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The Relative Efficiency of International, Domestic, and Budget Airlines: Nonparametric Evidence

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ABSTRACT

This study determines whether the inclusion of low-cost airlines in a dataset of international and domestic airlines has an impact on the efficiency scores of so-called 'prestigious' purportedly 'efficient' airlines. This is because while many airline studies concern efficiency, none has truly included a combination of international, domestic and budget airlines. The present study employs the nonparametric technique of data envelopment analysis (DEA) to investigate the technical efficiency of 53 airlines in 2006. The findings reveal that the majority of budget airlines are efficient relative to their more prestigious counterparts. Moreover, most airlines identified as inefficient are so largely because of the overutilization of non-flight assets.

JEL classifications: D24, L93.

Keywords: data envelopment analysis, efficiency, airlines.

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1. Introduction

Many extant studies concern airline efficiency, including Schefczyk (1993), Banker and Johnston (1994), Good, Roller and Sickles (1995), Charnes, Galleous and Li (1996), Gillen and Lall (1997), Tofallis (1997), Alam, Semenick and Sickles (1998), Adler and Golany (2001), Scheraga (2004) and Inglada et al. (2006), among others. However, most of these studies focus on major airlines and the results generally suggest high levels of technical efficiency, especially in the case of Asian airlines such as Cathay Pacific and Singapore Airlines. In empirical justification, Inglada et al. (2006), for instance, argue that Singapore Airlines and Cathay Pacific have characteristics that made them more efficient than other (e.g., US) airlines because of their "…prestigious reputation, for their passenger customer service, efficient collection and delivery of baggage, the cleanliness of their aircraft, and so on". This is somewhat confusing in that the question at hand is whether quality of service translates into efficiency, complicated by the fact that a focus on quality of service does not necessarily increase output.

In addition, existing studies in this area generally concern airlines with relatively similar cost structures. That is, a standard flight may include a range of on-board costs, typically in-flight entertainment, beverages, and meals. However, while these on-board costs are common among major international airlines, they are not in most budget airlines or in other airlines with the objective of a low cost structure. Indeed, Scheraga (2004) is the only known study to include the analysis of airline efficiency across the wide range of cost structures found in the industry. Further, the number of individual airlines included in past work is relatively small and these do not typically include budget airlines. When considering the sampling of the airlines in these studies, one would then expect a considerable portion to be efficient as most are possibly already adopting best practice and have learnt from longstanding past experiences in operations and management. Accordingly, the very restricted criteria used to include airlines in existing studies implies a very heterogeneous sample of airlines, many of which appear relatively efficient given the absence of markedly different input/output combinations as comparators.

In order to investigate whether large and prestigious airlines are truly efficient, this study includes other airlines, both domestic and international, including those with manifestly different cost structures. In essence, the inclusion of budget airlines should provide an alternative perspective on airline efficiency not hitherto investigated. One qualification that is important to note at the outset is that given the diversity of airlines included in the sample, at least some do not operate in competition with others. For example, domestic airlines operating within the United States are not competing with domestic airlines primarily operating in Europe. Therefore, the study is effectively excluding the issue that competition is a factor of concern in the analysis of efficiency. The focus of the study is twofold. First, determine whether the inclusion of differently cost-structured airlines influence the relative efficiency of major airlines; second, explain the differences in the inefficiencies observed.

The paper itself is divided into five main sections. Section 2 presents the empirical methodology employed in the study. Section 3 describes the inputs and outputs employed and the limitations faced. Section 4 discusses the technical and scale efficiency scores. The paper concludes with some brief remarks.

2. Methodology

We employ the data envelopment analysis (DEA) approach to measure the efficiency of ‘decision making units’ or DMUs. Developed by Charnes, Cooper, and Rhodes (CCR) in 1978, DEA is a nonparametric method that does not require the specification of the functional form relating inputs to outputs or the setting of weight for the various factors. Hence, DEA optimizes at each observation for constructing an efficient frontier—the maximum output empirically obtainable for any DMU in the observed population, given its level of inputs. The distance to the frontier and a measure of efficiency are then assessed using a mathematical method. Frontier estimation employing DEA methodology has been applied to many studies relating to air transportation, including Schefczyk (1993), Banker and Johnston (1994), Good, Roller and Sickles (1995), Charnes, Galleous and Li (1996), Gillen and Lall (1997), Alam, Semenick and Sickles (1998), and Adler and Golany (2001). Following the CCR model, consider S air carriers, each producing m outputs using n inputs. The efficiency of the DMU is measured as follows:

$$h_s = \sum_{i=1}^{m} u_i y_{is} / \sum_{j=1}^{n} v_j x_{js} \qquad (1)$$

where y_{is} is the amount of ith output produced by the sth airline, x_{js} is the amount of jth input used by the sth airline, u_i is the output weight, v_j is the input weight, i=1,2,…,m, and j=1,2,…,n. The efficiency ratio (h_s) is then maximised subject to the following:

$$\sum_{i=1}^{m} u_i y_{ir} / \sum_{j=1}^{n} v_j x_{jr} \leq 1 \text{ for } r = 1, \ldots, n \text{ and } u_i \text{ and } v_j \geq 0 \qquad (2)$$

This constraint ensures that the efficiency ratios for all airlines must be less than or equal to one and that the weights are positive. The weights are determined such that each airline maximises its own efficiency ratio. This fractional linear program (2) can be transformed into the following equivalent linear programming problem:

$$\max\ w_s = \sum_{i=1}^{m} u_i y_{is} \qquad (3)$$

subject to:

$$\sum_{j=1}^{n} v_j x_{jr} = 1 \qquad (4)$$

$$\sum_{i=1}^{m} u_i y_{ir} - \sum_{j=1}^{n} v_j x_{jr} \le 0$$

$$u_i \ge \varepsilon$$

$$v_j \ge \varepsilon$$

whose linear programming dual is:

$$\min\ z_s = \theta - \varepsilon \sum_{i=1} s_i^+ - \varepsilon \sum_{j=1} s_j^- \qquad (5)$$

subject to:

$$\sum_{s} \lambda_r Y_r - s^+ = Y_s$$

$$\theta X_r - \sum_{s} \lambda_r X_r - s^- = 0$$

$$\lambda_r, s_i^+, s_j^- \ge 0 \qquad (6)$$

Where Y is the $r \times m$ matrix of output measures, X is the $r \times n$ matrix of input measures, θ is the proportional reduction applied to all inputs of a DMU to improve efficiency, and ε is an infinitesimal constant which effectively allows the minimisation of θ to pre-empt the optimisation involving the slacks (s^+ and s^-), where s^- imply input surpluses and s^+ imply output shortfalls. The vector λ defines a point on the envelopment surface. As the current study employs a constant returns-to-scale (CRS) model, this point is a linear combination of airlines that lie on the envelopment surface. Both the primal (envelopment form) and dual problem (multiplier form) always have solutions; hence the duality theorem of linear programming can be used to guarantee that $z_s = w_s$ (i.e. equation (3) = equation (5)). Thus if $z_s = w_s = 1.00$ and all slacks are zero, then the airline is operating at the most efficient level and lies on the envelopment surface.

3. Data and specification of inputs and outputs

The data used in the study are dependent on how the operations of airlines are characterised. As the focus lies on airline performance and efficiency, we adopt the model in Schefczyk (1993) in which finance/purchasing 'sells' available ton kilometres and other inputs to operations. In turn, operations 'sells' revenue passenger kilometres (RPK) and other services to marketing, which in turn determine the pricing structure and sell the airline's products to customers. Drawing on Schefczyk (1993), we define the two outputs as revenue passenger-kilometres (RPK) and non-passenger revenue and the three inputs as available ton-kilometres (ATK), operating costs, and non-flight assets (NFA)

Here RPK, also referred to as "traffic", is one revenue-paying passenger transported one kilometre. This equals the number of revenue passengers during some report period multiplied by the number of kilometres flown by passengers during that period. Non-passenger revenue is total operating revenue less total passenger revenue. This figure thus reflects the revenue generated from non-passenger activity. Available ton-kilometres are the sum of available ton kilometres for scheduled and chartered services. This figure then reflects the available aircraft capacity. Operating cost is total operating expenses less aircraft rent and depreciation and amortization. This figure then reflects operating costs excluding capital costs. Non-flight assets reflect all assets not already reflected by available ton-kilometres, and potentially include facilities, office equipment, reservation systems, and other current assets.

The study focuses on the 2006 with the data primarily drawn from the International Civil Aviation Organization Data (ICAOData). The ICAOData provides information on 162 air carriers of which 53 air carriers makes up the dataset in our analysis. We omit the remaining carriers because of missing data. Where possible, we supplement the data using the World Air Transport Statistics (WATS). As this essentially incorporates information from ICAO, it helps ensure consistency in our dataset. When asset data is not available (especially for airlines operating within China), data from annual reports is necessarily relied upon.

<TABLE 1 HERE>

The data on revenue and costs drawn from ICAOData are in USD. We convert these back into their national currencies before converting them into a numeraire currency using transport purchasing power parity (PPP). The PPPs are from the World Bank's (2008) Global Purchasing Power Parities and Real Expenditures: 2005 International Comparison Program. These PPPs, however, relate to 2005 as the benchmark year and were extrapolated to 2006 using the following expression:

$$PPP_{j,t+1} = PPP_{j,t} \times \frac{Transport\ Def_{j,(t,t+1)}}{Transport\ Def_{US,(t,t+1)}} \tag{7}$$

where $PPP_{j,t}$ is the PPP for country j in period t relative to the United States. The national price movements are measured through the transport, storage, and communications deflator for the period *t+1* relative to period *t* under the assumption that the deflators are representative of the changes in prices of air carriers. Table 1 presents the data used in deriving the efficiency scores.

4. Empirical results

We employ two alternative assumptions to obtain the required DEA measures of technical efficiency: namely, constant returns-to-scale (CRS) and variable returns-to-scale (VRS). An assumption of constant returns-to-scale is most suitable where the premise is that there is less opportunity for airlines to engage in mergers or acquisitions, or undertake divestitures and less limited to operating in a specific region through regulation (Schefczyk, 1993). In contrast, an assumption of variable returns-to-scale is most appropriate for budget airlines that only begun operations during the mid-2000s, meaning that their underlying production functions are unknown. We adopt an input-oriented model to analyse airline operational efficiency in view of the objective of airlines to obtain the efficient utilisation of resources. The use of input-oriented model is also driven by the fact that the current study aims to compare airlines of various cost structures and their level of efficient allocation of resources. Table 2 details the efficiency scores and the airline rankings.

<TABLE 2 HERE>

In Table 2, airlines with a technical efficiency score of 1.00 are operating efficiently and lie on the carrier production frontier in 2006. As shown, eight airlines under CRS are then fully efficient: Allegiant Air, Continental Airlines, Czech Airlines, EasyJet Airlines, Oman Aviation Services, SATA Internacional, SkyEurope Airlines, and US Airways. Among these eight airlines, three are budget carrier: Allegiant Air, EasyJet Airlines, and SkyEurope Airlines. The least efficient airline is Frontier Airlines with a technical efficiency score of 0.443. Theoretically, this implies that Frontier Airlines would have to reduce its input consumption by 55.7 percent of its current level to become technically efficient. By comparing the budget airlines with other airlines, it is apparent that budget airlines are relatively more efficient, with the exception of Frontier Airlines. The overall results show an average efficiency score of 0.773 and a standard deviation of 0.142. From the results in Table 2, major airlines such as Cathay Pacific and Singapore Airlines are not as efficient as the literature asserts; see Schefczyk (1993), Tofallis (1997), Scheraga (2004) and Inglada et al. (2006).

However, Schefczyk (1993) pointed out that one limitation of DEA is that when the sample size is small (as here), the results can lead to many DMU's being assessed as technically efficient. One way the current study used to address this concern was by including a variety of airlines of different cost structures in the sample. The current study investigates this phenomenon by also undertaking a separate DEA analysis of nineteen major airlines, including Air Canada, British Airways, Cathay Pacific, Korean Airlines, Qantas, and Singapore Airlines. The results (not shown) indicated that all of these airlines (with the exception of Cathay Pacific with a score of 0.927), were fully efficient (scoring 1.00). However, the results from Table 2 show that the inclusion of other airlines with different cost structures reveal quite a different outcome. The current study shows that most of these airlines, except Qantas which dropped slightly to 0.912, to be relatively inefficient: Air Canada from 1.00 to 0.679, British Airways from 1.00 to 0.599, Cathay Pacific from 1.00 to 0.736, Korean Airlines from 1.00 to 0.823, and Singapore Airlines from 1.00 to 0.686. Besides the error of making claims that airlines such as Singapore Airlines and Cathay Pacific are efficient based on a limited sample size and the choice of airlines included, the labelling of airlines as 'prestigious' can clearly lead to erroneous conclusions.

Inglada's et al. (2006) comment on Singapore Airlines and Cathay Pacific having characteristics that made them more efficient, to some extent, is also inaccurate according to the results in the current paper. This is largely due to how one determines what inputs eventually result in the appropriate outputs. First, passenger customer service and the efficient handling of baggage has no connection to RPK nor non-passenger revenue. In fact, baggage handling is undertaken by airport staff and has little to do with the airline. It is then vital to clearly separate the production functions of airports and airlines as these are typically independent. Nevertheless, if one wishes to take into account the efficiency of baggage handling as a form of output, then the time taken for baggage to be transported from plane to baggage belt needs to be considered. However, we do not consider this in our study as we focus on revenue passenger-kilometres and non-passenger revenue as outputs. Second, the cleanliness of aircraft also does not make an airline more efficient. In fact, this should result in less efficiency if one considers the additional investment in cleaning equipment required.

Under VRS, seventeen airlines are now efficient. In addition to the above, nine other airlines have now become efficient; American Airlines, Delta Airlines, ExpressJet Airlines, JAL, Korean Airlines, Qantas, Singapore Airlines, SouthWest Airlines, and United Airlines. Interestingly, eight of the nine airlines are some of the largest airlines (in terms of ATK) and exhibit some evidence of decreasing returns-to-scale (that is, they are too large and contracting scale would result in an improvement in technical efficiency). The overall results show an average value of 0.846 and a standard deviation of 0.140. Table 3 includes the detailed results for the abovementioned airlines, which aims to interpret the information and provide an understanding of which inputs require better utilisation.

<TABLE 3 HERE>

From the results presented in Table 3, seven of the nine airlines exhibit inefficient utilisation of non-flight assets. This observation is also evident in most of the other airlines (not shown) exhibiting inefficient utilisation of this input. As NFA mainly reflects assets not part of flight operations, one has to question whether activities such as facilities, office equipment, reservation systems and current assets have anything to do with RPK and/or non-passenger revenue. Such input needs to be closely examined to determine its link to the outputs in concern, but this is not the focus of the current study as this discussion requires greater detail in the dataset. To determine whether NFA should be considered in the current study and its impact on the efficiency scores, a CRS and VRS DEA is attempted again but with 2 outputs and 2 inputs with input NFA not included in the analysis. The results shown in Table 4 are interesting in that the efficiency scores are more or less the same as before, with the exception of Airtran Airways, ExpressJet, Jet2.com and, to some extent, Allegiant Airlines, JetBlue Airways, Mid-West Airlines, Frontier Airlines, Pinnacle Airlines and SouthWest Airlines. What Table 4 reveals is that the input NFA is not significant enough to affect the efficiency scores in most airlines. While some airlines have shown a slight decline in efficiency, it is worth noting that the majority of these airlines are the budget airlines.

<TABLE 4 HERE>

Conclusion

The present study uses the nonparametric technique of DEA to investigate the relative technical efficiency of 53 airlines comprising domestic, international and budget airlines. The main contribution of the paper is the extension of empirical work to include budget airlines in measuring airline efficiency. Under a two output–three input CRS, eight airlines were found to be efficient; these were Allegiant Air, Continental Airlines, Czech Airlines, EasyJet Airlines, Oman Aviation Services, SATA Internacional, SkyEurope Airlines, and US Airways, of which three are budget airlines: Allegiant Air, EasyJet Airlines, and SkyEurope Airlines. Other major airlines, including Cathay Pacific, JAL, Korean Airlines and Singapore Airlines, have relatively low levels of technical efficiency mostly because of the inefficient utilisation of non-flight assets. The airline efficiency analysis was further tested by employing a subset of only 19 major airlines. With this test acting as our control, the results revealed that the abovementioned airlines had become more efficient thus suggesting that the choice of airline in the sample does affect the relative efficiency scores.

When VRS was employed, the airlines' efficiency scores improved, indicative of the presence of decreasing returns-to-scale. The study further adopted a two output–two input DEA analysis to determine whether the input NFA played a significant role in the efficiency scores. The significant number of airlines exhibiting slacks in this input was the main reason for this extension of analysis. The outcome revealed that this input had little impact on the technical efficiency scores in both CRS and VRS thus suggesting that this input needs closer inspection concerning its relationship with the outputs specified.

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Table 1: Input/Output data for 53 airlines, 2006					
	Inputs			Outputs	
	Available ton km	Operating cost	Non-flight assets	Revenue passenger-km	Non-passenger revenue
Air Asia	853	251	610	6,702	25
Air Canada	12,773	4,713	5,719	78,389	574
Air China	13,265	6,068	8,618	60,322	1,890
Air France	23,682	8,653	6,047	123,464	1,864
Air India (a)	4,163	2,345	2,261	20,876	898
Air Macao	692	291	155	3,040	126
AirTran Airways	3,264	1,590	766	22,138	84
Alaska Airlines	4,456	2,547	2,187	28,515	317
Allegiant Air	454	201	41	3,602	52
America West Airlines	5,779	3,414	2,254	37,694	1,020
American Airlines	40,063	20,123	13,146	223,126	4,650
AMR American Eagle	1,984	1,551	1,355	15,955	2
British Airways	22,481	5,854	5,889	112,851	464
Cathay Pacific	18,866	5,000	5,599	71,156	1,745
China Eastern Airlines	9,183	5,235	6,153	50,272	1,292
China Southern Airlines	11,231	6,694	6,318	69,582	1,024
Continental Airlines	15,809	11,550	5,628	143,227	3,708
Czech Airlines	1,222	34	17	6,388	11
Delta Airlines	28,126	15,908	8,746	158,949	5,679
Deutsche Lufthansa	26,827	8,641	9,319	110,330	1,231
EasyJet Airlines	2,852	1,294	1,382	31,621	127
Ethiopian Airlines	2,080	976	721	6,640	302
ExpressJet Airlines	2,332	1,168	409	16,475	3
Frontier Airlines	5,478	1,010	418	13,385	180
Gol Transportes Aeros	2,285	1,106	684	14,922	114
Hawaiian Airlines	1,956	730	567	10,942	85
Horizon Airlines	658	547	226	4,306	22
Iberia-Lineas Aereas De Espana	9,193	3,726	4,048	52,421	1,317
JAL	18,056	8,503	7,088	62,598	4,035
Jet2.com	665	209	137	3,664	51
Jet Airways	2,028	1,658	2,405	12,307	162
JetBlue Airways	5,027	1,992	1,952	37,312	141
Korean Airlines	20,440	5,963	4,439	51,105	3,189
Malaysian Airlines System	7,675	4,061	2,526	41,099	1,377
Mesa Airlines	1,227	868	679	9,781	15
Mid-West Airlines	957	497	228	6,123	80
NorthWest Orient Airlines	21,350	11,055	10,680	116,170	3,504
Oman Aviation Services	281	298	195	1,750	127
Pakistan International Airlines	3,369	1,959	1,123	15,124	263
Pinnacle Airlines	1,109	429	271	6,862	8
Qantas Airways	14,306	5,567	4,823	78,844	2,060
SATA Internacional	315	105	37	829	69
Scandinavian Airlines	5,213	2,180	1,067	27,506	452
Singapore Airlines	24,014	4,425	6,685	89,149	1,357
SkyEurope Airlines	458	25	36	2,801	3
SkyWest Airlines	2,235	963	923	15,284	20
SouthWest Airlines	18,311	3,728	2,325	108,306	270
SpanAir	1,590	871	382	8,465	322
Sri Lankan Airlines	1,704	895	386	9,536	195
Swiss International Airlines	4,884	1,580	751	22,077	341
Thai Airways	10,269	5,810	2,632	53,989	1,409
United Airlines	33,214	17,571	15,350	188,691	5,444
US Airways	10,290	7,353	3,566	59,408	3,007

Notes: Figures in millions. Coat and revenue values are in US$ (PPP based). Shaded airlines are budget airlines. Refers to 2005-06 as 2006-07 unavailable.
Source: ICAOData and World Air Transport Statistics, 2007. Non-flight assets for Air China, China Eastern Airlines and China Southern Airlines from their respective Annual Reports.

Table 2: DEA constant AND variable returns-to-scale technical efficiency and scale efficiency scores, 2006						
	CRS		VRS			
	TE	Rank	TE	Rank	SE	
Air Asia	0.876	16	0.900	23	0.974	irs
Air Canada	0.679	41	0.833	29	0.815	drs
Air China	0.754	25	0.812	30	0.930	drs
Air France	0.701	34	0.843	28	0.832	drs
Air India (a)	0.882	15	0.923	21	0.955	drs
Air Macao	0.903	11	0.919	22	0.983	drs
AirTran Airways	0.746	26	0.874	26	0.854	drs
Alaska Airlines	0.619	48	0.620	51	0.999	irs
Allegiant Air	1.000	1	1.000	1	1.000	-
America West Airlines	0.851	17	0.865	27	0.984	drs
American Airlines	0.711	33	1.000	1	0.711	drs
AMR American Eagle	0.725	29	0.758	38	0.957	irs
British Airways	0.599	49	0.805	31	0.744	drs
Cathay Pacific	0.736	28	0.924	20	0.797	drs
China Eastern Airlines	0.712	32	0.729	41	0.977	drs
China Southern Airlines	0.625	47	0.678	47	0.922	drs
Continental Airlines	1.000	1	1.000	1	1.000	-
Czech Airlines	1.000	1	1.000	1	1.000	-
Delta Airlines	0.885	14	1.000	1	0.885	drs
Deutsche Lufthansa	0.537	51	0.642	49	0.836	drs
EasyJet Airlines	1.000	1	1.000	1	1.000	-
Ethiopian Airlines	0.652	45	0.687	46	0.949	drs
ExpressJet Airlines	0.820	22	1.000	1	0.820	drs
Frontier Airlines	0.443	53	0.691	45	0.641	drs
Gol Transportes Aeros	0.680	40	0.734	40	0.926	drs
Hawaiian Airlines	0.628	46	0.632	50	0.994	drs
Horizon Airlines	0.657	43	0.772	37	0.851	irs
Iberia-Lineas Aereas De Espana	0.904	10	0.976	18	0.926	drs
JAL	0.897	12	1.000	1	0.897	drs
Jet Airways	0.599	49	0.603	52	0.993	irs
Jet2.com	0.779	24	0.787	33	0.990	irs
JetBlue Airways	0.737	27	0.776	36	0.950	drs
Korean Airlines	0.823	21	1.000	1	0.823	drs
Malaysian Airlines System	0.843	18	0.885	25	0.953	drs
Mesa Airlines	0.719	30	0.792	32	0.907	irs
Mid-West Airlines	0.715	31	0.719	42	0.994	irs
NorthWest Orient Airlines	0.819	23	0.887	24	0.924	drs
Oman Aviation Services	1.000	1	1.000	1	1.000	-
Pakistan International Airlines	0.490	52	0.490	53	0.999	irs
Pinnacle Airlines	0.695	37	0.697	44	0.997	drs
Qantas Airways	0.912	9	1.000	1	0.912	drs
SATA Internacional	1.000	1	1.000	1	1.000	-
Scandinavian Airlines	0.686	38	0.736	39	0.932	drs
Singapore Airlines	0.686	38	1.000	1	0.686	drs
SkyEurope Airlines	1.000	1	1.000	1	1.000	-
SkyWest Airlines	0.656	44	0.656	48	1.000	-
SouthWest Airlines	0.826	19	1.000	1	0.826	drs
SpanAir	0.891	13	0.944	19	0.944	drs
Sri Lankan Airlines	0.699	35	0.700	43	0.999	drs
Swiss International Airlines	0.663	42	0.785	34	0.844	drs
Thai Airways	0.697	36	0.785	34	0.888	drs
United Airlines	0.824	20	1.000	1	0.824	drs
US Airways	1.000	1	1.000	1	1.000	-

Table 3: CRS DEA results of selected airlines

Firm		Original value	Slack movement	Projected value
1	American Airlines			
	Outputs			
	RPK	223126	0	223126
	Non-Passenger revenue	4650	0	4650
	Inputs			
	ATK	40063	0	28472.07
	Operating costs	20123	0	14301.06
	Non-flight assets	13146	-1978.78	7363.848
2	Delta Airlines			
	Outputs			
	RPK	158949	0	158949
	Non-Passenger revenue	5679	0	5679
	Inputs			
	ATK	28126	0	24887.05
	Operating costs	15908	0	14076.06
	Non-flight assets	8746	-1343.36	6395.463
3	ExpressJet Airlines			
	Outputs			
	RPK	16475	0	16475
	Non-Passenger revenue	3	187.161	190.161
	Inputs			
	ATK	2332	0	1912.499
	Operating costs	1168	-106.633	851.257
	Non-flight assets	409	0	335.425
4	JAL			
	Outputs			
	RPK	62598	0	62598
	Non-Passenger revenue	4035	0	4035
	Inputs			
	ATK	18056	0	16189.37
	Operating costs	8503	0	7623.961
	Non-flight assets	7088	-2841.34	3513.899
5	Korean Airlines			
	Outputs			
	RPK	51105	0	51105
	Non-Passenger revenue	3189	0	3189
	Inputs			
	ATK	20440	0	16829.79
	Operating costs	5963	0	4909.786
	Non-flight assets	4439	-1872.33	1782.631
6	Qantas			
	Outputs			
	RPK	78844	0	78844
	Non-Passenger revenue	2060	0	2060
	Inputs			
	ATK	14306	0	13043.93
	Operating costs	5567	0	5075.881
	Non-flight assets	4823	-1902.01	2495.511
7	Singapore Airlines			
	Outputs			
	RPK	89149	0	89149
	Non-Passenger revenue	1357	0	1357
	Inputs			
	ATK	24014	0	16479.96
	Operating costs	4425	0	3036.721
	Non-flight assets	6685	-2752.06	1835.617
8	SouthWest Airlines			
	Outputs			
	RPK	108306	0	108306
	Non-Passenger revenue	270	333.136	603.136
	Inputs			
	ATK	18311	0	15128.19
	Operating costs	3728	0	3080.001

	Non-flight assets	2325	0	1920.87
9	United Airlines			
	Outputs			
	RPK	188691	0	188691
	Non-Passenger revenue	5444	0	5444
	Inputs			
	ATK	33214	0	27359.59
	Operating costs	17571	0	14473.88
	Non-flight assets	15350	-5732.68	6911.68

Table 4: DEA scores under CRS and VRS				
	2 Outputs 3 Inputs		2 Outputs 2 Inputs	
	CRS TE	VRS TE	CRS TE	VRS TE
Air Asia	0.876	0.900	0.876	0.900
Air Canada	0.679	0.833	0.679	0.833
Air China	0.754	0.812	0.754	0.812
Air France	0.701	0.843	0.701	0.843
Air India (a)	0.882	0.923	0.882	0.923
Air Macao	0.903	0.919	0.903	0.919
AirTran Airways	0.746	0.874	0.612	0.624
Alaska Airlines	0.619	0.620	0.619	0.620
Allegiant Air	1.000	1.000	0.948	1.000
America West Airlines	0.851	0.865	0.851	0.865
American Airlines	0.711	1.000	0.711	1.000
AMR American Eagle	0.725	0.758	0.725	0.758
British Airways	0.599	0.805	0.598	0.805
Cathay Pacific	0.736	0.924	0.736	0.924
China Eastern Airlines	0.712	0.729	0.712	0.729
China Southern Airlines	0.625	0.678	0.625	0.678
Continental Airlines	1.000	1.000	1.000	1.000
Czech Airlines	1.000	1.000	1.000	1.000
Delta Airlines	0.885	1.000	0.885	1.000
Deutsche Lufthansa	0.537	0.642	0.537	0.642
EasyJet Airlines	1.000	1.000	1.000	1.000
Ethiopian Airlines	0.652	0.687	0.652	0.687
ExpressJet Airlines	0.820	1.000	0.637	0.664
Frontier Airlines	0.443	0.691	0.432	0.505
Gol Transportes Aeros	0.680	0.734	0.628	0.631
Hawaiian Airlines	0.628	0.632	0.623	0.624
Horizon Airlines	0.657	0.772	0.597	0.761
Iberia-Lineas Aereas De Espana	0.904	0.976	0.904	0.976
JAL	0.897	1.000	0.897	1.000
Jet Airways	0.599	0.603	0.779	0.784
Jet2.com	0.779	0.787	0.599	0.603
JetBlue Airways	0.737	0.776	0.716	0.776
Korean Airlines	0.823	1.000	0.823	1.000
Malaysian Airlines System	0.843	0.885	0.843	0.885
Mesa Airlines	0.719	0.792	0.719	0.792
Mid-West Airlines	0.715	0.719	0.676	0.696
NorthWest Orient Airlines	0.819	0.887	0.819	0.887
Oman Aviation Services	1.000	1.000	1.000	1.000
Pakistan International Airlines	0.490	0.490	0.487	0.489
Pinnacle Airlines	0.695	0.697	0.603	0.678
Qantas Airways	0.912	1.000	0.912	1.000
SATA Internacional	1.000	1.000	1.000	1.000
Scandinavian Airlines	0.686	0.736	0.680	0.711
Singapore Airlines	0.686	1.000	0.686	1.000
SkyEurope Airlines	1.000	1.000	1.000	1.000
SkyWest Airlines	0.656	0.656	0.633	0.656
SouthWest Airlines	0.826	1.000	0.742	1.000
SpanAir	0.891	0.944	0.883	0.907
Sri Lankan Airlines	0.699	0.700	0.688	0.689
Swiss International Airlines	0.663	0.785	0.654	0.704
Thai Airways	0.697	0.785	0.693	0.711
United Airlines	0.824	1.000	0.824	1.000
US Airways	1.000	1.000	0.962	1.000