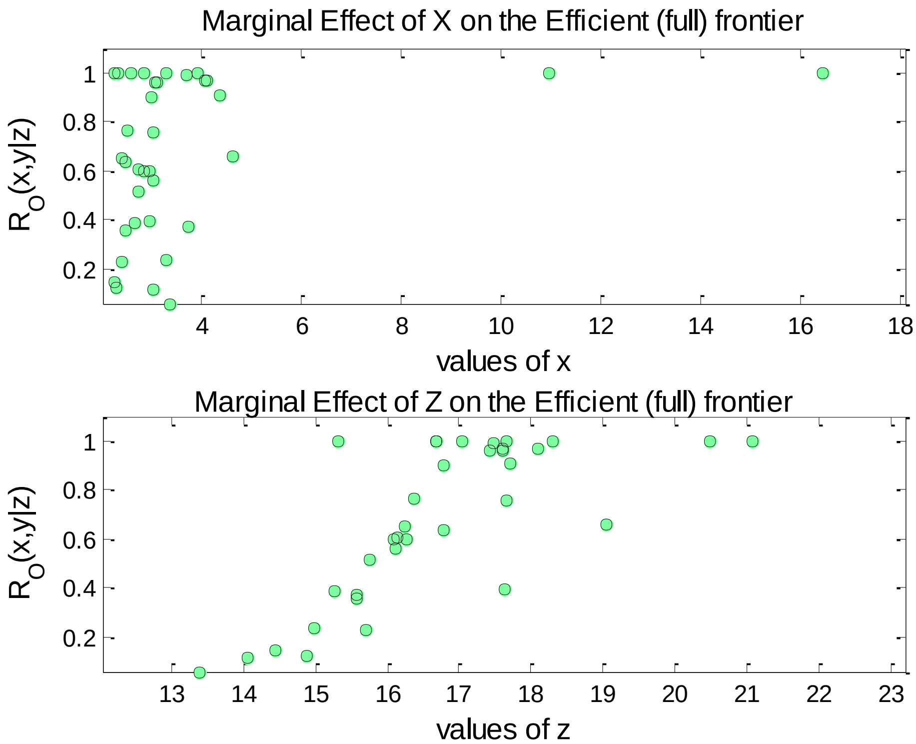

Fig. 4: Marginal effect of X and Competition Factor (Z) on the full efficient frontier.

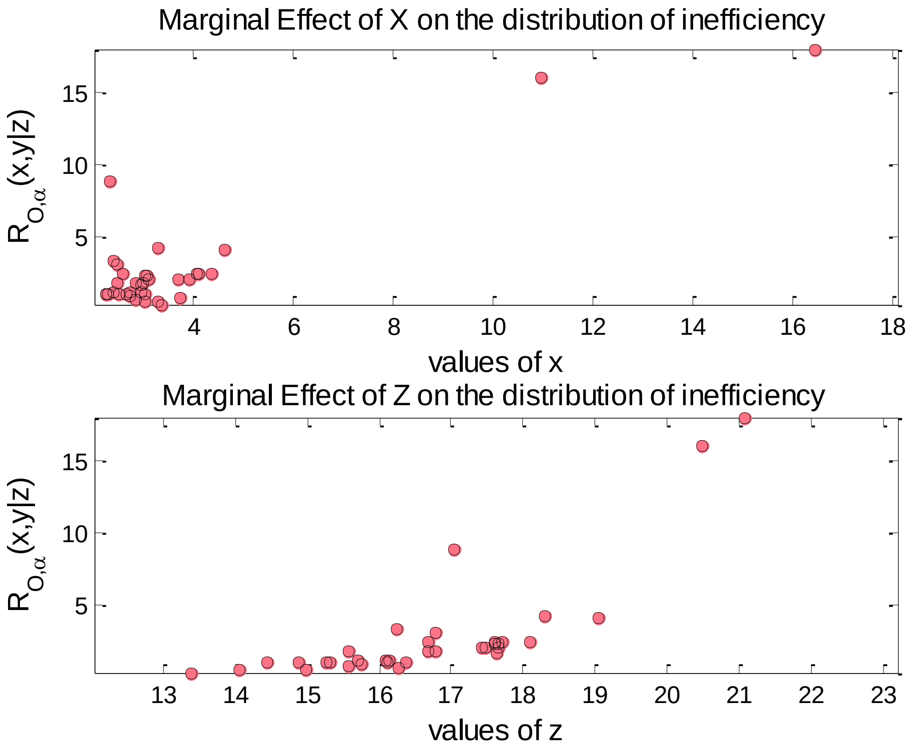

Fig. 5: Marginal effect of X and Competition Factor (Z) on the distribution of inefficiency ($\alpha = 0.5$, i.e. median of the distribution of efficiencies)

By inspecting the three dimensional plots (see Figures 2 and 3), 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 4 and 5). On the contrary, the competition factor Z has a positive impact on the full frontier ratios, i.e. there is an increasing pattern of the full frontier ratios with increasing competition factor CF (see Figure 4, bottom panel). The impact is much less severe – but still positive - on the partial frontier ratios and so on the distribution of inefficiency scores (see Figure 5, bottom panel).

5.3. Second Stage Analysis on the Conditional Efficiency Scores

According to the procedure described in Section 4.2, we regress the conditional efficiency scores against the Competition Factor, CF. We only remind here that the nonparametric model is $\lambda(X, Y|Z = z) = \mu(z) + \sigma(z)\varepsilon$, where $\mu(z)$ characterizes the average behavior of the conditional efficiency as a function of z, and $\sigma(z)$ allows some heteroskedasticity. The residual ε is supposed to be not correlated with Z and so 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 6 illustrates the results for the full-conditional efficiencies estimates as a function of Z.[7] We find that there is a local variable effect of competition (Z) on the average conditional scores. In particular, it appears that competition has firstly a positive effect and after that a negative effect on $\hat{\lambda}(X, Y|Z = z)$, showing an inverse U-shape effect on the technical efficiency of Italian airports.

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

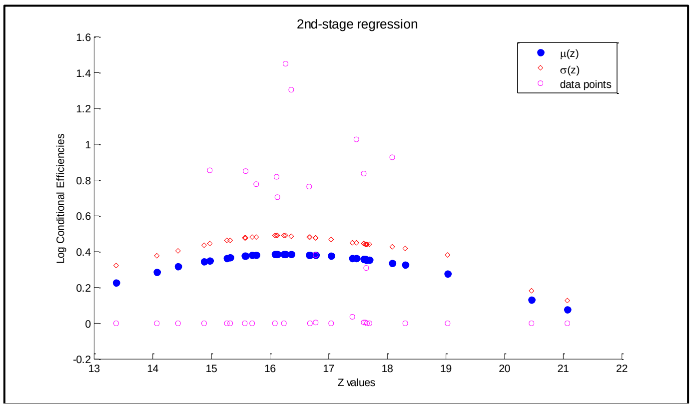

Fig. 6: Effect of competition index (Z) on conditional efficiencies.

The result is emphasized in Figure 7, which presents a zoom of Figure 6.

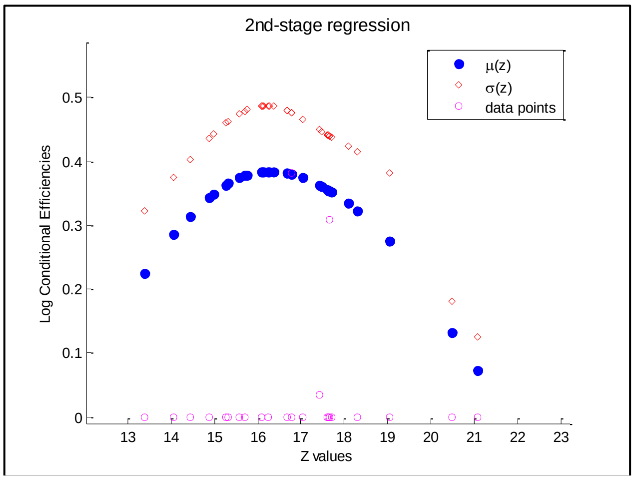

Fig. 7: Effect of Competition Index (Z) on conditional efficiencies: zoom to highlight the inverse U-shape effect of Z.

Finally, 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, it allows us to 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[8].

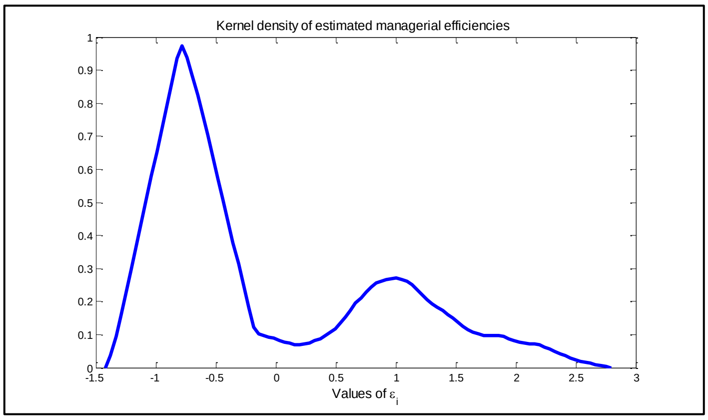

Fig. 8: Nonparametric density of estimated pure efficiencies of Italian airports (year 2010).

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

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 -0.04 and the Spearman rank correlation is -0.05. Hence, the ranking of Italian airports according to $\hat{\varepsilon}_i$, reported in Table 5, is cleaned from the effect of competition.

Table 5: Conditional efficiency scores (CondEff) and Pure efficiency (PureEff) of Italian airports (year 2010).

DMU	**NAME**	**PureEff**	**CondEff**
OLB	Olbia Costa Smeralda	-0.806	1.000
CTA	Catania Fontanarossa	-0.806	1.000
LIN	Milano Linate	-0.805	1.000
BGY	Bergamo Orio al Serio	-0.805	1.000
FLR	Firenze Peretola	-0.803	1.000
TSF	Treviso	-0.798	1.000
CIA	Roma Ciampino	-0.796	1.000
VBS	Brescia Montichiari	-0.790	1.000
GOA	Genova G. Colombo	-0.790	1.000
PSR	Pescara Liberi	-0.789	1.000
BRI	Bari Palese	-0.789	1.000
AOI	Ancona Falconara	-0.789	1.000
PEG	Perugia Sant'Egidio	-0.788	1.000
BLQ	Bologna G. Marconi	-0.778	1.000
BZO	Bolzano	-0.761	1.000
NAP	Napoli Capodichino	-0.732	1.034
MXP	Milano Malpensa	-0.725	1.000
VCE	Venezia Marco Polo	-0.723	1.000
CUF	Cuneo Levaldigi	-0.698	1.000
FCO	Roma Fiumicino	-0.580	1.000
VRN	Verona	-0.104	1.362
CAG	Cagliari Elmas	0.004	1.465
AHO	Alghero Fertilia	0.658	2.022
SUF	Lamezia T. Sant'Eufemia	0.796	2.145
TRS	Trieste Ronchi dei Leg.	0.821	2.167
TPS	Trapani Birgi	0.887	2.259
BDS	Brindisi Casale	0.993	2.330
PMO	Palermo Punta Raisi	1.078	2.299
REG	Reggio Cal. Tito Menniti	1.140	2.348
PSA	Pisa Galilei	1.398	2.525
TRN	Torino	1.488	2.788
FRL	Forl ìLuigi Ridolfi	1.891	3.679
RMI	Rimini Miramare	2.181	4.245
CRV	Crotone	N.A.*	N.A.
PMF	Parma	N.A.**	N.A.

*****only two points to estimate the conditional distribution function
******only one point to estimate the conditional distribution function

From a managerial point of view, the results reported in Table 5 are of great interest. CondEff is $\hat{\lambda}(X, Y|Z = z)$, while PureEff is $\hat{\varepsilon}_i$. When the conditional efficiency score, CondEff, is one the airport is efficient given its level of competition; if it is higher 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 6 shows some descriptive statistics on CondEff and PureEff, according to three characteristics of interest that are the effect of localization, type of concession agreement and size.

Table 6: Comparison with respect to localization, type of concession agreement and size of conditional efficiency scores (CondEff) and pure efficiency (PureEff) of Italian airports (year 2010, average value).

Effect	PureEff	CondEff
Effect of localization		
South	-0.366	1.283
North	-0.093	1.616
Centre	0.286	1.764
Effect of concession agreement		
Total	-0.296	1.345
Partial Precaria	0.055	1.597
Partial	0.395	2.098
Effect of size		
>5 millions	-0.744	1.004
1<millions<3	0.017	1.594
3<millions<5	0.132	1.608
< 1 million	0.264	1.930

Strikingly, it appears that the airports located in the South 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 Centre present the worst results. This means that southern airports have a higher level of technical efficiency since, once purified from the effect of competition, they are able to combine their inputs (see Table 3) to obtain a higher level of outputs in terms of passengers, cargo and movements. A suggested interpretation could be that less favorable infrastructure and socio-economic conditions stimulate airport management to try to maximize their technical efficiency.

Moreover, big airports (>5 millions of passengers), such as Catania Fontanarossa, Bergamo Orio al Serio, Roma Fiumicino or Milano Linate, seem to be more efficient given their level of competition. On the contrary, small airports (<1 millions of passengers) tend to show the worst performance. However, the relation between size and efficiency, on average, is not monotone. In facts, small-medium airports (1< millions of passengers <3) appear to be more efficient that medium-high airports (3< millions of passengers <5) once purified by the level of competition. A suggested interpretation could be that small-medium facilities, such as Olbia Costa Smeralda, Alghero Fertilia or Trapani Birgi, have a touristic vocation so that a deeper specialization might imply higher technical efficiency.

A total concession agreement also seems to produce a significant 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 ADR in the case of Rome Fiumicino and Roma Ciampino, or SEA in the case of Milano Malpensa and Milano Linate - 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 benefit of liberalization. Interestingly, Catania Fontanarossa, which shows the highest ranking in term of pure efficiency, turned out to a total concession agreement in 2007.

6. Concluding Remarks

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 to analyze the relationship between competition and technical efficiency. In addition, the methodology adopted allows us to obtain a proxy for measuring the managerial efficiency of airports. Indeed, the measure of pure efficiency depends only upon the managers' ability and not upon the competition faced, since we are able to whiten the conditional efficiency scores. In this way, it is possible to compare airports between them and to rank those facing different environmental conditions, because the main effects of these factors have been eliminated. This is certainly one of the most important contributions of the paper with respect to previous literature.

In particular, we disentangle the impact of competition on the efficient frontier and on the distribution of inefficiency scores. 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 firstly positive and, after a certain threshold, it becomes negative, confirming that competition has an inverse U-shape impact on 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 findings show that airports located in the South 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 Centre present the worst results. A suggested interpretation could be that less favorable infrastructure and socio-economic conditions stimulate airport management to further improve their technical efficiency. Moreover, total concession agreements seem to produce a significant increase in airport productivity. This may be due to the fact that the airport management company is often privatized and, as a consequence, this has implied an increase in investments and a more efficient utilization of their resources. Lastly, big airports seem to be more efficient given their level of competition. On the contrary, small airports tend to show the worst performance. However, the relation between size and efficiency, on average, is not monotone. A suggested interpretation could be that small-medium facilities have a touristic vocation so that a deeper specialization might imply higher technical efficiency. This consideration leads us to put forward a conjecture: the effect of size on technical efficiency could be mediated by airport specialization. However, a deeper investigation of this issue is out of the scope of this paper and is left for further developments.

Finally, airports located in the same metropolitan area or managed by the same company show some remarkable evidence. ADR owned Rome Ciampino appears to be more efficient, given the level of competition faced, than Rome Fiumicino, managed by the same company. Similarly, Bergamo Orio al Serio is more efficient than Milano Linate. This can be explained looking at many regional airports which have increased their traffic by attracting new airlines, and especially LCCs obtaining a higher utilization of their assets. In the cited examples, data on LCCs dominance, in terms of percentage of ASKs provided, reach 100% in the case of Rome Ciampino (21,7% in the case of Rome Fiumicino) and 95,4% in the case of Bergamo Orio al Serio (5,1% in the case of Milano Linate) (ICCSAI Factbook, 2011) ([33]). This may suggest the opportunity of inducing small airport specialization within the same territorial system. Consequently, it would be interesting to investigate the impact of low cost carriers' dominance and size on technical efficiency of airports and further developments of the work might go along this direction.

7. References

[1] D. Starkie. Airport regulation and competition. Journal of Air Transport Management, 2002, 8 (1), 63–72.

[2] European Commission, 1992. Council Regulation on fares and rates for air services (No 2409/92). Official Journal of the European Union (Legislation): The Publications Office of the European Union.

[3] T.H. Oum, X. Fu. Impacts of airports on airlines competition: focus on airport performance and airports–airlines vertical relations. In: Proc. of the International Transport Forum (ITF). Paris. 2008.

[4] A. Graham. How important are commercial revenues to today's airports? Journal of Air Transport Management. 2009, 15 (3), 106–11.

[5] E. Pels, N. Njegovan, C. Behrens. Low-cost airlines and airport competition. Transportation Research Part E: Logistic and Transportation Review, 2009, 45 (2), 335–344.

[6] OECD (Organization for Economic Co-operation and Development). Competitive interaction between airports, airlines and high-speed rail. In: Proc. of the International Transport Forum (ITF). Paris. 2009.

[7] D. Pavlyuk. Airport Benchmarking And Spatial Competition: A Critical Review. Transport and Telecommunication, 2012, 13 (2), 123-137.

[8] P. Forsyth, D. Gillen, A. Knorr, O.G. Mayer, H.M. Niemeier, D. Starkie. The Economic Regulation of Airports: Recent Developments in Australasia, North America and Europe. Ashgate, 2004.

[9] P. Forsyth, Regulation under stress: developments in Australian airport policy. Journal of Air Transport Management. 2003, 9 (1), 25–35.

[10] S. Gitto, P. Mancuso. Bootstrapping the Malmquist indexes for Italian airports. International Journal of Production Economics. 2012, 135 (1), 403-411.

[11] D. Scotti, P. Malighetti, G. Martini, N. Volta. The impact of airport competition on technical efficiency: A stochastic frontier analysis applied to Italian airport. Journal of Air Transport Management. 2012, 22, 9–15.

[12] G. Abrate, F. Erbetta. Efficiency and patterns of service mix in airport companies: an input distance function approach. Transportation Research Part E: Logistics and Transportation Review. 2010, 46 (5): 693–708.

[13] C.P. Barros, P.U.C. Dieke. Performance evaluation of Italian airports with data envelopment analysis. Journal of Air Transport Management. 2007, 13 (4): 184–191.

[14] C.P. Barros, P.U.C. Dieke. Measuring the economic efficiency of airports: A Simar–Wilson methodology analysis. Transportation Research Part E: Logistics and Transportation Review. 2008, 44 (6): 1039–1051.

[15] C. Curi, S. Gitto, P. Mancuso. The Italian airport industry in transition: a performance analysis. Journal of Air Transport Management. 2010, 16 (4), 218–221.

[16] C. Curi, S. Gitto, P. Mancuso. New evidence on the efficiency of Italian Airports: A bootstrapped DEA analysis. Socio-Economic Planning Sciences. 2011, 45 (2), 84-93.

[17] C. Daraio, L. Simar. Introducing Environmental Variables in Nonparametric Frontier Models: a Probabilistic Approach. Journal of Productivity Analysis. 2005, 24 (1): 93-121.

[18] C. Daraio, L. Simar. Advanced Robust and Nonparametric Methods in Efficiency Analysis. Methodology and Applications. Springer, 2007a.

[19] C. Daraio, L. Simar. Conditional nonparametric frontier models for convex and nonconvex technologies: a unifying approach. Journal of Productivity Analysis. 2007b, 28 (1), 13-32.

[20] L. Badin, C. Daraio. L. Simar. How to Measure the Impact of Environmental Factors in a Nonparametric Production Model. European Journal of Operational Research. 2012, 223 (3): 818-833.

[21] N. Adler, V. Liebert, E. Yazhemsky. Benchmarking airports from a managerial perspective. OMEGA – The International Journal of Management Science. 2012, 41 (2): 442-458.

[22] P. Arocena, D. Oliveros, The efficiency of state-owned and privatized firms: Does ownership make a difference? International Journal of Production Economics. 2012, 140 (1): 457-465.

[23] D. Gillen, A. Lall. Developing measures of airport productivity and performance: an application of data envelopment analysis. Transportation Research Part E: Logistic and Transportation Review. 1997, 33 (4), 261–274.

[24] D. Gillen, A. Lall. Non-parametric measures of efficiency of US airports. International Journal of Transport Economics. 2001, 28 (3), 283–306.

[25] P.F. Wanke. Capacity shortfall and efficiency determinants in Brazilian airports: Evidence from bootstrapped DEA estimates. Socio-Economic Planning Sciences, 2012, 46 (3), 216 – 229.

[26] C.P. Barros. Technical change and productivity growth in airports: a case study. Transportation Research: Part A: Police and Practice. 2008(a), 42 (5): 818–832.

[27] C.P. Barros. Technical efficiency of UK airports. Journal of Air Transport Management. 2008b, 14 (4): 175–178.

[28] T.H. Oum, J. Yan, C. Yu. Ownership forms matter for airport efficiency: A stochastic frontier investigation of worldwide airports. Journal of Urban Economics. 2008, 64 (2), 422-435.

[29] L. Simar, P. Wilson. Estimation and inference in two stage, semi-parametric models of productive efficiency. Journal of Econometrics. 2007, 136 (1), 31–64.

[30] D. Pavlyuk. Spatial competition pressure as a factor of European airports' efficiency. Transport and Telecommunication, 2009, 10 (4), 8–17.

[31] D. Pavlyuk. Multi-tier spatial stochastic frontier model for competition and cooperation of European airports. Transport and Telecommunication, 2010, 11 (3), 57–66.

[32] N. Adler, V. Liebert. Competition and regulation (when lacking the former) outrank ownership form in generating airport efficiency. Proc. of the GAP workshop "Benchmarking of Airports". Berlin: GAP. 2010, pp. 27.

[33] ICCSAI. ICCSAI Factbook, 2011. Air transport in Europe. BookSurge Publishing, 2011.

[34] T. D'Alfonso, C. Daraio, A. Nastasi. Assessing the impact of competition on the efficiency of Italian airports, Department of Computer, Control, and Management Engineering Antonio Ruberti Technical Reports, 2013, 2 (1): 1-40.