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International Air Transportation Carriers: Evidence from SFA and DEA Technical Efficiency Results (1991-2000)*

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In this paper we estimate technical efficiency in International Air Transport, by means of Stochastic Frontier Analysis (SFA) using a panel set of the world's twenty-four (24) largest network airlines, for the period 1991-2000. The results are compared to those from Data Envelopment Analysis (DEA), a popular approach for efficiency measurement in the literature. Findings suggest that airlines experience constant returns to scale, while technical efficiency ranges between 51% and 97% approximately. Furthermore, the level of technology experienced a slight increase, while the privatization of few of the airlines in the data set didn't seem to affect their technical efficiency. Results from SFA and DEA do not vary significantly.

Keywords: Air Transportation; Technical Efficiency; Stochastic Frontier Analysis; Data Envelopment Analysis; Panel

1. Introduction

In this paper, the technical efficiency of international air transportation industry is estimated with the use of Stochastic Frontier Analysis (SFA). The data set consists of a panel of twenty four (24) international network carriers in the time period 1991-2000. The paper compares the levels of efficiency between American, European and Asian carriers. The paper also compares the technical efficiency measures between private, mixed and public carriers. With regard to the carriers that changed ownership in the study period, there will be a comparison in technical efficiency measures before and after the ownership change. Finally, the paper briefly compares the SFA-technical efficiency measures with estimates by Data Envelopment Analysis (DEA).

The purpose of this paper is to estimate technical efficiency for a selected number of carriers of the international air transportation industry given that these measures have widespread appeal, as both policymakers and industry managers are concerned about measuring performance. In

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this context, technical efficiency refers to the ability of a firm to minimize input use in the production of a given output vector, or the ability to obtain maximum output from a given input vector.

The measure of technical efficiency is very important, because it indicates the ability of a firm to survive in a competitive environment. In the United States of America (U.S.A.), competition increased in the 1970s after the deregulation of the U.S. air transportation industry. More precisely, in 1978 the so-called Air Deregulation Act reformed the relationship between the airlines companies and the state. This domestic deregulation affected U.S. carriers but its *Open Skies* initiative starting in 1992 has had more of an impact. These reforms increased competition, lowered prices, increased services, and brought substantial benefits for consumers.

The European Commission (E.C.) introduced in 1987 certain reforms to promote competition and thus increase the efficiency and productivity of the European airlines (European Commission's first Package of Liberalizing Measures). Most of the changes experienced in Europe due to the deregulation that took place occurred after 1993. As for Asia, most of the domestic markets have been deregulated, so far. Under these circumstances, many carriers have been fundamentally restructured in order to survive competition. Alliances between carriers have been contracted, and other carriers have been merged. Finally, some carriers that were unable to carry through competition, bankrupted.

2. Review of the Literature

Relatively few studies on technical efficiency of the air transportation industry in developed countries use frontier methodologies. Good et *al.* (1993) using SFA techniques compared technical efficiency and productivity growth among the four largest European airlines and eight of their American counterparts over the time period 1976-1986. The analysis showed that U.S. carriers were, on average, 15% more efficient than European airlines throughout the study period. Moreover, the U.S. average technical efficiency increased from 77% (1976) to 79.4% (1986), while the European average increased from 62.9% (1976) to 64.7% (1986), respectively.

Also, Good et *al.* (1995) examined the performance of the eight largest European and American airlines, respectively, in the 1976-1986 time span. During this period the American industry was deregulated and the European industry's market was significantly liberalized. The authors concluded that US carriers were, on average, relatively more efficient by some 15-20%.

Schecfczyk (1993) measured the operational performance for a panel of fifteen international airlines for the year 1990 using DEA. The most efficient airlines were Singapore Airlines, Cathay Pacific, Federal Express and UAL Corporation. The European carriers were less efficient.

Distexhe and Perelman (1994) measured technical efficiency for thirty-three international airlines, over the time period 1977-1988. The airlines were categorized into three groups: Asia-Oceania, North America and Europe. DEA was used to construct several production frontiers of airlines activities. The results suggested that average levels of technical efficiency in the 80s were higher than those obtained in the 70s. Singapore Airlines, Japan Airlines, American Airlines, TWA, Lufthansa, Finnair, and Air France, were the most efficient carriers. Generally, the airlines from Asia-Oceania, achieved the best scores during the investigation period, while European carriers were less efficient than the others.

Alam and Sickles (1997) evaluated technical efficiency of the US airline industry and explored the link between market structure and economic performance. DEA scores of technical efficiency for a sample of eleven (11) U.S. carriers were quarterly observed, during the time period 1970-1990. The results indicated that the scores moved together and, in fact, the firms were becoming more alike one another in terms of efficiency.

Using DEA and the Malmquist productivity index, the paper by Greer (2008) examined changes in the productivity of the major U.S. passenger airlines from 2000 to 2004. The analysis concluded that there was a significant improvement in the productivity of the carriers which came about from the efficiency laggards catching up with the efficiency leaders. Also, the adoption of new technologies improved productivity.

The paper by Scheraga (2004) investigated the drivers of operational efficiency on the eve of September 11th using a sample of thirty-eight airlines from North America, Europe, Asia and the Middle East and utilizing DEA to derive efficiency scores. The paper concluded that the airlines that had chosen relatively efficient operational strategies found themselves suffering the consequences in the post-September 11th environment.

Fethi et *al.* (2000) investigated the determinants of performance of the European airline industry. The panel data set consisted of seventeen European airlines, over the period 1991-1995. The technical efficiency of individual airlines was calculated using DEA. The variables which were used were consistent with Schecfczyk (1993). The findings confirmed the negative effects of concentration and subsidy policies, on individual efficiencies. However, the ownership did not seem to effect the efficiency scores of individual airlines.

Fethi et *al.* (2001) continued their efficiency and productivity analysis of the European airline industry, over the time period 1991-1995, using a modified DEA approach. The purpose of the study was to determine whether the measured effects of airline market liberalization have resulted in efficiency changes both in level and dispersion for the companies involved. However, it was not possible to determine a liberalization effect on technical efficiency.

Furthermore, Fethi et *al.* (2008) used a panel data sample of European airlines over the 1991-1995 time span to investigate whether productivity growth was affected in the immediate aftermath of market liberalization. The empirical measurement in the paper was based on the comparison of a time-varying stochastic parametric distance function with conventional DEA used to generate an estimate of the Malmquist productivity indices. The measures of productivity change were consistent with efficiency change dominating technical change in the response to the third liberalization package in the European airline industry.

Inglada et *al.* (2006) compared the technical efficiency of international airlines, within the new liberalization framework that characterized the time period 1996-2000. For this purpose, two stochastic frontiers were estimated, one for the cost function, and the other for the production function. The data consisted of twenty international air carriers, over the time period 1996-2000. Seven of these carriers were European, six North American, one Canadian, two Mexican, and four Asian. Four air carriers from Northeast Asia were the most efficient. The European and American carriers were left behind.

The next study dealt with the effect of ownership structure on airlines' performance. Backx et *al.* (2002) examined the influence of an airline's ownership structure on multiple dimensions of its performance, in a panel data analysis using a sample of medium to large international passenger airlines (1993-1997). The empirical results showed that public sector airlines underperformed in comparison to private sector airlines, while the airlines with mixed ownership tended to perform better than public sector airlines, but worse than private sector carriers.

3. Methodological Framework

3.1 Stochastic frontier analysis

The so-called Stochastic Frontier Approach (SFA) requires a functional form in order to estimate the frontier production function and it is based on the idea that the data are contaminated with measurement errors and other noise (Bauer, 1990). The specification of the adopted model starts with the typical assumption that the technology applied in the production process can be described by a twice differentiable production function which relates the flow of output with various inputs of production. In algebraic terms the stochastic production frontier (SPF) can be expressed as (see e.g. Kumbhakar and Lovell, 2000):

$$y = f(\boldsymbol{X},\boldsymbol{\beta})\exp(\varepsilon),\ \varepsilon = (v-u),\ u>0 \qquad (1)$$

where: y is the observed output quantity; f is the deterministic part of the frontier production function, $\boldsymbol{X}$ is a vector of the input quantities, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, v is a symmetrical random error and u is a one-sided non-negative random error term representing technical efficiency. It is assumed that f is finite for every $\boldsymbol{X}$, and continuous for all nonnegative y and $\boldsymbol{X}$. The elements of v represent the conventional normal distribution of random elements. The elements of u indicate shortfalls of a firm from the efficient frontier. Thus, technical efficiency is measured as (Kumbhakar and Lovell, 2000):

$$\text{TE} = y \,/\, [f(\boldsymbol{X})\exp(v)] = \exp(-u)$$

and has a value between 0 and 1, with 1 defining a technically efficient firm. Given a parametric functional form for f and distributional assumptions about u and v, equation (1) can be estimated by Ordinary Least Squares (O.L.S.).[5]

Analytically, equation (1) can be written as (Kumbhakar and Lovell, 2000):

$$\ln(y) = \ln[f(\boldsymbol{X})] + v - u \qquad (2a)$$

$$\ln(y) = -\mu + \ln[f(\boldsymbol{X})] + (v-u+\mu) \qquad (2b)$$

where: $\mu = E(u)>0$.

The estimation by O.L.S. leads to consistent estimators under the assumption that v is normally and u is half-normally distributed.[6] Estimation of equation (2) by O.L.S. gives the residuals e_i, i = 1, 2, …, N. The second and third central moments of the residuals, $m_2(e)$ and $m_3(e)$ respectively, are calculated as follows:

$$m_2(e) = [1/(N-k)]\cdot \Sigma e_i^2 \qquad (3a)$$

$$m_3(e) = [1/(N-k)]\cdot \Sigma e_i^3 \qquad (3b)$$

where: N is the number of observations and k is the number of regressors, the constant term included. Then, we estimate σ^2_u and σ^2_v using the formulae (Georganta 1993):

$$\sigma^2_u = [(\pi/2)[(\pi/(\pi-4)]m_2(e)]^{2/3} \qquad (4a)$$

$$\sigma^2_v = m_2(e) - [(\pi-2)/\pi)]\,\sigma^2_u \qquad (4b)$$

Following Battese and Coelli (1988), the point measure of technical efficiency is:

$$\text{TE}_i = E(\exp\{-u_i\}/\varepsilon_i) = [[1-F[\sigma_\cdot-(M_i^*/\sigma_\cdot)]/[1-F_\cdot(-M_i^*/\sigma_\cdot)]\exp[-M_i^* + (\sigma_\cdot^2/2)] \qquad (5)$$

where $F_\cdot$ denotes the distribution function of the standard normal variable. Also:

$$M_i^* = (-\sigma^2_u\varepsilon_i)(\sigma^2_u + \sigma^2_v)^{-1} \qquad (6a)$$

$$\sigma_\cdot^2 = \sigma^2_u\,\sigma^2_v\,(\sigma^2_u + \sigma^2_v)^{-1} \qquad (6b)$$

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[5] Equation (1) could be estimated using the Maximum Likelihood (ML) method (Aigner *et al.* 1977). However, the O.L.S. estimators have statistical properties at least as desirable as those of the ML estimators (Olson *et al.* 1980), are easier to obtain and tend to provide encouraging results (Kumbhakar and Lovell, 2000).

[6] Half-normal and exponential distributions are traditionally employed for u. However, these two assumptions lead to very similar estimates (Caves and Barton 1990).

This model is attractive because of its simplicity. Of course, technical efficiency (TE) could be estimated in numerous ways where distributional assumptions on the two error components have to be made. The rationale behind the normality assumption is convenience at the estimation stage plus the fact that we lack information upon which to base alternative stochastic specification assumptions (Kumbhakar and Lovell, 2000). However, other distributional assumptions and methods are employed but less frequently because of their increased computational complexity (Kumbhakar and Lovell, 2000).

3.2 *Data envelopment analysis*

As discussed, for instance, in Poitras et *al.* (1996), DEA is an efficiency evaluation model based on mathematical programming techniques that offers an alternative to classical statistics in extracting information from sample observations. In contrast to parametric approaches, DEA optimizes each individual observation with the objective of calculating a discrete piece-wise frontier determined by the set of Pareto efficient Decision Management Units (DMUs). An advantage of DEA is that multiple inputs and outputs can be considered simultaneously. Furthermore, DEA is non-parametric and requires no specific functional form for the production function (Fried *et al.* 1993). For many applications, these features make DEA a flexible tool.

DEA constructs a relative efficiency measure based on a single "virtual" output and a single "virtual" input. Because DMUs on the efficient frontier have efficiency score equal to 1, inefficient DMUs are measured relative to the efficient DMUs. The efficiency ranking is relative to other DMUs.

Mathematically, assume that there are n DMUs to be evaluated with DMUj. consuming varying amounts of m different inputs to produce s different outputs. Specifically, DMUj consumes amounts Xj = {xij} of inputs (i = 1,....., m) and produces amounts Yj = {yrj} of outputs (r = 1,....., s). The s × n matrix of output measures is denoted by Y, and the m ×n matrix of input measures is denoted by X. Also, assume that xij > 0 and yrj > 0. Consider the problem of evaluating the relative efficiency for any one of the n DMUs, which will be identified as DMU0. Relative efficiency for DMU0 is calculated by forming the ratio of a weighted sum of outputs to a weighted sum of inputs, subject to the constraint that no D.M.U can have a relative efficiency score greater than unity, as follows (7):

$$\max_{u,v} \frac{\sum_r u_r y_{ro}}{\sum_t v_t x_{to}} = \frac{u^T Y_0}{v^T X_0} \quad \text{where } u = (u_1,\ldots,u_s)^T,\ v = (v_{1,\ldots,}v_m)^T \qquad (7)$$

Subject to:

$$\frac{u^T Y_j}{v^T X_j} = \frac{\sum_r u_r y_{rj}}{\sum_t v_t x_{tj}} \leq 1$$

$$\textit{for } j = 1, 2, \ldots, n;\ u_{r,} v_i \geq 0 \ \textit{for } r = 1,2,\ldots,s,\ i = 1,2,\ldots,n$$

where: ur and vi are weights assigned to input r and output i respectively.

For this fractional programming problem with a potentially infinite number of optimal solutions, Charnes et *al.* (1978) were able to specify an equivalent linear programming problem. This requires introduction of a scalar quantity (θ) to adjust the input and output weights:

$$\theta = \frac{1}{v^T X_0}, \quad \mu^{\mathrm{T}} = \theta u^T, \quad \omega = \theta v^T$$

Appropriate substitutions produce the following linear programming problem:

$$\max_{\mu,v} \Lambda_0 = \sum_r \mu_r y_{r0} = \mu^{\mathrm{T}} Y_0 \qquad (8)$$

subject to:

$$\omega^T X_0 = \sum_t \omega_t x_{t0} = 1, \sum_r \mu_r y_{rj} - \sum_t \omega_t x_{tj} \le 0, \mu_{r,} \omega_t \ge \varepsilon$$

where Λ_0 is the relative efficiency of DMU_0 and ε, is a positive constant.

4. Data

The panel data set consists of annual observations for the twenty-four (24) largest international network carriers in the time period 1991-2000.[7] The airlines come from: five (5) from the U.S.A.; eight (8) from Europe; seven (7) from southeastern Asia; one (1) carrier from Canada; two (2) from South America and one (1) comes from Australia. The airline companies are private, public or mixed. Also four (4) of them changed ownership during the study period. Specifically, Swissair, Lufthansa and SAS, which until 1996 were mixed, they then became private, and Varig, which was private until 1996, it then became mixed.

The main source of the data is Air Transport World (Vol. 29-40, June 1992- June 2001). Also, the data set was based on the kind of service the carriers offer, since they all had to be oriented mainly towards passengers' transportation. The carriers should also serve as international carriers, while they should annually carry at least 2500000 passengers. Finally, all the carriers should be of large-scale.

The panel consists of variables that are typically used in relevant studies in the literature and has been subject to data availability. Analytically, we use three (3) input variables and one (1) output variable. The output is measured as the total annual passenger-kilometers. The inputs are: (1) the total number of persons employed annually which practically means employee headcounts (pilots, co-pilots, cabin attendants, etc.); (2) the total annual energy expanded (fuel and oil) in physical units consumed; and (3) total annual available annual aircraft capacity, which practically means the total number of aircrafts that each carrier uses for passenger operations.[8]

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[7] The year 2001 is not included in the analysis because the events of September 11 and the enhanced security procedures as well as the drop-off in passenger traffic undoubtedly had an impact on airline technical efficiency.

[8] At this point it should be noted that the results of our investigation are largely dependent on the variables used, the selection and quality of which has been subject to data availability. More precisely, one problem with employee headcount data is that different airlines have different mixes of full-time and part-time employees. Because raw headcount data are being used in this paper, airlines that rely more heavily on full-time employees will be advantaged in their efficiency scores compared to airlines that rely more heavily on part-time employees. Ideally, the labor data should be on full-time equivalent employees. Unfortunately, no relevant data are available so as to further elaborate on this. Moreover, another problem with the fuel variable is the fact that part of an airline's fuel consumption is attributable to cargo hauling instead of passenger hauling, and different airlines place different emphases on the passenger and cargo operations. More specifically, an airline that has a relatively large cargo-hauling operation will be disadvantaged in the efficiency analysis, which would implicitly assume that all fuel is use in the passenger-hauling function. If the fuel variable is not adjusted to take this into account, then the airline efficiency scores could be, at least partly, misleading. Of course, a similar concern would seem to

5. Empirical Results

From a methodological point of view the question of efficiency is examined by estimating the Cobb-Douglas specification of the production function[9]:

$\ln Y = a_o + a_1 T + a_2 \ln K + a_3 \ln L + a_4 \ln E + v - u$

where: Y is a measure of output, T is a measure of time expressing technological change, K a measure of capital stock, L is a measure of labor, and E a measure of energy spending. Table 1 presents the estimate of the production function.

Table 1: Production function estimate

Determinant	Value	T-statistic
a_0	1.318	2.857*
a_1	0.034	4.605*
a_2	0.299	5.273*
a_3	0.269	3.766*
a_4	0.458	8.075*
R^2	0.838	
$Radj^2$	0.829	
D.W.	1.893	
S.E.E.	0.316	

Turning now to the regression results reported in Table 1, we can see that the estimated coefficients are highly significant for all parameters. Consequently, there is no need to remove any variable from the model. The regression explains a very high 83.8% of the variability of output. Also, there are no signs of serious violation of the other basic assumptions concerning the residuals, as was easily confirmed with the aid of the relevant procedures: specifically, the normality of the errors was assessed through the examination of the frequency distribution of the residuals as well as by reference to the Q-Q and P-P normality plot for checking normality. As far as the assumption of homoscedasticity is concerned, compliance with this assumption was evaluated by examination of the scatter plot of the standardized residuals against the predicted values. Finally, as for the assumption that the residuals are independent of each other, investigation of the scatter plot of the standardized residuals against the time variable provided no evidence of autocorrelation of the residuals as was the case with the D.W. statistic, as well.[10] These results clearly imply that the estimated model is very satisfactory.

Since the total output and the regressors are expressed in *logs,* the coefficients are directly interpretable as output elasticities. As we know, returns to scale (RTS) are calculated from the sum of the inputs' coefficients as[11]:

$R.T.S. = a_2 + a_3 + a_4 = 0.299 + 0.269 + 0.458 = 1.026$

This result implies that the air transportation industry practically experiences constant returns to scale. This result is consistent with the findings by Good et *al.* (1993) who found that RTS for the air transportation industry is equal to unity. Finally, since a_1 which expresses the average annual

apply to the labor variable when different airlines have different mixes of passenger-hauling and cargo-hauling. We would like to thank an anonymous referee for this insightful comment.

[9] Specifications such as the translog provide the opportunity to characterize the data in a more flexible way. However, the translog specification tends to be seriously over-parameterized and, following Coelli *et al.* (1998), the translog estimates are likely to suffer from degrees of freedom and multicollinearity problems resulting in inefficient estimates.

[10] Any results not illustrated explicitly are available upon request by the authors.

[11] Note that if: (i) $a_2 + a_3 + a_4 = 1$, then there are constant returns to scale, (ii) $a_2 + a_3 + a_4 < 1$, decreasing returns to scale and (iii) $a_2 + a_3 + a_4 > 1$, increasing returns to scale.

growth rate of technology was found to be equal to 3.4%, the positive effect of technological progress in the model is confirmed.

The next step is to estimate the annual technical efficiency (T.E.) for each carrier, for the 1991-2000 time span. Summary statistics for technical efficiency are presented in Table 2. The same data was employed to estimate technical efficiency using D.E.A (Synodinos, 2005). The efficiency estimates computed by DEA are used for the comparison with SFA estimates (Table 2). See section 6.1 (below).

Table 2. Results of efficiency estimates

Carrier	SFA	DEA
United airlines	0.938	0.706
American airlines	0.909	0.645
Delta airlines	0.929	0.697
Northwest airlines	0.935	0.708
British airways	0.926	0.617
Japan airlines	0.957	0.790
Continental ailines	0.917	0.687
Swissair	0.714	0.472
Lufthansa	0.757	0.392
Air france	0.773	0.444
Qantas airways	0.952	0.722
Singapore airlines	0.968	0.926
KLM	0.941	0.719
All Nippon airlines	0.914	0.640
Aeromexico	0.875	0.595
SAS	0.512	0.261
Cathay pacific	0.965	0.824
Korean airlines	0.921	0.559
Alitalia	0.795	0.424
Air Canada	0.839	0.500
Thai international	0.941	0.672
Garuda	0.776	0.532
Iberia	0.742	0.411
Varig airlines	0.848	0.492
Mean	*0.864*	*0.601*
Standard Deviation	*0.132*	*0.157*

The SFA average technical efficiency of all the carriers with only one exception is over 70% while technical efficiency of fourteen of the twenty four carriers is over 90%. Figure 1 shows the average technical efficiency, by continent of origin. The U.S. carriers are - on average - the most efficient carriers, with an average technical efficiency equal to 92.55%. The Asian carriers follow with 92.04%, and then the South American carriers with 86.14%, while, the European carriers with 77.00% are the least efficient. It should be noted that the Canadian carrier and especially the Australian Qantas Airways are highly efficient with 84% and 95.2% average technical efficiency measures, respectively.

Next, figure 2 suggests that the average annual technical efficiency of the carriers of the sample does not follow a clear trend in time. More precisely, the least efficient are the years 1991 and 2000 with measures equal to 82.57% and 85.04% respectively, while the years 1996 and 1997 are the most efficient years with an average equal to 87.95% and 88.01% respectively.

Also, figure 3 illustrates graphically that the private carriers are indeed the most technically efficient. Specifically, the average technical efficiency measures of eleven of the thirteen private carriers range is equal to 92.12%. The carriers with mixed state ownership appear less efficient (87.38%) than the private ones. Finally, public carriers appear far less efficient (75.89%).

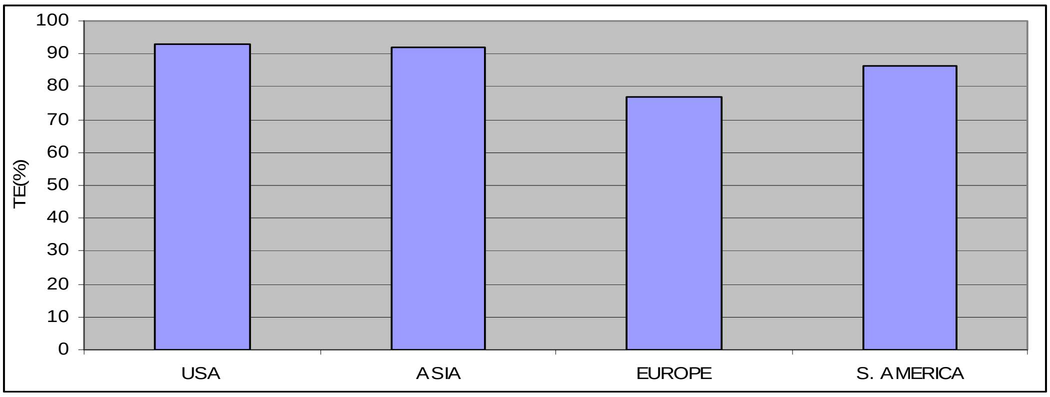

Figure 1. Average Technical Efficiency (%) by Continent of Origin

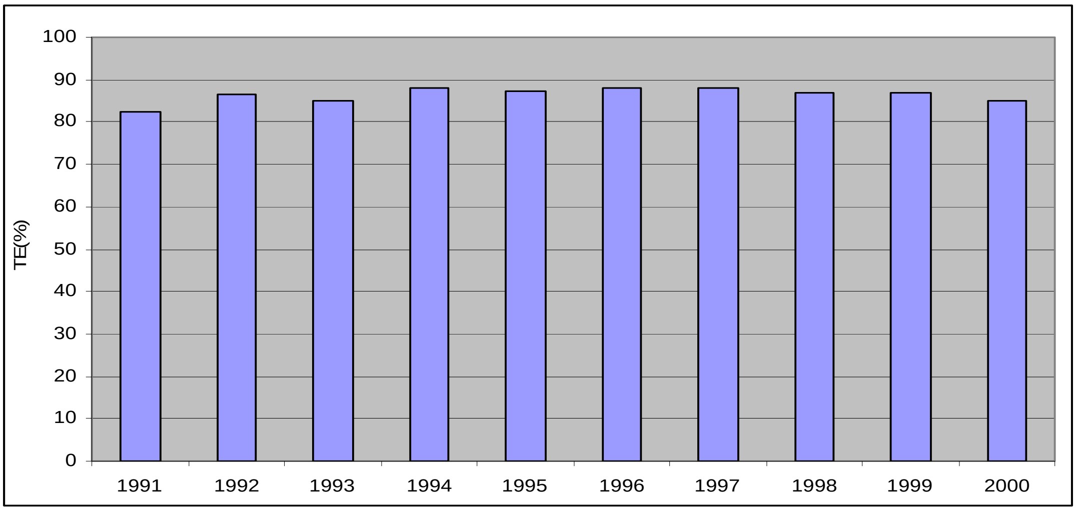

Figure 2. Average Annual Technical Efficiency (%)

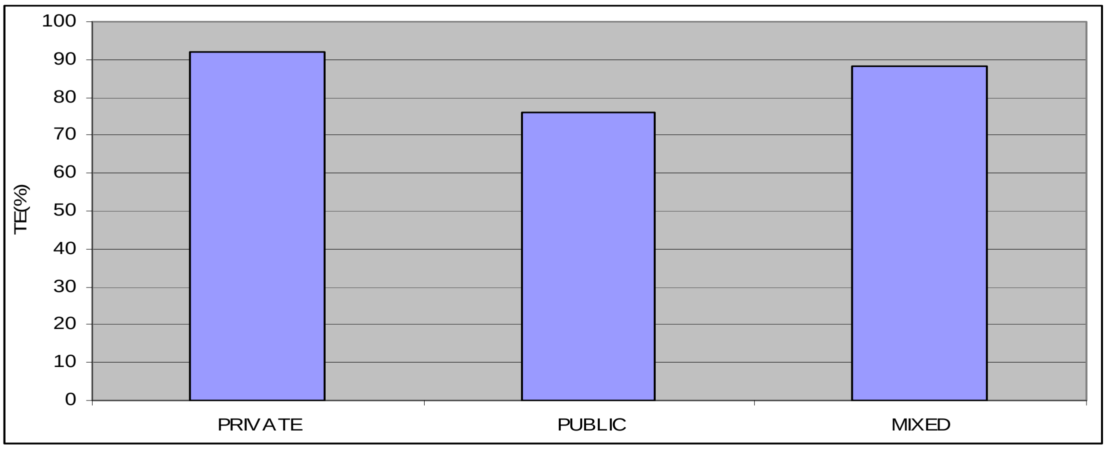

Figure 3. Average Technical Efficiency (%) per State Ownership

Regarding the carriers which changed ownership status within the study period, the change didn't affect their technical efficiency levels, at least in a consistent way. More specifically, the average technical efficiency of Swissair before the privatization was 73.23%, and 68.68% after, of Lufthansa 74.89% and 76.87% after, and of SAS 51.97% and 50.19% after. Finally, Varig experienced an increase of its technical efficiency score from 83.36 to 86.96%.

Our empirical results are consistent, in general terms, with the findings by other researchers (e.g. Good et al., 1993; Good et al., 1995; Schefczyk, 1993; and Inglada et al., 2004). For instance, these studies conclude that the Asian and U.S. carriers appear to be relatively more technically efficient. More specifically, Singapore Airlines and Cathay Pacific rank in the top positions in most of these studies. Contrary to this, the European carriers are considerably less efficient, except for KLM and British Airways. They are also consistent with the findings by Backx et al. (2002), as the private airlines appear to be more efficient than the mixed which, in turn, are more efficient than the public ones.

6. Discussion

6.1 Comparison with DEA

Table 2 presents the average technical efficiency of each carrier of the sample, estimated by the two different approaches, the parametric SFA and the non-parametric DEA for the 1991-2000 time span. The average technical efficiency estimated by DEA is lower than the one estimated by SFA as conventional DEA cannot discriminate between inefficiency and noise (Bruemmer, 2001).

Figure 5 illustrates that the SFA and DEA estimates of technical efficiency follow a similar pattern in time.

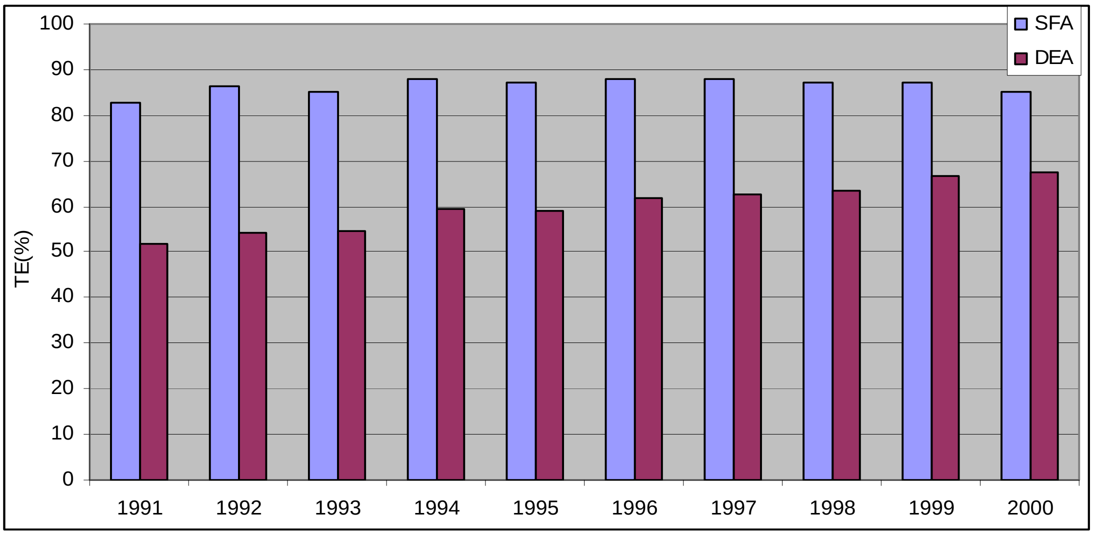

Figure 5. Average Annual Technical Efficiency

The correlation coefficient and the ranking correlation index confirm the consistency of the empirical results derived by these two different methodologies. The correlation coefficient based on the estimates of the two different methods (see Table 2) is 89%, which is considered as very satisfactory for this type of investigations. Meanwhile, Table 3 illustrates the carriers' ranking. The corresponding ranking correlation is 94.87%, which is also very high. This means that, regardless of the method used, the carriers' ranking is almost identical.

Table 3. Airlines' Ranking

Ranking	SFA	DEA
1	Singapore Airlines	Singapore Airlines
2	Cathay Pacific	Cathay Pacific
3	Japan Airlines	Japan Airlines
4	Qantas Airways	Qantas Airways
5	Thai International	KLM
6	KLM	Northwest Airways
7	United Airlines	United Airlines
8	Northwest Airways	Delta Airlines
9	Delta Airlines	Continental Airlines
10	British Airways	Thai International
11	Korean Airlines	American Airlines
12	Continental Airlines	All Nippon Airlines
13	All Nippon Airlines	British Airways
14	American Airlines	Aeromexico
15	Aeromexico	Korean Airlines
16	Varig Airlines	Garuda Airlines
17	Air Canada	Air Canada
18	Alitalia	Varig Airlines
19	Garuda Airlines	Swissair
20	Air France	Air France
21	Lufthansa	Alitalia
22	Iberia	Iberia
23	Swissair	Lufthansa
24	SAS	SAS

It can be inferred from Table 3 that all four of the top-ranked airlines fly a very high proportion of long-haul routes, probably (among) the highest of all other airlines in the dataset. In this context, it is possible that their high efficiency scores are attributable, at least partly, to the long average stage-length of their flights, since those resources used in the terminal function are spread over more passenger-kilometers, the longer the stage length is.

Next, it can be inferred from Table 4 that the SFA and DEA annual estimates of technical efficiency are highly correlated.

Table 4. TE Estimates' Correlation by Year

Year	Correlation
1991	0.897
1992	0.871
1993	0.902
1994	0.881
1995	0.883
1996	0.832
1997	0.782
1998	0.798
1999	0.836
2000	0.744

Furthermore, regardless of the methodology used, the U.S. and the Asian carriers appear to be the most technically efficient. The carriers from South America follow, while the European carriers are far less efficient. In other words, both methodologies produce consistent results (see Figure 6, Table 5).

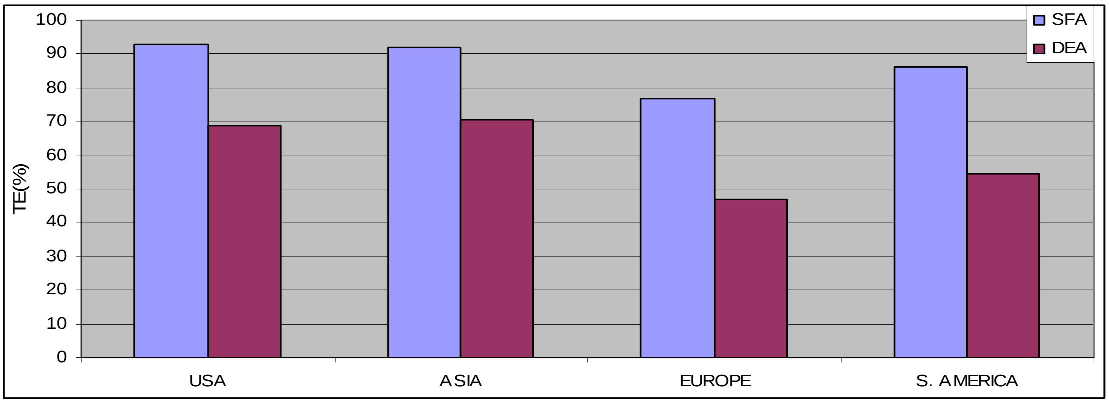

Figure 6. Average Technical Efficiency (%) by Continent of Origin

Table 5. TE Estimates by Continent of Origin

Continent	TE % (SFA)	TE % (DEA)
USA	92.55	68.87
Asia	92.04	70.62
Europe	77.63	47.33
S. America	88.36	53.86

6.2 *Privatization*

Although the number of airline companies that changed ownership status during the study period is not large enough so as to infer about the effect of these change on the airlines' technical efficiency, the importance of this issue cannot be ignored. As it was mentioned earlier, the airlines which changed state ownership during the study period were: Swissair, Lufthansa and SAS in Europe, which until 1996 were mixed and after 1996 became private. There is also Varig in Asia which until 1996 was private and then became mixed.

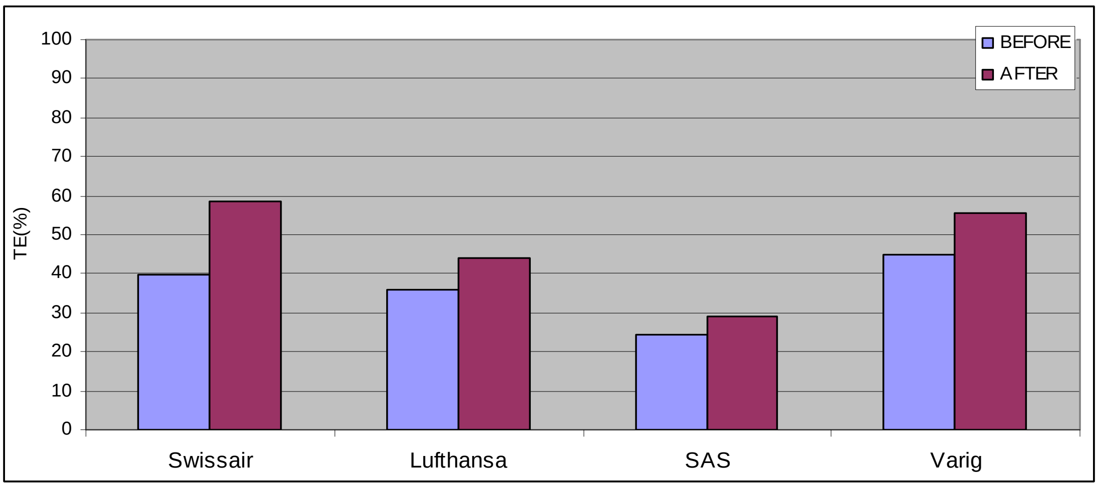

Figure 7. Average Technical Efficiency and Change of the State Ownership in DEA

As it was illustrated earlier (Section 5), there is no clear evidence about the impact of the state ownership change. In fact, Lufthansa and Varig experienced an increase in terms of technical efficiency while Swissair and SAS experienced a decrease. See Figure 7 where we note that both methodologies produce consistent results.

Also, as illustrated in Figure 8 and Table 6, private carriers appear to be the most technically efficient, while the mixed ownership carriers are less efficient and the public ones are the least efficient. Once again, we note that both methodologies produce consistent results.

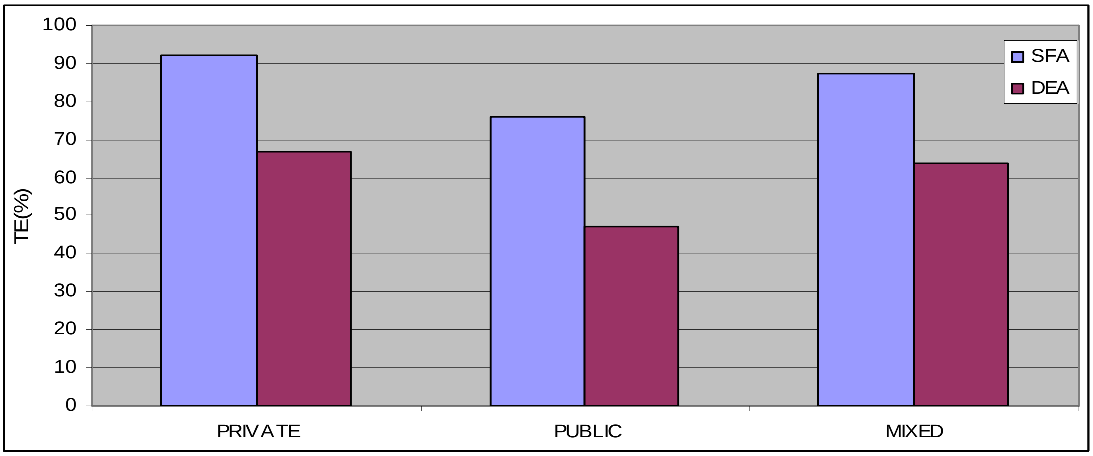

Figure 8. Average Technical Efficiency (%) by Ownership Structure

Table 6. TE Estimates by Ownership Structure

Ownership	TE % (SFA)	TE % (DEA)
Private	92.12	66.86
Public	79.06	47.18
Mixed	91.18	63.69

Finally, despite the fact that the sample is quite large, very few airline carriers changed ownership structure. Consequently, it cannot be inferred whether a change in the ownership structure affected the carriers' technical efficiency.

7. Conclusions

The present paper estimated technical efficiency in International Air Transport, within the framework of Stochastic Frontier Analysis (SFA). It was based on Panel Data for twenty four (24) airline network carriers worldwide, over the time period 1991-2000 by employing the Cobb-Douglas specification of the production function.

A first finding of our investigation was that air transportation carriers, worldwide, experienced almost constant returns to scale. A second interesting result was that technical efficiency of air transportation carriers, worldwide, ranged between 51.20% and 96.80% with an arithmetic average equal to 86.40%. However, the industry's performance worldwide in terms of technical efficiency did not follow a clear trend in time, whereas some differences in performance depending on the corporation's continent of origin were observed. More precisely, the American, Australian and Asian have left behind the European carriers. Also, the level of technology experienced a slight increase, while the privatization of very few air transportations did not seem to consistently affect their performance in terms of technical efficiency. Finally, the SFA results were compared with the results using DEA and the two methodologies were found to produce largely consistent results.

In closing, we would like to stress that all estimates of technical efficiency are subject to a margin of error. Also, the production function estimate is contingent on the quality of the variables used. In other words, the methodology we used is popular and appropriate but it should be treated with caution since the measures of technical efficiency are estimates whose accuracy cannot be treated as certain. For the case of the International Air Transportation Carriers the uncertainty may indeed increase as the panel data set is heterogeneous and the industry seems to have undergone some significant changes during the 1990s.

Of course, there are still several issues that could serve as good examples for future investigation which go beyond the widening of the database and the inclusion of a dummy variable to account for the change in the ownership structure of the firms. For instance, one could make an attempt to identify the causal factors that are associated with efficiency performance and incorporate them into the model. Moreover, one could make an effort to extend the model to account for spillovers across sectors. No doubt, future and more extended research on the subject would be of great interest.

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