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EFFICIENCY IN AIRPORTS MANAGEMENT:

A TWO STAGE ANALYSIS APPLIED TO ITALIAN AIRPORTS.

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CONTENT

Introduction

Air transport is one of the main drivers of the economy, as it creates jobs and it improves the accessibility, making some geographic area more attractive and competitive. It should be noted, indeed, that the presence of efficient airport infrastructures caused the development of activities such as hotel and tourism services, facilitating, above all, commercial transactions and workers' mobility. It is clear therefore that air transport business and consequently airport management are a source of significant positive externality for the territory on which an airport infrastructure is located, contributing to economic and employment growth.

The importance of the air transport system for the development of the country imposes a strategic and systemic vision of the airport network which include a single trans-European transport network (TEN-T). The Ministry for Infrastructure and Transport (MIT) issued the National Airports Program since 2012, definitively approved by the "Conferenza permanente per i rapporti tra lo Stato, le Regioni e le Province autonome di Trento e di Bolzano" on February 2015. For the first time the "National Airport Program" suggested systemic vision of the Italian airport network, being an useful instrument in order to identify the public investment strategy in the connection infrastructure between airports.

During the last decade the increasing strategic importance of airports in the movement of people and cargo in the globalized world increased considerably. The air transport industry has been characterized by structural changes related both to the regulatory framework and to the market scenario.

With reference to the regulatory framework, European regulation - largely transposed by the national legislator - has been aimed at the air transport liberalization and the reduction of the local monopoly in the airports management/ownership. In particular, in the airport sector, the legislator aimed at stimulating competition in both aeronautical and commercial activities managed by airport operators. The deregulation and liberalization process caused the increase of the competition among airlines placing airports in a much more competitive environment. As result, airports are now under pressure to upgrade their efficiency taking as benckmark the one of their competitors.

As effect of the liberalization process in the EU air transportation market, indeed, European airlines can now provide intra-European connections without restrictions since there is slot availability. As a result, considering all the 460 airports of the 18 countries that belonged to the European Common Aviation Area (ECAA) in 1997, the total number of connections among these airports rose from 3.410 in 1997 to 4.612 in 2008. This implies a compounded annual growth rate of 2.78%, with the number of connecting flights increasing from 4.102.484 to 5.228.688 (Scotti et al, 2012). In this context of network expansion airports have to compete both directly for airlines and indirectly for passengers and freights and it emerged, also, an airline new business models, the low cost carries (LCC), which had a relevant driver in airport costs. This involved that travellers had the possibility now to choose their travel suppliers from different airlines at the same airport (direct competition) or from ones operating at nearby ones (indirect competition).

Furthermore, the privatization and a commercialization process has affected many airports so that non-aeronautical revenues have become the main income source for many airports (Bracaglia et al., 2014; Graham, 2009). In this context, airports have been restructured in order to attract private investments, search for new sources of revenues and attract full service or low-cost carriers (Starkie, 2002).

With reference to the market scenario, the decade from 2006 to 2016 - which is the focus of this analysis - has been characterized not only, as already sad, by the low cost carriers development which contributed to increasing passenger volumes and the regional airports significancy but even by the economic and financial crisis, which began in 2008 leading to a fall in the volume of goods and passengers transported, and the intermodal competition between air transport and high-speed rail transport, which in part withdrawn air transport market share especially on domestic routes but on the contrary it supported some airports access by increasing their consumer base.

In this scenario, airport benchmarking is one of the way to drive airports towards the frontier of the best practices (De Borger et al., 2002). For this reason, it has become 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, indeed, has become a popular tool in order to improve their efficiency so they can survive in a competitive environment. There has been an increasing of study using Data Envelopment Analysis (DEA) to benchmark airport efficiency. Others used stochastic frontier models (SFA) in order to analyse airports. Some other papers compare the DEA model with the SFA model. Recent studies included in the analysis environmental factors which 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), type of competitive environment (competitive versus monopolistic airports, HSR pressure), type of ownership (private, public, mixed) and so on (D'Alfonso et al., 2015). These factors can be included in the analysis as exogenous variables that can help to detect and analyse influential factors which may affect airports' productivity patterns, to explain the (in)efficiency differentials, as well as to improve policy decisions.

Referring to Italian airports, it is noted that the most popular analysis methodology was the DEA. In particular, among others Barros and Dieke (2008) applied the two-stage analysis of Simar and Wilson (2007) in order to estimate which factors are able to affect the efficiency of 31 airports from 2001 to 2003. Curi et al. (2011) implemented a bootstrapping procedure analysing DEA outcomes of 18 Italian airports from 2000 to 2004 in the case of constant return to scale having regard to operations and financial activities. Subsequently, Gitto and Mancuso (2012) developed the Barros and Dieke's analysis (2008) by employing a DEA analysis on 28 Italian airports in the period from 2000 to 2006 from which they derived a Malmquist index adapted to an inferential context.

In this context, this analysis considering previous works of Barros and Dieke (2008), Curi et al. (2011) and Gitto and Mancuso (2012), aims to provide a contribution to the Italian airport network development strategies by assessing the performance of airports included in the "National Airport Program". The main purpose of this work is to analyse the competitiveness of Italian airport infrastructures through the non-parametric analysis model, Data Envelopment Analysis, in order to estimate its technical and operational efficiency taking into consideration a wider period than the one analysed in previous Italian studies - the years from 2006 to 2016 - and above all by valuating, for the first time in Italy, the effects on airports efficiency of other relevant external factor, such as the size of the airport and the presence of low-cost carriers (LCCs). This research, indeed, improves on the samples used by previous authors since none of them evaluated the long period that has been affected by the liberalization process which revolutionised the aviation sector, considering both the greater power acquired by Italian airports and the influence of the LCCs on the airports efficiency. None of the previous papers on Italian airports efficiency evaluated how much the LCCs have impacted Italian airport efficiency. At the same time, differently to previous papers regarding Italian airports, it was analysed the effect of cargo traffic on airports efficiency, which are expected to have higher variable factor productivity scores, because "handling cargo is capital intensive and therefore more productive than handling passengers" (Oum et al. 2006).

This study has been divided into two phases. The first phase analyses efficiency through an analysis of DEA's performance scores taking into consideration a sample of 34 Italian airports during the wide period 2006-2016 for which it has been collected data referred to the main input and output of the airport management companies along with financial information. The performance analysis allowed to outline the critical points of several airport operators through the identification of any best practices applicable to the relevant field and the distance between the latter and the remaining DMUs. The second phase assesses how external factors impact the efficiency level. Using the Tobit model, it was regressed the efficiency scores obtained during the first stage, on three explanatory variables: airport size, share of LCC passenger and share of cargo traffic. Based on the results obtained, it is discussed some general sector considerations and it is suggested some improvements in order to enhance the efficiency of the companies under consideration.

The choice of this topic is linked to the crucial importance of achieving an efficient airport network for the economic system, not only in order to satisfy the demand for mobility, but especially considering the high economic impact associated with the airports infrastructures and the role that air carriers play in ensuring an adequate level of connectivity within the Country. Two important aspects have to be taken into account: the impact of airport infrastructure on the relevant areas in terms of employment, income and added value, and the effect on the definition of the economic system arising from a suitable level of airport connectivity.

In Italy, in order to meet successfully both the potential growth in demand and to ensure a service and safety level compliant with the European standards, it was issued the National Airport Program (PNA) whose main goal is to increase airport capacity through the rationalization and optimization of existing capacity (even in order to minimize the environment and landscape impacts thanks to the implementation of new air side and land side infrastructures); and the use of available capacity within existing airports which today it represents a "network capacity reserve".

The PNA takes into account even two other problems that have to be solved: airports accessibility and the integrated transport.

Travelling to/from the airports it is not so easy, even for airports near to the relative urban centres. In many cases, indeed, access times are slowed down by local traffic or an insufficient road system. In case of airports out from urban centres, such as Rome Fiumicino and Palermo, accessibility is affected by the traffic jam caused by the metropolitan conurbation and by new urban attraction poles along the access road.

Even the intermodal transport between trains and planes is still insufficient and very far from European standards: currently only Fiumicino, Malpensa, Palermo, Pisa, Turin and Ancona airports are accessible by train. Even if the rail link is working, however, travel times, frequencies and trains characteristics discourage users and these do not create a competitive rail connections. Since the integrated transport represent an essential element for competitiveness and sustainable development of the country, it is strongly urged by Local Authorities to set up and implement projects aimed at supporting the proper development of the airport system. In this regard, the National Airport Program identifies specific actions to perform, indicating how to achieve them.

The shares represented by the National Plan of Airports determine the amount of investment of around 80 billion euro.

The present work consists of three papers strictly related to each other. The 1st Paper outlines the airport efficiency evaluation literature applying the Data Envelopment

Analysis and then focused on the DEA method, its origins and the different ways of its applications. The 2nd Paper aims to analyse the financial and operating efficiency of 34 Italian airports during the period 2006-2016 through the DEA analysis. The 3rd Paper, following the efficiency analysis carried out in the 2nd Paper, aims at studying the effect of the airport size presence, low-cost carrier presence and cargo traffic on efficiency applying the Tobit model, a second stage regression analysis.

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1st Paper

HAVING A LOOK AT THE DATA ENVELOPMENT ANALYSIS

Introduction

The topic covered in this paper concerns the efficiency analysis of a set of independent organizational units. Over the last decade, this argument has been heavily discussed as, in the current economic context of increasing competitiveness and dynamism, it is crucial for a company to know both its degree of efficiency compared to its competitors and the relative efficiency of different internal operating units (divisions, departments, functions) or individual employees. This work lies in a field of managerial studies defined with the term benchmarking, a theory based on the identification of excellent references to compare the performance of the various units. Benchmarking is an effective method for measuring and enhancing the performance of an operating unit. The systematic use of Benchmarking methodologies and tools stimulates and integrates learning and change processes while at the same time it stimulates the effectiveness and efficiency of business processes and the renewal of corporate culture, ensuring continuous improvement thanks to constant comparison with other internal or external units. This technique involves several phases such as identifying the area where analysis is needed, the indicators to compare, the collection of data, the results processing and finally the evaluation and control of these. In this thesis it is presented the Data Envelopment Analysis, a benchmarking and performance evaluation technique that over the last few years it has been recognized mainly through the development of specific software.

Data Envelopment Analysis (DEA) is a method for measuring decision-making units (DMUs) efficiency, such as, for example, companies or public institutions. It was developed theoretically by Charnes, Cooper and Rhodes in 1978 as a technique based on linear programming.

This paper is inherent to the theoretical definition of DEA, which starts from the bases dictated by Farrell to reach the most complex and most recent introduction. The first chapter will deal with DEA's story, especially focusing on the application of the DEA model for evaluating the efficiency of Italian airports. The second chapter deals with Farrell's contribution, the basic models of slack and model orientation. The third chapter after a short digression on the choice of the model, it will introduce the model Charnes, Cooper and Rhodes (hereafter CCR), and the Model Banker, Charnes and Cooper (henceforth BCC) (with an in-depth study on scale returns), Additive and finally conclude analysing some of the advantages and disadvantages of the technique.

1.1 The DEA's story

The performance analysis of firms or business sectors naturally leads with productivity and efficiency measures. These productivity analysis allow to determine what is the optimal production scale and what are the best management methods and organizations of production networks.

Two methods are mainly used to measure efficiency: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). SFA was first introduced by Aigner, Lovell and Schmidt, 1977, and Meeusen and Van den Broeck 1977. It consists in estimating a parametric frontier econometric model. The first DEA article was published by Charnes, Cooper and Rhodes in 1978.

DEA is a nonparametric method implemented to measure the productive efficiency of Decision Making Units (DMUs). Its main advantage over SFA is that it does not require any parametric assumption on the production frontier. The envelope of the observed DMUs' input and output levels is calculated by linear programming and can be considered as a best-practice frontier. By measuring the distance between a firm and the efficient frontier, it is possible to calculate the DMU's efficiency.

Today, many different DEA models are used in the literature and additional statistical inference methods can strengthen results validity.

The main economic sectors applying DEA were mostly the banking industry, education, health care and communication while the transport sector was never mentioned as a potential application field according to Seiford. Transportation appeared very recently as the fourth DEA application field according to Liu, Lu L.Y.Y., Lu W.M., Lin (2013) who state that 53% of the referred articles were published during the period 2005 and 2009.

The economic theory underlying efficiency analysis is based on Koopmans (1951), Debreu (1951), and Farrell (1957), who made the first efforts on measuring the efficiencies for a set of observed production units (Simar and Wilson, 2008). Farrell introduced the concept of *best practice frontier* which delineates the technological limits of what a country can achieve with a given level of resources. The distance from the frontier can be used as a performance indicator (Terzi, Pierini, 2015).

Inserted in this context, the DEA original model, was introduced by Charnes, Cooper and Rhodes (1978).

Charnes et al. gave to this concept more precision and suggested a way of dealing with efficiency in practice. They defined efficiency and justified the necessity for a ‘‘relative’’ rather than an ‘‘absolute’’ measure thereof: more than 20 years later, the CCR model remains central in the DEA literature.

“[The] distinction between effectiveness and efficiency need not to be emphasized in evaluating private enterprise activities. We lay aside the more difficult problem of effectiveness and assume that this has been decided in the choice of inputs (resources) to be used and outputs (benefits) to be achieved, as well as the way in which the inputs and outputs are to be measured:

100% of efficiency is attained for any Decision Making Unit (DMU) only when:

(a) None of its outputs can be increased without either
i. increasing one or more of its inputs or
ii. decreasing some of its other outputs

(b) None of its inputs can be decreased without either
i. decreasing some of its outputs or
ii. increasing some of its other inputs.

The Charnes, Cooper and Rhodes’ publication (CCR) represents the birth of data envelopment analysis (DEA). They formulated the evaluation of a firm’s efficiency ‘‘in a stringent mathematical form more readily understood and absorbed by the research community’’. It described the DEA method as a “mathematical programming model applied to observed data that provides a new way of obtaining empirical estimates of extremal relationships such as the production functions and/or efficiency production possibility surfaces that are the cornerstones of modern economics”. Since then, numerous applications employing the DEA methodology have been presented and they involved a wide area of contexts. DEA aimed at evaluating data management units (DMUs), which use multiple inputs to produce multiple outputs, without a clear identification of the relation between them, but then it has progressed throughout a variety of formulations and uses to other kind of industries. It was decided to use the DEA method because it can be applied to scenarios where the data cannot be strictly interpreted as inputs or outputs or there is no direct functional relationship between variables.

In the airport sector, the first application of DEA analysis for research studies started in the 1990s.

Gillen and Lall (1997) employed DEA to assess the performances of 23 US airports in the years ranging from 1989 to 1993 and estimated two Tobit regression models for explaining terminal and movement’s efficiency. The first one reveals that the increase in efficiency is positively associated with hubbing and negatively with the proportion of international passengers. For the latter increased efficiency is found to be negatively associated with hubbing and positively with the proportion of general aviation movements.

Murillo-Melchor (1999) applied DEA to assess the performance of 33 Spanish civil airports. They used DEA input CRS model as well as DEA input VRS model.

Parker (1999) used the DEA method in two different stages estimating the technical efficiency of British airports prior to and after privatization. Assessing, in the second model, the technical efficiency of 22 UK airports including six BAA (British Airports Authority) he found that privatisation had no noticeable impact on technical efficiency.

Salazar (1999) applied DEA output CRS model to assess the performance of 16 main Spanish airports in 1993 – 1995 and empirically, observed the extent to which input and output contribute to the change in efficiency by visualizing from a graph.

Sarkis (2000), considering the period 1990-1994, applied the DEA input CRS and DEA input VRS model as to analyse the operational efficiencies of 44 major US airports. The main characteristic of the paper is that the author used a variety of other DEA models including simple cross efficiency, aggressive cross efficiency and ranked efficiency in addition to the basic models: constant and variable return scale models. So it was possible to assess the consistency of the results and to gain additional insights.

Anne and Holvad (2000) employing DEA analysed the performance of 25 European and 12 Australian airports during the period from 1992 to 1993.

Adler and Berechman (2001) applied DEA input VRS model for evaluating the performance of 26 airports in Western Europe, North America and Far East. Fernandes and Pacheco (2001) employed the DEA model for assessing the efficiency of 35 Brazilian airports in 1998, focusing on domestic airports. Martin & Roman (2001) applied the DEA to evaluate the performance of 37 Spanish airports. Differently from Parker (1999), they highlighted that privatization will improve the airport's performance, stating that in order to ensure the efficiency it would be necessary a simultaneous process of economic regulation.

Applying a Malmquist total factor productivity index and DEA, Abbot and Wu (2002) investigate the efficiency and productivity of Australian airports during the 1990s. Their results showed that Australian airports recorded strong growth in technological change and total factor productivity during this period. However, this growth was based almost exclusively on a shift of the production frontier, with growth in technical and scale efficiency lagging behind.

Subsequently, Pels, Nijkamp and Rietveld (2003) analyzed 33 European airports from 1995 to 1997, employing both DEA and SFA models in a complementary way. In DEA, in fact, the distance from the efficiency frontier is regarded as inefficiency and random deviations are not possible; otherwise, a SFA model determines inefficiency according to the distance from the stochastic border and take into consideration possible deviations. From the SFA analysis, authors concluded that the airports analysed operate under constant return to scale for aircraft movements and with increasing return to scale having regard to passenger movements.

Sarkis and Talluri (2004) assessed the efficiency of 44 US airports from 1990 to 1994 applying the DEA analysis and clustering methods in order to provide policy recommendations with respect to certain improvement targets. The advantage of clustering is to group information based on inputs in order to obtain homogeneous groups of comparable information.

Diana (2009) analysed 10 US airports for the summer periods over the years 2000, 2007 and 2008 in order to determine whether delay propagation differs in case of airports operating in highly concentrated markets with respect to airports operating in markets with lower levels of concentration. Based on non-parametric tests and proximity analysis, the study concluded that it is not possible to find a clear evidence, in terms of delayed propagation, on the difference between airports operating in highly concentrated markets and those operating in less concentrated markets. The importance of the study lies in the impact assessment of the market structure on the operation and efficiency of the analysed airports.

Ming-Miin Yu (2010) used a three-stage DEA analysis to evaluate 14 Taiwanese airports from 1998 to 2000. In detail, the author changed the stage one of the DEA approach into three different stages in order to take into account non-output desirable such as airplane noise and used a directional distance function defining a DEA with output-oriented approach. Additionally, at stage two the regression analysis provided variations in output considering components such as technological change and management inefficiency. The third stage of DEA can be considered as a repetition of the first one taking into account the effects of the variation of the above mentioned components. Empirical analysis has shown the validity of the three stages DEA approach in case in which environmental impacts, technological factors and unwanted outputs are too important to be ignored.

More recently, Adler, Ülkü, Yazhemsky (2013) focused their analysis on small regional airports. In particular, through the DEA model, the authors assessed the efficiency of 85 small European regional airports over a period of 8 years from 2002 to 2009. In a second stage regression some environmental variables (ie military use of the airport, membership of an airport system, presence of public service obligations) in order to recognise their impact on the airport management efficiency. The work ends with a break-even analysis aimed at determining the level of passenger flow needed to cover the costs, and therefore the airports located on the Pareto border. Adler, Ülkü, Yazhemsky's analysis fills a gap in economic literature focusing on small airports.

Focusing on the economic literature analysis relating to Italian airports, it is noted that the most widely used methodology was DEA. The DEA offers an inefficiencies measurement ("Farrell approach"), where SFA allows both to measure and provide inefficiency explanation (“Leibenstein approach”). In particular, in order to exceed these limits of DEA, Barros and Dieke (2008) applied the two-stage Simar and Wilson procedure to estimate the efficiency determinants of 31 airports from 2001 to 2003. In the first stage DEA has allowed to classify airports according to their productivity. In the second stage, the Simar and Wilson procedures allowed a "bootstrap" with truncated regression of the DEA results. The analysis revealed that the main efficiency determinants are size, ownership structure and workload units (WLUs) and that most Italian airports operate under constant return to scale.

Malighetti, Martini, Paleari and Rodondi (2007) applied a Tobit regression to the DEA results on physical inputs for 34 Italian airports from 2005 to 2006. The analysis showed that the main efficiency determinants are the proprietary structure and the hub premium; the analysis has shown, moreover, that larger airports mainly operate with decreasing returns to scale, while smaller airports operate under increasing return to scale, different from what Barros and Dieke (2007) had come up with.

Abrate and Erbetta (2010) used a parametric input distance function as an innovative methodology to evaluate efficiency and characteristics of 26 Italian airports observed over a six-year period from 2000 to 2005. This approach removes the cost minimization hypothesis and avoids price input, which represents a limit to traditional methodologies of estimating the cost function. In addition, the authors analysed the relationship and synergies between aeronautical, handling and commercial activities, concluding that outsourcing of handling activities is a valid strategy, although conditioned by the airport size in terms of traffic volumes.

More recently, Curi, Gitto and Mancuso (2011) implemented a bootstrap procedure for DEA's results having regard to 18 Italian airports over the period 2000 - 2004, in the case of constant return to scale, with reference to operational nature and financial activities. In particular, the authors analysed the most recent statistical inference tools for DEA (bias correction, and confidence intervals associated with DEA results), particularly useful considering small samples and different sizes production models, such as Italian airports.

Scotti, Malighetti, Martini and Volta (2012) analysed 38 Italian airports considering the period from 2005 to 2008, using a SFA model in order to assess whether the competitiveness degree of each airport influences its efficiency. The authors concluded that airports with local monopoly power were more efficient than airports in a competitive market condition and that following the analysis public airports appeared more efficient than those with private or mixed ownership structure.

Gitto and Mancuso (2012) developed the work of Barros and Dieke (2007) employing a DEA on 28 Italian airports on data from 2000 to 2006 from which derived the

Malmquist index which was adjusted to an inferential context. The Malmquist index calculated in a deterministic way, indeed, would not allow to verify whether the productivity variations identified correspond to real / actual variations or, alternatively, represent a shift of production frontiers over the time. The use of the bootstrap procedure (Simar and Wilson, 1999) has enabled to obtain confidence intervals for the Malmquist index, the efficiency and technological variation. The analysis of Malmquist indices indicates that the productivity growth of Italian airports network is polarized on the Rome and Milan systems and on a few other airports. The analysis found even that airports run by managers with mixed corporate structure with a government majority are not significantly less efficient than airports run by managers with a public-sector structure.

D'Alfonso, Daraio and Nastasi (2015), instead, analysed the effect of competition on technical efficiency of 45 Italian airports by applying a novel conditional nonparametric frontier analysis for the first time to the airport industry. This novel two stage approach has shown that, on average, competition has a negative impact on technical efficiency. They estimated 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.

1.2 Literature review

In this paper it has been stated some economic considerations about the possibility to measure the airport efficiency through the Data envelopment analysis, and so, to have an idea of the relevant literature in this specific topic, we have interrogated the Scopus database using the Boolean search parameters “Airport competition OR Airport efficiency”. Through this search it was possible to find the literature concerning two different kinds of problems. The first one is to identify the paper applying the traditional literature of the airports efficiency sector. The second one is to understand which variables are able to affect the airports efficiency.

This research showed a huge number of documents, 2.497 in total. In order to narrow the documents to analyse there were introduced two more parameters: the language, “English”, and the document source, “journals”; in this way we have reduced the number of documents to 1.033. Since this number of documents was too big to analyse, the research was focused on the title, abstract, and keywords, in this way obtaining 35 documents containing the words “Airports + competition+ DEA OR Airports + efficiency + DEA”.

Analysing the contents of the 209 documents it was found that only eight of them were economic papers analysing Italian airports. This is consistent with the research of Cavaignac and Petiot (2017). Applying a bibliometric analysis, they have shown that

Italian articles using DEA in transport analysis in a broad sense (Transport, Maritime, Road, Rail, Air), between 1989 and 2016, are only 21.

In table 1.1, below, it has been reported the most significant papers with regard to the Italian airports, synthetizing what is the nature of them, the model used and the variables considered in them.

Table 1.1. Inputs and outputs used in previous studies on the efficiency of the Italian airport system.

Selected Studies	*Method*	*Units*	*Input*	*Output*
Malighetti et al. 2007	DEA and Tobit regression model	33 Italian airports 2005 - 2006	Number of aircraft parking position	Number of aircraft movements
			total airport area	Number of passengers
			total runways lenght	
Abrate-Erbetta 2010	Input distance function	26 Italian airports 2000 - 2005	Labour costs	Number of passengers
			Soft cost	handling receipts
			Runway area	commercial receipts
			apron size	
			total airport area	
Curi et al. 2010	DEA and truncated regression model	36 Italian airports, 2001–2003	Labour costs	Number of passengers
			operational costs excluding labour costs	Number of aircraft movement
			capital invested	commercial sales
				Number of cargo
				aeronautical sales
				handling receipts
Curi et al. 2011	DEA and two-stage bootstrapping	18 Italian airports 2000–2004	employees	Number of aircraft movements
			apron size	Number of passengers
			Number of runways	Number of cargo
Gitto-Mancuso 2011	two different DEA models: physical and monetary	28 Italian airports during the 2000–2006	Number of employees	aeronautical cost
			Runway area	non aeronautical costs
			Airport area	
Gitto-Mancuso 2012	DEA-Malmquist with bootstrap	28 Italian airport 2000–2006	Number of aicraft movements	labour costs
			Number of passengers	soft costs
			Number of cargo	capital invested
			aeronautical revenues	
			non-aeronautical revenues	
Scotti et al. 2012	SFA – two-stage analysis	38 Italian airport 2005–2008	runway capacity	Number of aircraft movements
			Number of aircraft parking position	Number of passengers
			Terminal area	Number of cargo
			Number of check in desks	
			Number of baggage claims	
			Number of employees	
D'Alfonso et Al	DEA and second-	34 airports	Airport area	Number of passengers

2015	stage regression	for 2010	Number of runways	Number of cargo
			Number of passenger terminals	Number of aicraft movements
			Number of gates	
			Number of check in	
			Number of employees	

Table source: V. Recupero

Table 1.1 shows clearly that almost all economic literature analysed related to the Italian airports efficiency is focused on empirical works and that the main techniques used are the Data Envelopment analysis and a two-stage regression analysis.

This literature gap brings to generate uncompleted empirical model to explain which is the effective process that bring an Italian airport to be efficient. In a similar situation it is hard to answer questions like: is it possible to measure efficiency of Italian airports after the liberalisation process? What kind of influence can the low-cost companies have on Italian airport efficiency? Can cargo traffic affect airport efficiency?

This research contributes to the literature by analysing the efficiency of a larger and balanced dataset of Italian airports. There were analysed, indeed, all the Italian airports of the National Airport Program having regard to the wider period ranging from 2006 to 2016. This research improves on the samples used by previous authors showed up since none of them evaluated the long period that has been affected by the liberalization process which led to a change in the aviation sector, especially given the greater power acquired by Italian airports. Taking into consideration previous research, indeed, it is possible to noticed that the larger period (from 2000-2006), was analysed by Gitto and Mancuso while some other authors studied airport efficiency during a single reference year, ie. D'Afonso et al. and Malighetti et al.

In this study it was also considered another important aspect linked to the aviation liberalization which is the influence of the LCCs on the airports efficiency. None of the previous papers on Italian airports efficiency evaluated how much the LCCs have impacted Italian airport efficiency. At the same time, differently to previous papers regarding Italian airports, this work it was analysed the effect of cargo traffic on airports efficiency, which are expected to have higher variable factor productivity scores, because "handling cargo is capital intensive and therefore more productive than handling passengers" (Oum et al. 2006).

1.3 DEA analysis: the Farrell's contribution

As already sad, DEA's bases were set around 1957 by Farrell, which introduced a linear production function, but failed to determine a line-up programming program to explain the graphical efficiency indices obtained.

The production function is estimated by solving a system of linear equations satisfying the convexity and the exclusion conditions of the origin of the axes on the one isoquant.

Farrell's contribution to measuring efficiency is only useful in three cases:

• one input and one output;

• two inputs with equal output;

• Two outputs with equal input.

Farrell also decomposed the efficiency of a production unit into two-component, technical efficiency and allocative efficiency. The first one is the ability of the production unit to get the most output given a certain (and limited) set of inputs. Therefore, in a technically inefficient unit, there is a waste of productive resources, which implies a non-minimization of production costs, in the direction of Input, while in output orientation, the product is less than the maximum obtainable data factors employed. Allocation efficiency, on the other hand, reflects the ability of the unit to use in optimal proportions, given the respective prices. In the case of units characterized by allocative inefficiency, assuming orientation to the inputs, the mix of inputs chosen is not able to ensure a technically efficient level of output (the marginal rate of substitution of the factors does not equal the ratio between their prices) while, in the case of orientation to the output, the multi-product enterprise, does not gather that output mix that maximize revenues (the MRS does not match the price ratio).

Technical and allocative inefficiencies can occur both separately and jointly, contributing to increasing production costs to the minimum possible. Therefore, all cases in which costs are not minimized may depend on both technical and allocative inefficiency.

By indicating input and output, a production level will be technically efficient when the combination (X, Y) lies beneath the efficient frontier. In the Figure below, point P is technically inefficient because in order to produce the quantity of output YP would be enough the amount of rebates XC or, alternatively, because with the same amount of resources XP could produce a higher quantity of goods, equal to YB.

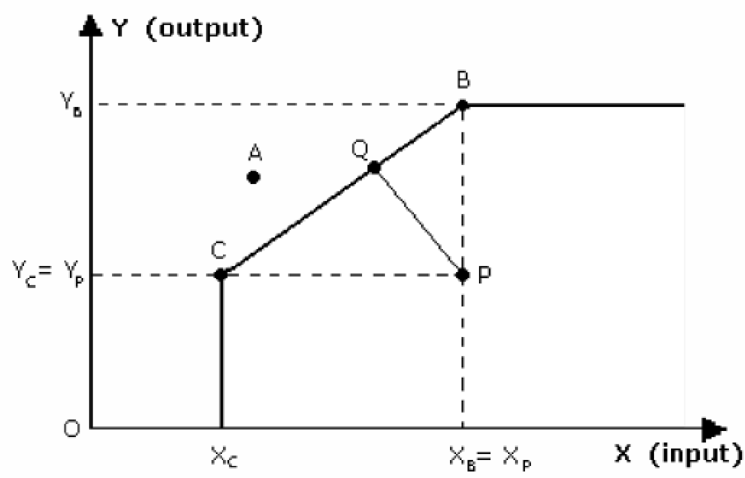


Figure 1.1

The ratio commonly used in DEA to evaluate efficiency is ***Output/Input***, when it has been analysed an homogeneous DMU sample, using the same resource set.

1.4 Input/output oriented model

In order to determine whether a DMU is efficient or not, it has to be measured if there is waste in production. A production unit can be technically inefficient not only when it wastes inputs during production (input orientation) but even when inputs cannot reach the maximum amount of production to be produced. Then it will have an exit orientation when the goal of the analysis is to define the amount of production to be produced so that production steps from inefficient to efficient.

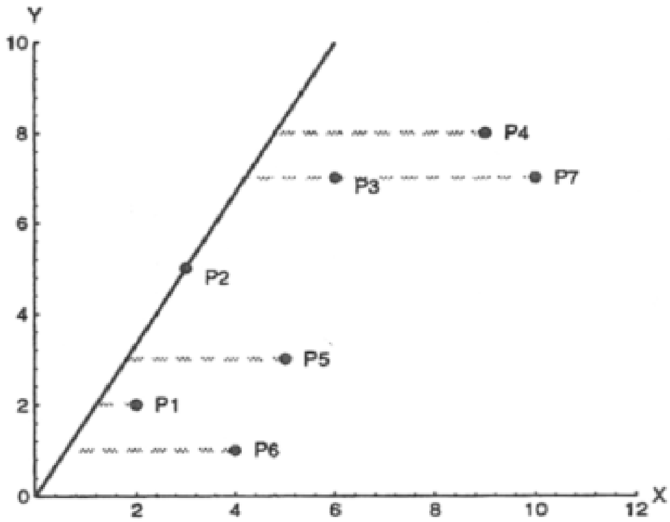


Figure 1.2（A. Charnes, W. Cooper, A. Lewin, L. Seiford）

The above figure shows an input oriented measurement. This will be performed by measuring the horizontal distance between the points inefficient, to the right of the efficient frontier, and the latter. For point P3:

$$E_{P3} = \frac{x_{P'3}}{x_{P3}} = \frac{4,2}{6} = 0,7$$

Point P3 has an efficiency of 70%, so with a 30% reduction in inputs it will continue to get an output of seven units, but with a lower amount of resources.

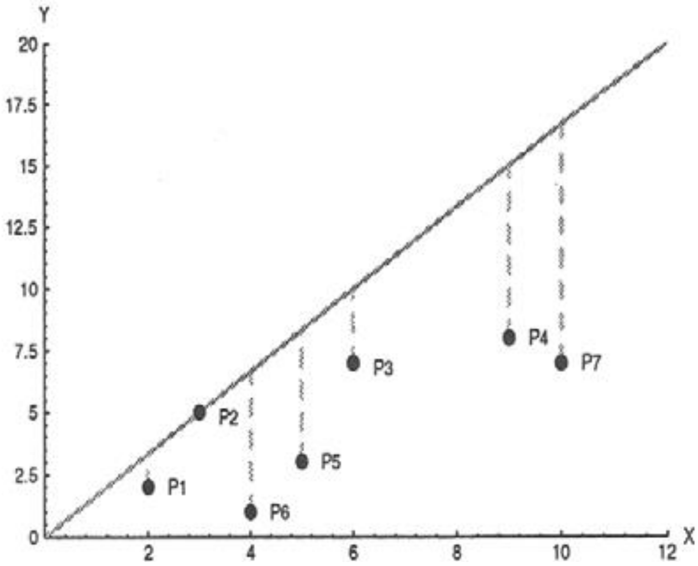


Figure 1.3（A. Charnes, W. Cooper, A. Lewin, L. Seiford）

This figure, however, shows an output oriented analysis. The measurement, this time, will be carried out on the vertical distance between the point representing the inefficient production and the efficient frontier. For point P"3:

$$E_{P''3} = \frac{y_{P3}}{y_{P''3}} = \frac{7}{10} = 0,7$$

It can be noticed that with models characterized by CRS the efficiency does not vary depending on the choice of one or the other orientation. The same thing, however, does not happen for models characterized by VRS. This difference is graphically shown in the figure below:

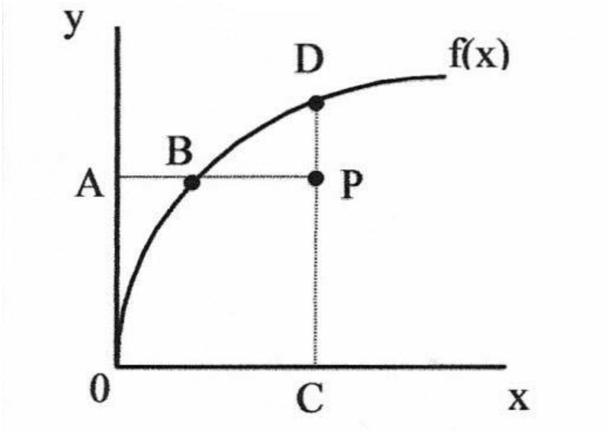


Figure 1.4 (T. Coelli)

1.5 The different DEA models

All DEA models are useful for assessing the efficiency of DMUs but their orientation and effort are focused on different concepts and assumptions. The analyst, before performing the analysis by the DEA model, must first choose the most appropriate model. This choice has to be weighted considering whether the formulation of the problem allows constant or variable returns to scale, and whether the problem is to maximize output, minimize inputs, or both.

Based on the above, the analyst will be able to choose one of the models shown below:

	Input	*Output*	*Both*
Constant Return to Scale	*CCR input*	*CCR output*	*Additive*
Variable Return to Scale	*BCC input*	*BCC output*	*Additive*

It is necessary to evaluate the performance of *n* DMUs consuming different resources to produce different goods or services. In general, DMUj consumes a quantity $X^j = \{x_i^j\}$ of input (i = 1, ..., *m*) and produces a quantity $Y^j = \{y_r^j\}$ of output (r = 1, ..., t), by convention, non-negative. The production possibilities set is reduced to:

$$T \equiv \{(x; y) \in \Re_+^{t+m} | \; x \; produce \; y\}$$

while the possible sets of input (L (y)) and output (P (x)) will be:

$$P(x) = \{y \in \Re_+^t | \; (x^T; y^T)^T \in T\}$$

$$L(x) = \{y \in \Re_+^m | \, (x^T; y^T)^T \in T\}$$

In particular, we assume the existence of an inverse relation between $L\ (y)\ e\ P\ (x)$: $x \in L\ (y) \Leftrightarrow y \in P\ (x)$ y and a production function F (x; y) such that:

$$T(P(x), P(y)) \equiv \{(x; y) \in \Re_+^{t+m} | \, F(x; y) \leq 0\}$$

For these constants, which generally take the form of observations, we assume that the output matrix (t × n) is denoted by Y, and the input matrix (m × n) is indicated by X.

Non-parametric DEA models are characterized by the presence of a set of hypotheses that the production set must satisfy:

(1) Convexity of the input production sets:

If for $y^o \in \Re_+^t, x^j \in L(y^o), e\ \lambda_j \geq 0\ e\ \sum_{j=1}^n \lambda_j = 1\ \forall j$

Then $\sum_{j=1}^n \lambda_j\, x^j \in L(y^o)$

(2) Convexity of the output production sets:

If for $x^o \in \Re_+^t, y^j \in P(x^o), e\ \lambda_j \geq 0\ e\ \sum_{j=1}^n \lambda_j = 1\ \forall j$

Then $\sum_{i=1}^n \lambda_i\, y^j \in P(x^o)$

(3) Convexity of the production set:

If $(y^j; x^j) \in T, e\ \lambda_j \geq 0\ e \sum_{j=1}^n \lambda_j = 1\ \forall j$

Then $\sum_{j=1}^n \lambda_j\, (y^j; x^j) \in T$

(4) Strong input availability:

If $(y^j; x^j) \in T, e\ x^* \geq x$

Then $(y; x^*) \in T$

(5) Strong output availability:

If $(y^j; x^j) \in T, e\ 0 \leq y^* \leq y$

Then $(y; x^*) \in T$

(6) Constant return to scale:

If $(y^j; x^j) \in T$

Then $(ky; kx) \in T, \forall k \geq 0$

(7) Belonging to the feasible region:

The osservation $(y_j; x_j) \in T, \forall J$

(8) Minimum extrapolation:

If a production set

T' fulfills (1), (2), (4)−(7) *or* (3)−(7),

Then $T' \subset T$

The 1st and 2nd hypotheses are included in 3rd hypothesis, but, even if satisfied, they do not imply the 3rd. The 6th hypothesis, as it shall be seen below, is a necessary condition for the CCR model, characterized by constant returns to scale. In addition, they only take DMUs:

• homogeneous in terms of industry, input and output;

• of which is intended to maximize outputs or minimize inputs.

1.5.1 The CCR model

This is the base model and its name comes from its creators, Charnes, Cooper and Rhodes in 1978. This model is characterized by:

• Constant Return to Scale (CRS);

• relative efficiency;

• is constrained by the fact that numeric data must be positive;

• all inputs and all outputs are traced to a single virtual input (expressed as the weighted sum of the inputs) and a single output (expressed as the weighted sum of the outputs).

The model, using linear programming (LP), will determine the weights of the various inputs and outputs that maximize the ratio

$$\frac{virtual\ output}{virtual\ input} = \frac{\sum_{j=1}^{J} v_j y_j}{\sum_{i=1}^{I} u_i x_i}$$

where *u* and *v* are, mutually, the optimal weights of inputs and outputs which vary according to the decision unit. This report also represents our objective function and it will be subject to the constraint that expected to be less than or equal to one. It also raises the constraint of the positivity of the weights. It will be possible, therefore, to have the following fractional programming model:

$$\max E_m = \frac{\sum_{j=1}^{J} v_{jm} y_{jm}}{\sum_{i=1}^{I} u_{im} x_{im}}$$

s.t.

$$\frac{\sum_{j=1}^{J} v_{jm} y_{jm}}{\sum_{i=1}^{I} u_{im} x_{im}} \leq 1 \quad j = 1,2, \dots, n$$

$$v_{jm}, u_{im} \quad i = 1,2, \dots, I; \;\; j = 1,2, \dots, J$$

This, however, is a fractional linear programming problem which, to be solved, must be converted into a PL problem. To bring the fractional form to the linear one, it is sufficient to normalize the denominator assigning it an arbitrary value equal, for example, to the unit. Therefore, the solution will be obtained by maximizing the numerator and including the constraint $\sum_{i=1}^{I} u_{im} x_{im} = 1$. .Then it will be obtained:

CCR INPUT ORIENTED MODEL

The Multiplier model

Matrix form:

$$\max v\, y_o$$

s.t.

$$u x_o = 1$$

$$vY - uX \leq 0$$

$$v, u \geq 0$$

Linear form:

$$\max H^0 = \sum_{r=1}^{t} v_r y_r^o$$

s.t.

$$\sum_{i=1}^{I} u_i x_i^o = 1$$

$$\sum_{r=1}^{t} v_r y_r^j - \sum_{i=1}^{m} u_i x_i^j \leq 0 \;\; \forall j$$

$$v_r, u_i \geq 0 \;\; \forall j, r$$

The Envelope model

Matrix form:

$$
\begin{gathered}
\min \theta \\
\text{s.t.} \\
\theta x_o - X\lambda \geq 0 \\
Y\lambda \geq y_o \\
\lambda > 0
\end{gathered}
$$

Linear form:

$$
\begin{gathered}
\min \theta \\
\text{s.t.} \\
\theta X^o - \sum_{j=1}^{n} \lambda_j X^j \geq 0 \\
\sum_{j=1}^{n} \lambda_j Y^j \geq Y^o \\
\lambda_j \geq 0 \ \forall J
\end{gathered}
$$

It could be possible also place vr, ui≥ε≥0, where ε is a positive infinitesimal amount imposed to avoid that a DMU clearly inefficient in the consumption of a certain xi can make "transparent" their inefficiency by assigning a zero weight to that factor.

A DMU will be efficient if and only if, at the same time, its efficiency is equal to the unit and all slack variables are equal to zero. Indeed, the presence of slack points out that the DMU is not Pareto-Koopmans efficient and it would therefore be possible to maintain the same level of production by reducing the resources employed.

The transition from the primary problem to its dual involves changing the number of variables and constraints to be met: the problem of multipliers will have as many variables as are the constraints, and so many constraints as are the variables of the envelope problem (being its dual). It has to be noted also that the duality of the issue of output oriented multipliers is nothing more than the problem of input oriented development (and *vice versa*).

CCR OUTPUT ORIENTED MODEL

The Multiplier model

Matrix form:

$$
\begin{gathered}
\min p\, x_o \\
\text{s.t.} \\
q y_o \ = 1 \\
qY - pX \leq 0 \\
p, q \geq 0
\end{gathered}
$$

Linear form:

$$
\begin{gathered}
\min\ q^o = \sum_{i=1}^{m} u_i x_j^o \\
\text{s.t.} \\
\sum_{r=1}^{t} v_r y_r = 1 \\
\sum_{i=1}^{m} u_i x_i^j - \sum_{r=1}^{t} v_r\, y_r^j \geq 0 \\
v_r, u_i \geq 0\,; \forall j, r
\end{gathered}
$$

The Envelope model

Matrix form:

$$\max \tau$$
$$\text{s.t.}$$
$$x_o - X\mu \geq 0$$
$$\tau y_o - Y\mu \leq 0$$
$$\mu \geq 0$$

Linear form:

$$\max \varphi$$
$$\text{s.t.}$$
$$\varphi Y^o - \sum_{j=1}^{n} \lambda_j Y^j \leq 0$$
$$\sum_{j=1}^{n} \lambda_j X^j \leq X^o$$
$$\lambda_j \geq 0 \; \forall J$$

The efficiency of each DMU, as mentioned above, is a relative efficiency, that is, it is evaluated compared to the other DMUs. Indeed, for the highest efficiency DMUs:

$$\sum_{i=1}^{I} u_{i0} x_{i0} = 1$$

while the others will have an efficiency between one and zero.

1.5.2 The BCC model

While the CCR model of 1978 assumes CRS, in reality often the opposite happens, and for the analysis it is necessary to know beforehand the scale with which used to operate the units to be analysed, or to know the input / output size at which inefficiency becomes a direct consequence of scale returns. The BCC model is characterized by variable return to scale and then it is taken into account the possibility that the production function can assume increasing or decreasing returns to scale.

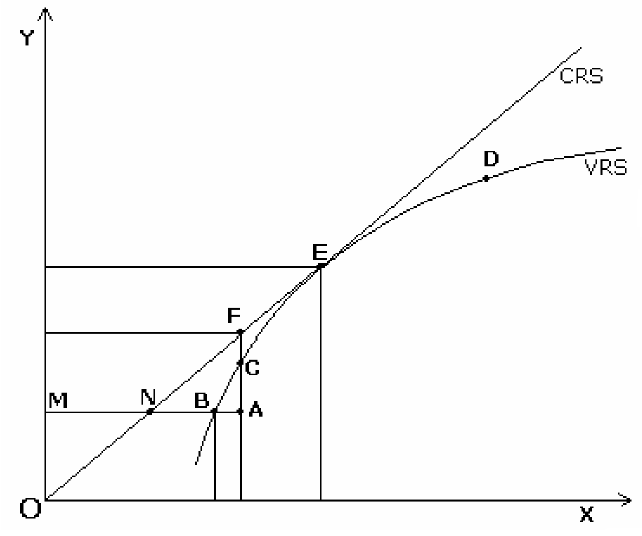


Figure 1.5 (S.C.Ray)

The figure above shows the trends of two efficient frontiers. The BED curve corresponds to a production function with VRS, while the straight line coincides with the efficient frontier if it is characterised by CRS. Looking at the graph, it can be said that the unit A does not belong to the production frontier (for the case of VRS and CRS). Similarly to the CCR model, unit A should be compared with point C in case of output orientation and, with point B, in the case of orientation to the inputs; Similarly to the CCR model, unit A should be compared with point C in case of output orientation and, with point B, in the case of orientation to the inputs; It can be measured then its efficiency:

- $E_I^A = \frac{x_B}{x_A}$, it is the pure technical efficiency of A input oriented;
- $E_O^A = \frac{y_C}{y_A}$, it is the pure technical efficiency of A output oriented.

Comparing the two models and the respective efficient frontiers it is noted that along the straight line with the average productivity CRS ($AP_j = {y_j}/{x_j}$ having only one input and one output) remains constant, while in the frontier with VRS varies at each point. The highest average productivity point along the VRS border is point E (CRS point tangency point) and it corresponds to what Banker called "most productive scale size (MPSS)." The average productivity of the MPSS is equal to the average productivity of the efficient CRS frontier. The overall (technical and scale) efficiency is obtained by comparing the same unit with E or N points (DMUs that reach the same average productivity as they belong to the CRS border). Using an orientation to the input it is obtained from the ratio ${x_N}/{x_A}$.

The efficiency of scale at each point belonging to the efficient frontier is equal to the ratio between the average productivity of that point and that of the MPSS. Therefore, the DMU A scale efficiency will be ${x_B}/{x_N}$ which is also the horizontal distance between the CRS and VRS borders.

Finally, it can be noted that the product between overall efficiency and scale efficiency is the pure technical efficiency:

$$\frac{x_N}{x_A} \times \frac{x_B}{x_N} = \frac{x_B}{x_A}$$

However, these concepts are not applicable in a more complex context, where numerous inputs and outputs are considered, given the impossibility of determining a common set of weights that can be accepted by all DMUs in the weighting of variables. It is therefore necessary to develop a model capable of assessing the "pure technical" efficiency share in a multi-input and multi-output situation so as to correct the error of the CCR model to attribute the technical inefficiency of the single DMU any disadvantages caused by economies of scale.

This model, called BCC, is similar to the CCR and it satisfies all the DEA hypotheses, but it has tighter constraints as the convex constraint (Σλ = 1) is inserted, which allows the variable return to scale.

The fractional programming problem is:

$$\max \frac{vy_o - v_o}{ux_o}$$

s.t.

$$\frac{vy_j - v_0}{ux_o} \leq 1 \quad j = 1, \dots, n$$

$$v, u \geq 0 \; v_0 \; libero$$

from which we get the linear programming models listed on the following pages.

BCC INPUT ORIENTED MODEL

The Multiplier problem

Matrix form:

$$\max_{v,u,v_0} z = vy_o - v_0$$

s.t.

$$vx_o = 1$$

$$vY - uX - ve \leq 0$$

$$v, u \geq 0 \; v_0 \; libero$$

Linear form:

$$\max \; H^0 = \sum_{r=1}^{t} v_r y_r^o + \mu^o$$

s.t.

$$\sum_{i=1}^{m} u_i x_i^o = 1$$

$$\sum_{r=1}^{t} v_r y_r^j - \sum_{i=1}^{m} u_i x_i^j + \mu \leq 0 \;\; \forall j$$

$$u_r, v_r \geq 0; \; \mu^o \; libero$$

The Envelope problem

Matrix form:

$$\text{BCC}-\text{I})\ \min_{\theta_B,\lambda} \theta_B$$
$$\text{s.t.}$$
$$\theta_B x_0 - X\lambda \geq 0$$
$$Y\lambda \geq y_o$$
$$e\lambda = 1$$
$$\lambda \geq 0$$

Linear form:

$$\min \theta$$
$$\text{s.t.}$$
$$\theta X^o - \sum_{j=1}^{n} \lambda_j X^j \geq 0\ \forall i, j$$
$$\sum_{j=1}^{n} \lambda_j Y^j \geq Y^o\ \forall j$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \geq 0;\ \theta\ libero$$

BCC OUTPUT ORIENTED MODEL

The Multiplier problem

Matrix form:

$$\min_{v,u,u_0} z = ux_o - u_0$$
$$\text{s.t.}$$
$$vy_o = 1$$
$$vY - uX - ve \leq 0$$
$$v, u \geq 0\ u_0\ libero$$

Linear form:

$$\min\ q^0 = \sum_{i=1}^{m} u_i x_i^o + \rho^o$$
$$\text{s.t.}$$
$$\sum_{r=1}^{t} u_r y_r^o = 1$$
$$\sum_{i=1}^{m} v_i x_i^j - \sum_{r=1}^{t} u_r y_r^j + \rho^o \geq 0\ \forall j$$
$$u_r, v_i \geq 0;\ \rho^o\ libero$$

The Envelope problem

Matrix form:

$$\max_{\eta_B,\lambda} \eta_B$$
$$\text{s.t.}$$
$$\eta_B y_0 - Y\lambda \leq 0$$
$$X\lambda \geq x_o$$
$$e\lambda = 1$$
$$\lambda \geq 0$$

Linear form:

$$\max \varphi$$
$$\text{s.t.}$$
$$\varphi Y^o - \sum_{j=1}^{n} \lambda_j Y^j \leq 0\ \forall j$$
$$\sum_{j=1}^{n} \lambda_j X^j - X^o \leq 0\ \forall j$$
$$\sum_{j=1}^{n} \lambda_j = 1$$

1.5.3 Returns to Scale

As already mentioned above the BCC model (but also the CCR model) is characterized by possible returns to scale. By this, it is meant the relationship existing between the variation of production input in a production unit and the variation of its output.

The returns to scale are defined as:

• Constants (CRSs): If an increase (decrease) in inputs follows a proportional increase (decrease) in output;

• Increasing (IRS): If an increase (decrease) in inputs follows an increase (decrease) of more than proportional output;

• Decreasing (DRS): If an increase (decrease) in the input follows an increase (decrease) less than proportional to the output.

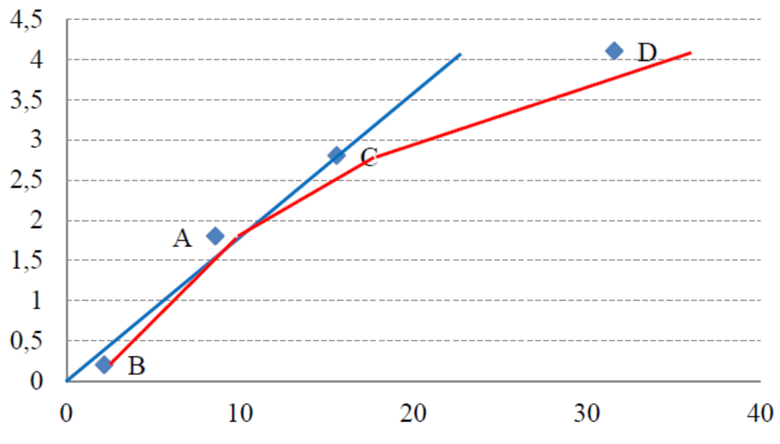


Figure 1.6. X: Cpital invested; Y: Added Value

Now let's look at the Figure representing a CRS frontier (in blue) and a VRS frontier (in red). A is the only one to be both efficient considering BCCs and CCRs and is MPSS since its average productivity coincides with average productivity according to the CCR model. Let's now look at the model solutions shown in the table below:

DMU	*Efficiency*	*λ*
A	1	1
B	0,434	0,256
C	0,858	1,814
D	0,620	3,674

Source: R.Ramanathan (2003)

It is possible to notice that λA, the only efficient one, is equal to the unit. Units operating at a lower magnitude of scale (for example B - λB <1) are characterized by increasing returns to scale while, conversely, the units C, D with larger λ unit are distinguished by decreasing returns to scale.

Referring to the envelope problem, it is possible to summarize thus:

- $\sum_{n=1}^{N} \lambda_n < 1$ Increasing return to scale (IRS);
- $\sum_{n=1}^{N} \lambda_n > 1$ Decreasing return to scale (DRS);
- $\sum_{n=1}^{N} \lambda_n = 1$ Constant return to scale (CRS).

However, with reference to the multipliers problem, it should be taken into account the value of u0 and v0, assuming that $(xo; yo)$ belongs to the efficient frontier, this point will be characterized by returns to scale:

- Increasing if and only if $u0 * or\ v0 * < 0$ for all the best solutions;
- Decreasing if and only if $u0 * or\ v0 * > 0$ for all the best solutions;
- Constant if and only if $u0 * or\ v0 * = 0$ for all the best solutions.

Consider now a "forcing" (R. Ramanathan) of the BCC model in which we put $\sum_{n=1}^{N} \lambda_n \leq 1$ instead of $\sum_{n=1}^{N} \lambda_n = 1$. If we put this constraint a unit (such as B) characterized by IRS will be considered efficient only if $\sum_{n=1}^{N} \lambda_n = 1$ is forced but with $\sum_{n=1}^{N} \lambda_n \leq 1$ this does not happen. Without a convex constraint the unit B will have the constraint $\sum_{n=1}^{N} \lambda_n < 1$. This is allowed by the condition $\sum_{n=1}^{N} \lambda_n \leq 1$, therefore, the unit will not be considered efficient. On the contrary, the units C, D, with $\sum_{n=1}^{N} \lambda_n > 1$ which is not allowed by the constraint, and they will be considered efficient because they will force the condition $\sum_{n=1}^{N} \lambda_n \leq 1$. Thus, units operating under the IRS will be considered inefficient while, units operating under DRS, will be evaluated efficiently. It will then be said that the model operates under non-incremental return to scale (NIRS).

Similarly, setting the contrary condition to the previous one, ie $\sum_{n=1}^{N} \lambda_n \geq 1$, the model will be characterised by non-decreasing returns to scale (NDRS). Therefore, unit B will become efficient while units C and D will be considered inefficient.

1.5.4 The Additive Model

In the Additive model, developed by Charnes et al. in 1985, unlike the previous ones, a DMU will be efficient if and only if the indexes of envelope and multipliers problems simultaneously take null value. It will be inefficient, however, when such values will be negative and slack variables (on inputs and outputs) will be positive. The efficiency frontiers will always be estimated by imposing the transition to efficient DMUs. A special feature of the Additive model is that there is no distinction between input oriented and output oriented. Indeed, both directions are considered simultaneously by adopting slack variables which, if positive, it indicates (graphically) the distance the inefficient unit must travel to reach both the frontier and the direction. In strategic terms this reveals the variation in the input / output quantities the inefficient unit must bring to its performance to make it efficient. The Additive model is also characterized by VRS as it is shown below.

THE ADDITIVE MODEL

The Multiplier problem

Matrix form:

$$\max_{u,v,v_0} z = vy_o - ux_0 + v$$

s.t.

$$vY - uX - ve \leq 0$$

$$v, u \geq 1;\ v_0\ libero$$

Linear form:

$$\max w^0 = \sum_{r=1}^{t} v_r y_r^o - \sum_{i=1}^{m} u_i x_i^o + \mu^o$$

s.t.

$$\sum_{r=1}^{t} v_r y_r^j - \sum_{i=1}^{m} u_i x_i^j + \mu^o$$

$$v_r, u_i \geq 1;\ \forall i, r, j$$

The Envelope problem

Matrix form:

$$\min_{\lambda,s,t} -s - t$$

s.t.

$$\lambda X - s = -x_o$$

$$\lambda Y - t = y_o$$

$$e\lambda = 1$$

$$\lambda, s, t \geq 0$$

Linear form:

$$\min Z^0 = -\left(\sum_{i=1}^{m} s_i + \sum_{r=1}^{t} s_r\right)$$

s.t.

$$-\sum_{j=1}^{n} \lambda_j X^j - s_i = -X^o$$

$$\sum_{j=1}^{n} \lambda_j Y^j - s_r = Y^o$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j, s_i, s_r \geq 0;\ \forall i, j, r$$

Conclusion

DEA advantages and disadvantages

As it has been possible to see so far, the DEA analysis, thanks to its flexibility, can be applied in different contexts and for different purposes.

It is possible to show some distinction between models and different contexts application on the efficient frontier. Unlike in the CCR model, which takes the form of a straight line allowing constant returns to scale, indeed, in the BCC model and in the Additive model the efficient frontier takes the form of a broken line that allows variable returns to scale.

Taking into consideration the purposes of the different models, instead, it is possible to point out that the three models are aimed at achieving three different goal. If the main goal is to reach an objective assessment of the overall efficiency it is necessary to apply the CCR model. The BCC model, instead, allows to distinguish the technical inefficiency from the scale efficiency differently from the Additive model which connects efficiency to Pareto-efficiency.

It could be sad that DEA analysis has some weaknesses that, if neglected, will alter the validity of the whole analysis. One of the main problem is the inability to give an absolute assessment of the single unit efficiency. It should be noted, indeed, that the efficiency value that is attributed to each DMU is relative therefore it depends on the efficiency of the other units that make up the sample, which involve, for example the inability of all units to be ineffective and the effortlessness of moving the efficient frontier. It is sufficient, indeed, that a unit produces more than the others in the sample so that it can be considered efficient and therefore it could be able to change the production frontier. Moreover, DEA can simultaneously handle multiple variables, each of which can be expressed in different and incongruous units of measurement, while still providing a single real number as a relative performance efficiency index. This process may give rise to errors in measurement, approximation, etc. Finally, DEA model need to have an higher number of decision-making units (at least three times) to the sum of inputs and outputs so that it can occur a significant difference between efficient and inefficient DMUs.

However, it should be pointed out that DEA presents some features which distinguish it from other analysis methods and could make it preferable compared to other techniques.

DEA allows to (A. Charnes, W. Cooper, A. Lewin, L. Seiford):

- Investigate individual observations and not on the media;

- Produce an aggregate efficiency measure for each DMU using productive factors as known variable (independent variables) and goods produced (dependent variables);
- Use a multiplicity of input and output factors, considering each measurement unit, even if different from each other;
- Incorporate dummy variables;
- Do not know input and output prices a priori;
- Evaluate the efficiency of homogeneous operating unit;
- Obtain objective values to which the inputs and outputs of the inefficient units are to be aimed;
- Identify the best combination of production factors;
- Get Pareto efficient solutions.

Regardless of the model type, indeed, all the DEA models produce a large set of concrete, relevant and useful results. Besides the efficiency score for each observed entity, for each inefficient entity it is possible to assign a potential performance target, in terms of inefficiency sources and amounts, proposed improvements in each of the inputs and outputs (resulting in efficient projection onto the frontier) or reference set (defined by the closest efficient units). These results provide policy-makers with information crucial for operating more efficiently in today's dynamic business environment, where competitive rivalry is increasing exponentially (Rabar, 2017). Therefore, the DEA model presented can be considered as a good tool for decision makers evaluating alternative policies and projects especially in case within the decision-making body there are conflicting perspective. The main advantage of DEA, indeed, is that it enables the decision maker to handle multiple criteria without relying on subjective judgments involved in the evaluation process. It also incorporates multiple incommensurate attributes, while allowing for measures of uncertainty.

2nd Paper

EFFICIENCY IN AIRPORT MANAGEMENT.
A MODEL ANALYSIS APPLIED TO ITALIAN AIRPORTS.

This paper aims to analyse the financial and operating efficiency of Italian airports, by applying a nonparametric frontier analysis to the airport industry. It seems interesting identify the best practices on national level in order to address any improvements to inefficient airports. It becomes even more important particularly in the current period in which there has been a privatization process of airport infrastructure in order to extract some policy considerations for increasing the efficiency of the services. The analysis was carried out on a sample of 34 Italian airports during the period 2006-2016 for which it has been collected data referred to the main input and output of the airport management companies along with financial information. The study was carried out through a DEA analysis (Data Envelopment Analysis), which allows to analyse the technical efficiency and performance of each individual Italian airport and then to point out the critical points of several airport operators through the identification of any best practices applicable to the relevant field and the distance between the latter and the remaining DMUs. Results obtained pointed out some interesting features of the Italian airports system especially on the effect of the overall technical, pure technical, and scale efficiency on airport efficiency. It was found not only that the dominant source of efficiency is the efficiency of scale but even that, in Italy, only a minority of airports appear inefficient from an operational point of view, which makes to conclude that overall Italians airports are well managed with regard to the pure technical efficiency. In other words, air transport privatization and deregulation can positively affect regional airport efficiency.

Keywords: Airport competition; Italian airports; data envelopment analysis; Efficiency

Introduction

Air transport market can be considered essential in the process of cultural, social and therefore economic globalization. It is also important to notice the derived character of transport: an increase in economic activity, industrial production and expanding trade relations will inevitably result in an ever-greater need for transport. A decrease of the same parameters will result in a decreasing demand for transport (Blauwens et.al., 2008, p. 291). In the European Union the air transport system currently plays a fundamental economic role. It had started to grow when the three *deregulation packages* became effective. Until that period the aviation market has been characterized by the supremacy of the domestic carriers, or *Flag carriers*, and bilateral agreements between nations. Over the years it has been felt the need of give back to the market the air transport sector, which up to that moment was considered over regulated and with an high incidence of public monopolies.

The deregulation process in Europe followed four steps (ELFA, 2004; Graham, 1998; Malighetti et al., 2008; Mawson, 1997) that led to a unique domestic market for the continent. The last step took place in 2008 when, thanks to the Regulation (EC) No. 1008/2008, reviewing the regulations of 1992, European Institutions have perfected the process of liberalization: EU routes it has become reserved "freely" to community air carriers. European States, indeed, from now on would have been obliged to accept the entry into their airspace to all "authorized" carriers.

This situation, clearly, 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). Airlines have become more *footloose*, having a greater freedom to choose where they fly to and from, and generally set fares, frequencies, capacities and routes according to commercial consideration (Koo et al., 2015). It was quite important in order to provide opportunity for airport to grow attracting new routes but also challenging the existing ones (around 2,500 new routes were opened in 2011; ATCONF 2013). One of the main result of the regulation process was the entrance and the development of *Low Cost Carriers* (LCCs).These new players have greatly stimulated a part of demand which was "neglected" by the great carriers: customers highly price sensitive and therefore willing to receive a low profile service ("no frills").Thanks to an unscrupulous pricing policy, indeed, these new operators have attracted millions of passengers. They have also developed a network called "point-to-point" indicating a connection of pairs of destinations and with an high frequency gain (thus maximizing the number of passengers boarded per way). In doing so LCCs were focused especially on secondary airport due to the lower level of airport charges, increasing the chance for competition among airports. It is important to notice that LCCs played an important role in the aviation market changing the traditional business relationship between airport and airline. The capability of LCCs to guarantee high level of passengers, indeed, created an asymmetry between airlines and airports, with more market power in the hand of the airlines (Barbot, 2006; Laurino and Beria 2014).

Turning to the airport industry, the sector in Europe was traditionally characterised by public sector ownership and national requirements (Graham, 2014). However, at the same time as Europe's internal air transport market was being liberalised, a number of governments in Europe began to transfer the ownership or operation of larger airports to the private sector. Many smaller airports in Europe are still publicly owned but the majority is now operated by corporatised entities. Transformations in the way that airports are owned and operated mean that, just as airline decisions are driven more by commercial considerations, so too are the decisions of airports (Koo et al., 2015). This context is quite interesting in order to examine the efficiency of the European Airports, especially the Italians one.

The transport sector has gained importance for economists taking into consideration that it deals with classical economic problems, such as externalities, economies of scale and sunk costs, among others (Fernandez et al., 2014).

This work aims to develop certain issue of the air transport sector, analysing the efficiency of Italian airports.

This research aims at investigating how certain factors impact the level of efficiency using Data Envelopment Analysis (DEA) method, scores of overall technical, pure technical, and scale efficiency, were estimated for Italian airports over the period 2006-2016.

The remainder of the paper is set out as follows: Literature review, Methodological consideration, Data, Results of DEA analysis, Performance analysis, Performance breakdown, Conclusion.

2.1 Literature

With airport privatization, globalization and increased competition have come business pressures that wakened interest both in performance benchmarking and encouraging airports to place more emphasis on quality (Graham, 2003). The airport industry is varied and heterogeneous with a high degree of quality differentiation, different ownership and regulatory structures, different mixes of services and operating characteristics, etc. (Buhalis and Costa, 2006; Graham, 2008). Assessing and comparing the performance of airports, hence, is an intricate issue. However, due to the increasing strategic significance of airport infrastructures in the movement of people and cargo (Barros and Dieke, 2007), the analysis of airports efficiency has become crucial because, as argued by Sarkis and Talluri (2000), it allows airlines to select the more efficient airports, municipalities to understand their capacity to attract business and tourists, and the governments to optimally allocate resources to airport improvement programs, rather than being subject to lobbies and political pressures. Therefore, measuring and benchmarking of airports has in the recent past seen an increased interest from practitioners, regulators and academics alike. Studies which can be used to assess the performance of the management of transportation infrastructure can be classified into two groups according to the technique applied. One refers to parametric methods such as stochastic frontier analysis (SFA) that measure efficiency through econometric techniques (Abrate and Erbetta, 2010; Assaf et al., 2012; Barros, 2008; Martin-Cejas, 2002; Oum et al., 2008; Scotti et al., 2012; Yoshida and Fujimoto, 2004; Yu et al., 2008). The other group comprises studies applying the non-parametric methodology called Data Envelopment Analysis (DEA)(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 Pacheco, 2002, 2003; Gitto and Mancuso, 2012; Wanke, 2012; Wanke, 2013). Other papers compare the DEA model with the SFA model (Pels et al., 2001, 2003). DEA measures the relative efficiency of decision making units on the basis of multiple inputs and outputs. The efficiency of a unit is defined as the weighted sum of its outputs divided by a weighted sum of its inputs. "*The weights for inputs and outputs are estimated by a linear programme so as to maximize the relative efficiency of each unit*" (Despotis, 2005). Farrel (1957) introduced the concept of *best practice frontier* which delineates the technological limits of what a country can achieve with a given level of resources. The distance from the frontier can be used as a performance indicator (Terzi and Pierini, 2015). DEA is a methodology directed to frontiers and proves particularly adept at uncovering relationships that remain hidden from other methodologies (Cooper et al. 2004). The initial DEA model was consolidated by Charnes, Cooper and Rhodes -CCR (1978). Charnes et al. (1978), in their seminal paper, describe the DEA methodology as a "mathematical programming model applied to observed data that provides a new way of obtaining empirical estimates of extremal relationships such as the production functions and/or efficiency production possibility surfaces that are the cornerstones of modern economics". Since then, numerous applications employing the DEA methodology have been presented and involve a wide area of contexts. DEA was designed to evaluate data management units (DMUs), which use multiple inputs to produce multiple outputs, without a clear identification of the relation between them, but then it has progressed throughout a variety of formulations and uses to other kind of industries. It was decided to use the DEA method because it can be applied to scenarios where the data cannot be strictly interpreted as inputs or outputs or there is no direct functional relationship between the variables. In the air transport sector, from the pioneer work of Gillen and Lall (1997), an exponential growth of studies applying DEA methods in the airport industry has emerged especially from 2008. Before 2003, only a small number of papers were published. On average, two papers were published yearly during the period 1997-2007, while in the last five years (2008-2014) the number of studies was more than doubled. Although fewer in number, the emergence of these studies suggests greater research interest in the air transport economics and management field. Among the most prominent papers in this scenario are: Martín and Roman (2001, 2007); Barros and Dieke (2007, 2008); Barros et al. (2012 and 2013); Curi et al. (2008, 2010, 2011); Morrison (2009); Yiu and Wing (2011); Yiu et al. (2008a and b); Yu (2004, 2010a and b). Lam et al. (2009) and Adler et al. (2013) offer recent literature reviews on DEA studies of airport efficiency. Up to 2007, few works have focused on European airports (Murillo-Melchor, 1999; Parker, 1999; Martín and Román, 2001; Martín-Cejas, 2002; Pels et al., 2001; Barros and Sampaio, 2004; Martín and Román, 2007). But Since 2008 to date it is possible to find some researches which have mainly covered Italian cases (Barros and Dieke, 2007, 2008; Curi et al., 2008, 2010, 2011; Gitto and Mancuso, 2012). As far as the Italian case is concerned, a number of DEA-based researches have appeared in recent years, but with mixed results. Malighetti et al. examined the efficiency and productivity variations of 34 Italian airports for the period 2005 e 2006. Low average efficiencies were found with evidence of improved performance among airports larger than 5 millions of passengers. Further, hub premiums and the privatization process have been considered as positive drivers of performance, while military activities and seasonality effects seem to operate as obstacles. The authors also studied business scale inefficiency, finding that Milano Malpensa and Roma Fiumicino work under decreasing returns to scale, while other airports with less than 5 millions of passengers operate with increasing returns to scale.

Barros and Dieke, through two different papers, analysed 31 Italian airports during the period 2001-2003. They introduced the Simar and Wilson methodology shown high values of efficiency, positively affected by drivers such as size, private management, as well as high levels of workload units (WLU). Results were different from those of Malighetti et al., Barros and Dieke which found that most airports in their sample operated under a constant returns to scale. Recent work by Curi et al., extend the results by Barros and Dieke and found low levels of efficiency among Italian airports, in line with results offered by Malighetti et al. Another paper of Curi et al. (2010) measured the efficiency of 18 Italian airports during the period 2000-2004, separating the efficiency related to ability to manage airside activities (operational) from that related to the management of all business activities (financial). They found that airport dimension does not allow for operational efficiency advantage but allow for financial efficiency advantage of hubs and disadvantages of smallest airports.

2.2 Methodology

The economic theory underlying efficiency analysis is based on Koopmans (1951), Debreu (1951), and Farrell (1957), who made the first efforts on measuring the efficiencies for a set of observed production units (Simar and Wilson, 2008). Inserted in this context, the DEA original model, introduced by Charnes et al. (1978), represents an improvement on those seminal works.

The Data Envelopment Analysis is also the basic method that will be used in order to assess the performance of transportation infrastructure management. Originally, the development of DEA aimed at solving problems that had been resistant to other approaches. This resistance was due to the complex (frequently unknown) nature of the relations among the multiple inputs and outputs involved in the activities (Cooper et al., 2007).

In DEA, the basic premise is homogeneity, that is, the DMUs must perform similar activities and produce comparable products and/or similar services, so that it can be set as a common range of products (Dyson et al., 2001).

Each DMU's score is individually optimized through mono-objective linear programming, comparing the resources used (inputs) and the quantities produced (outputs) to the levels of other units. The result is the construction of an efficient frontier. The DMUs lying on it are efficient (score of 100%), the other are inefficient (score of less than 100%).

Besides efficiency scores, the envelope formulation of DEA models provides targets and a reference set for the inefficient DMUs. The targets are the levels that the inputs and outputs of those inefficient units must achieve in order to be efficient. The reference set represents the efficient DMUs (benchmarks) used as references for good management practices. A linear combination of these benchmarks provides the targets for each inefficient DMU. Such targets are, in most cases, virtual, as they do not characterize a real efficient DMU.

Depending on the industry characteristic, there are different DEA models: input or output oriented or both. An input orientation focuses on proportional decrease of the input vector, the output orientation adjusts the proportional increase of the output vector and the output/input orientation does not discriminate the importance of possible increase of output or decrease of input. In the air transport sector, it fixes more suitable an output-oriented model. This choice is largely justified in literature since it is not possible to recover investments in infrastructure which normally are made well in advance. On the contrary the goal of the manager will be to expand as much as possible the demand and to use airport facilities as intensively as possible, since factors of production are fixed or semi-fixed. In terms of returns to scale model, there are three basic DEA models: variable returns to scale (VRS), constant returns to scale (CRS) and additive model. These can be used to seek which ones of then DMUs determine the frontier of the envelopment surface. Units that do not lie on the frontier are inefficient and the measurement of the grade of inefficiency is determined by the selection of the model. The paper will be focused on both Constant and Variable returns to scale (CCR and VRS) models, the study is thus able to analyse the financial and operating performance of Italian airports following, in both cases, an output-oriented approach.

A summary of the linear programming which underlies the output-orientated DEA models, with constant and variable returns to scale, is presented below. For the jth airport out of n airports, the output-orientated technical efficiency under constant return to scale (CRS) is obtained by solving the following linear programming problem (Coelli, 1996):

$$\underset{\theta_j^{CRS}\lambda}{Max}\,\theta_j^{CRS} subject\ to : \theta Y_j \leq Y\lambda; X_j \geq X\lambda; \lambda \geq 0 \qquad (1)$$

where X and Y are the input and output vectors, respectively, ΦCVS = 1/ ΦjCVS is the technical efficiency of airport j under CRS and λ is an n x 1 vector of weights. The non-negative weights λ measures the contribution of the efficient airports selected to define a point of reference for the inefficient jth airport. In general, 0 ≤ ΦjCRS ≤ 1, where ΦjCRS =1if the airport is producing on the production frontier and hence, technically efficient. When ΦjCRS < 1, the airport is technically inefficient.

In the case of variable returns to scale, one can find technical efficiency ΦjVRS under variable return to scale (VRS) by adding the convexity constraint ∑ λj = 1 to (1) (Banker et al., 1984).

2.3 Data

The data used in the DEA calculations represent a panel data of airports in Italy which differ in ownership, financing and operational characteristics. It regards a sample of all 34 Italian airports certified by ENAC - the Italian Civil Aviation Authority, over 10 years for the period 2006-2016. The selected period considers the very last deregulation step occurred with the Regulation (EC) No. 1008/2008, but it especially takes into account the revitalisation of air traffic after 2011 (attack on the twin towers) up to the present. It does not take into consideration 2017 period since for many airports it was not possible to find the relevant financial statements. The set is made of national and regional airports according to the classification of European Commission (2005).

Data were collected from ENAC airport annual statistics with regard those data strictly related to aeronautical activities (such as passengers served, aircraft movement etc.) and AIDA with reference to financial data information of airports management companies.

Table 2.1: variables and their sources

	Description	***Data Source:***	
		ENAC	**AIDA**
***Input*:**			
CL	Labour Costs (euro)	X	
CI	Invested capital (euro)	X	
CO	Other Expenses (euro)	X	
***Output*:**			
Mov	Number of aircraft movements		X
Pass	Number of passengers movement		X

Cargo	Tons of Cargo		X
AR	Revenues from aeronautical activities (euro)		X
HR	Revenues from handling activities (euro)		X
CR	Revenues from commercial activities (euro)		X

As can be seen from the explanatory table above, it could be briefly outlined that the source of the input data, as financial data, is AIDA while the source of the output data, being data related to aeronautical operations in the broad sense, is ENAC.

Going back to the airport characteristics, table 2.2 shows the current characteristics of Italian airports.

Table 2.2: Italian airports characteristics year 2016 (values are expressed in Italian numerical form)

N.	AIRPORTS	WLU (euro)	TURNOVER OF CAPITAL EMPLOYED (sales volume/invested capital)	STATE MANAGEMENT (100% public = 1; joint = 0)	PASSENGERS (n. Arrival)
1	Alghero	1.343.480	0,75	0	669.035
2	Ancona	540.922	0,10	0	236.607
3	Aosta	0	0	0	0
4	Bari; Brindisi; Foggia; Taranto*	6.709.335	0,16	0	3.291.615
5	Bergamo	12.235.828	0,54	0	3.098.844
6	Bologna	8.036.179	0,30	0	1.912.771
7	Bolzano	6.193	0,13	1	4.514
8	Cagliari	3.740.848	0,20	0	3.064.706
9	Catania	7.909.248	0,41	0	5.384.838
10	Comiso	459.235	0,26	-	394.396
11	Cuneo	131.526	0,31	0	94.031
12	Elba	9.548	0,13	0	4.502
13	Firenze; Pisa*	7.590.186	0,52	0	1.770.875
14	Genova	1.263.739	1,07	0	687.091
15	Grosseto	2.172	0,16	0	250

16	Lamezia Terme	2.525.898	0,76	0	2.035.288
17	Lampedusa	225.936	0,51	1	222.142
18	Milano Linate; Milano Malpensa*	34.589.106	0,46	0	7.591.537
19	Napoli	6.837.419	0,67	0	2.352.234
20	Olbia	2.250.668	0,44	0	1.346.747
21	Palermo	5.316.698	0,42	0	4.139.739
22	Pantelleria	140.687	0,92	0	139.922
23	Parma	190.307	0,07	0	129.538
24	Perugia	220.649	0,30	0	42.127
25	Pescara	566.972	0,23	1	254.520
26	Reggio Calabria	479.797	0,21	1	479.437
27	Roma Ciampino; Roma Fiumicino*	48.721.613	0,39	0	12.716.081
28	Salerno	7.005	0,08	1	1.332
29	Torino	3.953.762	0,52	0	1.998.985
30	Trapani	1.492.256	0,26	0	1.151.525
31	Treviso	2.605.273	0,58	0	779.350
32	Trieste	727.451	0,74	1	447.545
33	Venezia	10.039.835	0,23	0	1.303.949
34	Verona; Brescia*	2.851.388	0,32	0	889.158
Average		**5.109.446**	**0,39**	**-**	**1.724.566**
Median		**1.417.868**	**0,315**	**-**	**733.221**
Standard Deviation		**10.001.898**	**0,26**	**-**	**2.597.203**
* = Airports managed by one single company.					

From the table above it can be inferred that:

- About the workload units (WLU) and the total number of passengers, the standard deviation is higher than the mean, meaning that the sample is not very homogeneous. This is largely due to the presence in the sample of large airports beside those of small size, a characteristic resulting from the local population density;

- Having regard to the rate of change in invested capital it is possible to notice that the lowest ratios are those referring to small airports, most of which are managed by a capital company 100% public. The best results are recorded by the airports of Genova, which have a rate of change in invested capital greater than 1, and Pantelleria, Alghero, Lamezia Terme and Trieste which have a rate of change close to 1. It seems important to notice that those airports are mostly managed by partially privatized company. This shows that it could be expected a greater efficiency by privatized or partially privatized airport.

- In connection with the operational category, it is easy to notice that none of the listed airports is completely privatized. The majority of airports is characterized by a Joint Management system (public-private) whereas the remaining, mostly small airports, are totally public managed.

As already said in the previous section and in order to better understand the data used it must be pointed out that DEA measures the relative efficiency of decision making units on the basis of multiple inputs and outputs. To measure airport productivity, it has to be identified firstly the outputs that an airport produces and then the inputs used in producing those outputs. The most commonly used output measure for airports is the number of passengers served, as most airports serve mainly passenger traffic. Air cargo, however, is becoming increasingly important for many airports. Therefore, this research considers air cargo as a separate output. Passengers and cargo handling are usually considered as the outputs of airport landside operations (also considered as final outputs of an airport). Aircraft movements, on the other side, are considered as an output of airside operations generating revenues for airports in the form of landing and aircraft parking charges, although they are also an intermediate output meaning that they carry passengers and cargo which generate additional revenues in airports' landside operations. In addition to passenger traffic, cargo traffic and aircraft movements, airports revenues arise from concessions, car parking, and numerous other services. These services are not directly related to aeronautical activities in a traditional sense, but they are becoming increasingly more important for airports around the world. Thus, it is considered a fifth output which consists of revenues from commercial or non-aeronautical services.

On the input side, three general input categories have been considered: labour, which is measured by the number of employees who work directly for an airport operator; capital, which consists of various infrastructure and facilities. The other cost input is measured by all expenses not directly related to capital and personnel, and it is considered to reflect the extent of an airport's outsourcing activities. Its inclusion allows to take into account of the effects of airports' operation strategy with respects to outsourcing activities on production.

Briefly, for each airport we have information on five output variables: the number of passenger movements (APM), the ton of cargo and the yearly number of aircraft movements (ATM), revenues from aeronautical activities (AR), revenue from handling services (HR) and revenues from commercial activities (CR). In selecting the output variable section, it has been considered that the airport industry is a paradigmatic case of joint production (see Yoshida, 2004; Tovar et al., 2009; and Coto-Millan et al., 2014).

The input variables are classified according to the type of expenditures as follows: (1) labour cost, (2) capital invested, expressed by the book assets value and (3) other expenses, which includes expenses for the remaining variable inputs, according to Oum et al. (2003).

The chosen combination of indicators meets the various conventions DEA. Indeed, in the use of DEA methodology, there exists a direct correlation between the number of variables used (inputs and outputs) and the number of observations considered "efficient." As demonstrated by Seiford and Thrall (1990), a low ratio of observations to the number of inputs and outputs weakens the discriminatory power of DEA model. In this sense, given enough factors, most DMUs could be rated efficient. Liebert and Niemeier (2013) suggest that this should not be considered a flaw of the methodology but rather a direct result of the dimensionality of the input/output space (m inputs + s outputs), relative to the number of observations (n). In this case, too few inputs and outputs would reduce the capacity of the DEA extract the efficient airports.

With respect of the minimum set of data points in the evaluation set, there exist, in the DEA literature, various guidelines (Kumar and Gulati, 2008). The first states that the sample size should be greater than the product of the number of inputs and outputs. The second rule states that number of observation in the data set should be at least three times the sum of the number of input and output variables. The sample size used in the present study exceeds the desirable size as suggested by these rules to obtain sufficient discriminatory power.

Table 2.3 below shows the characteristics of the variables used in the analysis:

Table 2.3: characterisation of the variables (values are expressed in Italian numerical form)

	Description	**Minimum**	**Maximum**	**Average**	**Standard Deviation**
Input:					
CL	Labour Costs (euro)	6.381	182.971.000	15.514.250	30.310.452
CI	Invested capital (euro)	829.198	3.170.288.000	217.162.765	536.705.823
CO	Other Expenses (euro)	220.042	769.102.000	43.154.425	92.879.174
Output:					

Mov	Number of aircraft movements	8	392.246	43.390	76.917
Pass	Number of passengers movement	50	46.935.875	4.441.731	8.357.661
Cargo	Tons of Cargo	0	564.132	34.335	93.810
AR	Revenues from aeronautical activities (euro)	177.558	400.779.800	35.222.420	86.551.173
HR	Revenues from handling activities (euro)	118.372	267.186.533	23.481.613	57.700.782
CR	Revenues from commercial activities (euro)	59	28.181.155	3.792.186	6.458.595
					Source of ENAC and AIDA data

It may be observed that the Italian airport authorities are relatively heterogeneous, being the standard deviation higher than the average for all the considered variables.

2.4 Results

The results were obtained using the Open Source DEA software for processing the CCR and the BCC models, both following the ouput-oriented approach, assuming that airports aim to maximize the profits resulting from their activity. Adopting an output-oriented approach, indeed, it is possible to determine whether an airport is able to produce the same level of output with fewer inputs.

The DEA technique is used to measure the efficiency of the units belonging to the sample. However, it should be noted that this is a "relative" efficiency measure and therefore its value is referred only to the context in which the measurement occurred. Changing the characteristics of the test sample, i.e. by increasing the number of units, or by varying the analysis model (returns to scale, orientation of the model) it could be possible to obtain different efficient units, or different efficiency values. The methodology used allow the identification of the strengths and weaknesses of each DMU and, through a benchmarking analysis, the improvement targets. The relative performance of an airline is hence defined as the ratio of the weighted sum of its outputs to the weighted sum of its inputs. The weights are not predetermined, but rather allocated by the model, avoiding bias resulting from subjectively assigned weights. Generally, a DEA production frontier can be operationalised non-parametrically either with an input or output orientation, under the alternative assumptions of constant returns to scale (CRS) or variable returns to scale (VRS).

These values, which are identified on the basis of the units' efficiency levels, match the changes in the mix production and therefore the changes in the resources employment being the output equal or, *vice versa*, they match the variations in production levels being the input equal. Concretely, the target values are found as the sum of the original values, the slack and radial movements.

Additional information is represented by the "peer group", which is the set of units that are considered as reference models in technical efficiency for the inefficient unit. Usually, only those defined by DEA as eligible for this purpose are selected as peer groups, so the frequency in becoming a "peer unit" represents an indicator of good conduct: whether it is higher than the number of units of the analysed sample, it means that this unit is efficient not only according to its own weight system, but also with the one of the other DMUs. Conversely, in case of low frequency, the analysed unit cannot be considered a good example, being unusual. Normally it has been used to call "Mavericks" the efficient units which have a too much unusual behaviour, even if it cannot be excluded *a priori* that the "special" weight of such units is those capable of representing in a more indicative way the analysed productive economy. For this reason, the peer group analysis allows to distinguish the efficient units, which adopt a very balanced weight system, from those equally efficient but which are unattractive since they have adopted an unusual weights system.

2.4.1 Performance analysis

The DEA analysis was carried out using the constant returns to scale model (CCR) via an output-oriented approach, as it ensures accounting the objective of exploiting the facilities to satisfy the steady growth demand in the aviation market (Martìn and Romàn, 2001), maximizing sales volume and air traffic. With the constant returns to scale model it is possible to obtain the unit’s technical efficiency score which represent the capacity thereof to produce a certain amount of output, given a set of input. It was subsequently conducted an assessment of the breakdown of the efficiency measures in its three components: overall, pure technical and scale.

In the tables below, it is possible to find the inputs and outputs used in the sample analysis for each airport. Table 2.4 shows the average values of the input / output related to the 2006-2016 period. The latter value will be used for the DEA analysis.

Table 2.4 Average Data – Period 2006-2016

N.	AIRPORTS	CL	CI	CO	Mov	Pass	Cargo	AR	HR	CR
1	Alghero	8.025.864	36.052.732	13.677.810	12.866	1.443.013	2.226	9.613.708	6.409.138	6.473.765
2	Ancona	4.049.976	39.608.618	10.554.594	11.719	495.208	6.331	2.567.103	1.711.402	6.530.518
3	Aosta	1.094.952	9.722.395	2.056.300	147	1.863	0	1.160.011	773.340	282.409
4	Bari, Brindisi, Foggia, Taranto*	16.420.571	321.136.731	54.919.104	47.428	4.952.786	5.835	31.928.605	21.285.736	28.181.155

5	Bergamo	20.855.345	168.863.971	63.098.381	66.881	7.498.016	118.846	59.666.133	39.777.422	5.950.929
6	Bologna	19.155.505	204.834.129	40.858.309	61.337	5.580.005	28.973	45.083.791	30.055.861	1.640.828
7	Bolzano	1.294.115	24.026.015	3.912.906	2.193	47.190	0	2.768.064	1.845.375	1.085.631
8	Cagliari	5.698.746	131.131.392	27.463.390	31.878	3.334.477	3.729	5.641.924	3.761.282	113.338
9	Catania	12.842.151	127.452.805	33.661.739	56.603	6.449.803	7.721	34.367.013	22.911.342	2.465.137
10	Comiso	631.540	19.381.025	2.038.015	2.176	304.144	1			
11	Cuneo	1.208.104	8.462.489	4.727.013	1.871	166.680	686	2.772.736	1.848.490	815.392
12	Elba	352.581	3.355.756	597.399	764	12.211	0	349.462	232.975	569.368
13	Firenze, Pisa*	23.920.438	130.935.629	41.453.079	67.199	6.197.995	7.929	41.476.200	27.650.800	1.444.333
14	Genova	11.375.395	20.766.869	11.843.283	16.227	1.242.709	849	13.367.713	8.911.809	1.832.522
15	Grosseto	153.468	3.697.845	343.922	1.764	3.975	0	320.292	213.528	38.459
16	Lamezia Terme	10.501.380	28.881.847	10.473.308	16.364	1.976.029	1.750	13.414.410	8.942.940	1.165.734
17	Lampedusa	1.329.054	2.552.140	766.069	3.548	192.356	29	1.400.025	933.350	59
18	Milano Linate, Milano Malpensa*	147.076.237	1.492.519.434	292.537.314	286.070	28.453.800	467.073	345.320.721	230.213.814	22.333.333
19	Napoli	17.286.071	111.631.557	37.211.266	54.995	5.714.451	5.143	44.559.699	29.706.466	1.732.137
20	Olbia	10.829.469	50.440.841	15.045.089	19.964	1.901.930	452	16.784.081	11.189.387	3.503.293
21	Palermo	15.828.236	101.536.608	33.567.418	44.932	4.590.243	2.623	28.895.596	19.263.730	3.507.620
22	Pantelleria	883.887	1.759.243	743.175	3.965	139.359	57	941.855	627.903	3.982
23	Parma	1.270.366	24.531.039	5.367.039	3.732	205.617	158	1.067.534	711.689	349.086
24	Perugia	1.774.005	7.130.874	2.550.339	3.148	164.830	10	1.261.548	841.032	1.618.795
25	Pescara	2.418.650	25.141.532	7.798.159	6.265	482.548	1.566	4.610.930	3.073.953	2.257.978
26	Reggio Calabria	2.889.940	24.331.288	4.280.518	5.995	515.081	135	2.239.858	1.493.238	143.177
27	Roma Ciampino, Roma Fiumicino*	97.201.545	2.730.020.455	429.363.545	363.707	41.019.736	169.270	400.779.800	267.186.533	19.479.666
28	Salerno	1.189.313	3.190.573	1.606.269	978	7.713	0	177.558	118.372	38.413
29	Torino	12.315.576	134.879.749	37.571.120	42.486	3.475.463	1.639	6.447.551	4.298.367	1.999.882

30	Trapani	3.301.846	31.779.539	8.419.712	14.853	1.245.434	325	5.787.979	3.858.653	2.819.165
31	Treviso	5.106.233	37.278.326	14.540.126	14.792	1.926.415	5.797	12.140.877	8.093.918	737.758
32	Trieste	5.587.525	14.749.260	9.569.079	11.259	761.813	198	7.929.407	5.286.271	3.020.194
33	Venezia	22.076.250	418.140.375	53.564.125	78.398	7.747.417	28.738	65.964.400	43.976.266	6.293.333
34	Verona, Brescia*	10.517.572	120.563.482	35.169.083	33.646	3.103.782	18.732	21.392.893	14.261.928	3.807.184

The following table shows the efficiency results obtained by the application of output-oriented CCR model (for more details see paper 1, section 1.5.1) to the 34 analysed unit, with reference to the average for the 2006-2016 period:

Table 2.5: DEA CCR output-oriented results

N.	AIRPORTS	Objective Value
1	Alghero	1
2	Ancona	1
3	Aosta	0,52
4	Bari,Brindisi,Foggia,Taranto*	1
5	Bergamo	1
6	Bologna	0,94
7	Bolzano	0,85
8	Cagliari	1
9	Catania	1
10	Comiso	0,92
11	Cuneo	1
12	Elba	1
13	Firenze, Pisa*	0,86
14	Genova	1
15	Grosseto	1
16	LameziaTerme	1
17	Lampedusa	1
18	Milano Linate, Milano Malpensa*	1

19	Napoli	1
20	Olbia	0,97
21	Palermo	0,87
22	Pantelleria	1
23	Parma	0,47
24	Perugia	1
25	Pescara	0,94
26	Reggio Calabria	0,59
27	Roma Ciampino, Roma Fiumicino*	1
28	Salerno	0,19
29	Torino	0,67
30	Trapani	1
31	Treviso	1
32	Trieste	1
33	Venezia	1
34	Verona, Brescia*	0,78

The achieve results reveal the following:

- Value < 1, indicates that the unit is inefficient, as the input data, is unable to reach the maximum amount of deliverable output (for more details see paper 1, section 1.5.3). For each inefficient unit then the original values will differ from the target values. It is expected to achieve a slack which is the improvements needed in order to move spatially the inefficient unit to the efficient frontier. As explained in Paper 1, section 1.5.3, the sum of the original values and the slacks configure the target values to be achieved. Therefore there are 16 inefficient airports out of 34, namely: Aosta, Bologna, Bolzano, Comiso, Firenze/Pisa, Olbia, Palermo, Parma, Pescara, Reggio Calabria, Salerno, Torino, Verona/Brescia.

- Value = 1, reveal that the unit is efficient. This means that the original values of the input / output unit variables match the target values and there are no slacks. The peer group is in fact made by the unit. The efficient airports are the remaining airports of 34: Alghero, Ancona, Bari/Brindisi/Foggia/Taranto, Bergamo, Cagliari, Catania, Cuneo, Elba, Genova, Grosseto, Lamezia Terme, Lampedusa, Milano Linate/Milano Malpensa, Napoli, Pantelleria, Perugia, Roma Ciampino/Roma Fiumicino, Trapani, Treviso, Trieste, Venezia.

2.4.2 Performance breakdown

Table 2.6 shows the performance indicators breakdown in relation to the type of returns to scale (CRS, IRS or DRS) listed in the last column. The output-oriented CCR model, at constant returns to scale, allowed to measure the overall efficiency of each DMU while the pure technical efficiency is measured through a variable return to scale model (model output-oriented BBC). The ratio between the overall technical efficiency and that pure technique efficiency, however, measure the efficiency of scale:

Table 2.6: Performance breakdown (values are expressed in Italian numerical form)

N. (1)	**AIRPORTS** (2)	**Overall Efficiency CCR-O CRS model** (3)	**Pure Technical Efficiency BCC-O VRS model** (4)	**Efficiency of scale** (5)	**Returns to Scale** (6)
1	Alghero	1	1	1	CRS
2	Ancona	1	1	1	CRS
3	Aosta	0,52	0,52	1	DRS
4	Bari, Brindisi, Foggia,Taranto*	1	1	1	CRS
5	Bergamo	1	1	1	CRS
6	Bologna	0,94	1	0,94	IRS
7	Bolzano	0,85	0,75	1,13	DRS
8	Cagliari	1	1	1	CRS
9	Catania	1	1	1	CRS
10	Comiso	0,92	1	0,92	IRS
11	Cuneo	1	0,94	1,06	DRS
12	Elba	1	1	1	CRS
13	Firenze, Pisa*	0,86	1	0,86	DRS
14	Genova	1	1	1	CRS
15	Grosseto	1	1	1	CRS
16	LameziaTerme	1	1	1	CRS
17	Lampedusa	1	1	1	CRS
18	Milano Linate, Milano Malpensa*	1	1	1	CRS
19	Napoli	1	1	1	CRS
20	Olbia	0,97	1	0,97	IRS
21	Palermo	0,87	0,96	0,91	DRS
22	Pantelleria	1	1	1	CRS
23	Parma	0,47	0,46	1,02	DRS
24	Perugia	1	1	1	CRS
25	Pescara	0,94	0,72	1,31	IRS
26	Reggio Calabria	0,59	0,63	0,94	DRS
27	Roma Ciampino, Roma Fiumicino*	1	1	1	CRS
28	Salerno	0,19	0,21	0,92	DRS

29	Torino	0,67	0,77	0,86	DRS
30	Trapani	1	1	1	CRS
31	Treviso	1	1	1	CRS
32	Trieste	1	1	1	CRS
33	Venezia	1	1	1	CRS
34	Verona, Brescia*	0,78	0,75	1,03	DRS

CRS = Constant Return to Scale; DRS = Decreasing Return to Scale; IRS = Increasing Return to Scale.

The table above shows the results relating to the various airport operators, and it includes the efficiency values and the returns to scale classification. The third column represents the scores obtained by assuming constant returns to scale (CRS), obtained using the CCR model estimated for the output or CCR Output oriented model (CCR-O), which indicate the overall technical efficiency measure (see Paper 1, sections 1.5.1 and 1.5.2). The application of this model (DEA CCR-O) implies that the efficiency evaluation includes both the pure technical efficiency and the scale efficiency, accordingly, the DMU placed on the border (which assume, therefore, value 1) are fewer than those obtained taking into account the same set with the DEA BCC-O model. The efficiency scores obtained by DMU applying the VRS model are included in the fourth column and it reveals the pure technical efficiency, or managerial efficiency, which is not influenced by the firm's size. The efficiency of scale value (fifth column) can be easily obtained, as previously mentioned, through the ratio between the overall technical efficiency (CRS) and the pure technical efficiency (VRS), in other words dividing each value in column 3 for each value in column 4. The sixth column, finally, shows the type of "Returns to Scale" (Return to Scale) presented by the DMU which are estimated by comparing the variation of production input of a considered DMU and the variation of its output. The outcomes are able to show constant, increasing or decreasing Returns to Scale (see Paper 1, section 1.5.3).

The table points out the following:

- The CCR model results reveal that 20 out of 34 airports are efficient, while the remaining 14 are not;

- All technically efficient airports under the assumption of constant returns to scale (CRS) are technically efficient even under the assumption of variable returns to scale (VRS), which means that the dominant source of efficiency is the efficiency of scale. This is consistent with previous study of Barros and Dieke (2008);

- Based on BCC results concerning the pure technical efficiency due to management skills, 24 airports out of 34 are efficient over the timeframe involved. The rationale for explaining the BCC in terms of management skills is based on the contrast between the CCR and BCC models. The CCR model identifies the overall inefficiency, while the BCC model distinguishes between technical efficiency and scale efficiency (Gollani and Roll, 1989). On the basis of this differentiation, the relationship between CCR and BCC allows evaluating the efficiency of scale and, assuming that the efficiency is due to the management capacity and the scale efficiency, the BCC scores are explained as management capacity. As a result, according to BCC scores, only 10 airports are inefficient from an operational point of view;

- Considering the scale efficiency, 26 of 34 units analysed were efficient, while the remaining are not;

- The efficiency score has to be considered as an average value during the period and it suggests that approximately 71% of the analysed airports reveal pure technical efficiency, but some of them (4 units, 16.7%) do not point out efficiency of scale. Italians airports are so overall well managed, with regard to the pure technical efficiency, but the size make the difference and, therefore, some airports have decreasing returns to scale, while others have increasing returns to scale.

- Airports efficiency is not related to the geographic area. These results diverge from previous studies (D'Alfonso et al, 2015; Gitto and Mancuso, 2012) in which airports located in the Center and in the North used to present the best result in terms of efficiency and, on the contrary, those located in the south present the worst results.

- Finally, 4 airports exhibit increasing returns to scale (they are either small- and medium-sized), while 10 have decreasing returns to scale many of which are small-sized, differently from Malighetti et al. (2007) research in which the decreasing returns to scale was a prerogative of large airports. The units characterized by increasing returns to scale (IRS) may improve efficiency by increasing the productive dimension; conversely, units characterized by decreasing returns to scale (DRS) could gain in efficiency just by reducing the size of production. The units characterized by constant returns to scale (CRS) work, instead, in optimal production conditions and the size of their pure technical efficiency is equal to one, given the concurrence of overall efficiency and scale efficiency.

Conclusion

This paper raises a performance evaluation of the main Italian airport authorities, adopting the Data Envelopment Analysis model, a non-parametrical analysis, which allows to merge multiple input and output in determining the relative efficiency. The benchmark provides an overview of the efficiency level of the analysed airports, and it enables to make certain assumptions about the efficiency / inefficiency results.

It should be restated that the results obtained applying the DEA method for measuring the sampled units efficiency can be framed as "relative" efficiency therefore their value has to be considered only in respect of the context in which the measurement was made. Changing the characteristics of the test sample, for example by increasing the number of the units, or by varying the analysis model (returns to scale, orientation of the model) it may be obtained different efficient units, or different efficiency values.

In addition, it has also to be noted that in the analysed sample the airports managed by a single company have been considered as one single airport due to the fact that it was not possible to find the analytical balance sheet data of each individual airport.

Going back to the analysis results carried out, in general terms it is possible to point out that Italians airports reveal a relatively high management skill. The application of the BCC model, indeed, has given results equal to one for most of them and, since these results measure the pure technical efficiency, assuming that efficiency is due to the management and to the efficiency of scale capacity (measured by the ratio of CCR and BCC), the BCC scores are interpreted as managerial skills.

Based on the available information it is difficult to explain the managerial inefficiency causes for the remaining airports. Most of these companies are managed by a public-private joint venture, in total management regime. Even if several studies have stressed the importance of airports privatization for the sake of improving their efficiency e among others, Gillen (2011), Oum et al. (2008), Barros and Sampaio (2004), Martín and Roman (2001), in my opinion, according to the opinion of Scotti et al. (2012) and Parker (1999), this is grounds for suspecting that the opening towards the airports privatization is not the answer to ensure the expected efficiency improvement. It is also true, however, that the State presence in the airport management company is still strong and, therefore, it is still early to make a comparison between the management in public and private form. It will possible to see the results only by making a new performance analysis of airport infrastructure once the privatization process is completed.

Further research is needed to examine additional factor that may affect technical efficiency. These include the effect of the proportion of cargo traffic relative to total traffic, and the effect of external relevant factors: the size of airport and the presence of low-cost carriers airlines (LCCs).

3rd Paper

EFFICIENCY IN THE ITALIAN AIRPORTS MANAGEMENT. APPLYING A SECOND STAGE ANALYSIS.

Following the efficiency analysis of Italian airports, this paper aims at studying the effect of the cargo traffic proportion compared to total traffic. To this purpose a comparative technical efficiency analysis was already developed for 34 Italian airports over the period 2006-2016. In a second stage, using a Tobit regression, it is analysed the airport size presence, low-cost carrier presence and cargo traffic on efficiency.

Keywords: Airport competition; Italian airports; Tobit regression analysis; Efficiency.

Introduction

It is already known that air transport market can be considered essential in the process of cultural, social and therefore economic globalization. It is also important to notice the derived character of transport: an increase in economic activity, industrial production and expanding trade relations will inevitably result in an ever-greater need for transport. A decrease of the same parameters will result in a decreasing demand for transport (Blauwens et.al., 2008, p. 291).

In the European Union the air transport system currently plays a fundamental economic role. Two important phenomena have driven the development of air transport and consequently renewed the interest in studying airport management systems. The first was the liberalisation of the air transport market which had led to the expansion of air traffic and the entry within the market of the Low-cost carriers. The Second was the emergence of the new economy which is linked to the development of new information and communication technologies as well as globalisation, reinforcing the role of air transport in relation to the mobility of people and goods.

This situation, clearly, 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). As already sad in the previous paper, airlines had the freedom to choose according to commercial consideration (Koo et al., 2015), giving to airports the opportunity both to grow attracting new routes and to challenge the existing ones (around 2,500 new routes were opened in 2011; ATCONF 2013). The principal repercussion of the deregulation of the European air transport market was the entrance and the development of *Low Cost Carriers* (LCCs). These new players have greatly stimulated a part of demand which was "neglected" by the great carriers: customers highly price sensitive and therefore willing to receive a low-profile service ("no frills"). Many airports serving LCCs have experienced dramatic growth rates in passengers, but at the same time have had to respond and adapt to the characteristic volatile nature of such airlines (Graham, 2013). Indeed, they allowed to develop a network called "point-to-point" indicating a connection of pairs of destinations and with a high frequency gain (thus maximizing the number of passengers boarded per way). One obvious service differential was the airport served, since Low cost carriers started to use secondary airports located at some distance from the cities they purport to serve, due to the lower level of airport charges. This caused the increasing of the chance for competition among airports. Therefore, LCCs played an important role in the aviation market changing the traditional business relationship between airport and airline, forcing airports to modify their approach in negotiating with airlines. This is because the capability of LCCs to guarantee high level of passengers creates an asymmetry between the two partners, with more market power in the hands of the airlines (Barbot, 2006; Laurino and Beria 2014).

Although the air cargo industry was deregulated an year before the passage of the Airline Deregulation Act (November 9, 1977), its deregulation has not sparked nearly as much research interest as deregulation of the passenger airline industry. Some of the earliest works that address economies of density and scale in the air cargo industry are by Smith (1974) and Carron (1981).

Global air cargo traffic has grown by around 5% per year over the last three decades (BOEING, 2014; Kupfer et al., 2011a). Air cargo industry will continue to flourish in the wake of air transport liberalization (Wang and Heinonen, 2015), prospective long-haul low-cost carriers (Poret et al., 2015), and the implementation of the open skies agreement (Alves and Forte, 2015).

For decades, major airports around the world have predominantly served passenger markets (Mayer, 2016), and thus their operations and infrastructure were designed primarily to meet the needs of passengers. Such airports are also referred to as “gateway airports”. Most gateway airports (and airlines) serve passengers first, with their remaining capacity serving air cargo. This phenomenon can be attributed to the fact that the volume of air cargo is not sufficiently large to reach a critical mass. To a great extent, air cargo plays a complementary role for passengers, filling the excess capacity of aircraft.

This pace of growth instilled great concern in policy makers and airport planners. Wide studies have mostly been interested in assessing the impacts of increased air cargo traffic on the state’s economy and, more immediately, on capacity-constrained airports (TranSystems, 2010; Tsao, 1998; BAEF, 2000a, b; Erie et al., 2005).

This context is quite interesting in order to examine the efficiency of European Airports, especially the Italians one. The transport sector has gained importance for economists taking into consideration that it deals with classical economic problems, such as externalities, economies of scale and sunk costs, among others (Fernandez et al., 2014).

This work aims to develop certain issue of the air transport sector. First, by analysing the efficiency of Italian airports, taking into account the impact of cargo traffic on airport's efficiency; and second by valuating the effects on airports efficiency of other relevant external factor, such as the size of the airport and the presence of low-cost carriers (LCCs).

Moreover it will be investigated how external factors impact the level of efficiency, applying two stage procedure: on the first stage, using Data Envelopment Analysis (DEA) method, scores of overall technical, pure technical, and scale efficiency, were estimated for Italian airports over the period 2006-2016; on the second stage, it was regressed the efficiency scores obtained during the first stage, on three explanatory variable: airport size, the share of LCC passenger and the share of cargo traffic. In order to proceed with the regression, it was used the Tobit model.

3.1 Literature review

Differently to previous papers regarding Italian airports, this work will consider the effect of cargo traffic on airports' efficiency, which are expected to have higher variable factor productivity scores, because "handling cargo is capital intensive and therefore more productive than handling passengers" (Oum et al. 2006). Furthermore, this work considers also, only at a later stage, the effect of external relevant factors: the size of airport and the presence of low-cost carriers airlines (LCCs).

The performance of economic producers, indeed, is often affected by external or environmental factors which may affect 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. These factors can be included in the model as exogenous variables and can help explaining the efficiency differentials, as well as improving policy.

In order to explore the influence of exogenous factors in the airport's efficiency, as mentioned above, it will be employed a two-stage procedure. On the first stage, as for the first paper, the Italian airports technical efficiency it was already analysed using DEA, taking into account the period 2006-2016. On the second stage a second regression analysis it has been carried out.

The efficiency estimated from the first stage is regressed on environmental factors which are considered to be outside the control of airport managers. Previous research shows that airport characteristics such as hub status or traffic structure, outsourcing policies, regulatory procedures and ownership structure all may contribute to airport efficiency (Gillen and Lall, 1997; Oum et al., 2006). Banker and Natarajan (2008) demonstrated that two-stage procedures in which DEA is applied in the first stage and regression analysis in the second stage provide consistent estimators and outperform parametric one- or two-stage applications. In previous airport studies it has been employed simple ordinary least squares (Yuen and Zhang, 2009), Tobit regression (e.g. Gillen and Lall, 1997) and truncated regression (Barros, 2008) for this purpose. A recent debate in the literature discusses the most appropriate second stage regression model to be applied when investigating DEA efficiency estimates. While Simar and Wilson (2007) argued that truncated regression, combined with bootstrapping as a re-sampling technique, best overcomes the unknown serial correlation complicating the two-stage analysis; Banker and Natarajan (2008) concluded that simple ordinary least squares, maximum likelihood estimation or Tobit regression dominate other alternatives since outperform the other parametric methods. In the same way, Hoff (2007), after comparing different approaches to modelling DEA efficiency scores against exogenous variables in second stage DEA, concluded that the Tobit approach is the best option for second-stage estimation.

According to Liebert and Niemeier (2013), the majority of DEA studies utilize a second-stage regression where the first-stage DEA efficiency estimates are regressed against a set of explanatory variables in order to evaluate their significance. Among those who have used tobit at second stage it is possible to include Bjurek et al. (1992), Oum and Yu (1994), Chilingerian (1995), Ruggiero and Vitaliano (1999), Fethi et al. (2002), Vestergaard et al. (2002), Latruffe et al. (2004), and Bravo-Ureta et al. (2007). Moreover, they concluded that an advantage of second-stage approaches is that environmental variables are not included in the DEA model, hence not affecting the discriminatory power of the first-stage approaches.

Taking into consideration that all efficiency scores obtained on the first-stage are defined to lie between zero and one, the dependent variable is a limited variable. Therefore, this study in the second stage uses the Tobit regression model (Tobin, 1958), which is a nonlinear model that provides consistent estimators. It is estimated through maximum-likelihood techniques.

The Tobit regression model, as second stage analysis of DEA efficiencies, has been widely used in the transport literature. In the airport literature, the works of Gillen and Lall (1997); Abbott and Wu (2002); Yoshida and Fujimoto (2004); and Chi-Lok and Zhang (2009) provide examples of two-stage estimation using Tobit regressions.

3.2 How to improve DEA using a Tobit regression model

The Tobit model is a statistical model proposed by Tobin (1958), also called censored regression model, because the latent variable cannot always be observed while the independent variable is observable.

The Tobit regression is an alternative to ordinary least squares regression (OLS) and is employed when the dependent variable is bounded from below or above or both, with positive probability pileup at the interval ends, either by being censored or by being corner solutions (Wooldridge, 2002). In the former case (censored) observations outside the limiting interval are recorded as the border values. That is if the range is given by the interval [a;b], observed y < a is recorded as y = a, and likewise observed y > b is recorded as y = b. In the latter case (corner solutions) the observations are by nature limited from below or above or both with a positive probability at the 'corners'(interval ends). The possible determinants of the efficiency are investigated using a random effect Tobit model. A random effects model assumed that the unobservable effects are uncorrelated with the observed exploratory variables, whereas a fixed effect model assumes that they are correlated. DEA scores are limited to the interval]0; 1] and accordingly only has a positive probability to attain one of the two corner values. An introductory approach may however be to use an ordinary least squares (OLS) linear regression of the scores against the exogenous variables, as this represents a first order Taylor approximation to the more complex non-linear models. The OLS model will clearly predict scores outside the interval]0; 1] but in those cases in which the effects (the regression parameters) predicted by this model do not differ significantly from the effects predicted from non-linear models, OLS may be considered adequate for modelling these effects.

Despite the advantages to blending nonparametric DEA with censored regression models in practice, some conceptual problems arise. The main difficulty of using Tobit to regress efficiency scores is that DEA does not exactly fit the theory of a censored distribution. The theory of a censored distribution argues that due to an underlying stochastic choice mechanism or due to a defect in the sample data there are values above (or below) a threshold that are not observed for some observations (Maddala, 1983): DEA produces a concentration of ones due to the mathematical formulation of the model. A second difficulty of using Tobit is that it opens up the possibility of rank ordering superior efficiency among physicians on the frontier – or 'hypothetical' scores > 1. In production economics, the idea that some DMUs with DEA scores of 1 may possibly have scores > 1 makes no sense. It suggests that some candidates for technical efficiency (perhaps due to random changes such as luck, or measurement error) are actually less efficient. Despite these drawbacks, mixing DEA with Tobit model estimates can be informative. Although DEA does not fit the theory of a censored regression, it definitely fits the Tobit model and makes use of the properties of a censored regression in practice. For example, the output can be used to adjust efficiency scores based on factors strongly associated with efficiency. Tobit may have the potential to improve a DEA analysis when expert information on input prices or exemplary DMUs are not available. Thus, in a complex area like airports competition, Tobit could help researchers to understand the need to introduce boundary conditions for the DEA model's virtual multipliers.

Tobit model has been used, indeed, in a large number of application where the dependent variable is observed to be zero for some individuals in the sample. This model, which assumed that the dependent variables are observed to be a limiting value (above or below some cut level), was subsequently extended by Rosset and Forest (1975) in order to provide for cases in which the dependent variable in a regression is subject to both an upper and a lower limit. The model can be expresses as follow:

$$\begin{aligned} Y_t^* &= \beta X_t + \varepsilon_t ; \mathrm{t} = 1, 2 \ldots \mathrm{N} \\ Y_t &= Y_t^* if 0 \leq Y_t^* \leq 1 \\ Y_t &= 0 \text{ if } Y_t^* \leq 0 \\ Y_t &= 1 \text{ if } Y_t^* \geq 1 \end{aligned} \qquad (1)$$

Where N is the number of observation, y* is an unobserved latent variable, Yt is the dependent variable (DEA scores), Xt is a vector of independent variables, is a vector of unknown coefficients and εt is an independently distributed error term, assumed to be normal with zero mean and constant variance σ2. Thus, the model assumes that there is an underlying, stochastic index that is observed only when it bound) a threshold that are not observed for some observations (Maddala, 1983).

As it is possible to see from the model, an important feature of it is the explanatory variable Xt which takes the actual observations as explained variables. Yi can only be observed by restricted manner: when Yi *≥ 0, the limit values were observed to take the actual observations; when Yi *≤ 0, the limited observations are interception to 0. So, the Tobit regression model is one of the constrained model explanatory variables (Limited Dependent Variable). It can be shown that the β and σ of the Tobit regression model that calculated by using the maximum likelihood estimate is the same estimate value.

Tobit regression can be applied in order to identify the important impact of airport productivity factors and to distinguish which factors are more significant and how those factors are able to influence airports efficiency. It could be quite useful since airports manager could to pay more attention to these factors in the future course of business activities that ultimately improve the efficiency of the airport themselves.

In this paper, Tobit regression model as an analytical tool, select the 34 airports samples for the study. The first stage efficiency value is interpreted as a variable, a number of other important factors which may affect the production efficiency (the number of Work Load Units the percentage of passengers handled by low-cost carriers and the percentage of cargo traffic) as the explanatory variables, so it can be possible to investigate the relationship between these factors and technical efficiency, overall efficiency and scale efficiency scores. In the Tobit regression model, it is supposed that regression coefficient is independent of time, the greater the value of technical efficiency, the more efficient airport, so when the regression coefficient is positive, there is a positive correlation between the explanatory variables and the technical efficiency. The greater the value of explanatory variables, the more they affect the technical efficiency.

Only after an international literature review it was possible to choose the explanatory variables in the present explanatory model of the sources of efficiency. In particular, Pels et al. (2003) stated that airport size is an important factor in determining the operational performance of airports. The WLU (or work load unit), indeed, is considered a common measure in aviation management (Graham, 2005; Jessop, 2003), aggregating passengers and freight in the following form: 1 WLU = 1 passenger = 100 kg of freight. It aims to capture demand effects on efficiency (Barros and Dieke, 2007; Martin et al 2009; Mayer 2016). Whereas, there is a limited amount of literature on the effect of LCCs on airport efficiency. Only Botasso et al (2012), Choo and Oum (2013) and Coto-Millán et al (2014) analysed LCCs passenger behaviour obtaining conflicting results. Finally, since the airport industry is an example of joint production, it has to be considered as explanatory variable not only the number of passengers and the number of aircraft movements, but even the amount of cargo (Yoshida, 2004; Tovar and Rendeiro Martín-Cejas, 2009). According to Tovar and Rendeiro Martín-Cejas (2009) and Chi-Lok and Zhang (2009), the importance of cargo traffic has increased over the years and its handling differs from that of passengers. The choice of cargo traffic is consistent also 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.

Therefore, airport size, the share of LCC passengers, and the share of cargo traffic were considered as independent variables.

The relationship between production efficiency and the contextual variables examined can be expressed as follows:

$$yi = 0 + \beta 1sizei + \beta 2lcci + \beta 3cargoi + \varepsilon i \qquad (2)$$

where yi represents overall technical efficiency scores, pure technical efficiency scores, and scale efficiency scores, respectively. The three environmental variables for each airport are measured in terms of: (1) the number of Work Load Units or WLU (size); (2) the percentage of passengers handled by low-cost carriers (lcc); and (3) the percentage of cargo traffic relative to total WLUs (cargo).

The table below summarizes characteristics and sources of the variables mentioned so far.

Table 3.1: characterisation of the variables

Description		***Data Source:***	
		DEA Analysis	**ENAC**
Dependent Variables:			
Overall Efficiency CCR-O CRS model		X	
Pure Technical Efficiency BCC-O VRS model		X	
Efficiency of scale		X	
Independent Variable:			
Size	Work Load Unit		X
Low Cost Carriers	Percentage of passengers handled by low-cost carriers		X
Cargo traffic	Percentage of cargo traffic relative to total WLUs		X

3.3 Results of regression analysis

In the previous research, DEA analysis was adopted in order to compute the overall technical efficiency, pure efficiency and the magnitude of scale. The table below reports the three types of efficiency, ranking airports according to overall efficiency based on an output model.

Table 3.2: Performance Breakdown (values are expressed in Italian numerical form)

AIRPORTS	**Overall Efficiency CCR-O CRS model**	**Pure Technical Efficiency BCC-O VRS model**	**Efficiency of scale**
Alghero	1	1	1
Ancona	1	1	1

Aosta	0,52	0,52	1
Bari, Brindisi, Foggia,Taranto*	1	1	1
Bergamo	1	1	1
Bologna	0,94	1	0,94
Bolzano	0,85	0,75	1,13
Cagliari	1	1	1
Catania	1	1	1
Comiso	0,92	1	0,92
Cuneo	1	0,94	1,06
Elba	1	1	1
Firenze, Pisa*	0,86	1	0,86
Genova	1	1	1
Grosseto	1	1	1
LameziaTerme	1	1	1
Lampedusa	1	1	1
Milano Linate, Milano Malpensa*	1	1	1
Napoli	1	1	1
Olbia	0,97	1	0,97
Palermo	0,87	0,96	0,91
Pantelleria	1	1	1
Parma	0,47	0,46	1,03
Perugia	1	1	1
Pescara	0,94	0,72	1,31
Reggio Calabria	0,59	0,63	0,94
Roma Ciampino, Roma Fiumicino*	1	1	1
Salerno	0,19	0,21	0,92
Torino	0,67	0,77	0,86
Trapani	1	1	1
Treviso	1	1	1
Trieste	1	1	1
Venezia	1	1	1
Verona, Brescia*	0,78	0,75	1,03

From the table, it is possible to notice that the highest level of technical efficiency is reached for the airports of Alghero, Ancona, Bari/Brindisi/Foggia/Taranto, Bergamo, Cagliari, Catania, Cuneo, Elba, Genova, Grosseto, Lamezia Terme, Lampedusa, Milano Linate/Milano Malpensa, Napoli, Pantelleria, Perugia, Roma Ciampino/Roma Fiumicino, Trapani, Treviso, Trieste, Venezia. Taking into consideration the pure technical efficiency score, 24 of 34 airports under analysis reach the maximum level of pure efficiency (1.0) and the average score is high showing that Italian airports are generally achieving optimum in relation to their operating scale.

The following table, instead, show the data regarding Italian airports on 2016.

Table 3.3: *Italian airports characteristics year 2016 (values are expressed in Italian numerical form)*

AIRPORTS	Work Load Unit	Low Cost Passengers	%LCCs	Tons of Cargo	% Cargo
Alghero	1.343.480	715.755	53,3	10	-15,5
Ancona	540.922	258.319	54,2	6.074	-9,5
Aosta	0	0	0	0	0
Bari, Brindisi, Foggia,Taranto*	6.709.335	3.025.742	70,2	7.572	0,11
Bergamo	12.235.828	10.357.211	93,7	117.659	-2,7
Bologna	8.036.719	4.452.574	58,1	37.471	21,5
Bolzano	6.193	0	0	0	0
Cagliari	3.740.848	1.812.512	48,9	3.000	-7,4
Catania	7.909.248	4.858.537	62,1	6.367	2,5
Comiso	459.235	412.517	89,9	1	0
Cuneo	131.526	92.423	71	0	0
Elba	9.548	0	0	0	0
Firenze, Pisa*	7.590.186	4.986.714	30,6	9.986	0,13
Genova	1.263.739	447.848	35,5	207	-24
Grosseto	2.172	0	0	0	0
LameziaTerme	2.525.898	1.655.649	65,9	1.182	-15,9
Lampedusa	225.936	29.584	13,2	14	-16,3
Milano Linate, Milano Malpensa*	34.589.106	9.933.400	52,24	564.132	1,91
Napoli	6.837.419	3.506.558	51,9	8.378	-1
Olbia	2.520.668	1.165.137	46,3	173	-29,9
Palermo	5.316.698	3.497.778	65,9	407	-65,7
Pantelleria	140.687	23.354	16,7	27	-21,3
Parma	190.307	167.115	88,7	0	0
Perugia	220.649	172.776	79,1	0	0
Pescara	566.972	476.934	86	16	-51,4
Reggio Calabria	479.797	2.552	0,5	36	-31,6
Roma Ciampino, Roma Fiumicino*	48.721.613	16.233.449	52,87	176.659	0,37
Salerno	7.005	118	4	0	0
Torino	3.953.762	2.028.565	51,5	1.528	29,7
Trapani	1.492.256	1.441.041	96,6	23	-9,3
Treviso	2.605.273	2.585.705	99,3	1	316,8
Trieste	727.451	253.387	35	62	-31,1
Venezia	10.039.835	3.730.428	39,1	49.024	14,9

Verona, Brescia*	2.851.388	1.096.416	65,78	8.841	0,31

In the table below, the findings suggest a positive association between overall technical efficiency and the proportion of cargo traffic and Low-cost carriers.

Table 3.4: Tobit outcomes

Explanatory factor	Overall technical efficiency (Costant Return to Scale)	Pure technical efficiency (Variable Return to Scale)	Scale efficiency (economies of scale)
	Marginal effect (t-statistic)	Marginal effect (t-statistic)	Marginal effect (t-statistic)
Size	0,97***	1,24**	0,76***
Low -cost carriers	1,88**	1,83**	0,62***
Cargo traffic	0,34***	0,03***	0,87***
LR chi2 (3)	6.32	6.94	6.26
Prob >chi2	0.9314	0.0740	0,983

*The reported coefficients measure marginal effects. *** Significant at the 1% level; ** Significant at the 5% level.*

The table above displays the estimation of the three regression models for the sample of 34 airports with scores for overall technical efficiency scores, pure technical efficiency, and scale efficiency as dependent variable for models. The Likelihood Ratio Test indicates that in all three cases, the variables included in the model have a statistically significant effect on the dependent variable. Parameters with a positive sign reveal a positive influence of the corresponding explanatory variable on the dependent variable.

Considering all three models, it is possible to notice that the fist explanatory variable (airport size) turns to be significant, with a positive coefficient. This shows that larger airports are expected to have higher overall technical efficiency, pure technical efficiency, and scale efficiency scores compared to smaller airports. These results are in line with previous similar research. Malighetti et al (2007), applying a DEA model to a sample of 34 Italian airports, founded that efficiency is related to airports size. Perelman and Serebrisky (2012), applying DEA analysis model for Latin American airports, conclude that larger airports have higher technical efficiency than smaller ones. Similarly, Murillo-Melchor (1999), Salazar (1999), Martin and Roman (2001), Martín et al. (2009), and Coto-Millan et al. (2014), achieved that larger airports are significantly more efficient. Pels et al. (2003) applied the DEA and stochastic frontier models in order to analyse the technical efficiency of European airports confirming that larger airports are more efficient than smaller ones. It is not only the economies of scale in airport operations which could explain these phenomenon (Murillo-Melchor, 1999);

larger airports are also more efficient than smaller airports under variable returns to scale.

It has also to be noted that even the presence of low-cost carriers (LCC) is positively associated with technical efficiency, pure efficiency and scale overall efficiency (scale efficiency). The introduction of LCCs generated a substantial growth in demand for Italian airports, especially taking into consideration small and medium in size, where they operate under increasing returns to scale, which turns on improved overall efficiency (see Coto-Millan et al., 2014). Even Cavaignac and Petiot (2017), following a bibliometric analysis of articles applying DEA to the transport sectors, concluded that LCCs increase airports efficiency. Even if there is a very limited amount of literature on the effects of LCCs on airport operations and performance, the results obtained are in line with those obtained by Bottasso et al. (2012) who, taking into consideration British airports, concluded that LCCs entry on European markets has stimulated airports productivity improvements and then it positively affects the total factor productivity. They are also in line with results obtained by and Coto-Millan et al. (2014) who concluded that the share of LCC passengers has a positive effect on the efficiency of Spanish airports. Having regard to the Italian airport systems, instead it is possible to find just a single research which analyses the relationship between low cost carriers and three Italian secondary airports (Aeroporti di Puglia, Alghero and Emilia-Romagna airports), resulting from the deregulation process (Laurino and Beria 2014). The results obtained in that paper confirm the significant influence exerted by LCCs especially on smaller airports which have generally a single dominant carrier (the Low-Cost Carrier), making them more vulnerable to airline switching to other airports. So, they do not negotiate with the same frequency and do not have the same quality of information about the terms the carriers can obtain elsewhere. This fact determines an asymmetry of information that strongly penalizes airports.

Taking into consideration the cargo traffic, instead, the analysis reveals that cargo is significant with a positive coefficient. It means that airports with a higher proportion of cargo traffic establish higher overall technical efficiency, scale efficiency and pure efficiency. Once more, this confirms the evidence of previous works (none of them pertaining to Italian airports system), for which airports with a large proportion of cargo traffic are expected to disclose a higher variable factor productivity, since handling cargo is capital intensive and therefore more productive than handling passengers Oum et al. (2006).

Conclusion

After measuring and comparing the productive efficiency of 34 Italian airports for the period 2006 to 2016 in the previous paper, in this research it was applied the Tobit regression model, as a second stage analysis, with the aim of investigating whether airport size, LCC presence, and cargo traffic have a significant influence on the technical and scale efficiency of Italian airports.

Airport size, in all models, is significant with a positive coefficient. It demonstrates that larger airports are expected to have higher overall technical efficiency, pure technical efficiency, and scale efficiency than the ones of smaller airports. These results are in line with previous works on the same sector (i.e. Murillo-Melchor, 1999; Salazar, 1999; Martin and Roman, 2001; Pels et al., 2003, Martín et al., 2009; and Coto et al., 2014 for European airports; Malighetti et al. 2007 for Italian airports; Gillen and Lall, 1997, for US airports; Hooper and Hensher, 1997, for Australian airports and Perelman and Serebrisky 2012, for Latin American airports).

Even the presence of LCC has a positive effect on overall, pure and scale efficiency. These results are wholly in accordance with those of other papers. Laurino and Beria (2014) showed that LCCs have a significant impact on smaller Italian airports. Bottasso et al. (2012) concluded that LCC passengers have a positive effect on the total factor productivity of the British airports. Coto et al. (2014) found that low cost carriers generate a growth in demand, especially taking into consideration small to medium airports. Similarly, Cavaignac and Petiot (2017) concluded their bibliometric analysis arguing that LCCs increase airports efficiency.

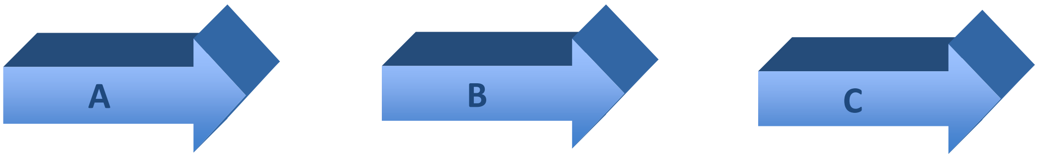
Finally, all three models pointed out the significant impact of cargo airport efficiency. Even the variable cargo is positively related to the overall, pure, and scale efficiency. It confirms previous work on the subject for which airports with a large proportion of cargo traffic are expected to disclose a higher variable factor productivity scores since handling cargo is capital intensive and therefore more productive than handling passengers.

The results achieved thanks to this paper, especially taking into consideration the privatisation process of Italian airports, are of major interest not only for the airport industry, policy makers, regulators but also for airport managers and operators. Thanks to this research, indeed, it is possible to understand how an airport's performance could be improved as well as how airport size and traffic distribution between passengers and cargo have an effect on airport efficiency.

The European policies on air transport liberalization have had positive effect on environment as much as they have improved the natural resources use.

General Conclusion

The research activity carried out during the three years of the PhD was summarized whitin three different papers analyzing the competitiveness and sustainability of Italian airports. Having regard to this purpose, it has been carried out a problem analysis framework as schematized below



Literature analysis concerning the methodology used to study airport efficiency problems

A description concerning Italian airport and comparison with previous work

Proposal of a model able to better explain Italian airport management performances

In the first paper, I have conducted an in-depth study of the literature on Data Envelopment Analysis methodology applied in the air transport sector. This part analyses the literature related to the models used in order to define which are the airport efficiency variables, focusing the attention mainly on the overall technical, pure technical, and scale efficiency of Italian airports.

The analysis showed that the most efficient models for analyzing the problem of airport management efficiency are DEA models, highlighting limit advantages. Notably, the main advantage of DEA is that it enables the decision maker to handle multiple criteria without relying on subjective judgments involved in the evaluation process.

The main disadvantage is that DEA scores can reach only one of the extreme value 0;1 so that we have a high probability to obtain a wrong results in case of data noise, for example measurement error can cause significant problems. To overcome this problem, in the third paper it was applied the Tobit regression which is able to identify the important impact of airport productivity factors and to distinguish which factors are more significant and how those factors are able to influence airports efficiency.

In the second paper I pass through the empirical examination of Italian airports analysing several factors and their impact on efficiency level. It was investigated the economic and environmental performance of 34 Italian airports in the period 2006–2016. In order to achieve clear and satisfactory answer, it was used the DEA method which appears to be particularly suitable since it allows to get scores measuring overall technical, pure technical, and scale efficiency. This allows to point out some interesting features of the Italian airport system. First, scale economies is able to affect significantly the efficiency outcome, so that, in case of increasing returns to scale, the airport managers should aim at extending the catchment area of the airport or developing strategies that are able to attract new carriers and new business activities, such as cargo activity. Second, most of Italian airports are well managed having regard to the pure technical efficiency.

In the third paper, it has been applied a Tobit regression model, with the aim of investigating whether airport size, LCCs presence and cargo traffic are able to exert a significant influence on technical and scale efficiency of Italian airports. Outcomes obtained suggest a positive association between overall technical efficiency and the above-mentioned variables, confirming the key role of market in achieving a more sustainable and efficient airport economy. It means that a regional airport can be considered as economically sustainable if the airport managing authority acts on the market so as to improve both cargo demand and LCCs demand. This is consistent with the theoretical hypothesis whereby regional airports can reach the economic sustainability with the intensive use of the infrastructure, otherwise they risk becoming a burden – instead of being a resource—for its Country (Freestone, 2009).

Even if, the airport efficiency analysis was carried out following the idea that political determinants are very influential on management system, it showed that it could be of major interest not only for airport managers and operators, but also for policy makers and regulators. Their duty, indeed, is to clarify how airports' performance and environmental sustainability could be improved as well as to investigate how airport size and traffic distribution between passengers and cargo can affect airport efficiency.

In the light of the above, therefore, it has to be concluded that air transport privatization and deregulation is able to positively affect the transport environmental efficiency. The results of the present work can help for a better understanding of the market mechanism roles aimed at achieving transport sustainability. Indeed, there are few papers analysing the airport efficiency of the whole Italian airport system (only eight). Moreover, none of these considered the average of data for such a large period of time nor the effect of LCCs passenger and Cargo on performance. For this reason, the topic needs further investigation and, consequentially, further publication in order to increase the consistency and variety of Italian literature.

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