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# *The influence of LCC, fleet mix and ownership on airports' environmental efficiency: evidence from Italy*

by

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# The influence of LCC, Fleet mix and Ownership on airports' environmental efficiency: evidence from Italy

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**Abstract**

This paper analyses the efficiency of 33 Italian airports for the period 2005–2008. In addition to the conventional outputs (i.e., flights, passengers and cargo), two undesirable outputs have been considered: noise and local air pollution. The Directional Distance Function (DDF) approach shows that the inclusion in the analysis of the undesirable effects of airport operations leads to greater and closer airports' efficiency scores. Furthermore, we perform a second stage regression to investigate the determinants of efficiency. First, we clearly identify the presence of a fleet effect: airports are more environmentally efficient, the lower is the percentage of flights made through narrow–body aircrafts, in comparison to the percentage of flights made by regional jets. Second, we find that the higher is the stake of public local authorities in the airports' ownership structure, the higher is their environmental efficiency. Third, the presence of Low Cost Carriers (LCCs) seems not to be significant from the environmental point of view, in contrast to the common perception that LCCs are more environmentally friendly because they use more modern fleets. Interestingly, most of our results are confirmed also when looking at a more long run scenario.

Keywords: Directional Distance Function Airport Environmental Efficiency Second Stage Analysis

# 1 Introduction

Aircraft emissions of air pollutants (produced by aircraft engines) and noise emissions are the two main environmental concerns related to the aviation sector. Although noise is currently the primary environmental constraint for airport operations, many airports are going to put air quality issues on the same level (GAO, 2000). Furthermore, while the connection between noise and human health is somewhat still unclear, emission are known to have a direct impact on population (Daley, 2010), especially on people living nearby the airports. Hence, efforts to integrate productivity measures in air transport policies that specifically target these environmental issues are evident at the global (International Civil Aviation Organization, ICAO), regional (EU) and national level, with different decision-making procedures and policy instruments.

As a consequence, it is more and more important to include environmental impacts into airport efficiency and productivity assessments: accounting also for environmental undesirable outputs should provide a more complete measure of airport efficiency. Yu (2004) and Yu (2008) are the only two contributions considering one of the airports' environmental externalities (i.e., the noise) in airports' efficiency assessment. To the best of our knowledge, no efficiency studies consider both the production of desirable outputs, and the production of noise and local air pollution. Furthermore, no studies investigate the determinants of airport "environmental efficiency". In this sense, the major contributions of the paper are threefold. First, we make the first attempt to assess the productivity of Italian airports by taking into account jointly desirable output (i.e., passengers, aircraft movements and cargo), noise and air pollution. Second, we compare the results from a model that considers both desirable and undesirable outputs and outline the potential misleading results inherent in ignoring undesirable outputs. Third, we investigate the influence of some exogenous variable such as airports' ownership structure, airports' fleet mix, and the presence of LCCs, in order to test some research hypothesis about their influence on airport environmental efficiency. Finally we show that the obtained results are confirmed also when looking at a more long run scenario.

The remainder of this paper is organized as follows: section 2 briefly reviews the related literature, section 3 formally presents the model, environmental indexes and the database's issues are explained in section 4 and empirical results are summarized in section 5. This analysis is briefly concluded in section 6.

## 2 Literature review

Only few contributions regarding airport efficiency assessment consider the production of undesirable outputs. Yu (2004) estimate the physical efficiency of 14 domestic Taiwan's airports for the period 1994–2000, considering aircraft noise (measured in 1,000 New Taiwan dollars) as undesirable output. The results of a DDF approach shows that ignoring undesirable outputs increases both the frequency and the degree of inefficiency. Yu *et al.*(2008) analyze the productivity growth of 4 Taiwan's airport for the period 1995–1999, showing that the average TFP growth increase if undesirable outputs are ignored. Pathomsiri *et al.*(2008) consider congestion (delays) as undesirable output and apply a DDF approach to a panel of 56 US airports (period 2000–2003). Their main results show that if delayed flights are not included in the analysis, many large but congested airports are found to be on the frontier. On the contrary, when accounting for delays, the number of efficient airports increases; with small, less congested airports also resulting efficient. Lozano and Gutierrez (2010) apply a slack based efficiency measure to a panel of 39 Spanish airports (period 2006–2007). They consider delayed flights and delays as undesirable outputs and, differently from the previous contributions, they find that disregarding bads generally improves the efficiency assessment. However, this last approach is proved to be only a special case of the more general concept of DDF (Färe and Grosskopf, 2010). For this reason, we adopt the DDF approach in this paper.

To the best of our knowledge, no contributions consider the production of local air pollution. Furthermore, there are no papers which try to explain the efficiency scores, obtained after the inclusion of undesirable outputs, through a second stage regression, in order to investigate the determinants of airport environmental efficiency.

The concept of Directional Distance Function is introduced by Chambers *et al.*(1996) and Chambers et al.(1998) at theoretical level, and firstly explored in duality term by Färe *et al.*(2000). The power of this tool is the possibility to modify the direction in which to search for an the efficient counterpart of each firms. This is a key aspect because allow to credit airports for pollution reduction and to discredit them for each increases of undesirable outputs, without applying transformation to the data (for an overview see Scheel, 2001). DDF is an additive concept then all the conditions to identify the best practice frontier are linear. Standard Data Envelopment Analysis (DEA) procedure could be applied and no assumption are needed on the functional forms of technology. Many application arise in environmental field with firms focus such as Chung *et al.* (1997) about paper and pulp mills in US, Boyd *et al.* (2002) on glass US manufacturing firms; Picazo-Tadeo *et* *al.* (2005) and Picazo-Tadeo and Prior (2009) consider Spanish ceramic industry; McMullen and Noh (2007) analyze transit buses firms in US; Färe *et al.* (2007) and Kumar and Managi (2010)a consider a sample of power generating firms in US, Bellenger and Herlihy (2010) apply DDF to invertebrate comparison in ecological field. Also some application to aggregate level extend the standard analysis on micro-units, for example Macpherson *et al.*, 2010, Kumar and Managi (2010)b. In many articles applying standard efficiency analysis big attention is devoted to interpret results. Often this process is performed using econometrical technique which are proved to be inconsistent on the basis of a seminal paper by Simar and Wilson (2007). In this paper Simar and Wilson strongly recommend the use of maximum likelihood, and in particular applied to a truncated regression model, focusing estimates efforts only on inefficient observations. In the airport field we are able to find one of the rare paper, Barros and Dieke (2008), that already apply this results for a robust second stage phase, detecting the effect of geographical and structural variables on estimated efficiency. Moreover only few previous works combine DDF methods and a strong second stage phase: Nakano and Managi (2008) analyse the Japanese power generating sector, Watanabe and Tanaka (2007) investigate the Chinese industry at provincial level and Kumar (2006) on international comparisons. A common feature is that they perform biased Tobit estimates. Starting with the results in Simar and Wilson (2007) we try to extend these previous work on DDF by analyzing our deterministic efficiency measures in semi-parametric second stage step. In particular some suitable determinants of environmental efficiency scores are identified and their effect on the estimated score is statistically tested.

# 3 Environmental efficiency: the directional distance function approach

## 3.1 Theoretical framework

In this section we formalise some ideas that are commonly accepted in the field of production process with undesirable outputs. First of all undesirable are a sort of byproduct results, then a positive production of good output is not compatible with a zero production of them. Secondly reducing bad outputs is only possible, from a technological perspective, by reducing good outputs volume.

Some notation have to be introduced in order to clarify the points. Let $x = (x_1, ..., x_N) \in R_+^N$ be a vector of inputs, $y = (y_1, ..., y_M) \in R_+^M$ a vector of good outputs and $b = (b_1, ..., b_J) \in R^J_+$ a vector of bad outputs. To model production process with pollution and noise, the directional output distance function by Chambers *et al.* (1996) is applied here. The output set $P(x)$ collect all the combinations of good and bad outputs that could be produced using each particular input vector $x$.

$$P(x) = \{(y, b) : x \quad \text{can produce} \quad (y, b)\}, x \in R^N_+. \tag{1}$$

Following Färe *et al.* (2007) we introduce some standard axioms which are satisfied by airport's environmental technology.

1. *Inactivity.* From a technical point of view the choose of remaining inactive is always possible. Then $0 \in P(x), \forall x \in R^N_+$.

2. *Compactness.* $P(x)$ is compact, then for each finite input mix $x$ one could obtain a finite couple of vector $(y, b)$.

3. *Free disposability of inputs.* As in standard technology representation, an increasing quantity of inputs allow to produce a fixed quantity of outputs. Inputs are freely disposable: $P(x) \subseteq P(x')$ if $x' \geq x$, or a Decision Making Units (DMU) could always obtain the same amount of outputs by implying more inputs and this is technically feasible. Macpherson *et al.* (2010) underline how that assumption could be strong in environmental field, given the close linkage among input consumption and pollution production.

These standard assumptions are always valid in modeling a production process. In presence of undesirable outputs one have to formalize the joint production idea and the cost of reducing. Färe *et al.*(1989) introduce two additional axioms:

4. *Null jointness.* It is impossible to observe positive amount of good outputs without observing also a positive amount of bad outputs, or in formulae
$$(y, b) \in P(x) \text{ and } b = 0 \Longrightarrow y = 0 \tag{2}$$

5. *Weak disposability assumption on outputs.* Each couple of vectors $(y, b)$ is assumed to be weakly disposable, then they cannot be freely reduced:
$$(y, b) \in P(x) \text{ and } 0 \leq \alpha \leq 1 \Longrightarrow (\alpha y, \alpha b) \in P(x). \tag{3}$$
In words only proportional contraction of both good and bad outputs are feasible, because the decrease on bad outputs could only be performed by reducing desirable outputs. In our context there are no clear

regulations which impose airports to reduce and control for bad outputs such as pollution and noise. Free disposability is still valid on the subset of good outputs for which every reduction is technically feasible without costs and maintaining inputs constant.

$$(y,b) \in P(x) \text{ and } y' \leq y \Longrightarrow (y',b) \in P(x) \tag{4}$$

The Directional Output Distance Function model (DODF), defined on the output set that meets previous axioms, gives the maximum feasible expansion of outputs in a pre-assigned direction maintaining inputs unchanged. We want to treat asymmetrically good and bad outputs then we expect to discredit airports which increase noise or pollution and to credit them for reductions; of course also each increase in good outputs production have to be considered. An appropriate direction should be choose in order to guarantee this asymmetrical treatment of desirable and undesirable outputs. DODF allows to search for the efficient counterpart of an airport along non-radial projections and the value DODF take represents directly the distance between observed airport and the technical frontier. DODF takes a value equal to 0 for efficient DMUs and increase with inefficiency. For each theoretical properties and duality correspondences we refer to Chambers *et al.* (1998) or Färe and Grosskopf (2000). Formally the DODF is defined as follows:

$$\overrightarrow{D}_O^W(x,y,b;g_y,g_b) = \max\{\beta : (y,b) + (\beta g_y, \beta g_b) \in P(x)\} \tag{5}$$

where $g = (g_y, g_b)$ is the directional vector and $g_y \in R_+^M$, $g_b \in R_+^J$. The production possibility set $P(x)$ could be estimated via linear programming thanks to the additive features of DODF, but before computations a particular directional vector have to be fixed. The asymmetry between desirable and undesirable outputs have to emerge in the choose of the directional vector. In the case of Italian airports we underline 2 different objective that must be jointly achieved in order to meet all the involved interests: managers try to maximise good outputs production, but local community and institution impose to reduce environmental damages. Following what firstly recommends Färe and Grosskopf (2000) and what is done in many applications to ecological field (Domazlicky and Weber, 2004; Chung *et al.*, 1997), we choose the vector $g = (y, -b)$ that gives an immediate meaning to estimated $\beta$.

$$\begin{aligned}
\overrightarrow{D}_O^W(x^{k'}, y^{k'}, b^{k'}; y^{k'}, -b^{k'}) &= \max \beta \\
\text{s. t.} \qquad x^{k'} &\geq \sum_{k=1}^{K} z_k x_{kn}, \quad n = 1, ..4 \\
(1+\beta) y^{k'} &\leq \sum_{k=1}^{K} z_k y_{km}, \quad m = 1, 2 \\
(1-\beta) b^{k'} &= \sum_{k=1}^{K} z_k b_{kj}, \quad j = 1, 2 \\
\sum_{k=1}^{K} z_k &= 1 \\
z_k &\geq 0
\end{aligned} \tag{6}$$

Return to scale are assumed to be variable in order to focus the attention on inefficiency which can be reduced by managers in the short run, then excluding potential scale inefficiencies.

A standard DEA model output oriented is also run in order to compare results of classical Technical Efficiency with the Environmental Efficiency score computed. The production of bad outputs is here ignored and the value or TE is bounded below by unity instead of zero[1], VRS are assumed.

$$\begin{aligned}
TE &= \max \theta \\
\text{s. t.} \qquad x^{k'} &\geq \sum_{k=1}^{K} z_k x_{kn}, \quad n = 1, ..4 \\
\theta y^{k'} &\leq \sum_{k=1}^{K} z_k y_{km}, \quad m = 1, 2 \\
\sum_{k=1}^{K} z_k &= 1 \\
z_k &\geq 0
\end{aligned} \tag{7}$$

## 3.2 Second stage analysis

External and internal variables could have influence on environmental efficiency results, in particular the attention has to be concentrated on those

[1]In the table placed in appendix the scores are transformed applying 1/TE to have more readable results

variables that are not under the direct decision of manager, in particular some long term choices could affect observed results. These approach is normally investigated in classical DEA models, but in DDF framework a second stage analysis is not so performed. Daraio and Simar (2008) listed directional distance function among the extension of classical DEA models which inherit the same statistical properties of standard DEA scores. A common practice in the few previous works applying a second stage analysis was to estimate a Tobit model for censored data. (Watanabe and Tanaka, 2007; Blancard *et al.*, 2006). Only Picazo-Tadeo *et al.* (2007) apply the recent features in Simar and Wilson (2007) to the case of DDF efficiency scores. According to Simar and Wilson (2007) classical estimation method based censored model, could lead to misleading conclusion: they suggest a truncated regression method in order to totally exclude from second step efficient DMUs which drive the unknown technological frontier. Using a Montecarlo simulation the unbiasness of truncated regression coefficients is demonstrated in contrast with biased Tobit results. In their seminal paper Simar and Wilson also suggest a bootstrap procedure in order to better off confidence interval around estimated parameters, this leads to a better inference stage. Following Barros and Dieke (2008), we assume the following regression model:

$$EE_k = w_k\gamma + \varepsilon_k, \quad k = 1, ...K \tag{8}$$

To operationalize the theoretical model, the unknown efficiency score based on an unknown technological frontier are estimated according to DODF framework assuming that all previous hypothesis are still valid. The only restriction which differ from standard second stage DEA approach is the truncation point: in original Simar and Wilson (2007) approach efficiency score are assumed bounded by unity, here, under DODF, they are lower bounded by zero. The assumption on $\varepsilon_k$ remain the same before truncation, normal distribution with zero mean and unknown variance. What change is the truncation point derived by the new condition $\varepsilon_k \geq -w_k\hat{\gamma}$[2]. The econometric model is then estimated via maximum likelihood technique applying a non parametric truncated regression model. In order to obtain better confidence interval a single bootstrap procedure is the minimal request in order to obtain more reliable inference. The procedure we apply roughly correspond to the Algoritm 1 proposed by Simar and Wilson (2007) in order to correct for the expected correlation among dependent variable and regressors. On the basis of theoretical findings by Simar and Wilson, Picazo-Tadeo*et al.*

[2]In the analysis the second stage is also performed on standard DEA efficiency score. In this case the truncation point follows standard formulation and the condition became $\varepsilon_k \geq 1 - w_k\hat{\gamma}$

(2011) stated some practical steps in order to obtain more robust confidence interval:

1. We apply the truncated regression model to estimate, via maximum likelihood method, a set of coefficient $\hat{\gamma}$ and the estimated variance of error term $\hat{\sigma}_\varepsilon$. We use as dependent variable the set of environmental efficiency score obtained from DDF estimate: that scores are bounded below by 0 rather than by 1 as in the classical DEA framework. No transformation are applied on efficiency results as in Blancard *et al.* (2006).

Then we loop over S time the next three steps with the aim of obtaining a set of estimates for our coefficient $\hat{\gamma}$ and $\hat{\sigma}_\varepsilon$.

2. We draw a casual extraction for $\varepsilon_k$ from a normal distribution:

$$N(0, \hat{\sigma}_\varepsilon^2), \text{ left truncated at the point } (-w_k\hat{\gamma}) \tag{9}$$

   and we repeat these procedure for each inefficient observation on efficiency score.

3. We correct the computed environmental efficiency score for the potential bias by adding the casual extraction $\varepsilon_k$ to each inefficient term predicted by the truncated regression model.

$$EE_k^* = w_k\hat{\gamma} + \varepsilon_k \tag{10}$$

4. Using maximum likelihood we estimate the truncated regression of these new variable on the original explanatory variable we include in the first model. By repeating S times the previous 3 steps we obtain a set of bootstrap estimates:

$$G = [(\hat{\gamma}^*, \hat{\sigma}_\varepsilon^*)_g]_{g=1}^S \tag{11}$$

5. Finally we use the bootstrap value in G to construct new confidence intervals around estimated parameter $\hat{\gamma}$ and $\hat{\sigma}_\varepsilon$ coming from the first truncated regression.

# 4 Data

## 4.1 Noise Index

The non-linear characteristic of noise, which is measured in decibels (dB), makes difficult to calculate an index able to take into account airport noise production. However, the noise level from the operation of several flights can be estimated and, as a consequence, it is possible to get the level of noise of all the flights provided by a single airport during a year. The main source of noise characterizing airports is represented by aircraft engines, especially during take-off and landing operations, with peaks of high intensity during the phase of take-offs. Obviously, the increase in airport noise is dependent on both the growth of air traffic and the type of fleet operating at the airport. Our data, collected using the databases European Aviation Safety Agency (EASA) and Federal Aviation Administration (FAA), allow a classification according to the noise produced by aircrafts operating in Italian airports. EASA and FAA databases report the certified noise produced by an aircraft on the basis of its engines and take-off weight.[3] Hence, combining the Official Arline Guide (OAG) database with the EASA, we have been able to associate to each aircraft model in our data set the level of noise produced in each phase (i.e., take-off, landing). Then we convert the data of Effective Perceived Noise Level (EPNL) provided in the noise certification in the Sound Exposure Level (SEL). The latter is the most common metric in the calculation of noise maps, since it gives the value of sound energy produced by an acoustic event.[4] We build an average daily noise exposure index, $LVA_{year}$, over a year.[5] In

[3]The certification procedure determines the Effective Perceived Noise Level (EPNdB) for take–off and landing operations in three specific spots called reference noise measurement points. The EPNL is an indicator constructed from measurements of sound pressure level for 24 third-octave bands through a process that takes into account spectral irregularities and duration of the event. To evaluate landing operations the measurement point, called Approach, is placed under the trajectory at 2,000 meters from the threshold. To evaluate take–off operations there are two reference noise measurement points. The first, called Flyover is placed under the trajectory at 6,500 meters from the start of roll, the second, called Lateral is that point at 450 meters from the runway where the highest level is measured (several measuring stations parallel to the runway must be deployed).

[4]Since there is no a precise relation between the two metrics (that strongly depends on the noise spectrum and the measurement point), we simulated with the Integrated Noise Model (INM) the operations of the certification process (also reproducing the weather conditions required), computing both EPNL and SEL for each aircraft and for each measurement point. Then, in order to minimize errors arising from not certain correspondence between simulated and actual flight profile, we considered four categories of aircraft identifying an average difference between EPNL and SEL.

[5]In doing so, we refer to the approach applied by Hsu and Lin (2005). Notice that the index proposed in this contribution describes the average noise exposure for communities in airport environs. It does not captures precisely the damage cost of noise that is usually valued in the literature in two ways: (1) via hedonic pricing studies, based on the impact of noise on property prices, or (2) via stated preference techniques, based on peoples willingness to pay for a quieter environment (Dings et al., 2003). Given the difficulties to get this kind of information for an entire sample of airports, both these approaches have been applied mostly to single airport analysis, producing different results.

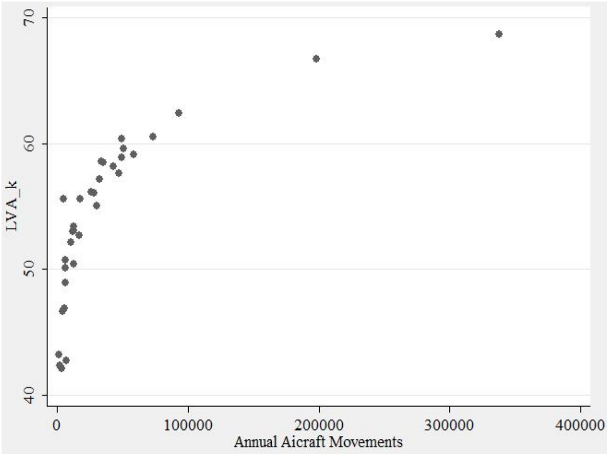


Figure 1: Noise (Db) created by movement and airport size

particular, we first compute a $LVA_p$ value for each measurement point $p$ taking into account all operations at airport level (arrivals and departures) as follows:

$$LVA_p = 10log(\frac{1}{3,600 \times 24 \times 365} \times \sum 10^{\frac{(SEL+W)}{10}}) \tag{12}$$

where W is a penalty equal to 10 dB applied to the levels of SEL if the event takes place during the night. Then, in order to obtain a synthetic index for the single airport, we compute the energetic mean of the values of the three measurement points.[6] The fact that the departures are doubly represented in relation to arrivals (Flyover and Lateral Measurement Point) can be considered acceptable, since the take-off causes more disturbance to people living near the airport infrastructure. The index of airport noise is therefore:

$$LVA_{year} = 10log(\frac{1}{3} \times \sum_{p=1}^{3} 10^{\frac{LVA_y}{10}}) \tag{13}$$

## 4.2 Local Air Pollution Index

Also in case of LAP, it is relevant the Landing Take-Off (LTO) cycle. We compute the emissions produced by each aircraft type taking into account

[6]Since we are working with acoustic variables expressed in dB, we have to consider that these variables are logarithms and they cannot follow the same calculations rules than with ordinary numbers.

both (1) the emission factors for the aircrafts specific engines and (2) the number of engines installed on each aircraft type. Our references are the values specified in the aircraft certification, established in accordance with the criteria set out on the basis of Annex 16 of the ICAO Convention (Volume 2), dealing with the protection of the environment from the effect of aircraft engine emissions. In order to compute the emissions produced by each airport in our data set we matched five databases: OAG, EASA, International Register of Civil Aircraft (IRCA), FOI database by the Swedish Defence Research Agency and ICAO Engine Emissions Databank. OAG gives the number of landing and take-off operations for the different model of aircraft in each Italian airport. IRCA and EASA provide information about the engine models installed on the different aircraft types. ICAO and FOI supply information about the emission factors (i.e., the emitted quantities in grams per kilogram of fuel consumed) for each engine model in each LTO phase.[7] The pollutants considered in this contribution are: hydrocarbons (HC), carbon monoxide (CO), and nitrogen oxides (NOx). In order to compute the total emission of pollutant $p$ produced by aircraft $i$ ($Q_{pi}$ during the LTO cycle, we apply the following equation:

$$Q_{pi} = n_{ij} \times \sum_{f=1}^{4} (E_{jpf} \times d_f \times FC_{fj}) \tag{14}$$

where $n_{ij}$ is the number of engine of type $j$ installed on aircraft $i$, $E_{jpf}$ is the specific engine $j$ emission factor of pollutant $p$ (kg) for the phase $f$, $d_f$ is the duration of the phase and $Fc_{fj}$ is the indicated specific fuel consumption in kg/sec of engine j. Hence, multiplying $Q_{pi}$ by the number of flights made by aircraft $i$ in airport $A$ ($m_{iA}$), we get the total amount of pollutant $p$ kg produced in one year at the same airport:

$$\widetilde{Q}_{pA} = m_{iA} \times Q_{pi} \tag{15}$$

To aggregate these data into a single index representing the LAP produced by each airport, we consider the cost of damage imposed by each pollutant ($c_p$). Such estimates are provided by Dings *et al.*(2003) and are applied to the emission levels computed for each airport. The LAP index is obtained as the sum of the produced kg of each pollutant weighted for its relative cost of damage:

[7] The ICAO LTO cycle model is divided into four phases, Take–Off, lasting 0.7 minutes, Climb Out, lasting 2.2 minutes, Approach, lasting 4 minutes, and Idle, which is divided into two sub–phases: Taxi In, lasting 7 minutes and Taxi Out, lasting 19 minutes.

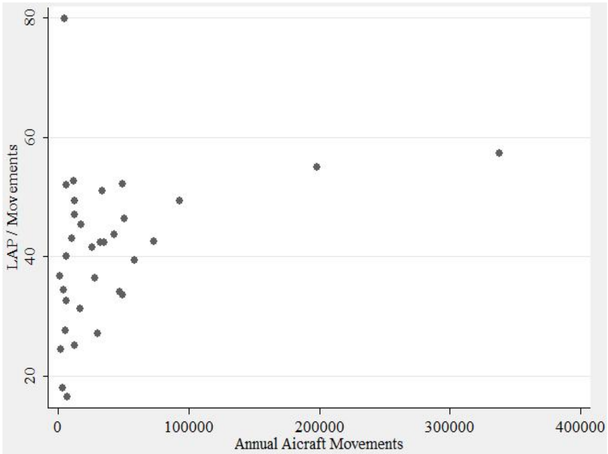


Figure 2: Cost of damage (Euros) created by movement and airport size

$$LAP_A = \sum_{p=1}^{3} (c_p \times \widetilde{Q}_{pA}) \tag{16}$$

### 4.3 Descriptive statistics of Input and Output variables

$LVA_{year}$ and $LAP$ are the undesirable outputs included in our analysis. Table 1, Figure 1 and Figure 2 show the values of the two indexes for each airport belonging to our sample. Notice that the LAP has been divided by the number of movements to show that there is a relevant part of the differences among airports in terms of LAP, which is not due to the traffic volume. Given that different aircraft types produce different levels of LAP (and noise), the key - factor is the fleet mix operating in each airports.

Concerning the other (good) outputs and the inputs, the data sources are Italian Civil Aviation Authority (ENAC) and OAG for outputs (i.e., aircraft, passenger, and freight movements) and the technical information provided by the airports official documents for inputs. The latter have been integrated by a direct investigation with the managing boards of the airports. As the vast majority of previous contribution we consider two output variables: the yearly number of Work Load Units (WLU) and of aircraft movements (ATM).[8] Regarding inputs, following many previous contributions investigating the efficient inputs utilisation, we include in our data set

[8]Passengers and freight are combined as work load units, a measure common in aviation management, so that 1 WLU = 1 passenger = 100 kg of freight.

Table 1: Noise index (Db) and pollution over movement (1000s Euros), 2008

| Airport | LVA | LAP | Airport | LVA | LAP |
|---|---|---|---|---|---|
| Alghero | 53.35 | 616.3 | Olbia | 55.55 | 785.4 |
| Ancona | 42.77 | 112.5 | Parma | 46.62 | 133.4 |
| Brindisi | 52.14 | 454.0 | Palermo | 58.17 | 1894.1 |
| Bergamo | 60.33 | 2584.9 | Pantelleria | 42.15 | 63.0 |
| Bologna | 58.88 | 1651.8 | Pisa | 58.50 | 1495.6 |
| Bari | 56.16 | 1082.0 | Pescara | 46.93 | 144.8 |
| Cagliari | 57.11 | 1365.0 | Reggio Calabria | 50.71 | 253.4 |
| Catania | 59.56 | 2360.2 | Rimini | 43.18 | 62.6 |
| Rome Ciampino | 58.58 | 1712.4 | Lamezia | 53.07 | 588.9 |
| Rome Fiumicino | 68.65 | 19333.5 | Trapani | 48.92 | 203.4 |
| Florence | 55.03 | 822.8 | Turin | 57.60 | 1614.1 |
| Forlì | 50.09 | 319.8 | Trieste | 50.38 | 323.6 |
| Genoa | 52.70 | 536.8 | Treviso | 53.03 | 643.8 |
| Milan Linate | 62.37 | 4594.1 | Brescia | 55.56 | 392.7 |
| Lampedusa | 42.33 | 55.1 | Venice | 60.53 | 3117.8 |
| Milan Malpensa | 66.68 | 10883.0 | Verona | 56.07 | 1017.6 |
| Naples | 59.09 | 2303.0 | Total | 54.33 | 1924.9 |

the runway length, the total number of aircraft parking positions, the terminal surface area and the number of baggage claims. The descriptive statistics regarding outputs and inputs are presented in Table 2. We are able to collect 4 observation for each variable and for each airports, covering a period of 4 years, from 2005 to 2008. In Table 1 and 2 only data relative to the last year are reported.

Table 2: Descriptive statistics of inputs and outputs

| Variable | Mean | Std Dev. | Min. | Max. |
|---|---|---|---|---|
| *Inputs* | | | | |
| terminal area | 38811.52 | 73320.04 | 1100 | 350000 |
| baggage claims | 4.48 | 3.32 | 1 | 15 |
| runway length | 3414.96 | 2354.51 | 1688 | 14709 |
| aircraft parking position | 26.22 | 26.17 | 2 | 142 |
| *Desirable outputs* | | | | |
| WLU(1000s) | 4136.56 | 6949.51 | 69.06 | 36758.41 |
| ATM | 38782.77 | 62876.25 | 434 | 337986 |
| *Undesirable outputs* | | | | |
| LAP(1000s) | 1805.86 | 3451.58 | 22.68 | 19333.54 |
| LVA | 53.67 | 7.26 | 31.76 | 68.65 |

## 4.4 Explanatory variables in the second stage

Our paper is focused on understanding the effect on airport's environmental performance of a set of exogenous variables affecting the efficient utilization of airport infrastructures. Of course we have to solve the task of translated this aspect in measurable and observable variable which have to be inserted as explanatory variable of eco–efficiency. More in details we include in the analysis a set of variables, each belonging to one of the following 4 subsets:

- *fleet mix*: as mentioned before, it is clear the existence of a fleet mix effect, looking at the different values of the ratio between LAP and movements characterizing airports (Table 1 and Figure 2). In order to describe the composition of the fleets operating at different airports, we use the percentage of flights made using narrow–body aircrafts (i.e., NB).[9] Since the majority of Italian airports have no flights made with

[9]A narrow–body is an aircraft with a fuselage aircraft cabin width of 3 to 4 meters,

wide–body aircrafts, the main differences consist in the percentage of narrowbodies with respect to the sum of the percentages of regional jets and power propeller aircrafts. Given that the impact in terms of noise and pollution is greater in case of narrowbody, we expect that the higher is the percentage of narrowbodies, the lower is airport environmental efficiency (i.e., the higher is the percentage of regional jets and power propeller, the higher is airport environmental efficiency).

- *airports' ownership structure*: we consider the percentage of airport's assets owned by Public Local Authorities (PLA). Our purpose is to test if the stronger is the presence of public local authorities, the higher is the attention paid to environmental concerns, since noise and LAP negative effects are essentially local.[10]

- *size*: we control for size (using natural log of the yearly aircraft movements of each airport) to understand if there are scale economies.

- *airlines*: we control for both the presence of Low Cost Carriers and the level of dominance of the main carrier operating at each airport of our sample. Since low cost carriers use modern fleets, they are often considered leaders in terms of environmental efficiency. In this sense, one should expect that the stronger is the presence of LCCs at one airports, the higher is airport's environmental efficiency. This is the reason why we include a variable representing the yearly share of the available seats offered by LCCs (LCC). Furthermore, we include also a variable representing the share of available seats per year offered by the main airline in the airport (DOM). In general, a strong dependence on the main carrier is a risky situation for an airport. However, a dominant airline at an airport might also be interested in reducing negative externalities, especially if this strategy prevents operational restrictions (e.g., during nighttime) and facilitates capacity enhancement programs. Finally, we also include the interactions of these two variable in order to study the effect coming from LCCs' dominance.

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and seats arranged along a single aisle. In contrast, a wide–body is a larger aircraft and is usually configured with multiple travel classes with a fuselage diameter of 5 to 7 meters and twin aisles. Notice that a typical wide–body aircraft can accommodate between 200 and 600 passengers, while the largest narrow–body aircrafts (e.g., the Boeing 757-300) carry a maximum of about 250. Regional jets carry fewer passengers than mainline jets but generally travel at similar speeds, cruise at similar altitudes, and require runways of about the same length.

[10]Notice that in many countries the ownership share of local authorities decreases with the size of the airport. However this is not the case for Italy, where the majority of airports is still under the control of local public authorities.

The descriptive statistics regarding explanatory variables are presented in Table 3.

Table 3: Descriptive statistics of explanatory variables

| Variable | Mean | Std Dev. | Min. | Max. |
|---|---|---|---|---|
| NB | 0.703 | 0.270 | 0.000 | 1.000 |
| PLA | 0.494 | 0.345 | 0.000 | 1.000 |
| LCC | 0.380 | 0.323 | 0.000 | 1.000 |
| DOM | 0.487 | 0.216 | 0.127 | 1.000 |
| SIZE | 9.739 | 1.317 | 6.073 | 12.731 |

# 5 Empirical findings

## 5.1 Environmental efficiency results

For each Italian airport in our sample with complete data, environmental efficiency score are calculated by solving linear program represented by Eq. (6). All programs are written and solved using R. Table 5 shows the scores by airport for the period 2005–2008. We run 4 separate frontier, one for each period, in order to obtain a better representation of reality and to avoid problems relative to annual effect. Before results interpretation, it should be underlined that efficiency is a relative concept and then what we get from estimation is the position of each airport in respect to the best of the sample in a specific time period. Furthermore, we run a second standard DEA model[11] without bad outputs (see Table 6), in order to make a comparison between the scores. Notice that, as in previous studies, we observe an overall increase in airports' efficiency scores. Specifically, our results indicate that airports tend to be more efficient, on average, when negative externalities of production are included in the analysis. Especially those airports that are highly technical inefficient when only "good" outputs are considered (because they have a low utilisation rate of their aeronautical inputs), show strong improvements in their efficiency when also "bad" output are considered. This is mainly due to the fact that airports producing *ceteris paribus* few movements (i.e., "inefficient airports" according to the traditional efficiency specification) produce also low level of noise and LAP and, as a consequence, recover efficiency when these negative externalities are included in the analysis.

[11]We assume the same inputs and outputs and we reports individual results choosing an input orientation. Second stage analysis is performed on transformed efficiency score.

## 5.2 Second stage estimates

We try to test several hypothesis on the determinant of environmental efficiency and in doing so we follow the approach proposed in Picazo-Tadeo*et al.* (2011). We set the number of replication in the bootstrap procedure equal to 1000. Two model of second stage analysis are performed, both following the statistical procedure we reports in section 3.2. Some problems arise in the second stage, due to the limited number of inefficient observations, especially in the DDF model. In order to partially solve this issue we perform our second stage by putting together efficiency score from different annual frontier. This seems to be reasonable because each score is computed relatively to the best practice of each year.

Table 4 shows the second stage estimates for both Model 1 (with bads) and Model 2 (with only good outputs). Notice that the two models differ in terms of both significance and sign of the coefficient of many variables. This is a further confirmation of the fact that ignoring negative externalities of airport activity, when they exist, could produce misleading results. Differently from both significance and sign, the magnitude of coefficient is not comparable given the two different range of Environmental Efficiency (EE) by DDF and the transformed Technical Efficiency (TE) by DEA. EE vary between 0 and 0.9 in our sample, while TE vary between 1 and 7.25 which represent the detected threshold for outliers.[12]

Looking more carefully at the scores obtained including noise and local air pollution, 3 variables are significant: NB, PLA and SIZE. Among these, both NB and SIZE show a different sign in the two model. More in details, the higher is the percentage of narrow–body aircrafts in the airport fleet mix, the lower is airport environmental efficiency. In other words, given that the majority of Italian airports' fleet mix is composed essentially by narrowbodies, regional jets and power propeller, if a percentage of flight is made by regional jets rather than narrowbodies, the environmental efficiency of the airports increases. Notice that the result is confirmed by the fact that if we replace in the second stage regression NB with both RJ and PP, these two variables result significant with negative sign. This finding is extremely interesting considering that the gap between regional and narrowbody traditional jets stage lengths appears to be close: regional jets offer jet–like features but with smaller capacities meaning that they can be used to replace narrow–

[12]We consider as outliers observation that are over the value of:

$$\mu(TE) + 3sd(TE)$$

In our sample 3 observation are dropped according to this criteria.

Table 4: Bootstrap results of truncated regression estimates, 90 percent of confidence

| | Model 1 EE | | | Model 2 TE | | |
|---|---|---|---|---|---|---|
| Explanatory Variables | Estimated Coefficient | Lower bound | Upper bound | Estimated Coefficient | Lower bound | Upper bound |
| NB(%) | **0.060** | **0.037** | **0.081** | -0.850 | -0.882 | 0.897 |
| PLA(%) | **-0.049** | **-0.062** | **-0.035** | **1.570** | **0.033** | **1.167** |
| LCC(%) | -0.009 | -0.058 | 0.043 | **-4.201** | **-6.210** | **-2.044** |
| DOM(%) | 0.029 | -0.009 | 0.066 | **-3.116** | **-5.724** | **-2.569** |
| LCCxDOM | -0.019 | -0.095 | 0.055 | **6.369** | **3.252** | **9.339** |
| SIZE | **-0.057** | **-0.063** | **-0.049** | **-2.144** | **-1.251** | **-0.763** |
| Constant | 0.622 | 0.555 | 0.712 | 23.103 | 11.679 | 17.318 |
| Sigma | 0.028 | 0.013 | 0.019 | 1.523 | 1.094 | 1.398 |
| Num. of obs. | | 51 | | | 95 | |

Significant variable at 90% are marked in bold

bodies on routes that are normally served by mainline jets (Brueckner and Pai, 2009). Given the different capacity, this is important especially for those routes that are characterized by the penalty of empty seats, because, in this case, the replacement would not cause congestion problems associated with an increased number of flights.[13] Hence, considering that the environmental impact of a traditional jet is usually greater than a regional one, having flights with low load factors and high negative externalities in terms of pollution and noise is extremely inefficient. We provide an example to clarify this concept.

Table 5 shows some examples of domestic flights, departing from Rome Fiumicino Airport (FCO). For all these flights we compute an average load factor (i.e., the ratio between the number of yearly passengers and the number of seats offered). Table 5 also shows the percentage of flights made by three narrowbody aircrafts (i.e., MD–80, MD–82 and Airbus A320) and one regional jet (i.e., Canadair Regional Jet 900, CRJ–900). These models are comparable in terms of available seats: MD–80 and MD–82 have 131 and 150 seats respectively; the A320 has 131 seats, while the CRJ–900 has 90 seats. Notice that, in the majority of the cases, the load factor multiplied

[13]For example, the regional jets Embraer ERJ-145 and Canadair CRJ-200 have 50 seats, while a Boeing B737-500 has 132 seats, a B737-800 189 seats and an Airbus A319 has 142 seats.

Table 5: Examples of domestic routes with low load factor (year 2006)

| **Dep Airport** | Rome Fiumicino | | | | |
|---|---|---|---|---|---|
| **Arr Airport** | Venice | Turin | Bari | Trieste | Genoa |
| **Passengers** | 286,470 | 434,076 | 268,125 | 138,566 | 235,521 |
| **Seats** | 474,583 | 667,802 | 433,524 | 245,044 | 376,757 |
| **Load Factor** | 0.60 | 0.65 | 0.62 | 0.57 | 0.63 |
| **% MD-80/82 (131-150 seats)** | 63% | 43% | 43% | 50% | 73% |
| **% Airbus A320** (131 seats) | - | 4% | 8% | 3% | 6% |
| **% CRJ-900 (90 seats)** | 2% | 2% | 7% | 9% | 3% |
| **Pas. per MD flight** | 84 | 93 | 89 | 79 | 91 |
| **CRJ Seats - MD Pas.** | 6 | -3 | 1 | 11 | -1 |
| **Pas. per A320 flight** | 79 | 85 | 81 | 74 | 82 |
| **CRJ Seats - A320 Pas.** | - | 5 | 9 | 16 | 8 |

by the available seats of MD aircrafts and A320 is smaller than 90. Hence, the same amount of passengers could be transported, for the same routes, by a regional jet such as the CRJ–900. Table 6 shows the relevant differences between the MD aircrafts and the CRJ–900 in terms of emissions and noise. Notice that a 3 dB increase (decrease) corresponds to a doubling (halving) in the sound level.

Table 6: LTO emissions by aircraft model

| **Aircraft Model** | **HC** | **CO** | **NOx** | **Noise** | **Seats** |
|---|---|---|---|---|---|
| MD–80 | 0.861 | 7.176 | 10.462 | 90.96 | 131 |
| MD–82 | 0.863 | 7.019 | 10.424 | 91.37 | 150 |
| Airbus A320 | 0.471 | 6.767 | 10.893 | 92.53 | 131 |
| CRJ–900 | 0.035 | 4.126 | 4.442 | 87.19 | 90 |

Pollutants are expressed in kg.

Noise is the energetic mean of the approach and flyover levels of EPNL (dB)

Since many of these aircrafts are daily used on the same city–pair market, replacing an aircraft model with another one would not lead to network problems. Clearly, it would be different if the same aircraft was used on routes with different load factors. However, notice that even the replacement of an MD with two CRJ–900 would be desirable in terms of emissions per seat, but this kind of practice would lead to potential problems of congestion, as already mentioned, and also to an increase in the airline's costs (e.g., two cockpit crews).[14]

[14]Notice that a change in the fleet mix at an airport or a reduction in the number of movements are not the unique ways to reduce airports' environmental impact. First, airlines often can purchase kits to upgrade aircraft engine in the fleet and, sometimes, there is also the possibility to convert aircraft on order to the newest engine configuration prior to

As far as airports' ownership structure, the higher is the presence of public local authorities, the higher is airport environmental efficiency. This seems to suggest that public local authorities pay a particular attention to environmental concerns such as noise and local air pollution, which essentially affect people leaving nearby the airports. This result is confirmed by the fact that in model 2 the variable is significant with a positive sign, suggesting that, in terms of technical efficiency, the result is completely different.

As far as the variable representing size, it is significant with a negative sign in both model 1 and model 2 . This suggests the existence of scale economies allowing bigger airports to reach higher efficiency scores in terms of both environmental and technical efficiency.

Moreover if we consider the variables regarding airlines, the presence of LCCs seems not to influence airport environmental efficiency. This means that the hypothesis that LCCs are greener than traditional carriers is not confirmed. On the contrary, the higher is the value of LCC, the higher is airports' technical efficiency according to the traditional airport benchmarking approach (i.e., model 2).[15]This may be due to the fact that the presence of LCCs often resulted in a relevant rise in both domestic and international traffic, thus leading to a better utilization of the existing infrastructures. However, the significance with positive sign of the interaction between LCC and dominance suggests that when LCCs are too much strong, their effect becomes negative. This negative dominance effect may be explained in terms of entry deterrence adopted by the dominant LCC. As a consequence, the airports capacity to attract new carriers is limited, and, in turn, its utilization of assets.

Finally, we compare the above results obtained through the DDF model with undesirable output (i.e., Model 1) with a DDF model in which the negative outputs are considered as inputs. Our purpose is to verify whether our results can be considered robust when some hypothesis are relaxed. In particular, the weak disposability assumption in Model 1 is quite restrictive and

aircraft delivery. Furthermore, there are other operational options in order to reduce actual emissions: for example, airports might reduce taxi times (leading to a reduction of local air pollution) or apply noise abatement procedures (e.g., preferred runways, minimum noise routings). The impact of these last operational procedures cannot be taken into account in this contribution.

[15]European large LCCs (i.e., Ryanair and Easyjet) only operate narrow–body aircrafts. However, many LCCs operating at Italian airports during the period 2005–2008 also use regional jets (e.g., MyAir, Blue 1, Brussels Airlines, Clubair, . . . ). Furthermore, many traditional carrier operate narrow–body aircrafts. As a result, the correlation between LCC and NB is not so high (0.396), meaning that eventual problems of multicollinearity are reduced. Notice also that, if we do not include LCC in the analysis the results regarding environmental efficiency do not change significantly.

provides a sort of short run look at relative efficiency scores. However, by changing the mix of aircraft flying into an airport or by imposing night curfews, an airport can reduce negative outputs (i.e., noise and pollution), while maintaining positive outputs (total flights, total passengers, total frights, etc.). This is especially true in the long run when technological progress produce new more environmentally friendly aircrafts. Obviously, this possibility is not in line with the weak disposability assumption on outputs, since the tight coupling of the negative and the positive outputs, at least in the long run, fails. Hence, in order to look also at a more long run scenario, we compute efficiency scores by considering the negative outputs as inputs and minimizing the inputs plus negative outputs subject to the positive outputs. Notice that this is a less restrictive look at relative efficiency. Table 10 shows the efficiency scores of the long run model (i.e., Model 3). Note that they are very similar to those obtained with Model 1: unless some exceptions efficient airport are the same. Furthermore, also the results of the second stage seem to be confirmed (Table 7) in the sense that the significant variables (i.e., NB, PLA and SIZE) retain the same sign they have according to Model 1. Furthermore, the interaction between LCC and DOM retains its negative sign but becomes significant.

Table 7: Bootstrap results of truncated regression estimates, 90 percent of confidence

| | Model 3 EE | | |
|---|---|---|---|
| Explanatory Variables | Estimated Coefficient | Lower bound | Upper bound |
| NB(%) | **0.412** | **0.283** | **0.476** |
| PLA(%) | **-0.109** | **-0.169** | **-0.032** |
| LCC(%) | 0.076 | -0.154 | 0.295 |
| DOM(%) | 0.044 | -0.157 | 0.238 |
| LCCxDOM | **-0.564** | **-0.848** | **-0.201** |
| SIZE | **-0.208** | **-0.225** | **-0.153** |
| Constant | 2.944 | 2.496 | 3.269 |
| Sigma | 0.160 | 0.072 | 0.105 |
| Number of Obs. | | 64 | |

Significant variable at 90% are marked in bold

Focusing on the econometric property of our results we have to underline a fact that arise from Table 4 and Table 7. Some estimated coefficient value lie outside the bootstrap confidence interval (CI). This is an issue that emerge also in Simar and Wilson (2007), when they present their empirical analysis and it is probably due to the ML problem in finite samples. In case of a limited number of observation this limitation should appear stronger then in other case. A further point to support our findings regards is that the bootstrap CI incorporate an implicit bias correction which is not considered in the original estimates of $\hat{\gamma}$ from Eq. (7).

# 6 Conclusion and discussion

In this paper, a DDF approach for airport efficiency assessment considering undesirable outputs has been applied to a sample of 33 Italian airports for the period 2005–2008. In order to consider both local air pollution and noise, we computed two indexes describing the total amounts of pollutants and noise produced for each Italian airport included in our data set. Notice that there are no contributions in the existing literature on airport efficiency assessment which consider the production of local air pollution.

The results show that the efficiency scores of the airports, when their undesirable outputs are ignored, are generally different and can therefore be misleading. Especially those airports that are highly technical inefficient when only "good" outputs are considered (because they have a low utilization rate of their aeronautical inputs), show a strong improvements in their efficiency when also "bad" output are considered. However, this is mostly not due to managerial effort, but to econometric specification: inefficient airports improve their scores because they get closer to the environmental frontier thanks to the low number of movements realized.

Furthermore, we perform a second stage regression in order to investigate the effect of some potential determinants of airport efficiency. The results of the second stage confirm that ignoring undesirable output may produce a distortion, also in testing the determinants of efficiency.

First, we clearly identify the presence of a fleet effect. More environmental friendly fleets reduce (*ceteris paribus*) emissions and noise, making airports more environmentally efficient. More in details, we find that airports are more efficient, the lower is the percentage of flights made through narrow–body aircrafts, in comparison to the percentage of flights made by regional jets. The fact that the partial substitution of narrow–bodies with regional jets increases the environmental performance of airports has an important policy implication. Obviously, given the different capacities of the two aircraft models, this finding is especially valuable for those flights that have low load factor, because, in this case, it would not be necessary to increase the number of flights (given the number of passengers) with the risk of experiencing congestion problems. In this sense, the airports could encourage airlines to use cleaner aircrafts for example through reduction of airport charges. Policy makers could alternatively provide an incentive scheme that rewards the greenest airports: such incentives could then be shared between the airport and the airlines that have contributed to the objective.

Second, we find that the higher is the stake of public local authorities in the airports ownership structure, the higher is their environmental efficiency. The fact that local authorities may be more sensitive to the problems related to noise and local air pollution, it is not surprising and seems to be an argument down the privatization of airports. However, the theme of the ideal ownership structure of airports is very complex as demonstrated by the fact that the influence on traditional technical efficiency is, contrariwise, positive.

Third, with regard to the influence of airlines on airport efficiency, the presence of low cost is not significant from the environmental point of view. This result is interesting as it seems to deny, at least on average, the common perception that LCC, using modern aircrafts, are more environmentally friendly. On the contrary, the presence of LCCs seem to be positive for airports technical efficiency as long as there is no a dominance by the main LCC operating at the airport.

Finally, when we look at a more long run scenario, allowing airports to reduce the level of bad outputs without necessarily reduce that of good outputs, we find similar results in terms of both efficiency scores and second stage analysis.

## Appendix

Table 8: Estimated Environmental efficiency score for each airport by year

| Airport | 2005 | 2006 | 2007 | 2008 | Total |
|---|---|---|---|---|---|
| Alghero | 0.000 | 0.000 | 0.105 | 0.114 | 0.055 |
| Ancona | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Brindisi | 0.249 | 0.180 | 0.154 | 0.149 | 0.183 |
| Bergamo | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Bologna | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Bari | 0.158 | 0.143 | 0.094 | 0.078 | 0.118 |
| Cagliari | 0.091 | 0.079 | 0.089 | 0.078 | 0.084 |
| Catania | 0.000 | 0.020 | 0.012 | 0.000 | 0.008 |
| Rome Ciampino | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Rome Fiumicino | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Florence | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Forlì | 0.192 | 0.000 | 0.120 | 0.126 | 0.109 |
| Genoa | 0.088 | 0.071 | 0.000 | 0.081 | 0.060 |
| Milan Linate | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Lampedusa | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Milan Malpensa | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Naples | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Olbia | 0.140 | 0.134 | 0.110 | 0.124 | 0.127 |
| Parma | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Palermo | 0.063 | 0.040 | 0.054 | 0.046 | 0.051 |
| Pantelleria | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Pisa | 0.035 | 0.000 | 0.000 | 0.000 | 0.009 |
| Pescara | 0.126 | 0.108 | 0.105 | 0.081 | 0.105 |
| Reggio Calabria | 0.266 | 0.000 | 0.155 | 0.131 | 0.138 |
| Rimini | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Lamezia | 0.168 | 0.072 | 0.077 | 0.096 | 0.103 |
| Trapani | 0.123 | 0.173 | 0.000 | 0.000 | 0.074 |
| Turin | 0.033 | 0.032 | 0.013 | 0.000 | 0.019 |
| Trieste | 0.124 | 0.095 | 0.000 | 0.000 | 0.055 |
| Treviso | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Brescia | 0.000 | 0.245 | 0.000 | 0.222 | 0.117 |
| Venice | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Verona | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Total | 0.056 | 0.042 | 0.033 | 0.040 | 0.043 |

Table 9: DEA efficiency score for each airport by year

| Airport | 2005 | 2006 | 2007 | 2008 | Total |
|---|---|---|---|---|---|
| Alghero | 0.553 | 0.601 | 0.677 | 0.546 | 0.590 |
| Ancona | 0.275 | 0.301 | 0.290 | 0.306 | 0.293 |
| Brindisi | 0.398 | 0.405 | 0.303 | 0.329 | 0.353 |
| Bergamo | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Bologna | 0.655 | 0.693 | 0.681 | 0.672 | 0.675 |
| Bari | 0.356 | 0.512 | 0.551 | 0.650 | 0.493 |
| Cagliari | 0.589 | 0.580 | 0.410 | 0.541 | 0.519 |
| Catania | 1.000 | 0.776 | 0.863 | 0.985 | 0.896 |
| Rome Ciampino | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Rome Fiumicino | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Florence | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Forlì | 0.409 | 0.453 | 0.509 | 0.273 | 0.389 |
| Genoa | 0.373 | 0.371 | 0.352 | 0.347 | 0.360 |
| Milan Linate | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Lampedusa | 0.634 | 1.000 | 0.409 | 0.374 | 0.520 |
| Milan Malpensa | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Naples | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Olbia | 0.237 | 0.238 | 0.252 | 0.271 | 0.249 |
| Parma | 0.398 | **0.121** | 0.138 | 0.514 | 0.201 |
| Palermo | 0.631 | 0.745 | 0.712 | 0.742 | 0.704 |
| Pantelleria | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Pisa | 0.535 | 0.852 | 1.000 | 0.869 | 0.770 |
| Pescara | 0.202 | 0.333 | 0.296 | 0.302 | 0.273 |
| Reggio Calabria | 0.446 | 1.000 | 0.578 | 0.460 | 0.560 |
| Rimini | **0.085** | **0.122** | 0.186 | 0.164 | 0.127 |
| Lamezia | 0.408 | 0.465 | 0.496 | 0.395 | 0.437 |
| Trapani | 0.325 | 0.357 | 0.598 | 0.578 | 0.431 |
| Turin | 0.595 | 0.543 | 0.581 | 0.610 | 0.581 |
| Trieste | 0.181 | 0.234 | 0.299 | 0.318 | 0.246 |
| Treviso | 1.000 | 0.405 | 0.477 | 0.564 | 0.545 |
| Brescia | 0.233 | 0.189 | 0.230 | 0.225 | 0.218 |
| Venice | 0.721 | 0.837 | 0.993 | 0.833 | 0.835 |
| Verona | 0.560 | 0.507 | 0.605 | 0.567 | 0.557 |
| Total | 0.413 | 0.429 | 0.456 | 0.477 | 0.442 |

Efficiency score are reported as input oriented, then variable between 0 and 1, with unity represent airports on the technological frontier

Outliers are marked in bold

Table 10: Long run environmental efficiency score for each airport by year

| Airport | 2005 | 2006 | 2007 | 2008 | Total |
|---|---|---|---|---|---|
| Alghero | 0.781 | 0.871 | 0.827 | 0.793 | 0.818 |
| Ancona | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Brindisi | 0.608 | 0.733 | 0.669 | 0.675 | 0.671 |
| Bergamo | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Bologna | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Bari | 0,736 | 0,785 | 0,833 | 0,843 | 0,799 |
| Cagliari | 0.851 | 0.873 | 0.804 | 0.816 | 0.836 |
| Catania | 1.000 | 0.963 | 0.978 | 1.000 | 0.985 |
| Rome Ciampino | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Rome Fiumicino | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Florence | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Forlì | 0,687 | 0,755 | 0,787 | 0,72 | 0,737 |
| Genoa | 0,836 | 0,877 | 0,906 | 0,857 | 0,869 |
| Milan Linate | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Lampedusa | 0.888 | 1.000 | 1.000 | 1.000 | 0.972 |
| Milan Malpensa | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Naples | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Olbia | 0.781 | 0.786 | 0.782 | 0.744 | 0.773 |
| Parma | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Palermo | 0,878 | 0,93 | 0,884 | 0,897 | 0,897 |
| Pantelleria | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Pisa | 0.94 | 1.000 | 1.000 | 0.967 | 0.977 |
| Pescara | 1.000 | 0.819 | 0.828 | 0.821 | 0.867 |
| Reggio Calabria | 0.609 | 1.000 | 0.759 | 0.76 | 0.782 |
| Rimini | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Lamezia | 0.721 | 0.819 | 0.853 | 0.83 | 0.806 |
| Trapani | 0.81 | 0.717 | 0.876 | 0.885 | 0.822 |
| Turin | 0.937 | 0.932 | 0.972 | 1.000 | 0.96 |
| Trieste | 0.755 | 0.836 | 0.868 | 1.000 | 0.865 |
| Treviso | 1.000 | 0.932 | 0.95 | 0.929 | 0.953 |
| Brescia | 0.999 | 0.651 | 0.93 | 0.51 | 0.773 |
| Venice | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Verona | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Total | 0.903 | 0.918 | 0.924 | 0.911 | 0.914 |

Efficiency score are reported as input oriented, then variable between 0 and 1, with unity represent airports on the technological frontier

Outliers are marked in bold

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