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Evaluation of the Italian transport infrastructures: A technical and economic efficiency analysis

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A R T I C L E   I N F O

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A B S T R A C T

By applying a DEA (Data Envelopment Analysis) framework and Tobit analysis, this paper aims to measure 32 Italian airports' technical efficiency and investigate how several characteristics impact on their productivity and sustainability. Our findings show that some Italian hubs are technically efficient, although smaller airports that are dominated by low-cost carriers prove to be not least productive. Another conclusion of this paper is that efficiency and environmental impact is independent of an airport's size, although the size matters in determining an airport’s superior performance. This article highlights how the Italian public shareholder’s system became decisive to increase efficiency in small airports due to the lack of private financing.

1. Introduction

Nowadays, mobility-related activities play a crucial role in economic and social development, mainly if professionally managed and exploited. Air transport is a vital part of the transport system, enabling quick travel around the globe. In a national economic system, and efficient airport network is crucial because it meets the demand for mobility and achieves an adequate level of connection between the internal territories and other countries.

Until the beginning of the early '70s, civil aviation has been strictly regulated around the world (Baumol et al. 1982). Later, the air transport market experienced a progressive process of deregulation leading to airport privatization program started, in Europe, with the sale of major British airports to British Airports Authority (Becker, 2007; Koo et al., 2016; Starkie, 2002). Consequently, since 2000 this sector has been under intense pressure to expand and reorganize existing airports and create new ones (Scotti et al. 2012; Yang et al., 2015).

The deregulation process plays a crucial role in airport efficiency, and this has awakened interest in evaluating the technical and economic efficiency of air transport infrastructures (Abrate and Erbetta, 2010; Adler et al., 2013; Venckus and Gaydelis, 2011). This liberalisation process has led to the abolition of restrictions, capacity, and tariffs (which were previously dictated by strict civil aviation regulations). All decisions are a result of supply and demand.

Moreover, in the deregulated market, airlines can choose origin and destination airports without restrictions (Basso and Zhang, 2008). Therefore, airport management needs to revise their strategies often to attract new routes and preserve the existing ones (Arbolino et al., 2018a; Bel and Fageda, 2008). In Italy, the direct consequence has been an increasingly competitive environment where public resources have been used to create new airports (or expand existing ones) with low traffic volumes (D’Alfonso et al., 2014; Laurino and Beria, 2014; Martini et al., 2013). Nowadays, in Italy, there are about 112 airports, of which only 38 are used for scheduled commercial traffic with a concentration of 55.6 per cent of passengers’ traffic and 51.1 per cent of movements in the first five airports (Rome Fiumicino, Milan Malpensa, Milan-Linate, Bergamo, and Venice) (ENAC, 2019).

The airport network of a country is a critical asset since hubs with adequate size and interconnectedness bring a relevant benefit to the hosting country in terms of employment, added value, GDP and sustainability (Chow et al., 2016; Olfat et al., 2016; Yimga, 2020).

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The efficiency of airport infrastructure has captured an increasing interest among practitioners, academics, and policymakers.

In air transport-related literature, many studies are focusing on airport efficiency. Still, they have seldom analysed the correlation between technical and economic efficiency in the airport sector, and this
might seem surprising given the relevance of the problem.

To fill this gap, our study proposes a measurement of the efficiency of Italian airports intending to find the best performance achieved through the available inputs employed in the management of the activity.

In this work we deploy a non-parametric method, Data Envelopment Analysis (DEA), to measure Italian airports sector technical efficiency in the era of deregulation, currently a technique useful to measure the urban land use efficiency at county level (Yu et al. 2019; Minato & Morimoto 2011). We supply a critical viewpoint and point out that high technical efficiency (the maximum equi-proportional reduction of all the inputs that allows obtaining a given quantity of output, orienting itself to the input) does not always match economic efficiency (the production at minimum cost). (Adler et al., 2013; Dewita et al., 2018; Minato & Morimoto 2011).

The study bridges the gap inherent in the difference between technical efficiency and economic efficiency in the airport sector. Indeed, the novelty of the results highlights the possible disconnection between the two efficiency levels.

The paper is organized as follows. After this introduction, Section 2 conducts methodological support based on a representative review of the literature. Section 3, Method, and Section 3.1 introduce a theoretical background, and subsection 3.2 Methodology application describes the methodology application and statistical analysis. The econometrical analysis and the main results are in section 4. Finally, the paper in Section 5 carried out Discussion and Conclusions.

2. Literature review

Airports have become an essential element in the transportation network, contributing to connectivity and cooperation on a trans-continental scale (D’Aleo., 2016; D’Aleo and Sergi, 2017). Moreover, airports play a key role in the ongoing economic and social globalization (Carlucci et al. 2018). According to Bilotkach et al. (2012), airport operators are innovative companies that supply services beyond those typical as take-off and landing and provide parking and retail.

Many essays browse the existing literature on airport benchmarking and assess the advantages and disadvantages of partial productivity measures (PPM). The comparative analysis of the airports has gained considerable interest in academic literature and everyday practice (Merkert et al., 2012). Stakeholders such as transportation authorities, airlines, and airport companies are increasingly interested in measuring airports’ performance (Barros and Peytopch, 2008). Indeed, benchmarking techniques support airlines in selecting more efficient airports and policymakers in defining air transport policies (Barros, 2018; Barros and Dieke, 2008).

As far as airport performance is concerned, some studies are based on DEA, which supplies a measure of the airports’ efficiency (Cassette et al., 2015; Cooper et al., 2007). DEA is a non-parametric technique that uses linear programming to fit a frontier based on best practices (Ji and Lee, 2010). It has been employed in many studies to analyse the efficiency of many airports around the world. Several scholars use this approach to estimate airports’ efficiency (Bezerra and Gomes, 2016; Chang et al. 2016; Fasone and Zapata-Aguirre, 2016). Ngo & Tsui (2020) used the Slack-Based Measure (SBM) DEA-Window Analysis model to address the small sample issue during the first-stage analysis and used an instrumental variable (IV) in the Tobit model to solve the endogeneity issue during the second-stage analysis. Data from a sample of 11 New Zealand airports between 2006 and 2017 were used for analysis. The key findings showed the positive impact of tourism, regional economic development, an airport’s domestic networks, airport privatisation, low-cost carrier services, and the Christchurch earthquakes on New Zealand airports’ performance and efficiency. In contrast, an airport’s international systems have a negative impact.

Through the DEA method, Lu et al. (2019) identified the efficiency of 27 Chinese airports during the period from 2014 to 2018. Nine variables, including six input and three output variables, have been identified. Notably, the integration of the fuzzy Multiple-criteria decision-making method (MCDM) and the DEA approach proved optimal for developing a dependable and reliable analysis. Therefore, an integrated CFPR (Consistent Fuzzy Preference Relation)/DEA-WindowAR model was developed to evaluate the airport efficiency of Chinese airports. Besides, a comparison of efficiency levels with and without defined criteria weights was conducted. The results proved that considering weights using the CFPR approach is both practical and dependable.

The treatment of undesirable outputs in DEA has received research attention recently (Halkos and Petrou, 2019). In their work, they describe method brings with it, benefits and drawbacks which each researcher should consider at every stage of their research and assess which way is more proper to use.

Kutlu and McCarthy (2016) adopt a stochastic frontier analysis to analyse the efficiency differences for alternative airport ownership types of US commercial airports. They find that while the form of ownership may matter for cost efficiency, in general, its effect is relatively small. The nature of public sector ownership does have cost efficiency implications in specific environments. Liu (2016) evaluates the overall efficiency and the operational efficiencies of aeronautical service sub-process and commercial service sub-process for 10 East Asia airport companies from 2009 to 2013 using Network Data Envelopment Analysis (NDEA) and identifies the key influencing factors of respective sub-processes efficiency by employing the Panel Data model. His findings show how non-aeronautical revenues and service quality have significant and positive influences on commercial service efficiency.

Orkcu et al. (2016) use the Malmquist productivity index (classical and bootstrapping) to assess 21 Turkey airports’ operational performance from 2009 through 2014. The findings showed that most Turkish airports’ efficiency and productivity increased during the period under investigation. Moreover, decomposition of the Malmquist index showed that most Turkey airports experienced losses in efficiency; however, about technology, they have progressed. Two significant factors (i.e., operating hours and percentage of international traffic) were found by the Simar-Wilson double bootstrapping regression analysis explaining variations in airport efficiency. In order to compare total factor productivity of private and public infrastructures in Latin America, Perelman and Serebrisky (2012) computed Malmquist indexes showing that private had higher rates of total factor productivity growth than public ones.

Ferreira et al. (2016) study the efficiency of holding a business model to individual management model of airports, employing some robust non-parametric partial frontier-based methods to examine the statistical distributions of efficiency under different scenarios, to find out which group of airports yields better global performance. Their results provide evidence that European airports are highly productive. The individual management model presented a significant frontier shift concerning the holding cluster frontier, meaning that the former is much more productive than the latter.

Hannigan et al. (2015) employ a resource-based lens to explore the competitive implications of firm strategies under market commonality and shared resource pools. The firms’ core capabilities in these environments may focus on operational efficiency, as firms look to compete under significant resource heterogeneity constraints. Using data from the USA airline industry from 1996-2011, they find that price has a positive relationship with firm performance, while quality has a negative relationship. Operational efficiency is the driver of both strategies. Extending the findings to the global setting may need recognising other competitive dimensions. Firms that focus on non-core activities perform less well. The results offer insights into an industry that has interested strategy researchers for many years and may suggest other sectors with similar characteristics.

According to Vander Kraats (2000), alliances and code-sharing have become increasingly popular among airlines of all sizes as costs
associated with expansion become impractical. Most airlines have formed partnerships to keep cost-efficient and useful in various markets and further their economic potential. Economic benefits of alliances and code sharing are examined. Either arrangement gives the airline a competitive advantage over those that do not enter into these agreements.

Concerning the Italian system, Barros and Dieke (2008) have applied the two-stage procedure of Simar and Wilson to estimate the determinants of the efficiency of 31 Italian airports in the period from 2001 to 2003. In the first stage, the DEA has allowed sorting airports according to their productivity. In the second stage, this procedure enabled a bootstrap using truncated regression of the DEA results. Curi et al. (2011) extended the work of Barros and Dieke (2008), and Pey- pock (2008), using a DEA of 28 Italian airports on data from 2000 to 2006. They show that the Italian airport network's productivity growth is polarised on the Rome and Milan systems. A few other airports and their ownership structure will not affect the management's efficiency. The analysis also shows that there are no significant differences in effectiveness between the airports managed by a corporate structure by a majority government than those running with the organisational structure with a public majority. Abbruzzo et al. (2016) give evidence on the relationship within a set of financial and operational indicators for Italian airports over 2008–2014. Results suggest that the low-cost carrier's effect has been heterogeneous throughout the sample, which may show new opportunities to expand the business to intercept this category of travellers' surplus.

3. Method

3.1. Theoretical Background

The paper aims to estimate the efficiency of Italian airports. The efficiency is an operational concept that mirrors the accountant's idea of value for money, whereby the best possible relationship between actual infrastructure and services delivered, and their potential is supported. To have an accurate measure of the efficiency, we used a twofold approach: i) we estimate the technical efficiency employing DEA; ii) a Tobit model allows us to understand the shareholder's impact on efficiency score (Qi et al., 2015).

The definitions of DEA and TOBIT are briefly reported here, to improve reading of the paper:

- The Data Envelopment Analysis (DEA) is an empirical nonparametric method that is useful for measuring the productive efficiency of decision-making units (DMUs), both in operations research and economics estimation; moreover, it is commonly used for benchmarking in operations management.

As a non-parametric method, the DEA approach requires neither the a priori explanation of a functional form of the production function nor the preliminary identification of the input variables' weighting factors. The main advantage of the DEA, therefore, is that of supplying objective results (Banker et al. 1984). The Decision-Making Units (DMU) give the frontier from which the efficiency coefficients are calculated. This step allows us to efficiently identify a group of WLUs and, consequently, provide useful guidance to inefficient DMUs. Among the disadvantages of DEA is its deterministic nature. Every deviation from the frontier is inefficient without the possibility of identifying random elements or external factors that may have influenced the results. With a different approach, the statistical error would catch them. Still, we preferred not to use other methods precisely because the study's focus was centralised on the chosen variables. We had to avoid diverting attention to random elements or external factors. To avoid these drawbacks and obtain robust estimates, bootstrap procedures are used (Simar and Wilson, 2000). Through the bootstrap procedure, it is possible to build random samples from the original data and extract the confidence intervals of the undistorted DEA scores. The bootstrap procedure uses an algorithm with the intent to simulate the distribution of the DEA efficiency scores to approximate the real ones. Our model is accurate, and a bootstraps technique would not offer a definitively better method since it relies on asymptotic arguments. Thus, its primary use is to get standard errors in complicated models where asymptotic distribution is too hard to obtain analytically. There are exceptions when using bootstrap yields faster convergence, for instance, when bootstrapping pivotal statistics, but this does not seem to be such a case.

- The Tobit model, according to Tobin (1958), is also called a censored regression model. It is designed to estimate linear relationships between variables when there is either left- or right-censoring in the dependent variable.

In Tobit regression modelling, the error term must be normally distributed. With a sample size of 32 could allow verifying the distribution of the error term. However, as a caveat, the overall smallest sample size is \( n = 30 \). Then again, for distribution verification of non-time series, Anderson-Darling goes as low as \( n = 5 \). The test statistic employs the maximum probability, even with a sample of 32 elements as an observed data set, so you could use a Monte Carlo simulation to estimate the outcomes.

Data Envelopment Analysis (DEA) is a method for measuring the efficiency of DMUs using linear programming techniques to envelop observed input-output vectors as tightly as possible (Boussofiane et al., 1991; Coelli and Perelman, 1996; Coelli et al., 2005; Gitto and Mancuso, 2010). Our data are sourced from the AIDA database – Bureau van Dijk – and information raised from airport offices. The choice of the variables is after a careful analysis concerning the scientific literature on the subject, which allowed us to identify those which are the variables that create the least errors in the use of the DEA model and return statistically more significant results. An increase of input and output number is associated with the units' growth, placed on the efficiency frontier. In light of the scientific literature, data availability, and the relevant constraint that only one airline company serves some small airports (i.e., island’s airports, airports located by mountains or the sea), we employ technical efficiency analysis on 32 civilian airports (Table 1).¹

Table 1 gives primary data on the 32 airports (i.e., airport name, IATA identification code, shareholder, and workload unit). IATA Codes are an integral part of the travel industry and essential for identifying an airline, its destinations, and its traffic documents. They are also fundamental to the smooth running of hundreds of electronic applications that have been built around these coding systems for passengers and cargo traffic purposes. Since the output is heterogeneous, a common unit called WLU equivalent to one passenger or 100 kg of freight has been defined (Dogannis, 1992). The workload unit (WLU) is one of the essential units used in the aircraft sector. In relative terms, the costs are expressed per unit of the airport output. Indeed, the WLU is an indispensable contributor for assessing the total cost of airport operations, referred for WLU, for example, staff cost for WLU, total revenue for WLU, and nonaeronautical revenue WLU, aeronautical revenue for WLU, and WLU produced per employee. This unit is convenient for cost comparison and checking the cost-efficiency concerning the volume of the output at a given airport. The table is a photograph of the situation of Italian airports at the time of the research.

First consider the constant-returns-to-scale (CRS) model. Let there be 4-inputs and 3-outputs on each of 32-DMUs. For the \( i \)th DMU, these are represented by the vectors \( x_i \) and \( y_i \), respectively. The \( 4 \times 32 \times 4 \times 32 \) input matrix \( X \) and the \( 4 \times 32 \times 4 \times 32 \) output matrix \( Y \) represent the data of all 32-DMUs. The purpose of DEA is to construct a non-parametric

¹The data and econometrics that support the findings of this study are available from the authors.
envelopment frontier over the data points such that all observed points lie on or below the production frontier.

The mathematical form is:

\[
\max_{\theta, \lambda} \ s. \ t. \ - \theta_i + \lambda Y_i \geq 0, \quad (1)
\]

\[
x_i - X \lambda \geq 0, \quad (2)
\]

\[
\lambda \geq 0 \quad (3)
\]

where \( \theta \) is a scalar and is a \( 32 \times 1 \) vector of constant. The value of 1/\( \theta \) obtained will be the efficiency score for the \( i \)th DMU. It will satisfy \( \theta \geq 1 \), with a value of 1 showing a point on the frontier and a technically efficient DMU. The output cannot increase without an increase in inputs). The linear programming problem must be solved for each DMU in the sample and the value of \( \theta \) obtained for each DMU.

However, the CRS assumption is only proper when all DMUs are running at the best scale. When not all DMUs are running at the best level, the use of CRS specifications will result in technical efficiency measures confounded by scale efficiencies. The VRS (variable-returns-to-scale) model will allow the calculation of technical efficiency, excluding these scale effects. The CRS linear programming problem can be modified to account for VRS by adding the convexity constraint \( \lambda > 0 \) to the equation seen above to provide:

\[
\max_{\theta, \lambda} \ s. \ t. \ - \theta_i + \lambda Y_i \geq 0, \quad x_i - X \lambda \geq 0, \quad N \cdot \lambda = 1, \quad \lambda \geq 0 \quad (4)
\]

where \( N \cdot \lambda = 1 \) is a vector of one. This approach forms a convex hull of intersecting planes, which envelop the data points more tightly than the CRS hull. Thus, it supplies technical efficiency scores greater than or equal to those obtained using the CRS model.

Finally, if the DMU's technical efficiency scores differ between CRS and VRS models, the DMU has scale inefficiency. The scale inefficiency can be calculated from the ratio of the CRS and VRS technical efficiency scores (Chen and Soo, 2010).

Subsequently, we used Tobit analysis to understand the shareholder’s impact on efficiency score. A held view is that the use of the Tobit model can manage the characteristics of the distribution of efficiency measures and thus give results that can guide policies to improve performance. Recently, many DEA applications use a two-stage procedure involving both DEA and Tobit. A Tobit regression analysis estimates linear relationships between variables when there is either left- or right-censoring in the dependent variable (also known as censoring from below and above, respectively).

The model, in its purest form, can be written as:

\[
y^* = X^{*} \epsilon + \theta \epsilon + \eta, \quad \theta \epsilon, \quad \eta \sim N(0, \sigma^2) \quad (5)
\]

\[
y = y^* \text{if } y^* > 0, \ y = 0 \text{ if } y^* < 0 \quad (6)
\]

where the efficiency score, calculated by DEA, is used as a dependent variable.

Censoring from above takes place when cases with value at or above some threshold, all take on the value of that threshold, that is, the real value might be equal to the limit, but it might also be higher. In the case of censoring from below, values that fall at or below some threshold are censored. The efficiency score is a dependent variable that helps to understand how much the percentage of public shareholders and transits impact on efficiency score.

### 3.2. Methodology application

Table 2 shows the variables in the considered period (2015 – 2018).

The relevance of the used variables is well documented in the scientific literature. The terms “runway length (m)” defined from the International Civil Aviation Organization (ICAO), “rectangular area on a land
aerodrome prepared for the landing and takeoff of aircraft’, accounts for more than 8,760 academic results. 'Check-in Desk (num.)' return 1.460 results; "a number of airplane/hour" return 19.300 results; "number of runways" returns 8.400 results. About the Output: "total number of passengers" return 15.700 results; "total aircrafts movements" return 17.000 results; "number of runways" return 5.650 results. This simple exercise proofs how the choice of the variables used is correct.

The most significant difference in our analysis compared with the reference literature was the ability to rework through a new methodological model to highlight their impact on the sector in a well-defined geographical area. The choice of the variables has also taken into consideration that all variables must be compared. Therefore, they must present the characteristics of homogeneity, independence, and autonomy. Once the traits the units must have been defined, it is necessary to set up the sample analysis number, which must be realistic and dependable.

Observing the table above, we have seen that runway length was, in mean, equal to 2,763.69 meters: this means that the significant part of analysed airports was made to take-off and landing of airplanes of medium size, as Airbus A320 and A360. Only a few airports in Italy can allow take-off and landing of giant airplanes, like A380 or 747 Boing.

Concerning the number of check-in desks, we have registered that in mean Italian airports have 46 (Standard Deviation ± 79) desks. This is related to the necessity to accommodate different airline companies, like flags and low-cost carriers, other than carriers of different European Countries— a low-cost carrier emphasis on minimizing operating costs. To make up for revenue lost in decreased ticket prices, these airlines may charge extra fees for carry-on baggage. Moreover, many domestic flights in Italy are dependent upon political agreements to incentivize tourism and guarantee territorial continuity. Therefore, a different approach would invalidate this paper’s goal. Although the literature shows how some variables influence the presence of low-cost carriers, Italian airports, and local actualities, definitively dictate this methodological approach, and it still provides us with commendable and usable results.

Although some airports – as Milano Malpensa and Roma Fiumicino - have more than one runway to allow a correct direction of air traffic control, in mean, however, Italian airports have one runway.

Each apron can accommodate, in just an hour, 25 airplanes in mean (S.D. ± 29): all small airports cannot adjust to a considerable number of planes simultaneously. Concerning outputs, we have considered three variables: total number of passengers (mean value equal to 4,888,739, S.D. ± 7,558,033), total aircrafts movements (41,153.09 in mean with S.D. ± 60,173.97) and Share Low-cost carrier (low-cost carriers have a percentage equal to 56.13 per cent with S.D. ± 29.79 per cent, although some airports have no low-cost airlines).

In Table 3, we analysed the percentages of passengers, cargos – measured as cargo hold – and movements. The use of percentage values is the correct methodology for comparing data that is not homogeneous or refers to different units of measurement, otherwise not comparable.

### Table 2

| Variables                  | Obs | Mean   | St. Dev. | Min | Max |
|----------------------------|-----|--------|----------|-----|-----|
| Runway length (m)          | 32  | 2763.69| 511.89   | 1750| 3920|
| Check-in Desk (num.)       | 32  | 46     | 79       | 1   | 355 |
| Number of Airplane/Hour    | 32  | 25     | 29       | 1   | 142 |
| Number of Runways          | 32  | 1      | 1        | 1   | 4   |
| Total number of passengers | 32  | 4,877,739| 7,558,033| 476 | 4.02 e +07 |
| Total aircrafts movements  | 32  | 41,153.09| 60,173.97| 345 | 315,168 |
| Share Low-cost Carrier (%) | 32  | 56.13  | 29.79    | 0   | 99.7 |

### Table 3

| Airport                  | % movements | % passengers | % cargo (ton) | % transits |
|--------------------------|-------------|--------------|--------------|-----------|
| Alghero, Fertilia        | 0.91        | 1.07         | 0.00         | 0.19      |
| Ancona, Falconara        | 0.78        | 0.33         | 0.72         | 0.18      |
| Bari, Palese             | 2.43        | 2.53         | 0.22         | 2.07      |
| Bergamo, Orio al Serio   | 5.65        | 6.60         | 13.03        | 1.22      |
| Bologna, Guglielmo       | 4.57        | 4.39         | 3.32         | 4.79      |
| Marconi                  |             |              |              |           |
| Brindisi, Casale         | 1.29        | 1.44         | 0.00         | 0.91      |
| Cagliari, Elmas          | 2.24        | 2.38         | 0.35         | 0.26      |
| Catania, Fontanarossa    | 4.14        | 4.50         | 0.67         | 1.94      |
| Crotone                  | 0.14        | 0.18         | 0.00         | 0.00      |
| Florence, Amerigo        | 2.31        | 1.52         | 0.01         | 0.01      |
| Verona, Cristoforo       | 1.06        | 0.87         | 0.03         | 0.54      |
| Colombo                  |             |              |              |           |
| Lamezia Terme            | 1.28        | 1.49         | 0.15         | 1.94      |
| Milan Malpensa           | 11.89       | 11.82        | 55.08        | 25.30     |
| Milan Linate             | 7.29        | 6.18         | 1.69         | 0.46      |
| Naples, Capodichino      | 3.94        | 3.92         | 0.91         | 3.79      |
| Olbia, Costa Smeralda    | 1.42        | 1.42         | 0.03         | 1.24      |
| Palermo, Falcone         | 3.16        | 3.14         | 1.03         | 2.74      |
| Brescelino               |             |              |              |           |
| Parma                    | 0.17        | 0.12         | 0.00         | 0.00      |
| Perugia, San Francesco d’Assisi | 0.34  | 0.17  | 0.00       | 0.06      |
| Pescaia, Abruzzo          | 0.55        | 0.38         | 0.00         | 0.05      |
| Pisa, Galileo Galilei    | 3.03        | 3.08         | 0.84         | 0.90      |
| Reggio Calabria          | 0.31        | 0.31         | 0.01         | 0.00      |
| Rimini, Miramare         | 0.16        | 0.10         | 0.00         | 0.38      |
| Rome Ciampino            | 3.60        | 3.73         | 1.70         | 0.00      |
| Rome Fiumicino           | 23.93       | 25.77        | 15.62        | 45.50     |
| Taranto, Grottaglie      | 0.03        | 0.00         | 0.72         | 0.03      |
| Turin, Castelle          | 2.67        | 2.34         | 0.13         | 0.93      |
| Trieste, Leghorni        | 0.87        | 1.02         | 0.00         | 0.13      |
| Treviso, Sant’Angelo     | 1.22        | 1.51         | 0.00         | 0.11      |
| Trieste, Ronchi dei      | 0.70        | 0.47         | 0.01         | 0.17      |
| Venica, Marmo Polo       | 6.04        | 5.56         | 4.60         | 1.33      |
| Verona, Valerio Catullo  | 1.84        | 1.65         | 0.03         | 2.83      |

| Airport                  | % movements | % passengers | % cargo (ton) | % transits |
|--------------------------|-------------|--------------|--------------|-----------|
| BGY, CIA, FCO, TAR, LIN, PEG, MXP, CRV, and TSF.  

### 4. Results

Table 3 stands for the percentage of airplane movements, passengers, ton-cargo, and transit in each airport: Roma Fiumicino and Milano Malpensa registered values higher than other airports.

At this point, we can introduce the model results, in which we have performed both CRS and VRS models, calculating Scale and Return to scale, in which Scale is equal to the ratio between CRS and VRS. Table 4 reports the rank for each airport: we have noted that for 26 airports mean values of both CRS and VRS technical efficiency are high, which is higher than 0.500. The efficient airports have a value equal to 1.000, and we have found nine efficient airports: BGY, CIA, FCO, TAR, LIN, PEG, MXP, CRV, and TSF.

In the second place, we have found BGL, which has a $\text{T}_{\text{CRS}}$ equal to 0.961295, while it is considered efficient for $\text{T}_{\text{VRS}}$. The same trend is noted about CTA ($\text{T}_{\text{CRS}} = 0.953208$ and $\text{T}_{\text{VRS}} = 1.0000$).

For simplicity, it is essential to note that the first nine airports (Table 4) for this model are the most efficient. The first fact that appears is that the geographic factor is significant in the upper positions indeed we account four airports from North Italy (GGY; LIN; MXP; TSF); three from the main area (PEG; CIA; FCO) and two from south Italy (CRV; TAR). The airport size stands for the second element that seems relevant; in the north of Italy are the large airports (LIN; MXP; GCY) to be efficient than the south where small airports (CRV; TAR) are the masters. The major international hubs for passengers and cargo (FCO; MXP) are efficient. In the last three positions, we found one airport from north Italy (TRS), one from central Italy (RMI), and one from south Italy...
Finally, other technical efficiency information is worked out concerning the current value. The same trend is registered for transit \((4.54 \times 10^{-6}, p < 0.0001)\). In general, the Tobit model is confirmed by F-test, which reports a \(p\)-value equal to 0.0144. The Pseudo R2 is equal to 43.45 per cent, so showing the goodness of fit significant. We have performed the analysis using errors robust to heteroskedasticity to avoid heteroskedasticity problems. This information framework illustrating the slack variables, and the projection of efficiency is of foremost importance for the management to correct the problems. In addition to finding the critical factors of Input and Output, it also allows the frame of the new production levels.

5. Discussion and Conclusions

Improving the economic efficiency of existing air transport infrastructures influences local land use planning in terms of land-saving and congestion reduction (Wang et al., 2018). These arguments also have an essential impact on the environment: inefficient flying generates different negative environmental externalities.

Air traffic growth causes negative externalities on land use and environments, such as the unavoidable increase in air pollution levels, aircraft noise, and land contamination (Daley, 2016). Air transport-related literature highlights that private ownership improves economic efficiency because of complementary take-off and landing services. In this way, it can mitigate environmental impact and soil consumption of airport infrastructure (Salabun et al., 2019).

Airport privatization programmes stimulate innovation and technical efficiency in the use of aircrafts and infrastructures and enhance long-term environmental sustainability and country competitiveness (Czerny, 2006; Ioppolo et al., 2016; Szopik-Depczyńska et al., 2018). However, since the airport system is affected by many intangible factors, such as tourists’ preferences and concessions, and climatic and land factors, performance assessment becomes more difficult (Hinnüber et al., 2019). Moreover, due to a lack of adequate empirical evidence, as
Regional airports' management could be summarised. Strategic and operational solutions to address the low profitability of the smaller airports for services, personnel, and margins. The strategic aspect is the deficiencies in the intermodal connections for accessing the airport. Private capital concentrates on the larger airport and improve airport accessibility, it creates the proper conditions to attract a high number of passengers may improve profitability and revenues but increases local externalities for the natural environment if technical efficiency is low. Moreover, our analysis reveals much information, including the sign of efficient and sustainable policies should focus on new management systems and attract public and private capital to achieve the maximum efficiency of local airports.

From a theoretical perspective, our findings show that efficiency and local impact is independent of the airport's size, although the size matters in determining an airport's superior performance. The analysis reveals much information, including the sign of efficient and sustainable airports and corrective measures, as well as the adjustments that airports consider inefficient to improve their performance and move closer to efficiency and sustainability. An increasing number of flights that would attract a high number of passengers may improve profitability and revenues but increases local externalities for the natural environment if technical efficiency is low. Moreover, our analysis proves that technical efficiency does not always coincide with economic and financial profitability. A rigid cost structure sets the operating costs of the smaller airports for services, personnel, and margins. The strategic and operational solutions to address the low profitability of the regional airports' management could be below summarised.

Airports efficiency has become a priority policy issue for many municipalities because of the importance of air transport for business and tourism. Therefore, the study's insights and findings help a better understanding of local governments' role in achieving airport efficiency (Yang et al., 2015).

From a policymaker point of view, our findings reveal that country policies should focus on new management systems and attract public and private capital to achieve the maximum efficiency of local airports. However, the expected growth in passenger traffic and cargo volumes in Italy recommends circumscribing in greater detail the need for investment in the sector.

Moreover, the paper's results suggest that economic and financial equilibrium is necessary but not enough to attract private capital. One critical aspect is the deficiencies in the intermodal connections for access to airports. Private capital concentrates on the larger airport management companies that can secure profitability in the short/medium-term. The size of the airports of less than one million passengers per year would be unlikely to attract private capital. The holding structure of airport operators covered is intended to be made up of local government bodies that distribute economic resources for economic and social development.

The role of public authorities in the transport system should be twofold. First, to support the development of the intermodal network and improve airport accessibility, it creates the proper conditions to enable managers to operate competitively. Second, to conduct a better role for local governments in the administration of small airports.

The study is valuable in light of the new prospects of the Italian airport sector following the COVID-19 health emergency. The Italian Ministry of Infrastructure and Transport, in agreement with the Ministry of Health, rationalised the air transport service by decree of 12 March 2020, closing some airports and ensuring essential functions and operation services at 17 airports (Ancona, Bari, Bologna, Cagliari, etc.).
Catania, Genoa, Lamezia Terme, Lampedusa, Milan Malpensa, Naples Capodichino, Palermo, Pantelleria, Pescara, Pisa, Rome Fiumicino, Turin, Venice Tessera and Rome Ciampino for flights only of the state, organ transport, Canadair and emergency services’. The current gov-
ernment’s policymaking concerning the COVID-19 health emergency partially follows the outcome of our study about airport efficiency. This study’s usefulness would allow political decision-makers to better an-
chor clearer strategies to the reopening or definitive closure of those airports that have been found less efficient (e.g., Trieste, Rimini, and Reggio Calabria).

In terms of this paper’s management implications, the comparative methodology allows us to implement those interventions that would improve airport performance, thereby avoiding closure. The increase in return would be easily applicable between structures of comparable size.

Finally, our study raises future research opportunities, both theory development and concept validation (Arbolo et al., 2018b). The study offers a different point of view about economic and technical infra-
structure efficiency. It will need further refinement of both its elements and internal dynamics (Yigitcanlar, 2010) and find ideal types of sampleable and knowledgeable managers. The model discussed here could benefit some hypotheses for further empirical testing using a broader sample and quantitative methods.

Credit Author Statement

The authors contributed fully and equally to this work Sergio Bruno S, Vittorio D’Aleo, Giuseppe Ioppolo defined the research design. Roberta Arbolo and Fabio Carlucci, analysed the sources and liter-
ture and the applied methodology. All authors carried out a detailed revision and wrote the body of the paper, read and approved the final manuscript.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:10.1016/j.landusepol.2020.104961.

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