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Research highlights

> Two-stage DEA approach is employed to assess technical and scale efficiency of low-cost carriers and mainstream airlines. > In first stage, results showed US mainstream airlines and most of the major European airlines need to scale-down their operations. > Second stage employs a bootstrap truncated regression to explain efficiency levels. > Results in second stage generally showed environmental variables having a significant impact on technical efficiency of airlines.

Technical efficiency of mainstream airlines and low-cost carriers: New evidence using bootstrap data envelopment analysis truncated regression

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ABSTRACT

Between 2001 and 2005, the US airline industry faced financial turmoil while the European airline industry entered a period of substantive deregulation. Consequently, this opened up opportunities for low-cost carriers to become more competitive in the market. To assess airline performance and identify the sources of efficiency in the immediate aftermath of these events, we employ a bootstrap data envelopment analysis truncated regression approach. The results suggest that at the time the mainstream airlines needed to significantly reorganize and rescale their operations to remain competitive. In the second-stage analysis, the results indicate that private ownership, status as a low-cost carrier, and improvements in weight load contributed to better organizational efficiency.

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1. Introduction

The primary motivation for this paper stems from three events that took place contemporaneously in the global airline industry between 2001 and 2005. First, the sluggish performance of the US airline industry, which ultimately resulted in net aggregate loss of US$40 billion, saw several legacy airlines, including US Airways, United Airlines, Delta, and Northwest, filing for bankruptcy. Protected by Chapter 11bankruptcy provisions, these airlines regained solvency by in part focusing on cost-cutting measures and downsizing operations as part of their restructuring efforts to remain competitive and become more productive. These efforts had largely paid off by 2006, with the US airline industry moving back into the black with a net profit of some US$3 billion (ATA, 2007). Second, this period also witnessed the emergence of US low-cost carriers (LCC) as genuine competitors in terms of lower airfares, suggesting the presence of lower cost structures and higher levels of efficiency and productivity. Finally, the period 2001–05 was also associated with intense market volatility associated with the deregulation of the European airline market (Barros and Peypoch, 2009).

There is a vast amount of literature concerning the modeling of airline efficiency and performance using a variety of approaches. Early studies, including Caves et al. (1981 and 1984), Atkinson and Cornwell (1994), Baltagi et al. (1995), Oum and Yu (1998a and 1998b) and Liu and Lynk (1999), tend to employ cost functions. Elsewhere, Windle and Dresner (1992), Oum and Yu (1995), Oum et al. (2005), Forsyth (2001), Vasigh and Fleming (2005) and Barbot et al. (2008) apply the concept of total factor productivity. Then there are studies that use the parametric stochastic frontiers, such as Sickles (1985), Sickles et al. (1986), Good et al. (1995), Captain and Sickles (1997), Coelli et al. (1999) and Inglada et al. (2006). Lastly, nonparametric approaches like data envelopment analysis (DEA) are also widely used, including in Good et al. (1995), Tofallis (1997), Alam and Sickles (2000), Adler and Golany (2001), Scheraga (2004), Greer (2006 and 2008), Barros and Peypoch (2009), Bhadra (2009) and Ouellette et al. (2010).

This paper contributes to the literature on airline efficiency by undertaking an international comparison of airline performance in 2006 following Simar and Wilson's (2007) bootstrapped truncated regression approach. Focusing on 2006 helps to determine whether the airlines undertook appropriate cost cutting and operational restructuring in the aftermath of the seismic industry wide events of 2001-05. In addition, our analysis includes environmental variables to help quantify the impact discretionary and non-discretionary inputs have on airline efficiency as measured. As noted by Ouellette and Vierstraete (2004), nondiscretionary inputs are present in virtually all industrial and commercial sectors, even in the long-run, and these must be incorporated into production models so as to correctly ascertain organizational efficiency. Importantly, few studies of airline performance currently account for environmental variables, and of these most focus on specific regions.

For instance, Barros and Peypoch (2009) considered the efficiency of European airlines between 2000 and 2005. One contribution of their study was the use of Simar and Wilson's (2007) two-stage approach, which analysed the impact environmental variables on efficiency. Bhadra (2009) examined the performance of US airlines over the period 1985–2006, but using a Tobit model, which Simar and Wilson (2007) argued earlier, entailed several limitations. Lastly, Barbot et al. (2008) assessed the performance of 49 international airlines, including LCCs, in 2005 using Simar and Wilson's (2007) model. While our study appears superficially similar, a key difference lies in the year of analysis, with our study focusing exclusively on 2006 to best assess the aftermath of the global events of 2001–05. As detailed in ATA (2006, 2007), the US airline industry made a net loss of –US$5.7 billion in 2005 while by 2006 it made a net profit of US$3 billion, thereby suggesting a dramatic turnaround in 2006, the data year of the current study.

In our study, we use the approach first presented in Simar and Wilson (2007). In the first stage, we derive bootstrapped DEA scores (i.e. bias-corrected efficiency scores) are derived for each of the 42 airlines in 2006. In the second stage, we regress these estimated efficiencies on environmental variables (both discretionary and nondiscretionary inputs) using a double bootstrap truncated regression model. Determining how these environmental variables impact on efficiency is essential for airline management to identify viable performance improvement strategies. The objective of the paper is threefold. First, determine if there is evidence of efficiency in mainstream airlines in the aftermath of the events of 2001–05. Second, assess the efficiency levels of LCCs against mainstream airlines in 2006. This is an ideal year for an efficiency assessment as it provides sufficient time for airlines to respond to the industry events in terms of restructuring and the adoption of best-practice management. Finally, estimate the principal economic drivers of the environmental variables underlying our measures technical efficiency.

The remainder of the paper itself comprises five main sections. Section 2 presents the empirical methodology. Section 3 describes the inputs and outputs as well as the environmental variables and the limitations of the chosen data. Section 4 discusses the technical, scale efficiency scores and the results of the second-stage regression analysis. Section 5 concludes.

2. Methodology

Data envelopment analysis (DEA), as developed by Charnes, Cooper, and Rhodes (CCR) in 1978 and later modified by Banker, Charnes and Cooper (BCC) in 1984, builds on the frontier efficiency concept first elucidated in Farrell (1957). In general, DEA is a nonparametric method that measures the efficiency of decision making units (DMUs), but less conventionally does not require the specification of a specific functional form relating inputs to outputs or the setting of weights for the various factors. DEA thus optimizes for each set of observations an efficient frontier—the maximum outputs empirically obtainable for any DMU in the observed population given its level of inputs. For a general overview of DEA, see Coelli et al. (2005).

However, DEA also assumes that DMUs have full control over their inputs, suggesting that such variables are all discretionary. This is a major limitation, especially given that Ouellette and Vierstraete (2004) and others have argued that nondiscretionary inputs are present in virtually all sectors, both profit and not-for-profit, and that these ‘environmental’ factors therefore need to be incorporated into any DEA model. Several approaches are found in the literature for handling nondiscretionary variables, including work in Banker and Morey (1986), Ray (1991), Ruggiero (1996 and 1998), Mũniz (2002), Nemoto and Goto (2003), Bilodeau et al. (2004), Ouellette and Vierstraete (2004) and Essid et al. (2010). Of these, we can broadly categorize the handling of nondiscretionary inputs into two basic approaches.

In the first approach—exemplified by the single-stage model in Banker and Morey (1986) and Ruggiero (1996), among others —we directly incorporate nondiscretionary inputs in the DEA program. In the second approach—as in the multistage model in Ray (1991) and Mũniz (2002), and most recently Simar and Wilson (2007) —we omit the nondiscretionary inputs from the initial DEA analysis and introduce them in sequential non-DEA stages. Simar and Wilson (2007) noted that many studies adopted a two-stage approach whereby DEA scores in the first stage are regressed on covariates (i.e. environmental variables) in the second stage. However, Simar and Wilson (2007) argued that in regressing DEA estimates on environmental variables in a two-stage analysis, these studies face a key problem in that the DEA efficiency estimates themselves are by construction serially correlated. To address this problem, Simar and Wilson (2007) proposed an alternative estimation and statistical inference procedure based on a double-bootstrap approach. We employ this approach in our analysis.

2.1 Stage 1 — Data envelopment analysis

We use the output-oriented variable returns-to-scale (VRS) model to derive efficiency scores. We do this because a constant returns-to-scale (CRS) assumption is only appropriate when firms are operating at their optimal scale, an unlikely situation in a context like the airline industry where there is considerable evidence of ongoing structural change. Further, imperfect competition and finance constraints are additional factors associated with firms not operating at their optimal scale, as well evidenced in the US airline industry of the early 2000s with many firms operating under Chapter 11 bankruptcy protection and constraints in borrowing. The assumption of VRS also appears appropriate given that our study includes airlines of a range of sizes. Following Bhadra (2009), we assume an output-oriented model consistent with the aim of airlines in maximising output with a given set of inputs. We express the output-oriented VRS DEA model as:

$$\hat{\theta}_i = \max_{\theta_{i0},\lambda}\left\{\theta_{i0}\left|\theta_{i0}y_{i0} \le \sum_{i=1}^{n} y_{i0}\lambda; x_{i0} \ge \sum_{i=1}^{n} x_i\lambda; \lambda \ge 0; 1\times\lambda = 1\right.\right\}, \qquad i = 1, \ldots n \text{ firms} \tag{1}$$

where y_i is a vector of outputs, x_i is a vector of inputs, and λ is a I x 1 vector of constants. The value obtained for $\hat{\theta}_i$ is the technical efficiency score for the *i*th airline. A measure of $\hat{\theta}_i = 1$ indicates that the airline is technically efficient, whereas it is inefficient if $\hat{\theta}_i > 1$. We then solve the linear programming problem *n* times, once for each airline in the sample.

However, Simar and Wilson (2007) criticized the potential bias in efficiency estimates given the strong correlation between the resulting efficiency scores, that is, calculation of the efficiency of one firm incorporates observation of all other firms in the same data set. Hence, direct regression analysis is invalid owing to the dependency of the efficiency scores. Following Simar and Wilson (2007), we overcome this problem by employing the double bootstrap approach. By combining DEA with bootstrapping technique, we successfully generate a set of bias-corrected estimates of DEA efficiency scores (denoted $\hat{\hat{\theta}}_i$) and confidence intervals that help resolve this problem.

2.2 *Stage 2 — Truncated regression*

In the second stage of our analysis, we regress the bias-corrected efficiency scores derived from the bootstrap algorithm on a set of environmental factors using the following regression model:

$$\hat{\hat{\theta}}_i = a + Z_i\delta + \varepsilon_i, \qquad i = 1, \ldots, n \tag{2}$$

where $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ with left-truncation at $1\text{-}Z_i\delta$; a is a constant term and Z_i is a vector of specific variables for airline i expected to affect airline efficiency. Simar and Wilson (2007) detail the bootstrap truncated regression algorithm, also described in a step-by-step approach in Barros and Assaf (2009) and Barros and Barrio (2011). We refer the interested reader to these studies for details.

3. Data and specification of inputs and outputs

We draw the data used in the first stage of the procedure are primarily from World Air Transport Statistics (WATS), supplemented with data from the International Civil Aviation Organization (ICAO). We ensure the consistency of the dataset by verifying the data across these two sources. Conceptually, we model airline activity based on a production approach whereby airlines utilize inputs, such as the amount of labour and the number of aircraft, to transport a fixed number of passenger seats (or passenger tonnage) and freight tonnage over a certain distance. However, we need to address some qualifications before determining our set of inputs and outputs. For instance, we are unable to specify the number of aircraft as the sizes of aircraft used vary across the airlines in our sample, thus making it incomparable. This is especially important given the sampled airlines include both mainstream and low-cost carriers with typically larger and smaller aircraft, respectively.

Given data availability, we define three inputs representative of airline operations: (i) the average number of employees, (ii) total assets in US dollars, and (iii) kilometres flown. In turn, we define a single output: available tonne kilometres (ATK), which according to WATS, comprises the tonnage of passengers, freight, luggage and mail. This output successfully captures the total amount of ATK produced by each airline and is generally controllable by management as derived from the specified inputs.

The production framework we employ is similar to Bhadra (2009). However unlike Bhadra (2009) which uses available seat miles (ASM) as an output, we use ATK. As described above, ATK encapsulates both passengers and freight, whereas ASM only accounts for passengers. However, Bhadra (2009) did include two additional inputs. The number of seats per aircraft and aircraft utilization in hours. Unfortunately, owing to a lack of data, we are unable to include these in our analysis. Other studies, such as Adler and Golany (2001) and Barros and Peypoch (2009), have also considered other forms of outputs including airline revenue and profits and inputs such as expenditures and costs. However, as we employ a production approach framework, we do not include these variables into our model with the exception of total assets as this comes closest to capturing capital stock of airlines.

In addition, we also do not include several alternative output indicators, such as revenue passenger kilometres (RPK) and revenue tonne kilometres (RTK), in our framework as these are heavily dependent on demand-side conditions, circumstances normally beyond the control of airline management on a day-to-day basis (Bhadra, 2009). Moreover, Coelli et al. (1999) argue that the use of ton kilometres bests reflects the ticketing and marketing aspects of airline rather than their actual flying operations. We also concur with the common heuristic in DEA studies that the minimum number of DMUs should be three times the number of inputs plus outputs [42 > 3 (3 + 1)]. We also draw our data only from scheduled services in order to maintain a consistency with airline operations.

The data used in the second stage regression analysis comprise environmental variables, which are both discretionary and nondiscretionary (comprising operational and organizational factors) in nature. Similar to Barbot et al (2008), which considered internal (i.e. operational factors) and external conditions (i.e. organizational factors), our study also incorporates these nondiscretionary factors which thus supports our choice of determinants. However, even when technically discretionary, they may not be amenable to change in the short run. We therefore expect all of these variables to have some impact on airline efficiency even though they are not included in the input–output specification. We include the following environmental variables. First, a dummy variable indicating the type of ownership (i.e. whether state-owned (or quasi state-owned) or privately owned). Second, a dummy variable identifying low-cost carriers. Finally, the number of departures and weight load factor (WLF) as indicator of the ability of firms to behave efficiently in light of external market pressure on (Bhadra, 2009)[1]. Table 1 presents the characteristics of inputs and outputs used in the first stage analysis and the environmental variables used in the second stage regression.

<TABLE 1 HERE>

4. Empirical Results

Table 2 presents the technical efficiency scores for the 42 airlines in 2006. Airlines with a technical efficiency score of unity are operating efficiently and lie on the production frontier in 2006. Under VRS, six airlines are then technically efficient as a result of management skill. Of these six airlines, only three are scale efficient: that is, operating at an appropriate scale of operations (neither too big or too small). These include Singapore Airlines, Frontier Airlines and Ryanair. We then calculate the measures of scale efficiency using the ratio of efficiency scores of CCR/BCC (Banker, 1984). As pointed out by Golany and Roll (1989), CCR under CRS measures overall efficiency, made up of pure technical efficiency and scale efficiency, while BCC under VRS measures only pure technical efficiency and excludes any scale effects.

<TABLE 2 HERE>

In terms of explaining the measures of efficiency, in Europe, deregulation and liberalization effectively opened up the airline industry, and this created intense competition between 2001 and 2005. Amongst the European airlines, only SATA Internacional and Ryanair adopted best-practice management as indicated in their VRS efficiency scores. Of these two airlines, only Ryanair was

[1] WLF includes tonnage of passengers, freight and mail. Hence, we do not consider passenger load factor since this is already accounted for in WLF.

operating at its optimal level as indicated by its returns to scale. From the final column in Table 2, we can see that based on those displaying DRS (decreasing returns-to-scale), nearly all mainstream European airlines (except SATA Internacional and Swiss International Airlines) were too large and required downsizing their operations. For this, a range of strategies is available. These include the closure of (especially regional) hubs, the cutting of unprofitable routes, changing the composition of the existing fleet toward smaller more economical aircraft, encouraging higher load factors on retained routes, and the spinning off of aircraft and/or personnel and/or facilities into new carriers (especially as LCCs) or their contracting-out to outside providers.

One inference from these results is that deregulation has had at least some impact on the major national airlines. It also suggests that new competitors through the opening up of the airline industry have eroded the market power of Air France, British Airways, Lufthansa, and Scandinavian Airlines. In contrast, airlines such as Iberia, SATA Internacional, Spanair and Swiss International Airlines with IRS (increasing returns-to-scale) suggest that competition has opened up opportunities for these airlines to expand their operations and achieve better economies of scale. Typically, airlines can accomplish this by opening new routes and hubs and expanding the size of both their fleets and individual aircraft.

In the US, American Airlines, Frontier Airlines and United Airlines were technically efficient through best-practice management (i.e. VRS = 1 in Table 2). However, in terms of the scale of operations, only Frontier Airlines was efficient (scale efficiency = 1). Based on the events surrounding the US airline industry between 2001 and 2005, the results suggest that while airlines were adopting best-practice management through cost-cutting measures, the restructuring in operations took some time to have any discernible impact on scale efficiency. We can see this most clearly in the returns-to-scale in the final column in Table 2 with the US legacy airlines (American Airlines, Continental, Delta, United Airlines and US Airways) suggesting that their scale of operations were too large for the market, thus demanding the need to rescale their operations to remain competitive in the changing circumstances.

The inclusion of the Asian airlines provide a useful benchmark for the US and European airlines as a means of detecting globally better or more poorly performing airlines. In turn, benchmarks provide ways for such airlines to improve on management and operations. To test the validity of the Asian airlines as benchmarks, we applied DEA to two airline subsamples in two separate analyses, first excluding only Singapore Airlines and then excluding all Asian airlines. The results (not shown but available on request) from the first subsample analysis showed that some US airlines and two Asian airlines, JAL and Cathay Pacific, were technically efficient. In the second subsample analysis, most of the European airlines and US airlines were technically efficient. Hence, the results suggest that omission of Asian airlines can provide exaggerated efficiency scores, thus indicating that appropriate performance measurement of the global airline industry requires the inclusion of non-US /non-European airlines.

In order to examine the hypothesis that environmental variables of a nondiscretionary nature exert a significant impact on measured airline efficiency, we follow the two-step approach, as suggested by Coelli et al. (2005). It is well documented in the DEA literature that if the efficiency scores obtained in the first stage are correlated with the explanatory variables in the second stage, it can make the second-stage estimates inconsistent and biased. A bootstrap procedure can overcome this problem (Efron and Tisbhirani, 1993). Hence, following Simar and Wilson (2007), we employ the double bootstrap approach using MATLAB. The estimated specification for the regression is:

$$\hat{\hat{\theta}}_i = \beta_0 + \beta_1 Ownership_i + \beta_2 LCC_i + \beta_3 Departures_i + \beta_4 WLF_i + \varepsilon_i \tag{3}$$

where $\hat{\hat{\theta}}_i$ is the bootstrapped bias-corrected efficiency score, LCC is a low cost carrier and WLF is the weight load factor.

<TABLE 3 HERE>

Table 3 provides the estimated coefficients and 95 percent confidence intervals for this second-stage estimation. Overall, the results suggest that environmental variables exert a significant impact on the technical efficiency of airlines. Of the environmental variables, ownership, LCC and WLF have a positive impact on efficiency. That is, ownership contributes positively to efficiency, which suggests that privately-owned airlines are managed relatively more efficiently than state-owned (or quasi state-owned) airlines. Further, LCC contributes positively to efficiency, suggesting that being a LCC enhances their ability to transform inputs into outputs efficiently, as driven by their incentive to remain competitive by adopting best-practice management and operations. The finding that LCC and ownership having significant impact on efficiency complements the findings of Fu et al. (2010) whereby liberalization and increased competition promoted growth and efficiency. WLF also contributes positively to efficiency suggesting that demand factors, which are outside management control, also provide external market pressure on airlines to perform productively. This confirms similar findings in Bhadra (2009). Finally, 'departures' contributes negatively to efficiency suggesting that either the current number of departures is not fully utilized or that airlines should cut back on the number of departures. This would require, for each airline, coordination of fleet planning, schedules planning, passenger reservations, flight operations, ground operations and aircraft maintenance. Reducing the number of departures would also reduce aircraft maintenance and reduce the time out-of-service, and in turn, improves aircraft utilization and thus efficiency. In contrast, Bhadra (2009) found no statistical significance for 'departures', though the coefficient was negative which could be influenced by the very small sample size in that analysis.

What then do the sources of efficiency suggest? Considering demand factors are nondiscretionary and play a significant role in airline efficiency, one may conclude that influences on consumer choice can affect airline efficiency. One approach is to employ marketing and advertising strategies to win consumers over. For example, we commonly observe that airlines offer consumers frequent flyer membership, thereby rewarding members when they purchase flights. Other marketing strategies include advertising and promotions. However, this approach may not be as successful as the initial outlay of advertising and promotions does not guarantee returns. Nonetheless, it would be worthwhile considering further the impact between advertising and promotions on consumer decisions.

5. Conclusion

In this paper, we employed the DEA double bootstrapping model proposed by Simar and Wilson (2007) to measure technical efficiency of a sample of international and domestic airlines for the year 2006. Bootstrap DEA scores derived in the first-stage analysis are estimated simultaneously with a bootstrapped truncated regression model to explain efficiency drivers.

Benchmarks in the form of non-US and non-European international airlines are considered as these airlines were relatively unaffected by the events that took place in these regions. That said, the results do suggest that the non-US and non-European international airlines, mainly Singapore Airlines and to a lesser extent, JAL and Cathay Pacific, do perform at efficient levels which provides a benchmark for poorly performing airlines in the US and Europe to find ways to improve their management and operations. Generally, the efficiency scores of the US airlines and European airlines suggest that the LCCs played a significant role in intensifying airline competition. For the US legacy airlines and some of the major European airlines to remain competitive in the future, they need to rescale their operations as the current levels were no longer sustainable because of LCCs becoming more competitive in the market. There is substantial evidence of this process already. In the second stage analysis, we found the results justified that ownership, LCCs and WLF have a significant impact on efficiency levels. On the other hand, the number of departures contributes negatively to efficiency.

The contribution of this paper to the literature of airline efficiency is the assessment of the performance of international airlines for the period after events of deregulation in the European airline industry and financial turmoil in the US airlines. By combining DEA approach with the Simar and Wilson (2007) double-bootstrap truncated regression method, an econometric analysis enables better explanation of drivers of efficiency while simultaneously producing standard errors and confidence intervals for these scores.

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Table 1: Descriptive statistics of inputs, output and environmental variables

Variables	Minimum	Maximum	Mean	Std. dev.
Output ('000)				
Available ton kilometres	155,579	40,043,833	10,569,866	10,713,151
Inputs ('000)				
Kilometres Flown	6,976	1,602,735	375,987	376,397
Number of employees	0.47	94.51	19.25	20.94
Total Assets	17,009	25,849,615	7,590,385	8,245,059
Second stage variables				
Ownership	0	1	0.74	0.45
LCC	0	1	0.29	0.46
Departures	4,981	1,092,343	240,913	234,441
Weight load factor	22.50	84.50	63.22	10.44

Table 2: Airline efficiency scores, 2006

Airline	Home country	VRS	CRS	Scale efficiency	Returns to scale
Air Asia (LCC)	Malaysia	2.9226	3.1362	1.0731	IRS
Air Canada	Canada	1.4095	1.7270	1.2253	DRS
Air France	France	1.2338	1.7253	1.3984	DRS
Air India	India	1.2394	1.2579	1.0149	IRS
Air One (LCC)	Italy	2.9697	3.2268	1.0866	IRS
AirTran Airways (LCC)	US	1.9056	2.4926	1.3080	DRS
Alaska Airlines	US	1.9549	2.5637	1.3114	DRS
America West Airlines	US	1.4079	2.5927	1.8416	DRS
American Airlines	US	1.0000	1.9468	1.9468	DRS
British Airways	UK	1.2138	1.6701	1.3759	DRS
Cathay Pacific	Hong Kong, SAR	1.0306	1.0330	1.0024	IRS
Continental Airlines	US	1.0574	2.2257	2.1049	DRS
Delta Airlines	US	1.0837	1.8928	1.7466	DRS
Deutsche Lufthansa	Germany	1.1190	1.6723	1.4945	DRS
EasyJet Airlines (LCC)	UK	2.4882	2.5737	1.0344	IRS
Ethiopian Airlines	Ethiopia	1.5790	1.6400	1.0386	IRS
Flybe (LCC)	UK	3.5605	3.8221	1.0735	IRS
Frontier Airlines (LCC)	US	1.0000	1.0000	1.0000	CRS
Gol Transportes Aeros (LCC)	Brazil	2.5932	2.5966	1.0013	IRS
Hawaiian Airlines	US	1.1485	1.2034	1.0478	IRS
Iberia	Spain	1.5178	1.7856	1.1764	DRS
JAL	Japan	1.2000	1.2624	1.0520	DRS
Jet Airways	India	3.0017	3.0437	1.0140	IRS
JetBlue Airways (LCC)	US	1.9631	2.2634	1.1530	DRS
Korean Airlines	South Korea	1.1413	1.1434	1.0019	IRS
Mesa Airlines (LCC)	US	4.7756	4.8797	1.0218	DRS
Mid-West Airlines (LCC)	US	2.2947	2.4252	1.0568	IRS
NorthWest Orient Airlines	US	1.3319	1.8706	1.4045	DRS
Oman Aviation Services	Oman	2.3609	2.9145	1.2345	IRS
Pakistan International Airlines	Pakistan	1.2893	1.3178	1.0221	IRS
Qantas Airways	Australia	1.5159	1.5165	1.0004	IRS
Ryanair (LCC)	Ireland	1.0000	1.0000	1.0000	CRS
SATA Internacional	Portugal	1.0000	2.0663	2.0663	IRS
Scandinavian Airlines	Sweden	2.0063	2.1697	1.0814	DRS
Singapore Airlines	Singapore	1.0000	1.0000	1.0000	CRS
SouthWest Airlines (LCC)	US	1.1154	2.1130	1.8943	DRS
SpanAir	Spain	3.1291	3.1870	1.0185	IRS
Sri Lankan Airlines	Sri Lanka	1.1294	1.1980	1.0607	IRS
Swiss International Airlines	Switzerland	1.6136	1.6140	1.0002	IRS
Thai Airways	Thailand	1.1665	1.1687	1.0018	IRS
United Airlines	US	1.0000	1.7127	1.7127	DRS
US Airways	US	1.1428	2.1682	1.8974	DRS

Table 3: Truncated regression results

Variable	Coefficient	Confidence Interval	
		Lower bound	Upper bound
Constant	-2.827576	-7.458141	1.794334
Ownership	1.114817*	0.486686	1.962070
LCC	2.865333*	1.813201	4.410752
Departures	-0.000007*	-0.000013	-0.000005
WLF	0.052062*	0.035661	0.115708

* Significant at 5% confidence interval; total number of iterations = 2000.