The Impact of Local Air Pollution on Italian Airports' Efficiency

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Abstract

We estimate technical efficiency of 33 Italian airports for the period 2005–2008. In addition to conventional desirable outputs (aircraft, passenger and cargo movements), we consider also a negative externality of airport activity: local air pollution. We apply a hyperbolic distance function to estimate a multi–output stochastic frontier. Such approach allows to treat the outputs' vector asymmetrically by allowing desirable outputs expansion and undesirable outputs contraction. We show that airports' efficiency scores (obtained by maximum likelihood estimation) are greater and closer when local air pollution is included in the analysis and that there is a fleet effect. Those airports where airlines use environmental friendly aircrafts get the largest efficiency improvements. We observe that this happens mainly in regional airports.

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Keywords: Airport efficiency, hyperbolic distance function, undesirable outputs, local air pollution

1 Introduction

Airport efficiency has been the subject of many contributions. Traditionally, the inputs considered are either the production factors (e.g., labor and capital) or the physical infrastructure of the airports (e.g., runways and terminal area), while the outputs are given by the number of aircraft movements, passengers, and freights.[1] Efficient airports are those that maximize their outputs/inputs ratios. Hence, under this perspective, the pursuit of efficiency aims at increasing the number of aircraft operations as well as the number of passengers transported and cargo handled, for a given level of inputs.

This traditional approach to estimate airport efficiency does not consider some important environmental externalities (e.g., noise annoyance and pollutants' emissions) associated to airport activities, that should be instead considered in the performance evaluation. Not considering these "bad" outputs may give rise to two errors: (1) efficiency estimates may be biased and, as a consequence, the obtained benchmarking is misleading; (2) the benefits created by airport activities are overestimated, since they do not take into account the full social cost produced.

This is the aim of the present paper, i.e. to evaluate airports' technical efficiency using a more general approach. We adopt a stochastic frontier model taking into account that airports exploit their inputs to produce, at the same time, the conventional "good" outputs and some undesirable outputs. More in details, in this contribution, we focus our attention on the level of Local Air Pollution (LAP) produced by aircraft movements.[2] During the Landing–Take Off (LTO) cycle, an aircraft gives off several pollutants (i.e., hydrocarbons, carbon monoxide, nitrogen oxides, sulphur dioxide and particulate matter) affecting the quality of local air. Also CO_2 is produced by aircraft engines, but it affects only global warming and not local air quality. In this contribution we focus on the pollutants emissions produced during the LTO cycle

[1]For a summary of the input and output included in the previous efficiency analysis refer to Tovar and Martín-Cejas (2009).

[2]Other types of negative externality related to air transportation are noise and climate change. The first one is not considered here because of the difficulties connected to both the non–linear properties and the subjectivity characterizing noise annoyance. Climate change is mainly associated with emissions of aircrafts during the cruise stage, regardless of departure and arrival airports. In fact, as pointed out by Givoni and Rietveld (2010), to account for aircraft operation impact on climate change the whole flight must be accounted.

and certified by ICAO, i.e., hydrocarbons, carbon monoxide and nitrogen oxides.

Following the approach of Cuesta *et al.* (2009), we estimate a stochastic production frontier using a hyperbolic distance function model that is both parametric and stochastic. In this way, we are able to represent the proportion by which desirable outputs can be expanded and undesirable outputs and inputs can be reduced in a multiplicative manner. Furthermore, this methodology allows us to apply a conventional econometric technique based on maximum likelihood estimation (Battese and Coelli, 1992). The econometric model is applied to a dataset of 33 Italian airports for the period 2005–2008, covering more than 90% of the total number of passenger movements.

To the best of our knowledge, no previous study regarding airport efficiency has considered Local Air Pollution as undesirable output. Moreover, there are no parametric studies about airport efficiency that take into account the simultaneous production of desirable and undesirable outputs. The structure of this paper is as follows. A review of previous related airport efficiency studies is presented in Section 2. In Section 3, we formulate the hyperbolic distance function model and the methodology by which the index for LAP has been constructed. Section 4 reports the results of the proposed approach. Finally, Section 5 summarizes and concludes the paper.

2 Literature review

Technical efficiency refers to the ability to maximize outputs from a given vector of inputs or to minimize inputs utilization in the production process of a given vector of outputs (Coelli *et al.*, 2005). Thus, in order to describe the structure of production technology, it is necessary to employ information on input and output levels realized in the different units composing the industry (or a sample of them) (Kumbhakar and Lovell, 2000). Estimation could be done using both a parametric approach (i.e., Stochastic Frontier Analysis, SFA) and a non–parametric approach (i.e., Data Envelopment Analysis, DEA).

The literature on the estimation of airport technical efficiency presents few parametric contributions. Among them, we mention Pels *et al.* (2001, 2003), since they were the first to estimate airports' production function applying a SFA.[3] However, they ignore that airports are multi–product firms and estimate separately two production functions: one for aircraft movements and another one for passengers. If instead airports are treated as mutli–output units, it is necessary to adopt a stochastic distance function approach (Coelli and Perelman, 2000),[4] as in Chow and Fung (2009), Tovar and Martín-Cejas (2009) and Scotti *et al.* (2010).[5] However, all these studies focus only on desirable outputs.

Non–parametric distance functions have been introduced by Charnes *et al.* (1978) and dominate the empirical analysis of airport performance: Lozano and Gutiérrez (2009) present a recent and detailed review of this branch of the literature. A major drawback of the DEA approach is that all the distance between the firm and the estimated frontier is treated as inefficiency, without considering the possible impact of random shocks. Furthermore, since it does not specify the functional relation between input and output variables, it is not possible to rank the relative importance of the various productive factors. For these reasons, we adopt a stochastic frontier approach.

Few previous contributions have taken into account both desirable and undesirable outputs produced by airports. Yu (2004) estimates airports' technical efficiency using aircraft movements as desirable output and aircraft noise as undesirable output. His dataset covers 14 Taiwanese airports and includes the following inputs: runway area, terminal area, apron area, number of routes connections with other domestic airports, and city population. He finds that including noise in the efficiency analysis can provide a better understanding of airports' performances. More in details, airports are in general more efficient when both desirable and undesirable outputs are considered, and airports located in a smaller population area achieve the same efficiency than other ones. A similar result is found by Yu *et al.* (2008) by investigating a panel dataset composed by 4 Taiwanese airports for the period 1995–1999 and estimating

[3]Some contributions, Barros (2008), Oum *et al.* (2008) and Martín *et al.* (2009), estimate a cost stochastic frontier using accounting data. In doing so, they may incur in some distortions when assessing inputs prices.

[4]Input and output oriented distance functions have been introduced first by Debreu (1951), Malmquist (1953) and Shepard (1953).

[5]Unlike Chow and Fung (2009) and Tovar and Martín-Cejas (2009), Scotti *et al.* (2010) did also investigate the determinants of airports' estimated efficiency scores.

a revenue frontier.[6] Pathomsiri *et al.* (2008) consider passenger movements, cargo, and non–delayed flights as desirable outputs and time delays and number of delayed flights as undesirable outputs. The inputs included are the land area, the number of runways and the total runway area. They investigate 56 US airports for the period 2000–2003, showing that if delayed flights are excluded from the model, many large but congested airports are found to be efficient. If instead undesirable outputs are taken into account, many other airports can be classified as efficient, since they can compensate a lower desirable outputs/inputs ratio with shorter delays per inputs. Furthermore, they also provide evidence of a lower airports' productivity when undesirable outputs are included. Lozano and Gutiérrez (2010) confirm these results by analyzing the efficiency of 39 Spanish airports for the period 2006–2007, considering two undesirable outputs, i.e., the percentage of delayed flights, and the average conditional delay of delayed flights.[7]

While aircraft noise is clearly a negative externality of airport operations, flight delays may be also regarded as a signal of low quality in providing a desirable output. Hence, we do not consider delays in this contribution. Noise is also excluded for its non–linear features that cannot easily be considered with linear desirable and undesirable goods. Furthermore, some authors have shown that the social costs of aircraft pollution are relevant (Dings et al., 2003 and Givoni and Rietveld, 2009 and 2010). Hence, our contribution is a first attempt to assess airport technical efficiency when local environmental emission are taken into account.

3 Methodology

3.1 Hyperbolic distance functions and environmental efficiency

Airports' efficiency is estimated using a hyperbolic distance function. Such approach allows for the inclusion of undesirable outputs as shown in Cuesta et al. (2009). To define it, we begin by considering a production technology that transforms input vectors $x_i = (x_{1i}, \ldots, x_{Ki}) \in R_+^K$ into output vectors $o_i = (o_{1i}, \ldots, o_{Vi}) \in R_+^P$, consisting of desirable and undesirable output subvectors $y_i = (y_{1i}, \ldots, y_{Mi}) \in R_+^M$

[6] They consider total airport revenues as desirable output and aircraft noise as undesirable output. They find that total factor productivity is three times lower if bad output are considered.

[7] The inputs are the runways area, the number of aircraft parking positions, the number of baggage belts, the number of check–in desks and the number of boarding gates.

and $w_i = (w_{1i}, \ldots, w_{Ri}) \in R_+^R$, and where the subscript $i = (1, 2, \ldots, N)$ refers to a set of observed airports. T is the production possibility set representing the technology, i.e., $T = \{(x, y, w) : x \in R_+^K, (y, w) \in R_+^P, x \ can \ produce \ (y, w)\}$. T is assumed to satisfy the axioms stated in Färe and Primont (1995).

If negative output are not considered, airports' production function is tipically represented by an output distance function $D_O(x; y) = inf\{\varphi > 0 : (x; y/\varphi) \in T\}$.[8] The output distance function has been largely used in the literature, but it has no environmental interpretation. Differently from D_O, the hyperbolic distance function represents, for a given amount of inputs, the maximum expansion of the desirable output vector and equiproportionate reduction of the undesirable output vector that places a producer on the boundary of the technology T. Following Cuesta *et al.* (2009), we can represent it by the following expression:

$$D_H(x; y; w) = inf\{\theta > 0 : (x; y/\theta; w \times \theta) \in T\}.$$

This function has the virtue of treating desirable and undesirable outputs asymmetrically, thus providing an environmentally friendly characterization of the production technology. The range of the hyperbolic distance function is $0 < D_H(x, y, w) \leq 1$. If the technology satisfies the customary axioms, then the hyperbolic distance function fulfills the property of almost homogeneity (of degrees 0, 1, -1, 1):[9]

$$D_H(x, \mu y, \mu^{-1} w) = \mu D_H(x, y, w), \ \mu > 0. \tag{1}$$

Furthermore, D_H is also (i) non–decreasing in desirable outputs, (ii) non–increasing in undesirable outputs, and (iii) non–increasing in inputs.

Since Eq. (1) fully characterizes the technology assuming weak disposability, if $D_H(x, y, w) < 1$, the producer is inefficient and could improve environmental performance by expanding production of "good" outputs and by reducing undesirable pollutants.

Another possible representation of technology can be obtained by introducing an enhanced hyperbolic distance function. Unlike the previous one, the enhanced

[8]The output distance function has range between 0 and 1. It is homogeneous of degree one in outputs, non–decreasing in outputs and non-increasing in inputs (Shephard, 1970).

[9]For more information, see Aczél (1966) and Lau (1972).

hyperbolic distance function calls also for a further proportional reduction on the input side. The enhanced hyperbolic distance function is defined as:

$$D_E(x, y, w) = inf\{\phi > 0 : (x \times \phi; y/\phi; w \times \phi) \in T\}.$$

Again, D_E assumes values between 0 and 1, satisfies (i), (ii), (iii) while it has a more inclusive degree of almost homogeneity:

$$D_E(\mu^{-1}x, \mu v, \mu^{-1}w) = \mu D_E(x, v, w),\ \ \mu > 0.$$

As shown in Cuesta *et al.* (2009) and in Cuesta and Zofio (2005), D_H and D_E not only provide a flexible approximation to the unknown production technology, but also prove to be suitable to the imposition of almost homogeneity restrictions.

Furthermore, the necessary $(1 + M + K + R)$ restrictions that ensure almost homogeneity of degrees 0, 1, -1, 1 for D_H are satisfied choosing the Mth desirable output for normalizing purposes and obtaining:

$$D_H(x, \frac{y}{y_M}, w \times y_M) = \frac{D_H(x, y, w)}{y_M}.$$

Hence, adopting a translog specification for D_H, we get:

$$\begin{aligned} ln(D_{Hi}/y_{Mi}) = {} & \alpha_0 + \sum_{k=1}^{K} \alpha_k\ ln\ x_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl}\ ln\ x_{ki}\ ln\ x_{li} \\ & + \sum_{m=1}^{M-1} \beta_m\ ln\ y^*_{mi} + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \beta_{mn}\ ln\ y^*_{mi}\ ln\ y^*_{ni} \\ & + \sum_{r=1}^{R} \chi_r\ ln\ w^*_{ri} + \frac{1}{2}\sum_{r=1}^{R}\sum_{s=1}^{R} \chi_{rs}\ ln\ w^*_{ri}\ ln\ w^*_{si} \\ & + \frac{1}{2}\sum_{k=1}^{K}\sum_{m=1}^{M-1} \delta_{mr}\ ln\ x_{ki}\ ln\ y^*_{mi} + \frac{1}{2}\sum_{k=1}^{K}\sum_{r=1}^{R} \xi_{kr}\ ln\ x_{ki}\ ln\ w^*_{ri} \\ & + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{r=1}^{R} \upsilon_{mr}\ ln\ y^*_{mi}\ ln\ w^*_{ri} \\ & i = 1, 2, ..., N \quad t = 1, 2, ..., T, \end{aligned} \tag{2}$$

where $y^*_{mi} = y_{mi}/y_{Mi}$ and $w^*_{ri} = w_{ri} \times y_{Mi}$.

Following the same procedure for the enhanced hyperbolic distance functions, we obtain:

$$
\begin{aligned}
ln(D_{Ei}/y_{Mi}) = \alpha_0 &+ \sum_{k=1}^{K} \alpha_k \; ln \; x^*_{ki} + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \alpha_{kl} \; ln \; x^*_{ki} \; ln \; x^*_{li} \\
&+ \sum_{m=1}^{M-1} \beta_m \; ln \; y^*_{mi} + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{n=1}^{M-1} \beta_{mn} \; ln \; y^*_{mi} \; ln \; y^*_{ni} \\
&+ \sum_{r=1}^{R} \chi_r \; ln \; w^*_{ri} + \frac{1}{2} \sum_{r=1}^{R} \sum_{s=1}^{R} \chi_{rs} \; ln \; w^*_{ri} \; ln \; w^*_{si} \\
&+ \frac{1}{2} \sum_{k=1}^{K} \sum_{m=1}^{M-1} \delta_{mr} \; ln \; x^*_{ki} \; ln \; y^*_{mi} + \frac{1}{2} \sum_{k=1}^{K} \sum_{r=1}^{R} \xi_{kr} \; ln \; x^*_{ki} \; ln \; w^*_{ri} \\
&+ \frac{1}{2} \sum_{m=1}^{M-1} \sum_{r=1}^{R} \upsilon_{mr} \; ln \; y^*_{mi} \; ln \; w^*_{ri} \\
& i = 1, 2, ..., N \quad t = 1, 2, ..., T,
\end{aligned}
\tag{3}
$$

where $y^*_{mi} = y_{mi}/y_{Mi}$, $w^*_{ri} = w_{ri} \times y_{Mi}$ and $x^*_{ki} = x_{ki} \times y_{Mi}$.

In a stochastic frontier model the distance separating a producer from the frontier is given by two components: (1) its technical inefficiency and (2) a random shock beyond producers' control. To incorporate this two components in our estimation, the error term is modeled as $\epsilon_{it} = (v_{it} - u_{it})$, where v_{it} is the two–sided random noise capturing the effect of random shocks, while u_{it} is non–negative and represents the inefficiency. As in standard SFA, v_{it} are normally distributed as $N(0, \sigma^2_v)$ while u_{it} is noramlly distributed and truncated at 0 as as $N^+(m_{it}, \sigma^2_u)$. Hence, if we add the random disturbance, the estimated distance function of Eq. (2) is given, in a multi–period framework, by $ln(D_{Hit}/y_{Mit}) = TL(x_{it}, y^*_{it}, w^*_{it}, \alpha, \beta, \chi, \delta, \xi, \upsilon) + v_{it}$. Since inefficiency (i.e., the distance $ln(D_{Hit})$) is represented by u_{it}, the translog hyperbolic distance function to be estimated becomes:

$$
-ln(y_{Mit}) = TL(x_{it}, y^*_{it}, w^*_{Mit}, \alpha, \beta, \chi, \delta, \xi, \upsilon) - u_{it} + v_{it}. \tag{4}
$$

Similarly, the translog enhanced hyperbolic stochastic distance function of Eq.

(3) can be written as:

$$-ln(y_{Mit}) = TL(x^*_{it}, y^*_{it}, w^*_{Mit}, \alpha, \beta, \chi, \delta, \xi, \upsilon) - u_{it} + v_{it}. \quad (5)$$

The assumptions regarding the distribution of the u_{it} and v_{it} involve estimating the variance parameters $\sigma^2 = \sigma^2_v + \sigma^2_u$ and $\gamma = \sigma^2_u/(\sigma^2_v + \sigma^2_u)$. We regress Eq. (4) and Eq. (5) using the standard maximum–likelihood technique developed by Battese and Coelli (1992) and then compute the posterior expected values of the error components. In this way, we obtain time variant hyperbolic efficiency estimates that can be transformed into efficiency scores as follows:

$$TE_{it} = e^{-u_{it}}.$$

3.2 Local Air Pollution

The quality of the air nearby the airports is an increasingly important issue for airports managers, particularly in the European Union, where environmental directives have been approved.[10] As a result, airports' managers have to provide detailed assessments of their environmental impact. At the local level, airports are working alongside regional partners and stakeholders to assess the contribution of airport emissions on local air quality and to develop strategies and plans to reduce emissions. As a first step in this direction, a rigorous evaluation of the airports' environmental effects on local air is required. Our contribution provides a method to evaluate airports' local air pollution. In doing so, we first take into account that aircrafts affect Local Air Pollution (LAP) only when they operate along the Landing Take–Off (LTO) cycle. The LTO cycle, following ICAO standards, is split into four stages: take–off, climb (up to 3,000 ft), approach (from 3,000 ft to landing), and idle (when the aircraft is taxiing or standing on the ground with engines–on).[11]

[10]Within the European Union, local air quality is regulated by the Framework Directive 96/62/EC7 on local air quality assessment and management. The Daughter Directive relevant to local air quality at airports is 99/30/EC8, which covers SO_2, NO_x, PM_{10}, and Pb. These EU Directives are in line with the World Health Organization recommendations for Europe.

[11]The 3,000 ft (approximately 915 m) boundary is the standard set by the ICAO for the average height of the mixing zone, the layer of the earth atmosphere where chemical reactions of pollutants can ultimately affect ground level pollutant concentrations (US Environmental Protection Agency, 1999).

We compute the emissions produced by each aircraft type taking into account both (1) the emission factors for the aircrafts specific engines and (2) the time spent in each phase of the LTO cycle. 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.

The study considers all the operations of aircraft with a maximum take–off weight (MTOW) greater than 5,700 kg with turbine engines, i.e., turboprop and turbojet. Therefore, aircrafts with internal combustion piston engine (necessarily helical), used only in the light aviation, are ignored.

In order to compute the emissions produced by each airport in our data set we matched five databases: OAG, EASA, IRCA, FOI and ICAO Engine Emissions Databank databases.[12] 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.[13] 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. The pollutants considered in this contribution are: hydrocarbons (HC), carbon monoxide (CO), and nitrogen oxides (NO_x).[14]

In order to compute the total emissions for the LTO cycle (Q_{ip}) for the engine i and the pollutant p, we sum the specific engine emission factor (E_{ipf}) of pollutant p (kg) for each phase f multiplied by the duration of the phase (d_f) and by the indicated specific engine fuel consumption (F_{fi}) in kg/sec. Hence we have:

[12] OAG is the database provided by Official Airlines Guide; IRCA is the International Register of Civil Aircraft for engines; EASA is the European Aviation Safety Agency, FAA is the Federal Aviation Administration for engines noise certification; ICAO Engine Emission Databank is provided by the International Civil Aviation Organization and FOI Database (for engines pollutant emissions) is provided by the Swedish Defence Research Agency.

[13] The matching is realized on the basis of both the aircraft model and the MTOW. In case of not identical weight, we estimate the level of emissions considering only the combinations between the OAG data and the EASA with similar MTOW, i.e., with differences lower than ±3%.

[14] Notice that also SO_2 emission and Particulate Matter (PM) emission are contributors to LAP (US Environmental Protection Agency, 1999), but they are (still) not part of the engine certification process. Emission of these pollutants is directly related to fuel consumption and therefore can be incorporated in the analysis. However, results of previous studies (Givoni and Rietveld, 2005, and Dings *et al.*, 2003) show that the cost of LAP from aircraft operation during the LTO cycle strictly depends on the volume of NO_x emission.

$$Q_{ip} = \sum_{f=1}^{4} E_{ipf} \times d_f \times F_{fi}$$

Since the computed emissions refer to the single engine, we had to match each aircraft with its engine (considering the number of engines) in order to get aircrafts emissions (HC, CO, NO_x) for the LTO cycle. The sum of the emissions (kg) produced by each aircraft in a particular airport multiplied by the number of movements of the same aircraft over a year gives the total amount of HC, CO and NO_x produced by the airport. Table 1 shows the yearly average total kilograms per pollutant produced in each airport of our sample.[15]

Table 1: Average yearly values of pollutants produced by airport (kg)

Airport	HC	CO	NO_x	**Airport**	HC	CO	NO_x
Alghero	3,892	45,247	55,139	Olbia	6,798	62,401	74,743
Ancona	877	11,949	14,095	Palermo	15,467	164,305	197,459
Bari	8,975	96,925	101,426	Pantelleria	210	5,712	5,567
Bergamo	15,959	165,091	232,956	Parma	441	4,888	5,875
Bologna	18,948	183,283	165,914	Pescara	1,701	16,858	16,114
Brescia	4,612	24,336	22,541	Pisa	10,288	112,269	132,92
Brindisi	3,327	34,453	43,561	Reggio Calabria	2,303	22,596	27,539
Cagliari	9,77	96,469	120,726	Rimini	523	5,738	5,884
Catania	18,223	192,436	240,694	Rome Ciampino	13,169	131,27	187,176
Florence	13,325	109,064	79,231	Rome Fiumicino	145,583	1,350,748	1,844,126
Forlì	1,787	18,643	29,117	Trapani	1,321	18,656	20,079
Genoa	3,831	49,672	53,733	Treviso	3,967	38,467	58,366
Lamezia Terme	4,482	46,064	55,574	Trieste	2,338	26,957	32,209
Lampedusa	293	5,833	5,897	Turin	16,921	175,923	165,52
Milan Linate	36,867	385,55	498,737	Venice	33,009	314,971	311,884
Milan Malpensa	112,569	944,858	1,250,709	Verona	10,426	100,409	94,54
Naples	21,141	223,346	229,965				

To aggregate these data into a single index, representing the LAP produced by each airport, we consider Dings et al. (2003) estimates of the cost of damage they impose. The index Weighted Local Pollution (WLP) is obtained as the sum of kg produced of each pollutant (w_p) weighted for the relative cost of damage (c_p). The latter are equal to 4 Euro/kg for HC and 9 Euro/kg for NO_x. Carbon monoxide (CO) emissions from aircraft operation do not appear to result in substantial health effects and therefore a cost estimate for emission of this gas is assumed equal to 0 Euro/kg (Dings *et al.*, 2003; Givoni and Rietveld, 2010). Hence we have:

$$WLP = \sum_{p} w_p \times c_p$$

[15] Notice that non–aircraft emissions from airport and airport–related activities such as fleet vehicles and ground access vehicles are not considered in this contribution.

Table 2 shows the value of the WLP index divided by the number of movements for each airport of our dataset (for the year 2008). The different values show that the fleet mix characterizing airports may have a significant impact on the amount of LAP produced. In particular, the average value is about 41 euros per flight. Notice that the two Italian hubs, i.e., Rome Fiumicino and Milan Malpensa, show very similar values (respectively 57.2 and 55 euro both greater than the average), while the maximum and minimum values are respectively 79.7 euro for Brescia airport and 16.49 euro for Ancona airport. A possible explanation for this result is that in Brescia airports a lot of flights have been done by MD–80 aircrafts, an old and very polluting aircraft introduced into commercial service in 1980, while in Ancona by ATR 42, a twin–turboprop that is much more environmentally friendly than the MD–80: as a result, Brescia airport presents a WLP much higher than Ancona airports.

Table 2: WLP on aircraft movements by airport (year 2008).

Airport	**WLP/Movements**	**Airport**	**WLP/Movements**
Alghero	49.27	Olbia	45.31
Ancona	16.49	Palermo	43.74
Bari	41.61	Pantelleria	18.01
Bergamo	52.13	Parma	34.41
Bologna	33.49	Pescara	27.60
Brescia	79.72	Pisa	42.36
Brindisi	43.02	Reggio C.	40.03
Cagliari	42.35	Rimini	36.75
Catania	46.32	Rome Ciampino	50.91
Florence	27.09	Rome Fiumicino	57.20
Forlì	51.95	Trapani	32.49
Genoa	31.25	Treviso	52.69
Lamezia	47.00	Trieste	25.13
Lampedusa	24.38	Turin	34.02
Milan Linate	49.25	Venice	42.50
Milan Malpensa	55.00	Verona	36.32
Naples	39.38	**Mean**	**40.88**

If we classify the airports on the basis of their size, we can check if there is a size effect on the local emission. More in details, we have grouped the airports in 4 categories based on the average annual number of aircraft movements: (1) small airports (with less than 15,000 movements per year); (2) small/medium airports (with annual movements between 15,000 and 45,000); (3) medium/large airports (with annual movements between 45,000 and 90,000); (4) large airports (with annual movements over 90,000).

Table 3 shows the costs of the local emissions for the different airports groups. Large airports produce more costly emissions per aircraft movement (Euro 53.82) than medium/large ones (Euro 41,31) and small/medium airports (Euro 40.10).

Table 3: Average yearly values of WLP per airport size (year 2008)

	small	small/medium	medium/large	large
WLP (Euro)	38.60	40.10	41.31	53.82
number of airports	15	9	6	3

Small airports have instead the lower small costs of pollution per aircraft movement (Euro 38.60). This result may suggest that, on average, the fleets operating at small airports are more environmental friendly, maybe for the the large presence of either young airlines or low cost carrier with new generation aircrafts.

4 Results

In this section, we present and discuss our econometric results regarding the estimation of a stochastic frontier for "good" and "bad" outputs on a data set composed by 33 Italian airports for the period 2005–2008.

Following many previous contributions estimating airports' technical efficiency, we considered as inputs both capital assets (i.e., most of the airports' existing infrastructures) and labor. We collected information on the runway capacity (CAP)[16], the number of aircraft parking positions ($PARK$), the terminal area ($TERM$) and the number of check–in desks ($CHECK$). Labor is given by the number of employees measured in terms of Full–Time Equivalent units (FTE). All the data have been obtained through a direct investigation.

The desirable outputs are the annual passenger movements and freights (WLU)[17] provided by the Italian airport authority (Ente Nazionale Aviazione Civile, ENAC), and the annual aircraft movements (ATM) collected from the OAG database. The undesirable output is given by the emissions produced during the LTO cycles computed using the WLP index presented in Section 3.[18]

Table 4 shows the descriptive statistics regarding outputs and inputs.

[16]This variable takes into account both the runway length and the airport's aviation technology level—e.g., some aviation infrastructures such as ground–control radars and runway lighting systems.

[17]In air transportation, by convention, passengers and freight are combined in a single output measure, WLU, such that 100 kilograms of freight corresponds to one passenger.

[18]Notice that we check the validity of the chosen inputs and outputs by testing for their isotonicity—i.e., outputs should be significantly and positively correlated with inputs (Charnes *et al.*, 1985). Pearson correlation coefficients between all the inputs and the outputs is significant (at a 1% level) and positive. Moreover, the input correlation is positive, significant, and very high, as a confirmation that in managing airports, inputs are jointly dimensioned to avoid bottlenecks (Lozano

Table 4: Descriptive Statistics of Inputs (I), Desirable (D) and Undesirable (U) Outputs

	Average	**Median**	**Std. Dev.**	**Max**	**Min**
ATM (D, number)	38,782	16,932	62,876	337,986	434
WLU (D, number)	4,136,556	1,732,196	6,949,506	36,758,411	69,059
WLP (U, euro)	1,805,864	667,303	3,451,583	19,333,542	22,675
TERM (I, sqm)	38,102	13,505	73,578	350,000	256
CHECK (I, number)	42	19	65	358	3
FTE (I, number)	237	110	408	2,186	2
CAP (I, number per hour)	19	15	18	90	2
PARK (I, number)	26	18	26	142	2

Since our main purpose is to analyze the impact on efficiency of local emissions, we estimate three different multi–output stochastic distance functions: Model (I) is an output distance function D_O including only desirable outputs (see Equation (6) below); Model (II) represents a hyperbolic distance function D_H with both desirable and undesirable outputs (Equation (7)); Model (III) is an enhanced hyperbolic distance function D_E (Equation (8)) that not only includes both "good" and "bad" outputs, but also estimates proportional reductions in inputs.

$$\begin{aligned}-ln(ATM_{it}) = TL(&WLU_{it}/ATM_{it}, TERM_{it}, CHECK_{it},\\ &FTE_{it},\ CAP_{it},\ PARK_{it}, \alpha, \beta, \chi, \delta, \upsilon)\\ &+\lambda_1 HUB_{it} + v_{it} - u_{it},\end{aligned} \tag{6}$$

$$\begin{aligned}-ln(ATM_{it}) = TL(&WLU_{it}/ATM_{it}, WLP_{it} \times ATM_{it}, TERM_{it}, CHECK_{it},\\ &FTE_{it},\ CAP_{it},\ PARK_{it}, \alpha, \beta, \chi, \delta, \upsilon)\\ &+\lambda_1 HUB_{it} + v_{it} - u_{it},\end{aligned} \tag{7}$$

$$\begin{aligned}-ln(ATM_{it}) = TL(&WLU_{it}/ATM_{it}, WLP_{it} \times ATM_{it}, TERM_{it} \times ATM_{it},\\ &CHECK_{it} \times ATM_{it}, FTE_{it} \times ATM_{it},\ CAP_{it} \times ATM_{it},\\ &PARK_{it} \times ATM_{it}, \alpha, \beta, \chi, \delta, \upsilon) + \lambda_1 HUB_{it} + v_{it} - u_{it},\end{aligned} \tag{8}$$

In Eqs. (6)–(8), ATM_{it} is the normalizing output and HUB is a dummy variable equal to 1 if the airport is classified as an hub, to control for the presence of a

and Gutiérrez, 2009).

technology difference among hub and non–hub airports.[19] Prior to estimation, all the output and input variables have been divided by their respective geometric means. Consequently, the first–order coefficients of the estimated production functions can be regarded as (partial) distance elasticities when evaluated at the variable means of the empirical sample.

Table 5 presents the maximum likelihood estimates of Models (I)–(III).

Table 5: Estimation results

	Model 1: D_O		Model 2: D_H		Model 3: D_E	
Variable	Coefficient	Std.Error	Coefficient	Std.Error	Coefficient	Std.Error
$Cost.$	0.787 (***)	0.107	0.120 (***)	0.019	0.060 (***)	0.016
WLU	0.565 (***)	0.165	0.312 (***)	0.040	0.276 (***)	0.027
WLP	-	-	-0.464 (***)	0.009	-0.397 (***)	0.015
$TERM$	0.122	0.090	-0.060 (***)	0.017	-0.025 (*)	0.013
$CHECK$	-0.149 (*)	0.084	-0.061 (**)	0.024	-0.058 (***)	0.018
FTE	-0.504 (***)	0.079	-0.021	0.017	-0.005	0.014
CAP	-0.384 (**)	0.167	0.112 (***)	0.033	-0.020	0.023
$PARK$	-0.064	0.092	0.025	0.027	-0.019	0.022
$WLU \times WLU$	0.388 (**)	0.186	-0.037	0.065	-0.035	0.038
$WLU \times WLP$	-	-	-0.060 (***)	0.017	0.004	0.023
$WLU \times TERM$	-0.136	0.125	-0.002	0.044	-0.068 (**)	0.029
$WLU \times CHECK$	0.045	0.199	0.090	0.056	0.079 (**)	0.040
$WLU \times FTE$	0.106	0.089	0.065 (**)	0.031	0.038 (*)	0.022
$WLU \times CAP$	0.377	0.311	0.001	0.073	-0.003	0.058
$WLU \times PARK$	-0.709 (***)	0.202	-0.151 (**)	0.059	-0.094 (**)	0.044
$WLP \times WLAP$	-	-	-0.048 (***)	0.008	0.015	0.031
$WLP \times TERM$	-	-	0.053 (***)	0.015	0.036	0.026
$WLP \times CHECK$	-	-	0.007	0.022	0.001	0.035
$WLP \times FTE$	-	-	0.019 (.*)	0.010	-0.027 (*)	0.016
$WLP \times CAP$	-	-	-0.060 (***)	0.023	0.020	0.037
$WLP \times PARK$	-	-	0.012	0.021	-0.108 (***)	0.036
$TERM \times TERM$	0.361 (**)	0.154	-0.110 (***)	0.037	-0.027	0.032
$TERM \times CHECK$	0.080	0.181	-0.007	0.045	0.024	0.039
$TERM \times FTE$	0.050	0.088	0.064 (**)	0.031	0.089 (***)	0.024
$TERM \times CAP$	-0.437 (**)	0.181	-0.065	0.047	-0.110 (***)	0.038
$TERM \times PARK$	0.310 (**)	0.156	-0.043	0.041	-0.024	0.038
$CHECK \times ba$	-0.416	0.544	0.012	0.121	-0.089	0.100
$CHECK \times fte$	0.234 (**)	0.107	0.045	0.042	0.025	0.033
$CHECK \times CAP$	0.172	0.334	-0.113	0.073	-0.031	0.060
$CHECK \times PARK$	-0.363	0.222	0.086	0.073	0.093	0.059
$FTE \times FTE$	-0.126	0.084	-0.093 (***)	0.024	-0.108 (***)	0.019
$FTE \times CAP$	0.039	0.196	0.103 (***)	0.037	0.033	0.031
$FTE \times PARK$	-0.221	0.169	-0.105 (**)	0.050	0.036	0.037
$CAP \times CAP$	-0.524	0.475	0.220 (**)	0.098	0.079	0.071
$CAP \times PARK$	0.694 (**)	0.286	0.047	0.074	0.002	0.057
$PARK \times PARK$	-0.153	0.222	0.088	0.059	0.040	0.049
HUB	-2.345 (***)	0.556	0.068	0.084	-0.046	0.067
σ^2	1.112 (***)	0.364	0.009 (***)	0.003	0.004 (***)	0.002
γ	0.992 (***)	0.003	0.907 (***)	0.039	0.856 (***)	0.068
$time$	-0.031 (***)	0.010	0.069 (**)	0.031	0.075	0.045
$logl$	45.89		237.20		265.17	

Note that *,**,*** denote significance at 10%, 5% and 1% respectively.

The MLE estimated coefficients for the output, hyperbolic and enhanced hyperbolic distance functions' specifications, and their associated standard errors allow us

[19]The literature on air transportation (Graham, 2008) highlights that airports with hub–and–spoke system employ different technologies (e.g., different BHS) than non–hub ones. Hence, the variable HUB exerts an influence on the production function and not on managerial efficiency.

to determine (i) the effect that the outputs and the inputs have on the distance functions, and (ii) whether the magnitude corresponding to each direct partial elasticity is statistically significant or not.

In all the econometric models the desirable output (WLU) is statistically significant with the expected positive sign. This indicates that any increase in the amount of WLU produced, *ceteris paribus*, would imply a smaller distance to the frontier. Hence the three estimated frontiers meet the monotonicity condition of being non–decreasing in desirable outputs (at the sample mean).

The estimated coefficient of the undesirable output WLP is significantly different from zero both for D_H and D_E, also has the expected negative sign. This finding indicates that the estimated translog functions are non–increasing in the WLP at the sample mean, as required by the already mentioned monotonicity condition. When compared to the sizes of the input elasticity values, the WLP elasticity values (respectively -0,46 and -0,39) are considerably higher indicating that pollution has relatively more importance in the frontiers' characterization.

Concerning the inputs, first–order coefficients indicate the magnitude of the respective partial input elasticities at the sample mean. Table 5 shows that all the significant coefficients have the expected negative sign with the exception of the variable CAP in the Model (III). Hence, any increase in the amount of inputs, *ceteris paribus*, would imply a greater distance to the frontier. This result indicates that the estimated translog functions for all model's specifications satisfy the monotonicity property of being non–increasing in inputs (at the geometric mean of the data). Moreover, in case of non–significance of the first–order coefficient, in all the model either second–order coefficients or interaction terms result significant.

Table 5 also shows that when only the desirable outputs are considered (i.e., Model (I)), the hub different technology has a positive impact on the frontier: its coefficient is negative and statistically significant. This effect instead vanishes if the undesirable output is introduced (Models (II) and (III)), i.e., the hub different technology has no impact on the frontier: hub airports have not lower emissions per inputs than the other airports.

As mentioned in Section 3.1, the likelihood function is expressed in terms of the variance parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$. Table 5 also shows that these parameters are always statistically significant at the 1% level, with the estimated γ equal respectively to 0.99, 0.91 and 0.86. Hence, a relevant part of the distance between the observed output levels and the maximum feasible ones is due to technical inefficiency in all the three model's pecifications.

Table 6 compares the average estimated efficiency scores of the three models described by Eqs. (6), (7) and (8). Notice that, when local air pollution is included in the airport production function, (1) the average efficiency increases (as shown by Yu, 2004, Yu et al., 2008, Pathomsiri at al., 2008, and Lozano and Gutiérrez, 2010); (2) the efficiency gaps among the airports become smaller and (3) the greater gains are obtained by medium airports (the average increase in efficiency scores is 46% for small airports, 50% for medium airports (in particular 41% for small/medium and 68% for medium/large) and 33% for large airports). The overall increase in efficiency arises because, in our framework, an airport is efficient if, given its current input utilization, carries out as many aircrafts and WLU movements as possible and, *at the same time*, produces the minimum feasible amount of pollution. Hence, airport inefficiency can come from two main sources: low utilization (much less traffic than the nominal capacity) or high production of undesirable outputs. Many airports are inefficient if only desirable outputs are considered because, since the level of several inputs is fixed across airports (e.g., the runway length), they have low utilization rates. When instead emissions are introduced, these airports benefit from very low emission rates per input. For instance, the same underutilized runway gives rise to low efficiency in terms of desirable outputs, but high efficiency in terms of emissions. The results may change if different weights are given to desirable outputs and emissions. This is left for future research. Furthermore, in Italy medium airports are mainly regional ones that have grown a lot in recent years. This sharp increase is due to two factors: (1) the entrance of Low Cost Carriers (LCC); (2) the opening of new routes by existing airlines, using small turboprop aircrafts (e.g., ATR 42 in its different specifications). Both these factors have positive effects in terms of emissions: LCC uses new generation aircraft with lower rates of local emissions and small turboprop are environmentally friendly too in terms of emissions. Once again, these results highlight the important of the fleet mix for environmental efficiency.

Table 6: Technical efficiency scores by model

Airport	D_O	D_H	D_E	Airport	D_O	D_H	D_E
AHO	0.490	0.977	0.970	OLB	0.953	0.984	0.989
AOI	0.390	0.855	0.915	PMO	0.355	0.950	0.977
BRI	0.182	0.979	0.981	PNL	0.385	0.921	0.848
BGY	0.271	0.948	0.973	PMF	0.934	0.861	0.875
BLQ	0.355	0.850	0.885	PSR	0.780	0.898	0.962
VBS	0.512	0.990	0.993	PSA	0.267	0.891	0.907
BDS	0.351	0.980	0.966	REG	0.752	0.988	0.994
CAG	0.235	0.969	0.934	RMI	0.942	0.836	0.967
CTA	0.176	0.972	0.972	CIA	0.233	0.919	0.947
FLR	0.376	0.872	0.910	FCO	0.898	0.968	0.980
FRL	0.345	0.933	0.906	TRN	0.309	0.947	0.979
GOA	0.587	0.866	0.936	TPS	0.240	0.975	0.964
SUF	0.779	0.769	0.937	TSF	0.554	0.935	0.968
LMP	0.922	0.975	0.976	TRS	0.284	0.976	0.983
LIN	0.272	0.983	0.986	VCE	0.196	0.938	0.950
MXP	0.612	0.979	0.983	VRN	0.707	0.862	0.888
NAP	0.415	0.893	0.969	**Mean**	**0.487**	**0.928**	**0.951**

5 Conclusion

In this paper, a hyperbolic stochastic distance function econometric model has been applied to estimate the efficiencies of Italian airports during the period 2005–2008. Differently from previous parametric contributions we include in the efficiency estimation both desirable outputs (i.e., passengers, freights and aircraft movements) and an undesirable output (i.e., local air pollution produced by aircrafts during the LTO cycle). Hence, this paper estimates a desirable outputs/emission production frontier.

In order to include local air pollution, we computed an index describing the social costs of the total amounts of pollutants produced for each Italian airport included in our data set.

We show that, when the undesirable outputs are ignored, airport efficiency scores are totally different and can therefore be misleading. 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 utilization rate of their aeronautical inputs), show a strong improvements in their efficiency when also "bad" output are considered. However, this is not due to managerial effort, but to econometric specification: "bad" and "good" outputs have the same weight in the distance function, and inefficient airports improve their scores because they get closer to the environmental frontier thanks to the low number of movements realized. When airports with similar number of movements are considered, we clearly identify the presence of a fleet effect. More environmental friendly fleets reduce the emissions and make airports more efficient.

Our results yield the following policy implications: first, there is less need of implementing a tight regulatory mechanism that provides incentives to improve airports' technical efficiency if environmental effects are included in the benchmarking analysis. We provide evidence that almost all airports are very close to the estimated frontier. However, we have also found that the vast majority of airports are technically inefficient (and rather far from the frontier) when only desirable outputs are considered. These insights create a friction that has to be taken into account when designing the airports' regulatory settings: on the one hand, including undesirable outputs is important because all the social costs related to airport operations are considered. On the other hand, it is necessary to find an optimal balance of weights between desirable and undesirable outputs, in order to give the necessary incentives to improve the current low level of technical efficiency if only "good" outputs are analyzed. This is a possible future development. Second, airports should induce airlines to update their fleet, either through engine updating or by replacing old aircrafts with new environmental friendly ones. This target may be achieved by imposing emission charges, maybe linked to fuel consumption (e.g., carbon tax).

Another possible extension of this work may be the inclusion in the efficiency analysis of noise to obtain a more complete desirable/undesirable outputs frontier. This implies to treat in a linear framework a non–linear variable such as noise, and to estimate the social cost of noise annoyance.

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