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Understanding the Operating Landscape of the Global Airline Industry: A DEA Integrated Alternating Conditional Expectation Approach

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Abstract

Purpose: This study investigates the relationships between service efficiency in 5 major cost centres (namely, business orientation, network coverage, physical resources, maintenance, repair and overhaul (MRO), and human resources) and profitability in the global airline industry.

Design/methodology: The study integrates the Slack-based Model (SBM) of Data Envelopment Analysis (DEA) with the Alternating Conditional Expectation (ACE) regression to understand the relationships between an airline's profitability and its efficiencies in 5 identified operations areas.

Findings: Based on the observational data obtained from 75 international airlines, the relationships between operational performances and profitability are found to be curvilinear and contingent on an airline's operating model.

Research limitations/implications: The omission of non-IATA airlines and many low cost carriers may hinder a holistic view of the airline industry.

Practical implications: Management can influence the profitability of an airline through its strategic operations decisions that affect an airline's cost, service quality, and financial structure after the influences of location and size have set the stage. Airlines pursuing cost leadership should seek to increase productivity especially in MRO, human resources and physical resources; whereas airlines pursuing service differentiation may choose to provide quality service at lower efficiencies or pursue an approach to improve quality and efficiencies simultaneously.

Originality/value: Identifying operations practices that are consistent with a firm's competitive priorities is important in the multifaceted service environment today. An integrated SBM-ACE regression model, which permits different input-output mix, variable return to scale and non-linear relationship, is proposed and applied to analyze the profit impact of service efficiencies in the five key operations areas.

Keywords: service quality, efficiency, cost-centric airlines, service-centred airlines.

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1. Introduction

Competition in the global airline industry has heightened and become more multi-layered in recent years, following the deregulation of the airline industry and globalization of many economies. In the past, most airlines were fully or partially owned by governments as "state carriers" were highly regarded as important entities with monopolistic powers associated with national pride and prestige. With globalisation and liberalisation of the airline industry in the 1980s, many airlines ranging from upstarts to state behemoths were privatised in the quest for higher efficiency and customer responsiveness. At the same time, significant shifts in the scale, nature, and geography of aviation services occur and push many airlines towards expanding both their domestic and international services. In a globalizing environment, Oum and Yu (1998) suggested that airlines must map out proper strategies to improve their productivity and competitiveness to survive and prosper.

As competition in the market place intensifies with the expansion of low-cost carriers in Asia and other airlines in the Middle East, Doganis (2010) advised that the pursuit of efficiency should not be at the expense of customer service. In general, there is a strong agreement on improving service as a major operational objective in the service sectors, and airlines are no exception (Chase & Hayes, 1991; Park, Robertson & Wu, 2004). Some scholar seven prodded the view that service quality is always positive on financial performance even though Lambert (1998) and Steven, Dong and Dresner (2012) found that the marginal effect of service quality on revenue diminishes as service quality improves. Dresner and Xu (1995) and Ballou (1999) further proposed that the marginal cost of improving service might even escalate once a firm has achieved a high level of service quality. On that note, Mellat-Parast, Golmohammadib, McFadden and Miller (2015) found negative curvilinear relationships between some measures of service quality and airline profitability. In sum, pursuing service quality without regard to efficiency, and vice versa, may hurt airline profitability.

This study investigates the relationships between efficiency and profitability of airlines. Specifically, we postulate that improvements inefficiency reduce costs and in turn increase the profitability of an airline, especially if its service quality is not compromised. We propose that the overall efficiency of an airline is a sum of its efficiencies in five key areas (according to an IATA survey for 2013, flight deck crew and cabin attendant expenses, aircraft rentals and depreciation, maintenance, repair and overhaul (MRO), and airport and navigation charges constitute 13.1%, 10.3%, 9.6% and 8.3% of the total operating cost of an airline, respectively, with fuel cost accounting for the largest portion of 34 % of the total operating cost.). These areas are its business orientation, network coverage, physical resources, maintenance, repair and overhaul (MRO), and service staff employed for on-ground and on-board services, forming the cornerstones of its operations. Briefly, business orientation of an airline is measured in terms of its extent of internationalization, privatization, and operating experience. These characteristics can affect its global reach, market focus, financial strength and operating cost due to access to management expertise and customer's expectations (Lapré & Tsikriktsis, 2006). Network coverage measured by number of routes, number of international and domestic departures and stage length, affects the costs of fuel consumption, airport fees, and navigation charges. Physical resource, which comprises the aircrafts used, enables an airline to serve its network with minimal schedule delay, and thereby capture a bigger market share (Douglas & Miller, 1974). Some airlines are equipped with heavy-haul planes to support the longer-haul routes between hubs and higher density routes, while others operate mainly middle or low-haul planes to target smaller and regional markets. The composition and size of a fleet canal so have a profound impact on the complexity and cost of MRO. Since MRO canal so affect flight safety (Seristo, 1995), it is not only a key cost factor but also an important component of customer value. Finally, an airline needs to deploy qualified pilots, and sufficient flight and ground staff to serve passengers both on-board and on-ground.

Undeniably, many factors can affect the profitability of an airline. Some of these factors, such as operating experience or location of its hub, are difficult to alter for most airlines. Nevertheless, most airlines do have some or full controls over certain factors that can influence its financial outcomes. The extent of these controls can range from complete control of decisions relating to aircraft mix and number of staff to partial control of decisions pertaining to choice of routes and frequency of flights for each route. This study integrates the Slack-based Model (SBM) of Data Envelopment Analysis with the Alternating Conditional Expectation (ACE) regression to understand the relationships between an airline's profitability and its efficiencies in various areas of operations. The SBM model with variable returns is chosen for the Data Envelopment Analysis because it does not impose the strict assumptions of fixed input-output mix and constant return to scale. This is important as airlines operate in vastly different continents with very different factor endowments and sizes. Similarly, ACE provides a non-linear regression technique to determine any linear or non-linear associations between profitability and efficiencies of different areas of operations more accurately without the restrictive assumption of linear relationships in conventional linear regression models.

Analysing a data set of 75 international airlines, this paper provides insights on managing the efficiencies of operating an airline to improve its profitability. Our results show that profitability increases continuously as efficiency in business orientation and physical resource increases. However, profitability does not always increase with increased efficiency in network coverage, MRO and service staff. To improve its profitability, an airline must thus manage the efficiency of these three areas cautiously. The efficiency of each of the three areas has to be steered to the 'right' level to maximise profitability.

The rest of this paper is organised as follows: Section 2 reviews the extant literature on airline performance and competitiveness. Section 3 introduces the conceptual model, and Section 4 presents the empirical analysis and discusses the results. Section 5summarises and concludes the paper, with some limitations of the current study and directions for future research.

2. Literature Review

The understanding of the complex relationship between service quality and profitability requires simultaneous investigation of other relationships such as the link between productivity and profitability (Zeithaml, Berry & Parasuraman, 1996). In view of the many input factors and multiple outputs inmost production systems, the total factor productivity (TFP) measure taken as a weighted sum of important partial productivity factors is widely favoured over partial productivity factors to study the overall efficiency of a system. Specific to airlines in selected regions, Caves, Christensen and Tretheway (1981) compared 11 US trunk airlines between 1972 and 1977; Gillen, Oum and Tretheway (1985, 1990) studied 7 Canadian air carriers for the period from 1964 to 1981; Forsyth (2001) considered airlines in Australia in the 1980s and 1990s; Siregar and Norsworth (2001) analysed US airlines between 1970 and 1992. Some of the more recent papers include Vasigh and Fleming (2005), Oum, Fu and Yu (2005) and Homsombat, Fu and Sumalee (2010). The study by Vasigh and Fleming (2005) revealed a consistent trend of higher productivity among US airlines from 1996 to 2001. Oum et al. measured and compared the performance of 10 major North American airlines in terms of their residual TFP, cost competitiveness, and residual average yields during the period from 1990 to 2001.The carriers showed improved productivity over the entire period, despite rising input prices. Nevertheless, the study revealed evidence of declining productivity, yield, and unit costs because of the September 11th attack. Subsequently, Homsombat et al. (2010) examined changes in productivity and cost competitiveness of US carriers from 1990 to 2007. Significant productivity improvements were noted over the study period, but the gains were largely offset by increases in fuel prices.

Other studies compared the TFP of airlines across different countries. For examples, Caves, Christensen, Tretheway and Windle (1987) and Windle and Dresner (1992) compared US and non-US airlines over the period from 1970 to 1983. By decomposing a cost function analysis in Caves et al. (1987), Windle and Dresner (1992) indicated that although US carriers had higher productivity gains in 1983, these gains were offset by higher labour costs. Implications from the study suggested the need to increase traffic density (more passengers on each route) through some forms of deregulation to enable increased demand, reduced fares, network re-configuration, and restructuring. Encaoua (1991) presented evidence on differences in costs and global factor productivity among the main European national flag carriers from 1981 to 1986. The author showed that unit costs per passenger-kilometre are lower in North Atlantic routes while unit profits are higher in European routes because of economies of scale due to longer distances and higher traffic density on North Atlantic routes and lower level of competition between airlines in Europe. Ehrlich, Gallais-Hamonno, Liu and Lutter (1994) focused on the effect of state versus private ownership on the rates of firm-specific productivity growth and cost decline in 23 international airlines of varying levels of state ownership over the period from 1973 to 1983. Their results suggested that state ownership can lower the long-run annual rate of productivity growth and cost decline but not necessarily their levels in the short run. Oum and Yu (1995) computed the unit costs of 23 major airlines between 1986 and 1993, and compared their 'gross' and 'residual' TFP before and after removing the effects of variables beyond managerial control. In that study, US carriers were found to have higher productivity levels on average, but higher growth rates in newly industrialized countries diminished the overall productivity gap. Among the different factors, stage length and load factor were found to be important contributors.

To avoid the use of subjective weights in computing TFP, some scholars have suggested and used Data Envelopment Analysis (DEA) to benchmark the operational efficiencies of airlines. DEA allows an assessment of efficiencies of multiple inputs using a single overall efficiency score computed via the use of objectively chosen weights for the inputs and outputs. Instead of using a set of subjectively defined weights assigned a-priori, the DEA methodology assigns the "right" weights by considering the efficiencies of all decision-making units (DMUs), and other relevant constraints and objectives. DEA also does not have heavy data requirements or impose a parametric structure on the data such that data measured in different units can be used simultaneously within the same model.

In fact, DEA models are widely used both within and beyond the airline industry owing to their inherent advantages. Schefczyk (1993) studied the impact of productivity on financial performance of 15 international air carriers and found that productivity is linked to return on equity. Fethi (2000) studied the performance of 17 European airlines over the period from 1991 to 1995. Through a DEA window analysis, liberalisation policies were found to have considerable impact on small airlines, which were disadvantaged with small home markets. Small airlines might find it difficult to keep their market share under the pressure of increased competition. Adler and Golany (2001) examined the efficiency of the hub-and-spoke configuration of airlines in the Western European markets, recognizing that airlines are likely to provide higher quality service to encourage passenger loyalty in hub-and-spoke network. Airport charges, airline station costs (such as ground staff salaries) and airline operating cost (such as fuel and crew salary)approximate the service costs; while hub shopping facilities, surface transport system and comfort of airport hubs are inputs that represent the quality of services. To avoid possible imprecision in the DEA estimate of efficiencies when there are excessive numbers of inputs and outputs, Adler and Golany (2001) used principal component analysis to cluster and aggregate the inputs and outputs. Their results revealed that service quality improvements decrease profits in the short term, although passenger loyalty may been hanced in the long term. Bhadra (2009) examined the inter-temporal self-efficiency and peer-group efficiency of 13 US airlines between 1985 and 2006. He demonstrated that fuel cost affects inter-temporal inefficiency more than peer-group efficiency while labor cost reduces inter-temporal inefficiency and increases peer-group inefficiency. Notably, airlines efficiency tends to be robustly affected by block hours; reducing them increases efficiency. Barros and Peypoch (2009) ranked the operational performance of 29 European airlines from 2000 to 2005 and used a bootstrapped truncated regression model to evaluate the drivers of efficiency. The authors concluded that scale is dominant source of efficiency and managerial skills play an important role in increasing efficiencies beyond operations scale.

The effects of efficiency improvements on cost and profitability depend on the existing position of airlines. Lapré and Scudder (2004) found that airlines operating close to their asset frontiers faced initial trade-offs, whereas airlines operating farther away from their asset frontiers were able to improve quality and cost simultaneously. While most organizations are able to reduce their operations cost over time due to the economies of experience, Lapré and Tsikriktsis (2006) observed that customer dissatisfaction follows a U-shaped function of operating experience and organizational learning as customer dissatisfaction are heterogeneous across airlines. The authors highlighted that customer dissatisfaction may arise due to increasing customer expectations that offset the savings from operating cost reductions gained with experience. Taking a step further, Tsikriktsis (2007) investigated the overall impact of operational performance on profitability in service organizations with reference to the airline industry. Defining "focused" airlines as airlines that fly from point to point and full-service airlines as those that operate several hubs, Tsikriktsis showed that late arrivals affect the profitability of "focused" airlines but not that of the full-service airlines. He also found that capacity utilization is a stronger driver of profitability for full-service airlines relative to focused airlines. Successively, Steven et al. (2012) looked at the linkages between customer service, customer satisfaction, and firm performance in the US airline industry. Steven et al. agreed that increasing customer service brings about greater customer satisfaction; and satisfied customers are likely to result in repeated purchases. However, the authors recognized that the relationship is likely to be non linear due to diminishing marginal returns to customer service. Examining the effect of market power and market concentration, their study found that the effect of customer satisfaction on financial performance is stronger when the market is less concentrated. Mellat-Parast et al. (2015) extended the work in Steven et al. (2012) by investigating the effect of airline strategy on the relationship between service level (i.e., service failures) and profitability. Specifically, the authors found that certain types of service failures, such as mishandled baggage and customer complaints, affect the profitability of focused airlines more negatively than non-focused airlines. Additionally, the relationship between arrival delays on profitability is universally negative for focused airlines, but displays an inverted U-shaped relationship for non-focused airlines.

From the literature review above, the general consensus is that cost increases bring down productivity and traffic density promotes efficiency through economies of scale. Meanwhile, increase in service quality increases cost in the short term with improvements in customer loyalty to be realised only in the longer term. While liberalization in the industry hurts smaller airlines with intensifying competition, privatization helps to speed up productivity gain and rate of cost reduction. Our study takes on a similar approach in Tsikriktsis (2007) to consider the impact of operational performance on airline profitability. However, instead of broadly classifying airlines into "focused" or "non-focused" airlines, our analysis characterises airlines with some of their intrinsic features such as their operational efficiencies in business orientation, network coverage, physical resources, maintenance, repair and overhaul (MRO), and customer service. Using observation data, we analyse the ways that airlines organize and deploy its resources, and explore their possible relations with profitability to shed light on the winning strategies in today's airline industry.

3. Methodology

3.1. The Conceptual Model

Figure 1 provides a hierarchical presentation of the constituent inputs in the conceptual model. At the top of the hierarchy, business orientation governs the operating regime (which includes the scale of international operations, degree of privatization and market entrenchment) of an airline which may exert an exogenous influence on its overall efficiency and profitability. The network coverage is measured by the number of routes, numbers of international and domestic departures and average flight length. Based on its intended service network, an airline determines the number and type of aircrafts to operate as its physical resources. Depending on the size, composition, and turnaround of its fleet, an airline also has to employ certain number of MRO staffs to support its service network (which is also conditional on the extent that this function is outsourced). Finally, customer service inputs, comprising the numbers of pilots, co-pilots, cabin crews and ground support staff, will likely affect the quality of customer service experienced by passengers.

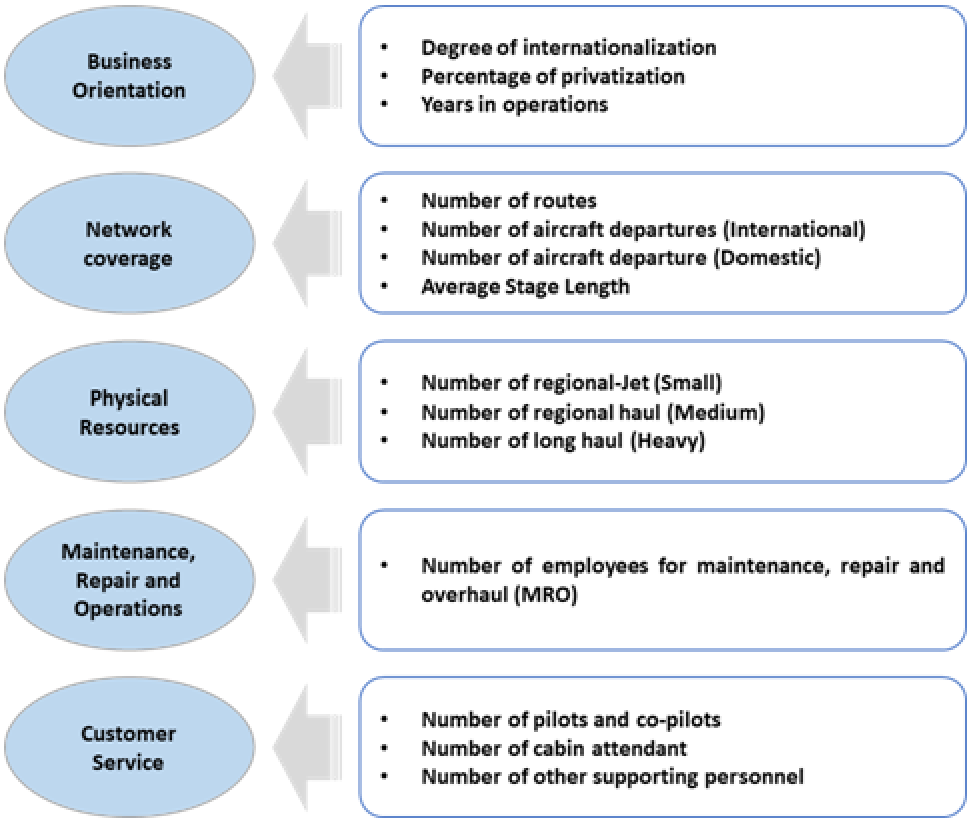


Figure 1. Key Operation Areas and Inputs

3.1.1. Input Variables

The constituent inputs in Figure 1 are grouped into the 5 key input variables, namely business orientation, network coverage, physical resources, MRO and customer service. The business orientation of an airline represents its degrees of internationalization, privatization, and length of experience. Some airlines, described as "geographical generalist" in Lapré and Scudder (2004), serve large proportions of international city-pairs while other "geographical specialist" may choose to be more focus and concentrate on domestic markets. In addition, "geographical specialist" may have more market dominance in local markets compared with "geographical generalist" (Steven et al., 2012). The extent of airline privatization varies between the extremes of fully privatized and totally government-owned, with the effect of privatization being two-fold. First, privatization might enhance the operating efficiency of an airline to compete for funds. Second, it allows airlines to tap on resources and supports from private sectors and, thereby, improve their management expertise. With more years of operations, an airline may gain better reputation and recognition in the industry. While airlines could potentially lower their operating costs as they ride down the learning curve, Lapré and Tsikriktsis (2006) highlighted that increasing customer expectations may offset the gains.

Network coverage provides another lever for an airline to not only improve its brand awareness, but also capture untapped markets and demands for its services. Network coverage, consists of the number of international and domestic aircraft departures, number of routes, and average stage length, is moulded by an airline in response to market forces, with profound impact on its revenue, airport fees and navigation charges. An increase in the number of departures can result in higher flight frequencies (which reduce schedule layovers relative to its competitors) and flights to more destinations (implying a comprehensive network). Since a disproportionate percentage of an airline's operating costs on each route is incurred at the end points of a flight (i.e., take-off and landing fees, fuel consumed during take-off and landing, and terminal fees), short haul flights tend to have higher costs per flight-kilometre than long haul flights (Doganis, 2010; Steven et al., 2012). Although short haul flights enjoy higher yields for an airline, Low and Lee (2014) found that the provision of distant direct flights (i.e., longer average stage length) can offer full-service legacy carriers a competitive edge over the low cost carriers.

Aircraft is an indispensable operating asset as its availability ensures that an airline is able to serve its customers with adequate flight frequencies with minimal schedule delay, and thereby capture a bigger market share (Douglas & Miller, 1974). Airlines can choose to purchase or lease aircrafts to operate their flights. Given that aircraft rental and depreciation together accounts for 19% of the flight operating cost, under-utilization of these physical assets is costly. Physical capitalization differs among airlines with some having a large fleet of heavy-haul flights while others having a fleet consisting of mainly middle or low-haul flights to target smaller or regional markets. According to Givoni and Rietveld (2009, 2010), having heavy-haul aircrafts is beneficial as they can be allocated to longer-haul routes between hubs or higher density routes for higher operating (or fuel) efficiency. Larger aircraft also increases the probability of seat availability when airlines substitute frequency with larger aircraft at congested airports. On the other hand, the use of smaller aircraft may be able to help airlines to offer higher flight frequencies with good loadings on low density routes even though airlines having primarily short-haul flights in their fleet are restricted from flying long distance itineraries due to technological constraints. While diversity in aircraft fleet allows greater operational flexibility in assigning aircraft to routes of varying densities and distances, many airlines prefer a more homogenous aircraft fleet as a means to cap their MRO expenditure, which is the third largest component of an airline's total operating costs.

MRO typically constitutes 10-15 per cent of an airline's operating cost and it is a critical operating aspect of an airline owing to its potential impact on aviation safety (Seristo, 1995). Heikkila and Cordon (2002) observed that many airlines, especially new entrants, which cannot afford large capital investments in MRO, tend to adopt outsourcing as an alternative. At the same time, established airlines have also started to streamline their operations by outsourcing non-core, labour-intensive MRO activities and focusing only on fewer value-added MRO activities (Rosenberg, 2004). Hence, airlines that perform their MRO function primarily in-house are characterised by a larger number of MRO employees under their payroll while those that outsource their MRO functions hire fewer employees relative to the size of their operations.

Flight operating cost accounts for 55% of the total operating cost. Often, labour costs for customer service represent the second largest operating expense for airlines (after fuel), with deck and cabin crew contributing to 12% and 18.7% of the flight operations cost, respectively (IATA, 2013). Nonetheless, having qualified pilots and flight attendants to serve passengers on-board, as well as, sufficient ground and back-end staffs at the airport to smooth transits and bookings of passengers can translate into better customer service and higher revenue.

It is noted in the above discussion that each of the 5 key input variables can affect the performance and profitability of an airline beyond the notion of cost and efficiency. Our goal in this study is to examine any linear or non-linear relationship between profitability and the efficiencies of the 5 key areas. This is to provide a stepping stone for future research to better understand and manage these input variables effectively beyond efficiency.

3.1.2. Output Variable

The total number of passengers, volume of cargo, and distance flown are used as output constituents for the output variable, instead of the conventional combined measures of tons-kilometres or passengers-kilometres. According to Coyle et al. (2015), aggregated output measures such as tons-kilometres or passengers-kilometres can be misleading because these measurements are heterogeneous. To illustrate their point, the authors explained that 500 tons-miles can be achieved by carrying 100 tons of cargo over 5 miles or 500 tons of cargo over 1 mile. Obviously, for each scenario, a very different input, cost, and profitability structure is required to "efficiently" produce the same aggregated output of 500 tons-miles. Non-heterogeneous measures, such as traffic volume carried and distance flown, are thus better measures of outputs for DEA models to accurately compute the efficiency of the inputs used to produce the outputs. The passenger traffic volume is further split into domestic and international passengers in recognition that international passengers may have higher service needs or expectations relative to domestic passengers.

3.2. Establishing the Relationships between Efficiency and Profitability

In this study, an input-oriented SBM model with variable returns to scale is chosen in preference over other Data Envelopment Analysis models, such as the CCR and BCC models (The CCR model proposed in Charnes, Cooper and Rhodes (1978) evaluates the efficiencies of decision-making units (i.e., airlines, in the context of this study) under the assumptions of fixed input-output proportions and constant economy of scale prevails. The BCC model, proposed by Banker, Charnes and Cooper (1984), includes a convexity constraint into the CCR model to allow variable returns to scale, but fixed input-output proportions). Airlines often operate on different scales with different inputs as well as produce different outputs, influenced by other exogenous factors beyond their controls. For instance, airlines facing higher domestic labour cost may choose to hire fewer workers, and operate fewer flights with larger aircrafts. Through a non-radial, slack-based measure (SBM) of efficiency that is based on a mean reduction rate of input relative to the other airlines, the SBM model evaluates the optimal weights without the constraints on fixed input-output proportions (Tone, 2001). The input-oriented SBM model can be written mathematically as:

$$\min_{s^-,\lambda} \theta_{SBM} = \frac{1}{m}\sum_{i=1}^{i=m} \frac{x_{io} - s^-}{x_{io}}$$

subject to

$$\boldsymbol{x}_o = X\boldsymbol{\lambda} + \boldsymbol{s}^-$$

$$Y\boldsymbol{\lambda} \geq \boldsymbol{y}_o$$

$$\boldsymbol{\lambda} \geq 0, \boldsymbol{s}^- \geq 0$$

where the objective function seeks to find an optimum input mix which minimises the input excesses s^- of the test airline. x_o and y_o are m and s dimensional vectors representing the levels of each input used in the production and levels of each output produced by airline o, respectively. Given a reference set of n airlines, X is an $(m \times n)$ matrix and Y is an $(s \times n)$ matrix. λ is a vector in $\mathfrak{R}^n$ comprising of the scalars λ_k ($k \in \{1,2,\ldots,n\}$).

Taking into considerations the possibility of input substitutions, the same set of outputs is used to assess how various inputs contribute to the outputs. The results of the SBM model are the efficiency scores for each of the 5 key operations areas, namely, business orientation, network coverage, physical resource, MRO and customer service for each of the 75 airlines in our data set. The efficiency scores and the location variable of the 75 airlines are then regressed as independent variables against profitability in the ACE regression model. Profitability is used as opposed to net profit because it is not confounded by differences in accounting practices concerning owning versus leasing of airplanes, interest on loans, and others (Tsikriktsis, 2007).

The regression model developed using the ACE algorithm is the best-fitting additive model produced by estimating an individual smooth transformation for each variable in the regression model to maximize the correlation between the dependent and independent variables. Unlike other regression techniques (Box & Cox 1964), ACE transformations are unambiguously defined and estimated without the use of heuristics, restrictive distribution assumptions, or restriction of transformation of a particular parametric family. In theory, ACE algorithm cannot fit a model that is worse than Ordinary Linear Regression. If the variables are related linearly, ACE algorithm will simply suggest linear transformations, i.e. no transformations, for the variables. The regression model proposed by the ACE algorithm thus represents the most likely relationship between the dependent variable and independent variables.

4. Empirical Study

4.1. The Sample and Data

75 airlines were selected on the basis of data availability. European airlines, Asian airlines, American airlines, African airlines and Oceanian airlines make up 43%, 32%, 10%, 8% and 7% of the sample, respectively. These airlines are categorised into regions according to the AIU World Airline Directory.

The data on the airline performance and their outputs (such as operating profits, number of international and domestic passengers and volume of freight carried, and distance flown in 2014) are collected from the IATA's World Air Transport Statistics (2015). Data on the input variables representing the 5 key operating areas are obtained from the same report. These include the degree of internationalization (computed as the proportion of distances flown on international services over the total distance flown in the network) under the 'business orientation';the number of international and domestic aircraft departures under the 'network coverage'; the number and types of aircraft under the 'physical resources'; the number of staffs in maintenance, repair and overhaul under the 'MRO'; and the number of pilots, cabin attendants and other supporting ground staffs under the 'customer service'. The aircrafts in the fleets are aggregated into categories of light, middle and heavy haul flights according to the classification in http://www.airlinecodes.co.uk/arctypes.asp. Similar to Vasigh and Fleming (2005), the stage length (which measures the average distance flown per aircraft departure) is calculated by taking the sum of distance flown (international and domestic) divided by the total number of aircraft departures (international and domestic). The number of operation years is derived from the year of establishment obtained from http://www.airlineupdate.com while the data on number of routes are taken from http://openflights.org/#. Individual airline official websites provide information on the degrees of airline privatizations. Table 1 tabulates a summary of the data set.

Parameters	Average	Maximum	Minimum	Deviation
Business Orientation				
- Degree of Internationalization	72.36%	100%	0	32.14%
- Percentage of Privatization	64.48%	100%	0	37.15%
- Years in Operations	40.39	92	1	26.83%
Network Coverage				
- Number of routes	268	2,180	2	398
- Number of aircraft departures (Int'l)	51,914	418,708	0	69,124
- Number of aircraft departures (Domestic)	58,153	788,137	0	120,675
- Average Stage length in kilometers	2,000	7,000	0	1,000
Physical Resources				
- Number of Regional-Jet (Small)	2.28	139	0	15
- Number of Regional Haul (Medium)	45.84	379	0	67
- Number of Long Haul (Heavy)	28.46	330	0	52
Maintenance, Repair and Overhaul Staff				
- Number of MRO staffs	1,691	20,079	0	2981
Customer Service Staff				
- Number of pilots and co-pilots	1352	11,516	4	2,183
- Number of cabin attendants	3432	25,988	15	5,234
- Number of ground staffs	6564	63,702	45	11,133
Outputs				
- No. of passengers carried on int'l flights	7,343,626	48,244,196	0	9,988,742
- No. of passengers carried on domestic flights	6,857,521	105,189,971	0	15,645,116
- Volume of freight carried (tonnes)	194,879	2,288,460	0	394,638
- International kilometres flown	139,329	803,202	0	189,752
- Domestic kilometres flown	66,511	1,097,070	0	184,721
Performance measure: Operating profit	106,814	3,696,403	-2,546,150	743,470

Table 1. Summary Statistics

The SBM efficiency scores for each airline are computed using the DEA SolverPro, which is an Excel Add-in commercialized by SaiTech. The ACE algorithm is available in the data management software, DBANK, written for Microsoft Windows and is accessible at http://www.tsDbank.com. It is used to develop the nonlinear regression model between profitability and the efficiency scores of the 5 key operations areas and location variable. The ACE algorithm and a build-in stepwise variable selection procedure in DBANK are used to select variables that produce the best regression model. The software is run to read in the data, execute the ACE algorithm, and produce graphical transformations of the selected variables that produce the best fitting regression model. The approach used is a forward-backward stepwise inclusion and deletion of independent variables to prevent over-fitting a regression model. As in all regression models, the residual errors between the raw and fitted data are tested and checked before a model is deemed to fit the data well. Following the recommendation of Neter, Wasserman and Kutner (1985), the residual errors are checked for (i) non-linearity, (ii) non-constancy of error variance, (iii) presence of outliers, (iv) non-independence, (v) non-normality, (vi) omission of independent variables, and (vii) extra independent variables.

4.2. Results

4.2.1. Efficiency Results from SBM model

Table A-1 tabulates the efficiency scores in the 5 decision areas for the 75 airlines. The associated ranks are used to reflect the relative rankings of the airlines in each decision area since direct comparisons within each decision area can be distorted by the number of variables used in characterising the areas. The results in Table A-1 provide clues on how each airline can improve its efficiencies in the different areas. For example, an airline with high efficiency in its 'network coverage' can further improve its network efficiency by adjusting or expanding its current network to increase its outputs. In contrast, an airline with low 'network coverage' efficiency on an overly extended network can consider trimming off the inefficient routes and frequencies in its current network, whereas an airline with low 'network coverage' efficiency on a small network can consider reconfiguring its current inefficient network to better capture the demands.

A cursory review of the results in Table A-1 indicates that airlines that more efficient in some areas are generally more efficient in other areas. Emirates, Lufthansa, Pegasus, United airlines, US airways and Virgin Australia are airlines that achieve full efficiency in all aspects. Table 2 tabulates the correlation indices between the efficiency scores of the 5 decision areas. The correlation indices are generally positive, supporting our assertion that efficient airlines generally perform efficiently across all 5 areas, simultaneously. Interestingly, even though past literature has extensively suggested that efficient 'business orientation' increases financial discipline and market access, 'business orientation' has a relatively weaker correlation with the other decision areas. For examples, Air India and Air Tahiti airlines have full efficiency on 'business orientation' but significantly underperform on 'network coverage' relative to their counterparts. Air India is a fully state-own airline which operates a substantial number of short haul international flights. Air Tahiti is largely a domestic carrier, limiting the comprehensiveness of its service coverage in the international market. This result suggests that a more efficient 'business orientation' only serves as a trigger to improve efficiency; overt actions must be taken to actually improve the efficiency of the 4 other areas, which are more operational in nature. In other words, an airline cannot depend solely on a more efficient business orientation (through privatization and internationalisation) to improve its operational efficiency; it must take overt actions in the 4 other areas to improve its overall efficiencies.

The efficiencies of the 4 other areas are more strongly correlated with each other. 'MRO', for example, is strongly correlated with 'network coverage', 'physical resource' and 'customer service', with correlation indices equal to 0.410, 0.398 and 0.370, respectively. As a support function for the 3 areas, 'MRO' is strongly and positively correlated with the efficiency of the 3 areas. This underscores the importance of managing the 'MRO' function well as it affects not only the efficient use of 'physical resource' to support the 'network coverage',but also the efficient delivery of customer service. The stronger correlation index between 'MRO' and 'network coverage' also suggests that 'MRO' has a more direct and immediate impact on 'network coverage' than on 'physical resource' or 'customer service'.

Airlines reporting high 'MRO' efficiencies fall mainly into two categories: (i) airlines that demonstrate their ability to run and manage the MRO function effectively and efficiently in-house, and (ii) airlines that have outsourced their MRO functions to third parties and companies. Air Transat, Biman Bangladesh Airlines, Jet Lite and IBERIA Airlines are some examples of airlines in the sample that have scored extremely low on MRO efficiency due to an overpopulated number of MRO employees. However, it should be cautioned that outsourcing MRO is not a one-size-fit-all strategy (compared to the 4 other areas, larger disparities are observed in MRO efficiency as airlines adopt different strategies in managing their MRO function. Some airlines prefer to keep their MRO totally in-house to retain control and ensure timely maintenance and repair for their aircrafts, while others prefer to partially or fully outsource their MRO function to focus on their core competencies and leverage on the expertise of their outsourcing partners). Lufthansa and TAP-Air Portugal have achieved above average 'MRO' efficiency scores even though they have a large number of in-house MRO employees. A common characteristic of Lufthansa and TAP-Air Portugal is the heavy traffic volume carried by both airlines, which makes in-house MRO more economically feasible. In addition, Lufthansa provides MRO services to many other airlines through Lufthansa Technik.

Among the correlation indices, Table 2 shows that the efficiencies of 'network coverage' and 'physical resource' are the most highly correlated, with a coefficient index of 0.599. Operationally, choosing the right aircrafts for different parts of a flight network affects both the efficiencies of 'physical resource' and 'network coverage' concurrently. It is therefore not surprising to notice a high correlation in efficiencies between 'physical resource' and 'network coverage'. Having the right number and mix of aircrafts to support an airline service network is very important in ensuring aircraft availability and good loading. Airlines that have full efficiency in 'network coverage' and 'physical resource' are Air France, Air Tahiti Nui, Atlasjet, China airlines, Com Air, Delta Airlines, Emirates, Hawaii Airlines, Hong Kong airlines, Pegasus, SAS, SATA- Acores, Surinam, Thai Airways, United Airlines, US airways, Virgin Australia and Xiamen airlines. In contrast, the mismatch in Air Europa, Air Pacific, Biman Bangladesh Airlines, Ethiopian Airlines, Finnair Oyj, IBERIA, Iran Air, Kenya Airways, LOT Polish Airlines, Oman Air, Royal Jordanian, South African Airways, Sri Lankan Airlines and Tunis Air results in these airlines faring below average in both dimensions. Despite the fact that discrepancy between 'network coverage' and 'physical resource' efficiencies in airlines is generally small, a handful of airlines fare significantly better in one area over the other. For example, Air Mauritius, Air Tahiti, COPA airlines, Croatia and Tarom TAP are more efficient in 'physical resource' while many airlines such as Air Transat, Cathay Pacific, Estonian Air, Jazeera Airways, KLM, Mahan, Qantas, Rossiya - Russian, Singapore Airlines, Transaero Airlines and UT Air are more efficient in 'network coverage'. A further scrutiny reveals that airlines that register high efficiency scores in 'physical resource' are usually equipped with a homogenous fleet of all medium haul aircrafts. Likewise, those airlines that perform better on 'network coverage' usually operate a comprehensive network of short and long routes. These airlines require a variety of planes to support their large number of routes of varying lengths and density.

	Business Orientation	Network Coverage	Physical Resources	MRO	Customer Service
Business Orientation	1	0.216 (0.100)	$.342^{**}$ (0.008)	0.166 (0.208)	0.083 (0.530)
Network Coverage	0.216 (0.100)	1	$.599^{**}$ (0.000)	$.410^{**}$ (0.001)	0.134 (0.312)
Physical Resources	$.342^{**}$ (0.008)	$.599^{**}$ (0.000)	1	$.398^{**}$ (0.002)	0.085 (0.522)
MRO	0.166 (0.208)	$.410^{**}$ (0.001)	$.398^{**}$ (0.002)	1	$.370^{**}$ (0.004)
Customer Service	0.083 (0.530)	0.134 (0.312)	0.085 (0.522)	$.370^{**}$ (0.004)	1

*figures in parenthesis represent the p-values

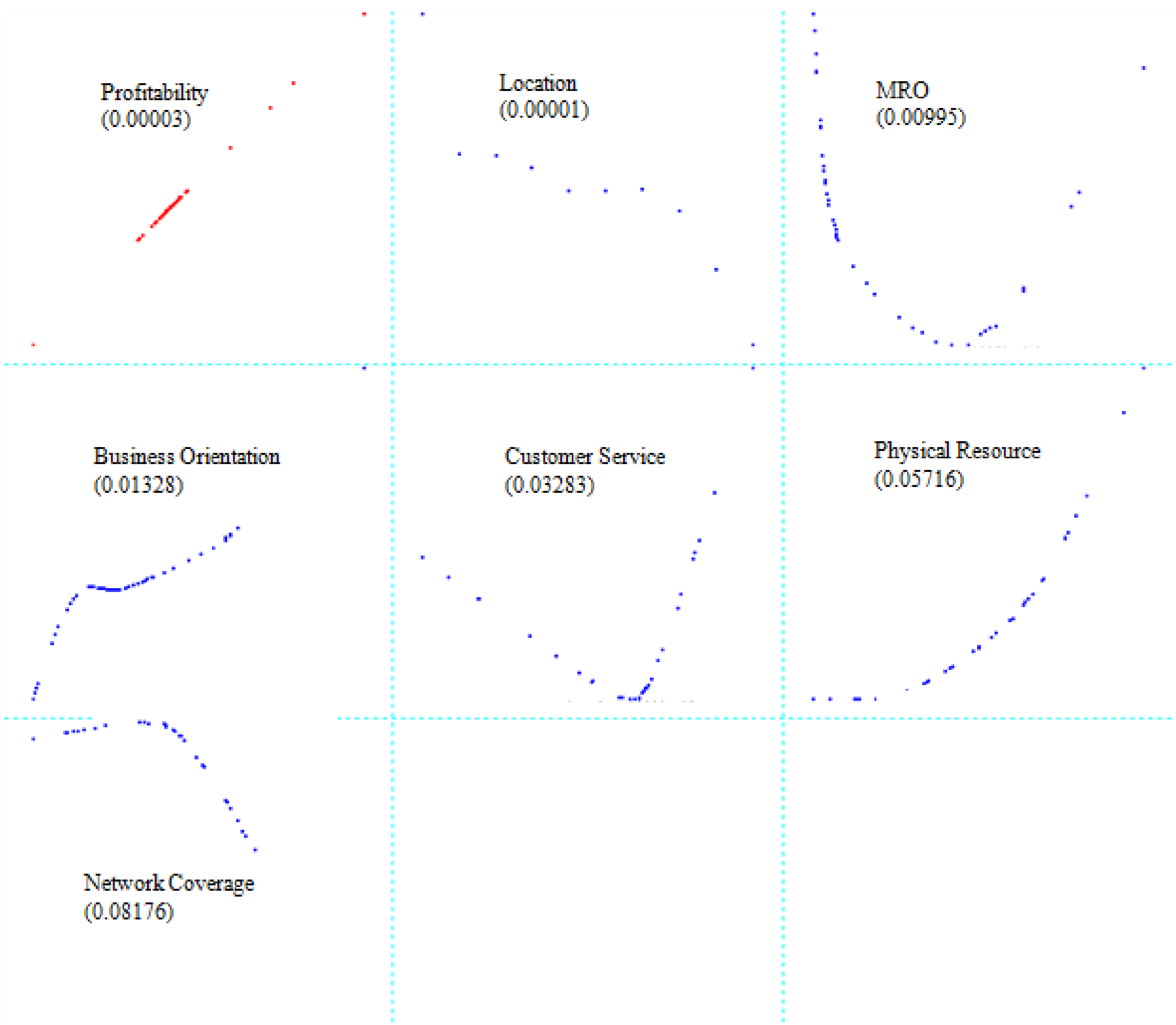
Table 2. Efficiency Correlations among the 5 Operations Areas

Johnson (2002) pointed out that the size of cabin crew and other supporting staff does not increase proportionally when airlines use larger aircrafts to serve more passengers. While this statement suggests possible economies of scale, customer service efficiency falls into the 2 extreme poles reflecting the focus on service quality versus efficiency. Airlines that are highly efficient in this aspect include Aeroflot Russian, Alitalia, Cathay Pacific, Delta, JetLite, KLM, Korean Air, LAN, LOT Polish, SAS, SWISS and United Airlines while Air Seychelle, Iran Air, Mahan Airlines and Malmo aviation are among those that employ a significantly larger number of personnel relative to the traffic volume. Apart from the intensity of personnel deployment, the 'customer service' efficiency scores do not reveal the possible differences among airlines to vary their allocation of staffs into different customer service functions, such as cabin service, ticketing and airport handling to improve their efficiency. But interestingly, the efficiency scores for customer service are found to display the lowest variations among the different airlines. The interpretation is two-fold. On one hand, it may be explained that most airlines perform well in this dimension and operate as a lean organization with minimal over-hiring of customer service staffs. On the other hand, it could be a case that airlines are deploying the number of staffs benchmarked to the standard industry practice.

4.2.2. The link between efficiency and profitability

In the ACE-regression model, a set of independent variables, comprising the 5 efficiency scores and a categorical location variable that represents the geographical location of the airline's primary hub, is regressed against operating profit. The model registers a high R-square value of 0.6054, which is particularly encouraging given that panel data is used. The R-square of 0.6054 for the ACE model represents a significant improvement over the linear regression model with R-square of 0.257.

Figure 2 shows the graphical relation between profitability and efficiencies via the ACE regression model. It should be noted that increases (decreases) in efficiencies may be a result of higher (lower) outputs, lower (more) inputs or both. Each of the sub-graphs demonstrates changes in profitability along the vertical axis as the efficiency of each selected area of operations increases along the horizontal axis.



*Numbers in parentheses indicate the p-values of each variable

Figure 2. Relationships between profitability and efficiencies of key decision areas

'Location' emerges as the most important factor affecting airlines' profitability. It reflects the significant impacts of location on profitability beyond efficiency, representing the intensity of competition and pricing power in different locations. In sub-graph for location in Figure 2, North America and Australia constitute the most profitable and least profitable region, respectively. According to IATA (2016), North American carriers are leading the industry's performance and are expected to generate considerably more than half the global industry's total profits in both 2015 ($19.4 billion) and 2016 ($19.2 billion). On a per passenger basis, profits of $21.44 in 2016 also place their performance at the top of the industry as a result of a strong US economy, appreciating US dollar, lower oil prices, and a restructured aviation industry. On the other hand, for Asia-Pacific region, the overall profits per passenger for 2016 are at $5.13, well behind both US and Europe. Many Asian airlines are negatively affected by weakness in cargo revenue and rising cost pressure due to the depreciating Asian currencies. Market competition in Asia-Pacific has also intensified in recent time with the proliferation of low-cost carriers. In contrast, airlines based in Middle East are doing well for their location. Located at the crossroads between Asia, Africa, and Europe, airlines in the Middle East are well-positioned to compete for traffic connecting these regions. Lower fuel costs combined with the fact that they are well-funded further contribute to their competitiveness on international routes.

The significance of 'customer service', 'business orientation', 'MRO', 'physical resource' and 'network coverage' observed suggests that even when the impact of location on profitability is captured by the model, airlines operators can further improve their profitability by controlling these decision areas. For both 'customer service' and 'MRO', Figure 2 shows that profitability decreases to a lowest point and then increases as efficiency increases. Implicitly, at the lowest profitability point, an airline is offering its customers the least attractive package of customer service or MRO supports. To improve its profitability, an airline should thus operate away from this bitter spot. There are two options. Option one is to adopt a cost-benefit trade-off between efficiency and service quality. An airline can accept a lower efficiency for 'customer service' or 'MRO' by hiring more customer service or MRO staffs to improve its service quality for premium pricing, i.e., operate at a lower efficiency to the left of the lowest profitability point. Option two is to pursue the notion of continuous improvement by embracing technology, including hardware and software, to improve 'customer service' or 'MRO' efficiency without hiring more staff or hurting service quality. An airline, for example, can increase its 'customer service/MRO' efficiency by embracing training and automation to improve the service quality and productivity of its customer service/MRO staffs simultaneously. These can include the use of automation, computerization and outsourcing to improve the efficiency of its in-house staffs on core services. To improve profitability, both options one and two are equally viable and attractive as Figure 2 shows that profitability increases significantly when 'customer service/MRO' efficiency changes in either direction beyond the bitter spot of lowest profitability.

Consistently positive associations are indicated for 'business orientation' and 'physical resource' efficiencies on airlines' profitability. The former exhibits a continual improvement in profitability through greater efficiency in internationalization, privatization and operating experience of an airline. The interpretation of the latter is straightforward: Efficient utilization of aircrafts is important to improve profitability because aircrafts are expensive investment. Nevertheless, 'physical resource' is a less critical differentiator compared to the 'customer service' and 'business orientation' as loadings of an average flight across big and small airlines in all parts of the world are generally high (Doganis, 2010).

In contrast, 'network coverage' exhibits an inverted U-shaped curve where profitability first rises gradually until it hits a plateau. Specifically, initial increases in network efficiency mean that airlines can enjoy higher traffic densities on its flights and thereby increase their operating profits. This higher traffic density can be achieved with a more concentrated network with fewer routes and departure frequencies using larger aircrafts. However, as the efficiency of 'network coverage' reaches a saturation point, further increases in traffic density lead to network congestion and coverage in adequacy resulting in profitability drops. This is particularly true if the higher traffic density is attracted through lower fares, which directly reduces the contribution margin of the passenger or cargo carried. An expansion in the network by means of offering more routes, longer distant flights and higher frequencies is seen to be beneficial for airlines that operate beyond the saturation point of 'network coverage'. This finding is in congruent with Low and Lee (2014) who suggested that the offering of direct flights can help full legacy carriers differentiate themselves from low cost carriers. Longer distance itineraries can also help reduce fuel consumption per kilometre flown in the overall network, leading to cost savings and higher operating profits. Offering better connectivity at the expense of lower network efficiency gives airlines the option to charge premium prices and attract customers who value connectivity. In gist, improved 'network coverage' efficiency benefits all airlines up to a saturation point. Beyond the saturation point, all airlines are equally affected by congestion and limited connectivity. Our result shows that a sizable number of airlines are operating above the saturation point, and these airlines can increase their profitability by expanding their 'network coverage' rather than focusing on increasing their 'network coverage' efficiency.

5. Conclusions

An integrated SBM-ACE regression model, which permits different input-output mix, variable return to scale and non-linear relationship, is applied to analyze the impact of service efficiencies in five key areas of operations on the profitability of 75 international airlines. The five decision areas examined include business orientation, network coverage, physical resource, maintenance, repair and overhaul (MRO), and customer service.

Our results indicate different levels of correlation between the five decision areas. Interestingly, business orientation, i.e., privatization and internationalisation, is least correlated with the other four decision areas. This implies that a more efficient 'business orientation' only serves as a trigger to improve efficiency. Overt actions must be taken to actually improve the efficiencies of the four other areas, which are more operational in nature. The strong correlations between efficiencies of the four decision areas suggest that decisions in one area can affect the efficiencies of other areas. For example, choosing the right number and mix of aircrafts under 'physical resource' can also affect the efficiency of 'network coverage'. These results also underscore the importance of managing the 'MRO' function well as a support function for the other three areas. Particularly, the strong correlation between 'MRO' and 'network coverage' efficiencies suggests that 'MRO' has a direct and immediate impact on 'network coverage'.Nevertheless, despite these correlations, airlines do encounter trade-offs, such as between having comprehensive 'network coverage' and efficient utilization of 'physical resource'. While the latter is enhanced through aircraft homogeneity that promotes 'MRO' efficiency, operating a more comprehensive service network may require the provision of a variety of aircrafts to serve itineraries of different distances and traffic densities.

The ACE regression model suggests that airlines' profitability is always positively linked to increased 'business orientation' and 'physical resource' efficiency. In contrast, the impacts of 'customer service', 'MRO', and 'network coverage' efficiencies on airlines' profitability vary with the levels of efficiency in these three areas. Both increasing and reducing 'customer service' or 'MRO' efficiency beyond a bitter-spot of lowest profitability leads to higher profitability. To improve profitability, an airline can choose to operate at a lower efficiency below the bitter spot by hiring more 'customer service' or 'MRO' staff to provide better service quality. Alternatively, the same airline can try to improve its efficiency above the bitter spot by embracing technology, with hardware and software, into its 'customer service' or 'MRO' functions to achieve 'real' improvement in efficiency without compromising its service quality. Accepting a lower 'customer service' or 'MRO' efficiency refers to airlines that subscribe to the traditional notion of cost-versus-quality trade-off to achieve greater service differentiation and premium pricing to increase profit. Increasing the 'customer service' or 'MRO' efficiency without compromising service quality characterises airlines that embrace the notion of continuous improvement in service quality and efficiency to improve profits.

Finally, the efficiency of 'network coverage' similarly has a non-linear impact on profitability. Increasing the efficiency of 'network coverage' towards the saturation point of highest profitability leads to higher profitability. Above the saturation point, increasing the 'network coverage' efficiency results in sharp drops in profitability. In their pursuit of higher efficiency in 'network coverage', airlines should thus beware of network congestion. Airlines that are currently operating above the saturation point can improve their profits by expanding their networks and offer better connectivity with lower 'network coverage' efficiency. These observations suggest that airlines should always maintain a clear strategic focus on 'customer service', 'MRO' and 'network coverage'. Value-air is a case in point. As a low-cost carrier, Value-air attempted to differentiate itself from other low-cost carriers by offering frills, i.e. better customer service, such as larger baggage allowance, in-flight food, and allocated seats, which significantly affect the efficiency of its customer service staffs. The airline also attempted to offer flights beyond the traditional five-hour radius of low-cost carriers. Without a clear focus on its network coverage, Value-air was eventually forced to concede defeat in a highly-competitive local marketplace. Its attempt to offer better customer service and expand its network coverage beyond the established threshold adversely affected its efficiencies and profitability.

Admittedly, this paper is not without its limitations. Firstly, the data are extracted largely from IATA's World Air Transport Statistics. As non-IATA airlines are excluded, a holistic view of the airline industry may be hindered as there are limited records on low cost carriers. Secondly, certain intrinsic factors that may affect an airline's profitability are not captured in the input data. For examples, cultural differences and language barriers may be crucial in personalized services as airlines expand their international and domestic services. The success of outsourcing or privatization may also depend on the existence and selection of the right partners. Thirdly, the value of the service perceived by consumers varies as service bundles seek to address important considerations and preferences (such as availability of direct flights, aviation safety, flight schedules, and frequent flyer programmes). Nonetheless, recognizing that airlines are a complicated business, detail modelling of every aspect (such as yield management in airfare pricing, and aviation safety) is beyond the scope of this paper. Future research can thus further examine the success factors that contribute to the efficiency and profitability of airlines.

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Annex. Table A-1. Efficiency Scores

	Airlines	Business Orientation		Network		Physical Resource		Maintenance, Overhaul, Repair		Customer service	
		Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
1	**Aeroflot Russian Airlines**	0.383	54	0.786	40	0.710	44	0.521	23	1	1
2	**Aeromexico**	0.432	41	0.730	44	0.665	48	1	1	0.816	40
3	**Air Astana**	0.767	12	0.661	56	0.782	38	0.037	53	0.686	53
4	**Air Europa**	0.367	58	0.662	55	0.618	51	0.376	28	0.902	35
5	**Air France**	0.431	42	1	1	1	1	NIL	NIL	0.767	42
6	**Air India**	1	1	0.679	51	0.768	40	0.076	40	0.657	58
7	**Air Mauritius**	0.333	60	0.795	39	0.441	66	0.028	56	0.805	41
8	**Air Pacific**	0.285	66	0.627	60	0.516	59	0.039	52	0.707	51
9	**Air Seychelles**	0.405	48	1	1	0.868	31	0.034	55	0.297	66
10	**Air Tahiti**	1	1	0.664	54	1	1	0.034	54	0.151	70
11	**Air Tahiti Nui**	0.522	28	1	1	1	1	0.055	44	0.675	54
12	**Air Transat**	0.372	56	1	1	0.382	70	0.076	39	1	1
13	**Alitalia**	0.299	64	0.634	59	0.845	34	0.572	20	1	1
14	**Atlasjet Airlines**	0.499	31	1	1	1	1	1	1	0.426	65
15	**Bangkok Airways**	0.267	68	0.603	63	NIL	NIL	0.053	45	0.540	63
16	**Biman Bangladesh Airlines**	0.715	15	0.646	57	0.414	69	NIL	NIL	NIL	NIL
17	**Binter Canarias**	0.435	40	1	1	NIL	NIL	NIL	NIL	1	1
18	**Bulgaria Air**	0.415	46	0.767	42	0.801	37	0.165	35	0.739	44
19	**Cathay Pacific Airways**	0.361	59	1	1	0.845	35	1	1	1	1
20	**China Airlines**	0.417	45	1	1	1	1	0.305	30	1	1
21	**Comair**	0.384	53	1	1	1	1	1	1	0.901	36
22	**COPA Airlines**	0.704	17	0.616	62	1	1	0.303	31	1	1
23	**Croatia Airlines**	0.537	27	0.695	48	0.846	33	0.016	61	1	1
24	**Czech Airlines**	0.233	72	0.495	72	0.742	42	NIL	NIL	1	1
25	**Delta Air Lines**	1	1	1	1	1	1	1	1	1	1
26	**El Al**	0.238	71	0.814	37	1	1	0.042	51	0.720	48
27	**Emirates**	1	1	1	1	1	1	1	1	1	1
28	**Estonian Air**	0.476	34	1	1	0.918	28	1	1	1	1
29	**Ethiopian Airlines**	0.708	16	0.497	71	0.348	71	0.048	48	1	1
30	**Finnair Oyj**	0.292	65	0.508	70	0.577	54	NIL	NIL	1	1
31	**Hawaiian Airlines**	0.245	69	1	1	1	1	0.640	18	0.709	50
32	**Hong Kong Airlines**	0.589	25	1	1	1	1	1	1	NIL	NIL
33	**IBERIA**	0.232	73	0.567	64	0.612	52	0.042	50	0.543	62
34	**Iran Air**	0.277	67	0.635	58	0.477	64	0.004	65	0.220	69
35	**Jat Airways**	1	1	NIL		0.995	26	NIL	NIL	NIL	NIL
36	**Jazeera Airways**	0.421	44	1	1	0.702	45	0.191	34	1	1
37	**Jet Airways**	0.512	29	0.800	38	0.803	36	0.262	32	0.697	52
38	**Jet Lite (India) Ltd**	NIL				0.875	30	0.021	60	1	1
39	**Kenya Airways**	0.327	61	0.562	65	0.484	63	0.064	43	1	1
40	**KLM**	0.319	62	1	1	0.961	27	0.424	27	1	1
41	**Korean Air**	0.448	38	1	1	1	1	0.638	19	1	1
42	**Kuwait Airways**	0.242	70	0.726	45	0.474	65	0.016	62	0.852	38
43	**LAN Airlines**	1	1	1	1	1	1	0.474	26	1	1
44	**LOT Polish Airlines**	0.311	63	0.515	68	0.490	62	0.510	24	1	1
45	**Lufthansa**	1	1	1	1	1	1	1	1	1	1
46	**Mahan Airlines**	0.446	39	1	1	0.568	56	0.007	64	0.295	67
47	**Malaysia Airlines**	0.390	52	0.695	47	0.642	49	0.089	37	0.662	57
48	**Malmö Aviation**	0.739	14	0.675	53	NIL	NIL	0.256	33	0.255	68
49	**Oman Air (SAOG)**	0.413	47	0.619	61	0.493	61	0.068	42	0.589	59
50	**Pegasus Airlines**	0.465	36	1	1	1	1	1	1	1	1
51	**Philippine Airlines**	0.396	50	0.767	43	0.888	29	1	1	0.862	37
52	**Qantas Airways**	0.559	26	1	1	0.677	46	0.554	21	0.757	43
53	**Rossiya - Russian Airlines**	0.593	24	1	1	0.675	47	0.126	36	0.847	39
54	**Royal Jordanian**	0.391	51	0.439	73	0.431	68	0.051	47	0.732	45
55	**SAS - Scandinavian Airlines**	0.373	55	1	1	1	1	0.808	16	1	1

56	**SATA-Air Açores**	NIL		1	1	1	1	NIL	NIL	NIL	NIL
57	**Shenzhen Airlines**	1	1	1	1	NIL	NIL	0.479	25	1	1
58	**Singapore Airlines**	0.455	37	1	1	0.534	57	1	1	1	1
59	**South African Airways (SAA)**	0.691	18	0.676	52	0.609	53	0.027	57	0.717	49
60	**SriLankan Airlines**	0.368	57	0.717	46	0.437	67	0.026	59	1	1
61	**Sun Express**	0.486	33	0.773	41	0.764	41	0.043	49	0.726	46
62	**Surinam Airways**	0.680	20	1	1	1	1	0.052	46	0.665	56
63	**SWISS**	0.761	13	0.831	36	0.852	32	0.332	29	1	1
64	**TAROM**	0.689	19	0.543	66	0.775	39	0.012	63	0.666	55
65	**Thai Airways**	0.397	49	1	1	1	1	0.072	41	0.587	60
66	**Transaero Airlines**	1	1	1	1	0.572	55	NIL	NIL	1	1
67	**Tunis Air**	0.475	35	0.690	49	0.528	58	NIL	NIL	0.495	64
68	**Ukraine International Airlines**	0.508	30	0.524	67	0.510	60	0.027	58	0.726	47
69	**United Airlines**	1	1	1	1	1	1	1	1	1	1
70	**US Airways**	0.622	23	1	1	1	1	1	1	1	1
71	**UT Air**	0.495	32	1	1	0.623	50	0.782	17	0.553	61
72	**Virgin Australia (International)**	1	1	1	1	1	1	1	1	1	1
73	**Wideroe**	0.426	43	0.511	69	1	1	NIL	NIL	NIL	NIL
74	**Xiamen Airlines**	0.652	22	1	1	1	1	0.536	22	1	1
75	**TAP-Air Portugal**	0.678	21	0.687	50	0.738	43	0.078	38	1	1