MEASURING OPERATING EFFICIENCY OF GLOBAL AIRLINES FOR STRATEGIC IMPLICATIONS

Jong Soon Park, Hasan School of Business, Colorado State University-Pueblo, 2200 Bonforte Blvd., Pueblo, CO 81001, 719-549-2579, jongsoon.park@colostate-pueblo.edu
Seong-Jong Joo, Hasan School of Business, Colorado State University-Pueblo, 2200 Bonforte Blvd., Pueblo, CO 81001, 719-549-2579, seongjong.joo@colostate-pueblo.edu
Karen L. Fowler, Hasan School of Business, Colorado State University-Pueblo, 2200 Bonforte Blvd., Pueblo, CO 81001, 719-549-2165, karen.fowler@colostate-pueblo.edu

ABSTRACT

This paper attempts to measure and benchmark comparative operating efficiencies with data envelopment analysis in the global airlines industry for strategic and competitive insight. Findings indicate that some airlines rated highly by customers may not necessarily rank highly in terms of efficient operations.

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 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 efficiency. This paper attempts to measure and benchmark comparative operating efficiencies with data envelopment analysis in the global airlines industry for strategic and competitive insight. Findings indicate that some airlines rated highly by customers may not necessarily rank highly in terms of efficient operations.

STRATEGIC CHANGES IN THE AIRLINE INDUSTRY

In line with Porter's research on generic business strategies, airline companies traditionally followed differentiation and segmentation strategies [18]. The pressures stemming from both the external environment in general (9/11, fuel prices, technological advances, etc.) and from the competitive industry environment more specifically (global competition, entry of new low cost carriers, formation of strategic alliances, mergers and acquisitions, etc.) have forced airline companies to pay closer attention to operating efficiencies. While some airline companies have been able to simultaneously follow differentiation strategies and cost leadership strategies, 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 [21]. Using Porter's [18] 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 [14]. Lazzarini analyzed the patterns of memberships in multilateral agreements and relationships to operational performance [14]. Oum and Yu also examined airline partner alliance noting that criteria such as safety, efficiency and cost effectiveness are critical variables for effective partnering [17].

Other studies have examined the relationship between the low-cost strategy of new entrants and changes in airline revenue management systems [11]. 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 [16].

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 [20]. 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 [22]. 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 [13]. 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 [24]. 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 [15]. Scheraga investigated the structural drivers of operational efficiency in relation to the events of 9/11 [23]. 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 [10]. 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,

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

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

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

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 [25] 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 Charnes, Cooper, and Rhodes (CCR) [7] and Banker, Charnes, and Cooper (BCC) [3] models. First, we measure the efficiency scores of airlines using the two models. Next, using the CCR and BCC efficiency scores, we compute the scale efficiencies, which show different environments of businesses.

Data and Variables

We collected financial and traffic data for world airlines from the 2008 World Airline Report published in 2009 [2]. After excluding missing data, we have 146 airlines for analysis. 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

	Expenses	Revenues	Passengers	RPKs	LF
Maximum	33,121,127.00	35,028,169.00	109,376.00	223,922.00	92.80
Minimum	2,926.00	2,637.00	6.00	3.00	23.20
Mean	3,226,042.42	3,031,094.29	12,137.95	23,405.42	70.83
Standard Deviation	6,222,829.69	5,851,955.32	19,705.55	41,347.98	10.39
Variable Type	Input	Output	Output	Output	Output

Because we included all airlines available for analysis, the variables exhibit wide ranges and large standard deviations.

RESULTS AND DISCUSSION

Since the majority of variables are output variables, we ran output oriented CCR and BCC models. Table 2 shows the comparative efficiency scores of 45 airlines out of 146 in the models.

TABLE 2: Comparative Efficiency Scores

Airlines	**TE**	**PTE**	**SE**
ANA Group	0.8332	0.9322	0.8938
Asiana Airlines	0.8385	0.8914	0.9407
Cathay Pacific	0.7861	0.9323	0.8432
China Airlines	0.7902	0.8778	0.9002
China Eastern Airlines	0.6335	0.8320	0.7614
China Southern Airlines	0.7836	0.9171	0.8544
Deraya Air Taxi	1.0000	1.0000	1.0000
JAL Group	0.8096	0.9132	0.8866
Korean Air	0.8377	0.9106	0.9199
Malaysia Airlines	0.8705	0.9236	0.9425
MIAT, Mongolian Airlines	1.0000	1.0000	1.0000
National Aviation Co. of India	0.6553	0.7346	0.8921
Quantas Group	0.9151	1.0000	0.9151
Singapore Airlines	0.9076	1.0000	0.9076
Thai Airways Int'l	0.7930	0.8952	0.8858
Aeroflot Russian Airlines	0.9190	0.9594	0.9579
Aerosvit Airlines	0.8061	0.8112	0.9937
Air Europa	0.8676	0.9226	0.9404
Air France KLM	0.8377	1.0000	0.8377
Air Italy	0.8712	0.8712	1.0000
British Airways	0.8381	0.9756	0.8591
EuroLOT	1.0000	1.0000	1.0000
Finnair Group	0.8271	0.8899	0.9294
ItAli Airlines	0.7242	0.7297	0.9925
Lufthansa Group	0.8762	1.0000	0.8762
SASGroup	0.8175	0.9063	0.9020
Spanair	0.7581	0.8099	0.9360
Swiss	0.9281	1.0000	0.9281
Turkish Airlines(THY)	0.9481	1.0000	0.9481
Ukraine Int'l Airlines	0.9092	0.9164	0.9921
Air Canada	0.4071	0.9427	0.4318
Air Tran Airways	0.8527	0.9267	0.9201
Alaska Airlines	0.8159	0.8908	0.9159
AMR Corp (American Airlines)	0.7981	1.0000	0.7981
Continental Airlines	0.8401	1.0000	0.8401
Delta Air Lines	0.6220	1.0000	0.6220
Frontier Airlines	0.8761	0.9344	0.9376
Hawaiian Holdings	0.9389	0.9692	0.9687
JetBlue Airways	0.9018	0.9732	0.9266
Northwest Airlines	0.8225	1.0000	0.8225
Republic Air Holdings	1.0000	1.0000	1.0000
Skywest Airlines	0.9027	0.9757	0.9252
Southwest Airlines	0.9063	1.0000	0.9063
United Air Lines	0.7031	1.0000	0.7031
US Airways Group	0.7444	0.9166	0.8121
Mean (Overall)	**0.8412**	**0.9030**	**0.9321**

TE or technical efficiency is computed with a CCR model. PTE or pure technical efficiency is generated using a BCC model. SE represents scale efficiency. The relationship among the three efficiency scores is expressed as follows: TE = PTE×SE. Accordingly, SE is TE/PTE, where PTE is greater than equal to TE. PTE reveals pure managerial efficiency. SE shows efficiency on the different operating environment of companies. Some airlines, for example, Air France KLM, Lufthansa, Delta, and United Air Lines are 100 percent efficient on pure technical efficiency but not on technical efficiency. It is due to low scale efficiencies that reflect different operating environments or markets. Small airlines such as Mongolian Airlines and Deraya Air Taxi are 100 percent efficient across models. Republic Air Holdings, which will take over Frontier Airlines, is also 100 percent efficient in all models. In our models, they are industry leaders for operating efficiency. We measure the operating efficiency of airlines without including the measures of customer satisfaction. Singapore Airlines, that has been ranked number 1 in a row for the recent three years, also show high operating efficiency scores over 90 percent in the models.

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 [19] [9]. For example, Heracleous, Wirtz, and Johnston explain how Singapore Airlines has achieved sustainable competitive advantage [12]. 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 [18].

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

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