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Efficiency Evaluation in an Airline Company: Some Empirical Results

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Abstract: During the last years, enormous attention has been given to the assessment and improvement of the performance of productive systems. Economic activities at the firm, industry, regional or national level are affected by the world-wide trend for improved performance. The growing competition and the recent recession have also forced many airlines to reduce costs and to improve productivity and efficiency. In this context, there are two types of modelling methods of efficiency measurement: a non parametric one, represented by Data Envelopment Analysis and a parametric one, represented by Stochastic Frontier Analysis. The main objective of this empirical study is to evaluate the operational performance of an Italian airline for the year 2007 by using these two alternative methodologies.

Key words: Airline industry, performance measurement, technical efficiency, Stochastic Frontier Analysis (SFA), Data Envelopment Analysis (DEA), undesirable output

INTRODUCTION

Over the past two decades airline companies have faced many changes in markets. The context of air transportation has seen a rapid development, determined by the growing of air transport demand, technological progress, strong investments in the field and aviation deregulation.

Recently, considerable attention has been focused on the performance of various air carriers in terms of efficiency and the operational performance of airlines has received significant attention in the literature. In fact, the deregulation process has been primarily argued for on the basis of improving competition and hence efficiency in the provision of air transport services and experience has demonstrated that progressive liberalisation produces substantial benefits for air transport services that are efficient.

There are many ways in which one may define and measure efficiency of industrial activities such as air transportation. It must be remembered that modern efficiency measurement began with Farrell (1957), who drew upon the work of Debreu (1951) and Koopmans (1951) and introduced a measure for technical efficiency. He suggested measuring the efficiency of a firm in terms of distance to the best unit on the production frontier, represented by the production function of the efficient units. The efficiency frontier is unknown and it must be estimated from sample data. Drawing inspiration from his argument, two classes of methods, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), were developed for estimating the efficiency of organisational units, also called Decision Making Units (DMUs), which typically perform the same function, by using the same set of inputs to produce the same sets of outputs. The DEA technique assumes that all deviations from the efficient frontier are due to inefficiency, whereas the SFA technique assumes that deviations from the efficient frontier can be either a realisation of inefficiency or a random shock.

SFA and DEA methods are estimating the same underlying efficiency values but they can give different efficiency estimates for the units under analysis, due to the differences between the underlying assumptions. Although the two approaches are traditionally thought to be competing, there is no consensus as to which is the most appropriate technique, each has its own strengths and weaknesses (Coli *et al*., 2007). DEA is a convenient method of analysing performance for a variety of reasons. First of all, it is non-parametric, which means that it does not require the specification of an explicit functional form for the production frontier, so the danger of imposing a-priori wrong functional forms is avoided, unlike the econometric methods. On the other hand, SFA has the advantage that it allows random noise to be incorporated into the model, whilst DEA is deterministic, which means that any statistical noise, measurement errors, omitted variables and other misspecifications are counted as inefficiency.

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There is no easy answer as to which of the two alternative approaches to the estimation of production frontiers performs better: the performance of the two methods is highly dependent upon the data set which is being analysed. In our opinion, the two methods should be used in conjunction and compared when examining the same data set. However, except for a few studies (Nissi and Rapposelli, 2008), efficiency analysis using either DEA or SFA methods have not been conducted frequently on the airline industry and a comparative approach has not been widely applied in the literature (Good *et al*., 1995; Sharma *et al*., 1997; Sengupta, 2000; Tsionas, 2003).

Hence, the aim of the present paper is to analyse the productive efficiency of an Italian private airline, Air One, for the year 2007 by estimating a parametric function using econometric methods (SFA) and a non-parametric function using mathematical programming approach (DEA). For this purpose, we limit our analysis to evaluating the relative technical efficiency of Air One domestic routes: a Cobb-Douglas production function with different distribution assumptions for the inefficiency term and a constant returns to scale input-orientated DEA model are estimated. Then, the technical efficiency estimates obtained from the two techniques are compared.

METHODS

Stochastic Frontier Analysis (SFA): As stated in the introduction, there are two main empirical methodologies for the measurement of efficiency: the parametric one and the non-parametric one. A parametric frontier model depends on specifying a functional form which relates the outputs to the inputs and then estimating the parameters of this production function using one of the standard estimation techniques.

The econometric approach to modelling efficiency has evolved over the past twenty years. Researchers struggled with the problem of how to incorporate stochastic features into deterministic parametric frontier models: this was done by using a composite error term which separates inefficiency from random events. Stochastic Frontier Analysis (Aigner *et al*., 1977; Meeusen and van den Broeck, 1977) assumes ε_i is the composite error term and measures the technical efficiency relative to a stochastic parametric frontier.

The SF general formulation is:

$$y_i = f(x_i, \beta) + \varepsilon_i, \text{ with } \varepsilon_i = v_i - u_i,\ i = 1,...,n \qquad (1)$$

where, y_i denotes the amount of the output produced by DMU i, x_i is the vector of inputs, β is the $(k\times1)$ vector of parameters to be estimated, v_i represents the traditional symmetric normal term which captures all stochastic events outside the control of the DMU (measurement errors, any misspecification in the model being used, effects of weather, luck, etc.) and u_i is the one-sided component measuring unit-specific inefficiency, so all the events that are under the firm's control, such as defective or damaged products. The v_i's are assumed to be independently and identically distributed as $N(0, \sigma^2_v)$, whilst u_i is non-negative and is assumed to be distributed independently of v_i. In the literature many distributional forms for the inefficiency term have been employed, such as half-normal (Aigner *et al*., 1977), exponential (Aigner *et al*., 1977; Meeusen and van den Broeck, 1977), truncated normal (Stevenson, 1980), which is a generalisation of the half-normal distribution and Gamma (Greene, 1990).

The choice of a distributional form for the technical inefficiency effects is important because the estimates depend on it. However, this is a problem as there do not seem to be good a priori arguments for the selection of any particular distributional assumption. The specification of more general distributional forms, such as the truncated normal and the two-parameter Gamma, have partially alleviated the problem. The advantage of Gamma distribution is that its asymmetry is determined by one of its parameters, but the disadvantage is the increase in the number of parameters needing to be estimated. The truncated normal model appears to suffer from fewer computational problems than the Gamma distribution. Hence, these two distributions allow for a wider range of distributional shapes, but at the cost of computational complexity (Coelli *et al*., 1998). Most of the literature has considered the half-normal distribution: it seems likely that this is the most popular method due to the fact that this was the first method proposed by Aigner *et al*. (1977) and that it is the easiest to work with computationally (Read, 1998).

With regard to production technology, several different functional forms have been proposed to represent it, but the most used is the Cobb-Douglas function. In this case the stochastic frontier production function is defined as:

$$\ln y_i = f(x_i, \beta) + \varepsilon_i, \quad i = 1,...,n \qquad (2)$$

The stochastic production function can be estimated by Corrected Ordinary Least Squares (COLS) or by the maximum likelihood method, which generally gives better estimates than the COLS method. Once the stochastic frontier has been estimated, the average efficiency across the entire sample of firms can be determined. Then, for each observation the technical inefficiency u_i is required.

In the Cobb-Douglas case the technical efficiency of DMU i is defined as $TE_i = \exp(-u_i)$ and to estimate the DMU specific efficiencies the conditional distribution of u_i given the value of the total error ε_i ($E(u_i/\varepsilon_i)$) is used.

Data Envelopment Analysis (DEA): An alternative method for assessing the efficiencies of organisational units is Data Envelopment Analysis. Rather than explicitly stating the form of the frontier, it measures efficiency relative to a deterministic frontier using linear programming techniques to envelop observed input/output vectors as tightly as possible.

The basic DEA model, proposed by Charnes *et al.* (1978) and known as CCR, has an input orientation (whose objective is to minimise inputs while producing at least the given output levels) and assumes constant returns to scale of activities (CRS). The relative efficiency of a DMU j is obtained from the following linear model:

$$e_0 = \min\theta_0$$

subject to:

$$\theta_0 x_{ij0} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, \quad i = 1,...,m \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj0}, \quad r = 1,...,s \tag{4}$$

$$\lambda_j \geq 0, \quad \forall j \tag{5}$$

where, y_{rj} is the amount of the r-th output to DMU j, x_{ij} is the amount of the i-th input to DMU j, λ_j are the weights of DMU j and θ is the shrinkage factor.

The CCR model seeks a set of λ values which minimise θ_0 to θ_0^* and identifies a point within the production possibility set which uses the lowest proportion θ_0^* of input levels of DMU j while offering output levels which are at least as high as those of DMU j. This point is a composite DMU corresponding to the linear combination of efficient DMUs:

$$\left(\sum_{j=1}^{n} \lambda_j^* x_{ij}, \sum_{i=1}^{n} \lambda_j^* y_{rj}\right)$$

with i = 1,...,m and r = 1,...,s. It can be said that:

$$\left(\sum_{j=1}^{n} \lambda_j^* x_{ij}, \sum_{i=1}^{n} \lambda_j^* y_{rj}\right)$$

outperforms $(\theta_0 x_{j0}, y_{j0})$ when $\theta_0^* < 1$.

The technical efficiency of DMU j can be also determined under output expansion orientation, whose objective is to maximise outputs while using no more than the observed amount of any input. Due to the CRS assumption, the relative efficiency score of the output-orientated model relates to that of the input-orientated model via $e_0 = 1/h_0$.

DATA

As mentioned above, we use these two different methodologies to investigate the technical efficiency of the Italian airline Air One for the year 2007. Air One was in 2007 the top private Italian carrier operating mainly on Italian domestic routes with 37% of market share. The company's core business was scheduled passenger air services, in fact scheduled flights represented about 85% of passenger air services.

The sample on which this study is based consists of 42 domestic routes: in order to respect homogeneity assumptions about the units under assessment (Dyson *et al.*, 2001), we do not consider international routes, summer routes and any routes which have not been operating during the whole year.

After choosing the most appropriate DMUs to be evaluated, the most important stage in carrying out the assessment is the identification of the input and output variables to be used in an assessment of comparative performance: in order to model relative efficiency of a set of units it is necessary to define a production function which captures the key points of the production process under analysis. However, there is no definitive study to guide the selection of inputs and outputs in airline applications of efficiency measurement (Nissi and Rapposelli, 2008), but it must be remembered that the nature of performance measurement is heavily influenced by the input/output set identified in the airline production process (Schefczyk, 1993; Oum and Yu, 1998; Coelli *et al.*, 1999; Fethi *et al.*, 2001).

After having carried out different model selections, we define a model characterised by two inputs, total seats and total variable direct operating costs (DOCs) and one output, passenger scheduled revenue. Moreover, the application of efficiency techniques to the context of air transportation has motivated the inclusion of a special kind of output, an undesirable output (Scheel, 2001; Seiford and Zhu, 2005) represented by the number of delayed flights, which is a negative factor for the airline company in terms of costs and in terms of customer satisfaction. Each of the inputs and outputs selected in our model reflects, therefore, the operational characteristics of the airline company, because the aim of the present work is limited to the operational performance analysis.

With regard to the output side of the model, passenger scheduled revenue represents the main output for a typical passenger focused airline. We have not included charter revenue and all output that is not passenger-flight related, such as cargo revenue. As to the undesirable output, in our opinion the number of delayed flights is an important factor to be considered: the idea behind this belief is that a passenger's decision to use the same airline or switch for the subsequent flights depends on whether they have experienced flight delays or not (Suzuki, 2000). Note that the Bureau of Transportation Statistics (BTS) defines a flight to be on-time if it arrives no later than fifteen minutes after its scheduled arrival time and usually publishes rankings of airline on-time performance.

We will give a brief discussion of the inputs. First of all, the number of seats available for sale provides information about airline capacity. With regard to the costs structure, we have considered ICAO (International Civil Aviation Organisation) and US practice, which divides airline accounts into operating and non-operating categories, as most international airlines have adopted this approach (Doganis, 2002). We have decided to include in the model only direct operating costs because they reflect the airline operational characteristics and depend upon the efficiency of scheduling and the nature of the route system. DOCs are likely to be in the range of 30-45 per cent of total operating costs and depend upon the airline's activity level, that is, the amount of flying it actually does; allocating these costs is fairly straightforward, since nearly all of them are specific to individual flights. They are in fact directly avoidable in the short term, so they could be avoided if a flight or a series of flights was cancelled. This variable includes numerous items such as fuel costs, handling, variable flight crew costs (for example bonuses), landing and airport fees, passenger meals, variable maintenance expenses, check costs. We have not included asset-related inputs, i.e., those inputs that represent capital goods, because they contribute to costs only indirectly through depreciation, amortisation and interest.

Data were obtained from Financial Statements as at 31st December 2007 and from various internal reports.

EMPIRICAL RESULTS

Here, we discuss the results we have obtained by applying the two different frontier techniques to the same set of variables.

With regard to stochastic frontier analysis, we consider three alternative model formulations by employing three different distributional assumptions for the one-sided inefficiency term u_i: the original half-normal formulation of Aigner *et al*. (1977), the exponential distribution (Aigner *et al*., 1977; Meeusen and van den Broeck, 1977) and the truncated normal distribution (Stevenson, 1980). In a simulation study (Read, 1998) it has been shown that the choice of the inefficiency distribution between half-normal, truncated normal and exponential has little affect on the results: when the underlying inefficiency has a half-normal distribution, a half-normal, truncated normal or exponential assumption in the SFA method produces good results and when the underlying inefficiency distribution is uniform the performance of the method is adversely affected for all three of these assumptions.

In all model formulations, we specify the stochastic frontier production function as a Cobb-Douglas function with three inputs producing one output. The number of delayed flights, in fact, is an undesirable output and it is incorporated as an input, because of its negative interpretation (Scheel, 2001). In particular, the deterministic core of the production frontiers is specified as follows:

$$\ln y_i = \beta_0 + \beta_1 \ln x_{i1} + \beta_2 \ln x_{i2} + \beta_3 \ln x_{i3} \tag{6}$$

where, y_i is the output, x_{i1} and x_{i2} are the input variables and x_{i3} is the undesirable output defined earlier. We have obtained maximum-likelihood estimates of the parameters of the stochastic frontier models analysed using the statistical software Stata, version 9.

Table 1 gives the three alternative models of the stochastic frontier production functions, with z values in parentheses. The three input variables have statistically significant coefficients for all inefficiency distributions considered. The null hypothesis of constant returns to scale ($\sum^{3}_{i=1} \beta_i = 1$) for Air One routes is not rejected for the evaluated models. Efficiency estimates obtained from the stochastic frontier models analysed are presented in Table 2.

On the other hand, the non-parametric efficiency measures are computed by using the input-orientated DEA model under the assumption of constant returns to scale (CRS) which, according to Good *et al*. (1995), is consistent with the vast majority of the airline literature. The choice about model orientation is based upon considerations of which factors are more easily controlled by the DMU: thus for instance, if producers are

Table 1: Stochastic frontier production functions

Parameter	SF1 (half-normal)	SF2 (exponential)	SF3 (truncated-normal)
Total seats	0.656	0.686	0.681
	(3.79)	(3.70)	(3.69)
DOCs	0.784	0.743	0.749
	(3.42)	(3.05)	(3.09)
Delayed flights	-0.361	-0.355	-0.355
	(-4.13)	(-4.00)	(-4.00)

Table 2: SFA and DEA efficiency scores by domestic routes for the year 2007

DMU	SF1 score	SF2 score	SF3 score	DEA score
1	0.5802	0.6768	0.6609	0.4813
2	0.3722	0.4074	0.4037	0.2624
3	0.8361	0.8893	0.8830	0.5751
4	0.9130	0.9305	0.9283	0.8796
5	0.9040	0.9274	0.9245	0.8486
6	0.9081	0.9285	0.9259	0.7656
7	0.7975	0.8721	0.8633	0.5972
8	0.4689	0.5458	0.5331	0.4190
9	0.7947	0.8650	0.8566	0.5969
10	0.7781	0.8544	0.8451	0.5388
11	0.7725	0.8563	0.8461	0.5670
12	0.7386	0.8294	0.8178	0.5349
13	0.8296	0.8859	0.8794	0.5683
14	0.5951	0.6950	0.6786	0.4150
15	0.8411	0.8911	0.8853	0.6054
16	0.8616	0.9019	0.8971	0.5752
17	0.8864	0.9168	0.9134	0.8457
18	0.7513	0.8373	0.8264	0.5290
19	0.4788	0.5384	0.5292	0.2574
20	0.8079	0.8751	0.8674	0.6306
21	0.5982	0.6963	0.6804	0.4200
22	0.6590	0.7680	0.7517	0.4956
23	0.8395	0.8906	0.8847	0.5419
24	0.9032	0.9273	0.9244	0.9714
25	0.6233	0.7187	0.7031	0.2981
26	0.6859	0.7894	0.7750	0.5997
27	0.9144	0.9318	0.9296	1.0000
28	0.6844	0.7904	0.7756	0.8346
29	0.7796	0.8607	0.8512	0.7235
30	0.7825	0.8629	0.8534	0.6919
31	0.8567	0.9030	0.8978	0.9661
32	0.8908	0.9194	0.9161	0.9322
33	0.8015	0.8717	0.8634	0.6102
34	0.9230	0.9354	0.9337	1.0000
35	0.7738	0.8598	0.8497	0.7407
36	0.7323	0.8295	0.8170	0.6412
37	0.7385	0.8348	0.8225	0.5843
38	0.6630	0.7745	0.7580	0.5660
39	0.8398	0.8926	0.8866	0.6993
40	0.9426	0.9473	0.9464	0.7899
41	0.6451	0.7581	0.7412	0.6650
42	0.6758	0.7852	0.7697	0.7367

required to meet market demand and can freely adjust input usage, then the input-orientated model is appropriate.

The general DEA formulation introduced earlier is made more specific for incorporating the undesirable output and the linear program associated with the model is solved using DEA-Solver, a software developed by Cooper *et al*. (2007). Note that in a DEA analysis the linear programming problem must be solved n times, once for each unit in the sample, in this case 42. Table 2 also shows the efficiency ratings, for each route assessed, obtained from the input-orientated CCR model.

The results provide similar rankings of the routes in terms of efficiency, although SFA efficiency ratings are not in the same order as those obtained from DEA model. The SFA results are not substantially different between the three models specified. Some different remarks can be made: although the parametric approach yields a higher average efficiency score and displays less variability for all inefficiency distributions considered than the non-parametric approach (Table 3), in terms of SFA no route is fully efficient while in terms of DEA model two routes are located on the best practice frontier.

Table 3: Summary statistics for SFA and DEA efficiency scores

Statistical analysis	SF1 (half-normal)	SF2 (exponential)	SF3 (truncated-normal)	DEA
Mean	0.7588	0.8255	0.8166	0.6429
Minimum	0.3722	0.4074	0.4037	0.2574
Maximum	0.9426	0.9473	0.9464	1.000
SD	0.1321	0.1157	0.1182	0.1884

Table 4: Spearman rank correlation coefficients

	SF1 (half-normal)	SF2 (exponential)	SF3 (truncated-normal)	DEA
SF1 (half- normal)	1.000			
SF2 (exponential)	0.9982	1.000		
SF3 (truncated-normal)	0.9987	0.9997	1.000	
DEA	0.6739	0.6665	0.6696	1.000

We can conclude that DMUs are operating at a fairly high level of efficiency, although there is room for improvement in several routes. Only three routes show very low DEA efficiency scores.

On the basis of these results we proceed to a correlation analysis among the efficiency measures obtained from the stochastic frontier and DEA models. We observe high Spearman rank correlation coefficients between the technical efficiency rankings obtained from the different stochastic frontier formulations and the DEA model (Table 4). The rank correlations between the different SFA efficiency scores are very high for all model formulations.

CONCLUSION

The aim of this work was to evaluate the efficiency of Air One routes by means of SFA and DEA methods and to compare the results obtained. We can conclude that taken as a group, Air One routes are performing quite well. However, by using different approaches one will obtain different technical efficiency rankings, but in this case study the results are not substantially different between the four models analysed. We must emphasise that the efficiency degree obtained by each unit is relevant only in the context analysed, in relation to the chosen model and to the sample examined: if we include a new DMU in the sample or if we assume different model specifications, we will obtain different efficient units or different efficiency degrees.

SFA and DEA are estimating the same underlying efficiency values but the natures of the two methods are very different: this can lead to different estimates for some, or all, of the units under analysis. Neither SFA nor DEA universally gives better results than the other method for all data sets, although the methods are generally used independently of each other. In our opinion, if both methods are applied to the same data set, a comparison between the results of the methods can be used to obtain a view as to which of the methods is more likely to be giving the better estimates.

It must be remembered that the models employed in this work can be improved. First of all, we could include additional key variables, such as other undesirable outputs and we could carry out a performance analysis over time (Sengupta, 2000). Moreover, a comparative evaluation of the two alternative approaches to efficiency measurement can be made relative to further application studies, for example we could also compare Air One international routes or different air carriers.

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