EVALUATING AIRLINE PERFORMANCE WITH NONORIENTED SLACKS BASED MEASURES OF SUPER EFFICIENCY

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ABSTRACT

The paper contributes to the literature on airline performance by estimating efficiency measures of airlines using the nonoriented super-efficiency slacks based approach to data envelopment analysis (DEA). The nonoriented aspect of the DEA captures the desire to improve both the inputs and outputs simultaneously; the super efficiency feature allows efficiency scores of more than unity so that efficient airlines can be fully ranked, especially under the variable returns to scale assumption that reflects pure technical efficiency; and the slacks-based aspect guarantees Pareto-efficiency and ensures the provision of a final efficiency score that accounts for all sources of inefficiency. The chosen method does not suffer from the infeasibility problems of the variable returns to scale formulation of super efficiency DEA. Input and output data on 46 international airlines covering the period from 2008 to 2012 were utilised. The sample includes a mixture of low-cost and full-service carriers, alliance affiliated and non-allied airlines, and airlines from different regions of the world to see whether the business model, alliance affiliation or region of origin made a difference. The airlines were ranked according to their efficiency scores under the constant and variable returns to scale assumptions.

Key words: airlines, super-efficiency, data envelopment analysis, slacks-based measure.
JEL Classification: L93.

1. INTRODUCTION

According to IATA, within the 2004-14 decade the number of passengers carried by the world's airlines rose from about 2.1 billion to a little over 3.1 billion, representing an average annual growth rate of about 5.9%. The corresponding revenue rose from just under $US300 billion to a little under $US600 billion (IATA, 2014). The upward trend in global air travel, the challenges posed by low cost carriers (LCCs) to full service carriers (FSCs), the histories of numerous defunct airlines[2] and failed alliances[3] in the past, the withdrawal/ejection or

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[2] For example: Ansett Airlines, in 2002; Swissair, in 2002; Spanair, in 2012; and Malév Hungarian Airlines, in 2012.

[3] Examples of defunct alliances and dates of demise are: European Quality Alliance, in 1993; Global Excellence, in 1997; Atlantic Excellence, in 1999; Qualiflyer, in 2002; and Wings, in 2003.

switching from one alliance group to another by airlines[4] and the high international media profile of airline accidents or mishaps mean that the performance of airlines continues to be topical even after the recovery from the shocks of the '9/11' incident in New York City on September 1, 2001, the SARS (Severe Acute Respiratory Syndrome) scare of 2003 and the global financial crisis (GFC) of 2008-09 on the aviation industry. Various analytical methods have been used to investigate airline performance, for example, the cost functions by Liu and Lynk (1999) and Oum and Yu (1998); the total factor productivity analysis by Barbot *et al.* (2008), Vasigh and Fleming (2005) and Forsyth (2001); the parametric stochastic frontiers analysis by Inglada *et al.* (2006) and Coelli *et al.* (2005). But by far the most widely used method for studying airline efficiency and performance benchmarking is the data envelopment analysis (DEA) method and variants thereof.

DEA is a linear programming based technique used to measure the relative efficiencies of peer decision making units (DMUs) in multiple-input multiple-output settings. The technique, which built on Farrell's (1957) idea was suggested by Charnes *et al.* (1978) who assumed constant returns to scale (CRS). The CRS production technology assumes a given proportional increase (decrease) in all inputs leads to the same proportional increase (decrease) in all outputs. The corresponding [overall] technical efficiency (OTE) measure reflects the ability of a DMU to obtain maximum outputs from the given inputs. DMUs deemed to be fully technically efficient receive a score of unity; those deemed to be inefficient receive a score less than unity. Hence, OTE ≤ 1. The CRS assumption implies all the DMUs are producing at the optimal size or scale. However, if some factors (i.e., constraints in the operating environment) prevent some DMUs from operating at the optimal scale, the OTE estimate will be confounded by scale inefficiency. A more flexible model developed by Banker *et al.* (1984) relaxes the assumption of CRS to variable returns to scale (VRS). The use of the VRS specification permits the calculation of scale inefficiency, making it possible to isolate what is called pure technical efficiency (PTE) from the OTE. The PTE obtained from the VRS specification reflects the proportion of OTE which is attributed to the efficient conversion of inputs into outputs given the scale of production; also, PTE ≤ 1. Comparatively, VRS ≥ CRS (which is equivalent to PTE ≥ OTE). Scale efficiency (SE), which is given as the ratio of OTE to PTE (i.e., SE = OTE/PTE which is equivalent to CRS/VRS), measures the impact of the size of operation on the efficiency of a DMU. It may be noted that SE ≤ 1.

DMUs deemed to be efficient receive a score of one and lie on a best-practice or efficient frontier; those deemed inefficient lie some distance from the frontier. The distance to the frontier (for an inefficient DMU) constitutes the measure of inefficiency. There are many measures of efficiency used in DEA models that may be grouped under two classifications: radial and nonradial measures of efficiency. In radial measures of efficiency the mix within inputs or within outputs is preserved in movements toward the frontier. That is, only percentage changes in all inputs collectively or all outputs at one time are considered. Radial measures may either be input or output oriented (but not nonoriented). Input orientation means the calculation of the distance to the frontier is done giving priority to input contraction when inputs, compared to outputs, are relatively more controllable by the DMU. Conversely, output orientation means priority is given to output expansion in the context when outputs are relatively more controllable. When a DMU is 100% radially efficient, all inputs collectively cannot be reduced pro rata without detriment to its outputs, nor can its

[4] Aer Lingus voluntarily left Oneworld in 2007 and Continental Airlines left SkyTeam to join Star Alliance in 2009 and merged with United Airlines in 2010.

outputs be raised pro rata without more inputs. However, a DMU 100% efficient in this sense is not necessarily Pareto-efficient (when no one output can be increased without decreasing another, given the input set) because the pro rata improvements to inputs, or alternatively to outputs, may not be possible but improvements to the individual levels of some inputs or outputs may be possible. Such improvements are captured in the slacks in the input and output constraints. To guarantee Pareto-efficiency, the model can be solved in a first stage (yielding radial efficiency) and then a second stage model can be solved by maximizing the slacks (yielding Pareto-efficiency) in the input-output constraints. Under CRS, input efficiency is equal to output efficiency but may not necessarily imply Pareto-efficiency. Under VRS, it is only when a DMU is Pareto-efficient in the input orientation that it will also be Pareto-efficient in the output orientation.

In contradistinction to radial measures of efficiency, nonradial measures of efficiency do not preserve the mix within inputs and within outputs in movements toward the frontier. They are useful for finding Pareto-efficient units and may be either oriented (input-conserving or output-expanding, depending on which factor is controllable) or nonoriented (both inputs and outputs are controllable and therefore both inputs and outputs are targeted for improvement). Measures of efficiency that are slacks based (SBM) are nonradial.

Standard oriented DEA tends to assign efficiency scores of one for multiple DMUs (depending on the number of inputs and outputs) and that makes it impossible to differentiate among those DMUs deemed to be efficient. The inconvenience of the inability to distinguish among the efficient (top-ranking) DMUs from standard DEA models led to the development of tie-breaking methods such as super-efficiency (Andersen and Petersen, 1993), crossed evaluation or assurance regions (Cooper *et al*., 2007), among others. Owing to the availability of the super-efficiency DEA model in commercial softwares, it has become the most widely used. The method breaks the tie among the efficient DMUs by letting them score values greater than one thus permitting scale ranking. The larger the value of the super-efficiency measure the higher the observation is ranked among the efficient units. Whereas the standard DEA identifies the DMUs as being efficient or inefficient, super-efficiency DEA allows the ranking of the DMUs into four categories: strongly super-efficient, super-efficient, efficient and inefficient. However, the super-efficiency routines in commercial softwares tend to generate infeasible solutions for some DMUs under VRS. This restricts the usefulness of super-efficiency DEA (Chen, 2005) unless the researcher writes their own program to fix the infeasibility. Examples of studies that have used DEA are Lee and Worthington (2010, 2014), Ouellett *et al.* (2010), Bhadra (2009), Barros and Peypoch (2009), Greer (2008), Scheraga (2004), and Adler and Golany (2001). Those studies typically report radial measures of efficiency for which either input orientation (when the focus is on the minimization of inputs) or output orientation (when the focus is on the maximization of outputs) must be assumed separately depending on whether it is only inputs or only outputs that are controllable. In the airline industry it is conceivable that all or some of both the inputs and outputs could be controllable and therefore the contraction of inputs and the expansion of outputs simultaneously are desirable. In such an instance, nonoriented measures of efficiency (which are necessarily nonradial) reflect the potential for improvement in desired input and output directions and thus can guarantee Pareto-efficiency (Fried *et al.*, 2008).

This paper contributes to the literature on airline performance by estimating efficiency measures of airlines using the nonoriented super-efficiency slacks based measure (SBM) approach. As argued earlier, the nonoriented aspect captures the desire to improve both the inputs and outputs simultaneously; the super efficiency aspect allows efficiency scores of more than one so that efficient DMUs can be fully ranked, especially under the variable returns to scale assumption that reflects pure technical efficiency; and the slacks-based aspect guarantees Pareto-efficiency and ensures the provision of a final efficiency score that accounts for all sources of inefficiency. The chosen method does not suffer from the infeasibility problems of the variable returns to scale formulation of super efficiency DEA. Input and output data on 46 international airlines covering the period from 2008 to 2012 were utilized. The sample includes a mixture of LCCs and FSCs, alliance-affiliated and nonallied airlines, and airlines from different regions of the world to see whether the business model, alliance affiliation or region of origin made a difference. The airlines were ranked according to their super efficiency scores under the constant and variable returns to scale assumptions. The rest of the paper is organized as follows: Section 2 presents a stylized version of the theory behind the evaluation of performance of production units and reviews empirical studies on airline performance; Section 3 outlines the model of choice and describes the data used and sources; Section 4 presents the analytical results; and Section 5 summarizes and concludes the paper.

2. LITERATURE REVIEW

2.1 Theoretical literature – measures of performance

Fried *et al*. (2008) note that although the ultimate yardstick of business performance is profit, the authors emphasize that profit, or any financial indicator, must be seen as a *reflection* rather than a *measure* of performance. Performance involves solving the technical and allocative problems associated with economic optimization (i.e., avoiding waste in using inputs and producing outputs in the right mix or proportions, given their prices). Three of the main measures of performance are efficiency, productivity and profitability. Efficiency is either technical or economic. Technical efficiency (TE) refers to the ability to obtain the maximum level of outputs from a given set of inputs or to minimize the inputs for producing a given amount of outputs. Allocative efficiency (AE) refers to the ability to attain the right mix of inputs and outputs, given their prices. Overall economic efficiency (EE) is the product of TE and AE, and it reflects the ability to generate the maximum profit; it is a result of the management of resources and outputs. Other things being equal, business performance varies because of differences in managerial ability, which, because it is unobservable, is inferred from TE relative to the competition. Thus TE involves the construction of a best-practice frontier with regard to either production or cost or revenue or profit and the measurement of distance to it for each production entity. Efficiency of a producer is measured by comparing the observed or actual and optimal values of its output and input (or best practice values). The 'best practice' can change through time. Frontier analysis benchmarks the performance of the rest against that of the best.

Productivity is the ratio of outputs to inputs, and is an indicator of how effectively resources are utilized. Variation in it is attributed to differences in the production technology and environment, and in the utilization of human resources. Hence, although efficiency is a performance metric in its own right, it is subsumed within productivity. Changes in productivity arising from development or adoption of new technologies bring improvements in both TE and AE. Profitability, defined as the ratio of revenue and cost, pertains to the size of the price-cost margin and is a composite measure made up of productivity and price recovery. Price recovery may be thought of as the degree to which input cost increases can be passed on to customers in the form of higher output prices. It helps to measure the abilities of firms to be price or allocatively efficient. The foregoing demonstrates that technical efficiency, a measurable plausible proxy of the managerial ability which drives the differences in business performance, is subsumed in productivity which in turn is a constituent element of profitability. Hence technical efficiency is at the core of the economic performance of any production unit.

2.2 Empirical literature

Empirical studies on airline efficiency have employed either data envelopment analysis (DEA) or stochastic frontier analysis (SFA) or both (Michaelides *et al*., 2009). These alternative methods can be used to estimate the frontiers indicative of best performance in production technology and have been applied extensively in efficiency analysis in various other industries, especially, banking, transportation and agriculture. Often both methods are utilized for comparative purposes. Whereas DEA (which is non-parametric) uses mathematical programming to estimate a deterministic frontier that incorporates only inefficiencies, SFA (which is parametric) uses econometric techniques to estimate a stochastic frontier that incorporates both inefficiencies and random error. The main advantage of DEA is that it does not require any information more than input and output quantities. Its main drawback is that it is sensitive to measurement errors or noise in the data because it attributes all deviations from the frontier to inefficiencies. SFA's strength lies in the fact that it considers random errors in the data and allows for statistical inference. The main complication of SFA is the set of assumptions about the functional form of the production technology and the distribution for the inefficiencies.

Since both methods have strengths and weaknesses, none trumps the other in all circumstances. Auspiciously also, there are high positive correlations between the technical efficiency scores estimated from the two methods (Coli *et al*., 2011; Cullinane *et al*., 2002; Lin and Tseng, 2005). However, the different underlying assumptions mean that different implications may flow from the efficiency estimates calculated from the different approaches. Choice between the two approaches may depend on data availability and the research objectives in respect of the distinctive inferences that a particular approach might permit. The two methods are adequately described by Coelli *et al*. (2005) and Fried *et al*. (2008). In airline efficiency studies, DEA seems to be more popular than SFA. Whereas only a handful of studies have employed SFA (e.g., Cornwell *et al*., 1990; Good *et al*., 1993, 1995; Coelli *et al*., 1999; Inglada *et al*., 2006; and Coli *et al*., 2011) several more studies have used DEA (e.g., Schefczyk, 1993; Distexhe and Perelman, 1994; Good *et al*., 1995; Fethi *et al*., 1999; Soares de Mello *et al*., 2003; Scheraga, 2004, 2006; Araujo *et al*., 2007; Barbot *et al*., 2008; Barros and Peypoch, 2009; Bhadra, 2009; Ouellette *et al*., 2010 and Merkert and Hensher, 2011).

In the available studies, different outputs and inputs have been chosen to analyze airline efficiency. Reviewing past studies, Chang and Yu (2014) summarise that available ton kilometres, operating cost, non-flight assets, fuel cost, personnel cost, and aircraft cost are popularly selected as input variables. And for output variables, revenue passenger kilometres (RPK), number of flights, and seat miles/kilometres are generally used. Different studies have used different combinations of inputs and outputs depending on the objectives and so there seems to be complete discretion in the selection of input and output variables. For example, Good *et al.* (1995) used aggregated revenue output including passenger service, cargo service and incidental services while inputs included labour, energy and other materials, and aircraft fleet. They took into account the stage length, load factor, network size, percentage of wide body aircraft and percentage of turbo-prop aircraft as the environmental variables. Coli *et al.* (2011) chose three inputs for producing one output. The inputs included total seats, total variable direct operating costs and number of delayed flights. The output was passenger-scheduled revenue.[5] With respect to the orientation in empirical DEA models, some studies assumed input orientation only, others output orientation only, and others reported and compared input-oriented and output-oriented results. A sample of recent airline DEA studies and the input and output variables utilized and the orientation employed is provided in Table 1. Each study rationalized the orientation it adopted. In general, therefore, either orientation is tenable. If this inference is logical, then the nonoriented approach (which integrates input and output orientations) should be valid. But to the knowledge of the current author, no study on airline performance using DEA has employed the nonoriented approach.[6] This study will employ the nonoriented approach to reflect the possibility that airlines do not exclusively target input minimization or output maximization but do in fact have varying degrees of control over both their inputs and outputs.

Table 1: A sample of recent airline DEA studies and the input-output indicators used

Study	Inputs	Outputs	Orientation
Assaf and Josiassen (2012)	(i) Number of employees; (ii) Total assets; (iii) Fuel; (iv) Other operating costs	(i) RPK; (ii) Incidental revenues	Output-orientated
Barbot *et al*. (2008)	(i) Labour; (ii) Fleet; (iii) Fuel	(i) ASK; (ii) RPK; (iii) RTK	Input-orientated
Barros and Peypoch (2009)	(i) Number of employees; (ii) Operational cost; (iii) Number of planes	(i) RPK; (ii) EBIT	Output-orientated
Lee and Worthington (2014)	(i) Number of employees; (ii) Total assets; (iii) Kilometres flown	ATK	Output-orientated
Merkert and Hensher (2011)	(i) ATK; (ii) Staff number	(i) RPK; (ii) RTK	Input-orientated
Scheraga (2004)	(i) ATK; (ii) Operating cost; (iii) Non-flight assets	(i) RPK (ii) Non-passenger RTK	Input-orientated

Note: ASK = Available seat kilometre; ATK = Available ton kilometre; EBIT= Earnings before interest and taxes; RPK = Revenue passenger kilometre; RTK = Revenue ton kilometre.

[5] Coelli *et al.* (1999) in their SFA model used one output measure and two input measures, which were labour and capital. The labour input was an aggregate of two separate categories of employment used in the production of air travel while capital input was the sum of the maximum take-off weights of all aircraft multiplied by the number of days the aircraft were able to operate during a year.

[6] Chang and Yu (2014) apply the slacks-based network DEA (NDEA) to a cross section of 16 low-cost carriers to measure their input-oriented production and output-oriented consumption efficiencies in a unified model. Although essentially also nonradial, the slacks-based NDEA is different from the nonoriented super-efficiency SBM employed in the current study. Another study using NDEA is Zhu (2011). NDEA assumes each DMU is made up of multiple divisions that are connected by links of network structure. The nonoriented super-SBM assumes no such network features of the internal structure of the DMUs.

This study will utilize three inputs and three outputs. The input variables are: available seat kilometre (ASK), number of employees and operational expense; the output variables are: revenue, number of passengers carried and revenue-passenger-kilometre (RPK). Among the inputs, ASK is obtained from multiplying the seating capacity (whether filled by passengers or not) and the distances in kilometres flown; and among the outputs, RPK is the product of the number of paying passengers and the number of kilometres they travelled (Barros and Peypoch, 2009). Compared to ASK, RPK reflects the difference between seat capacity and number of passengers transported.

3. METHODOLOGY AND DATA

3.1 Methodology – specification of the super-SBM

This study estimates the CRS and VRS nonoriented SBM of super efficiency using *DEA Solver-Pro*. For the methodology, therefore, we present an abridged description of the mathematical specification of super-SBM by Tone (2002) that underlies the implementation of super-SBM in *DEA Solver-Pro*.[7]

Assume there are n-DMUs using varying amounts of m-inputs to produce k-outputs. The j^{th} DMU, DMU_j (j = 1, …, n) consumes amounts X_j (= x_{ij}) of inputs (i = 1, …, m) and produces amounts Y_j (= y_{rj}) of outputs (r = 1, …, k). The m-by-n input matrix is denoted by $X = (x_{ij}) \in R^{mxn}$; and the k-by-n output matrix is denoted by $Y = (y_{rj}) \in R^{kxn}$. Assume also that $X > 0$ and $Y > 0$; these represent the data on all the n-DMUs.

The production possibility set, P, is defined as

$$P = \{(\mathbf{x}, \mathbf{y}) \mid \mathbf{x} \geq X\boldsymbol{\lambda}, \mathbf{y} \leq Y\boldsymbol{\lambda}, \boldsymbol{\lambda} \geq \mathbf{0}\} \qquad (1)$$

where $\boldsymbol{\lambda}$ is a non-negative vector of intensity variables in R^n.

A DMU being targeted for evaluation is identified as DMU_0 and its input and output vectors are represented with $\mathbf{x}_0$ and $\mathbf{y}_0$, respectively.

$$\mathbf{x}_0 = X\boldsymbol{\lambda} + \mathbf{s}^- \qquad (2.1)$$

$$\mathbf{y}_0 = Y\boldsymbol{\lambda} - \mathbf{s}^+ \qquad (2.2)$$

with $\mathbf{s}^- \geq \mathbf{0}$ and $\mathbf{s}^+ \geq \mathbf{0}$, called input slacks and output slacks, respectively, are vectors $\mathbf{s}^- \in R^m$ and $\mathbf{s}^+ \in R^k$.

The SBM nonradial efficiency score for DMU_0 can be estimated by solving the following fractional program problem in $\boldsymbol{\lambda}$, $\mathbf{s}^-$ and $\mathbf{s}^+$.

$$\min \rho = (1 - [1/m \textstyle\sum_i s^-_i/x_{i0}]) / (1 + (1/k \textstyle\sum_r s^+_r/y_{r0}]) \qquad (3.1)$$

$$\text{subject to} \quad \mathbf{x}_0 = X\boldsymbol{\lambda} + \mathbf{s}^- \qquad (3.2)$$

[7] Readers interested in the full details of the specification of super-SBM may consult Tone (2002) and references therein. For the software's description of the model see also Cooper *et al*. (2007).

$$\mathbf{y}_0 = Y\boldsymbol{\lambda} - \mathbf{s}^+ \tag{3.3}$$

$$\boldsymbol{\lambda} \geq \mathbf{0},\ \mathbf{s}^- \geq \mathbf{0} \text{ and } \mathbf{s}^+ \geq \mathbf{0}. \tag{3.4}$$

where $0 < \rho \leq 1$. Let the SBM optimal solution for DMU_0 be $\{\rho^*, \lambda^*, s^{-*}$ and $s^{+*}\}$. Then DMU_0 is SBM-efficient if $\rho^* = 1$ and $\mathbf{s}^{-*} = \mathbf{0}$ and $\mathbf{s}^{+*} = \mathbf{0}$ (i.e., there are no input and output slacks). Assuming now that DMU_0 is SBM-efficient (i.e., $\rho^* = 1$ and $\mathbf{s}^{-*}, \mathbf{s}^{+*} = 0$), the super-efficiency score for SBM-efficient DMU_0 is obtained from the solution to the following fractional program in λ.

$$\delta^* = \min \delta = (1/m \textstyle\sum_i \bar{x}_i/x_{i0}) / (1/k \sum_r \bar{y}_r/y_{r0}) \tag{4.1}$$

subject to $\quad \bar{\mathbf{x}} \geq \sum_j \lambda_j \mathbf{x}_j, \qquad (4.2)$

$$\bar{\mathbf{y}} \leq \textstyle\sum_j \lambda_j \mathbf{y}_j, \tag{4.3}$$

$$\bar{\mathbf{x}} \geq \mathbf{x}_0 \text{ and } \bar{\mathbf{y}} \leq \mathbf{y}_0, \tag{4.4}$$

$$\bar{\mathbf{y}} \geq \mathbf{0},\ \boldsymbol{\lambda} \geq \mathbf{0} \tag{4.5}$$

where $\delta^* \geq 1$. The basic idea is that DMU_0 is excluded from the sample and the weighted distance of DMU_0 from the resulting production possibility set without DMU_0 is calculated. If the distance is small, the super-efficiency of DMU_0 is judged to be lower as it only marginally outperforms other DMUs. On the other hand, if the distance is large, the super-efficiency of DMU_0 is high compared with the remaining DMUs. Hence, it will make sense to rank the efficient DMUs in the order of the distance thus obtained. The super-SBM efficiency score δ^*, which reflects distances in both the input space and output space, is units invariant. The fractional program can be transformed into a linear programming (LP) problem using the Charnes-Cooper transformation (Charnes and Cooper, 1962) as

$$\tau^* = \min \tau = 1/m \textstyle\sum_i \tilde{x}_i/x_{i0} \tag{5.1}$$

subject to

$$1 = 1/k \textstyle\sum_r \tilde{y}_r/y_{r0} \tag{5.2}$$

$$\tilde{\mathbf{x}} \geq \textstyle\sum_j \Lambda_j \mathbf{x}_j, \tag{5.3}$$

$$\tilde{\mathbf{y}} \leq \textstyle\sum_j \Lambda_j \mathbf{y}_j, \tag{5.4}$$

$$\tilde{\mathbf{x}} \geq t\mathbf{x}_0 \text{ and } \tilde{\mathbf{y}} \leq t\mathbf{y}_0, \tag{5.5}$$

$$\boldsymbol{\Lambda} \geq \mathbf{0},\ \tilde{\mathbf{y}} \geq \mathbf{0},\ t > 0. \tag{5.6}$$

Represent the optimal LP solution with τ^*, $\tilde{x}^*$, $\tilde{y}^*$, Λ^* and t^*. Then, the optimal solution of super-SBM can be expressed as: $\delta^* = \tau^*$; $\lambda^* = \Lambda^*/t^*$; $\bar{x}^* = \tilde{x}^*/t^*$; and $\bar{y}^* = \tilde{y}^*/t^*$. The exposition so far depicts CRS nonoriented super-SBM.[8] The VRS case can be obtained by adding the constraint

[8] The input oriented super-SBM with CRS technology can be developed by re-specifying equations/inequalities (4.1) to (4.5): the denominator in the objective function Eqn (4.1) is replaced with 1, leaving only the numerator;

$$\sum_j \lambda_j \mathbf{y}_j = 1 \qquad (6)$$

to the set of equations/inequalities (4.1) to (4.5). The VRS nonoriented super-SBM is always feasible with finite optimum.

3.2 Data and sources

The data were obtained from the Flightglobal database supplemented with information from the annual reports of the top 100 airlines. At the start of the research, consistent useable panel data on the chosen variables could be obtained for 46 airlines for the 2008-12 period. The sampled airlines and their characteristics are presented in Table 2. The input variables are available seat kilometre (ASK), number of employees and operational expense; the output variables are revenue, number of passengers carried and revenue-passenger-kilometre (RPK). Tables 3 and 4 report the summary statistics and pair-wise correlations, respectively, of the input and output indicators. The ranges of values of the variables reflect the combination of small and big companies. After a dip in each of the variables in 2009 (reflecting the impact of the GFC of 2008-09 on the aviation industry) all the variables increased steadily in subsequent years. The positive and strong correlations, which range from 0.710 (between revenue and passengers) to 0.998 (between RPK and ASK), are auspicious for conducting the analysis.

4. ANALYTICAL RESULTS

4.1 Nonoriented SBM efficiency

Firstly, to show the need for tie-breaking among efficient airlines with super efficiency, the nonoriented [standard] SBM models under the CRS and VRS assumptions were estimated for each year and the contingent scale efficiency (SE) scores calculated from them. Secondly, the nonoriented super-SBM models, which are the subject of this paper, were estimated and the results analysed. The summary statistics of the CRS, VRS and SE scores from the nonoriented SBM models are presented in Table 5. It will be noticed that there is variation in the number of efficient DMUs selected by the different models in the various years. The lowest number of efficient airlines in any particular year (8 or 17% of total) was selected by the CRS model in 2012 and the highest number (28 or 61% of total) was selected by the VRS model in 2008. As expected, the VRS model always selected more efficient DMUs than the CRS in each year. Furthermore, there were several airlines that had the score of unity in TE, PTE and SE in each year. Hence the case to break the tie among the efficient airlines is compelling.

4.2 Nonoriented super-efficiency SBM

The yearly nonoriented super-SBM scores and the rankings from the annual averages for the CRS and VRS are reported in Tables 6 and 7, respectively. Super-efficiency can be interpreted as the degree of efficiency stability or the input contraction *and* output expansion achieved by an efficient DMU.

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in Eqn (4.4) $\bar{\mathbf{y}} \le \mathbf{y}_0$ is replaced with $\bar{\mathbf{y}} = \mathbf{y}_0$; in Eqn (4.5), $\bar{\mathbf{y}} \ge \mathbf{0}$ is dropped. For the output oriented super-SBM with CRS technology, the numerator in the objective function Eqn (4.1) is replaced with 1; Eqn (4.4) is replaced with $\bar{\mathbf{x}} = \mathbf{x}_0$ and $0 \le \bar{\mathbf{y}} \le \mathbf{y}_0$; and in Eqn (4.5), $\bar{\mathbf{y}} \ge \mathbf{0}$ is dropped.

Table 2: The sampled airlines and their characteristics

No.	Airline	Region	Alliance	Carrier
1	Aegean Airlines	Europe	Star Alliance [a/]	Full Service Carrier
2	Aer Lingus	Europe	Non-allied	Full Service Carrier
3	Aeroflot	Europe	SkyTeam	Full Service Carrier
4	Aeromexico	South America	SkyTeam	Full Service Carrier
5	Air Canada	North America	Star Alliance	Full Service Carrier
6	Air China	Asia	Star Alliance	Full Service Carrier
7	Air France-KLM	Europe	SkyTeam	Full Service Carrier
8	Air New Zealand	Oceania	Star Alliance	Full Service Carrier
9	AirAsia	Asia	Non-allied	Low Cost Carrier
10	airberlin	Europe	OneWorld [b/]	Full Service Carrier
11	American Airlines	North America	OneWorld	Full Service Carrier
12	ANA	Asia	Star Alliance	Full Service Carrier
13	Asiana Airlines	Asia	Star Alliance	Full Service Carrier
14	British Airways	Europe	OneWorld	Full Service Carrier
15	Cathay Pacific	Asia	OneWorld	Full Service Carrier
16	China Airlines	Asia	SkyTeam [c/]	Full Service Carrier
17	China Eastern	Asia	SkyTeam [d/]	Full Service Carrier
18	China Southern	Asia	SkyTeam	Full Service Carrier
19	Copa Airlines	South America	Star Alliance [e/]	Full Service Carrier
20	Croatia Airlines	Europe	Star Alliance	Full Service Carrier
21	Delta Air Lines	North America	SkyTeam	Full Service Carrier
22	EasyJet	Europe	Non-allied	Low Cost Carrier
23	Emirates	Middle East	Non-allied	Full Service Carrier
24	Ethiopian Airlines	Africa	Star Alliance [f/]	Full Service Carrier
25	EVA Air	Asia	Non-allied [g/]	Full Service Carrier
26	Finnair	Europe	OneWorld	Full Service Carrier
27	Japan Airlines	Asia	OneWorld	Full Service Carrier
28	JetBlue	Europe	Non-allied	Low Cost Carrier
29	Kenya Airways	Africa	SkyTeam	Full Service Carrier
30	Korean Air	Asia	SkyTeam	Full Service Carrier
31	Lufthansa	Europe	Star Alliance	Full Service Carrier
32	Malaysia Airlines	Asia	Non-allied [h/]	Full Service Carrier
33	Norwegian Air	Europe	Non-allied	Full Service Carrier
34	Qantas	Oceania	OneWorld	Full Service Carrier
35	Royal Jordanian	Middle East	OneWorld	Full Service Carrier
36	Ryanair	Europe	Non-allied	Low Cost Carrier
37	Scandinavian Airlines	Europe	Star Alliance	Full Service Carrier
38	Singapore Airlines	Asia	Star Alliance	Full Service Carrier
39	South African Airways	Africa	Star Alliance	Full Service Carrier
40	Southwest	North America	Non-allied	Low Cost Carrier
41	THAI	Asia	Star Alliance	Full Service Carrier
42	Turkish Airlines	Europe	Star Alliance	Full Service Carrier
43	United	North America	Star Alliance	Full Service Carrier
44	US Airways	North America	Star Alliance	Full Service Carrier
45	Virgin Australia	Oceania	Non-allied	Low Cost Carrier
46	Vueling	Europe	Non-allied	Low Cost Carrier

Notes: [a/] Aegean Airlines joined Star Alliance 30/6/2010; [b/] airberlin joined OneWorld 20/3/2012; [c/] China Airlines joined SkyTeam 28/9/2011; [d/] China Eastern joined SkyTeam 21/6/2011; [e/] Copa Airlines joined Star Alliance 21/6/2012; [f/] Ethiopian Airlines joined Star Alliance 13/12/2011; [g/] EVA Air joined Star Alliance 18/6/2013; [h/] Malaysia Airlines joined OneWorld 1/2/2013.

Table 3: Summary statistics on the input and output variables

Year	Statistic	Inputs			Outputs		
		Employees	Expense	ASK	Revenue	Passengers	RPK
2008	Mean	21121	8736	80937	8275	30174	62522
	Min	1013	417	2103	409	1870	1372
	Max	106932	28747	396101	26411	171724	326265
	Std dev	22493	7548	79421	6783	31207	64180
2009	Mean	21107	7475	79749	7553	30133	61985
	Min	1150	365	2027	325	1750	1245
	Max	104721	26113	370603	25815	161071	304075
	Std dev	22127	6359	74747	6255	29636	60742
2010	Mean	21779	8527	83445	9163	32485	66318
	Min	1142	351	1847	322	1641	1145
	Max	102012	26847	374469	28862	162615	310876
	Std dev	22424	7250	76357	7736	32602	62986
2011	Mean	23552	10107	91611	10438	35009	73026
	Min	1136	379	1965	369	1879	1317
	Max	101603	31456	377562	33080	163838	310161
	Std dev	24229	8809	86723	9100	34588	71383
2012	Mean	24392	10781	97693	11187	37265	78545
	Min	1128	476	2086	385	1951	1441
	Max	100744	32514	370738	32548	164591	310495
	Std dev	24078	8885	87446	9182	35178	72528
2008-12	Min	1013	351	1847	322	1641	1145
	Max	106932	32514	396101	33080	171724	326265
	Mean	22292	9083	86339	9280	32915	68197
	Std dev	23111	7912	81319	8007	32764	66760

Notes: Expense = total expenses (constant [2005] USD millions); ASK = available seat kilometres (number of available seats times kilometres travelled) in million seat-kilometres; Revenue = total revenue (constant [2005] USD millions); Passengers = number of passengers carried in thousands; RPK = revenue passenger kilometres (number of passengers times kilometres travelled) in millions of passenger-kilometres.

Table 4: Correlations between the input and output variables

Variable	Employees	Expense	ASK	Revenue	Passenger	RPK
Employees	1.000	0.886	0.891	0.869	0.768	0.887
Expense	0.886	1.000	0.888	0.993	0.720	0.879
ASK	0.891	0.888	1.000	0.875	0.887	0.998
Revenue	0.869	0.993	0.875	1.000	0.710	0.865
Passengers	0.768	0.720	0.887	0.710	1.000	0.888
RPK	0.887	0.879	0.998	0.865	0.888	1.000

Table 5: Summary statistics of the efficiency scores from the nonoriented SBM models

Technology	Statistic	2008	2009	2010	2011	2012	Annual Average
CRS	Mean	0.77252	0.78323	0.73247	0.69687	0.69382	0.73578
	Min	0.40190	0.44301	0.43781	0.41915	0.42836	0.44683
	Max	1	1	1	1	1	1
	Std dev	0.18870	0.17730	0.17124	0.18180	0.17424	0.15181
	No. on frontier	13	14	10	9	8	5
VRS	Mean	0.89235	0.86255	0.81165	0.77006	0.78500	0.82432
	Min	0.41944	0.47766	0.48711	0.46467	0.49099	0.48684
	Max	1	1	1	1	1	1
	Std dev	0.15566	0.15271	0.17441	0.18699	0.18526	0.13565
	No. on frontier	28	23	19	16	17	8
SE	Mean	0.86754	0.91098	0.91188	0.91396	0.89575	0.90002
	Min	0.52825	0.51098	0.49906	0.47133	0.42836	0.51852
	Max	1	1	1	1	1	1
	Std dev	0.14570	0.13416	0.13327	0.13071	0.13866	0.12317
	No. on frontier	13	14	11	9	9	5

Under the assumption of CRS, all the DMUs that were identified as efficient in any year were actually deemed to be super-efficient as they scored TEs more than one in the super-SBM models. As it would be seen in Table 6, during the study period the sampled airlines averaged a super-efficiency TE score of 0.75 annually (see the mean value in the penultimate column of Table 6). The annual mean CRS score rose slightly in 2009 and then fell continually reaching its lowest value (of about 0.708) in 2012. After 2008, the median CRS score fell continually to its lowest level (of about 0.671) in 2011 before rising slightly in 2012. Tests of the equality of the locations of the distributions of the scores for pairs of years with the Wilcoxon/Mann-Whitney test statistic show that the CRS scores for 2011 and 2012 lie significantly to the left of those for 2008 and 2009 but are similar to those for 2010 (See Table 8). The Kruskal-Wallis test suggests that the distributions all come from a similar parent distribution. The annual super-efficiency TE scores ranged from 0.402 (posted by Ethiopian Airlines in 2008) to 1.312 (posted by Ryanair in 2009). Some airlines (18 of them) were super-efficient in some years and inefficient in other years. A subset of 28 airlines were inefficient in all years; these were the airlines whose scores were always less than one. Seven airlines averaged as super-efficient over the study period but not all of them were super-efficient in every year. However, five airlines (Air China, Copa, Croatia, EasyJet and Ryanair) were deemed super-efficient in all years. The ranking from the annual averages puts Ryanair, Croatia Airlines, Air China, EasyJet and Vueling in the top five positions and United, Air France-KLM, Emirates, Finnair and British Airways in the last five positions (see Table 10).

Table 6: The nonoriented super-SBM CRS scores

Airline or DMU	2008	2009	2010	2011	2012	Average	Ranking
Aegean Airlines	1.07891	1.00737	0.78683	0.77461	0.79718	0.88898	10
Aer Lingus	0.66649	0.66089	0.70545	0.69222	0.68642	0.68230	30
Aeroflot	0.51643	0.63394	0.61545	0.62767	0.74057	0.62681	37
Aeromexico	0.58380	0.75497	0.71767	0.71318	0.67822	0.68957	29
Air Canada	0.60169	0.57281	0.52604	0.54753	0.54677	0.55897	40
Air China	1.01733	1.02718	1.09105	1.11214	1.01314	1.05217	3
Air France-KLM	0.52825	0.52397	0.50100	0.47812	0.47640	0.50155	43
Air New Zealand	0.61779	0.66038	0.59290	0.58341	0.57783	0.60646	38
AirAsia	0.84998	1.03703	1.05163	1.05498	1.03808	1.00634	7
airberlin	0.80539	0.80998	0.78134	0.77923	0.76535	0.78826	16
American Airlines	0.58357	0.57270	0.57339	0.54749	0.56021	0.56747	39
ANA	1.03845	0.91870	0.84343	0.78711	0.75946	0.86943	12
Asiana Airlines	0.82556	0.77022	0.75853	0.70672	0.68616	0.74944	20
British Airways	0.43247	0.44301	0.43781	0.44507	0.47578	0.44683	46
Cathay Pacific	0.74081	1.00339	0.53937	0.48304	0.46018	0.64536	35
China Airlines	0.75356	0.65255	0.71699	0.60182	0.56946	0.65888	32
China Eastern	0.59552	0.71528	0.79247	0.76749	0.73841	0.72183	23
China Southern	0.77084	0.86796	0.78434	0.76854	0.75315	0.78897	15
Copa Airlines	1.03992	1.01594	1.00078	1.00548	1.01076	1.01458	6
Croatia Airlines	1.06674	1.09394	1.11621	1.12645	1.11086	1.10284	2
Delta Air Lines	0.57083	0.66502	0.67975	0.67173	0.67911	0.65329	33
EasyJet	1.01602	1.02431	1.03104	1.03374	1.04170	1.02936	4
Emirates	0.52592	0.51098	0.49906	0.47133	0.42836	0.48713	44
Ethiopian Airlines	0.40190	0.75670	1.02121	1.05276	1.14967	0.87645	11
EVA Air	1.03674	1.02080	1.04413	0.59162	0.58746	0.85615	13
Finnair	0.48738	0.46213	0.48395	0.45907	0.49885	0.47828	45
Japan Airlines	1.00468	1.06274	0.70428	1.00414	0.69820	0.89481	9
JetBlue	0.66290	0.64761	0.66541	0.66336	0.67007	0.66187	31
Kenya Airways	0.57623	0.74994	0.63518	0.63958	0.60583	0.64135	36
Korean Air	0.84251	0.71027	0.67249	0.63928	0.64218	0.70135	27
Lufthansa	0.86004	0.73309	0.64831	0.63282	0.64005	0.70286	26
Malaysia Airlines	0.88889	1.01416	0.59319	0.49983	0.52363	0.70394	25
Norwegian Air	0.94221	0.91169	0.86853	0.88383	0.88374	0.89800	8
Qantas	0.58963	0.53272	0.53574	0.53458	0.52571	0.54367	41
Royal Jordanian	1.02774	1.03396	0.62751	0.57872	0.63258	0.78010	17
Ryanair	1.15142	1.31231	1.25709	1.27190	1.25774	1.25009	1
Scandinavian Airlines	0.77682	0.88836	0.75947	0.71621	0.68039	0.76425	18
Singapore Airlines	1.07509	0.63863	1.00225	0.41915	0.45161	0.71735	24
South African Airways	1.00461	0.73389	0.50863	0.47224	0.51497	0.64687	34
Southwest	0.69761	0.68401	0.80013	0.74986	0.73135	0.73259	21
THAI	1.01273	1.00523	0.61937	0.53483	0.58692	0.75182	19
Turkish Airlines	0.88481	0.86824	0.75362	0.72707	0.84722	0.81619	14
United	0.53957	0.54649	0.57519	0.52582	0.49356	0.53613	42
US Airways	0.71943	0.70452	0.68253	0.67047	0.67136	0.68966	28
Virgin Australia	0.85443	0.72681	0.70817	0.67127	0.65115	0.72237	22
Vueling	0.84280	1.04983	1.07641	1.08108	1.04944	1.01991	5
Statistics							
Mean	0.78492	0.79862	0.74751	0.71301	0.70842	0.75050	
Median	0.79111	0.75246	0.70681	0.67087	0.67479	0.71959	
Min	0.40190	0.44301	0.43781	0.41915	0.42836	0.44683	
Max	1.15142	1.31231	1.25709	1.27190	1.25774	1.25009	
Std dev	0.20513	0.20107	0.19828	0.21237	0.20349	0.17665	
No. of efficient DMUs	13	14	10	9	8	7	

Table 7: The nonoriented super-SBM VRS scores

Airline or DMU	2008	2009	2010	2011	2012	Average	Ranking
Aegean Airlines	1.10601	1.02166	0.84434	0.83374	1.04367	0.96988	14
Aer Lingus	0.67193	0.67243	0.70607	0.69302	0.70737	0.69016	38
Aeroflot	0.78956	0.63930	0.61670	0.63060	1.01627	0.73849	33
Aeromexico	0.68970	0.75598	0.72491	0.71417	0.68603	0.71416	36
Air Canada	0.71664	0.62963	0.56236	0.59660	0.59866	0.62078	43
Air China	1.03247	1.04296	1.16500	1.18830	1.17005	1.11975	5
Air France-KLM	1.05840	1.00728	0.68236	0.67612	0.66502	0.81784	25
Air New Zealand	0.65321	0.66388	0.59314	0.58362	0.58390	0.61555	44
AirAsia	0.85127	1.04269	1.05509	1.05515	1.04132	1.00911	10
airberlin	0.80583	0.82369	0.78737	0.78170	0.76622	0.79296	28
American Airlines	1.00789	0.81606	0.78096	0.76676	0.76906	0.82815	24
ANA	1.04176	1.00515	0.86313	0.80637	0.77567	0.89842	17
Asiana Airlines	0.86903	0.77465	0.75926	0.70876	0.68681	0.75970	31
British Airways	0.63019	0.59199	0.51672	0.55705	0.57931	0.57505	45
Cathay Pacific	1.01338	1.00907	1.00820	0.53378	0.51094	0.81507	27
China Airlines	0.78946	0.65764	0.72300	0.60601	0.56961	0.66915	39
China Eastern	0.76686	0.77765	1.00924	1.00309	1.00521	0.91241	16
China Southern	1.04445	1.06448	1.00349	1.01296	1.03803	1.03268	8
Copa Airlines	1.04108	1.02019	1.00737	1.00780	1.01248	1.01779	9
Croatia Airlines	1.96661	2.55008	2.83640	2.93706	2.36157	2.53034	1
Delta Air Lines	1.37006	1.55370	1.57009	1.19561	1.27536	1.39297	2
EasyJet	1.01653	1.02657	1.04063	1.06185	1.07367	1.04385	6
Emirates	0.77014	1.03002	1.07555	1.05983	1.00805	0.98872	13
Ethiopian Airlines	0.41944	0.76014	1.02674	1.05946	1.15349	0.88386	20
EVA Air	1.04917	1.03271	1.06550	0.59211	0.58743	0.86538	21
Finnair	0.50234	0.47766	0.48711	0.46467	0.50240	0.48684	46
Japan Airlines	1.08454	1.11571	0.73159	1.02193	1.01587	0.99393	12
JetBlue	0.66348	0.66741	0.67017	0.66361	0.67062	0.66706	41
Kenya Airways	0.66181	0.75602	0.65589	0.65066	0.61948	0.66877	40
Korean Air	0.91757	0.71619	0.67702	0.65309	0.69394	0.73156	35
Lufthansa	1.06532	1.04311	0.77268	0.80241	0.77953	0.89261	19
Malaysia Airlines	1.01816	1.01484	0.59373	0.50476	0.53476	0.73325	34
Norwegian Air	1.02638	1.00538	1.00574	1.00468	0.94775	0.99799	11
Qantas	1.02857	0.65743	0.60632	0.62776	0.61077	0.70617	37
Royal Jordanian	1.02857	1.03805	0.64609	0.59046	0.64876	0.79039	29
Ryanair	1.18174	1.33923	1.29104	1.33459	1.33553	1.29643	3
Scandinavian Airlines	1.02738	1.02652	1.00622	0.71664	0.68880	0.89311	18
Singapore Airlines	1.12483	1.01780	1.03972	0.48594	0.49099	0.83186	23
South African Airways	1.00544	0.73422	0.50967	0.47367	0.51573	0.64774	42
Southwest	1.08067	0.88530	1.10942	1.07586	1.06722	1.04370	7
THAI	1.06149	1.04116	0.62084	0.54119	0.65770	0.78448	30
Turkish Airlines	1.00907	0.87793	0.75362	0.73462	0.85854	0.84675	22
United	0.87978	0.77674	1.00529	1.02404	1.00921	0.93901	15
US Airways	1.00074	0.83020	0.74167	0.76040	0.74801	0.81621	26
Virgin Australia	1.00220	0.73518	0.70903	0.67234	0.65639	0.75503	32
Vueling	1.15904	1.15652	1.23382	1.21761	1.12603	1.17860	4
Statistics							
Mean	0.95000	0.93222	0.88892	0.84092	0.84485	0.89138	
Median	1.01123	0.94523	0.77682	0.72563	0.75712	0.83001	
Min	0.41944	0.47766	0.48711	0.46467	0.49099	0.48684	
Max	1.96661	2.55008	2.83640	2.93706	2.36157	2.53034	
Std dev	0.24348	0.31659	0.37174	0.38681	0.32047	0.30465	
No. of efficient DMUs	28	23	19	16	17	10	

Table 8: Results of Wilcoxon/Mann-Whitney tests of equality of location - CRS scores

	2009CRS	2010CRS	2011CRS	2012CRS
2008CRS	0.160083 [0.8728]	0.894122 [0.3713]	1.706250* [0.0880]	1.862429* [0.0625]
2009CRS		1.151817 [0.2494]	1.963945** [0.0495]	2.151359** [0.0314]
2010CRS			1.050301 [0.2936]	1.175243 [0.2399]
2011CRS				0.050758 [0.9595]

Note: figures in square brackets are p-values of the test statistic. A single asterisk, double asterisks and triple asterisks indicate significance at the 10%, 5% and 1% levels, respectively.

As in the case of the CRS, the airlines that were identified as efficient under the VRS assumption were also all deemed to be super-efficient (see Table 7). The super efficiency PTE scores ranged from 0.419 (posted by Ethiopian Airlines in 2008) to 2.937 (posted by Croatia Airlines in 2010), averaging 0.891. Starting from 2008 the annual mean VRS score fell continually to its lowest level (of about 0.841) in 2011 before rising slightly in 2012. The median VRS score behaved qualitatively in a similar manner. Tests of the equality of the locations of the distributions of the scores for pairs of years with the Wilcoxon/Mann-Whitney test statistic show that the VRS scores for 2010, 2011 and 2012 lie significantly to the left of those for 2008 and 2009 (see Table 9 below). The Kruskal-Wallis test suggests that the distributions do not all come from a similar parent distribution.

Table 9: Results of Wilcoxon/Mann-Whitney tests of equality of location - VRS scores

	2009VRS	2010VRS	2011VRS	2012VRS
2008VRS	1.132303 [0.2575]	2.112323** [0.0347]	2.764381*** [0.0057]	2.518388** [0.0118]
2009VRS		1.300186 [0.1935]	2.151359** [0.0314]	1.846811* [0.0648]
2010VRS			1.019065 [0.3082]	0.659854 [0.5093]
2011VRS				0.261599 [0.7936]

Note: figures in square brackets are p-values of the test statistics. A single asterisk, double asterisks and triple asterisks indicate significance at the 10%, 5% and 1% levels, respectively.

In every year more DMUs were selected to be efficient under VRS technology than under CRS technology. As noted about the CRS results, some airlines were VRS super-efficient in some years and inefficient in other years; and some airlines (10 of them) were inefficient in all years. Ten other airlines averaged super-efficient over the five years. Out of those, eight airlines (Air China, China Southern, Copa Airlines, Croatia Airlines, Delta Air Lines, EasyJet, Ryanair and Vueling) were deemed super-efficient in all years; the other two (AirAsia and Southwest) were not super-efficient in every year. The ranking from the annual averages puts Croatia Airlines, Delta Air Lines, Ryanair, Vueling and Air China in the top five positions and South African Airways, Air Canada, Air New Zealand, British Airways and Finnair in the last five positions (see Table 10). A scrutiny of Table 10 reveals that seven airlines (Ryanair, Croatia, Air China, EasyJet, Vueling, Copa Airlines and Air Asia) appear among the top 10 under both CRS and VRS. However, three of the airlines ranked among the top 10 under CRS (Norwegian, Japan and Aegean) were not selected among the top 10 under VRS. And correspondingly, three airlines that did not make it among the top 10 under CRS (China Southern, Southwest and Delta Airlines) were bumped into the top 10 under VRS. The suggestion is that pure technical efficiency (or managerial efficiency) may be high but scale issues (perhaps decreasing returns to scale) may be relatively nontrivial at China Southern, Southwest and Delta Airlines compared with Norwegian, Japan and Aegean, and vice versa.

Test of the equality of the locations of the distributions of the average scores with the Wilcoxon/Mann-Whitney test statistic shows that the VRS scores lie significantly to the right of that for CRS at the 1% level. The Spearman rank correlation between the rankings done by CRS and VRS was estimated to be 0.685, which is significantly different from zero at the 1% level. That means airlines with high CRS rankings tend to have high VRS rankings also but not necessarily the other way round.

To explore the extent to which the efficiency scores depended on year, the business model, affiliation/non-affiliation with a strategic airline alliance and region of origin, regression models were estimated for the CRS and VRS scores. The panel nature of the data dictated the use of a panel regression model. The explanatory variables comprised dummies representing year, the LCC or FSC business model, affiliation with one of the three global alliances or non-affiliation with any of them and the region of origin of the airline. The regions of the world consistent with the airlines in the sample are Africa, Asia, Europe, Middle East, North America, Oceania and South America. The modelling approach taken in this research means almost all of the control variables are constant over time. In panel regression modelling, the advantage of the random effects over fixed effects is that random effects allows for time invariant explanatory variables which the fixed effects drops. Because of that inherent advantage, the random effects model was implemented. The random effects regression results are reported in Table 11. The base group in the analyses is the non-allied, African FSCs in 2008. Although the explanatory power of the models is low for explaining the variation in both the CRS and VRS efficiency scores (R-squared values of 0.17 and 0.12, respectively) a number of interesting insights have been unearthed.

Table 10: Rankings by the super-SBM nonoriented models

Ranking	CRS ≡ OTE	VRS ≡ PTE
1	Ryanair	Croatia Airlines
2	Croatia Airlines	Delta Air Lines
3	Air China	Ryanair
4	EasyJet	Vueling
5	Vueling	Air China
6	Copa Airlines	EasyJet
7	AirAsia	Southwest
8	Norwegian Air	China Southern
9	Japan Airlines	Copa Airlines
10	Aegean Airlines	AirAsia
11	Ethiopian Airlines	Norwegian Air
12	ANA	Japan Airlines
13	EVA Air	Emirates
14	Turkish Airlines	Aegean Airlines
15	China Southern	United
16	airberlin	China Eastern
17	Royal Jordanian	ANA
18	Scandinavian Airlines	Scandinavian Airlines
19	THAI	Lufthansa
20	Asiana Airlines	Ethiopian Airlines
21	Southwest	EVA Air
22	Virgin Australia	Turkish Airlines
23	China Eastern	Singapore Airlines
24	Singapore Airlines	American Airlines
25	Malaysia Airlines	Air France-KLM
26	Lufthansa	US Airways
27	Korean Air	Cathay Pacific
28	US Airways	airberlin
29	Aeromexico	Royal Jordanian
30	Aer Lingus	THAI
31	JetBlue	Asiana Airlines
32	China Airlines	Virgin Australia
33	Delta Air Lines	Aeroflot
34	South African Airways	Malaysia Airlines
35	Cathay Pacific	Korean Air
36	Kenya Airways	Aeromexico
37	Aeroflot	Qantas
38	Air New Zealand	Aer Lingus
39	American Airlines	China Airlines
40	Air Canada	Kenya Airways
41	Qantas	JetBlue
42	United	South African Airways
43	Air France-KLM	Air Canada
44	Emirates	Air New Zealand
45	Finnair	British Airways
46	British Airways	Finnair

The CRS regression results are discussed first. The chosen explanatory variables explain only about 17% of the variation in the CRS efficiency scores. The LCCs significantly outperformed the FSCs in OTE at the 5% level. LCCs have consistently been shown to be generally more efficient than FSCs because of the unique business model they follow,[9] although not all of them are successful[10] (Oum and Yu, 1998; Fethi *et al*., 2001; Williams *et al*., 2003; Franke, 2004; Scheraga, 2004; Färe *et al*., 2007; Barbot *et al*., 2008; Bruggen and Klose, 2010). Star Alliance members significantly outperformed the other alliance group members as well as the non-allied airlines but the non-allied airlines did better than OneWorld and SkyTeam members although the difference is not statistically significant. The region of origin did not seem to make a significant difference although the South American, Asian, European and Middle East airlines performed marginally better than the African airlines whilst the North American and Oceania airlines performed slightly poorer than the African airlines. The coefficients of the year dummies suggest that after a slight improvement in the CRS efficiency scores in 2009, performance in OTE continually fell in subsequent years with the decreases in 2011 and 2012 being quite significant. These results are qualitatively similar to those from the nonparametric tests (i.e., the Wilcoxon/Mann-Whitney tests). It must be remembered that OTE scores are confounded by sale inefficiencies if the airlines are not all operating at their optimal scales. It is not likely that all the airlines operated at their respective optimal scales during the study period. That limits the usefulness of the CRS results and more attention may be paid to the VRS results.

On the VRS efficiency scores too, the LCCs are slightly ahead of the FSCs but the difference is negligible. This result suggests that the edge LCCs have over FSCs is significant only when scale of operation is overlooked but becomes negligible when scale of operation is taken into consideration. On PTE performance, Star Alliance members outperformed all the other groups even more significantly than in OTE. That suggests that Star Alliance members collectively have a much higher managerial efficiency than all the other groups. SkyTeam members edged out the non-allied airlines on PTE performance, but not by much. OneWorld members lagged behind the non-allied airlines in PTE but not by much. Again, although region of origin did not make a significant difference, the coefficients of the regional dummies indicate that the airlines from all the other regions, except Oceania, did only marginally better than those from Africa in PTE performance with the Middle East airlines leading the pack followed by the airlines from Europe, North America, South America and Asia. The coefficients of the year dummies indicate that, compared with the PTE performance in 2008, the sampled airlines experienced continual deterioration during the rest of the study period.

[9] Compared to FSCs, LCCs operate short-haul services with single aircraft type and high aircraft utilization through the use of uncongested and less costly secondary airports and offering only point-to-point services. LCCs also tend to use fewer crew members for similar aircraft used by FSCs. LCCs also gain a cost advantage over FSCs in distribution and on-board catering through selling tickets online directly to customers and not providing free food and drink in the cabin..

[10] Chang and Yu (2014) report that in 1999 UK carriers Debonair (one of Europe's low-cost pioneers) and Air Berlin Airlines as well as the Norwegian LCC ColorAir collapsed. In 2008, the Copenhagen-based LCC Sterling and the US LCCs ATA and Skybus went bankrupt; so did the Hong Kong-based LCC Oasis only after 18 months of operations.

Table 11: Results of the random effects panel regression models of the CRS and VRS nonoriented super-SBM efficiency scores

Variable	Dependent variable is CRS nonoriented super-SBM efficiency score	Dependent variable is VRS nonoriented super-SBM efficiency score
Intercept	0.6943*** (0.0879) [0.0000]	0.6830*** (0.1742) [0.0001]
Low Cost Carrier	0.1838** (0.0842) [0.0302]	0.1717 (0.1681) [0.3083]
OneWorld	-0.0522 (0.0652) [0.4241]	-0.0343 (0.1114) [0.7586]
SkyTeam	-0.0401 (0.0538) [0.4564]	0.0870 (0.0818) [0.2883]
Star Alliance	0.0774* (0.0464) [0.0968]	0.1578** (0.0704) [0.0260]
Asia	0.1232 (0.0922) [0.1826]	0.1805 (0.1897) [0.3423]
Europe	0.0879 (0.0891) [0.3251]	0.2610 (0.1833) [0.1559]
Middle-East	0.0010 (0.1426) [0.9945]	0.2878 (0.2912) [0.3242]
North America	-0.0897 (0.1030) [0.3848]	0.2049 (0.2117) [0.3343]
Oceania	-0.0963 (0.1418) [0.4980]	-0.0198 (0.2902) [0.9456]
South America	0.2057 (0.1393) [0.1415]	0.1877 (0.2864) [0.5128]
Dummy2009	0.0137 (0.0241) [0.5702]	-0.0178 (0.0308) [0.5637]
Dummy2010	-0.0391 (0.0241) [0.1064]	-0.0645** (0.0308) [0.0373]
Dummy2011	-0.0735*** (0.0244) [0.0028]	-0.1197*** (0.0312) [0.0002]
Dummy2012	-0.0787*** (0.0246) [0.0016]	-0.1185*** (0.0316) [0.0002]
R^2	0.1695	0.1241
Adjusted R^2	0.1154	0.0671

Notes: Figures in parentheses, "( )", are standard errors; those in square brackets, "[ ]", are *prob*-values. Triple asterisks indicate significance at the 1% level; double asterisks indicate significance at the 5% level; and a single asterisk indicates significance at the 10% level.

5. SUMMARY AND CONCLUSIONS

The paper set out to estimate nonoriented slacks-based measures of super efficiency for 46 international airlines using data covering the 2008-2012 period. Three inputs and three outputs were utilized. The chosen methodology guarantees simultaneous input-minimizing output-maximizing Pareto efficiency. The airlines were ranked according to the period averages of their efficiency scores under constant and variable returns to scale production technologies. The correlation coefficient between the two rankings is moderately high meaning airlines ranked highly as technically efficient overall are also likely to be ranked highly in terms of pure technical efficiency. In terms of pure technical efficiency, Air China, China Southern, Copa Airlines, Croatia Airlines, Delta Airlines, EasyJet, Ryanair and Vueling were deemed to be super-efficient in each year of the sample period. Random-effects panel models regressing the efficiency scores on dummies for year, carrier type, alliance affiliation and region of origin were also estimated. The business model (low-cost or network carriers), alliance affiliation, region of origin and year dummies do not explain more than 17% of the variation in the CRS and VRS efficiency scores. The low-cost carriers outperform the network carriers significantly in overall technical efficiency but not in pure technical efficiency. Collectively, Star Alliance members significantly outperform SkyTeam, OneWorld and non-allied airlines in both overall and pure technical efficiency, but especially in the latter. OneWorld members seem to be the least efficient group. Region of origin is not a significant driver of technical efficiency. Between 2008 and 2012, technical efficiency seems to have diminished among the airlines.

REFERENCES

Adler, N. and Golany, B. (2001), "Evaluation of Deregulated Airline Networks using Data Envelopment Analysis Combined with Principal Component Analysis with an Application to Western Europe," *European Journal of Operational Research* 132: 260–273.

Andersen, P., and Petersen, N. C. (1993), "A Procedure for Ranking Efficient Units in Data Envelopment Analysis," *Management science* 39 (10): 1261–1264.

Araujo, A. H., Santos, I. C. and Pires, C. C. (2007), "A Comparative Study of the Relative Efficiency of American, European, Asian and South American Airlines." 2007 Air Transport Research Society World Conference Paper. Retrieved January 11, 2016 from: http://www.mec.ita.br/~clarissa/_private/_files/Paper%20ATRS.pdf.

Assaf, A. G., and Josiassen, A. (2012), "European vs. US Airlines: Performance Comparison in a Dynamic Market," *Tourism Management* 33 (2): 317–326.

Banker, R. D., Charnes, A., and Cooper, W. W. (1984), "Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis," *Management Science* 30 (9): 1078–1092.

Barbot, C., Costa, Á. and Sochirca, E. (2008), "Airlines Performance in the New Market Context: A Comparative Productivity and Efficiency Analysis," *Journal of Air Transport Management* 14 (5): 270–274.

Barros, C. P. and Peypoch, N. (2009), "An Evaluation of European Airlines' Operational Performance," *International Journal of Production Economics* 122 (2): 525–533.

Bhadra, D. (2009), "Race to the Bottom or Swimming Upstream: Performance Analysis of US Airlines," *Journal of Air Transport Management* 16: 299–303.

Bruggen, A. and Klose, L. (2010), "How Fleet Commonality Influences Low-Cost Airline Operating Performance: Empirical Evidence," *Journal of Air Transport Management* 15 (5): 227–235

Chang, Y-C and Yu, M-M (2014), "Measuring Production and Consumption Efficiencies Using the Slack-Based Measure Network Data Envelopment Analysis Approach: The Case of Low-Cost Carriers," *Journal of Advanced Transportation* 48:15–31.

Charnes, A. and Cooper, W. W. (1962), "Programming with Linear Fractional Functionals," *Naval Research Logistics Quarterly* 15: 333–334.

Charnes, A., Cooper, W. W. and Rhodes, E. L. (1978), "Measuring the Efficiency of Decision Making Units," *European Journal of Operational Research* 2: 429–444.

Chen, Y. (2005), "Measuring Super-Efficiency in DEA in the Presence of Infeasibility," *European Journal of Operation Research* 161: 545–551.

Coelli, T., Perelman, S. and Romano, E. (1999), "Accounting for Environmental Influences in Stochastic Frontier Models: With Application to International Airlines," *Journal of Productivity Analysis* 11: 251–273.

Coelli, T. J., Rao, P., O'Donnell, C. J. and Battese, G. E. (2005), *An Introduction to Efficiency and Productivity Analysis* (New York: Springer).

Coli, M., Nissi, E. and Rapposelli, A. (2011), "Efficiency evaluation in an airline company: some empirical results," *Journal of Applied Sciences* 11 (4): 737–742.

Cooper, W. W., Seiford, L. and Tone, K. (2007), *Data Envelopment Analysis – A Comprehensive Text with Model, Applications, References and DEA-Solver Software*, 2^{nd} ed. (New York: Springer).

Cornwell, C., Schmidt, P. and Sickles, C. R. (1990), "Production Frontiers with Cross-Sectional and Time-Series Variation in Efficiency Levels," *Journal of Econometrics* 46: 185–200.

Cullinane, K. P. B, Song, D. W. and Gray, R. (2002), "A Stochastic Frontier Model of the Efficiency of Major Container Terminals in Asia: Assessing the Influence of Administrative and Ownership Structures," *Transportation Research A: Policy and Practice*, 36: 743–762.

Distexhe, V. and Perelman, S. (1994), "Technical Efficiency and Productivity Growth in an Era of Deregulation: The Case of Airlines," *Swiss Journal of Economics and Statistics* 130 (4): 669–689.

Färe, R., Grosskopf, S. and Sickles, R. C. (2007), "Productivity of US Airlines after Deregulation," *Journal of Transport Economics and Policy* 40: 93–112.

Farrell, M. J. (1957), "The measurement of productive efficiency," *Journal of the Royal Statistical Society Series A* (General): 253–290.

Fethi, M. D., Jackson, P. M. and Weyman-Jones, T. G. (1999), *Measuring the Efficiency of European Airlines: An Application of DEA and Tobit Analysis*, (Leicester: University of Leicester, Management Centre).

Fethi, M. D., Jackson, P. M. and Weyman-Jones, T. G. (2001), "European Airlines: A Stochastic DEA of Efficiency with Market Liberalization." Paper presented at the 7^{th} European Workshop on Efficiency and Productivity Analysis, University of Oviedo.

Forsyth, P. (2001), "Total Factor Productivity in Australian Domestic Aviation," *Transport Policy* 8 (3): 201–207.

Franke, M. (2004), "Competition between Network Carriers and Low-Cost Carriers – Retreat Battle or Breakthrough to a New Level of Efficiency?" *Journal of Air Transport Management* 10: 15–21.

Fried, H. O., Lovell, C. A. K. and Schmidt, S. S. (2008), "Efficiency and Productivity," in Fried, H. O., Lovell, C. A. K. and Schmidt, S. S., eds., *The Measurement of Productive Efficiency and Productivity Growth* (New York: Oxford University Press).

Good, H.D., Nadiri, M., Roller, L.H and Sickles, R.C. (1993), "Efficiency and Productivity Growth Comparisons of European and U.S. Air Carriers: A First Look at the Data," *The Journal of Productivity Analysis* 4: 115–125.

Good, H. D., Roller, L. H. and Sickles, R. C. (1995), "Airline Efficiency Differences between Europe and the US: Implications for the Pace of EC Integration and Domestic Regulation," *European Journal of Operational Research* 80: 508–518.

Greer, M. R. (2008), "Nothing Focuses the Mind on the Productivity Quite Like the Fear of Liquidation: Changes in Airlines Productivity in the United States, 2000–2004," *Transportation Research Part A* 42 (2): 414–426.

IATA (International Air Transport Association) (2014) *Annual Report* (Geneva).

Inglada, V., Rey, B., Rodriguez-Alvarez, A. and Coto-Millan, P. (2006), "Liberalisation and Efficiency in International Air Transport," *Transport Research Part A* 40 (2): 95–105.

Lee, B. L. and Worthington, A. C. (2010), "The Relative Efficiency of International, Domestic and Budget Airlines," Discussion Papers – Economics, Griffith University, Australia, No. 2010-02.

Lee, B. L. and Worthington, A. C. (2014), "Technical Efficiency of Mainstream Airlines and Low-Cost Carriers: New Evidence Using Bootstrap Data Envelopment Analysis Truncated Regression," *Journal of Air Transport Management* 38: 15–20.

Lin, L. C. and Tseng, L. A. (2005), "Application of DEA and SFA on the Measurement of Operating Efficiencies for 27 International Container Ports," Proceedings of the Eastern Asia Society for Transportation Studies 5: 592–607.

Liu, Z. and Lynk, E. L. (1999), "Evidence on Market Structure of the Deregulated US Airline Industry," *Applied Economics* 31 (9): 1083–1092.

Merkert, R. and Hensher, D. A. (2011), "The Impact of Strategic Management and Fleet Planning on Airline Efficiency – A Random Effects Tobit Model Based on DEA Efficiency Scores," *Transportation Research Part A: Policy and Practice* 45 (7): 686–695.

Michaelides P. G., Athena, B. R., Karlaftis, M. and Marinos, T. (2009), "International Air Transportation Carriers: Evidence from SFA and DEA Technical Efficiency Results (1991–2000)," *European Journal of Transport and Infrastructure Research* 9: 347–362.

Ouellett, P., Petit, P., Tessier-Parent, L. P. and Vigeant, S. (2010), "Introducting Regulation in the Measurement of Efficiency with an Application to the Canadian Air Carriers Industry," *European Journal Operation Research* 200 (1): 216–226.

Oum, H. T. and Yu, C. (1998), "Cost Competitiveness of Major Airlines: An International Comparison," *Transportation Research Part A: Policy and Practice* 32 (6): 407–422.

Schefczyk, M. (1993), "Operational Performance of Airlines: An Extension of Traditional Measurement Paradigms," *Strategic Management Journal* 14: 301–317.

Scheraga, C. A. (2004), "Operational Efficiency versus Financial Mobility in the Global Airline Industry: A Data Envelopment and Tobit Analysis," *Transportation Research Part A* 38: 282–404.

Scheraga, C. A. (2006), "The Operational Impacts of Governmental Restructuring of the Airline Industry in China," *Journal of the Transportation Research Forum* 45 (1): 71–86.

Soares de Mello, J., Angulo-Meza, L., Gomes, E., Serapião, B. and Lins, M. (2003), "Data Envelopment Analysis in the Study of Efficiency and Benchmarks for Brazilian Airlines," *Pesquisa Operacional* 23 (2): 325–345.

Tone, K. (2002), "A Slacks-Based Measure of Super-Efficiency in Data Envelopment Analysis," *European Journal of Operational Research* 143: 32–41.

Vasigh, B. and Fleming, K. (2005), "A Total Factor Productivity Based Structure for Tactical Cluster Assessment: Empirical Investigation in the Airline Industry," *Journal of Air Transport Management* 10 (1): 3–19.

Williams, G., Mason, K. and Turner, S. (2003), "Marker Analysis of Europe's Low-Cost Airlines – An Examination of Trends in the Economics and Operating Characteristics of Europe's Charter and No-Frills Schedule Airlines," Research Report 9, Air Transport Group, Cranfield University.

Zhu, J. (2011), "Airlines Performance via Two-Stage Network DEA Approach," *Journal of CENTRUM Cathedra* 4 (2): 260–269.