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Efficiency and Environment in the Aviation Sector

Doctoral Dissertation

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"Don't ever tell anybody anything.
If you do, you start missing everybody."

(The catcher in the rye, J.D. Salinger)

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Introduction and summary

Air transport system shows a great complexity, mainly linked to the dimensional and commercial fragmentation between a large number of players. However, a comprehension of the dynamics at the system level allows a contextualization of the activities operated by airports which play a crucial role not only within the air transportation sector, but also in the process of increasing the quality of life of regional and local communities, directly participating in wealth creation.

Precisely for these reasons, the topic of airport performance has gained increasing attention from researchers. Performance evaluation and improvement studies of airport operations have important implications for a number of airport stakeholders: (i) for airlines in identifying and selecting the more efficient airports at which to base their operations, (ii) for municipalities because of the benefits coming from efficient airports in terms of attracting business and passengers, (iii) for policy makers in making effective decisions on optimal allocation of resources to airport improvement programs, and in evaluating the efficacy of such programs. Airport activity can be considered as a key factor in promoting economic, productive, tourist and commercial upgrades of a territory, thanks to the "multiplier effect" in the number of potential business transactions it may stimulate (Jarach, 2005).

However, besides numerous and sizeable benefits to citizens and companies, airports also brings undesired and damaging side–effects to people living nearby and to the local and global environment. In particular, the continuously increasing passenger traffic and a rise in public awareness have made aircraft noise and emissions two of the most pressing issues hampering commercial aviation growth today. Aviation have come concerns regarding noise, air quality, water quality and impacts on climate. While aircraft have become more fuel efficient and less noisy over the last 35 years, most projections for the rate of growth of air transport exceed projections for the rate of technological advancement for noise and emissions such that the environmental consequences of aviation may increase. There are several challenges to limiting the environmental impact of aviation. As well known aviation growth is correlated with economic growth. Placing inappropriate constraints on aviation may have negative consequences for local, national and world economies. On the other hand, allowing environmental impacts to go unaccounted in consumer and producer behavior also produces negative economic impacts.

In the light of this, the research carried out in this thesis contributes in the assessment of aviation efficiency in presence of environmental impacts. The thesis is composed by three works describing: (i) the assessment of airport efficiency considering the production of pollution, (ii) a new comprehensive methodology to compute an economic environmental benchmarks and (iii) the analysis of the current aircraft global market with a computation of effective incentives to move towards greener fleets.

In the first paper a hyperbolic distance function model (proposed by Cuesta et al., 2009), has been applied for airport efficiency assessment considering local air pollution as undesirable output. In order to include the negative externalities connected to local air pollution, we created an index describing the total amounts of pollutants produced for each Italian airport included in our data set. We show that, if the undesirable outputs are ignored, airport efficiency scores can be misleading. Our results indicate that airports tend to be more efficient, on average, when negative externalities of production are included in the analysis. More in details, those airports that are highly technically inefficient when only "good" outputs are included (because they have a low utilization rate of their aeronautical inputs) showing a strong improvement in their efficiency when also undesirable outputs are considered. However, this is not due to managerial effort, but to the fact that same weights are given to "bad" and "good" outputs into the distance function. Consequently, inefficient airports improve their scores mainly because they get closer to the technical/environmental frontier thanks to their low volumes of aircraft and passengers movements. When instead airports with similar number of movements are considered, we show that a fleet effect may be identified as a driver for the gains magnitude in the efficiency scores, given that more environmentally friendly fleets produce lower amount of pollutants per movement. This suggests that a possibility for airports managements in order to improve efficiency is to promote carriers to use modern fleets (e.g., increasing airport charges).

In the second paper, a new methodology taking into account economic and environmental variables is developed. Following Fare and Grosskopf (2010) we present an additive model that benchmarks the decision making units (DMUs) on a unique eco-environmental frontier considering the production of both good and bad outputs productions. Our directional economic environmental distance (DEED) function describes the distance of each DMU to the efficient frontier evaluating it as potential monetary saving achievable by reaching such frontier. As suggested by Dyckhoff and Allen (2001) the normal assumption of considering all inputs as "bads" to be reduced is no longer valid in an ecological context. In an eco-environmental perspective ecologically good inputs (e.g., waste in a waste-burning power plant or in a recycling plan) have to be considered. In our study we extend the idea of desirable input allowing the decrease or the increase in desirable input utilization. Following Sueyoshi and Goto (2011), we propose an unified efficiency measurement considering both the production of good and bad outputs and allowing the constrained increase in desirable input utilization. Differently from the usual DEA approach, a DMU could reach the frontier decreasing input utilization or, alternately, increasing it. The model proposed is suitable in all the industries (e.g., aviation sector) in which it is necessary to account for the production of negative externalities.

Finally, in the third paper we identify the trade-offs that exist between the noise and air pollution generated by the existing aircraft-engine combinations. Furthermore, we apply the benchmarks resulting from directional economic environmental distance function in order to design a relatively efficient aircraft-engine fleet that could operate at Stockholm and Amsterdam airports given current technology and service levels. Since this implies substituting the inefficient aircraft-engine combinations with those lying on the frontier, we obtain estimates of the magnitude of the monetary incentives that may induce airlines to move towards a greener fleet. Accordingly, we provide some estimates on the optimal airport charges that may encourage a reduction in noise and emissions. Noise and emissions charges are not sufficient to incentivize the necessary fleet upgrades and it would appear that, depending on stage length, a federal or national fund is necessary to reduce the aviation externalities below current levels.

References

- Cuesta, R.A., Lovell, C.A.K., Zofío, J.L., 2009. Environmental efficiency measurement with translog distance functions: A parametric approach. Ecological Economics, 68, 2232-–2242.
- Dyckhoff, H., Allen, K., 2001. Measuring ecological efficiency with data envelopment analysis. European Journal of Operational Research 132, 312-325.
- Färe, R., Grosskopf, S., 2010. Directional distance functions and slacks-based measures of efficiency. European Journal of Operational Research 200, 320–322.
- Jarach, D., 2005. Airport marketing: strategies to cope with the new millennium environment, (Aldershot: Ashgate Publishing Limited).
- Sueyoshi, T., Goto, M., 2011. Methodological comparison between two unified (operational and environmental) efficiency for environmental assessment. European Journal of Operational Research 210, 684-693.

Considering the Local Air Pollution in the airport efficiency assessment.

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 as negative externality the local air pollution by proposing an indicator able to evaluate the environmental social cost produced by the airport activity. We apply a hyperbolic distance function to estimate a multi–output stochastic frontier. Furthermore, comparing the results with those obtained from a traditional stochastic frontier we show that airports' efficiency scores are greater and closer when local air pollution is included in the analysis. Our results suggest that, on the one hand, not considering the environmental negative externalities in assessing airport efficiency can lead to misleading results. On the other hand, an appropriate weights' balance between desirable and undesirable output seems to be necessary in order to design an airports' regulatory scheme able to boost airport technical/environmental efficiency.

1. Introduction

Aviation and environment is a growing matter of interest due to the projected increase in demand for air transport. Riberio et al. (2007) show that the CO_2 emission forecasts for commercial aviation in 2050 will be from 2 (best scenario) to 5 (worst scenario) times the actual emission level. Moreover, according to ICAO, in addition to green house gases, the air polluting surrounding airports has become a significant concern for local and regional environment. In particular, during the landing take-off (LTO) cycle, an aircraft gives off several pollutants affecting the quality of local air and human health (Dings et al., 2003). Finally, another important externality – i.e., the noise footprint – concerns the communities surrounding the airports. However, while the connection between air pollutants and human health is proven, the one between noise and human health is still not completely clear (Daley, 2010).

Airport efficiency has been the subject of many previous 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 the important environmental externalities associated to airport activities that should be instead considered in the performance evaluation. Not considering these undesirable outputs may give rise to two errors: (1) efficiency estimates may be biased and, as a consequence, the obtained benchmarking is misleading (Lozano and Gutierrez, 2010); (2) the economical benefits created by airport activities are overestimated, since they do not take into account the full social cost produced (Lu and Morrel, 2006).

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. He finds that airports are in general more efficient when both desirable and

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

undesirable outputs are considered, and airports located in a smaller population area achieve the same efficiency than other ones. Yu et al. (2008) provides a similar result and also finds lower average total factor productivity growth in case of noise inclusion. Pathomsiri et al. (2008), besides the conventional desirable outputs, consider time delays and number of delayed flights as undesirable outputs. They show 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 ratios with shorter delays per inputs. Furthermore, they also provide evidence of a lower airports' productivity when undesirable outputs are included. Lozano and Gutiérrez (2010) as well consider delays as undesirable outputs and argue that the inclusion of the undesirable effects related to airport operations leads to more valid findings.

Two issues remain unexplored regarding the efficiency computation in the airport analysis. First, none of the previous contributions apply a parametric approach (i.e. stochastic frontier analysis, SFA) in the inefficiency assessment when undesirable outputs are considered. Second, LAP has never been included despite some authors have shown that aircraft local emissions social costs are relevant (Dings et al., 2003 and Givoni and Rietveld, 2009 and 2010). Hence, the aim of the present paper is to assess airports' technical efficiency when local environmental emissions are taken into account applying a parametric approach. We compute the pollutant emissions produced during the LTO cycle and certified by ICAO for each airport in our sample and, following the approach of Cuesta et al. (2009), we estimate a stochastic production frontier using a hyperbolic distance function model. Finally, we compare the results with those coming from estimating a classical stochastic frontier (i.e. with no undesirable outputs). We apply these models to a data set composed by 33 Italian airports for the period 2005-2008.

The structure of this paper is as follows. In Section 2, we present the hyperbolic distance function model and the methodology to compute the index of local airport pollution. Section 3 reports our empirical results. Finally, Section 4 summarizes and concludes the paper.

2. Materials and Methods

This Section is split into three parts. First, we introduce the analytical foundations of the production technology in presence of multi-product firms and we point out the differences between the "classical" production function – i.e., when the bad output is not taken into account – and the technical/environmental frontier using a parametric approach. Different specifications of the latter are presented. Second, we show the procedure to include the computation of local air pollution as an yearly social cost linked to airports' operations. This index is then considered as undesirable output in the estimation of the technical frontier. Finally, we present the descriptive statistics of the variables included in our data set.

3 Distance functions and technical/environmental frontiers

Technical efficiency in presence of multi-product firms is estimated using a distance function. As shown by Coelli and Perelman (1999, 2000) and Kumbhakar and Lovell (2000), this can be done by estimating a stochastic distance function. In this framework we define T as the firms' production possibility set—i.e., the output vector $y \in R_{+}^{M}$ that can be obtained using the input vector $x \in R_{+}^{K}$. That is: $T = \{(x, y): x \in R_{+}^{K}, y \in R_{+}^{M}, x\ can\ produce\ y\}$. This kind of output distance function has been largely used in the literature on airport efficiency (Chow and Fung, 2009, Tovar and Martìn-Cejas, 2009 and Scotti et al., 2012), but it has no environmental interpretation. In this traditional framework only desirable output are considered: hence we classify this case as the "classical" distance function. By assuming that T satisfies the axioms listed in in Färe and Primont (1995), we introduce Shepard's (1970) output oriented classical distance function:

$$D_C(x, y) = inf\{\zeta > 0: (x, y/\zeta) \in T\}. \tag{1}$$

The range of the classical distance function is $0 < D_C(x, y) \leq 1$. Lovell *et al.* (1994) show that the classical distance function (1) is non-decreasing and convex in y, and decreasing in x. Furthermore, the classical distance function is homogeneous of degree 1 in y, i.e., $D_C(x, \mu y) = \mu D_C(x, y)$. $D_C(x, y) = 1$ means that y is located on the outer boundary of the production possibility set. If instead $D_C(x, y) < 1$, y is located below the frontier; in this case, the distance represents the gap between the observed output and the maximum feasible output. This gap may be due both to random shocks and to inefficiency, as will be shown later.

Following Cuesta and Zofio (2005) and Cuesta et al. (2009), we introduce a production technology where inputs are transformed into a desirable output vector y and undesirable output vector $w \in R_+^L$. Hence the technology is given by: $T = \{(x, y, w): x \in R_+^K, y \in R_+^M, w \in R_+^R, x\ can\ produce\ (y, w)\}$. A first characterization of this technology (Färe et al., 1989 and Cuesta et al., 2009) consists in computing only the maximum feasible expansion of the desirable outputs required to reach the boundary of the set T. Inputs and undesirable outputs are treated as fixed. We label this approach as the Output distance function, which is given by the following expression:

$$D_O(x, y, w) = inf\{\varphi > 0: (x, y/\varphi, w) \in T\}. \quad (2)$$

The output distance function has range $0 < D_O(x, y, w) \leq 1$ and it is homogeneous of degree 1 in y, i.e., $D_O(x, \mu y, w) = \mu D_O(x, y, w)$. Finally, we consider a hyperbolic distance function that represents, for a given amount of inputs, the maximum expansion of desirable outputs and equiproportionate reduction of undesirable outputs leading a firm on the boundary of technology T.[2] The hyperbolic distance function is defined by:

$$D_H(x, y, w) = inf\{\phi > 0: (x, y/\phi, w\phi) \in T\}. \quad (3)$$

Good and bad outputs are treated asymmetrically, yielding a first foundation of a technical/environmental production frontier. The function belong to the interval $0 < D_H(x, y, w) \leq 1$ and it is almost homogeneous of degree 0, 1, -1, 1 since $D_H(x, \mu y, \mu^{-1} w) = \mu D_H(x, y, w)$. Under all previous specifications the firm is efficient if the distance function is equal to 1.

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[2]The name is due to the hyperbolic path that the function follows to reach the production frontier.

We adopt the translog specification for the three distance functions described before, for its flexibility and suitability to the homogeneity conditions. The set of restrictions that has to the translog distance function are described in details in Cuesta et al. (2009). Using the homogeneity condition for D_C and D_O and the almost homogeneity condition for D_H, and choosing the M^{th} output for normalization, i.e., $\mu = 1/y_M$, we get the following translog specification for the classical distance function:

$$
\begin{aligned}
ln(D_{Cit}/y_{Mit}) = \alpha_0 &+ \sum_{k=1}^{K} \alpha_k \; ln\, x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} \; ln\, x_{kit} \, ln\, x_{lit} \\
&+ \sum_{m=1}^{M-1} \beta_m \; ln\, y^*_{mit} + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \beta_{mn} \; ln\, y^*_{mit} \, ln\, y^*_{nit} \\
&+ \frac{1}{2}\sum_{k=1}^{K}\sum_{m=1}^{M-1} \delta_{km} \; ln\, x_{kit} \, ln\, y^*_{mit} \\
& i = 1,2,\ldots,N \;\; t = 1,2,\ldots,T,
\end{aligned}
\tag{4}
$$

where $y^*_{mit} = y_{mit}/y_{Mit}$. The translog output distance function also considers the undesirable outputs as fixed, and it is given by:

$$
\begin{aligned}
ln(D_{Oit}/y_{Mit}) = \alpha_0 &+ \sum_{k=1}^{K} \alpha_k \; ln\, x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} \; ln\, x_{kit} \, ln\, x_{lit} \\
&+ \sum_{m=1}^{M-1} \beta_m \; ln\, y^*_{mit} + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \beta_{mn} \; ln\, y^*_{mit} \, ln\, y^*_{nit} \\
&+ \sum_{l=1}^{R} \chi_r \; ln\, w_{rit} + \frac{1}{2}\sum_{r=1}^{R}\sum_{s=1}^{R} \chi_{rs} \; ln\, w_{rit} \, ln\, w_{sit} \\
&+ \frac{1}{2}\sum_{k=1}^{K}\sum_{m=1}^{M-1} \delta_{km} \; ln\, x_{kit} \, ln\, y^*_{mit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{r=1}^{R} \xi_{kr} \; ln\, x_{kit} \, ln\, w_{rit} \\
&+ \frac{1}{2}\sum_{m=1}^{M-1}\sum_{r=1}^{R} \upsilon_{mr} \; ln\, y^*_{mit} \, ln\, w_{rit} \\
& i = 1,2,\ldots,N \;\; t = 1,2,\ldots,T.
\end{aligned}
\tag{5}
$$

Equiproportional reduction in the amount of the undesirable outputs are taken into account in the hyperbolic distance function, so that its translog specification is:

$$
\begin{aligned}
ln(D_{Hit}/y_{Mit}) = \alpha_0 &+ \sum_{k=1}^{K} \alpha_k \ ln\, x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} \ ln\, x_{kit}\, ln\, x_{lit} \\
&+ \sum_{m=1}^{M-1} \beta_m \ ln\, y^*_{mit} + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \beta_{mn} \ ln\, y^*_{mit}\, ln\, y^*_{nit} \\
&+ \sum_{l=1}^{R} \chi_r \ ln\, w^*_{rit} + \frac{1}{2}\sum_{r=1}^{R}\sum_{s=1}^{R} \chi_{rs} \ ln\, w^*_{rit}\, ln\, w^*_{sit} \\
&+ \frac{1}{2}\sum_{k=1}^{K}\sum_{m=1}^{M-1} \delta_{km} \ ln\, x_{kit}\, ln\, y^*_{mit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{r=1}^{R} \xi_{kr} \ ln\, x_{kit}\, ln\, w^*_{rit} \\
&+ \frac{1}{2}\sum_{m=1}^{M-1}\sum_{r=1}^{R} \upsilon_{mr} \ ln\, y^*_{mit}\, ln\, w^*_{rit} \\
& i = 1,2,\ldots,N \;\; t = 1,2,\ldots,T,
\end{aligned} \tag{6}
$$

where $w^*_{rit} = w_{rit} \times y_{Mit}$. In a stochastic frontier model the distance separating a producer from the frontier is given by two random components (Aigner et al., 1977): (1) its technical/environmental inefficiency and (2) a random shock beyond producers' control. Hence the error term of the translog regression equation is defined 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 time-varying inefficiency term. As in a standard stochastic frontier model, v_{it} are normally distributed as $N(0, \sigma_v^2)$ while u_{it} are normally distributed and truncated at 0 as $N^+(\nu_t, \sigma_u^2)$. Hence, if we add the random components, the estimated distance functions presented in Eqs. (4)–(6) can be written as:

$$
\begin{aligned}
ln(D_{Cit}/y_{Mit}) &= TL(x_{it}, y^*_{it}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\delta}) + v_{it} \\
ln(D_{Oit}/y_{Mit}) &= TL(x_{it}, y^*_{it}, w_{it}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\delta}, \boldsymbol{\chi}, \boldsymbol{\xi}) + v_{it} \\
ln(D_{Hit}/y_{Mit}) &= TL(x_{it}, y^*_{it}, w^*_{it}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\delta}, \boldsymbol{\chi}, \boldsymbol{\xi}, \boldsymbol{\upsilon}) + v_{it} \\
& i = 1,2,\ldots,N \;\; t = 1,2,\ldots,T.
\end{aligned} \tag{7}
$$

The expressions shown in (7) can be easily transformed so that the dependent variables are $-ln(y_{Mit})$ while $ln(D_{Cit})$, $ln(D_{Oit})$ and $ln(D_{Hit})$ are written in the right hand side of each equation, capturing the inefficiency components u_{it}.

We regress Eqs. (4)–(6) using the standard maximum–likelihood technique developed by Battese and Coelli (1992) and then compute the posterior expected values of the error components, obtaining the time varying efficiency estimates. The latter can be transformed in efficiency scores as follows: $TE_{it} = e^{-u_{it}}$. We obtain a set of estimated efficiency scores that can be used to investigate the impact on efficiency of including undesirable outputs. The changes in efficiency scores are then analyzed in order to identify whether some distinctive features of airports' activities have an impact on how efficient is the management in dealing with both technical (i.e., desirable outputs) and environmental (i.e., local air pollution) issues.

4 The Local Air Pollution Index

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. 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).[3]

We compute the emissions produced by each aircraft type taking into account both (1) the emission factors for the aircraft's 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.

[3]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).

The study considers 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.[4] The first one allows us to compute the number of landing and take–off operations for the different model of aircraft in each Italian airport. The second and the third ones allow us to link each model of aircraft both to its engine type and to the number of engines installed.[5] ICAO and FOI provide the Emission Factor (i.e., the quantity in grams emitted per kilogram of fuel consumed) for the four LTO phases and for each engine model. A more detailed explanation of all the steps adopted to match the above databases is provided in Grampella et al. (2012). The pollutants considered in this contribution are: hydrocarbons (HC), carbon monoxide (CO), and nitrogen oxides (NO_x).[6]

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:

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

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[4]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.

[5]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 $\pm 3\%$.

[6]Notice that also SO_2 emissions and Particulate Matter (PM) emissions 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, 2010, 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 emissions.

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.[7]

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
Boulogne	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	132,920
Brindisi	3,327	34,453	43,561	Reggio Calabria	2,303	22,596	27,539
Cagliari	9,770	96,469	120,726	Rimini	523	5,738	5,884
Catania	18,223	192,436	240,694	Rome Ciampino	13,169	131,270	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	165,520
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	94,540
Naples	21,141	223,346	229,965				

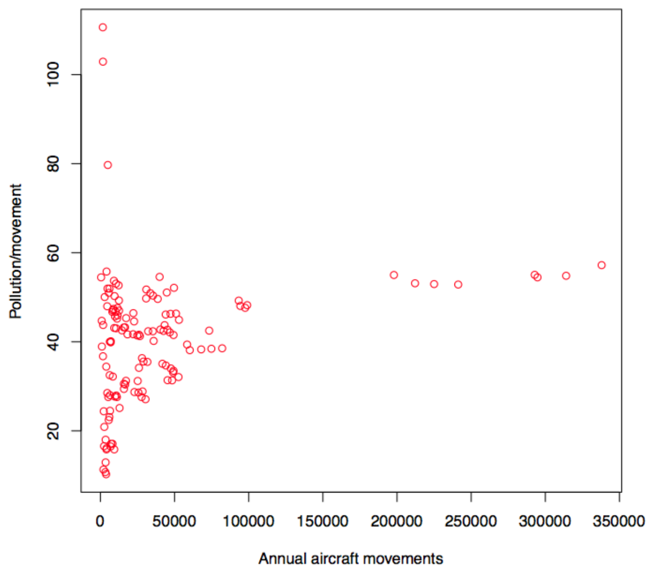
To aggregate these data into a single index, representing the LAP produced by each airport, we consider Dings et al. (2003) estimates of the cost of damage they impose. The index Weighted Local Pollution (WLP) is obtained as the sum of kg produced of each pollutant (w_p) weighted for the relative cost 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:

[7]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.

Figure 1 shows the value of the WLP index divided by the number of movements for each airport of our dataset. It is evident that there is a big dispersion in the amount of local pollution per aircraft movements across all Italian airports, and especially among the small and medium size ones (the two largest airports - i.e., Rome Fiumicino and Milan Malpensa - still exhibit some variation but of a smaller magnitude). This suggests that some airports are greener than the others in terms of fleet mix. Hence, including this variable into the efficiency assessment implies to penalize airports operating more polluting aircraft.

The average cost of local pollution is about 40 Euros per flight, while the maximum and minimum local pollution costs are respectively about 80 Euros and 16 Euros.

Figure 1 - Local pollution per movement (Euro) across airports (2005-08)



5 Airport data set

The data set includes input and output variables of 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)[8], 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 an aggregate measure of the annual passenger and freights movements (WLU)[9] provided by the Italian airport authority (Ente Nazionale Aviazione Civile, ENAC), and the annual aircraft movements (ATM) are collected from the OAG database. The undesirable output is given by the total local emissions produced by each aircraft during the LTO cycles and computed, at the airport level, using the WLP index presented in Section 2.2.[10] Table 2 shows the descriptive statistics regarding outputs and inputs.

Table 2 - 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)	38,812	13,850	73,320	350,000	1,100
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

6 Results

In this section, we present and discuss our econometric results regarding the estimation of the stochastic frontier models presented in Section 2.1. Model D_C is the classical distance function including only desirable outputs in the estimated frontier (Eq. (4)); Model D_O gives a output stochastic frontier with desirable outputs and the

[8]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.
[9]In air transportation, by convention, passengers and freights are combined in a single output measure, WLU, such that 100 kilograms of freight corresponds to one passenger.
[10]We have checked 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 are significant (at a 1% level) and positive. Moreover, the inputs correlations are positive, significant, and very high, as a confirmation that in managing airports, inputs are jointly dimensioned to avoid bottlenecks (Lozano and Gutiérrez, 2009).

undesirable good treated as a fixed input (Eq. (5)). D_H represents a hyperbolic distance function with both desirable and undesirable outputs (Eq. (6)).

In all the models ATM_{it} is treated as the normalizing output and HUB is a production function shifter: it is a dummy variable equal to 1 if the airport is classified as an hub, to control for the presence of a technology difference among hub and non–hub airports.[11] Prior to estimation, all the output and input variables have been divided by their respective geometric means. Consequently, inputs and outputs elasticities can be regarded as (partial) distance elasticities evaluated at the variable mean of the empirical sample.

Table 3 presents the maximum likelihood estimates of Eqs. (4)–(6). In all estimated frontiers the first order coefficient for WLU is positive and significant, as expected. This indicates that any increase in the amount of WLU produced, *ceteris paribus*, would imply a smaller distance to the frontier. Hence all the estimated frontiers meet the monotonicity condition of being non–decreasing in desirable outputs (at the sample mean). The first order coefficient of the bad output, i.e., WLP, when included in the frontier has the expected negative sign, and it is statistically significant. 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. The variable HUB is negative and statistically significant only in the D_C frontier, i.e., when the undesirable output is not considered. In all the other frontiers, where the amount of pollution is taken into account, it is instead not statistically significant; this implies that the hub different technology has no impact on the technical/environmental frontier: hub airports have not lower emissions per inputs than the other airports.

[11]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.

Table 3 - Estimation results

	Model D_C		Model D_O		Model D_H	
Variables	**Est. Coeff.**	**Std. Error**	**Est. Coeff.**	**Std. Error**	**Est. Coeff.**	**Std. Error**
Const	0.80 ***	0.10	0.16 ***	0.03	0.12 ***	0.03
WLU	0.59 ***	0.17	0.57 ***	0.06	0.31 ***	0.04
WLP	-	-	-0.80 ***	0.03	-0.46 ***	0.01
TERM	0.16 *	0.09	-0.10 ***	0.03	-0.06 ***	0.02
CHECK	-0.13	0.09	-0.11 ***	0.04	-0.06 **	0.02
FTE	-0.50 ***	0.08	-0.03	0.03	-0.01	0.02
CAP	-0.41 **	0.17	0.07	0.05	0.08 **	0.04
PARK	-0.03	0.09	-0.02	0.05	-0.01	0.03
WLU x WLU	0.41 **	0.19	0.04	0.10	0.00	0.07
WLU x WLP	-		-0.02	0.04	-0.05 ***	0.02
WLU x TERM	-0.11	0.13	-0.10	0.07	-0.03	0.05
WLU x CHECK	0.02	0.20	0.11	0.09	0.09	0.07
WLU x FTE	0.11	0.09	0.00	0.04	0.05	0.04
WLU x CAP	0.29	0.30	-0.01	0.12	-0.04	0.07
WLU x PARK	-0.64 ***	0.19	-0.20 **	0.09	-0.12 **	0.06
WLP x WLP	-	-	-0.18 ***	0.05	-0.04 ***	0.01
WLP x TERM	-	-	0.10 *	0.06	0.03	0.02
WLP x CHECK	-	-	0.03	0.07	0.03	0.03
WLP x FTE	-	-	0.00	0.03	0.01	0.01
WLP x CAP	-	-	-0.03	0.07	-0.03	0.02
WLP x PARK	-	-	-0.09	0.08	0.00	0.02
TERM x TERM	0.39 **	0.20	-0.18 **	0.09	-0.12 ***	0.05
TERM x CHECK	0.06	0.22	0.09	0.10	0.04	0.06
TERM x FTE	0.04	0.09	0.18 ***	0.06	0.11 ***	0.04
TERM x CAP	-0.37 *	0.20	-0.19 *	0.10	-0.09	0.06
TERM x PARK	0.26	0.17	-0.04	0.09	-0.04	0.05
CHECK x CHECK	-0.40	0.57	-0.21	0.24	-0.06	0.14
CHECK x FTE	0.24 **	0.11	0.07	0.08	0.00	0.05
CHECK x CAP	0.13	0.37	-0.13	0.16	-0.09	0.10
CHECK x PARK	-0.31	0.23	0.16	0.14	0.09	0.08
FTE x FTE	-0.13	0.08	-0.15 ***	0.04	-0.10 ***	0.03
FTE x CAP	-0.01	0.19	0.11 *	0.06	0.09 **	0.04
FTE x PARK	-0.19	0.17	-0.09	0.08	-0.05	0.05
CAP x CAP	-0.48	0.50	0.11	0.17	0.10	0.11
CAP x PARK	0.67 **	0.29	0.15	0.13	0.05	0.08
PARK x PARK	-0.14	0.22	0.11	0.13	0.04	0.08
HUB	-2.33 ***	0.55	0.11	0.15	0.11	0.09
TIME	-0.03 ***	0.01	0.10 **	0.05	0.07 **	0.03
σ^2	1.12 ***	0.37	0.01 ***	0.01	0.01 **	0.00
γ	0.99 ***	0.00	0.79 ***	0.09	0.90 ***	0.06
log lik.	45.13		159.48		231.22	

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

Concerning the inputs, first-order coefficients show the magnitude of the respective partial input elasticities at the sample mean.[12] When they are statistically

[12]The complete specification of the desirable output (i.e., aircraft movements) elasticity with respect to the inputs as follows: $\epsilon_C^{y,k} = \frac{\partial(-\ln y_i)}{\partial \ln x_{ki}} = \alpha_k + \sum_{l=1}^{K} \alpha_{kl} \ln x_{li} + \delta_{km} \ln y_{mi}^*$ (this is for the Classical distance function case). However, we have verified that these specifications, on average, coincide with the first-order coefficients, for the small magnitude of the logarithmic expressions.

significant they have the expected negative sign, with the exception of the variable CAP in the hyperbolic distance function (the variable TERM has a positive sign but only at 10% statistically significance in the classical distance function). 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. This implies that all inputs have impact in the estimated production functions.

The likelihood function is expressed in terms of the variance parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$. Table 3 also shows that these parameters are always statistically significant at the 1% level, with the estimated γ equal respectively to 0.99, 0.79 and 0.90. 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 specifications.

Table 4 compares the average estimated efficiency scores of the four models described by Eqs. (4)–(6). 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 et al., 2008, and Lozano and Gutiérrez, 2010) and (2) the efficiency gaps among the airports become smaller.

Table 4 - Average technical efficiency scores by model

Airport	D_C	D_O	D_H	Airport	D_C	D_O	D_H
Alghero	0.490	0.957	0.977	**Olbia**	0.953	0.972	0.984
Ancona	0.390	0.844	0.855	**Palermo**	0.355	0.942	0.950
Bari	0.182	0.969	0.979	**Pantelleria**	0.385	0.883	0.921
Bergamo	0.271	0.913	0.948	**Parma**	0.934	0.826	0.861
Boulogne	0.355	0.787	0.850	**Pescara**	0.78	0.946	0.898
Brescia	0.512	0.981	0.990	**Pisa**	0.267	0.828	0.891
Brindisi	0.351	0.977	0.980	**Reggio Calabria**	0.752	0.987	0.988
Cagliari	0.235	0.933	0.969	**Rimini**	0.942	0.933	0.836
Catania	0.176	0.925	0.972	**Rome Ciampino**	0.233	0.829	0.919
Florence	0.376	0.797	0.872	**Rome Fiumicino**	0.898	0.963	0.968
Forlì	0.345	0.844	0.933	**Trapani**	0.309	0.934	0.947
Genoa	0.587	0.851	0.866	**Treviso**	0.240	0.954	0.975
Lamezia Terme	0.779	0.794	0.769	**Trieste**	0.554	0.938	0.935
Lampedusa	0.922	0.955	0.975	**Turin**	0.284	0.957	0.976
Milan Linate	0.272	0.977	0.983	**Venice**	0.196	0.895	0.938
Milan Malpensa	0.612	0.947	0.979	**Verona**	0.707	0.808	0.862
Naples	0.415	0.885	0.893	**Mean**	**0.487**	**0.912**	**0.928**

To investigate the changes in the efficiency scores when bad outputs are taken into account, we study the differences in the estimated scores obtained by regressing the three different models. More in details, we study the differences between the classical stochastic frontier (D_C) and the other two frontiers considering bad output production (i.e., D_O with bad treated as fixed and D_H allowing bad output reduction). These comparisons are represented in Figures 2 and 3, where horizontal axes represent the score obtained by D_C, while vertical axes represent the differences between the scores of the horizontal axes and those obtained by respectively D_O and D_H.

Figure 2 - Delta scores analysis: Classical vs Output distance function

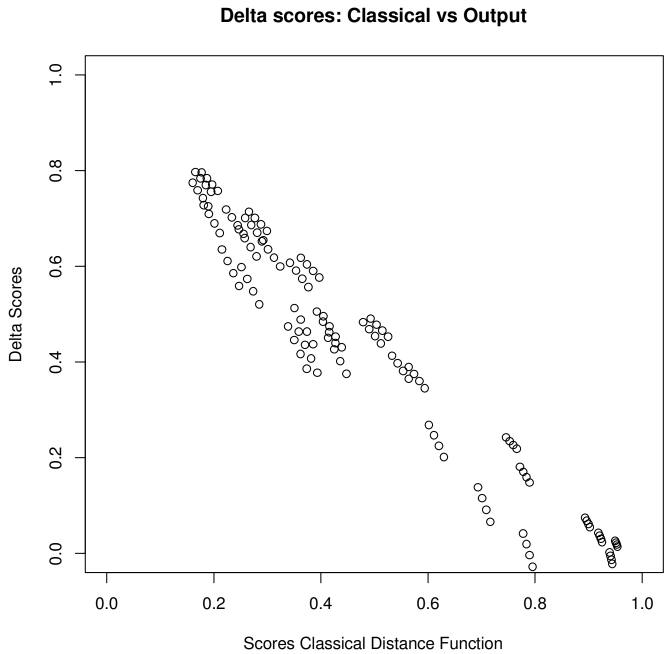
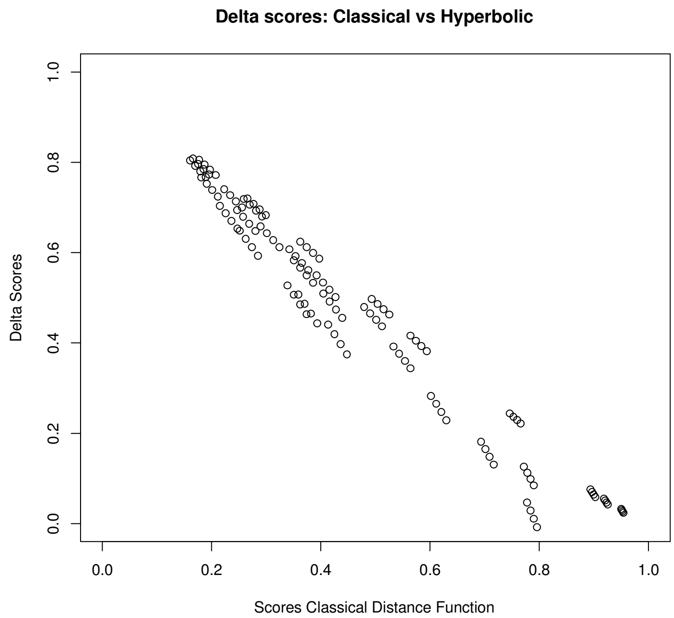


Figure 3 - Delta scores analysis: Classical vs Hyperbolic



Figures 2 and 3 show clearly that we observe greater gains in the efficiency scores for airports that are inefficient according to the classical definition of technical efficiency. This “inefficiency effect” is due to the fact that, 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 good outputs volumes (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, they have low good outputs volumes per installed inputs. When instead emissions are introduced, these airports benefit from very low emission rates per input. For instance, the same underutilized runway capacity gives rise to low efficiency in terms of desirable outputs, but high efficiency in terms of emissions.

7 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 local pollutants produced for each Italian airport included in our data set.

We show that, if the undesirable outputs are ignored, airport efficiency scores can be misleading. Our results indicate that airports tend to be more efficient, on average, when negative externalities of production are included in the analysis. More in details, those airports that are highly technically inefficient when only "good" outputs are included (because they have a low utilization rate of their aeronautical inputs), show a strong improvement in their efficiency when also undesirable outputs are considered. However, this is not due to managerial effort, but to the fact that same weights are given to "bad" and "good" outputs into the distance function. Consequently, inefficient airports improve their scores mainly because they get closer to the technical/environmental frontier thanks to their low volumes of aircraft and passengers movements. When instead airports with similar number of movements are considered, we can assume that a fleet effect may be identified as a driver for the gains magnitude in the efficiency scores, given that more environmentally friendly fleets produce lower amount of pollutants per movement.

Our results yield the following policy implications. A tight regulation to improve airports' technical efficiency would not be necessary if negative environmental externalities are included in the benchmarking analysis. When pollutants are considered, 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 in designing an airports' regulatory scheme fostering efficiency. An optimal balance of weights between good and bad outputs could overcome such a friction by enabling both the inclusion of undesirable output and the implementation of an effective regulatory mechanism. In this scenario, airports should have the incentives to induce airlines to renovate their fleet either through engine updating or by replacing old aircrafts with new environmental friendly ones. This practice may be implemented by imposing emission charges, maybe linked to fuel consumption.

A 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 a non–linear variable such as noise and to estimate the social cost of noise annoyance.

References

- Aigner, D.J., Lovell, C.A.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production functions models. International Economic Review 17, 377–396.
- Battese, G.E., Coelli, T.J., 1992. Frontier Production Functions, Technical Efficiency and Panel Data: with Application to Paddy Farmers in India. The Journal of Productivity Analysis, 3, 153–169.
- Charnes, A., Cooper, W.W., Golany, B., Seiford, L., Stutz, S., 1985. Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production function. Journal of Econometrics 30, 91e107.
- Chow, C.K.W., Fung, M.K.Y., 2009. Efficiencies and Scope Economies of Chinese Airports in Moving Passengers and Cargo. Journal of Air Transport Management, 15, 324-–329.
- Coelli, T.J., Perelman, S., 1999, 'A Comparison of Parametric and Non-Parametric Distance Functions: with Application to European Railways.' European Journal of Operational Research, 117, 326–339.
- Coelli, T.J., Perelman, S., 2000. Technical Efficiency of European Railways: A Distance Function Approach. Applied Economics, 32, 1967–1976.
- Cuesta, R.A., Zofío, J.L., 2005. Hyperbolic efficiency and parametric distance functions: with application to Spanish savings banks. Journal of Productivity Analysis, 24, 31-–48.
- Cuesta, R.A., Lovell, C.A.K., Zofío, J.L., 2009. Environmental efficiency measurement with translog distance functions: A parametric approach. Ecological Economics, 68, 2232-–2242.
- Dailey, B., 2010. Air Transport and the Environment, Farnham, Surrey, England: Ashgate Pub. Co.
- Dings, J.M.W., Wit, R.C.N., Leurs, B.A., Davidson, M.D., Fransen, W., 2003. External Costs of Aviation, (Berlin, Federal Environmental Agency, Umweltbundesamt).
- Fa□re, R., Grosskopf, S., Lovell, C.A.K., Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Review of Economics and Statistics 75, 90–98.

- Färe, R., Primont, D., 1995. Multi–Output Production and Duality: Theory and Applications, (Dordrecht, Kluwer Academic Publishers).
- Givoni, M., Rietveld, P., 2009. Airlines' choice of aircraft size–explanations and implications. Transportation Research A 43, 500–510.
- Givoni, M., Rietveld, P., 2010. The environmental implications of airlines' choice of aircraft size. Journal of Air Transport Management, 16, 159-–167.
- Grampella, M., Martini, G., Scotti, D., Tassan, F., Zambon, G., 2012. A Simplified Method for Airport Environmental Impacts Assessment. University of Bergamo, mimeo.
- Graham, A., 2008. Managing airports: an international perspective, (Oxford, Burlington, MA).
- Kumbhakar, S.C., Lovell, C.A.K., 2000. Stochastic Frontier Analysis, (Cambridge, U.K., Cambridge University Press).
- Lozano, S., Gutiérrez, E., 2009. Efficiency Analysis and Target Setting of Spanish Airports. Networks and Spatial Economics, doi: 10.1007/s11067–008–9096–1.
- Lozano, S., Gutiérrez, E., 2010. Slacks–based measure of efficiency of airports with airplanes delays as undesirable outputs. Computers and Operations Research, doi:10.1016/j.cor.2010.04.007.
- Lovell, C.A.K., Richardson, S., Travers, P., Wood, L., 1994. Resources and functionings: a new view of inequality in Australia. In: Eichhorn, W. (Ed.), Models and Measurement of Welfare and Inequality. Springer-Verlag, Berlin.
- Lu, C., Morrell, P., 2006. Determination and Applications of Environmental Costs at Different Sized Airports- Aircraft Noise and Engine Emissions. Transportation, 33, 45-61.
- Pathomsiri, S., Haghani, A.,Dresner, M., Windle, R.J., 2008. Impact of undesirable outputs on the productivity of US airports. Transportation Research Part E, 44, 235-–259.
- Ribeiro, S., Kobayashi, S., Beuthe, M., Gasca, J., Greene, D., Lee, D.S., Muromachi, Y., Newton, P.J., Plotkin, S., Sperling, D., Wit, R., Zhou, P.J., 2007. Transport and its infrastructure. In: Metz, B., Davidson, O.R., Bosch, P.R., Dave, R., Meyer, L.A. (Eds.), Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth

Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

- Scotti, D., Malighetti, P., Martini, G., Volta, N., 2012. The impact of airport competition on technical efficiency: A Stochastic Frontier Analysis applied to Italian airports. Journal of Air Transport Management, 22, 9-15.
- Shephard, R.W., 1970. Theory of Cost and Production Functions. Princeton University Press, Princeton, NJ.
- Tovar, B., Martin Cejas, R.R., 2009. Technical Efficiency and Productivity Changes in Spanish Airports: A Parametric Distance Functions Approach. Transportation Research Part E: Logistics and Transportation Review, 46, 249–260.
- Yu, M.M., 2004. Measuring physical efficiency of domestic airports in Taiwan with undesirable outputs and environmental factors. Journal of Air Transport Management,10, 295-–303.
- Yu, M.M., Hsu, S.H., Chang, C.C., Lee, D.H., 2008. Productivity growth of Taiwan’s major domestic airports in the presence of aircraft noise. Transportation Research Part E, 44(3), 543-–554.

DEED: a Directional Economic Environmental Distance function of efficiency

Abstract

In this paper we introduce a new data envelopment analysis (DEA) methodology in order to compute the efficiency measurement when considering the production of bad externalities. Starting from the approach of Fare and Grosskopf (2010), we design an additive model that allows for the constrained increase of inputs and for different disposability in the technology to analyze. The general model we propose is suitable and applicable in all these industries in which an economic environmental measure of efficiency is necessary.

1 Introduction

Modelling the production of bad outputs in a data envelopment analysis (DEA) framework has received growing interest in the recent literature. The concepts of efficiency and performance are being flanked to the new one of ecological efficiency. Usually decision making units (DMU) are evaluated only respect the input utilization and output production considered as “good”. However, as stated by Seiford and Zhu (2002), both desirable and undesirable output may be present in the production process. Following this idea, in the existing literature different industries were analyzed considering the undesirable output production: pulp and paper industry (Hailu and Veeman, 2001), solid waste collection and sorting programs (Courcelle et al., 1998), power plants (Fare et al., 1996; Korhonen, 2007; Zhou et al., 2008; Yang and Politt, 2010), industrial systems (Zhang et al., 2008), transportation sector (Lozano and Gutierrez, 2011; Yu, 2004), etc.

The common procedure in order to measure environmental performance is to incorporate undesirable outputs through data transformation in the traditional DEA framework to calculate the efficiencies. Koopmans (1951), Ali and Seiford (1990), Scheel (2001) and Seiford and Zhu (2002) present well known procedures to include bad outputs production in existing DEA models. Moreover, there has been an expansion of methodological approaches to empirical research on performance measurement models accounting for bad output production. Dyckhoff and Allen (2001), Sarkis and Talluri (2004), Zhou et al. (2008) and Gomes and Lins (2008) present an overview on the state of the art DEA models in presence of undesirable outputs. These studies have been predominantly based on the concept of radial efficiency measures.

Despite this, Fare and Lovell (1978) pointed out the short-comings of radial measurement. Radial measures of efficiency overestimate technical efficiency when there are nonzero slacks in the constraints. In order to consider slacks, the authors suggested the concept of non-radial measures introducing an input-oriented Russell measure that minimizes input slacks. Charnes et al. (1978) presented an additive model that maximizes the sum of both input and output slacks. The principal drawback in this approach is that input and output slacks are added without considering the different unit of measures. To solve this problem, Tone (2001) proposed a slack based model (SBM) that maximizes input and output slacks making them comparable. Cooper et al. (1999)

and Cooper et al. (2011) present respectively a range adjusted measure (RAM) and a bounded adjusted measure (BAM) that, as SBM, maximize input and output slacks following an additive measure approach. Fukuyama and Weber (2009) introduced the directional distance function technology into SBM approach to develop a generalised measure of technical efficiency. On the other hand, Fare and Grosskopf (2010) proposed a generalization of the SBM measure based on the directional distance function. The authors compute the efficiency based on the sum of directional distances describing the excess in input utilization and the losses in output production.

Following Fare and Grosskopf (2010), we present an additive model that benchmarks the decision making units (DMUs) on a unique eco-environmental frontier considering the production of both good and bad outputs productions. Our model describes the distance of each DMU to the efficient frontier evaluating it as potential monetary saving achievable by reaching such frontier. As suggested by Dyckhoff and Allen (2001) the normal assumption of considering all inputs as "bads" to be reduced is no longer valid in an ecological context. In an eco-environmental perspective ecologically good inputs (e.g., waste in a waste-burning power plant or in a recycling plan) have to be considered. Jahanshahloo et al. (2005) and Liu et al. (2010) apply this concept of desirable and undesirable input in their works. In our study we extend the idea of desirable input allowing the decrease or the increase in desirable input utilization. Following Sueyoshi and Goto (2011), we propose an unified efficiency measurement considering both the production of good and bad outputs and allowing the constrained increase in desirable input utilization. Differently from the usual DEA approach, a DMU could reach the frontier decreasing input utilization or, alternately, increasing it. Finally, our model permits to easily consider weak (Fare et al., 1989) or strong (free) disposability assumptions on outputs production.

The remainder of the paper is organised as follows. Section 2 deals with the mathematical definition of our model, Section 3 presents empirical comparisons with different models presented in literature. Finally, Section 4 concludes our study.

2 Methodology

In this section we present the new methodology we developed. We start defining our directional economic environmental distance (DEED) function (paragraph 2.1) following with a discussion on the objective function adopted (paragraph 2.2) and on the constraints presented in our model (paragraph 2.3).

2.1. Directional Eco Efficiency Distance (DEED) function

In order to develop our new methodology, we start assuming that there are $j = (1,2, \dots, n)$ DMUs using $X_j = (x_{1j}, x_{2j}, \dots, x_{mj})$ inputs to produce $Y_j = (y_{1j}, y_{2j}, \dots, y_{lj})$ outputs. Let now assume that the input used by the production technology can be divided in a set of desirable input and a set of undesirable input. In the same way, the production of output can be divided in a set of desirable outputs and a set of negative externalities treated as bad outputs. Thus, the input vector X_j can be split in $D_j = (d_{1j}, d_{2j}, \dots, d_{dj})$ desirable input and in $U_j = (u_{1j}, u_{2j}, \dots, u_{uj})$ undesirable input ($m = d + u$). Simultaneously, the outputs vector Y_j can be split into two sub-vectors: $G_j = (g_{1j}, g_{2j}, \dots, g_{sj})$ for good and $B_j = (b_{1j}, b_{2j}, \dots, b_{hj})$ describing bad outputs, with $l = s + h$. Rather than assuming that inputs and outputs are strictly positive we assume that:

1) $d_{pj} \geq 0, u_{qj} \geq 0, g_{rj} \geq 0, b_{fj} \geq 0 \; with \; p = 1, \dots, d; q = 1, \dots, u; \; r = 1, \dots, s; f = 1, \dots, h$
2) $\sum_{j=1}^{n} d_{pj} > 0, \sum_{i=1}^{d} d_{pj} > 0$
3) $\sum_{j=1}^{n} u_{qj} > 0, \sum_{i=1}^{u} u_{qj} > 0$
4) $\sum_{j=1}^{n} g_{rj} > 0, \sum_{r=1}^{s} g_{rj} > 0$
5) $\sum_{j=1}^{n} b_{fj} > 0, \sum_{f=1}^{h} b_{fj} > 0$

which allow some input or output to be zero (assumption 1) relaxing strict positivity. Moreover, assumptions 2-5 require that at least one type of each input and output is produced by at least one DMU.

Our model relaxes the typical assumption of null-jointness first introduced by Shepard and Färe (1974). Null-jointness describes the idea that good and bad outputs are jointly produced. More in detail, it means that if there is not a production of bad outputs, there is not even a production of good outputs. Otherwise, if some good outputs are produced, a quantity of undesirable outputs is produced. Our idea is that there exist application areas in which the technology design creates trade-offs within the bad outputs that can wipe out the production of some of them without impacting the input utilization or the good output production (e.g. shift in technology like moving from diesel to electric engines, or, in aviation, moving from turbo fan to turbo propeller engines)

Starting from the weighted additive model (Pastor, 1994) and following Färe and Grosskopf (2010), we design a directional eco efficiency distance (DEED) function as a linear program presented in Equations (1.1)-(1.7). Consider, again, $j = 1, \ldots, n$ DMUs using a column vector of d desirable inputs (D_j) and a column vector of u undesirable input (U_j) in order to yield a column vector of s desirable (good) outputs (G_j) and a column vector of h undesirable (bad) outputs (B_j).

$$\max_{\lambda,\alpha,\beta,\gamma,\delta} \partial = \sum_{p=1}^{d} P_p^d \alpha_p + \sum_{q=1}^{u} P_q^u \beta_q + \sum_{r=1}^{s} P_r^g \gamma_r + \sum_{f=1}^{h} P_f^b \delta_f \qquad (1.1)$$

$$s.t. \sum_{j=1}^{n} d_{pj} \lambda_j = d_{p0} - \alpha_p e_p \ \ (p = 1, \ldots, d), \qquad (1.2)$$

$$\sum_{j=1}^{n} u_{qj} \lambda_j = u_{q0} - \beta_q e_q \ \ (q = 1, \ldots, u), \qquad (1.3)$$

$$\sum_{j=1}^{n} g_{rj} \lambda_j = g_{r0} + \gamma_r e_r \ \ (r = 1, \ldots, s), \qquad (1.4)$$

$$\sum_{j=1}^{n} b_{fj} \lambda_j = b_{f0} - \delta_f e_f \ (f = 1, \ldots, h), \qquad (1.5)$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad (1.6)$$

$$-\sum_{1}^{u} P_p^d \alpha_p \leq \sum_{1}^{h} P_f^b \delta_f \qquad (1.7)$$

$$\lambda_j \geq 0, \qquad \alpha_p \ free\ in\ sign, \qquad \beta_q \geq 0, \qquad \gamma_r \geq 0, \qquad \delta_f \geq 0,$$

where the variables λ represent the targets identifying the linear combinations of efficient DMUs.

Consequently, model (1) is a non-oriented, directional distance function with a weighted additive measure of efficiency. Model (1) designs a single efficient frontier in which DMUs are benchmarked simultaneously with respect to all the variables.

2.2 Objective function (Equation 1.1)

In Model (1) the economic-environmental objective function maximizes the sums of the inputs slacks $\alpha_p$and β_q, the desirable outputs slacks γ_r and the undesirable outputs slacks δ_f, multiplied by their respective prices, i.e., P^d, P^u, P^g and P^b. Note that in in this case, the price vector translates the objective function in a weighted additive model in which the prices are such weights. Moreover, the price vector permits to compare variables and DMUs identifying a score in monetary units.

The estimated efficiency score ∂ is equal to 0 when the DMU is efficient, while the greater the values of ∂, the more inefficient the DMU. A higher value of ∂ implies larger monetary waste, the score obtained describes the maximum saving achievable for an inefficient DMU moving to the efficient frontier. It is important to consider that by modifying the objective function (equation 1.1.), it is possible to change the perspective of the analysis. As an example, it is possible to only maximize the reduction in bad output (i.e., $\max_{\lambda,\delta} \partial = \sum_{f=1}^{h} P_f^b \delta_f$) in order to only focus on the environmental problems.

Furthermore, it is possible to adapt the objective function (equation 1.1) in order to obtain efficiency values lying between zero and one. Range adjusted measure (RAM), proposed by Cooper et al. (1999), and bounded adjusted measure (BAM), proposed by Cooper et al. (2011), are the two most famous alternatives in order to obtain efficiency scores between zero and one in an additive approach. Even if BAM has a greater discriminatory power (Cooper et al., 2011), given the nature of this measure, it is not implementable in its original form in our DEED model. Deeply, the lower-side range for desirable input ($L_{p0}^d = d_{p0} - \underline{d_p}$) could be lower than the desirable input slack (α_p) yielding a mistake in efficiency scores computation (i.e. if α_p describe an increase in the input utilization it could be greater than the difference between the value and the lower bound of that input, $\alpha_p > d_{p0} - \underline{d_p}$).[1] In equation ($1.1b$) we present the DEED objective function adapted to the RAM approach.

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[1] A possibility to deal with this problem is to consider the maximum difference between the observation and the upper and lower input value (i.e., L = max ($d_{p0} - \underline{d_p}$; $d_{p0} - \overline{d_p}$)).

$$max_{\lambda,\alpha,\beta,\gamma,\delta}\, \partial = 1 - \frac{1}{(d+u+s+h)}\left(\sum_{p=1}^{d} \frac{\alpha_p}{\left(\overline{d_p} - \underline{d_p}\right)} + \sum_{q=1}^{u} \frac{\beta_q}{\left(\overline{u_q} - \underline{u_q}\right)} + \sum_{r=1}^{s} \frac{\gamma_r}{\left(\overline{g_r} - \underline{g_r}\right)} + \sum_{f=1}^{h} \frac{\delta_f}{\left(\overline{b_f} - \underline{b_f}\right)}\right), \qquad (1.1b)$$

where the upper case and the lower case stand respectively for the maximum and the minimum value of the variables. Adopting ($1.1b$) formulation the prices are not considered, so each slack has the same weight given by ($\frac{1}{(d+u+s+h)}$). As an alternative to function ($1.1b$), it is possible to weight each variable slack using prices as shown by equation ($1.1c$). Note that in this case results will not have a monetary interpretation.

$$max_{\lambda,\alpha,\beta,\gamma,\delta}\, \partial = 1 - \frac{1}{(P^d+P^u+P^g+P^b)}\left(\sum_{p=1}^{d} P_p^d \frac{\alpha_p}{\left(\overline{d_p} - \underline{d_p}\right)} + \sum_{q=1}^{u} P_q^u \frac{\beta_q}{\left(\overline{u_q} - \underline{u_q}\right)} + \sum_{r=1}^{s} P_r^g \frac{\gamma_r}{\left(\overline{g_r} - \underline{g_r}\right)} + \sum_{f=1}^{h} P_f^b \frac{\delta_f}{\left(\overline{b_f} - \underline{b_f}\right)}\right) \qquad (1.1c)$$

2.3 Constraints (1.2) – (1.7)

Equations 1.2, 1.3, 1.4 and 1.5 represent the constraints on desirable inputs undesirable output and, desirable and undesirable outputs respectively. As in Färe and Grosskopf (2010), if the column vector *e* is composed of ones it is assumed a freely disposable production of good and bad outputs. Thus, the production of undesirable output is a free activity, as commonly assumed in traditional production theory. However, as stated in Fare et al. (1989), some existing technologies may not dispose of free or costless disposability of bad outputs. Changing the values in vector *e* it is possible to connect the variables analyzed introducing weak disposability in our model. Weak disposability means that reduction in bad outputs is always possible if good outputs are reduced in proportion. As an example, consider a production using one input producing two desirable and two undesirable output. Introducing a vector *e* = [1, -1, -1, 1, 1] we are able to consider proportional weak disposability in our model. If this is the case, the objective function has to be changed as follow:

$$\max_{\lambda,\alpha,\beta,\gamma,\delta} \partial \;= \sum_{p=1}^{d} P_p^d \alpha_p + \sum_{q=1}^{u} P_q^u \beta_q - \sum_{r=1}^{s} P_r^g \gamma_r + \sum_{f=1}^{h} P_f^b \delta_f \qquad (1.1d)$$

Where good output slacks are negative in sign highlighting the reduction in production.

In this case good output are scaled if a decrease in bad output is achievable. If instead we want to introduce a non proportional weak disposability, it is possible to keep constant the production of good output and to reduce the undesirable ones using a vector such as e = [1, 0, 0, 1, 1]. Viceversa, it is possible to keep constant the bad output and to maximize the increase in good output using a vector e = [1, 1, 1, 0, 0]. If these are the cases, no changes in objective function are necessary. As stated in Yang and Politt (2010), in the same technology process both weak and strong disposability could be present on different variables. Following this, in our model it is possible to assume weak or strong disposability for each of the selected variable simply modifying as explained the vector *e*. Tadeo et al. (2005) and Färe et al. (2007) describe the differences in introducing weak or strong disposability assumptions within a directional distance function framework. For a deeper discussion on the implications of disposability choice, refer to Färe et al. (1985), Taskin and Zaim (2001), Cooper et al. (2006), Zhu and Cook (2007) and Sahoo et al (2011).

Equation 1.2 and 1.3 treat inputs with the same mathematical formulation. Differences between desirable and undesirable input are highlighted with the slacks boundaries. In DEED model the desirable input slacks α_p are free in sign, allowing for reductions in input utilization (with $\alpha_p > 0$), increases ($\alpha_p < 0$) or no changes in the input levels ($\alpha_p = 0$). Consequently, we identify potential increases in desirable inputs that may simultaneously reduce the utilization of undesirable input and the production of negative externalities, increasing the production of good outputs. Desirable inputs can be interpreted as those ecological/not environmental impacting variables (e.g. waste in a waste burning power plant, total workers, amount of money, etc…). Undesirable input slacks (β_q) describe a situation in which only the reduction ($\beta_q > 0$) or no change ($\beta_q = 0$) in utilization are allowed. Undesirable inputs can be interpreted as all that variables necessary to the production but directly affecting environment (e.g., water, fuel, electricity, chemicals, etc…)

Constraint (1.5) incorporates the undesirable outputs as inputs to be reduced. Alternative approaches would be to define them as negative outputs (and then using equation 1.5b) or to translate the inverse of the externalities as an undesirable output (Scheel (2001)). However, latter approach is not applicable in the DEED model because requires a non-linear transformation which renders the undesirable output slacks (δ_f) as no longer comparable to the other slacks in the model.

$$\sum_{j=1}^{n} b_{fj}\,\lambda_j \;= b_{f0} + \delta_f e_f \;(f\; = 1, \ldots, h), \qquad (1.5b)$$

Constraint (1.6) is the typical variable return to scale (VRS) constraint. It should be noted that the model allows for constant return to scale (CRS) technology by simply deleting this constraint.[2]

Finally, increases in desirable input utilization are limited by constraint (1.7) which implies that a higher expenditure in desirable inputs has to be at most equal to the reduction in the social costs of bad outputs. Constraint (1.7) may be changed following the preferences and the objective of the research. As an example, if there is no limitation in input increase, it could be simply deleted. Another possibility is to limit the utilization of the raw desirable input to the production of the raw bad output. If this case, it is enough to not consider the prices in the constraint (1.7). Clearly, the raw data has to be comparable in the unit of measure. Furthermore, it is possible to limit the increase in the utilization of some desirable inputs to, as maximum, the decrease in the utilization in the other desirable inputs. In this way we are in a zero-sum situation that implies that any desirable input increase has to be compensated by a reduction in the levels of other desirable inputs. The constraint describing this situation becomes as follows:

$$-\sum_{1}^{u} P_p^d\,\alpha_p \leq\; 0 \qquad (1.7b)$$

Further possibilities may be to link the increase in desirable input utilization to the reduction of undesirable input consumption or to connect the input utilization to the production of good outputs or, finally, to limit the increase in input to a certain value (e.g. an amount of money for new investments, a government incentive to move towards different technologies, a maximum or minimum threshold, etc…)

[2] Note that the RAM approach (equations 1.1b and c) only deals with VRS models (Cooper et al., 2011).

3 Empirical comparison

In the paragraph 3.1 we provide analysis showing how our model performs the efficient frontier. Moreover we provide a comparison with the model proposed in Sueyoshi and Goto (2011) (paragraph 3.2).

3.1 Numerical Example

We apply our model to a sample data set composed by five DMUs as shown in table 1. We identify two inputs, one good output and one bad output. In "Example 1" we apply our model 1 considering both the inputs as undesirable (i.e. they can only be decreased) and using a vector of prices composed by ones. In "Example 2" we allow for the constrained increase of inputs (i.e., input considered as desirable)using a vector of prices of ones. Finally in "Example 3", we still consider both the inputs as desirable increasing the input 2 price from 1 to 4.

Table 1 – data sample

DMU	Input 1	Input 2	Good output	Bad output
A	4	13	37	7
B	9	15	32	8
C	6	15	32	11
D	10	9	39	14
E	12	8	35	13

In Table 2 we show the scores obtained in Example (1)-(3), the relative reference sets and the slacks for each variable. Scores describe the distance from the efficient frontier: a DMU obtaining a score equal to 0 is defined as efficient. The greater the score, the greater is the level of inefficiency of the DMU. Lambdas describe the reference set, while the variables slacks (i.e. $\alpha_p,\ \gamma_r,\ \delta_f$) are the reductions (slack > 0) or the increases (slack < 0) that the particular DMU has to perform in order to reach the efficient frontier.

Table 2 – Scores, reference sets and slacks obtained in Example (1)-(3)

		Reference Set					Slacks			
							P_1^u=1	P_2^u=1	P^g=1	P^b=1
Example 1 Scores		λ_A	λ_B	λ_C	λ_D	λ_E	**Input1**	**Input 2**	**Good output**	**Bad output**
DMU A	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DMU B	13.00	1.00	0.00	0.00	0.00	0.00	5.00	2.00	5.00	1.00
DMU C	13.00	1.00	0.00	0.00	0.00	0.00	2.00	2.00	5.00	4.00
DMU D	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
DMU E	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
							P_1^u=1	P_2^u=1	P^g=1	P^b=1
Example 2 Scores		λ_A	λ_B	λ_C	λ_D	λ_E	**Input1**	**Input 2**	**Good output**	**Bad output**
DMU A	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DMU B	13.00	1.00	0.00	0.00	0.00	0.00	5.00	2.00	5.00	1.00
DMU C	13.00	1.00	0.00	0.00	0.00	0.00	2.00	2.00	5.00	4.00
DMU D	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
DMU E	11.00	1.00	0.00	0.00	0.00	0.00	8.00	-5.00	2.00	6.00
							P_1^u=1	P_2^u=4	P^g=1	P^b=1
Example 3 Scores		λ_A	λ_B	λ_C	λ_D	λ_E	**Input1**	**Input 2**	**Good output**	**Bad output**
DMU A	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DMU B	19.71	0.86	0.00	0.00	0.14	0.00	4.14	2.57	5.29	0.00
DMU C	21.86	0.43	0.00	0.00	0.57	0.00	-1.43	4.29	6.14	0.00
DMU D	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
DMU E	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00

The first important consideration to address is that the efficient set when the increase in input utilization is allowed (i.e., Example 2 and 3) is a sub set of the efficient set obtained when only decreases are possible (i.e., Example 1). In general, when it is possible to increase input utilization, DMUs looks for the best inputs trade off in order to maximize the final score constrained to the decrease in bad output production (constraint 1.7). The score describes the distance to the optimal profit frontier or, in the same sense, the maximum saving achievable for each DMU. Thus, when the increase input utilization is allowed, DMUs are able to achieve greater saving respect to the usual DEA framework. Another important consideration is that the prices applied in the objective function are able to change the efficient set. Prices work as weights that, linked with the possibility to increase input utilization, makes valuable or not a change in reference set and makes efficient or not a particular DMU.

Looking to the differences between Example 2 and Example 3 (where the price of input 2 increases from 1 to 4), it is interesting to observe that DMU C changes the input mix increasing the input 1 (from a reduction of 2 to an increase of 1.43) and decreasing the more expensive input 2 (from a reduction of 2 to a reduction of 4.29) allowing a greater good output production (from an increase of 5 to an increase of 6.14). On the contrary, DMU E, given the increase in input 2 price, does not gain in increasing that input utilization (as in example 2) and becomes efficient not having greater savings to achieve.

3.1 Sueyoshi and Goto (2011)

In this section we compare Model (1) with the following Sueyoshi and Goto (S&G) category II model, presented in Sueyoshi and Goto (2011) work:

$$\max \sum_{i=1}^{m} R_i^x \left(d_i^{x+} + d_i^{x-}\right) + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b \, d_f^b$$

$$\sum_{j=1}^{n} x_{ij} \lambda_j - d_i^{x+} + d_i^{x-} = x_{ik} \ \ (i = 1, \dots, m),$$

$$\sum_{j=1}^{n} g_{rj} \lambda_j - d_r^g = g_{rk} \ \ (r = 1, \dots, s),$$

$$\sum_{j=1}^{n} b_{fj} \lambda_j + d_f^b = b_{fk} \ \ (f = 1, \dots, h),$$

$$\sum_{j=1}^{n} \lambda_j = 1 \ (j = 1, \dots, n),$$

$$d_i^{x+} \geq 0 \ (i = 1, \dots, m), \ d_i^{x-} \geq 0 \ (i = 1, \dots, m),$$
$$d_r^g \geq 0 \ (r = 1, \dots, s) \ and \ d_f^b \geq 0 \, , (f = 1, \dots, h).$$

where R_i^x, R_r^g and R_f^b are the ranges for the unified model, while d_i^{x+}, d_i^{x-}, d_r^g and d_f^b are respectively the slacks for increasing input, decreasing input, good output and bad output. For a detailed explanation of the model refer to Sueyoshi and Goto (2011).

We run the models considering the data-base describing the electric power companies in Japan presented in Sueyoshi and Goto (2011) work (table 3). [3]

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[3] We run Sueyoshi and Goto (2011) model category II. Given the non linearity of the model, we compute the alternative *b* suggested by the authors. The mixed integer programming problem is solved using Wotao Yin. *Gurobi Mex: A MATLAB interface for Gurobi*, URL:

Table 3 – Electric power company data set (Sueyoshi and Goto (2011))

Variables		Input 1	Input 2	Desirable output 1	Desirable output 2	Undesirable output 1
Year	Electric power company	Total assets (100 Bilion JPY)	Labor Cost (100 Bilion JPY)	Total sales (100 GWh)	Number of customers (100 Thousand)	CO_2 emissions (100 Thousand ton)
2006	Hokkaido	14.3	0.8	315.1	39	156.6
	Tohoku	37.1	1.3	809.5	76.7	408.3
	Tokyo	129.2	4.6	2876.2	280.7	1073
	Chubu	52.9	1.4	1326.9	103.9	591.2
	Hokuriku	14.8	0.5	282	20.8	113.8
	Kansai	61.9	2.1	1472.6	132.8	520
	Chugoku	24.8	1.2	612.6	52.1	394.7
	Shikoku	13.8	0.5	281.6	28.5	108.3
	Kyushu	37.9	1.4	844	83.5	306
2007	Hokkaido	14.6	0.6	324.4	39.2	150.8
	Tohoku	36.8	1.4	840.7	76.7	357
	Tokyo	130.6	3.4	2974	283.2	976
	Chubu	52.4	1.5	1374.8	104.4	637.8
	Hokuriku	14.8	0.4	293	20.8	128.8
	Kansai	61.4	2.1	1504.2	133.4	498.1
	Chugoku	25.3	1.1	635.8	51.9	425.4
	Shikoku	13.6	0.6	292.7	28.3	103.6
	Kyushu	37.8	1.4	880.8	83.8	316
2008	Hokkaido	15.6	0.5	318.4	39.4	167.8
	Tohoku	36.8	1.5	811	76.8	397.9
	Tokyo	129.9	4.8	2889.6	284.9	1265
	Chubu	51.1	1.9	1297.3	104.6	646.7
	Hokuriku	14.2	0.5	281.5	20.8	185.2
	Kansai	62.4	2.4	1458.7	134	549.9
	Chugoku	26.1	1.1	612.2	51.9	430.7
	Shikoku	13.5	0.7	287	28.3	114.6
	Kyushu	38.3	1.4	858.8	84	341

In order to compare our DEED model to the one of S&G, we utilize two different versions namely "DEED 1" and "DEED 2". DEED 1 is our model as presented in paragraph 2.1. Thus, DEED 1 limits the maximum input increases to the obtained decrease in bad output production. While, when considering "DEED 2", we do not bound the input increase (i.e., as in S&G approach) not including constraint 1.7.

In order to obtain monetary values as final scores, we fix prices for the variables presented in Table 3. The price vector for the inputs is composed by ones, since both the inputs in the data sets are expressed in monetary values. Price for desirable output 1 is 24 Yen/KWh (source: Platts website) while, as price for desirable output 2 (number of

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http://convexoptimization.com/wikimization/index.php/gurobi_mex, 2009-2011.

costumer) we use the average Japanese yearly energy consumption in Yen (83,296 Yen/costumer, source: Platts website). Finally, price for the undesirable CO_2 emitted is 1641.7 Yen/ton (source: Sendeco2 website). Price vectors adopted in this comparison are shown in Table 4, note that prices are all converted in order to obtain billion of Yen as final unit of measure. In this comparison we consider both the two inputs as desirable (increases or decreases are possible). Then, we consider the vectors e as ones. Thus, the production of desirable and undesirable output is a free activity.

Table 4 – Price vector applied in the comparison

Inputs		Desirable output		Undesirable output
P_1^d	P_2^d	P_1^g	P_2^g	P_1^b
1	1	2.40	8.33	1.64

Table 5 presents in the first three columns the DMUs specifications. In columns 4, 5 and 6 the scores obtained respectively with Sueyoshi and Goto (2011) category II, with DEED 1 and with DEED 2 model. Finally in columns 7, 8 and 9 are reported the relevant targets obtained in the three models for each of the DMUs analyzed.

Table 5 – Sueyoshi and Goto (2011) DEED 1 and DEED 2 model compared: scores and reference set.

(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
		# DMU	S&G (2011) model	DEED 1	DEED 2	Reference set S&G (2011)	Reference set DEED 1	Reference set DEED 2
2006	Hokkaido	1	0.972	341.88	370.67	λ_8=0.944, λ_{12}=0.056	λ_{12}=0.057, λ_{17}=0.943	λ_{12}=0.061, λ_{17}=0.939
	Tohoku	2	0.896	1248.38	1328.02	λ_{12}=0.349, λ_{17}=0.651	λ_{12}=0.338, λ_{17}=0.662	λ_{12}=0.349, λ_{17}=0.651
	Tokyo	3	0.917	414.59	414.59	λ_{12}=1	λ_{12}=1	λ_{12}=1
	Chubu	4	0.836	1523.50	1644.75	λ_{12}=0.559, λ_{17}=0.441	λ_{12}=0.542, λ_{17}=0.458	λ_{12}=0.559, λ_{17}=0.441
	Hokuriku	5	0.983	186.56	187.91	λ_{12}=0.012, λ_{17}=0.988	λ_{12}=0.011, λ_{17}=0.989	λ_{12}=0.012, λ_{17}=0.988
	Kansai	6	0.958	342.02	375.34	λ_8=0.526, λ_{12}=0.474	λ_{12}=0.473, λ_{17}=0.527	λ_{12}=0.477, λ_{17}=0.523
	Chugoku	7	0.848	1734.35	1861.54	λ_{12}=0.334, λ_{17}=0.666	λ_{12}=0.316, λ_{17}=0. 684	λ_{12}=0.334, λ_{17}=0. 666
	Shikoku	8	0.991	68.07	70.54	λ_{12}=0.005, λ_{17}=0.995	λ_{12}=0.005, λ_{17}=0.995	λ_{12}=0.005, λ_{17}=0.995
	Kyushu	9	0.979	187.80	199.96	λ_8=0.772, λ_{12}=0.228	λ_{12}=0.230, λ_{17}=0.770	λ_{12}=0.232, λ_{17}=0.768
2007	Hokkaido	10	0.973	265.94	290.68	λ_{12}=0.054, λ_{17}=0.946	λ_{12}=0.051, λ_{17}=0.949	λ_{12}=0.054, λ_{17}=0.946
	Tohoku	11	0.944	707.99	756.73	λ_8=0.713, λ_{12}=0.287	λ_{12}=0.284, λ_{17}=0.716	λ_{12}=0.290, λ_{17}=0.710
	Tokyo	12	**1.000**	**0.00**	**0.00**	λ_{12}=1	λ_{12}=1	λ_{12}=1
	Chubu	13	0.805	1824.04	1975.98	λ_{12}=0.612, λ_{17}=0.388	λ_{12}=0.591, λ_{15}=0.409	λ_{12}=0.612, λ_{15}=0.388
	Hokuriku	14	0.967	295.40	306.51	λ_{12}=0.029, λ_{17}=0.971	λ_{12}=0.027, λ_{17}=0.973	λ_{12}=0.029, λ_{17}=0.971
	Kansai	15	0.973	**0.00**	82.17	λ_8=0.039, λ_{12}=0.452, λ_{17}=0.509	λ_{15}=1	λ_{12}=0.452, λ_{17}=0.548
	Chugoku	16	0.821	1960.47	2104.88	λ_{12}=0.369, λ_{17}=0.631	λ_{12}=0.348, λ_{17}=0.652	λ_{12}=0.369, λ_{17}=0.631
	Shikoku	17	**1.000**	**0.00**	**0.00**	λ_{17}=1	λ_{17}=1	λ_{17}=1
	Kyushu	18	0.976	186.95	205.77	λ_8=0.761, λ_{12}=0.239	λ_{12}=0.241, λ_{17}=0.759	λ_{12}=0.243, λ_{17}=0.757
2008	Hokkaido	19	0.956	437.53	468.75	λ_{12}=0.074, λ_{17}=0.926	λ_{12}=0.069, λ_{17}=0.931	λ_{12}=0.074, λ_{17}=0.926
	Tohoku	20	0.913	1149.25	1222.89	λ_{12}=0.337, λ_{17}=0.663	λ_{12}=0.327, λ_{17}=0.673	λ_{12}=0.337, λ_{17}=0.663
	Tokyo	21	**1.000**	**0.00**	**0.00**	λ_{21}=1	λ_{21}=1	λ_{21}=1
	Chubu	22	0.808	2083.98	2245.50	λ_{12}=0.623, λ_{17}=0.377	λ_{12}=0.599, λ_{15}=0.401	λ_{12}=0.623, λ_{15}=0.377
	Hokuriku	23	0.923	830.82	879.15	λ_{12}=0.094, λ_{17}=0.906	λ_{12}=0.087, λ_{17}=0.913	λ_{12}=0.094, λ_{17}=0.906
	Kansai	24	0.930	640.48	688.72	λ_8=0.491, λ_{12}=0.509	λ_{12}=0.505, λ_{17}=0.495	λ_{12}=0.512, λ_{17}=0.488
	Chugoku	25	0.816	2069.50	2213.59	λ_{12}=0.375, λ_{17}=0.625	λ_{12}=0.354, λ_{17}=0.646	λ_{12}=0.375, λ_{17}=0.625
	Shikoku	26	0.987	113.26	120.08	λ_8=0.993, λ_{12}=0.007	λ_{12}=0.012, λ_{17}=0.988	λ_{12}=0.013, λ_{17}=0.987
	Kyushu	27	0.962	467.17	499.22	λ_8=0.732, λ_{12}=0.268	λ_{12}=0.268, λ_{17}=0.732	λ_{12}=0.272, λ_{17}=0.728

In column 4 the score is equal to 1 if the DMU is fully efficient, while it is 0 if the DMU is totally inefficient. In column 5 and 6 the efficiency score is equal to 0 if the DMU is totally efficient, while the greater the values of ∂ the more inefficient is the DMU. In model DEED 1 and DEED 2 the scores have a monetary interpration, in particular it is the maximum saving achievable for an inefficient DMU expressed in billion of Yen.

Starting analyzing the efficient units, it is possible to observe that applying the DEED 2 model we obtain the same efficient frontier obtained in Sueyoshi and Goto, while computing DEED 1 we obtain the same result except for DMU 15 that is evaluated efficient. Given the constrained increase in input, DMU 15 is not able to improve her savings moving to the efficient frontier.

Analyzing the reference set, as shown in columns 7, 8 and 9, it is possible to draw an important observation. The DEED model overcomes the problem in the reference set present in S&G model. In particular, in S&G, given the coexistence of positive and negative input slacks, inefficient DMUs could be targets for other inefficient DMUs (e.g. DMU 8 is target for DMUs 1, 6, 9, 11, 15, 18, 24, 26 and 27). Practically, Sueyoshi and Goto (2011) model designs different frontiers for each combination of input slacks (namely d1+ d2+; d1- d2-; d1+ d2-; d1- d2+) and combine them selecting the minimum score obtained. Thus, it happens that if a DMU is efficient in some but not in all the frontiers designed, it could be target for other DMUs even if it is inefficient in the final score. Our model overcomes this problem by designing a single frontier and using as targets only efficient DMUs.

In Table 6 we show the slacks computed for each DMU obtained with the three models applied. Notice that in DEED 1 and DEED 2, a negative sign means an increase in the utilization of the variable, while a positive sign describes a reduction in such variable.

Table 6 – Sueyoshi and Goto (2011), DEED 1 and DEED 2 model compared: slacks.

	S&G (2011) model						
	$P_{x1}=1$	$P_{x2}=1$	$P_{x1}=1$	$P_{x2}=1$	$P_{g1}=2.4$	$P_{g2}=8.3$	$P_b=1.64$
DMU	d^{x+}_1	d^{x+}_2	d^{x-}_1	d^{x-}_2	good1	good2	bad
1	6.00	0.00	0.00	0.14	116.37	3.68	0.00
2	17.36	0.28	0.00	0.00	419.69	40.63	0.00
3	1.40	0.00	0.00	1.20	97.80	2.50	97.00
4	26.09	0.76	0.00	0.00	464.43	66.87	0.00
5	0.17	0.13	0.00	0.00	42.05	10.48	0.00
6	7.32	0.00	0.00	0.22	86.47	16.55	0.00
7	27.84	0.33	0.00	0.00	574.79	61.25	0.00
8	0.43	0.12	0.00	0.00	25.55	1.17	0.00
9	2.51	0.00	0.00	0.24	51.05	3.03	0.00
10	5.33	0.15	0.00	0.00	113.37	2.89	0.00
11	10.48	0.00	0.00	0.07	212.60	24.80	0.00
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	32.84	0.81	0.00	0.00	559.75	79.98	0.00
14	2.18	0.28	0.00	0.00	77.15	14.86	0.00
15	5.09	0.00	0.00	0.24	0.00	10.12	0.00
16	31.46	0.53	0.00	0.00	645.94	70.42	0.00
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	3.96	0.00	0.00	0.21	45.28	5.67	0.00
19	6.61	0.31	0.00	0.00	171.62	7.66	0.00
20	16.27	0.04	0.00	0.00	386.22	37.49	0.00
21	0.00	0.00	0.00	0.00	0.00	0.00	0.00
22	35.34	0.44	0.00	0.00	664.60	82.38	0.00
23	10.34	0.36	0.00	0.00	262.00	31.34	0.00
24	10.84	0.00	0.00	0.42	193.15	24.12	0.00
25	31.37	0.55	0.00	0.00	685.83	71.97	0.00
26	1.15	0.00	0.00	0.18	14.15	2.05	0.00
27	6.82	0.00	0.00	0.12	144.85	12.81	0.00

	DEED 1				
	$P_{x1}=1$	$P_{x2}=1$	$P_{g1}=2.4$	$P_{g2}=8.3$	$P_b=1.64$
DMU	input1	input 2	good1	good2	bad
1	-5.93	0.04	129.48	3.74	3.59
2	-16.03	-0.25	389.21	37.73	9.92
3	-1.40	1.20	97.80	2.50	97.00
4	-24.07	-0.72	418.03	62.46	15.10
5	-0.15	-0.13	41.53	10.43	0.17
6	-6.99	0.18	87.14	15.95	4.15
7	-25.72	-0.28	526.11	56.63	15.84
8	-0.39	-0.11	24.60	1.08	0.31
9	-2.64	0.16	66.12	3.50	1.51
10	-4.92	-0.14	103.90	1.99	3.08
11	-9.97	0.01	212.16	23.87	6.07
12	0.00	0.00	0.00	0.00	0.00
13	-30.31	-0.75	501.60	74.46	18.92
14	-1.99	-0.28	72.90	14.46	1.38
15	0.00	0.00	0.00	0.00	0.00
16	-29.05	-0.48	590.68	65.17	17.98
17	0.00	0.00	0.00	0.00	0.00
18	-3.97	0.13	57.51	5.88	2.34
19	-6.09	-0.29	159.67	6.52	3.89
20	-15.04	-0.02	358.04	34.81	9.17
21	0.00	0.00	0.00	0.00	0.00
22	-32.64	-0.38	602.79	76.51	20.11
23	-9.54	-0.34	243.50	29.58	6.02
24	-10.25	0.39	187.23	22.95	6.01
25	-28.96	-0.49	630.69	66.73	17.94
26	-1.46	0.07	36.90	2.97	0.85
27	-6.60	0.05	151.28	12.50	3.99

	DEED 2				
	$P_{x1}=1$	$P_{x2}=1$	$P_{g1}=2.4$	$P_{g2}=8.3$	$P_b=1.64$
DMU	input1	input 2	good1	good2	bad
1	-6.41	0.03	140.49	4.79	0.00
2	-17.36	-0.28	419.69	40.63	0.00
3	-1.40	1.20	97.80	2.50	97.00
4	-26.09	-0.76	464.43	66.87	0.00
5	-0.17	-0.13	42.05	10.48	0.00
6	-7.54	0.16	99.90	17.16	0.00
7	-27.84	-0.33	574.79	61.25	0.00
8	-0.43	-0.12	25.55	1.17	0.00
9	-2.84	0.15	70.77	3.94	0.00
10	-5.33	-0.15	113.37	2.89	0.00
11	-10.78	-0.01	230.82	25.64	0.00
12	0.00	0.00	0.00	0.00	0.00
13	-32.84	-0.81	559.75	79.98	0.00
14	-2.18	-0.28	77.15	14.86	0.00
15	-5.11	0.23	0.99	10.17	0.00
16	-31.46	-0.53	645.94	70.42	0.00
17	0.00	0.00	0.00	0.00	0.00
18	-4.29	0.12	64.71	6.56	0.00
19	-6.61	-0.31	171.62	7.66	0.00
20	-16.27	-0.04	386.22	37.49	0.00
21	0.00	0.00	0.00	0.00	0.00
22	-35.34	-0.44	664.60	82.38	0.00
23	-10.34	-0.36	262.00	31.34	0.00
24	-11.05	0.37	205.69	24.70	0.00
25	-31.37	-0.55	685.83	71.97	0.00
26	-1.58	0.06	39.51	3.21	0.00
27	-7.14	0.04	163.54	13.66	0.00

Starting from the results in table 6, it is possible to compute for each variable the comparison in total savings obtained with the different models. Table 7 shows the sum of each DMU slack multiplied by their price for all the variables.

Table 7 – Sueyoshi and Goto (2011), DEED 1 and DEED 2 model compared: total savings

	input1	input2	good1	good2	bad	total
S&G	-299.2	-2.1	14531.3	5703.9	159.1	20093
DEED1	-274.1	-2.5	13653.3	5267.9	435.1	19079.7
DEED2	-301.8	-2.8	14897.3	5762.2	159.1	20514.1

From table 7 it is possible to drawn some important observations. First, analyzing column 2 and 3, it is important to notice that all the three models increases the utilization of both the inputs (the total input slack value is negative). Different mixes of inputs are used in the three models in order to achieve the maximum savings. In particular, DEED 2 uses the biggest amount of increase in inputs to achieve the greatest increase in good outputs production. Total savings (last column of table 7) obtained with DEED 2 are the greatest respect to the ones obtained in the two models, while DEED 1 uses a mix of inputs in order to achieve the greatest reduction in bad outputs (column 6) and achieving the lowest global savings. DEED1 and DEED2 differ in constraint 1.7, without introducing this allows the model to be free to increase good output production as much as possible non considering the reduction in externalities. Comparing DEED 2 with S&G model, it should be noted that DEED 2 performs better than S&G model. Indeed, S&G is not able to achieve the greatest savings for inefficient DMUs obtaining a sub optimal solution respect to DEED 2 model.

4 Conclusions

The article proposes a new DEA model in order to compute the efficiency in an eco-environmental point of view. The directional economic environmental distance (DEED) function includes the analysis of undesirable output and it is suitable for different industries applications. The DEED function is a non-radial measure of efficiency that accounts for the presence of desirable and undesirable input and for the production of good and bad outputs. Moreover, the model designs a single frontier allowing a constrained increase in desirable input. The particular feature of the objective function specifies, as result, the maximum monetary savings achievable for inefficient DMUs given the prices of each variable. Another peculiarity of our model is the possibility to consider strong or weak disposability of output implementing different solution for the vector *e* in the constraints. We show how our DEED function over-performes present models and solve the problem in the existing literature.

References

- Ali, A., Seiford, L. M., 1990. Translation invariance in data envelopment analysis. Operations Research Letters 10, 403–405.
- Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. European Journal of Operational Research 2, 429-444.
- Cooper, W.W., Park, K.S., Pastor, J.T., 1999. RAM: a range adjusted measure of inefficiency for use with additive models and relations to other models and measures in DEA. Journal of Productivity Analysis 11(1), 5–42.
- Cooper W.W., Pastor J.T., Borras, F., Aparicio, J., Pastor, D., 2011. BAM: a bounded adjusted measure of efficiency for use with bounded additive models. Journal of Productivity Analysis 35, 85-94.
- Cooper, W.W., Seiford, L.M., Tone, K., 2006. Data Envelopment Analysis. New York: Springer.
- Cooper, W.W., Seiford, L.M., Zhu, J., 2011. Data Envelopment Analysis: History, Models, and Interpretations. New York: Springer, (Chapter 1).
- Courcelle, C., Kestemont, M.P., Tyteca, D., Installé, M., 1998. Assessing the economic and environmental performance of municipal solid waste collection and sorting programmes. Waste Management and Research 16 (3), 253-263.
- Dyckhoff, H., Allen, K., 2001. Measuring ecological efficiency with data envelopment analysis. European Journal of Operational Research 132, 312-325.
- Färe, R., Grosskopf, S., 2010. Directional distance functions and slacks-based measures of efficiency. European Journal of Operational Research 200, 320–322.
- Färe, R., Grosskopf, S., Lovell, C.A.K., 1985. The Measurement of Efficiency of Production. Boston: Kluwer Academic Publishers Group.
- Färe, R., Grosskopf, S., Pasurka Jr., C.A., 1989. Multilateral productivity comparison when some outputs are undesirable: a non parametric approach. The Review of Economics and Statistics 75, 374-380.
- Färe, R., Grosskopf, S., Pasurka Jr., C.A., 2007. Environmental production functions and environmental directional distance functions. Energy 32, 1055–1066.

- Färe, R, Lovell CAK., 1978. Measuring the technical efficiency of production. Journalof Economic Theory 19, 150–62.
- Färe, R., Grosskopf, S., Tyteca, D., 1996. An activity analysis model of the environmental performance of firms - application to fossil-fuel-fired electric utilities. Ecological Economics 18, 161-175.
- Fukuyama H, Weber WL., 2009. A directional slacks-based measure of technical inefficiency. Socio-Economic Planning Sciences 43, 274–87.
- Gomes, E.G., Lins M.P.E., 2008. Modelling undesirable output with zero sum gains data envelopment analysis models. Journal of the Operational Research Society 59, 616-623.
- Hailu, A., Veeman, T.S., 2001. Non-parametric productivity analysis with undesirable outputs: an application to the Canadian pulp and paper industry. American Journal of Agricultural Economics 83 (3), 605-616.
- Jahanshahloo, G.R., Hosseinzadeh Lotfi, F., Shoja, N., Tohidi, G., Razavyan, S., 2005. Unesirable inputs and outputs in DEA models. Applied Mathematics and Computation 169, 917-925.
- Korhonen, P.J., Luptacik, M., 2004. Eco-efficiency analysis of power plants: Am extension of data envelopment analysis. European Journal of Operational Research 154. 437-446.
- Liu, W.B., Meng, W., Li, X.X., Zhang, D.Q., 2010. DEA models with undesirable inputs and outputs. Annual of Operational Research 173, 177-194.
- Lozano, S., Gutierrez, E., 2011. Slack-based measure of efficiency of airports with airplanes delays ad undesirable output. Computer & Operational Research 38, 131-139.
- Pastor, J.T., 1994. New DEA additive models for handling zero and negative data, Working Paper, Departamento de Estadistica e Investigacion Operativa, Universidad de Alicante, 03071 Alicante, Spain.
- Koopmans, T.C., 1951. Analysis of Production as an Efficient Combination of Activities. In: Koopmans, T.C. (Ed.), Activity analysis of production and allocation. Wiley, New York, 33-97.

- Sahoo, B.K., Luptacik, M., Mahlberg, B., 2011. Alternative measures of environmental technology structure in DEA: an application. European Journal of Operational Research 215, 750–762.
- Sarkis, J., Talluri, S., 2004. Ecoefficiency measurement using data envelopment analysis: research and practitioner issues. Journal of Environmental Assessment Policy and Management,6 (1), 91-123.
- Scheel, H., 2001. Undesirable outputs in efficiency valuations. European Journal of Operational Research 132, 400-410.
- Schepard, R.W., Färe, R., 1974. The law of diminishing returns. Zeitschrift fur Nationalokonomie 34, 64-90.
- Seiford, L.M., Zhu, J., 2002. Modeling undesirable factors in efficiency evaluation. European Journal of Operational Research 142, 16-20.
- Sueyoshi, T., Goto, M., 2011. Methodological comparison between two unified (operational and environmental) efficiency for environmental assessment. European Journal of Operational Research 210, 684-693.
- Taskin, F., Zaim, O., 2001. The role of international trade on environmental efficiency: a DEA approach. Economic Modelling 18, 1-17.
- Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research 130, 498–509.
- Yang, H., Pollitt, M., 2010. The necessity of distinguishing weak and strong disposability among undesirable outputs in DEA: Environmental performance of Chinese coal-fired power plants. Energy Policy 38, 4440-4444.
- Yu, M. M., 2004. Measuring physical efficiency of domestic airports in Taiwan with undesirable outputs and environmental factors. Journal of Air Transport Management 10, 295–303.
- Zhang, B., Bi, J., Fan, Z., Yuan, Z., Ge, J., 2008. Eco-efficiency analysis of industrial system in China: a data envelopment analysis approach. Ecological economics 68, 306-316.
- Zhou, P., Ang., B.W., Poh, K.L., 2008. A survey of data envelopment analysis in energy and environmental studies. European Journal of Operational Research 189 (1), 1-18.

- Zhu, J., Cook, W.D., 2007. Modeling Data Irregularities and Structural Complexities in Data Envelopment Analysis. New York: Springer.

The Directional Economic-Environmental Distance function: The case of the global aviation fleet

Abstract

We develop a directional economic-environmental distance function (DEED) which accounts for the production of both desirable and undesirable output and the potential for constrained increases in input utilization. This research applies the modeling framework to analyze the potential to reduce noise and airborne pollutants emitted by aircraft-engine combinations given the current state of aeronautical technology. The global engine-aircraft market is viewed from the regulatory perspective in order to compare the single environmental and operational efficient frontier to that of the airline carriers and environmental objectives. The results of DEED are then applied in order to substitute the fleets serving Schipol, Amsterdam and Arlanda, Stockholm airports in June 2010 with the benchmark aircraft. The results highlight the inefficiencies of the current airline fleets and that the IPCC values of externalities are a magnitude of TEN too low to encourage changes in the global fleet hence the need for government intervention.

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1 Introduction

The impact of aviation on the environment is of growing concern, mainly due to the projected increase in demand for air transport. The 37th ICAO assembly hold in 2010 forecast a +4.7% growth in world revenue passenger kilometers flown between 2010 and 2030.[1] In the U.S. market alone, the Federal Aviation Administration Aerospace Forecasts 2011-2031 predict a growth in the number of commercial aircraft from 7,096 in 2010 to 10,523 by 2031 with an average increase of 163 new aircrafts annually (+1.9%). The Committee on Climate Change (2008) projected future CO_2 aviation emissions and reached the conclusions that under a high growth scenario the 2050 CO_2 emissions will be 7 to 8 times the 1990 levels.[2] According to ICAO, in addition to green house gases, the air pollution enveloping airports has become a significant concern for local and regional governments due to the increasing residential development surrounding airports and the continuing growth of commercial air travel. Two of the most important negative externalities generated by aviation include the noise footprint and the aircraft engine emissions. Of these two, noise has the largest impact on the community surrounding airports, while engine emissions have both local and global impacts (Marais and Waitz, 2009).

Aviation noise is generated from different sources: the combination of acoustic energy generated by non-smooth fluid mechanical processes within an engine, the interaction between the exhaust heat and the surrounding air and the fluctuating flow produced by the airframe. Aircraft noise interrupts speech, causes sleep disturbance, and affects property values in the neighborhood of the airport (Marais and Waitz, 2009). The importance of the noise problem clearly depends on the location of the specific airport and on whether there are alternative take-off or landing routes. Further advances in technology with respect to the airframe and engines are necessary in order to reduce the noise footprint, as well as investments in real estate infrastructure (e.g., double glazing).

Local emissions are known to have a direct impact on human health leading to an increased risk of premature death (Daley, 2010). Local air quality is directly affected and varies on a daily basis with emission volumes, while health impacts may take

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[1] Source: ICAO, September 2010.
[2] Source: Aviation CO2 Emissions Abatement Potential from Technology Innovation (2008).

longer to emerge and tend to persist over time. The levels of the most important local air pollutants (carbon dioxide (CO_2) and monoxide (CO), sulphur oxides (SO_X), particulate matter (PM) and hydrocarbon (HC)) are directly linked with fuel consumption. Hence, the simplest solution to the production of local aircraft emissions would be to reduce fuel consumption. However, reducing fuel consumption is insufficient, since a trade off exists among emissions that depend on the engine technology and aircraft design (ICAO Long Term Technology Goals for CAEP/7, 2011). For example, nitrogen oxides (NO_x) are more difficult to reduce because their source draws from the high temperatures and pressures necessary to increase engine efficiency. We may compare two specific engines, the CFM56-5B9/3 (CFM international) and the PW6122 (Pratt and Whitney), which are both currently employed on the Airbus A318-100. According to standard ICAO landing take-off certification, the former produces a higher amount of NO_x (6,754 grams versus 6,456 grams) whilst burning a lower amount of fuel (718 kilograms versus 802), hence emitting a lower quantity of HC (904 grams versus 996).[3] Consequently, the level of pollutants is not always proportional to fuel consumption. Furthermore, the different pollutants have varying impacts on human health (Dings et al., 2003). In addition to local air pollution, aircraft emit chemical species and produce physical effects, such as contrails, during the cruise stage which are likely to affect climate change, however the scientific literature has yet to explain the likely impact and so these are considered beyond the scope of this contribution.

Despite the importance of aircraft externalities, very few attempts have been implemented to quantify or limit their production. Capoccitti et al. (2010), Green (2009) and Lawrence (2009) describe possible technical improvements such as changes in propulsion and in-wings span. Moreover, they also describe possible improvements in air traffic management that may reduce emissions. Hence, they focus on both technical developments and operational improvements. Sgouridis et al. (2011) provide a computer simulation of the possible effects of technical and operational improvements, use of alternative fuels, negative demand shifts and carbon pricing.[4] They provide some

[3] Emission pollution and fuel consumption are computed per landing-take off cycle (LTO) as defined in the ICAO emissions databank.
[4] Sgouridis et al. (2011) argue that the strongest effect on CO_2 emissions are driven by negative demand shifts, while the other scenarios have similar weaker effects. However, none of the alternatives, if implemented individually, leads to an eco-sustainable growth for the air transportation industry.

evidence that carbon pricing may reduce CO_2 emissions without hurting airlines profitability substantially.

Several papers have focused on the impact of regulation and pricing on the reduction of externalities caused by aviation (Schipper, 2004; Lu and Morrell 2006; Brueckner and Girvin, 2008, and Lijesen et al., 2010). Tighter regulation could push aircraft manufacturers to further reduce emissions. ICAO introduced more stringent emissions and noise standards through CAEP/6 and Chapter 4 designation, however the main impact of these regulations will be on the medium and long-run technological designs. Hence, they do not impact the use of existing designs for aircraft currently in production and, moreover they will not influence the short-run airline decision regarding the adoption of greener aircraft already existing in the market. Doganis (2002) describes airline fleet purchase as a two-stage decision process. In the first-stage, the airline identifies a shortlist of models that are efficient for a given stage length. In the second-stage, the role of management becomes critical because they are responsible for choosing the optimal aircraft size as a function of the airport characteristics and demand magnitude. Hence, pricing may be a solution to limit externalities in the short-run by providing airlines with the necessary incentives (e.g., through airport charges) to move towards greener aircraft-engine combinations give current aircraft technology.

Schipper (2004) argues that noise social costs are substantially larger than air pollution social costs in the aviation market. His results show that the environmental costs represent only 2.5% of aviation prices and, that noise costs dominate the externality costs, representing 75% of the total costs. Lu and Morrell (2006) present a welfare analysis of movements, noise and pollution social costs which they apply to a small sample of European airports in order to identify the socially optimal production levels. They reach the opposite result to Schipper (2004) by arguing that noise social costs are less important than emission costs. The authors argue that the marginal environmental cost increases as aircraft movements increase, thus additional flights at hub airport causes more damage than a similar increase at a regional airport. Furthermore, they present evidence that the socially optimal number of annual aircraft movements is approximately 450,000 based on an analysis of five European airports[5].

[5] However, Lu and Morrell (2006) only consider the social benefits drawing from direct aviation activities such as the employment created by airport operations.

Brueckner and Girvin (2008) and Lijesen et al. (2010) focus on aircraft noise emissions at the local level. The former study suggests that individual airport noise limits would also be binding on other airports and that airport pricing could impact the upstream airframe manufacturers' design. Lijesen et al. (2010) analyze the impact of noise reduction in the area surrounding Amsterdam Schipol airport. They adopt a hedonic approach to estimate noise costs by comparing housing prices in the airport catchment area. They show that the marginal benefits from noise reduction are decreasing, as a function of the distance from the airport and that the marginal costs of noise reduction are steeply increasing. Consequently, the social optimal noise reduction is equal to about 3dB from the observed average level at Schipol.

Two issues remain unexplored in the literature to date. First, estimates of an economic-environmental frontier taking into account the aircraft models currently composing the worldwide industry fleet have not yet been evaluated. Second, no contributions to date have analyzed all potential aircraft-engine combinations which impact the level of externalities produced directly. The combination is important because there is a specific engine effect per aircraft model (as highlighted by the Airbus A318-100 CFM/P&W example discussed previously). This paper aims to fill these gaps by applying a new data envelopment analysis (DEA) model to estimate an economic-environmental function. The modeling approach accounts for the production of desirable outputs and negative externalities as well as the potential for constrained increases in input utilization. We apply this model to a data set consisting of the vast majority of aircraft-engine combinations existing in the market today.

In the first stage, we investigate three variations of the DEA model. First, we estimate the Pareto aircraft-engine frontier in which both desirable and undesirable outputs are taken into account, labeled as the regulatory perspective. Second, we estimate the aircraft-engine Pareto frontier when only desirable outputs are taken into account which implies a focus on private costs and revenues hence, we label the airline perspective. The outcome in this case is the airline economic efficient frontier. Third, we estimate a Pareto frontier in which only the externalities are included in the output, thus focusing only on noise and emissions without considering profitability which is labeled the green perspective. Hence, by comparing these three frontiers we identify whether the regulatory, airline and environmental objectives are aligned.

In a second-stage analysis, we apply the benchmarks resulting from the three first-stage estimated frontiers to obtain, from each perspective, the optimal aircraft-engine fleet that could operate at Stockholm and Amsterdam airports. Since this implies substituting the inefficient aircraft-engine combinations with those on the frontiers, we obtain estimates of the monetary incentives that may induce airlines to move towards a greener fleet. Accordingly, we provide some estimates on the optimal airport charges that may encourage a reduction in noise and emissions. To the best of our knowledge this contribution is the first attempt to analyze the performance of the existing aircraft-engine fleet and to evaluate the costs that would be incurred were the carriers to operate an economically and environmentally efficient fleet.

The results of the research highlight the fact that the cost of the negative externalities at current IPCC values is so low that they are unlikely to impact fleet choice. We find that at Schiphol airport, the fuel savings from the upgraded fleet more than cover the cost of the fleet modifications but given the level of profitability in the airline market, are likely to require government intervention, for example through loan guarantees, in order to encourage the replacement. At Arlanda airport, where flight stage lengths serving this market are shorter, the ownership cost requirements exceed the fuel savings, hence we suggest that at the very least the cost of externalities should be used in the form of loans to encourage fleet upgrades.

The structure of the paper is organized as follows: Section 2 describes the new DEA model designed to estimate the economic-environmental efficient frontier and the procedure applied in the second-stage analysis to substitute the current fleet operating at an airport. Section 3 presents the data set while in Section 4 we present the empirical results. Conclusions, policy implications and future research directions are discussed in Section 5.

2 Modeling framework

In this section we first develop a modified directional distance function which identifies the aircraft-engine combination Pareto frontier. Then we define the procedure adopted to substitute the inefficient combinations with the Pareto optimal fleet. Since airline fleet choices are per-stage length (Doganis, 2002), we estimate four Pareto frontiers, one for each of the following aircraft types: turbo propellers (TP), regional jets

(RJ), narrow-bodies (NB) and wide-bodies (WB).[6] Babikian et al. (2002) describe the differences between turbo propellers, regional jets and large jets, while Swan and Adler (2006) compute two cost functions, one for narrow-body and one for wide-body categories, highlighting that the two aircraft categories serve different markets. Whilst very occasionally, a widebody aircraft may be flown short haul, as occurs in the Japanese domestic market due to slot allocation issues (Adler et al., 2012), aircraft are generally designed to fly specific stage lengths.

2.1 Economic-environmental objective function

Technical and allocative efficiency concepts can be traced back to Farrell (1957) and Debreu (1951). A unit (i.e., a firm or a factory) is technically efficient if it produces outputs using a minimum of inputs and allocatively efficient if the input mix is chosen such that costs are minimized (Färe, Grosskopf and Lovell, 1994). Thus, it is necessary to collect information on the quantities of inputs and outputs in order to describe the structure of the production frontier as well as their prices. The frontier may be estimated using either parametric or non-parametric techniques. Parametric approaches such as stochastic frontier analysis require knowledge of the functional form of the production technology as well as that of the inefficiency distribution. Given these limitations, we have chosen the non-parametric DEA approach.

A DEA model is a multi-factor productivity analysis that measures the relative efficiency of a homogeneous set of decision making units (DMU), first introduced by Charnes, Cooper and Rhodes (1978). In order to identify the economic-environmental frontier for the engine-aircraft combinations, we develop a directional economic-environmental distance (DEED) function which is inspired by the directional distance function approach first introduced in Chambers et al. (1998) and by the additive model of Charnes et al. (1985). However, similarly to Färe and Grosskopf (2010), DEED does not set the slacks direction exogenously.

We design the DEED function as a linear program presented in Equations (1.1)-(1.6), which defines the regulatory perspective. Consider $j = 1, \dots, n$ DMUs using a

[6] DEA models require a certain degree of homogeneity among the different observations, hence categorizing the set of existing aircraft-engine combinations into four similar groups provides more consistent efficiency estimates.

column vector of m inputs (X_j) in order to yield a column vector of s desirable (good) outputs (G_j) and a column vector of h undesirable (bad) outputs (B_j), where $X_j = (x_{1j}, \dots, x_{mj})^T$, $G_j = (g_{1j}, \dots, g_{sj})^T$ and $B_j = (b_{1j}, \dots, b_{hj})^T$. It is assumed that $X_j, G_j, B_j > 0$ for all j=1,…, n.

$$\max_{\lambda,\beta,\gamma} \partial^{Reg} = \sum_{i=1}^{m} P_i^x \beta_i + \sum_{r=1}^{s} P_r^g \gamma_r + \sum_{f=1}^{h} P_f^b \delta_f \qquad (1.1)$$

$$s.t. \sum_{j=1}^{n} x_{ij} \lambda_j = x_{i0} - \beta_i e_i \ (i = 1, \dots, m), \qquad (1.2)$$

$$\sum_{j=1}^{n} g_{rj} \lambda_j = g_{r0} + \gamma_r e_r \ (r = 1, \dots, s), \qquad (1.3)$$

$$\sum_{j=1}^{n} b_{fj} \lambda_j = b_{f0} - \delta_f e_f \ (f = 1, \dots, h), \qquad (1.4)$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad (1.5)$$

$$-\sum_{1}^{m} P_i^x \beta_i \leq \sum_{1}^{h} P_f^b \delta_f \qquad (1.6)$$

$$\lambda_j \geq 0, \ \beta_i \ free \ in \ sign, \qquad \gamma_r \geq 0, \qquad \delta_f \geq 0$$

In Model (1) the economic-environmental objective function sums the input wastage β_i, the desirable output shortfalls γ_r and the excessive undesirable outputs slack production δ_f, multiplied by their respective prices, i.e., P^x, P^g and P^b. The estimated efficiency score ∂^{Reg} is equal to 0 if the DMU is efficient, while the greater the values of ∂^{Reg} the more inefficient the DMU. Consequently, a higher value of ∂^{Reg} implies larger monetary waste, since the objective function represents the monetary values of the excess inputs and externalities as well as desirable output shortfalls[7]. Consequently, model (1) is a non-oriented, slack based measure of efficiency. Equations (1.2)-(1.4) represent the constraints on inputs, desirable outputs and undesirable outputs respectively. The variables λ represent the targets that identify the linear combinations of efficient DMUs. As in Färe and Grosskopf (2010), the column vector e is composed

[7] It should be noted that if the P vectors are unitary values, the raw data must be expressed in the same unit of measure.

of ones. It is possible to balance the importance of a particular variable with respect to the others by changing the values of vector *e*. Model (1) designs a single efficient frontier in which DMUs are benchmarked simultaneously with respect to all variables. As noted in Färe and Grosskopf (2010), this model is monotonic and unit, translation and reference set invariant.

Constraint (1.4) incorporates the undesirable outputs as inputs to be reduced. Alternative approaches would be to define them as negative outputs (equation 1.4b) or to translate the inverse of the externalities as an undesirable output (Scheel, 2001). However, this requires a non-linear transformation which would render the undesirable output slacks (δ_f) as no longer comparable to the other slacks in the model.

$$\sum_{j=1}^{n} b_{fj}\,\lambda_j \;= b_{f0} + \delta_f e_f \;(f = 1, \ldots, h), \qquad (1.4b)$$

Constraints (1.4) do not directly connect the production of bad outputs to input utilization or to good output production. Consequently, we do not make any assumptions with regard to disposability. Thus, the production of undesirable output is a free activity, as commonly assumed in traditional production theory. This is a reasonable assumption in our analysis because it is possible to reduce the externalities without changing the maximum number of passengers carried or the size of the aircraft (e.g., by adopting a new generation of aircraft). Picazo-Tadeo et al. (2005) and Färe et al. (2007) describe the impact of introducing weak or strong disposability assumptions within a directional distance function framework.

An additional feature of the DEED model is that it permits both input reductions and increases. Input expansions may be necessary in order to move to the efficient frontier. For this reason in the DEED model, the input slacks β_i are free in sign, allowing for reductions in input utilization (with $\beta_i > 0$), increases ($\beta_i < 0$) or no changes in the input levels ($\beta_i = 0$). Consequently, we identify potential increases in inputs that may simultaneously reduce the production of negative externalities and increase the production of good outputs. However, increases in input utilization are limited by constraint (1.6) which implies that a higher expenditure in inputs must be at most equal to the reduction in the social costs of bad outputs from the regulatory perspective.

Hence, model (1) defines the regulatory perspective because it identifies the efficient fleet by maximizing the good output slacks (revenues) and the slacks on input (savings) as well as minimizing the environmental social costs.

We specify two additional perspectives including that of the airlines (Model (2)) and the environment (Model (3)). Model (2) assumes that airlines maximize profits by maximizing desirable outputs and minimizing input utilization whilst ignoring any environmental social costs. Constraint (2.5) implies that any input increase has to be compensated by a reduction in the levels of other inputs. In comparison with Model (1) the constraint on externalities (i.e., constraint (1.4)) is eliminated in Model (2).

$$\max_{\lambda,\beta,\gamma} \partial^{Air} = \sum_{i=1}^{m} P_i^x \beta_i + \sum_{r=1}^{s} P_r^g \gamma_r \qquad (2.1)$$

$$s.t. \sum_{j=1}^{n} x_{ij} \lambda_j = x_{i0} - \beta_i e_i \ \ (i = 1, \ldots, m), \qquad (2.2)$$

$$\sum_{j=1}^{n} g_{rj} \lambda_j = g_{r0} + \gamma_r e_r \ \ (r = 1, \ldots, s), \qquad (2.3)$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad (2.4)$$

$$-\sum_{1}^{m} P_i^x \beta_i < 0 \qquad (2.5)$$

$$\lambda_j \geq 0 \ , \quad \beta_i \ free\ in\ sign, \ \gamma_r \geq 0\ , \quad \delta_f \geq 0$$

Finally, according to the environmental perspective presented in Model (3), the objective function minimizes the production of negative externalities alone. In comparison with Model (1) the constraint on desirable outputs (i.e., constraint (1.3)) is eliminated, while with respect to Model (2), constraint (2.3) is replaced by (3.3).

$$\max_{\lambda,\delta} \partial^{Gre} = \sum_{f=1}^{h} P_f^b \delta_f \qquad (3.1)$$

$$s.t. \sum_{j=1}^{n} x_{ij} \lambda_j = x_{i0} - \beta_i e_i \ (i = 1, \dots, m), \qquad (3.2)$$

$$\sum_{j=1}^{n} b_{fj} \lambda_j = b_{f0} - \delta_f e_f \ (f = 1, \dots, h), \qquad (3.3)$$

$$\sum_{j=1}^{n} \lambda_j = 1, \qquad (3.4)$$

$$-\sum_{1}^{m} P_i^x \beta_i \leq \sum_{1}^{h} P_f^b \delta_f \qquad (3.5)$$

$$\lambda_j \geq 0 \quad \beta_i \, free \, in \, sign \quad \delta_f \geq 0$$

2.2 Replacement fleet

After estimating the Pareto efficient aircraft-engine combinations from the three perspectives, we identify the optimal fleet by replacing the inefficient combinations in the current existing fleet with their per aircraft category-benchmarks. As shown in Lijesen et al. (2010), fleet substitution is the only environmentally positive strategy feasible in the short-run that does not involve any restriction on the demand side (e.g., a reduction in total aircraft movements). We apply the estimated benchmarks to the current fleet operating in a given airport, and implement the necessary substitutions. We compute the changes in local pollutants emitted during the LTO cycle, the amount of CO_2 emitted during the flight, fleet value, payload and fuel consumption. The sum of these changes produces the cost of fleet substitution which represents the monetary incentive that may induce airlines to move towards a greener fleet.

Based on the results obtained from Models (1), (2) and (3), we identify the best aircraft-engine combinations per aircraft category per perspective. In order to avoid excessive variation in aircraft payload when substitution is required, we replace inefficient aircraft-engine combinations with their benchmarks not requiring more than a 20% increase or decrease in seat capacity.

In order to estimate the fleet value and the cost of the replacement, we develop an index that describes the operations of a specific aircraft model during a representative week at a given airport, i.e., the share of feasible hours of weekly operations that are dedicated to the route involving the airport under investigation. This utilization index, *UI*, is computed as follows:

$$UI_i = \sum_j \omega_{ij} (F_{ij}/7) \quad (4)$$

where ω_{ij} is a parameter that indicates the fraction of a day of operation in which aircraft i is engaged on route j. We assume that $\omega = \{0.25, 0.5, 1\}$. ω is equal to 0.25 (i.e., 1/4 of a day) if the route is short-haul with duration shorter than 3 hours, 0.5 (i.e., 1/2 of a day) if the route is medium-haul with duration between 3 and 6 hours, and 1 for long-haul routes, with duration above 6 hours. Hence, if an aircraft is operating on a short-haul route, we assume that it may fly four times per day while if it operates on a long-haul route it may fly only once daily. F_{ij} represents the weekly frequency of route j operated by aircraft i (i.e., the weekly number of flights on that route). Dividing frequency by 7 days and multiplying by ω_{ij}, we obtain the weekly number of aircraft that are allocated to route j. As an example, consider the case of aircraft i flying ten times on a two hour route j during a week: $\omega_{ij} (F_{ij}/7)$ = 0.25 * 10/7 = 0.36. This implies that aircraft i is allocated to route j at the airport under investigation for about one third of its feasible week's total flying hours. The remaining two thirds of the week, we assume that the aircraft serves alternative routes. Clearly, $0 \leq UI_i \leq 1$. Based on the Utilization Index, we compute the share of aircraft i's ownership costs that are attributed to route j at the airport under consideration. In order to calculate realistic fuel consumption at Schipol and Arlanda, we consulted the OAG database in order to compute the average stage length per aircraft category.

3 Data

In this section we present the aircraft database and descriptive statistics in section 3.1, the externality measures in section 3.2 and the price parameters expressed in the objective function in section 3.3. Finally, in section 3.4 we present the main features of the airports analyzed in the second stage of the analysis.

3.1 Aircraft database

The unit of observation for this analysis consists of a specific aircraft-engine combination. Ownership costs and fuel burn, proxies for the technology embedded in the aircraft, are inputs producing a given payload, a proxy for passengers and cargo capacity (i.e., the desirable output). ICAO certification data provides the emissions and noise values representing the undesirable outputs. The input vector $X_j = (Fuel_j, Value_j)^{\mathrm{T}}$ is composed of fuel consumption (in kilograms) during a standard flight per aircraft category and the aircraft ownership costs in euro per flight.[8] The desirable output, $G_j = (Seat\ capacity_j)^T$, is based on the certified maximum payload that a specific aircraft-engine combination carries divided by the average passenger weight[9]. We thus consider the theoretical maximum number of seats that an aircraft may carry irrespective of the different airline seat configurations.

Jane's All the World Aircraft (2011-2012 version) provides technical details on over 950 civil and military aircrafts currently being produced or under development by more than 550 air manufacturing companies, including the maximum take-off weight of each aircraft-engine combination. Any missing information was collected from the manufacturers' websites. The data set consists also of the most updated engine models produced by each engine manufacturer, assuming that the best engine technology is applied to the aircraft-engine combinations analyzed, ensuring a conservative estimate of the potential environmental achievements possible.

Our dataset is composed of 162 different aircraft-engine combinations, describing almost completely the current civilian market for passenger aircraft. Russian aircraft are not considered in the analysis due to a lack of financial information. The data set for commercial aviation includes 11 aircraft manufacturers and 8 engine manufactures, as listed in Table 1. Some of these manufacturers are no longer in business, but the aircraft produced are still in use and sold in the second-hand market.

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[8] In order to compute fuel consumption we consider 1,000 km flight legs for turbo propellers and regional jets, 5,000 km for narrow bodies and 10,000 km for wide bodies. To compute the per flight aircraft ownership costs we multiply the aircraft market value by the utilization index UI_i over a year. We assume 300 days of operation per year for all aircraft categories, and a maximum of 4 flights per day for TP and RJ, 2 flights per day for NB and 1 flight per day for WB.

[9] We assume the standard Work Load Unit weight: 1 passenger plus luggage = 100 kilograms.

Table 1 –Aircraft and Engine Manufacturers

Aircraft manufacturers	Engine manufacturers
Airbus	Allison Engine Company
Avions de Transport Regional	CFM International
BAE systems	Engine Alliance
Boeing Company	General Electric
Bombardier Inc.	International Aero Engines
Donier	Pratt & Whitney
Embraer	Rolls-Royce
Fokker	Textron Lycoming
McDonnell Douglas	
Saab	
Short Brothers	

3.2 Negative externalities

Aircraft cause local air pollution (LAP) only when operating inside the landing take-off cycle (LTO). According to ICAO standards, the LTO cycle consists of four stages: take-off, climb (up to 3,000ft), approach (from 3,000ft to landing) and idle (when the aircraft is taxiing or parked on the ground with engines-on)[10]. Furthermore, ICAO sets a standard profile for the LTO cycle based on engine power settings and average time at each stage. The engine certified emissions level i.e., the quantity, in grams, of hydrocarbons and nitrogen oxides emitted per kilogram of fuel consumed per engine is provided by the ICAO Engine Emissions Databank and by the FOI Database. Furthermore, the two data bases provide measures of the level of fuel consumption during the LTO cycle per engine model[11]. The vector of undesirable outputs includes the principal aviation local air pollutants (in kilograms), i.e., HC, NO_x, PM and SO_2, and the costs (in euro) of aircraft noise levels produced during the LTO cycle, i.e. $B_j = (HC_j, NOx_j, SO2_j, PM_j, Noise_j)^T$[12]. Particulate matter (PM) and Sulphur Dioxide (SO_2) are not part of the LTO engine certification process. The emission of these pollutants is directly related to fuel consumption. Based on Givoni and Rietveld (2010), Sutkus et al.

[10] The 3,000ft altitude boundary is the average height of the mixing zone, namely the layer of the earth's atmosphere in which chemical reactions affect ground level pollutant concentrations

[11] The ICAO Engine Emission Databank is provided by the International Civil Aviation Organization and the FOI Database is provided by the Swedish Defense Research Agency.

[12] Carbon Oxide (CO) is not included because Dings et al. (2003) estimate that its social costs are negligible.

(2001) and Dings et al. (2003), we assume an emission factor of 0.8 grams of SO_2 and 0.2 grams of PM per kilogram of fuel burn during the LTO cycle.

Noise certified data are measured in decibels of effective perceived noise (EPNdb) and are provided for each aircraft-engine combination's maximum take-off weight (MTOW). Noise emissions are computed at three reference points located in each airport: lateral, flyover and approach. The lateral measurement point is located 450 meters from the runway and captures the highest noise levels. The flyover measurement point is located under the over-flight trajectory at 6,500 meters from the point of brake release. The approach measurement point measures the noise generated on landing and is placed 2,000 meters from the point at which the landing aircraft is at 120 meters altitude above the ground.

The European Aviation Safety Agency (EASA) and the Federal Aviation Administration (FAA) provide the certified noise values for each combination of aircraft-engine-MTOW. The logarithmic nature of noise makes it difficult to aggregate and compare the three measurement points. Furthermore, to evaluate the impact of the level of noise damage, we ought to consider the size of population living in proximity to the airport. To standardize the analysis, we utilize the noise charges that are currently set by Swedish airports per aircraft movement[13]. The noise charge is based on a weighted energetic mean that assigns a monetary value to the noise level produced by an aircraft. The formula applied to obtain the noise charge is as follows:

$$C_N = C\,(10^{[(L_a-91)/10]} + 10^{[(L_d-86)/10]}) \tag{5}$$

where C_N is the noise charge, C is the airport specific unit noise fee, L_a is the approach noise level of the individual aircraft and L_d is the average of the lateral and fly-over noise levels. C is equal to 30 Swedish Crown (SEK) at Arlanda airport.

Descriptive statistics on all variables are presented in Table 2, clustered by aircraft type. We note that the minimum noise costs for the turbo propeller category is zero. Indeed, some aircraft-engine combinations emit a level of noise lower than the minimum noise impact threshold level shown in equation (5).

[13] See "Swedavia's conditions of Use and Airport Charges for all Swedavia Airports" 2011 edition.

Table 2 – Data set descriptive statistics

	Turbo Propellers							
	Fuel consumption (Kg/Flight)	**Ownership cost (€/Flight)**	**Seat capacity**	**HC (kg/LTO)**	**NO_x (kg/LTO)**	**SO_2 (kg/LTO)**	**PM (kg/LTO)**	**Noise (€/LTO)**
average	1,476	470	57	0.234	2.098	0.056	0.225	7.0
min	1,110	140	38	0.000	0.592	0.028	0.112	0.0
max	1,996	1,668	87	1.634	3.248	0.122	0.486	15.4
	Regional Jets							
	Fuel consumption (Kg/Flight)	**Ownership cost (€/Flight)**	**Seat capacity**	**HC (kg/LTO)**	**NO_x (kg/LTO)**	**SO_2 (kg/LTO)**	**PM (kg/LTO)**	**Noise (€/LTO)**
average	2,778	549	95	0.816	4.382	0.102	0.407	9.54
min	1,358	120	33	0.036	2.156	0.055	0.219	4.05
max	3,864	956	137	1.796	6.656	0.151	0.605	18.43
	Narrow-bodies							
	Fuel consumption (Kg/Flight)	**Ownership cost (€/Flight)**	**Seat capacity**	**HC (kg/LTO)**	**NO_x (kg/LTO)**	**SO_2 (kg/LTO)**	**PM (kg/LTO)**	**Noise (€/LTO)**
average	18,868	1,905	203	0.879	12.127	0.191	0.763	15.84
min	13,878	326	129	0.064	5.458	0.133	0.533	3.87
max	28,546	4,401	309	2.536	29.582	0.294	1.174	31.26
	Wide-bodies							
	Fuel consumption (Kg/Flight)	**Ownership cost (€/Flight)**	**Seat capacity**	**HC (kg/LTO)**	**NO_x (kg/LTO)**	**SO_2 (kg/LTO)**	**PM (kg/LTO)**	**Noise (€/LTO)**
average	80,728	10,485	505	2.481	37.737	0.450	1.800	43.79
min	49,788	3051	308	0.156	18.338	0.292	1.170	18.79
max	179,879	24,804	907	7.452	70.852	0.807	3.229	89.24

3.3 Objective Function Parameters

Table 3 provides a summary of the prices for inputs, good and bad outputs applied in the analysis. All prices are expressed in euro.[14] The input price vector is composed of the cost of a kg of jet fuel (0.749 €, source: IATA) plus the estimated social cost of CO_2 emitted during the entire flight (0.045 € per kg of jet fuel which is the 2010 average EU emission charges according to the trading scheme market).[15] In Model (2), i.e., the airline perspective, we consider the fuel price without incorporating the price for CO_2 emitted, given that in this scenario the externalities are not taken into account. Ownership cost is set equal to 1 because data are already expressed in monetary values (2010 euro). The price vector for revenues given by the aircraft payload is the average ticket price per passenger charged by the airlines in the period 2001-2010. The source is provided by the IATA Industry Statistics, June 2011. Hence, the revenue per passenger adopted in this work does not reflect the possible differences between aircraft typologies or stage length. Clearly, it would have been preferable to use average yields per stage length were such information available. However, our choice does not impact the DEA rankings and benchmarks because of the invariance of the models and the categorization into aircraft types. Finally, for the externality prices we apply the social cost of a kilogram of pollutant produced as estimated by Dings et al. (2003) for the year 2001. We adjust these values in order to be comparable to prices expressed in Euro 2010 by the deflator factor 1.24 (Source: Eurostat). Note that the price for noise is equal to 1 because the data is already in monetary values.

Table 3 – Price parameters

Fuel	Passengers ticket	HC	NO_x	PM	SO_2
€ 0.795/kg (Model 2 € 0.749/kg)	€ 133	€ 4.97/kg	€ 11.19/kg	€ 186.7/kg	€ 7.46/kg

[14] The SEK-Euro exchange rate considered for converting Swedish noise charge in euro is equal to 1 SEK/0.10486 €. The Dollar-Euro exchange rate is 1 $ = 0.75521 €. These values are the 2010 averages of daily exchange rates.
[15] The CO_2 price source was drawn from: http://www.sendeco2.com/it/precio_co2.asp?ssidi=5. We adopt a ratio of 3.152 kg of CO_2 per kg of fuel (Givoni and Rietveld (2010)).

The Aircraft Value Reference database (AVAC) provided 2010 aircraft market values rather than list prices.[16] Market values represent the fluctuations in the market capturing the dynamic nature of the industry. Aircraft values correspond to a new aircraft built in 2010. Regarding out of production aircraft, the market values correspond to the 2010 hypothetical value of a new aircraft with the same characteristics. In order to evaluate the aircraft value per flight, we divide the market value over an assumed lifecycle of 20 years, with a utilization of 300 days per year and 4 flights per day for TP and RJ, 2 flights per day for NB and 1 flight per day for WB (these values reflect the parameters used in the Utilization Index equation (4)).

3.4 Airport fleet data

In order to perform the second-stage analysis, we substitute the inefficient aircraft-engine combinations with their benchmarks. Then, we analyze the replacement fleets for two large European airports, and estimate the costs of the aircraft substitutions. We consider Amsterdam Schipol and Stockholm Arlanda. Amsterdam Schipol is the main international airport for the Netherlands and a primary hub for KLM. Schipol served 304,464 European aircraft movements and 81,852 intercontinental movements in 2010. Stockholm Arlanda is the major international airport in Sweden and primary hub for Scandinavian Airline (SAS). In 2010, Arlanda served 190,000 movements, of which 125,000 were international and 64,000 domestic. We analyze all aircraft movements operating during the first week of June 2010 at both airports and summary statistics are presented in Table 4.

Table 4 – Summary statistics per airport (7th to the 13th June 2010)

	Average Stage Length (km)		# of Departures	
	Schipol	**Arlanda**	**Schipol**	**Arlanda**
Turbo propeller	490	396	23	335
Regional jet	596	708	1,097	156
Narrow body	1,221	1,023	2,031	1,358
Wide body	7,013	5,550	460	42

[16] The Aircraft Value Reference database was kindly provided by The Aircraft Value Analysis Company (AVAC).

The data highlights the shorter average flight legs served at Arlanda in all categories, except the regional jets which represent 8% of the market in terms of number of departures. The differences in aircraft served and average stage lengths directly impact the results of the second stage analysis as discussed in section 4.3.

Information was drawn from the Official Airline Guide (OAG) database that collects data on all scheduled flights per airport. The OAG database identifies the aircraft model, maximum take-off weight, flight length and frequency for each flight scheduled in the chosen week. The OAG specifies the aircraft model but not the engines. To overcome this limitation, we collected technical information on aircraft currently flying and on the distribution of different types of engines on each aircraft model from the International Register of Civil Aviation (IRCA). For simplicity, we assume that each aircraft operating at Arlanda and Schipol airports adopted the engine most frequently purchased for that specific aircraft model (i.e., the mode of the specific aircraft-engine distribution). Thus, we compute the pollutant emissions and fuel consumption per aircraft, engine and maximum take-off weight combining the ICAO, FOI, FAA and EASA databases. Regarding the ownership cost of each aircraft operating at the two selected airports, we assume that the current aircraft value is given by the average of the AVAC market values from the first year of sale to the last year of production. If the aircraft's first year of production is prior to 1985, we assume (given the average passenger aircraft lifecycle in the aviation industry) that it started operating at each of the airports during 1985.

4 Results

In this section we show the results of our two stage empirical analysis. In Section 4.1 we describe the aircraft-engine efficiency scores estimated by applying Models (1)-(3). In section 4.2, we perform the second stage analysis using the estimated benchmarks to compute the cost of fleet substitution. Finally, in section 4.3 we discuss a pricing scheme that may induce the airlines to adopt a more efficient and environmentally friendly fleet.

4.1 The aircraft-engine economic- environmental efficiency frontier

Table 5 presents the results of the DEA models per aircraft-engine combination for each aircraft category. We analyze 16 turbo propeller combinations, 32 regional jets, 62 narrow bodies and 52 wide body aircraft-engine combinations in total. DMUs with a score equal to zero are considered efficient, i.e. lie on the economic-environmental frontier. On the contrary, the greater the score, the greater is the DMU inefficiency. The last three columns of Table 5 present ∂^{Reg}, ∂^{Air} and ∂^{Env}estimates. ∂represents the savings that could be obtained under each possible scenario, i.e. the total per flight cost savings were the aircraft-engine combination to lie on the frontier.

[TABLE 5: SEE APPENDIX]

Differences in the number of efficient units are observable across the three perspectives for all the aircraft categories analyzed. Combining the results, only six engine-aircraft combinations are efficient according to all three perspectives observed: turbo propellers ATR 42-300-PW120 engine and ATR42-400-PW121A engine; the regional jet Dornier 328 Jet-PW3068 engine, the narrow body Airbus A318-100-CFM56-5B8/3 engine and the two wide bodies, Boeing 767-200-CF6-80C2B2 engine and Boeing 767-300-CF6-80A2 engine. These engine-aircraft combinations represent the most efficient technologies currently available irrespective of the perspective analyzed. Furthermore, for all the aircraft categories, the efficient DMUs in Model (2) (the airline perspective) are a subset of the efficient units in Model (1) (the regulatory perspective).

Table 6 presents some descriptive statistics of the first-stage results. The turbo propeller category has the highest percentage of efficient units, partially because the data set consists of the smallest number of observations but also due to minimal engine heterogeneity in this category. In the turbo propeller category, manufacturers' efforts have been mostly directed to improving flight comfort including noise isolation and cabin size rather than with engine and airframe improvements.

Columns four and five of Table 6 present the input slack direction and numbers in parentheses represent input reductions. Input reductions are required much more than input increases for fuel consumption. This implies that efficient aircraft-engine combinations are those granting savings in fuel costs. However, there are a larger number of input increases for ownership costs. This implies that the newer and more expensive aircraft lie on the frontier due to their substantial fuel savings and lower levels of pollutants emitted. Moreover, as in a standard DEA model in which only input reductions are possible, a significant number of DMUs (23%) become efficient by reducing both inputs.

Table 6– First stage results descriptive statistics

Regulatory perspective	Total # of DMUs	# of efficient DMUs	# of DMUS that increase (decrease) fuel consumption	# of DMUs that increase (decrease) ownership cost
TP	16	10 (63%)	1 (5)	3 (3)
RJ	32	11 (34%)	0 (16)	12 (9)
NB	62	18 (29%)	7 (37)	27 (14)
WB	52	15 (29%)	0 (37)	10 (27)

Airline perspective	Total # of DMUs	# of efficient DMUs	# of DMUS that increase (decrease) fuel consumption	# of DMUs that increase (decrease) ownership cost
TP	16	4 (25%)	7 (5)	5 (7)
RJ	32	4 (13%)	0 (26)	26 (2)
NB	62	4 (6%)	2 (56)	50 (4)
WB	52	5 (10%)	2 (45)	19 (26)

Environmental perspective	Total # of DMUs	# of efficient DMUs	# of DMUS that increase (decrease) fuel consumption	# of DMUs that increase (decrease) ownership cost
TP	16	7 (44%)	1 (8)	2 (7)
RJ	32	10 (31%)	0 (23)	6 (21)
NB	62	7 (11%)	3 (51)	20 (35)
WB	52	5 (10%)	0 (47)	9 (38)

4.2 Substitution effect: the optimal green fleet results

Table 7 presents the results for the second-stage analysis considering the optimal economic-environmental frontiers applied to Amsterdam Schipol and Stockholm Arlanda. Estimates of the social costs of bad outputs, of inputs and of revenues are provided for the current operating fleet (column 2), for the regulatory perspective (column 3), for the airline perspective (column 4) and for the green perspective (column 5). The values for the three models are obtained by substituting the estimated benchmarks to the fleet currently operating at the two airports. All the values in Table 7 are expressed on an annual basis. In order to consider yearly values, we assume 26 weeks of high demand (replicates of the week analyzed, which belongs to a peak period) and 26 weeks of lower demand (one half of the movements with respect to the week analyzed).

Table 7 – Second-stage results

Amsterdam Schipol Airport (yearly)							
	Original fleet	**Regulatory perspective**		**Airline perspective**		**Green perspective**	
HC	€ 772,727	€ 556,789	-28%	€ 695,424	-10%	€ 509,468	-34%
NO_x	€ 18,733,702	€ 15,813,308	-16%	€ 16,769,852	-10%	€ 14,954,441	-20%
PM	€ 4,978,510	€ 4,355,203	-13%	€ 4,411,552	-11%	€ 4,177,829	-16%
SO_2	€ 796,562	€ 696,832	-13%	€ 705,848	-11%	€ 668,453	-16%
Noise	€ 2,645,553	€ 1,891,511	-29%	€ 2,151,652	-19%	€ 1,750,255	-34%
CO_2	€ 70,552	€ 64,385	-9%	€ 61,942	-12%	€ 61,740	-12%
Total externalities	€ 28,051,415	€ 23,425,697	*-16%*	€ 24,841,744	*-11%*	€ 22,168,935	*-21%*
Fuel consumption	€ 1,171,786,239	€ 1,069,357,477	-9%	€ 1,028,779,201	-12%	€ 1,025,426,073	-12%
Ownership cost	€ 189,494,669	€ 237,069,737	25%	€ 232,087,624	22%	€ 224,639,718	19%
Seat capacity	56,062,277	56,034,034	0%	59,673,949	6%	52,870,173	-6%

Stockholm Arlanda Airport (yearly)							
	Original fleet	**Regulatory perspective**		**Airline perspective**		**Green perspective**	
HC	€ 307,184	€ 290,137	-6%	€ 260,946	-15%	€ 283,54	-8%
NO_x	€ 7,036,472	€ 5,322,540	-24%	€ 5,729,612	-19%	€ 5,278,386	-25%
PM	€ 2,089,854	€ 1,883,170	-10%	€ 1,788,838	-14%	€ 1,822,261	-13%
SO_2	€ 334,376	€ 301,307	-10%	€ 286,214	-14%	€ 291,561	-13%
Noise	€ 1,068,653	€ 787,401	-26%	€ 1,002,410	-6%	€ 794,735	-26%
CO_2	€ 15,762	€ 14,628	-7%	€ 13,234	-16%	€ 13,612	-14%
Total externalities	€ 10,852,303	€ 8,599,186	*-21%*	€ 9,081,257	*-16%*	€ 8,484,103	*-22%*
Fuel consumption	€ 261,793,608	€ 242,966,901	-7%	€ 219,812,135	-16%	€ 226,095,421	-14%
Ownership cost	€ 43,808,735	€ 69,683,502	59%	€ 75,570,042	72%	€ 63,468,068	45%
Seat capacity	22,707,039	23,090,261	2%	26,025,067	5%	21,375,625	-6%

Table 7 shows that it is possible to obtain substantial reductions in the total cost of externalities by substituting the inefficient aircraft-engine combinations with the estimated benchmarks resulting from applying the DEA Models (1)-(3). The results with respect to the total cost of externalities show that it is possible to achieve up to a 21% reduction by replacing the majority of the current fleet[17]. Even from the airline perspective for which reducing fuel costs is the main priority, an 11% reduction is possible at Schipol and a 16% reduction at Arlanda. Hence, we provide some empirical evidence that the current operating fleets are not environmentally efficient. This is not due to a technological gap but to failures in adopting an optimal fleet given the current technology.

Table 7 also shows that, from the airline perspective, it is possible to achieve fuel consumption reductions equal to 12% at Schipol and to 16% at Arlanda. Moreover, relatively similar reductions under this perspective are obtained in pollutant emissions. However, as expected, the lowest reduction in NO_x is achieved under the airline perspective because it is the gas least correlated with fuel consumption. Hence, we provide some empirical evidence that the correlation between fuel consumption savings and reductions in the production of externalities are not strong. The same result is obtained by comparing the reductions in fuel costs and emissions costs under the regulatory perspective: the former are equal to -9% at Schipol and -7% at Arlanda, while the latter are greater at both airports.

Table 7 also shows that in general higher noise reductions can be obtained by adopting an optimal fleet than with emissions. For instance, under the regulatory perspective a -29% reduction in noise levels can be obtained at Schipol and a -26% at Arlanda. Regarding the different emissions, the evidence is mixed: for instance, under the regulatory perspective, the highest reduction is in HC at Schipol and in NO_x at Arlanda. Interestingly, at both airports the smallest reduction is in CO_2 (-10% at Schipol and -3% at Arlanda).

Under the green perspective, it is possible to achieve relatively large reductions in pollutant emissions (-22% on average), mostly through the adoption of a smaller size of aircraft (which is true for every aircraft category). The optimal fleet under the green

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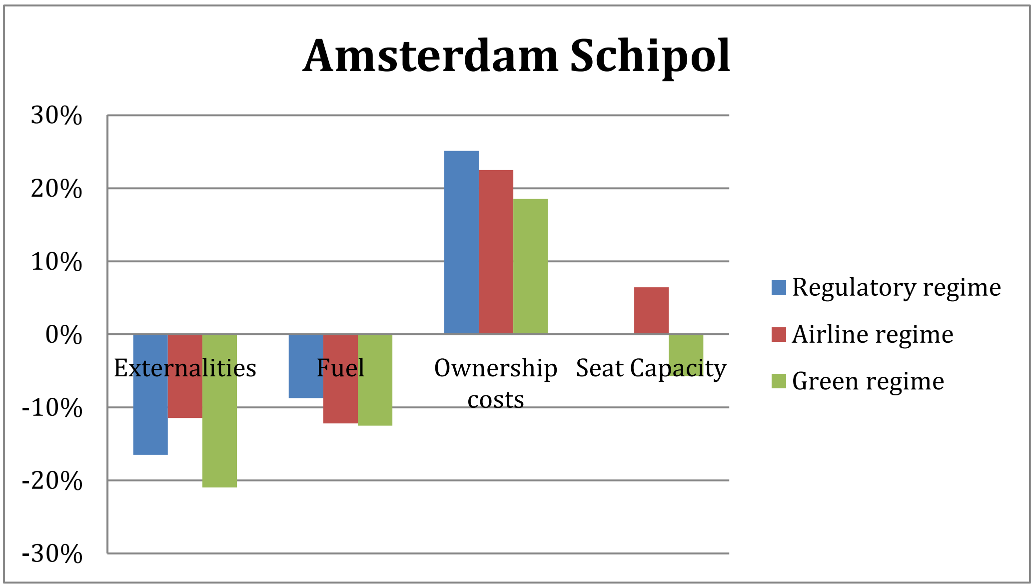
[17] At Schipol airport, 87% of the current fleet was replaced under the regulatory regime and 74% of the fleet was replaced at Arlanda.

perspective implies a reduction of 6% in the total seat capacity. Considering an average load factor of 75.6% (IATA 2009), it would appear that the current fleets may be slightly oversized with respect to demand and a natural way to reduce the pollutant emissions would be to reduce the size of the aircraft. On the other hand, the airlines would prefer to increase seat capacity and the more balanced regulatory perspective keeps seat capacity constant, which explains the higher fleet value as compared to the environmental perspective.

Figure 1 presents the percentage changes in inputs, good output and externalities under the three models. There is a general reduction in externalities across all perspectives hence there is a general alignment between private and social perspectives when considering the direction of variations in both noise and emissions. However, there is a difference in the magnitude of these variations which under the private perspective are lower than the socially optimal levels.

Figure 1 – Percentage changes in inputs, output and externalities with the upgraded fleet



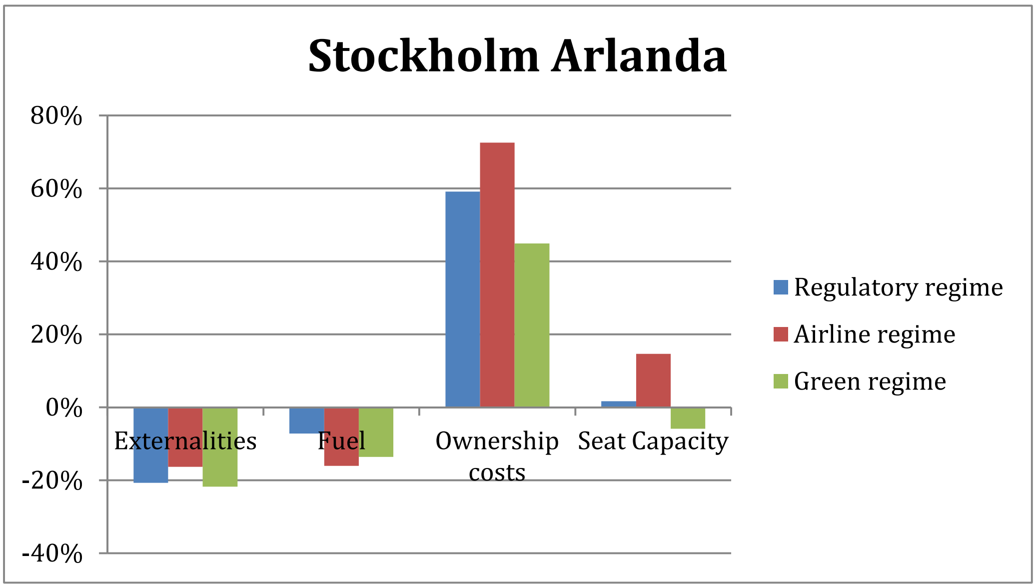


Table 8 presents the annual costs per seat for aggregated externalities, fuel consumption and ownership costs. It is evident from this table that the costs of fuel are substantial. Under the current fleets, ownership costs per seat are about 1/6 of fuel costs per seat, while externalities represent about 2% of fuel costs and 15% of ownership costs per seat at Schipol and 4% of fuel costs and 20% of ownership costs at Arlanda. Under the regulatory perspective, ownership costs increase to 22% of fuel costs, while externality costs are stable around 1% of fuel costs and drop to only 10% of ownership costs. The lowest levels per seat of ownership costs are obtained under the airline perspective, as expected. Interestingly, there is no difference in the externalities costs per seat under the three perspectives.

Table 8 – Values per seat capacity

Amsterdam Schipol Airport				
	Original fleet (€/seat)	**Regulatory perspective (€/seat)**	**Airline perspective (€/seat)**	**Green perspective (€/seat)**
Total Externalities costs	0.50	0.42	0.42	0.42
Fuel consumption	20.90	19.08	17.24	19.40
Ownership cost	3.38	4.23	3.89	4.25

Stockholm Arlanda Airport				
	Original fleet (€/seat)	**Regulatory perspective (€/seat)**	**Airline perspective (€/seat)**	**Green perspective (€/seat)**
Total Externalities costs	0.48	0.37	0.35	0.40
Fuel consumption	11.53	10.52	8.45	10.58
Ownership cost	1.93	3.02	2.90	2.97

4.3 Pricing externalities

Given the results of the two stage analysis, it is reasonably clear that the current IPCC environmental charges are too low: they should be a magnitude of 10 higher in order to provide an incentive for aircraft-engine substitutions. For example, the social marginal cost should be equal to € 49.7/kg of HC, € 111.9/kg of NO_x, € 1865/kg of PM and € 74.6/kg of SO_2. The sum of the charges for a narrow body aircraft would add a € 14.7 charge per passenger. Consequently, the savings in externalities that can be obtained by adopting the substitute fleet are rather low, ranging from a maximum of € 6 million at Schipol (Model (3)) to a minimum of € 1.7 million at Arlanda (Model (2)) under the IPCC pricing system as presented in Table 9. It should be noted that noise charges are already applied at both airports considered and emission charges are also in place at Arlanda[18]. However, the results of the current analysis identify potential improvements in the present situation.

Table 9 demonstrates that a one-shot change in the fleet would require a substantial annual investment. Assuming perfect second-hand markets for aircraft, under Model (1) it is necessary to invest € 48 million annually over a 20 year lifecycle

[18] At Arlanda, as with all Swedish airports, fees are charged with respect to noise, NO_x and HC produced by each aircraft.

to adopt an upgraded fleet at Schipol. Under Model (2), the investment requirements are approximately € 43 million, while under Model (3) they are equal to € 35 million annually. Lower, but still very significant figures, are obtained for Arlanda (see Table 9). On the other hand, the fleet replacement would lead to substantial fuel savings, in the range of double the ownership investment costs from the regulatory perspective, and triple the savings on an annual basis from the airline and environmental perspectives at Schipol. This leads us to the obvious question: why do airlines not upgrade without additional incentives simply based on the importance of the fuel input factor? Clearly the second hand market is not perfect and were all European airline to attempt to sell a large percentage of their current fleet immediately, the market value would likely collapse. Furthermore, given the state of profitability or lack thereof in the airline market, it is clear that the funds available are extremely limited. Hence, it is reasonable to assume that the replacements or upgrades should be gradual over a ten year timeframe in which case the environmental charges should be collected into a special fund to which airlines could apply, at the very least for interest free loans. In this manner, the European Union could also encourage replacements according to their perspective, which is slightly costlier than those of the airlines perspective at Schipol. At Arlanda, the results of the analysis are slightly different due to the smaller aircraft configurations serving the market and shorter distances flown. In this case, the fuel savings are lower than the additional ownership costs from the regulatory perspective, which leads to the argument that fleet replacements should be subsidized from a social perspective and again the environmental charges at the current levels could be directed towards this aim.

Table 9 – Marginal values comparing the current fleet with that of the benchmarks

Amsterdam Schipol			
	Regulatory perspective	**Airline perspective**	**Green perspective**
Savings			
Externalities costs	€ 4,625,718	€ 3,209,671	€ 5,882,479
Fuel consumption	€ 102,428,763	€ 143,007,038	€ 146,360,166
Costs			
Ownership costs	-€ 47,575,069	-€ 42,592,955	-€ 35,145,049
Seat capacity	-€ 3,191,461	€ -	-€ 360,707,691
Total	€ 56,287,951	€ 103,623,754	-€ 243,610,094

Arlanda Stockholm			
	Regulatory perspective	**Airline perspective**	**Green perspective**
Savings			
Externalities costs	€ 2,253,117	€ 1,771,046	€ 2,368,200
Fuel consumption	€ 18,826,708	€ 41,981,473	€ 35,698,187
Costs			
Ownership cost	-€ 25,874,767	-€ 31,761,308	-€ 19,659,334
Seat capacity	€ -	€ -	-€ 150,449,780
Total	-€ 4,794,942	€ 11,991,211	-€ 132,042,726

5 Conclusions

A directional economic-environmental distance (DEED) model has been developed in order to compute the relative efficiency of aircraft-engine combinations taking into account both the production of desirable and undesirable outputs such as noise and air pollutant emissions. Three different perspectives have been considered, namely a regulatory perspective in which a single operational and environmental frontier is developed, an airline perspective in which undesirable outputs are not internalized and a green perspective, in which only undesirable outputs are included. The different aircraft-engine combinations are grouped into four aircraft categories: turbo propellers, regional jets, narrow-bodies and wide-bodies. The results of the DEED model are then applied in order to design a replacement fleet according to each perspective and to estimate the costs (due to aircraft substitution) and benefits (from savings in pollution, noise and fuel consumption) drawing from implementation at Stockholm Arlanda and Amsterdam Schipol airports.

The first stage, DEED analysis identifies the relatively efficient fleet according to the three perspectives. We find evidence that airlines are presented with a choice of aircraft-engine combinations per stage length and that the choice yields different outcomes from both economic and environmental perspectives. Specifically, we show that within the same aircraft category, several trade-offs exist among the different aircraft-engine combinations. This implies that airline managers, when choosing their fleet, could take into account not only the route and stage length to serve, i.e. the market constraints, but also the importance that the company places on the environment. In the second stage, after replacing or upgrading the fleets serving Arlanda and Amsterdam, we identify potential emissions reductions using more fuel efficient aircraft-engine combinations without necessarily reducing profits. The fleets currently serving the two airports analyzed are neither efficient in terms of fuel consumption nor externalities produced, despite the presence of environmental charges over the past decade. As a result, we find that the current IPCC emissions values are probably too low to induce airline managers to pay sufficient attention to the issue of negative externalities when purchasing aircraft. This implies that, under the status quo, environmental improvements are a secondary effect, since they are most likely to occur only when directly coupled to economic performance through fuel efficiency. Furthermore, airport noise charges are mainly related to the density of the population in the communities surrounding the airport and currently are too low to impact managerial decisions with respect to fleet choice and aircraft purchase. Our solutions suggest that the level of pricing of negative externalities would need to be increased ten-fold in order to be taken into account during the aircraft purchase decision. Given the current economic situation of the airline industry, it is highly unlikely that carriers are in a position to bear the substantial investments needed to adopt a more environmentally friendly fleet. However, utilizing the IPCC pricing scheme may produce sufficient revenues to subsidize the purchase of new aircraft or upgrade the current fleet with the newest engine kits, so that both emissions and noise could be reduced gradually. For this to occur, a national or European wide fund would need to be managed in order to collect the funds and set up procedures to subsidize loans or provide subsidies for the purpose of fleet renewal according to the regulatory perspective.

References

- Adler, N., Gellman, A., 2012. Strategies for managing risk in a changing aviation environment. Journal of Air Transport Management, 21, 24-35.
- Adler, N., Fu, X., Oum, T.H., Yu, C., 2012. Air Transport Liberalization and Airport Slot Allocation: The case of the Northeast Asian Transport Market. Working Paper, Center for Transport Studies, University of British Columbia.
- Babikian, R., Lukachko, S., Waitz, I., 2002. Historical fuel efficiency characteristics of regional aircraft from technological, operational, and cost perspectives. Journal of Air Transport Management, 8, 389-400.
- Brueckner, Jan K., Girvin, R., 2008. Airport noise regulation, airline service quality, and social welfare. Transport Research Part B, 42, 19-37.
- Capoccitti, S., Khare, A., Mildenberger, U., 2010. Aviation Industry – Mitigating Climate Change Impacts through Technology and Policy. Journal of Technology Management & Innovation, 5(2), 66-75.
- Chambers, R.G., Chung, Y., Färe, R., 1998. Profit directional distance functions and Nerlovian efficiency. Journal of Optimization Theory and Applications, 95, 351–354.
- Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eurpean Journal of Operational Research, 2, 429-444.
- Charnes, A., Cooper, W.W., Golany, B., Seiford, L., Stutz, J., 1985. Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. Journal of Econometrics, 30, 91-107.
- Commission For Integrated Transport, 2007. Transport and Climate Change: Advice to Government from The Commission. London, UK.
- Dailey, B., 2010. Air Transport and the Environment. Farnham, Surrey.
- Debreu, G., 1951. The Coefficient of Resource Utilization. Econometrica, 19, 273-292.
- Dings, J.M.W., Wit, R.C.N., Leurs, B.A., Davidson, M.D., Fransen, W., 2003. External Costs of Aviation. Federal Environmental Agency (Umweltbundesamt), Berlin.
- Doganis, R., 2002. Flying off course: The economics of International Airlines. Routledge, London.
- Färe, R., Grosskopf, S., Pasurka Jr., C.A., 2007. Environmental production functions and environmental directional distance functions. Energy, 32, 1055–1066.

- Färe, R. and Grosskopf, S., 2010. Directional distance functions and slacks-based measures of efficiency. European Journal of Operational Research, 200, 320–322.
- Färe, R., Grosskopf, S., Lovell, C., 1994. Production Frontiers. Cambridge University Press, Cambridge.
- Farrell, M.J., 1957. The Measurement of Productive Efficiency. Journal of the Royal Statistical Society Series A, 120(3), 253-281.
- Givoni, M. and Rietveld, P., 2010. The environmental implications of airlines' choice of aircraft size. Journal of Air Transport Management, 16, 159-167.
- Green, J.E., 2009. The potential for reducing the impact of aviation on climate. Technology Analysis & Strategic Management, 21(1), 39-59.
- ICAO emissions databank. (http://easa.europa.eu/environment/edb/aircraft-engine-emissions.php).
- Kumbhakar, S.C., Lovell, C.A.K., 2000. Stochastic Frontier Analysis. Cambridge University Press, Cambridge.
- Lawrence, P., 2009. Meeting the challenge of aviation emissions: an aircraft industry perspective. Technology Analysis & Strategic Management, 21(1), 79-92.
- Lijesen, M., Van der Straaten, W., Dekkers, J., Van Elk, R., Blokdijk, R., 2010. How much noise reduction at airports? Transportation Research Part D, 15, 51-59.
- Lu, C. and Morrell, P., 2006. Determination and applications of environmental costs at different sized airports – aircraft noise and engine emissions. Transportation, 33, 45-61.
- Marais, K. and Waitz, I.A., 2009. Air Transport and the Environment. The global Airline Industry eds P. Belobabam, A.Odoni, C. Barnhart. John Wiley & Sons Ltd, Chichester.
- Picazo-Tadeo, A., Reig-Martinez, E., Hernandez-Sancho, F., 2005. Directional distance functions and environmental regulation. Resource and Energy Economics, 27, 141-142.
- Scheel, H., 2001. Undesirable outputs in efficiency valuations. European Journal of Operational Research, 132, 400-410.
- Schipper, Y., 2004. Environmental costs in European aviation. Transport Policy, 11, 141-154.
- Sgouridis, S., Bonnefoy, P., Hansman, J., 2011. Air transportation in a carbon constrained world: Long-term dynamics of policies and strategies for mitigating the

carbon footprint of commercial aviation. Transportation Research Part A, 45, 1077-1091.

- Sutkus, D.J., Baughcum, S.L., DuBois, D.P., 2001. Scheduled Civil Aircraft Emission Inventories for 1999: Database Development and Analysis. NASA/CR-2001–211216, Washington DC.
- Swan, W. and Adler, N., 2006. Aircraft trip cost parameters: A function of stage length and seat capacity. Transportation Research Part E, 42, 105-11.

Appendix

Table 5– First stage results

A score of zero in the last three columns implies efficiency and a positive score suggests the levels of savings that could be achieved according to each of the three models.

Turbo Propellers								
Aircraft Manufacturer	**Model**	**Engine Manufacturer**	**Model**	**DMU**	**Year**	**Regulatory**	**Airline**	**Green**
Avions de Transport Regional	ATR42-300	Pratt & Whitney	PW120	1	1997	0	0	0
Avions de Transport Regional	ATR42-320	Pratt & Whitney	PW121	2	1997	21	1	4
Avions de Transport Regional	ATR42-400	Pratt & Whitney	PW121A	3	1997	0	0	0
Avions de Transport Regional	ATR42-500	Pratt & Whitney	PW127E	4	2009	0	2752	0
Avions de Transport Regional	ATR42-500	Pratt & Whitney	PW127M	5	2009	2121	2875	5
Avions de Transport Regional	ATR72-200	Pratt & Whitney	PW127	6	1996	142	180	15
Avions de Transport Regional	ATR72-210	Pratt & Whitney	PW127	7	1998	0	0	15
Avions de Transport Regional	ATR72-500	Pratt & Whitney	PW127F	8	2010	0	108	5
BAE systems	ATP	Pratt & Whitney	PW126A	9	1993	372	1123	16
Bombardier Inc.	Q 200	Pratt & Whitney	PW123C	11	1996	2165	2948	12
Bombardier Inc.	Q 300	Pratt & Whitney	PW123B	10	1991	1732	3056	9
Bombardier Inc.	Q 400 NextGen	Pratt & Whitney	PW150A	12	2010	0	0	37
Fokker	50	Pratt & Whitney	PW125B	13	1996	0	1455	0
Saab	2000	Allison Engine Company	AE2100A	14	1999	0	1754	0
Saab	340	General Electric	CT7-9B	15	1999	0	1324	0
Short Brothers	SD3-60	Pratt & Whitney	PT6A-67R	16	1991	0	2628	0

Regional Jets								
Aircraft Manufacturer	**Model**	**Engine Manufacturer**	**Model**	**DMU**	**Year**	**Regulatory**	**Airline**	**Green**
BAE systems	Bae 146-200	Textron Lycoming	ALF 502R-3A	1	1993	1230	3466	41
BAE systems	Bae 146-200	Textron Lycoming	ALF 502R-5	2	1993	2164	3415	44
BAE systems	Bae 146-300	Textron Lycoming	LF507-1H	3	1993	1898	2576	52
BAE systems	Bae 146-300	Textron Lycoming	ALF 502R-5	4	1993	1051	2365	44
BAE systems	AVRO RJ70	Textron Lycoming	LF507-1F	5	2000	2899	3451	53
BAE systems	AVRO RJ85	Textron Lycoming	LF507-1F	6	2001	1038	1639	52
BAE systems	AVRO RJ100	Textron Lycoming	LF507-1F	7	2001	0	634	54
Bombardier Inc.	CRJ 200 ER	General Electric	CF34-3B1	8	2005	0	341	0
Bombardier Inc.	CRJ 200 LR	General Electric	CF34-3B1	9	2005	34	563	0
Bombardier Inc.	CRJ 701	General Electric	CF34-8C1	10	2005	0	2240	0
Bombardier Inc.	CRJ 701 ER	General Electric	CF34-8C1	11	2005	5	2271	0
Bombardier Inc.	CRJ 705	General Electric	CF34-8C5	12	2006	0	552	0
Bombardier Inc.	CRJ 900	General Electric	CF34-8C5	13	2005	160	1176	0
Bombardier Inc.	CRJ 1000 NextGen	General Electric	CF34-8C5A1	14	2010	0	0	7
Donier	328JET	Pratt & Whitney	PW306B	15	2002	0	0	0
Embraer	ERJ 135 ER	Allison Engine Company	AE3007A1/3	16	2005	0	779	0
Embraer	ERJ 135 LR	Allison Engine Company	AE3007A1/3	17	2005	0	527	0
Embraer	ERJ 140 ER	Allison Engine Company	AE3007A	18	2005	0	385	0
Embraer	ERJ 140 LR	Allison Engine Company	AE3007A1/1	19	2005	20	101	3
Embraer	ERJ 145 LR	Allison Engine Company	AE3007A1/1	20	2005	0	0	3
Embraer	E-Jets 170	General Electric	CF34-8E5	21	2010	2057	3465	9
Embraer	E-Jets 170 LR	General Electric	CF34-8E5	22	2010	2074	3489	9
Embraer	E-Jets 175	General Electric	CF34-8E5	23	2010	994	2421	9
Embraer	E-Jets 175 LR	General Electric	CF34-8E5	24	2010	1010	2444	9
Embraer	E-Jets 190	General Electric	CF34-10E5A1	25	2010	577	571	73
Embraer	E-Jets 190 LR	General Electric	CF34-10E5A1	26	2010	602	597	74
Embraer	E-Jets 190 AR	General Electric	CF34-10E5A1	27	2010	616	611	74

Embraer	E-Jets 195	General Electric	CF34-10E5A1	28	2010	0	0	72
Embraer	E-Jets 195 LR	General Electric	CF34-10E5A1	29	2010	33	33	73
Embraer	E-Jets 195 AR	General Electric	CF34-10E5A1	30	2010	46	45	74
Fokker	100	Rolls Royce	TAY 650-15	31	1996	1352	1273	67
Fokker	70	Rolls Royce	TAY 620-15	32	1996	626	213	65

Narrow Bodies								
Aircraft Manufacturer	**Model**	**Engine Manufacturer**	**Model**	**DMU**	**Year**	**Regulatory**	**Airline**	**Green**
Airbus	A318-100	CFM International	CFM56-5B8/3	1	2010	0	0	0
Airbus	A318-100	CFM International	CFM56-5B9/3	2	2010	722	3346	3
Airbus	A318-100	Pratt & Whitney	PW6122A	3	2010	4391	6741	9
Airbus	A318-100	Pratt & Whitney	PW6124A	4	2010	6213	8741	33
Airbus	A319-100	CFM International	CFM56-5B5/3	5	2010	0	0	3
Airbus	A319-100	CFM International	CFM56-5B6/3	6	2010	476	1237	5
Airbus	A319-100	CFM International	CFM56-5B7/3	7	2010	1825	4399	23
Airbus	A319-100	CFM International	CFM56-5A5	8	2010	0	1512	0
Airbus	A319-100	International Aero Engines	V2522-A5	9	2010	0	5637	0
Airbus	A319-100	International Aero Engines	V2524-A5	10	2010	657	6943	12
Airbus	A319-100	International Aero Engines	V2527M-A5	11	2010	0	6461	0
Airbus	A320-200	CFM International	CFM56-5B4/3	12	2009	5389	7212	26
Airbus	A320-200	CFM International	CFM56-5B5/3	13	2009	0	2353	6
Airbus	A320-200	CFM International	CFM56-5B6/3	14	2009	1043	3719	8
Airbus	A320-200	International Aero Engines	V2527-A5	15	2009	0	8422	4
Airbus	A320-200	International Aero Engines	V2527E-A5	16	2009	0	8422	4
Airbus	A321-100	CFM International	CFM56-5B1/3	17	2004	1900	3152	60
Airbus	A321-100	CFM International	CFM56-5B2/3	18	2004	2336	3595	73
Airbus	A321-100	International Aero Engines	V2530-A5	19	2004	1188	5189	77
Airbus	A321-200	CFM International	CFM56-5B1/3	20	2009	384	1215	65
Airbus	A321-200	CFM International	CFM56-5B2/3	21	2009	626	1659	77

Airbus	A321-200	CFM International	CFM56-5B4/3	22	2009	0	0	29
Airbus	A321-200	International Aero Engines	V2530-A5	23	2009	0	3258	78
Airbus	A321-200	International Aero Engines	V2533-A5	24	2009	652	3851	102
Boeing Company	717-200	Rolls-Royce	BR700-715C1-30	25	2006	0	11768	0
Boeing Company	737-300	CFM International	CFM56-3B1	26	1999	5755	6326	20
Boeing Company	737-300	CFM International	CFM56-3B2	27	1999	7772	8074	25
Boeing Company	737-400	CFM International	CFM56-3B2	28	1999	3834	4046	25
Boeing Company	737-400	CFM International	CFM56-3C1	29	1999	4073	6633	32
Boeing Company	737-500	CFM International	CFM56-3B1	30	1999	5067	5625	11
Boeing Company	737-600	CFM International	CFM56-7B18/3	31	2006	0	6864	0
Boeing Company	737-600	CFM International	CFM56-7B22/3	32	2006	3586	10601	5
Boeing Company	737-700	CFM International	CFM56-7B20/3	33	2009	0	6318	3
Boeing Company	737-700	CFM International	CFM56-7B22/3	34	2009	920	4897	7
Boeing Company	737-700	CFM International	CFM56-7B24/3	35	2009	1491	5186	12
Boeing Company	737-700	CFM International	CFM56-7B26/3	36	2009	2593	7356	25
Boeing Company	737-700	CFM International	CFM56-7B27/3	37	2009	7462	8406	43
Boeing Company	737-800	CFM International	CFM56-7B24/3	38	2009	2908	3784	22
Boeing Company	737-800	CFM International	CFM56-7B26/3	39	2009	836	5813	28
Boeing Company	737-800	CFM International	CFM56-7B27/3	40	2009	1388	6244	37
Boeing Company	737-900ER	CFM International	CFM56-7B26/3	41	2009	0	7586	28
Boeing Company	737-900ER	CFM International	CFM56-7B27/3	42	2009	2333	8186	37
Boeing Company	757-200	Rolls Royce	RB211-535C	43	2002	5109	7705	178
Boeing Company	757-200	Rolls Royce	RB211-535E4	44	2002	3656	10078	273
Boeing Company	757-200	Rolls Royce	RB211-535E4B	45	2002	4227	10686	252
Boeing Company	757-200	Pratt & Whitney	PW2037	46	2002	559	2630	136
Boeing Company	757-200	Pratt & Whitney	PW2040	47	2002	4247	3820	186
Boeing Company	757-300	Pratt & Whitney	PW2040	48	2003	0	0	189
Boeing Company	757-300	Rolls Royce	RB211-535E4	49	2003	0	2259	196
Boeing Company	757-300	Rolls Royce	RB211-535E4B	50	2003	0	3746	267

McDonnell Douglas	MD81	Pratt & Whitney	JT8D-209	51	1992	6302	6816	76
McDonnell Douglas	MD81	Pratt & Whitney	JT8D-217	52	1992	4677	8565	94
McDonnell Douglas	MD81	Pratt & Whitney	JT8D-219	53	1992	5112	8477	97
McDonnell Douglas	MD82	Pratt & Whitney	JT8D-217	54	1998	3326	5935	96
McDonnell Douglas	MD82	Pratt & Whitney	JT8D-219	55	1998	3152	5718	98
McDonnell Douglas	MD83	Pratt & Whitney	JT8D-217	56	1999	8031	7782	101
McDonnell Douglas	MD83	Pratt & Whitney	JT8D-219	57	1999	7937	7690	104
McDonnell Douglas	MD87	Pratt & Whitney	JT8D-217	58	1992	9771	9611	101
McDonnell Douglas	MD87	Pratt & Whitney	JT8D-219	59	1992	9686	9475	104
McDonnell Douglas	MD88	Pratt & Whitney	JT8D-217	60	1997	4126	6670	96
McDonnell Douglas	MD88	Pratt & Whitney	JT8D-219	61	1997	3968	6581	98
McDonnell Douglas	MD90-30	International Aero Engines	V2525-D5	62	1999	0	9147	0

Wide bodies								
Aircraft Manufacturer	**Model**	**Engine Manufacturer**	**Model**	**DMU**	**Year**	**Regulatory**	**Airline**	**Green**
Airbus	A300B4-600	General Electric	CF6-80C2A1	1	1992	4338	14606	64
Airbus	A300B4-600	General Electric	CF6-80C2A3	2	1992	6603	15571	74
Airbus	A300B4-600R	General Electric	CF6-80C2A5F	3	1998	10833	19107	77
Airbus	A300B4-600R	Pratt & Whitney	PW4158	4	1998	9448	17028	130
Airbus	A310-300	General Electric	CF6-80C2A2	5	1997	0	11086	12
Airbus	A310-300	Pratt & Whitney	PW4152	6	1997	5913	12427	48
Airbus	A330-200	General Electric	CF6-80E1A2	7	2010	9669	11957	231
Airbus	A330-200	General Electric	CF6-80E1A3	8	2010	13190	13667	307
Airbus	A330-200	General Electric	CF6-80E1A4	9	2010	12188	13013	280
Airbus	A330-200	Pratt & Whitney	PW4168A	10	2010	0	16407	0
Airbus	A330-200	Pratt & Whitney	PW4170	11	2010	12208	17966	134
Airbus	A330-200	Rolls Royce	Trent 772-60	12	2010	18601	20820	239
Airbus	A330-300	General Electric	CF6-80E1A2	13	2010	12573	15017	224
Airbus	A330-300	General Electric	CF6-80E1A3	14	2010	16553	16839	305

Airbus	A330-300	General Electric	CF6-80E1A4	15	2010	15506	16142	279
Airbus	A330-300	Pratt & Whitney	PW4164	16	2010	0	16713	0
Airbus	A330-300	Pratt & Whitney	PW4168A-1D	17	2010	14124	20357	124
Airbus	A330-300	Pratt & Whitney	PW4170	18	2010	15823	21375	134
Airbus	A330-300	Rolls Royce	Trent 768-60	19	2010	11228	21506	183
Airbus	A330-300	Rolls Royce	Trent 772	20	2010	22402	24453	238
Airbus	A340-200	CFM International	CFM56-5C2/P	21	1998	29017	35145	118
Airbus	A340-200	CFM International	CFM56-5C3/P	22	1998	32452	37284	148
Airbus	A340-200	CFM International	CFM56-5C4/P	23	1998	37005	39801	189
Airbus	A340-300	CFM International	CFM56-5C2/P	24	2008	18743	25812	118
Airbus	A340-300	CFM International	CFM56-5C3/P	25	2008	23307	28035	147
Airbus	A340-300	CFM International	CFM56-5C4/P	26	2008	27277	30651	182
Airbus	A340-500	Rolls Royce	Trent 553-61	27	2010	26482	42291	430
Airbus	A340-600	Rolls Royce	Trent 556-61	28	2010	0	22893	508
Airbus	A380-800	Engine Alliance	GP7270	29	2010	0	0	726
Airbus	A380-800	Rolls Royce	Trent 970-84	30	2010	0	6416	561
Airbus	A380-800	Rolls Royce	Trent 972-84	31	2010	0	10292	609
Boeing Company	747-400	General Electric	CF6-80C2B5F	32	2003	10551	20464	460
Boeing Company	747-400	Rolls Royce	RB211-524H2-T19	33	1999	27044	31903	574
Boeing Company	767-200	General Electric	CF6-80C2B2	34	1992	0	0	0
Boeing Company	767-200	Pratt & Whitney	PW4060A	35	1992	11936	15483	128
Boeing Company	767-200ER	General Electric	CF6-80C2B7F	36	1992	12142	20540	63
Boeing Company	767-200ER	Pratt & Whitney	PW4056	37	1992	10624	18209	91
Boeing Company	767-300	General Electric	CF6-80A2	38	2000	0	0	0
Boeing Company	767-300ER	General Electric	CF6-80C2B7F	39	2010	2738	10772	72
Boeing Company	767-300ER	Pratt & Whitney	PW4060	40	2010	5842	12023	129
Boeing Company	767-400ER	General Electric	CF6-80C2B8F	41	2003	0	9047	48
Boeing Company	777-200	General Electric	GE90-77B	42	2004	0	1808	0
Boeing Company	777-200	Pratt & Whitney	PW4077	43	2004	0	0	274

Boeing Company	777-200	Rolls Royce	Trent 877	44	2004	0	3724	270
Boeing Company	777-200ER	General Electric	GE90-94B	45	2010	0	8076	450
Boeing Company	777-200ER	Rolls Royce	Trent 895	46	2010	15080	15279	477
Boeing Company	777-200LR	General Electric	GE90-110B1	47	2010	16066	15750	594
Boeing Company	777-200LR	General Electric	GE90-115B	48	2010	20019	18884	699
Boeing Company	777-300	Rolls Royce	Trent 892	49	2006	0	0	404
Boeing Company	777-300ER	General Electric	GE90-115B	50	2010	9757	9278	702
McDonnell Douglas	MD11	General Electric	CF6-80C2D1F	51	1999	17291	17547	341
McDonnell Douglas	MD11	Pratt & Whitney	PW4460	52	1999	18928	18352	391