MEASURING AIRLINE EFFICIENCY DIFFERENCES: ASIA, EUROPE AND NORTH AMERICA

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ABSTRACT

For strategic and competitive insight this paper measures and benchmarks comparative operating efficiencies of 75 global airlines in Asia, Europe, and North America using data envelopment analysis. Results indicate no significant differences among the three global regions in terms of (TE) technical efficiency but statistically significant differences in PTE (pure technical efficiency) between the airlines in Asia and North America.

INTRODUCTION

Prior to deregulation of the airline industry, airline companies employed primarily business strategies of differentiation of services and segmentation of markets. Price regulation ensured that airlines could increase costs, and therefore prices, in order to deliver differentiated services and maintain routes with half full aircraft. Following deregulation, however, and in concert with globalization, airline strategies have shifted toward cost leadership strategies that demand unprecedented levels of operating efficiencies. Using data envelopment analysis, this paper measures and benchmarks comparative operating efficiencies of global airlines in three geographical market segments for strategic and competitive insight.

STRATEGIC RESTRUCTURING IN THE GLOBAL AIRLINES INDUSTRY

Since deregulation of the U.S. airline industry in 1978 and liberalization of the European airline industry in 1986, a dramatic restructuring of the global airlines industry has occurred, including a new competitive threat from Asian airlines. The pressures resulting from both the general external environment (e.g., 9/11, SARS, heightened travel security, fuel prices, recession, technological advances, etc.) and from the industry environment more specifically (e.g., entry of low-cost niche players, global market competition, formulation of strategic alliances, mergers and acquisitions among competitors, etc.) have resulted in difficult strategic choices and challenging market realities for airline companies around the world.

In line with Porter's research on generic business strategies, airline companies traditionally followed differentiation and segmentation strategies, with little pressure to contain costs [19]. Cost leadership as a competitive strategy is still a relatively new concept, given the long history of the airline industry and ensuing maturity stage in the product/market life cycle. The environmental and industry challenges facing global airline companies today have forced competitors to focus specifically on operating efficiencies and managing costs. While some airline companies have been able to follow differentiation strategies and cost leadership strategies simultaneously, many airlines continue to struggle with these strategic tradeoffs.

Historically, strategic decision making in the airline industry fell into two categories. The first category includes classical strategy research topics such as core business function, internationalization, deregulation and so on. The second stream of research addresses productivity issues [22]. Using Porter's [19] generic business strategies, Cappel, Tucci, and Wyld theoretically evaluated strategy research as applied to the US airline industry [6]. At that time, these authors found that airlines pursuing a combination strategy of cost leadership *and* differentiation attained a competitive advantage compared with airline companies adopting a singular strategic approach.

Subsequently, a number of low cost carriers (e.g., Southwest Airlines, Jet Blue, etc.) gained attention. Cappel, Pearson, and Romero extended this research stream and examined the airline industry structure in post deregulation in the EC and post 9/11 in order to determine whether the low cost strategy would result in superior performance [5]. Their theoretical question was whether external events (deregulation and 9/11) would have a temporary or permanent effect on the relationship between financial performance and generic business strategy choices.

There are additional external factors that might affect the trend toward the low-cost strategy. Customers who use the internet to purchase airline tickets find lower fares than customers who use travel agents. Research indicates the lower fares may be a by-product of a broader and more thorough search [4]. Additionally, the airline industry is witnessing the formation of multiple partner alliances competing against each other for both clients and members [15]. Lazzarini analyzed the patterns of memberships in multilateral agreements and relationships to operational performance [15]. Oum and Yu also examined airline partner alliance noting that criteria such as safety, efficiency and cost effectiveness are critical variables for effective partnering [18].

Other studies have examined the relationship between the low-cost strategy of new entrants and changes in airline revenue management systems [12]. These authors found that low-fare airline entrants can lead to substantial revenue losses for the incumbent carriers. However, both incumbents and low fare new entrants alike benefit substantially from the use of revenue management systems. A comprehensive review of revenue management and its development can be found in McGill and Van Ryzin [17].

Prince and Simon argue that much of the previous research on airline competitive behavior focused exclusively on price and only recently have researchers begun to test non-price forms of competition, e.g., service quality [21]. These researchers examined the relationship between multi-market contact and service quality. Findings indicate that multimarket contact increases delays and that this effect is greater for contacts on more concentrated routes. Also concerned with customer service, Scheraga examined the relationship between operational efficiency and customer service in a global study of thirty-eight large international airlines [23]. His research categorized areas of cost savings into 1.) Passenger services such as meals, drinks, and other services included in the fare, and 2.) Cost of sales, such as selling directly to the customers instead of using travel agents. As mentioned previously, the internet has been cited as an external technological factor affecting the trend toward low-cost strategies by airline companies [4].

What is apparent from the literature is that airline operating efficiencies and their relationship to selected business strategies are in need of further research. This study is designed to contribute to our knowledge base regarding global airline efficiencies and strategic insights.

MEASURING OPERATING EFFICIENCIES

Several authors have attempted to measure operating efficiencies. Lapre and Scudder analyzed ten major airlines by separating them into two groups based on geographic specialists and geographic generalists [14]. Sengupta developed an optimal control theoretic view of the time path of capital inputs which minimizes a discounted sum of total input costs using a Data Envelopment Analysis (DEA) model [25]. Charnes, Gallegos, and Li tested a model for situations of uncertainty to examine global efficient production functions in operations in the Latin American airline industry using a Multiplicative-DEA model [8]. Lin reviewed and analyzed previous research studies in terms of variables, terminologies, and models used to measure performance evaluation of Taiwanese domestic airlines using DEA applications [16]. Scheraga investigated the structural drivers of operational efficiency in relation to the events of 9/11 [24]. Adler and Golany used principal component analysis (PCA) in combination with DEA to analyze efficient network configurations in Western European airlines systems [1].

Data Envelopment Analysis

DEA is a special application of linear programming based on frontier methodology of Farrell [11]. Since Farrell, a major breakthrough for developing DEA was achieved by Charnes, Cooper, and Rhodes [7] and by Banker, Charnes, and Cooper [3]. Data envelopment analysis is a useful approach for measuring relative efficiency using multiple inputs and outputs among similar organizations or objects. An entity that is an object to be measured for efficiency is called a decision-making unit or DMU. Because DEA can identify relatively efficient DMUs among a group of given DMUs, it is a promising tool for comparative analysis or benchmarking.

To explore the mathematical property of DEA, let E_0 be an efficiency score for the base DMU *0* then,

$$\text{Maximize} \qquad E_0 = \frac{\left\{\sum_{r=1}^{R} u_{r0} y_{r0}\right\}}{\left\{\sum_{i=1}^{I} v_{i0} x_{i0}\right\}} \tag{1}$$

$$\text{subject to} \qquad \frac{\left\{\sum_{r=1}^{R} u_{r0} y_{rk}\right\}}{\left\{\sum_{i=1}^{I} v_{i0} x_{ik}\right\}} \le 1 \qquad \text{for all } k \tag{2}$$

$$u_{r0},\, v_{i0} \ge \delta \text{ for all } r,\, i, \tag{3}$$

where

y_{rk}: is the observed quantity of output r generated by unit $k = 1, 2, \ldots, N$,

x_{ik}: is the observed quantity of input i consumed by unit $k = 1, 2, \ldots, N$,

u_{r0}: is the weight to be computed given to output r by the base unit *0*,

v_{i0}: is the weight to be computed given to input i by the base unit *0*,

δ: is a very small positive number.

The fractional programming model can be converted to a common linear programming (LP) model without much difficulty. First, set the denominator of the objective function of the fractional model equal to one and move it to the constraint section. Next, transform constraints into linear forms by multiplying the respective denominator of each constraint, and the fractional model becomes a linear programming model. A major assumption of LP is a linear relationship among variables. Accordingly, an ordinary LP for solving DEA utilizes a constant returns-to-scale so that all observed production combinations can be scaled up or down proportionally [7]. However, when we use a piecewise LP, we can model a non-proportional returns-to-scale such as an increasing, decreasing or variable-returns-to-scale [3]. Depending on returns-to-scales used, and/or various modeling approaches, different types of DEA models are available.

Sherman and Ladino [26] summarize the capability of DEA in the following manner:

- Identifies the best practice DMU that uses the least resources to provide its products or services at or above the quality standard of other DMUs;
- Compares the less efficient DMUs to the best practice DMU;
- Identifies the amount of excess resources used by each of the less efficient DMUs;
- Identifies the amount of excess capacity or ability to increase outputs for less efficient DMUs, without requiring added resources.

In this study, involving comparative measures of airline performance for benchmarking, we utilize output-oriented system models with constant returns to scale and variable returns to scale, which can incorporate group differences into computing efficiency scores [10]. First, using the two models, we measure the efficiency scores of airlines in three regions (Asia, Europe, and North America). Next, we apply Oneway ANOVA (analysis of variance) to find the differences of efficiency scores among the airlines in the regions. Accordingly, we test the following hypotheses:

H1: There is no efficiency difference among the airlines in three regions;

H2: There is no efficiency difference between the airlines in two selected regions.

We need H1 for testing overall efficiency differences of airlines in three regions. If we reject H1, we will test H2 for detecting regional differences by comparing two regions at a time.

Data and Variables

We collected annual financial and traffic data for major world airlines from the 2008 World Airline Report published in 2009 [2]. We selected 75 airlines that reported annual revenues with US $500,000,000 or higher in three continents: Asia, Europe, and North America or 25 airlines in each region. The variables we chose are operating expenses in thousand U.S. dollars (Expenses), operating revenues in thousand U.S. dollars (Revenues), number of passengers in thousands (Passengers), revenue per kilometers in million U.S. dollars (RPKs), and load factors (LF) in percentage. Words and acronyms inside of parentheses represent variable names in models. Expenses, which are the input variable in the models, are highly relevant to cost reduction efforts for managing airlines, especially during recession. Revenues, Passengers, RPKs and LF are output variables. Revenues and Passengers will show the status of basic operations. RPKs will exhibit the pricing policy of airlines in conjunction with distance. LF is related to the utilization of aircraft capacity, indicating the ratio between aircraft weight and cargo (including passengers) weight. Table 1 shows the descriptive statistics of the variables.

TABLE 1
DESCRIPTIVE STATISTICS OF VARIABLES

	Expenses	Revenues	Passengers	RPKs	LF

Maximum	33,121,127.0	35,028,169.0	109,376.0	223,922.0	92.8
Minimum	551,667.0	565,376.0	896.0	2,426.0	63.6
Mean	6,061,693.4	5,692,013.9	22,340.4	43,847.2	75.2
Standard Deviation	7,669,373.1	7,216,767.1	23,236.9	49,657.9	5.4
Variable Type	Input	Output	Output	Output	Output

RESULTS AND DISCUSSION

Since the majority of variables are output variables, we ran output oriented system models with two different scales to return (RTS): constant and variable RTS. Table 2 shows the comparative efficiency scores of 75 airlines in three regions.

TABLE 2
COMPARATIVE EFFICIENCY SCORES

Asia (1)			Europe (2)			North America (3)		
Airlines	**TE**	**PTE**	**Airlines**	**TE**	**PTE**	**Airlines**	**TE**	**PTE**
Air Astana	0.9538	1.0000	Aer Lingus	0.8564	0.9007	Air Canada	0.4266	0.9743
Air China	0.8376	0.9322	Aeroflot Russian	0.9312	0.9744	Air Canada Jazz	0.9555	0.9614
Air New Zealand	0.9357	0.9846	Air Berlin	0.8774	0.9507	Air Tran Airways	0.9011	0.9268
AirAsia	1.0000	1.0000	Air Europa	0.8863	0.9266	Air Wisconsin	1.0000	1.0000
ANA Group	0.8337	0.9473	Air France KLM	0.8445	1.0000	Alaska Airlines	0.8262	0.9017
Asiana Airlines	0.8469	0.8944	Austrian Airlines	0.7481	0.8432	AMR Corp	0.8107	1.0000
Cathay Pacific	0.7958	0.9474	Brit Air	0.9155	0.9232	Comair	0.9338	0.9565
China Airlines	0.8002	0.8832	British Airways	0.8504	0.9820	Continental Airlines	0.8519	1.0000
China Eastern Airlines	0.6424	0.8433	CSA	0.8733	0.8748	Delta Air Lines	0.6286	1.0000
China Southern Airlines	0.8020	0.9455	Finnair Group	0.8344	0.8931	Frontier Airlines	0.9228	0.9569
Hainan Group	0.8050	0.8767	Flybe	0.9115	0.9126	Hawaiian Holdings	0.9928	1.0000
JAL Group	0.8109	0.9201	Iberia Group	0.8415	0.9478	Horizon Air	0.9108	0.9523
Jet Airways	0.7939	0.8332	Icelandair	0.8249	0.8901	JetBlue Airways	0.9501	0.9747
Jetstar	0.9681	0.9689	Jet2	0.9466	0.9488	Masa Air Group	0.9402	1.0000
Korean Air	0.8450	0.9242	Lufthansa Group	0.8765	1.0000	Midwest Airlines	0.5670	0.8216
Malaysia Airlines	0.8811	0.9279	Norwegian	0.8715	0.9428	Northwest Airlines	0.8327	1.0000
Nat’l Aviation Co. of India	0.6652	0.7385	Ryanair	0.9619	1.0000	Pinnacle Airlines	0.9848	1.0000
Pakistan Int'l Airlines	0.6862	0.7831	SASGroup	0.8182	0.9141	Republic Air Holdings	1.0000	1.0000
Philippine Airlines	0.9560	0.9586	Spanair	0.7786	0.8339	Skywest Airlines	0.9160	0.9801
Quantas Group	0.9194	1.0000	Swiss	0.9330	1.0000	Southwest Airlines	0.9653	1.0000
Shanghai Airlines	0.7804	0.8336	TC Airlines Scandinavia	1.0000	1.0000	Spirit Airlines	0.9624	1.0000
Singapore Airlines	0.9199	1.0000	Transavia Airlines	0.9533	0.9802	United Air Lines	0.7130	1.0000
SriLankan Airlines	0.9843	0.9846	Turkish Airlines	0.9582	1.0000	US Airways Group	0.7540	0.9255
Thai Airways Int'l	0.8065	0.9001	Virgin Atlantic Group	0.9336	0.9619	WestJet	1.0000	1.0000
Virgin Blue Airlines	0.9592	0.9906	Vueling Airlines	0.9637	1.0000	World Airways	0.9161	0.9213
Mean Score	**0.8492**	**0.9207**	**Mean Score**	**0.8876**	**0.9440**	**Mean Score**	**0.8665**	**0.9701**

We assign region codes to three continents such as 1 for Asia, 2 for Europe, and 3 for North America. TE or technical efficiency computed with constant RTS includes pure technical efficiency and operating conditions such as different markets. PTE or pure technical efficiency generated using variable RTS represent pure managerial aspects of efficiency. For measuring TE, five airlines such as AirAsia, Thomas Cook Airlines Scandinavia, Air Wisconsin, Republic Air Holdings, and WestJet exhibit 100 percent efficiency. The airlines in Europe demonstrate the highest average TE (0.8876) followed by those in North America (0.8665) and Asia (0.8492). For computing PTE, 24 airlines are 100 percent efficient such as 13 in North America, 7 in Europe, and 4 in Asia. The airlines in North America show the highest average PTE (0.9701) followed by those in Europe (0.9440) and Asia (0.9207). One caveat for interpreting these scores is that the scores are computed using data for operations by omitting customer satisfaction. When customer satisfaction is included, they will be different.

To confirm statistical significance on the differences in operating efficiency scores, we employ Oneway ANOVA (analysis of variance). Table 3 shows the results of Oneway ANOVA on two types of the efficiency scores.

TABLE 3
ONEWAY ANOVA RESULTS ON EFFICIENCY SCORES

		Sum of Squares	Degrees of Freedom	Mean Square	F-value	Significance
Technical Efficiency (TE)	Between Groups	0.019	2	0.009	0.788	0.459
	Within Groups	0.847	72	0.012		
	Total	0.865	74			
Pure Technical Efficiency (PTE)	Between Groups	0.031	2	0.015	4.765	0.011*
	Within Groups	0.231	72	0.003		
	Total	0.261	74			

*: Significant at $\alpha = 0.025$

For TE, we fail to reject H1. The differences among three regions are not statistically significant. It means that the TE differences can happen by chance. For PTE, we reject H1 at $\alpha = 0.025$. The PTE differences among three regions are statistically significant. At least one of them is different from the others. To find the differences between groups, we test H2 employing post hoc analyses with Tukey method. Table 4 exhibits the results of post hoc tests.

TABLE 4
POST HOC TESTS WITH TUKEY METHOD

(I) Region	(J) Region	Mean Difference (I-J)	Standard Error	Significance	95% Confidence Interval	
					Lower Bound	Upper Bound
1	2	-.0233021	.0160085	.318	-.061613	.015008
	3	-.0493942	.0160085	.008*	-.087705	-.011084
2	1	.0233021	.0160085	.318	-.015008	.061613
	3	-.0260921	.0160085	.240	-.064403	.012218
3	1	.0493942	.0160085	.008*	.011084	.087705
	2	.0260921	.0160085	.240	-.012218	.064403

*: The mean difference is significant at the 0.01 level.

We reject H2 only on testing the efficiency difference between airlines in Asia and North America. The differences between airlines Asia and Europe and between Europe and North America are not statistically significant. Overall, H1 and H2 are partially supported with pure technical efficiency. In a pure managerial aspect of operating efficiency, the airlines in North America are more efficient than those in Asia. However, this result may be different when one includes customer perspectives such as customer satisfaction.

SUMMARY AND CONCLUSION

This research has presented the development of the models to measure and benchmark comparative operating efficiencies in the global airlines industry to gain insight on the future strategies and competitive efforts of these airlines. From a strategic perspective, insight can be gained to compare efficiency ratings of specific airlines with other strategic performance measures. Following strategic thinking it would be intuitive that only industry leaders could be both efficient and simultaneously achieve high ratings on other performance variables leading to competitive advantage [20] [9]. For example, Heracleous, Wirtz, and Johnston explain how Singapore Airlines has achieved sustainable competitive advantage [13]. However, it could also be possible that some airlines could be efficient at the expense of other performance measures, such as customer service ratings and financial performance. This would be represented strategically by Porter’s early work that suggests being the low cost leader may prevent a competitor from doing well in other aspects of product or service differentiation [19].

Future research should extend this analysis to include additional performance variables, for example, customer satisfaction, in order to gain additional insight into the changing competitive nature of the passenger airline industry.

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