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An evaluation of the world's major airlines' technical and environmental performance

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Abstract

In this empirical study, we apply bootstrapped data envelopment analysis (DEA) models under variable returns to scale to examine both the environmental and technical efficiencies of airlines. Using the regional classification of the International Air Transport Association (IATA), we chose 48 of the world's major full-service and low-cost carriers from six different regions, and then estimated their performance over the period 2007-2010. Our empirical results show that many of the most technically efficient airlines are from China and North Asia, whilst many of the best environmental performers are from Europe. We also found that although the number of environmentally oriented full-service carriers is increasing, low-cost carriers are still more environmentally oriented. Our findings show that almost all the low-cost carriers are technically operating under increasing returns to scale in all the studied years. However, this result was quite the opposite of what we found for the largest airlines.

Keywords

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ABSTRACT

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Keywords: Aviation, Efficiency, Emissions, Data Envelopment Analysis, Bootstrap

JEL Classification: D21, C14, Q53

1. Introduction

In the last decade, global public consciousness about the aviation industry's environmental performance has increased. Under the Kyoto Protocol 1997, which came into force in February 2005, thirty-seven industrialized countries and the European Community (EC) agreed on binding targets to reduce greenhouse gas (GHG) emissions on average by five per cent over the period 2008 to 2012 compared to their respective emission levels of 1990 (UNFCCC, 2011). According to IPCC[1] (2007), approximately three per cent of the anthropogenic global warming in 2007 was attributable to aviation emissions, with a predicted contribution of five per cent until 2050.

Although researchers have shown an increased interest in financial and service performance of the aviation industry in recent years (see, inter alia, Assaf, 2009; Rey et al., 2009; Assaf, 2011), far too little attention has been paid to the environmental performance of the aviation sector. The present study estimates and compares both technical (service) and environmental efficiencies of the world's major airlines.[2] According to Koopmans (1951), a producer is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input; and if a reduction in any input requires an increase in at least one other input or a decrease in at least one output. A producer is environmentally efficient (compared to other firms) if it is producing the lowest amount of undesirable output per unit of desirable output.

Environmental efficiency analyses of the sector are particularly pertinent and timely because first, this helps policy makers to identify leaders and laggers amongst the companies and to take

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[1] Intergovernmental Panel on Climate Change.

[2] There has been an increasing amount of literature on the correlation between technical efficiency of the airlines and other variables such as union density, age of fleet, size of aircraft, stage length, per cent of passengers flying internationally, load factor, and legacy (for example, Coelli et al., 1999; Oum et al., 2005; Greer, 2009). However this study has a primary focus on the evaluation of the airlines' environmental efficiency.

measures that address environmentally poor performances (Färe et al., 1996; Tyteca, 1996). Second, airlines need to know about their relative environmental efficiencies in the market in order to eliminate existing shortcomings and show higher performance. The aviation industry has been included in the EU's emission trading scheme (EU-ETS, from January 2012) and the Australian emission trading scheme (AUS-ETS, from July 2012). These schemes place even greater pressure on the aviation industry and highlight the need for tools to undertake accurate and objective measurement of the performance of airlines with respect to the environment. Third, not only the airlines but also their shareholders have an interest in airlines' environmental efficiency for their future investment decisions. Recent policy changes, such as the EU-ETS and AUS-ETS, may cause additional cash outflows and expenses for airlines, reducing their annual profits in the near future. Finally, environmentally conscious travellers may purchase services from the more environmental friendly airlines in order to reduce their carbon footprint.

This study uses carbon dioxide equivalent (CO_2-e) emission as an undesirable output of the airlines in the DEA models to analyse the environmental performance of the aviation sector (Lu et al., 2013; Wang et al., 2013; Wu et al., 2013; Jin et al., 2014). Hence, an airline is considered as environmentally efficient if it produces the lowest amount of CO_2-e per unit of desirable output. DEA is a well-known non-parametric approach to evaluating the relative efficiency of decision-making units (here: airlines). Its main advantage over parametric approaches (such as Stochastic Frontier Analysis) is that it can readily incorporate multiple inputs and outputs (Barros and Garcia-del-Barrio, 2008; Lu, 2012). In this study, bBootstrapped DEA models under variable returns to scale are utilised providing a comprehensive and robust analysis of

airlines' technical and environmental efficiencies.[3] The remainder of this paper is structured as follows: Section 2 provides a brief literature review. Section 3 articulates existing institutional and regulatory frameworks relevant to the study. The methodology is presented in Section 4. Section 5 explains the data and Section 6 discusses the results, and is followed by some concluding remarks in Section 7.

2. Literature Review

By following Farrell's (1957) original setting for efficiency evaluation, Charnes et al. (1978) were the first to introduce DEA as an efficiency measure. This became a recognized nonparametric methodology aimed at evaluating comparable entities' relative efficiency given multiple inputs and outputs. DEA models have been widely applied within the field of airlines' efficiency (for example, Greer, 2006; Ray, 2008; Barros and Peypoch, 2009; Greer, 2009; Assaf and Josiassen, 2011; Markovits-Somogyi, 2011). In the literature that evaluates airlines' operational performance, various regions have been considered; for example, see Schefczyk (1993), Scheraga (2004), and Michaelides et al. (2009) for the world region, and Barros and Peypoch (2009) and Charnes et al. (1996) for European and Latin American regions. There are also some in-country studies for the UK (Assaf and Josiassen, 2011), and US (Greer, 2008; 2009), and even studies focusing on the domestic routes of a single company (Coli et al., 2011).

As well as the geographical differentiation, special attention is drawn to the operational efficiency differences between full-service carriers (FSCs) and low-cost carriers (LCCs) (for

[3] The bootstrap method, proposed by Simar and Wilson (1998; 2000a; 2000b), allows for determining the statistical properties of the non-parametric estimators in the multi-input and multi-output case, and therefore for constructing confidence intervals for DEA efficiency scores.

example, Gillen and Morrison, 2003; Greer, 2006; Barbot et al., 2008; Assaf and Josiassen, 2012; Change and Yu, 2012).[4] Gillen and Morrison (2003) argue that FSCs have greater financial resources, significant economies of scale and more sophisticated technologies, with the potential to be more technically efficient than LCCs (see also Chang and Yu, 2012). However, Greer (2006), Barbot et al. (2008), Assaf and Josiassen (2012) state that LCCs are generally more technically efficient than FSCs, mostly because of their low-cost business models. Extensive research has been carried out on the airlines' technical efficiency, but no single study exists that considers their environmental efficiency.

There has been an increasing interest in applying DEA models for quantifying the environmental performance of different industries in the last decade. The common procedures for applying DEA to measure environmental performance are first to incorporate undesirable outputs in the traditional DEA framework, and then to calculate the output-orientated environmental efficiencies. For instance, Jung et al. (2001) and Kumar-Mandal and Madheswaran (2010) utilised this method in their investigations of overall efficiency in the oil and cement industries, respectively[5]. The present study extends the airlines efficiency literature by including CO_2-e as an undesirable output, and thus gives consideration to both the environmental and operational performance of FSCs and LCCs. This undesirable output has been used broadly in other areas, such as the electricity industry and agricultural industry, but not the

[4] In general, FSCs have mixed fleets; provide long and short haul flights together with code–sharing and network alliances; provide full services and business class while their operating and maintenance costs are high. LCC, however, are characterized by having a uniform fleet, provide short haul flights with no frills and economy class only in order to achieve lowest operating and maintenance costs (Gillen and Morrison, 2003).

[5] Among other studies, Lu et al. (2013) and Jin et al. (2014) used CO2 emission as an undesirable output in their studies of CO2 emission efficiency of OECD countries and APEC economies, respectively. Wu et al. (2013) also used this output in an investigation of cost performance of CO2 reduction. See also Wang et al (2013) for a meta-frontier DEA analysis of energy efficiency.

airline industry. See, for example, Lansink and Silva (2003) and Sueyoshi and Goto (2012) as well as Zhou et al. (2008) for a comprehensive literature survey of DEA studies related to energy and the environment. In the context of airline operations, Coli et al. (2011) incorporate the number of delayed flights as an undesirable output in their sample of an Italian airline's 42 domestic routes. Yu (2004) also includes the level of noise as undesirable output in their efficiency study of Taiwanese airports.

3. Institutional and regulatory framework

Air transportation is a highly regulated and monitored industry. Institutional settings and regulatory frameworks impact significantly on airlines' operations and thus on their technical and environmental efficiency. This section will position airlines' within the current context of evolving climate policy, regulations and institutions as the background against which findings of this study have to be considered.

Domestic GHG emissions from the aviation industry are included in the national GHG inventories of Annex1 countries (for example, EU countries, the US, Japan, Russia, and so on)[6] covered under the Kyoto Protocol. Emissions from international air traffic, however, are not included in the respective national emission targets under the Kyoto Protocol, nor discussed in post-Kyoto emissions reductions negations (Gössling and Upham, 2009). The responsibility for reducing aviation emissions in Annex 1 countries was deferred to the International Civil Aviation Organization (ICAO, 1997) which rejected the idea of a global ETS (Emission Trading Scheme) during their annual assembly in 2004, but "endorsed the inclusion of aviation in

[6] A complete list of Annex1 countries can be found at: http://unfccc.int/parties_and_observers/parties/annex_i/items/2774.php

existing national/regional ETS as more cost-effective measure than fuel taxes" (Gössling and Upham, 2009, p. 9). Despite its position, the ICAO withdraw from this idea and decided that airlines should not be included in the EU-ETS (Environment News Service, 2007; Transport and Environment, 2007) as a response to the EU Parliament's November 2007 reading which mentioned a 10% emission reduction based on 2004–2006 average airline emissions to commence in 2011 (EU Parliament, 2007).

In Europe, from the beginning of 2012, all international and regional flights have been subject to the EU-ETS. For the calendar year 2012 the emission cap for each airline was set at 97% and will decrease to 95% for the 2013–2020 trading period (subject to revision) compared to their historical 2004–2005 CO_2 emission levels. Fifteen per cent of the allowances are auctioned (Euractive, 2012). In contrast to the mandatory EU-ETS in the US, the Chicago Climate Exchange (CCX), a voluntary permit trading exists, using legally binding targets but no requirements to join.

There are two legal decisions that could impact on North-American airlines' CO_2 emissions. First, The US Senate Committee of Environment and Public Works gave approval to the Lieberman-Warner Climate Security Bill in 2007 and forwarded it to the US Senate to be considered. The Bill aimed to create a nationwide ETS for the aviation industry in the US similar to the one in the EU, however in mid-2008 under the pressure of the Republicans it was abandoned. Second, there are already five Canadian provinces ~~and eight US states~~ that have set targets of 10–30% emission reduction for 2020 below a 1990 baseline. An additional two Canadian provinces and six US states have set a target of a 75–80% emission reduction for 2050 below a 1990 baseline (Gössling et al., 2008).

In July 2011 the Australian Government released its climate change plans: Securing a Clean Energy Future (Australian Government, 2011a). In late July 2011 the exposure draft of the Clean Energy Bill 2011 was released, and related exposure drafts of Bills and their commentary were released (Commonwealth of Australia, 2011) and were assented to in November 2012 (Australian Government, 2011b). Another mandatory emission trading exists in Australia, which covers four out of six GHGs mentioned under the Kyoto Protocol.[7] Under the Clean Energy Act 2011, airlines have to pay a fuel surcharge of for each litre of aviation kerosene of: 5.98 cents (2012–2013), 6.279 cents (2013–2014), and 6.604 cents (2014–2015) for international flights, and can choose to join emission trading after July 2015 or otherwise keep paying a surcharge (Australian Government, 2011b).

Apart from those mentioned above, China's twelfth five-year plan, realised in 2010, states that ETS is a key measure to cope with climate change and reduce carbon emissions in particular. In 2011, 17th Central Committee of the Communist Party of China (CPC) planned that seven provinces and cities in China would introduce carbon trading pilots, and also in 2012, the CPC made specifications of those pilot schemes which started in 2013 on a city level and for those which will start in 2014 on province level while the introduction of a nation-wide ETS is proposed by 2015–2016 (The Climate Group, 2011). It is yet to be determined if and when the aviation industry will be subject to a price on carbon. On a global stage, the 191 members of ICAO endorsed on its 38th assembly at the end of 2013 that a cap and trade market based mechanism for the aviation sector will be introduced by 2020 and that the next assembly will

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[7] Carbon dioxide, methane, nitrous oxide and perfluorocarbons from aluminium smelting (also called 'carbon dioxide equivalent').

specify the steps for its implementation. This implies that airlines face a price on their CO_2 emissions from 2020 onwards (ICAO, 2013).

The above discussion shows that airlines across different regions face different institutional and regulatory frameworks with different levels of (financial) pressure to adopt a more environmental friendly production plan. These might have affected airlines' decisions regarding investments to transform inputs into outputs with the least CO_2 emissions. Thus, political forces could be a driver of airlines' respective environmental efficiency and their attempts to reduce CO_2 emissions further. In this context, our DEA models help to assess the relative environmental efficiency of individual airlines throughout the world's regions to allow comparison and further policy recommendations until the global ETS endorsed by ICAO is introduced in 2020.

4. Methodology

Environmental DEA technology is very popular in the context of environmental performance measurement, and has been utilised by many studies, such as Färe et al. (1996), Zofio and Prieto (2001), Zaim (2004), and Zhou et al. (2006; 2007). Most studies follow the original characterization of environmental DEA technology by assuming that the production technology exhibits constant returns to scale (CRS). However, variable returns to scale (VRS) cases are more likely to be observed in actual situations (Tyteca, 1996); many airlines are not operating at optimal scale and face imperfect competition and finance constraints. A VRS model also has the advantage of ensuring that an inefficient airline is only judged against airlines of similar size. This can be achieved through a convexity constraint, which is not imposed in the CSR case. Hence, in this study, both traditional and environmental DEA technologies are utilised under VRS.

This technique constructs a non-parametric piece-wise surface or efficient frontier, and efficiency measures of decision-making units (DMUs) are then estimated relative to this frontier. DMUs that lie on the efficient border are the best practice institutions, and retain a value of one, and those DMUs that are enveloped by the efficient frontier and lie below this border are relatively inefficient and have values of between 0 and 1. The smaller values of efficiency scores reflect the lower relative efficiency of the DMUs. Both desirable and undesirable outputs are present and incorporated into the VRS models. For instance, if inefficiency exists in the production process where final airline services are produced with an increase of CO_2 emissions, the outputs of CO_2 emissions are undesirable and must be reduced to improve the performance.

Assume a set of *n* observations on the DMUs that each observation, $DMU_j\left(j=1,\ldots,n\right)$, uses *m* inputs $x_{ij}\left(i=1,2,\ldots,m\right)$ to produce *s* outputs $y_{rj}\left(r=1,2,\ldots,s\right)$. Also, $\sum_{j=1}^{n}\lambda_j y_{rj}(r=1,2,...,s)$ and $\sum_{j=1}^{n}\lambda_j x_{ij}(i=1,2,...,m)$ are possible outputs and inputs achievable by the DMU_j where $\lambda_j(j=1,2,...,n)$ are non-negative scalars, such that $\sum_{j=1}^{n}\lambda_j=1$. Then, according to Zhu (2009),the following DEA model with an undesirable output (in our case CO_2-e) can be solved to obtain the environmental efficiency value under the VRS:

$$\theta^* = \max \theta,$$

$$\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j y_{rj}^g \geq \theta y_{ro}^g,$$

$$\sum_{j=1}^{n} \lambda_j \overline{y}_{rj}^b \geq \theta \overline{y}_{ro}^g,$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}, \tag{1}$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0, \quad j = 1, ..., n.$$

where DMU_o represents one of the n DMUs under evaluation, and x_{io} and y_{ro} are the i^{th} input and r^{th} output for DMU_o, respectively. y_j^g is desirable outputs, y_j^b is undesirable outputs, and θ^* represents the output-oriented efficiency score of the DMU_o under evaluation. Each undesirable output has been multiplied by -1, and then a proper value of w is calculated to let all negative undesirable outputs be positive. That is, $\overline{y}_j^b = -y_j^b + w > 0$, which can be achieved by $w = \max_j \left\{ y_j^b \right\} + 1$.

In order to analyse airlines' "preferences" between meeting the market demands (the technical aspect) and reducing their fuel consumption/CO_2-e emission (the environmental aspect), EO values (indicative of environmental orientation) are also used in this study. These are the ratios of bias-corrected environmental efficiency and bias-corrected technical efficiency. If EO < 1, this indicates that the CO_2-e emission-adjusted efficiency of an airline is lower than its technical efficiency, and hence we may argue that the airline could be seen as a relatively market-oriented company. If EO > 1, this indicates that the CO_2-e emission-adjusted efficiency of an airline is higher than its technical efficiency, and therefore the airline could be seen as an

environmentally oriented company. If EO = 1, this means that the inclusion of CO_2-e emission in the model had no effect on the airline's efficiency.

In the multi-output or multi-input cases, bootstrap methodology is the only way to examine the sampling variability of DEA efficiency estimates, by means of correcting the bias inherent in the DEA procedure (Simar and Wilson, 2000b). The bootstrap simulation method suggested by Simar and Wilson (1998; 2000a; 2000b) is used in this study to obtain the bias-corrected estimates of efficiency scores for each airline, as well as their 95% confidence intervals. Hence, the bootstrap methodology allows us to test for significant differences in efficiency between airlines and verify the reliability of estimates.

The rationale behind bootstrapping is to approximate a true sampling distribution by mimicking the data-generating process. The procedure is based on constructing a pseudo sample and re-solving the DEA model for each airline with the new data. Repeating this process many times will construct a good approximation of the true distribution. The bootstrap algorithm is described in detail in Simar and Wilson (2000b).

5. The Data

The identification of an appropriate mix of inputs and outputs is a critical step in all efficiency analyses. In this study, physical inputs and outputs were chosen to avoid the use of monetary measures such as operational costs, fuel cost, and earnings before interest and taxes (EBIT). The reason is mainly because carriers face different prices, which would lead to different input units (Greer, 2009). All data were provided by RDC Aviation (www.rdcaviation.com) and were compared with the annual and/or sustainability reports of each airline so as to ensure their consistency. The data set used in this study covers the period 2007–2010 and contains 35 FSCs,

with nine from Europe and Russia, six from North America, one from Latin America, 12 from China and North Asia, three from Asia Pacific and four from Africa and Middle East. The data set also contains 13 low-cost airlines from Europe, North America, Asia, and the Asia Pacific (see Tables 2–5).

The variables used in this study are well established in the literature (see, for example, Barla and Perelman, 1989; Charnes et al., 1996; Inglada et al., 2006) and presented in Table 1. As inputs, our DEA data set includes labour and capital. As previously discussed in Coelli et al. (1999) and Greer (2008), labour is measured as number of full-time equivalent employees, and comprises two distinct categories employed in the production of air travel. These are: pilots, including co-pilots and other cockpit crew on the one hand; and flight attendants on the other. In these two categories, the subcontracting of certain operations (for example, maintenance, ground operations, and others) was disregarded in order to prevent biases such as those related to higher service levels which are more labour intensive but are not directly related to the airlines' core flying activities.[8] Capital is defined following Coelli et al. (1999, p. 262), as the "sum of the maximum take-off weights of all aircraft multiplied by the number of days the planes have been able to operate during a year (defined as the total number of flying hours divided by average daily revenue hours)". This definition of capital avoids performance prediction bias caused by maintenance operations, and is in line with Barla and Perelman (1989), Coelli (1999), Coelli et al. (2002), and Ray (2008).

< TABLE 1 ABOUT HERE >

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[8] See Coelli et al. (1999) and Greer (2008) for an in-depth explanation of this input.

As outputs, we used tonne kilometres available (TKA) and CO_2-e emissions. Following Barla and Perelman (1989), Coelli et al. (1999), and Inglada et al. (2006), TKA was chosen as the main desirable output , rather than RTK/RPK[9], because this paper investigates the technical efficiencies of the airlines' flying operation and not their marketing functions (Greer, 2009). TKA is the number of tonnes available for the carriage of revenue load (passengers, freight and mail) on each flight multiplied by the flight distance. The CO_2-e emission dataset depicts the undesirable output. The data are extracted based on a model that calculates the fossil fuel burn on a specific airline/aircraft combination according to the sector flown. Schedule information used in this calculation was derived from the Schedules Reference Service (SRS) Innovata database,[10] which contains 99% of all the world's scheduled movements. RDC Aviation was, hence, able to provide CO_2-e emission data modelled in a consistent manner across airlines. Therefore, individual airline's annual CO_2-e emissions would be built based on their actual operations (that is, flown air sectors and the aircrafts which flew in those sectors).

The RDC Aviation's CO_2-e emission data are regarded as superior to those found in annual or environmental reports of airlines for the following reasons: 1) data are provided by one (rather than multiple) sources, which avoids measurement inconsistencies; 2) data are standardized according to common weather conditions; for instance, with the aim of increasing airlines' comparability, differing wind conditions was excluded because it is an external factor that airlines cannot affect; 3) airport-specific emission-related impacts on data, as well as emissions

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[9] RPK, revenue passenger kilometre, is the total number of paying passengers multiplied by the kilometres they have flown, and RTK, revenue tonne kilometre, is the number of tonnes of revenue load carried on each flight stage multiplied by the stage distance. Ceha and Ohta (2000), Oum et al. (2005), Barbot et al. (2008), Barros and Peypoch (2009), and Assaf and Josiassen (2012) are among the studies that use RTK/RPK as an output.

[10] For more information about the SRS Innovata database see the following websites:
http://www.iata.org/ps/publications/srs/pages/innovata.aspx
http://www.innovata-llc.com/data/data.html

from grounding/taxiing were also excluded to reduce biases across airlines that depart from or land at small airports (for example, Ryanair departs from / lands at regional airports such as Frankfurt Hahn, which consists of only one runway); 4) the data exclude CO_2-e emissions from aircrafts waiting for departure or landing and other operational delays; and 5) data are free from variations in pilots' choice of route or other circumstances that could cause route alterations and thus higher or lower fuel consumption or CO_2-e emissions. Generally, we took RDC's data as being more reliable for this study because they exclude external factors that cannot be influenced by airlines and hence should not be part of our comparative technical efficiency analysis.

6. Empirical Results

We start with a brief interpretation of the statistical findings. The estimated 95% confidence intervals for technical and environmental efficiencies are shown in Figures 1 and 2, respectively. These figures depict the pooled sample observations (for the sample period of 2007–2010) ordered by the bias-corrected efficiency score. The confidence intervals and the bias-corrected efficiency scores shown in the figures were estimated using the bootstrap procedure with 2000 bootstrap draws. The bounds of the confidence intervals for each airline are shown by the upper solid line and the lower dashed line. All the efficiency scores are multiplied by 100 (giving a percentage measurement) for the sake of interpretation convenience. As shown in both figures, the original efficiencies (represented by "-") are not included in the confidence intervals and lie just above the upper bound line. This reflects the theory behind the construction of these intervals (see Simar and Wilson, 1998, for a detailed explanation). It is also evident from both figures that the airline efficiency ranking based on the bias-corrected efficiencies is very different from that derived from the original efficiencies in many cases. When the bias-corrected

efficiencies are considered there are many instances for which efficiency deteriorates severely. In the case of the most efficient firms (those with an original efficiency = 100), the bias-corrected efficiency deteriorates more dramatically in both figures. This issue is more apparent in Figure 2. In contrast, we observe that some airlines that seemed at first to be not perfectly efficient (original efficiency < 100) become more efficient (relative to the others) when the bias is corrected. The above-mentioned results point out the importance of using the bias-corrected estimates instead of the original ones, because they can either confirm what the original scores revealed or express a different efficiency behaviour.

As shown in Figures 1 and 2, the confidence intervals, which identify the statistical location of the true efficiency, are in some cases very wide, indicating a substantial variability in biases. In general, the estimated confidence intervals for the airlines' technical efficiency are narrower than those of the environmental efficiency. This is because of the greater number of the sample observations that have environmental efficiencies equal to unity. Wide confidence intervals for the most efficient firms have been found by many other bootstrap-related studies in different areas (see, for example, Simar and Wilson, 2000b and Tortosa-Ausina et al., 2008). Such confidence intervals make the interpretation of the efficiency scores more complicated, because the wider the intervals, the higher the chance of overlapping of the efficiency scores. In other words, when two confidence intervals overlap, we cannot conclude that there is (or there is not) a statistically significant difference between the two efficiency values. This issue is explained in more detail below, using Tables 2–5.

Overall, Figures 1 and 2 highlight the importance of using the bootstrap approach, and reveal that: 1) perfectly efficient (originally efficient) airlines become considerably less efficient

after bias correction, especially in the case of environmental efficiency; and 2) it is easier to identify the airlines with low efficiency scores than to identify high performers in the sample.

< FIGURES. 1 AND 2 ABOUT HERE >

We can now focus on the performance of the airlines. Tables 2–5 list several measures related to relative technical and environmental efficiencies of the individual airlines. They include the original efficiency estimates (Orig. Eff.), the bias-corrected estimates (BC Eff.), the bootstrap bias estimates (shown by "Bias"; that is, the difference between the original efficiency and bias-corrected efficiency), and the efficiency's lower and upper bounds (for the 95% confidence intervals) for 35 FSCs and 13 LCCs for years 2007 to 2010. The airlines are ordered by the size of capital.

As discussed previously, the measured bias-corrected efficiencies are lower than the original efficiency scores. The magnitudes of the difference of these measures (the bias) and the width of the confidence intervals are quite small in many instances (except for the most efficient firms), implying that the results are relatively stable. However, because of the overlapping issue, it is difficult to see which airlines are the most or least efficient ones in each year. To overcome this issue we have provided additional information on these firms, and each firm's confidence interval is compared with those of others. In Tables 2–5, columns represented by #M. Eff. (#L. Eff.) disclose information about the number of the airlines in the sample that were found to be "significantly" more (less) efficient than each corresponding airline. Airlines can be significantly more (less) efficient than the airline in question if their lower (upper) bounds are strictly greater (smaller) than the airline's upper (lower) bound. Hence, when the overlapping issue occurs, it is easier to see whether any meaningful differences exist between airlines' efficiency. For instance, in 2007 (Table 2) using the intervals in columns 5 and 6, we notice that KLM Royal Dutch

Airlines' technical efficiency overlaps with those of other most efficient airlines such as British Airways, Qantas, Emirates or Singapore Airlines despite their differing bias-corrected efficiency estimates. However, using columns 7 and 8, we can easily identify KLM Royal Dutch Airlines as the most technically efficient airline in 2007 because it is significantly more efficient than 33 airlines (#L. Eff. = 33) and no airline stands in a better position[11]. Similarly, we may also conclude that easyJet is (relatively) the most technically inefficient airline in 2007, because there are 46 airlines more statistically efficient than it in this year. It is worth mentioning that Ryanair is also ranked at the same position with easyJet (#M. Eff. = 46), but easyJet shows a lower level of technical efficiency and hence was chosen as the worst performer in 2007.

< TABLES 2–5 ABOUT HERE >

Based on Tables 2–5, Air India and Ryanair were found to be respectively the best and the worst technical performers in the years 2008, 2009, and 2010. The following airlines were ranked among the top-10 most technically efficient ones in at least three of the years: KLM Royal Dutch Airlines and British Airways (from Europe); Air India, China Airlines, Cathay Pacific Airways, Malaysia Airlines, Singapore Airlines, Korean Air (from China and North Asia); Etihad Airways and Emirates (from the Middle East and Africa); Eva Air (from the Asia Pacific). Evidently, Chinese and North Asian airlines technically performed very well in comparison with others during the period 2007–2008. Interestingly, none of the airlines from North America and Canada is positioned in the group of top-10 technically efficient airlines over the period 2007–2010.

[11] It should also be noted that KLM Royal Dutch Airlines' lower boundary is higher than those of British Airways, Singapore Airlines, Qantas and Emirates.

Concerning environmental efficiency scores (on the right hand side of Tables 2–5), KLM Royal Dutch Airlines (in 2007 and 2009) and Korean Air (in 2008 and 2010) are ranked as the best environmental performers respectively. The most environmentally inefficient airlines were Malaysia Airlines in 2007, Air India in 2008 and TAM Linhas Aereas, in both 2009 and 2010. Based on the environmental efficiencies presented in Tables 2–5, we may argue that airlines from the European region performed relatively better than those in other regions for two reasons. First, at least six out of the top-10 environmental performers belonged to this region in almost all the years under study. For instance, Alitalia, KLM Royal Dutch Airlines, and Turkish Airlines were among this group in all years. From other regions, only the following three airlines were graded in the top-10 best environmental performers in at least three of the studied years: Korean Air (from China and North Asia), Thai Airways International (from the Asia Pacific), and Allegiant Air (from the US and Canada). Second, only one or at the most two European airlines (Virgin Atlantic Airways and Iberia) were found among the 10 worst environmentally performing airlines in all the years under study.

Overall, a comparison of the findings based on the technical and environmental efficiencies reveals that: 1) KLM Royal Dutch Airlines and Korean Air were among the most efficient, irrespective of which performing aspect is considered; 2) the most technically efficient airlines seemed always to be FSCs, and were mostly from China and North Asia; 3) with regard to environmental efficiency, we located airlines from both FSC and LCC groups in the top-10 best performers; 4) European airlines, in general, were found to be more environmentally efficient than other airlines; 5) North American and Canadian airlines were predominantly ranked in the middle one-third of all airlines from both technical and environmental perspectives. This last

finding suggests that although they are not the best performers in the industry, they cannot be seen as the worst ones either.

Another interesting aspect of the results evident from Tables 2–5 is that some of the airlines have been doing remarkably well to optimize their technical efficiency, but at the same time managing their environmental performance poorly, or vice versa. A good example of this is Air India in 2008 (Table 3), which is ranked as the best airline from a technical efficiency point of view and the worst from an environmental perspective. The EO values, that are the ratios of bias-corrected environmental efficiency and bias-corrected technical efficiency and shown in the last columns of Tables 2–5, are used to analyse airlines' "preferences" between meeting the market demands (the technical aspect) and reducing their fuel consumption/CO_2–e emission (the environmental aspect). Importantly, the EO difference from unity does not necessarily show how good or bad an airline is performing. For instance, in 2010 (Table 5) Southwest Airlines shows an EO value of 1.13, which reveals its better environmental performance; however, simultaneously, both its technical and environmental efficiencies were very low in comparison with other airlines that had lower EO values.

A cursory look at Tables 2–5 reveals that most of the LCCs show EOs higher than unity; at least 10 LCCs (out of 13) were found to be environmentally oriented (EO > 1) in all years studied. One of the LCCs (Ryanair) points to its being the most environmentally oriented airline in the industry, because it shows very low levels of technical efficiency and high levels of environmental efficiency in all the years studied. Tables 2–5 also show a clear trend of an increasing number of environmentally oriented FSCs over the period 2007–2010. The number of such airlines increased from nine (out of 35) in 2007 to 14, 17, and 17 in 2008, 2009 and 2010 respectively; while in 2007 and 2008 none of the FSCs was among the top-five most

environmentally oriented airlines; however, this number increased from zero in 2007 and 2008 to one in 2009, and three in 2010. We may therefore assume that FSCs have been focusing more rigorously on the fuel-saving programs in their businesses over this period (2007–2010). The EO values presented in Tables 2–5 also show that although the airlines from Europe were relatively more environmentally oriented in most of the years, there is also an evident trend of an increasing number of environmentally oriented airlines from US and Canada during the sample period.

Finally, the RTS column (representing returns to scale in production) of Tables 2–5 indicates whether the airline is operating in an area of increasing or decreasing returns to scale. The RTS is the traditional measure of economies of scale and is used in many studies of efficiency analysis of individual firms (see, inter alia, Martin and Roman, 2001; Chiou and Chen, 2006; Barros and Peypoch, 2009). Where IRS holds, the airline is performing under increasing returns to scale; while if it expands (contract), its input levels by a small percentage, its output levels will expand (contract) by a larger percentage. Under CRS (that is, constant returns to scale), the expansion (contraction) of the airline's outputs will be by the same percentage as that of its inputs; while under DRS (that is, decreasing returns to scale), its output levels will expand (contract) by a smaller percentage than its inputs. Hence, where IRS holds, the airline should increase its scale size, because its additional input requirements may be more than compensated for by a rise in output levels. Similarly, a DMU operating at a point where DRS holds should decrease its scale size. The ideal scale size to operate at is where CRS holds. However, because this study tends to focus on the environmental performance of the airlines rather than their technical performance, a CO_2-adjusted measure of returns to scale (CARTS) can be far more useful. Very similar interpretations as those for RTS can be provided for CARTS values, but

with this difference: the corresponding airlines are directing their resources toward the reduction of CO_2-e emissions. Therefore, where IRS holds, the airline should increase its scale size by focusing on the expansion of those inputs whose developments would lead to a lower level of CO_2-e emission. A good example of this could be the replacement of their older aeroplanes with new, lighter, and more fuel-efficient ones. Likewise, where DRS holds, the airline would need to trim down its size to enhance its environmental efficiency. Such airlines might consider retiring their older aircrafts as a possible solution.

Based on the RTS values (returns to scale based on the airlines' technical efficiency) reported in Tables 2–5, all the LCCs (except Southwest Airlines) were operating in the area of increasing returns to scale in all the years under study. This finding implies that room exists for LCCs to increase their size to reap technical efficiency gains. This recommendation can also be made for 10 of the FSCs that have been performing under IRS continuously in all years studied. However, if we use the CO_2-adjusted measure of returns to scale (CARTS) to investigate economies of scale of the airlines, very different results are obtained. For instance, in 2010, many of the airlines performed under DRS; in fact, all except three FSCs and five LCCs. This result was highly predictable, because when CO_2 emission is considered as an undesirable output, any improvement in the capital (for example, increase of planes, flights, and so on.) will lead to a higher level of CO_2 emission and hence lower environmental efficiency levels. It would be a long-term process for airlines to change their operations (for example, by improving their aircrafts' fuel efficiency, replacing old planes or switching to green fuels) and become more fuel efficient. However, and interestingly, two of the airlines were performing under IRS based on both RTS and CARTS in years 2008–2010: Air India and Allegiant Air. These airlines have the potential to increase their staff and capital and become even more environmentally efficient. In

comparison, nine of the FSCs (Delta Air Lines, American Airlines, United Airlines, Emirates, Lufthansa, British Airways, Air France, Continental Airlines, and Qantas) and one of the LCCs (Southwest Airlines) were found to be performing under DRS under in terms of both RTS and CARTS in all the years studied. Almost all these airlines were the largest airlines in their own categories (FSCs or LCCs). Although these results may be interpreted in several ways (for example, increasing market share and profitability), we may argue that they would need to trim down their size to overcome both technical and environmental inefficiencies.

7. Conclusion

This paper uses DEA models to measure and test both technical efficiency and environmental efficiency of the world's major full service and low-cost airlines. The bootstrap method is also used to overcome the statistical limitations of the DEA models by obtaining the statistical properties of the efficiencies. Data used in the analyses range the years from 2007 to 2010 and cover 35 full service and 13 major low-cost airlines. The following groups of airlines were taken into account: Europe and Russia (13 airlines), North America and Canada (11), Latin America (one), China and North Asia (13), Asia Pacific (six), Africa and the Middle East (four). The aim was to include each region's major (largest) airlines as well as a representative sample of major LCCs.

Based on our DEA analysis results, airlines from the regions "China and North Asia" and "Europe and Russia" are the most technically and environmentally efficient airlines in the industry, respectively. One of the most obvious findings to emerge from this study is that LCCs are, in general, more environmentally oriented than FSCs. However, we also found that the number of environmentally oriented FSCs increased over the period. We may thus argue that

FSCs are focusing more rigorously on the reduction of their fuel consumption in their businesses, and this is particularly the case for the airlines from the region "US and Canada". These findings, while preliminary, suggest that businesses are increasingly aware of the importance of fuel/CO_2-e reduction, and this might have triggered investments into more fuel-efficient aircrafts and efforts to control fuel use.

Our returns-to-scale analysis shows that almost all the LCCs were technically operating under increasing returns to scale in all the years under study (2007–2010). We may thus suggest that room exists for them to increase their capital and staff in order to improve their technical efficiency. We also found that the largest airlines are performing under decreasing returns to scale based on both RTS and CARTS. Hence, we may hypothesise that these airlines would need to downsize their inputs to overcome their both technical and environmental inefficiencies.

Our findings are in line with the existing regulatory frameworks of ETSs. That is, Chinese Airlines have not yet faced the threat of being included in an emissions trading scheme (ETS); American airlines have no legal commitment to engage in the voluntary ETS, and airlines from the Middle East face a similar situation; while airlines from those countries are less likely to make additional capital expenses in order to achieve higher environmental efficiency. This is also underpinned by the reluctance of the ICAO to arrive at a binding consensus to establish a global ETS. Additionally, both the US and China have measures in place that mean that their airlines do not pay for the required carbon allowances under the EU-ETS. On the other hand, European airlines were under pressure to act due to ICAO's suggestion to include airlines at a national/regional level at a time (2004) when preparations about the EU-ETS were ongoing. The latest EU Parliament's discussion took place in 2007 regarding the inclusion of the aviation industry in the EU-ETS from 2011 onwards. During this, inclusion into the EU-ETS materialised

and if European airlines were to minimise expected burdens from the EU-ETS they had to improve their environmental efficiency. In Australia, airlines are able to forward partially their additional expenses in the form of a surcharge on fuel on international flights or construct international collaborations; for example, Qantas and Emirates might ally to avoid additional capital expenses into newer airplanes. Also, CO_2-e emissions from domestic flights are exempt from a price on carbon, which lowers the opportunity costs of keeping older aircrafts.

Our findings provide an indication of airlines' environmental efficiency which can be particularly useful to governments in their attempt to meet their national emission targets under the Kyoto Protocol and to assess their aviation industry's sensitivity towards a price on CO_2-e. Airlines with a relative low environmental efficiency would be more sensitive to environmental policy measures that target emission reductions. Since there are currently no commercial alternatives to combustion engines available to airlines, governments aiming for reduction of CO_2-e-footprint might need either to improve airlines' efficiency or provide alternative fuels. Therefore, governments might provide any of the following measures to their airlines in order to improve airlines' environmental efficiency and reduce CO_2-e: loans or government guarantees to purchase newer and more fuel-efficient aircrafts, shorter depreciation cycles for airplanes to spur replacement of older aircrafts, grants for development and marketization of renewal aviation fuels.

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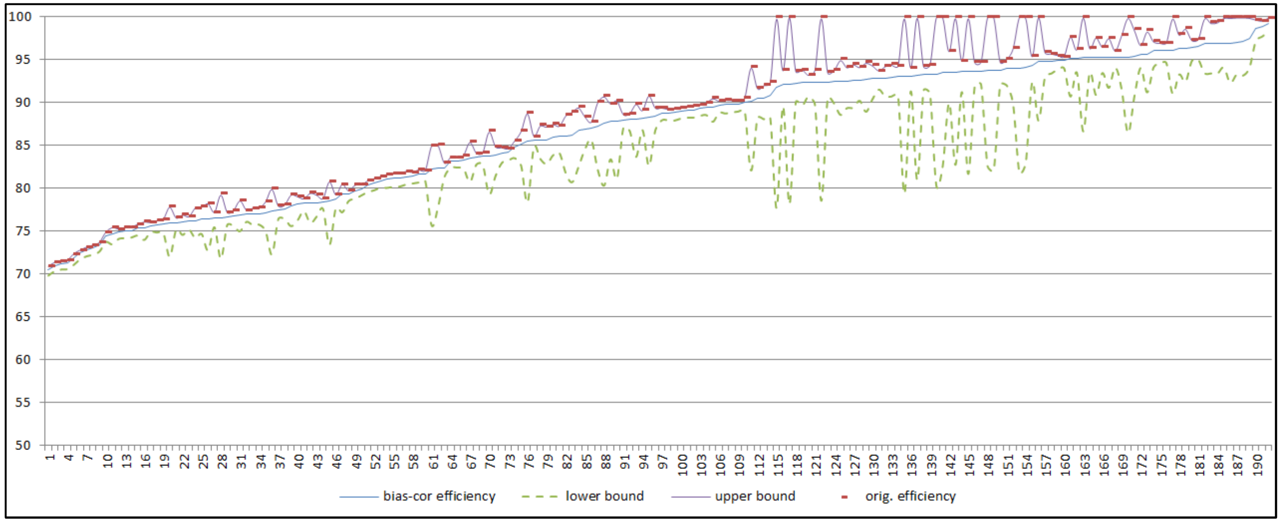

Figure 1. Confidence intervals and point estimated for the studied airlines' technical efficiency

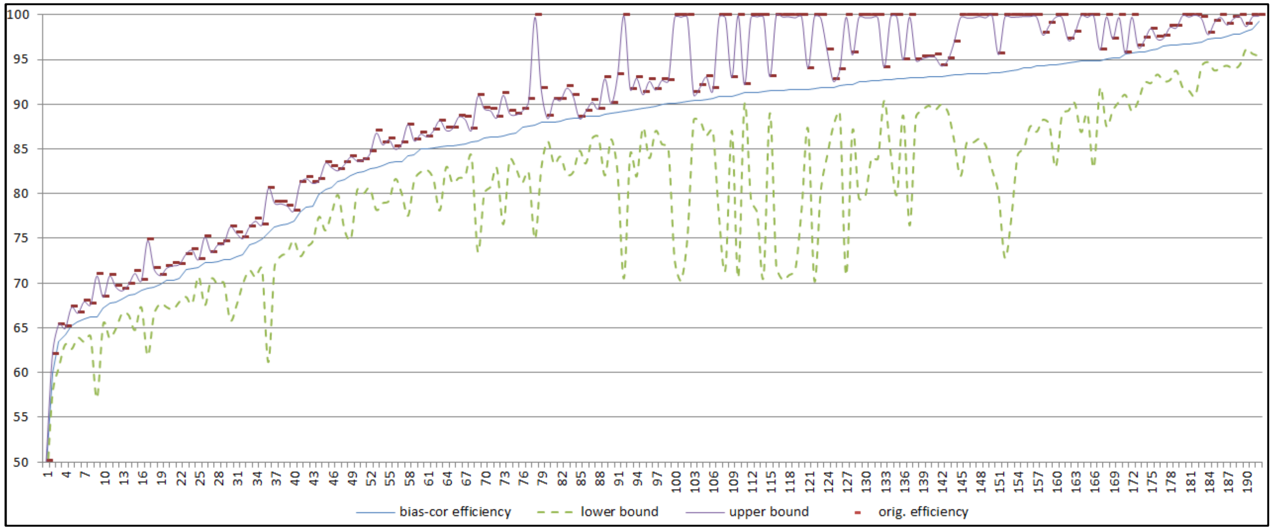

Figure 2. Confidence intervals and point estimated for the studied airlines' environmental efficiency

Table 1: Definitions of the variables used in this study

Inputs	Outputs
Labour: the number of full-time equivalent employees (pilots, including co-pilots and other cockpit crew, and flight attendants). **Capital**: the total number of flying hours divided by average daily revenue hours.	**TKA** (desirable output): the number of tonnes available for the carriage of revenue load (passengers, freight and mail) on each flight multiplied by the flight distance. **CO_2-e emission** (undesirable output): the fossil fuel burn on a specific airline/aircraft combination according to the sector flown. This output is only used in the Environmental Efficiency Model.

Table 2: Bootstrap of technical and environmental efficiency scores, 2007

		Technical Efficiency							Environmenal Efficiency							
Airline	**Region**	**Orig. Eff.**	**BC Eff.**	**Lower**	**Upper**	**#M.Eff.**	**#L.Eff.**	**RTS**	**Orig. Eff.**	**BC Eff.**	**Lower**	**Upper**	**#M.Eff.**	**#L.Eff.**	**CARTS**	**EO**
Full-Service Airlines																
Delta Air Lines	US and Canada	88.92	86.08	80.65	88.80	14	13	DRS	100	93.46	82.65	99.89	0	17	DRS	1.086
American Airlines	US and Canada	90.84	88.24	82.54	90.69	11	15	DRS	100	92.66	83.92	99.66	0	18	DRS	1.050
United Airlines	US and Canada	100	94.01	82.92	99.71	0	15	DRS	100	90.84	77.27	99.70	0	11	DRS	0.966
Emirates	Middle East and Africa	99.40	96.85	93.34	99.16	0	29	DRS	75.01	69.42	61.88	74.75	28	1	DRS	0.717
Lufthansa	Europe and Russia	94.27	92.81	90.66	94.12	1	27	DRS	93.06	89.44	81.92	92.92	2	17	DRS	0.964
British Airways	Europe and Russia	100	97.08	93.09	99.82	0	28	DRS	100	89.17	70.52	99.89	0	5	CRS	0.919
Cathay Pacific Airways	China and North Asia	96.73	95.58	94.00	96.58	0	29	DRS	81.73	79.90	77.41	81.48	23	11	IRS	0.836
Air France	Europe and Russia	94.47	92.85	90.66	94.29	1	27	DRS	91.04	88.38	82.40	90.91	2	17	DRS	0.952
Continental Airlines	US and Canada	87.53	85.86	83.79	87.37	18	16	DRS	96.19	91.86	84.17	96.02	0	18	DRS	1.070
Singapore Airlines	China and North Asia	100	96.80	93.39	99.68	0	29	DRS	100	91.58	70.37	99.76	0	5	DRS	0.946
Korean Air	China and North Asia	94.27	93.19	91.36	94.14	1	28	DRS	91.77	89.30	84.41	91.69	2	18	IRS	0.958
KLM Royal Dutch Airlines	Europe and Russia	97.42	96.46	94.92	97.32	0	33	DRS	100	98.39	95.65	99.78	0	31	IRS	1.020
Air Canada	US and Canada	87.74	86.93	85.58	87.65	18	18	DRS	86.08	84.32	81.54	85.90	10	17	DRS	0.970
Air China	China and North Asia	87.31	86.02	84.07	87.19	18	16	DRS	79.15	76.26	71.92	78.92	23	8	IRS	0.887
Qantas	Asia Pacific	99.55	96.85	93.33	99.23	0	29	DRS	71.03	66.22	57.12	70.78	32	1	DRS	0.684
US Airways	US and Canada	77.85	76.31	74.61	77.72	36	3	DRS	92.79	90.04	85.08	92.58	2	18	DRS	1.180
Thai Airways International	Asia Pacific	95.09	92.37	88.51	94.83	1	21	DRS	91.13	85.83	73.50	90.88	2	8	DRS	0.929
China Southern Airlines	China and North Asia	78.08	77.51	76.36	78.01	36	5	DRS	78.21	76.98	74.79	78.07	24	10	DRS	0.993
China Airlines	China and North Asia	95.87	94.71	92.89	95.78	0	28	IRS	62.18	59.93	57.60	61.97	43	1	IRS	0.633
China Eastern Airlines	China and North Asia	79.25	78.65	77.62	79.17	34	6	DRS	70.39	69.16	67.28	70.26	36	2	DRS	0.879
Japan Airlines International	China and North Asia	85.54	84.76	83.46	85.47	22	15	DRS	69.95	68.66	66.42	69.85	37	2	DRS	0.810
Iberia	Europe and Russia	90.53	89.37	87.71	90.38	14	21	DRS	75.33	72.24	67.53	75.13	27	2	IRS	0.808
Turkish Airlines (THY)	Europe and Russia	83.61	83.15	82.36	83.57	24	15	IRS	95.81	92.17	87.05	95.50	1	20	DRS	1.108
Eva Air	Asia Pacific	97.94	96.21	93.21	97.81	0	29	IRS	71.39	68.73	64.75	71.08	32	2	IRS	0.714
Virgin Atlantic Airways	Europe and Russia	100	95.17	86.58	99.78	0	18	CRS	100	91.77	70.28	99.75	0	5	CRS	0.964
Asiana Airlines	China and North Asia	89.19	88.74	87.88	89.16	14	21	IRS	98.19	94.73	90.13	97.92	0	21	DRS	1.068
Etihad Airways	Middle East and Africa	95.36	94.82	93.93	95.32	0	29	IRS	78.75	76.62	73.42	78.61	23	8	IRS	0.808
All Nippon Airways	China and North Asia	76.73	76.11	75.13	76.63	38	3	DRS	93.23	91.53	89.01	93.08	2	21	DRS	1.203
Malaysia Airlines	China and North Asia	95.46	94.26	92.32	95.28	0	28	DRS	50.17	48.14	45.79	49.89	47	0	IRS	0.511
TAM Linhas Aereas	Latin America	80.39	79.67	78.72	80.30	34	8	IRS	68.10	65.95	63.44	67.93	37	2	DRS	0.828
Air India	China and North Asia	100	95.26	86.39	99.74	0	18	CRS	100	94.09	87.53	99.82	0	20	CRS	0.988
Saudi Arabian Airlines	Middle East and Africa	88.60	87.92	86.97	88.54	14	18	IRS	74.43	72.37	69.91	74.24	28	4	DRS	0.823
Qatar Airways	Middle East and Africa	93.21	92.25	90.64	93.13	7	27	IRS	83.09	80.74	77.90	82.89	17	11	IRS	0.875
Aeroflot-Russian Airlines	Europe and Russia	89.67	89.08	88.19	89.60	14	21	IRS	88.82	85.47	81.77	88.57	4	17	DRS	0.959
Alitalia	Europe and Russia	84.62	84.10	83.20	84.56	22	15	IRS	100	99.22	95.41	99.86	0	30	DRS	1.180
Low-Cost Airlines																
Southwest Airlines	US and Canada	90.08	87.13	82.10	89.91	14	15	DRS	80.75	75.61	61.17	80.58	23	1	DRS	0.868
Ryanair	Europe and Russia	71.61	71.20	70.53	71.58	46	0	IRS	100	93.40	86.12	99.81	0	19	CRS	1.312
jetBlue Airways	US and Canada	82.08	81.58	80.78	82.02	31	14	IRS	87.09	82.92	78.21	86.77	9	12	DRS	1.016
easyJet	Europe and Russia	71.53	71.15	70.46	71.49	46	0	IRS	93.07	88.92	87.71	92.84	2	20	DRS	1.250
Air Berlin	Europe and Russia	76.01	75.58	74.83	75.96	39	3	IRS	98.08	94.29	88.27	97.74	0	20	DRS	1.248
airTran Airways	US and Canada	73.68	73.28	72.57	73.65	44	2	IRS	93.46	89.06	82.41	93.13	2	17	DRS	1.215
WestJet	US and Canada	80.40	79.89	79.11	80.35	34	8	IRS	71.01	67.80	63.85	70.77	32	2	DRS	0.849
Shenzhen Airlines	China and North Asia	79.25	78.25	76.65	79.13	34	6	IRS	81.37	77.93	73.02	81.15	23	8	IRS	0.996
Jetstar Airways	Asia Pacific	100	93.66	82.11	99.80	0	15	IRS	100	94.09	85.06	99.82	0	18	CRS	1.005
Virgin Australia	Asia Pacific	76.41	75.75	74.74	76.33	39	3	IRS	91.85	87.94	82.92	91.55	2	18	IRS	1.161
AirAsia	Asia Pacific	79.30	77.86	75.53	79.14	34	3	IRS	100	93.84	84.27	99.74	0	18	IRS	1.205
Allegiant Air	US and Canada	100	93.60	81.62	99.71	0	14	IRS	100	95.07	87.54	99.74	0	20	IRS	1.016
Norwegian Air Shuttle	Europe and Russia	80.77	78.40	73.34	80.69	33	2	IRS	100	90.22	70.26	99.73	0	5	CRS	1.151

Table 3: Bootstrap of technical and environmental efficiency scores, 2008

		Technical Efficiency							Environmenal Efficiency							
Airline	**Region**	**Orig. Eff.**	**BC Eff.**	**Lower**	**Upper**	**#M.Eff.**	**#L.Eff.**	**RTS**	**Orig. Eff.**	**BC Eff.**	**Lower**	**Upper**	**#M.Eff.**	**#L.Eff.**	**CARTS**	**EO**
Full-Service Airlines																
Delta Air Lines	US and Canada	90.82	87.52	80.26	90.59	11	12	DRS	100.00	92.48	79.52	99.68	0	12	DRS	1.057
American Airlines	US and Canada	90.26	87.76	81.07	90.11	12	13	DRS	100.00	92.80	79.90	99.74	0	12	DRS	1.057
United Airlines	US and Canada	100.00	92.29	78.49	99.71	0	10	DRS	100.00	91.34	77.84	99.77	0	11	DRS	0.990
Emirates	Middle East and Africa	98.53	95.32	90.66	98.33	0	26	DRS	91.32	86.44	76.58	91.00	1	10	DRS	0.907
Lufthansa	Europe and Russia	93.83	92.26	89.68	93.69	4	24	DRS	100.00	94.83	82.91	99.87	0	13	DRS	1.028
British Airways	Europe and Russia	98.67	96.28	92.36	98.47	0	27	DRS	100.00	92.91	76.45	99.75	0	9	CRS	0.965
Cathay Pacific Airways	China and North Asia	97.13	95.99	94.05	97.02	1	31	DRS	85.81	83.55	80.03	85.55	14	12	IRS	0.870
Air France	Europe and Russia	93.86	92.25	89.58	93.73	4	24	DRS	99.13	94.41	87.76	98.81	0	17	DRS	1.023
Continental Airlines	US and Canada	86.74	85.06	82.59	86.55	21	15	DRS	100.00	95.69	89.22	99.72	0	19	DRS	1.125
Singapore Airlines	China and North Asia	100.00	96.07	90.97	99.66	0	26	DRS	100.00	91.59	71.50	99.66	0	5	DRS	0.953
Korean Air	China and North Asia	94.42	93.21	90.97	94.32	2	26	DRS	99.77	97.83	94.00	99.54	0	27	DRS	1.050
KLM Royal Dutch Airlines	Europe and Russia	97.28	96.38	94.80	97.17	0	34	DRS	92.86	91.91	87.58	92.56	1	16	IRS	0.954
Air Canada	US and Canada	88.74	87.95	86.63	88.65	16	19	DRS	88.71	86.37	82.82	88.48	7	13	DRS	0.982
Air China	China and North Asia	87.21	85.60	82.78	87.07	20	15	DRS	88.98	86.81	82.82	88.80	7	13	DRS	1.014
Qantas	Asia Pacific	96.33	93.92	89.86	96.15	1	24	DRS	76.43	72.64	65.84	76.28	33	2	DRS	0.773
US Airways	US and Canada	78.49	77.09	74.95	78.36	34	3	DRS	90.60	87.54	82.37	90.31	2	13	DRS	1.136
Thai Airways International	Asia Pacific	94.70	92.61	88.88	94.51	2	21	DRS	97.39	94.61	89.28	97.16	0	19	DRS	1.022
China Southern Airlines	China and North Asia	77.94	77.38	76.37	77.88	35	5	DRS	76.40	74.29	71.42	76.23	33	5	DRS	0.960
China Airlines	China and North Asia	95.70	94.76	93.33	95.61	1	27	IRS	69.43	68.20	66.63	69.14	41	2	IRS	0.720
China Eastern Airlines	China and North Asia	78.79	78.19	77.29	78.71	33	7	DRS	69.77	67.81	64.92	69.54	41	1	DRS	0.867
Japan Airlines International	China and North Asia	84.75	84.08	82.92	84.66	22	15	DRS	74.73	72.62	70.02	74.42	33	5	DRS	0.864
Iberia	Europe and Russia	91.76	90.43	88.15	91.57	7	20	DRS	76.66	74.92	71.65	76.51	32	5	DRS	0.829
Turkish Airlines (THY)	Europe and Russia	83.59	83.11	82.32	83.55	22	15	IRS	96.64	95.87	90.35	96.36	0	21	DRS	1.153
Eva Air	Asia Pacific	97.69	95.06	90.66	97.55	0	26	IRS	77.28	74.47	70.66	76.93	31	5	IRS	0.783
Virgin Atlantic Airways	Europe and Russia	100.00	92.10	78.10	99.81	0	9	CRS	100.00	90.85	71.59	99.65	0	5	CRS	0.986
Asiana Airlines	China and North Asia	89.44	88.94	88.08	89.40	15	20	IRS	100.00	92.58	83.98	99.68	0	13	CRS	1.041
Etihad Airways	Middle East and Africa	95.49	94.80	93.79	95.42	1	30	IRS	90.49	88.71	86.19	90.22	2	14	IRS	0.936
All Nippon Airways	China and North Asia	76.56	75.95	75.10	76.48	37	3	DRS	90.62	88.06	84.15	90.41	1	13	DRS	1.159
Malaysia Airlines	China and North Asia	94.76	93.63	92.06	94.65	2	27	DRS	66.81	65.70	63.88	66.63	42	0	IRS	0.702
TAM Linhas Aereas	Latin America	82.00	81.27	80.40	81.91	28	12	DRS	65.44	63.48	60.54	65.40	44	0	DRS	0.781
Air India	China and North Asia	99.66	98.60	97.11	99.57	0	38	IRS	65.25	64.26	63.12	64.92	45	0	IRS	0.652
Saudi Arabian Airlines	Middle East and Africa	89.36	88.72	87.86	89.30	15	20	IRS	79.12	76.46	73.05	78.86	29	6	DRS	0.862
Qatar Airways	Middle East and Africa	93.54	92.34	90.50	93.39	4	25	IRS	86.48	85.02	82.67	86.36	11	13	IRS	0.921
Aeroflot-Russian Airlines	Europe and Russia	89.54	89.04	88.18	89.50	15	20	IRS	91.85	90.59	87.10	91.50	1	16	IRS	1.017
Alitalia	Europe and Russia	86.05	85.58	84.76	86.00	21	17	IRS	95.60	93.03	89.36	95.27	0	19	DRS	1.087
Low-Cost Airlines																
Southwest Airlines	US and Canada	94.13	90.10	82.02	93.94	3	15	DRS	100.00	93.35	85.72	99.66	0	14	DRS	1.036
Ryanair	Europe and Russia	71.36	70.95	70.28	71.32	47	0	IRS	100.00	93.42	85.38	99.66	0	13	CRS	1.317
jetBlue Airways	US and Canada	81.87	81.31	80.50	81.81	28	12	IRS	87.19	85.13	81.64	87.01	10	12	DRS	1.047
easyJet	Europe and Russia	72.79	72.37	71.68	72.75	45	1	IRS	87.83	84.23	77.54	87.75	8	11	IRS	1.164
Air Berlin	Europe and Russia	75.39	74.92	74.13	75.33	39	2	IRS	97.37	95.13	89.30	97.34	0	19	IRS	1.270
airTran Airways	US and Canada	74.87	74.41	73.68	74.83	41	2	IRS	92.83	89.69	83.97	92.54	1	13	DRS	1.205
WestJet	US and Canada	80.88	80.33	79.51	80.81	29	12	IRS	72.24	70.34	67.07	71.92	35	3	IRS	0.876
Shenzhen Airlines	China and North Asia	76.94	75.98	74.51	76.83	37	2	IRS	81.88	78.53	74.03	81.67	24	6	IRS	1.034
Jetstar Airways	Asia Pacific	100.00	93.49	82.69	99.71	0	15	IRS	100.00	94.28	86.92	99.75	0	15	IRS	1.009
Virgin Australia	Asia Pacific	75.43	74.66	73.41	75.36	39	2	IRS	100.00	94.48	88.87	99.69	0	19	CRS	1.265
AirAsia	Asia Pacific	79.50	78.20	75.90	79.35	33	5	IRS	92.06	88.28	82.14	91.79	1	13	IRS	1.129
Allegiant Air	US and Canada	100.00	91.67	77.62	99.67	0	7	IRS	100.00	93.35	85.72	99.66	0	14	IRS	1.018
Norwegian Air Shuttle	Europe and Russia	77.88	75.86	71.94	77.73	35	1	IRS	100.00	91.34	79.45	99.66	0	12	IRS	1.204

Table 4: Bootstrap of technical and environmental efficiency scores, 2009

		Technical Efficiency							Environmenal Efficiency							
Airline	**Region**	**Orig. Eff.**	**BC Eff.**	**Lower**	**Upper**	**#M.Eff.**	**#L.Eff.**	**RTS**	**Orig. Eff.**	**BC Eff.**	**Lower**	**Upper**	**#M.Eff.**	**#L.Eff.**	**CARTS**	**EO**
Full-Service Airlines																
Delta Air Lines	US and Canada	89.91	87.71	83.33	89.78	15	16	DRS	95.70	93.55	79.95	95.55	1	5	DRS	1.067
American Airlines	US and Canada	89.83	88.00	83.62	89.72	15	16	DRS	100.00	93.34	81.96	99.66	0	5	DRS	1.061
United Airlines	US and Canada	100.00	92.97	79.31	99.69	0	12	DRS	100.00	91.61	78.33	99.78	0	5	DRS	0.985
Emirates	Middle East and Africa	100.00	97.43	93.98	99.76	0	31	DRS	87.39	85.31	82.94	87.08	19	5	DRS	0.876
Lufthansa	Europe and Russia	94.34	92.79	90.34	94.21	2	28	DRS	95.22	94.85	93.81	95.06	1	23	DRS	1.022
British Airways	Europe and Russia	100.00	96.89	92.24	99.75	0	29	DRS	100.00	91.83	80.25	99.66	0	5	CRS	0.948
Cathay Pacific Airways	China and North Asia	96.53	95.23	93.39	96.40	1	29	DRS	92.24	90.42	88.15	91.89	9	13	IRS	0.950
Air France	Europe and Russia	94.14	92.57	90.15	94.02	4	27	DRS	95.80	95.63	91.04	95.66	1	20	DRS	1.033
Continental Airlines	US and Canada	87.39	85.59	83.39	87.19	21	16	DRS	95.12	92.88	88.74	94.94	1	14	DRS	1.085
Singapore Airlines	China and North Asia	100.00	96.88	94.02	99.74	0	33	DRS	100.00	92.15	70.88	99.72	0	2	DRS	0.951
Korean Air	China and North Asia	94.91	93.53	91.16	94.79	1	28	DRS	98.01	97.25	94.72	97.78	0	25	DRS	1.040
KLM Royal Dutch Airlines	Europe and Russia	96.98	96.02	94.56	96.90	1	34	DRS	98.09	97.61	96.31	97.87	0	31	IRS	1.017
Air Canada	US and Canada	89.10	88.14	86.72	88.99	16	19	DRS	88.72	87.99	85.84	88.39	16	10	DRS	0.998
Air China	China and North Asia	85.45	83.43	80.68	85.29	22	13	DRS	99.37	97.38	93.78	99.11	0	23	DRS	1.167
Qantas	Asia Pacific	97.91	95.25	91.51	97.72	1	28	DRS	84.21	82.00	74.93	84.11	24	5	DRS	0.861
US Airways	US and Canada	78.55	76.85	74.94	78.46	34	2	DRS	87.43	85.39	81.20	87.26	18	5	DRS	1.111
Thai Airways International	Asia Pacific	94.14	92.40	89.29	94.00	4	22	DRS	100.00	97.85	94.40	99.80	0	25	DRS	1.059
China Southern Airlines	China and North Asia	77.18	76.50	75.40	77.14	36	3	DRS	73.28	71.57	68.46	73.21	41	1	DRS	0.936
China Airlines	China and North Asia	95.06	93.91	91.95	94.96	1	29	IRS	85.29	83.53	81.64	84.96	23	5	IRS	0.889
China Eastern Airlines	China and North Asia	77.47	76.90	76.03	77.41	36	4	DRS	72.22	70.54	67.91	72.09	41	0	DRS	0.917
Japan Airlines International	China and North Asia	83.86	83.21	82.21	83.80	22	15	DRS	89.29	86.62	83.80	88.95	14	6	DRS	1.041
Iberia	Europe and Russia	92.10	90.48	88.01	91.92	8	20	DRS	70.96	69.80	67.71	70.83	42	0	DRS	0.772
Turkish Airlines (THY)	Europe and Russia	84.08	83.58	82.72	84.03	22	15	IRS	93.10	92.05	91.04	92.82	8	20	DRS	1.101
Eva Air	Asia Pacific	97.58	95.18	90.82	97.47	1	28	IRS	85.82	83.13	78.94	85.47	23	5	IRS	0.873
Virgin Atlantic Airways	Europe and Russia	100.00	93.26	80.26	99.81	0	13	CRS	100.00	91.09	70.60	99.92	0	1	CRS	0.977
Asiana Airlines	China and North Asia	90.15	89.63	88.75	90.09	14	21	IRS	95.41	92.93	89.32	95.09	1	18	DRS	1.037
Etihad Airways	Middle East and Africa	96.03	95.24	94.03	95.95	1	33	IRS	89.15	88.98	88.08	89.06	14	13	IRS	0.934
All Nippon Airways	China and North Asia	76.23	75.63	74.79	76.14	37	2	CRS	93.09	90.89	87.05	92.99	8	10	DRS	1.202
Malaysia Airlines	China and North Asia	94.09	92.98	91.24	93.98	5	28	IRS	87.30	85.83	84.15	87.07	19	7	DRS	0.923
TAM Linhas Aereas	Latin America	82.97	82.27	81.26	82.87	25	14	DRS	68.53	67.21	65.46	68.41	45	0	DRS	0.817
Air India	China and North Asia	99.89	99.21	98.23	99.81	0	41	IRS	84.74	82.82	80.60	84.44	23	5	IRS	0.835
Saudi Arabian Airlines	Middle East and Africa	89.96	89.36	88.49	89.90	14	20	IRS	98.80	96.62	93.75	98.53	0	23	DRS	1.081
Qatar Airways	Middle East and Africa	93.77	92.36	89.83	93.64	5	25	IRS	89.57	88.71	86.32	89.54	13	10	DRS	0.960
Aeroflot-Russian Airlines	Europe and Russia	90.22	89.73	88.80	90.17	13	21	IRS	99.79	97.00	94.27	99.55	0	25	DRS	1.081
Alitalia	Europe and Russia	89.72	89.24	88.38	89.68	15	20	IRS	100.00	96.77	91.50	99.75	0	20	CRS	1.084
Low-Cost Airlines																
Southwest Airlines	US and Canada	80.02	77.28	72.22	79.80	32	1	DRS	90.67	88.00	83.33	90.56	12	5	DRS	1.139
Ryanair	Europe and Russia	70.87	70.46	69.76	70.84	47	0	IRS	100.00	94.81	86.89	99.85	0	10	DRS	1.346
jetBlue Airways	US and Canada	81.37	80.82	80.00	81.32	27	13	IRS	94.14	92.79	90.40	94.14	4	19	DRS	1.148
easyJet	Europe and Russia	73.14	72.73	72.02	73.09	44	1	IRS	89.57	87.39	81.23	89.22	14	5	DRS	1.202
Air Berlin	Europe and Russia	78.80	78.36	77.52	78.75	34	7	IRS	94.13	91.65	87.23	94.08	5	12	DRS	1.170
airTran Airways	US and Canada	75.26	74.80	74.04	75.21	40	2	IRS	95.06	92.92	88.56	94.91	1	14	DRS	1.242
WestJet	US and Canada	81.13	80.56	79.71	81.07	28	12	IRS	73.53	72.33	70.47	73.43	41	1	DRS	0.898
Shenzhen Airlines	China and North Asia	76.08	75.28	73.93	76.00	38	2	IRS	83.93	82.43	80.05	83.79	25	5	DRS	1.095
Jetstar Airways	Asia Pacific	88.81	85.39	78.29	88.62	18	9	IRS	100.00	94.42	82.95	99.72	0	5	CRS	1.106
Virgin Australia	Asia Pacific	77.69	76.94	75.66	77.61	35	3	IRS	98.78	96.58	92.70	98.58	0	21	DRS	1.255
AirAsia	Asia Pacific	79.06	78.06	76.21	78.95	34	5	IRS	89.35	88.69	83.40	89.18	14	5	DRS	1.136
Allegiant Air	US and Canada	100.00	93.06	80.92	99.77	0	13	IRS	100.00	97.41	94.10	99.70	0	24	IRS	1.047
Norwegian Air Shuttle	Europe and Russia	78.27	76.38	72.67	78.13	35	1	IRS	100.00	92.50	79.63	99.66	0	5	CRS	1.211

Table 5: Bootstrap of technical and environmental efficiency scores, 2010

		Technical Efficiency							Environmenal Efficiency							
Airline	**Region**	**Orig. Eff.**	**BC Eff.**	**Lower**	**Upper**	**#M.Eff.**	**#L.Eff.**	**RTS**	**Orig. Eff.**	**BC Eff.**	**Lower**	**Upper**	**#M.Eff.**	**#L.Eff.**	**CARTS**	**EO**
Full-Service Airlines																
Delta Air Lines	US and Canada	85.11	82.26	77.76	84.91	22	8	DRS	100.00	91.55	71.95	99.94	0	4	DRS	1.113
American Airlines	US and Canada	89.47	86.67	82.47	89.30	15	15	DRS	100.00	90.13	72.56	99.69	0	4	DRS	1.040
United Airlines	US and Canada	100.00	93.47	82.55	99.81	0	15	DRS	100.00	93.76	77.15	99.72	0	8	DRS	1.003
Emirates	Middle East and Africa	100.00	94.71	87.83	99.82	0	20	DRS	100.00	91.58	70.90	99.77	0	2	DRS	0.967
Lufthansa	Europe and Russia	93.79	92.08	89.51	93.64	2	25	DRS	96.46	95.88	94.41	96.18	0	27	DRS	1.041
British Airways	Europe and Russia	98.42	95.59	91.14	98.15	0	28	DRS	100.00	95.16	90.31	99.67	0	20	DRS	0.996
Cathay Pacific Airways	China and North Asia	96.35	95.18	93.40	96.25	1	29	IRS	91.38	90.41	88.25	91.07	6	16	DRS	0.950
Air France	Europe and Russia	93.73	92.23	90.02	93.56	2	25	DRS	97.73	96.46	92.61	97.38	0	24	DRS	1.046
Continental Airlines	US and Canada	88.38	86.81	84.50	88.25	18	16	DRS	88.24	85.23	78.13	88.18	14	8	DRS	0.982
Singapore Airlines	China and North Asia	100.00	96.98	93.20	99.81	0	29	CRS	100.00	93.66	72.83	99.73	0	5	CRS	0.966
Korean Air	China and North Asia	94.77	93.71	92.03	94.63	1	28	IRS	99.00	98.17	96.18	98.69	0	29	DRS	1.048
KLM Royal Dutch Airlines	Europe and Russia	96.92	95.99	94.50	96.86	1	34	IRS	95.20	93.14	89.21	94.89	2	18	DRS	0.970
Air Canada	US and Canada	89.41	88.36	86.69	89.30	15	20	IRS	88.66	88.39	84.80	88.40	13	13	DRS	1.000
Air China	China and North Asia	86.70	83.68	79.24	86.48	22	9	DRS	100.00	92.79	84.61	99.70	0	13	DRS	1.109
Qantas	Asia Pacific	96.03	93.48	89.90	95.88	1	25	DRS	83.58	81.54	75.96	83.25	21	8	DRS	0.872
US Airways	US and Canada	77.70	76.15	74.14	77.63	37	2	CRS	92.91	90.00	85.54	92.67	3	13	DRS	1.182
Thai Airways International	Asia Pacific	94.56	92.52	89.35	94.35	2	25	IRS	100.00	96.70	91.88	99.90	0	23	DRS	1.045
China Southern Airlines	China and North Asia	77.71	76.94	75.71	77.64	37	3	IRS	73.82	71.61	67.71	73.69	35	2	DRS	0.931
China Airlines	China and North Asia	94.71	93.61	91.85	94.60	1	28	IRS	72.71	71.70	70.75	72.60	36	2	DRS	0.766
China Eastern Airlines	China and North Asia	77.19	76.64	75.66	77.13	38	3	IRS	75.14	73.17	69.93	74.98	33	2	DRS	0.955
Japan Airlines International	China and North Asia	82.17	81.55	80.63	82.09	27	11	IRS	88.63	85.55	81.94	88.29	13	9	DRS	1.049
Iberia	Europe and Russia	92.37	90.79	88.19	92.22	5	20	IRS	71.92	70.27	67.31	71.67	38	1	DRS	0.774
Turkish Airlines (THY)	Europe and Russia	84.14	83.64	82.69	84.11	23	15	IRS	98.51	96.02	92.37	98.48	0	24	DRS	1.148
Eva Air	Asia Pacific	97.52	95.23	91.67	97.38	1	28	IRS	75.69	72.94	67.52	75.56	32	1	DRS	0.766
Virgin Atlantic Airways	Europe and Russia	100.00	93.65	82.57	99.78	0	15	CRS	100.00	91.44	70.74	99.70	0	2	CRS	0.976
Asiana Airlines	China and North Asia	90.53	89.97	88.96	90.48	11	22	IRS	86.87	84.99	82.43	86.65	16	9	DRS	0.945
Etihad Airways	Middle East and Africa	96.22	95.12	93.42	96.10	1	29	IRS	91.39	89.50	87.38	91.06	6	15	DRS	0.941
All Nippon Airways	China and North Asia	75.84	75.28	74.43	75.75	38	2	IRS	93.21	90.54	86.47	93.05	3	14	DRS	1.203
Malaysia Airlines	China and North Asia	93.75	92.81	91.46	93.63	2	28	IRS	83.73	82.31	80.42	83.64	21	8	DRS	0.887
TAM Linhas Aereas	Latin America	81.63	81.01	80.00	81.55	29	10	IRS	67.47	65.18	62.63	67.27	45	0	DRS	0.805
Air India	China and North Asia	99.51	98.79	97.65	99.45	0	41	IRS	82.75	81.38	79.83	82.56	21	8	IRS	0.824
Saudi Arabian Airlines	Middle East and Africa	90.27	89.70	88.66	90.22	11	22	IRS	95.42	93.03	89.83	95.29	2	20	DRS	1.037
Qatar Airways	Middle East and Africa	94.33	92.94	90.79	94.19	2	28	IRS	94.35	93.12	89.96	94.27	3	20	DRS	1.002
Aeroflot-Russian Airlines	Europe and Russia	89.29	88.78	87.85	89.24	15	20	IRS	96.62	96.16	95.33	96.28	0	29	DRS	1.083
Alitalia	Europe and Russia	90.26	89.79	88.90	90.22	11	22	IRS	92.35	91.30	90.02	92.18	5	20	DRS	1.017
Low-Cost Airlines																
Southwest Airlines	US and Canada	79.35	76.52	71.73	79.14	35	0	DRS	89.53	86.30	80.75	89.26	11	8	DRS	1.128
Ryanair	Europe and Russia	72.35	71.86	71.03	72.32	45	0	IRS	100.00	94.83	88.93	99.72	0	18	DRS	1.320
jetBlue Airways	US and Canada	81.72	81.12	80.14	81.66	29	10	IRS	91.79	89.81	87.02	91.59	6	15	DRS	1.107
easyJet	Europe and Russia	73.35	72.95	72.20	73.32	45	0	IRS	83.55	80.52	75.89	83.41	21	8	DRS	1.104
Air Berlin	Europe and Russia	79.68	79.26	78.46	79.65	34	8	IRS	81.36	78.58	74.70	81.16	23	6	DRS	0.991
airTran Airways	US and Canada	75.44	75.01	74.21	75.40	42	2	IRS	86.20	83.45	79.22	86.02	17	8	DRS	1.113
WestJet	US and Canada	81.66	81.10	80.12	81.60	29	10	IRS	67.75	66.21	64.07	67.56	43	0	DRS	0.816
Shenzhen Airlines	China and North Asia	77.46	76.74	75.51	77.37	37	3	IRS	71.71	69.49	66.51	71.57	38	0	DRS	0.906
Jetstar Airways	Asia Pacific	88.62	86.04	81.70	88.37	18	14	IRS	97.09	93.26	86.01	96.90	0	13	IRS	1.084
Virgin Australia	Asia Pacific	84.87	83.76	81.37	84.79	22	11	IRS	100.00	90.36	75.04	99.70	0	7	CRS	1.079
AirAsia	Asia Pacific	80.48	79.25	77.14	80.39	31	5	IRS	89.69	86.27	80.01	89.49	11	8	IRS	1.089
Allegiant Air	US and Canada	100.00	93.96	81.75	99.86	0	14	IRS	100.00	96.89	90.96	99.96	0	20	IRS	1.031
Norwegian Air Shuttle	Europe and Russia	84.97	82.16	75.60	84.89	22	3	IRS	100.00	87.71	74.94	99.73	0	6	CRS	1.068