Efficiency Benchmarking of North American Airports: Comparative Results of Productivity Index, Data Envelopment Analysis and Stochastic Frontier Analysis

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Using three common methodologies for measuring airport efficiency, namely the productivity index method, Data Envelopment Analysis (DEA) method, and stochastic frontier analysis (SFA) method, this study examines the efficiency performances of 62 Canadian and U.S. airports. Unlike most previous studies, this study includes aeronautical and non-aeronautical outputs of airports as they are inexplicably tied to each other in airport production. The empirical results reveal that the efficiency scores and rankings measured by these alternative methods are quite similar to each other in the top 15 and bottom 15 ranked airports, whereas considerable differences exist among the airports in the middle range. We also found that the percentage of non-aeronautical revenue, passenger volume, average aircraft size, percentages of international and connecting traffic significantly affect our airport efficiency estimates in all of the three alternative approaches used.

INTRODUCTION

Airports have substantial market power over the majority of local traffic and airlines. In many North American cities, airlines,[1] passengers, and other airport users have limited choices when selecting airports. Regulatory, geographical, economic, social, and political constraints all tend to hinder competition between airports. Therefore, unlike airline markets, competitive pressure cannot be relied on to exert enough pressures for airport managers to pay serious attention to improve productivity and efficiency. However, by exposing inefficient airports to their stakeholders, the public and their regulatory authorities,[2] airport benchmarking helps spur competitive forces and shake up conventional thinking on airport efficiency performance.

The evolution of airport ownerships toward privatization and commercialization naturally leads airport managers to seek ways to gain insights into their operations and improve performance by benchmarking themselves against other airports. As benchmarking identifies the best practice standards for operations and services, it provides guidelines for airport managers to improve performance and deal with delays and congestion. This is a major reason why recently the ACI-North America has started to do benchmarking performance of its member airports, although its benchmarking results are not public and are used for internal purposes.

During the past two decades, there has been a plethora of research on airport benchmarking. Liebert and Niemeier (2010) reviewed and summarized literature on airport benchmarking, and found that there are many inconclusive or conflicting findings, including the effects of ownership, privatization, and size on airport performance.[3] The discrepancies in the results of airport benchmarking may due to the differences, including methodology and underlying assumptions, sample data and years, variables used for inputs, outputs and heterogeneities among the airports, such as ownership, regulatory framework, and other factors beyond management control.

Most studies in airport benchmarking utilize a single method to measure airport efficiency. So far, only a few studies have measured efficiencies by using different methodologies. Cullinane et al. (2006) applied data envelopment analysis (DEA) and stochastic frontier analysis (SFA) in the container port industry and found that there is a high degree of correlation between the results of the two approaches.

Coelli and Perelman (1999) compared three alternative methodologies: (1) parametric frontier using linear programming approach; (2) parametric frontier using corrected OLS method (including SFA); and (3) non-parametric piece-wise linear frontier using DEA. When applying them to a pool of data of 17 European railways from 1988 to 1993, the technical efficiencies emerging from the three methods displayed no substantial differences, with positive and significant correlations between each other. The authors claimed that a researcher could safely select one of these methods without too much concern for their choice having a large influence upon results.

For the aviation industry, Windle and Dresner (1995) compared seven methods of productivity measurement using 1983 U.S. airline data, and concluded that: "carrier rankings from the cost function decomposition bear no relationship to the rankings for the gross measure of productivity." This finding thus supports the need for second stage (regression) analysis to control for differences in output characteristics, especially when non-parametric methods such as TFP and DEA are used. Pels et al. (2001) compared the efficiency results of European airports measured from DEA and SFA. Unfortunately, this paper applies these two measurement methods separately to each of airside operations and terminal side operations as if they are two independent businesses and do not include non-aeronautical revenue outputs. Based on the dataset of European airports, the results emerging from the two methods were reasonably consistent despite the fact that SFA produced less dispersed efficiency scores.

As stated in Oum et al. (1992), productivity studies in the transportation industry using different measures of outputs and inputs cannot be compared directly with each other. To the best of our knowledge, no research has been directed toward the comparison between different methodologies and their empirical results in airport benchmarking. This study aims to offer the first step toward filling this gap. More importantly perhaps, to the knowledge of the authors, no airport performance benchmarking paper published so far treated both aeronautical operations and non-aeronautical operations within a single airport firm context. The omission of non-aeronautical revenue outputs invites bias against the airports that have tried to generate more revenue from commercial and business activities so that they could pass on the benefits to airlines, passengers, shippers, and other airport users by lowering airside charges. The size of the bias would be enormous if it is considered that major airports generate anywhere between 30% and 70% of their total revenues from non-aeronautical services while in general airports' inputs are inseparable between those used to generate aeronautical revenues and others for generating non-aeronautical services from airports' available accounting data.

The main objective of this study is to review and empirically compare the results of the three key methodologies employed in measuring airport efficiency, namely, productivity index method, DEA method, and SFA method using comprehensive output data, which include both aeronautical services outputs and non-aeronautical services outputs. The dataset consists of a cross-section of 55 U.S. airports and seven Canadian airports in 2006. There are several reasons for choosing North American airports. First, North America is currently the largest air transport market in the world. Second, the ownership and regulatory framework of North American airports are relatively consistent: airports are owned and/or operated either by government agencies or by airport authorities. Third, there are extensive and reliable data for airports in North America, which make it possible to conduct a valid study using relatively consistent data.

The rest of the study is organized as follows: the next section reviews the three methodologies of efficiency measurement (Index Number Method, DEA, and SFA), followed by the description of the data used in this study. This is followed by the estimation results and comparisons between the efficiencies scores and rankings stemming from the three methods, and the conclusion.

METHODOLOGIES ON PRODUCTIVITY AND EFFICIENCY MEASUREMENT

Productivity of a firm is the ratio of the output(s) produced to the input(s) used to produce the output(s) (Coelli et al. 2005). Hensher and Walters (1993) asserted that there are three quantitative methods to examine the productivity and efficiency among government enterprises, namely: (1) Non-parametric Index Number Method, (2) DEA, and (3) SFA. Liebert and Niemeier (2010), Forsyth (2000) and Oum et al. (2008) have provided an overview of the quantitative methods used for airport productivity and efficiency measurement. Since details of each of these methods are available in the papers just cited and many other sources, this section will only briefly describe and compare the major properties of the three methods.

Index Number Method

As a non-parametric approach, Index Number Method directly defines productivity as output index over input index. The method is easy to conduct for single output and input firms. However, airports utilize multiple inputs such as labor, capital, and other resources to produce various services for both airlines and passengers. Similar to Oum et al. (2006) in the airport industry and Obeng et al. (1992) in public transit systems, this paper uses the multilateral index number method proposed by Caves, Christensen, and Diewert (1982) to aggregate inputs and outputs. The total factor productivity of a firm is calculated as the ratio of aggregate output index over aggregate input index.

Unlike other inputs, capital cost is usually quasi-fixed and cannot be easily adjusted in the short-to-medium term. It is a major challenge to measure capital inputs and costs accurately, as well as to collect consistent and comparable data on capital expenditures. This is because 1) expenditures on capital equipment, buildings, and other infrastructural costs such as runways and terminals are often invested over many years and may be “hidden” in the explicit (or published) costs; 2) facilities at airports may be built and operated by airlines or other enterprises; and 3) the sources of financing and accounting systems vary among airports. Other reasons are 1) some direct and indirect subsidies are not in financial statements, 2) book value data do not resemble replacement value of the capital inputs, and 3) taxation and interest rates vary across states and cities. In the early stage of the ATRS (2001-2011) airport benchmarking, the task force examined the book values of capital accounts of U.S. and Canadian airports, and concluded that those capital accounting data are not comparable at all across airports, and cannot be relied on for any valid study. Consequently, the task force decided to focus on measuring and comparing just the operating efficiency and variable input costs of the airports, excluding capital inputs from their analysis.[4]

Following the well-known procedure devised by Caves, Christensen and Diewert (1982), the variable factor productivity (VFP) model used in this study is computed as follows:

(1)
$$\ln VFP_k - \ln VFP_j = (\ln Y_k - \ln Y_j) - (\ln X_k - \ln X_j) = \sum_i \frac{R_{ik} + \overline{R}_i}{2} \ln \frac{Y_{ik}}{\tilde{Y}_i} - \sum_i \frac{R_{ij} + \overline{R}_i}{2} \ln \frac{Y_{ij}}{\tilde{Y}_i}$$
$$- \sum_i \frac{W_{ik} + \overline{W}_i}{2} \ln \frac{X_{ik}}{\tilde{X}_i} + \sum_i \frac{W_{ij} + \overline{W}_i}{2} \ln \frac{X_{ij}}{\tilde{X}_i}$$

where

FP_k is the productivity of k^{th} firm; Y_{ik} and X_{ik} represent the i^{th} output and input of the k^{th} firm respectively; R_{ik} and W_{ik} are the weights for the i^{th} output and input of the k^{th} firm, respectively; A bar over weights represents sample arithmetic mean, while a tilde demonstrates geometric mean.

As implied from equation (1), the VFP index is formed by a series of binary comparisons between each observation and the sample mean. Ideally, revenue and cost elasticities should be used for output and input, respectively. However, as those numbers are usually not obtainable for most industries, including airports, Diewert (1992) suggests using revenue and cost shares as approximations. This adjustment comes with further assumptions on constant returns to scale (CRS) across all outputs.[5]

Data Envelopment Analysis (DEA)

DEA is a non-parametric frontier method and originated from a study in operations research, and was first proposed by Charnes et al. (1978). DEA uses linear programming to construct a piecewise linear "efficient frontier" that envelops Decision-Making Units (DMUs) or firms based on outputs and input quantities. Efficiency indices are then calculated relative to this frontier.

The model is presented with *n* units with *s* outputs denoted by *Y*, and *m* inputs denoted by *X*. For technical efficiency,[6] the following linear programming problem is solved under the assumption of constant returns to scale, i.e., the CCR model developed by Charnes et al. (1978):

$$(2)\ \ \mathrm{Min}_{\theta,\lambda}\ \theta,\ \textit{subject to}\ \theta x_i - X\lambda \geq 0,\ Y\lambda - y_i \geq 0,\ \lambda \geq 0$$

Where, θ is a scalar that indicates the radial contraction of all inputs, hence the technical efficiency (TE) score. λ is the weight of the efficient peers in the reference unit. The x_i's are the individual inputs and y_i the outputs for the *i*th firm. *X* and *Y* represent all input and output matrices.

The BCC model as introduced by Banker et al. (1984) can handle variable returns to scale (RTS) by adding the following constraint to the original CCR model.[7]

$$(3)\ \ e'\lambda=1$$

Where, *e* is a vector of one. The paper uses the CCR model with constant returns to scale in the first stage because the resulting (gross) DEA efficiency measures are more directly comparable with the (gross) VFP, which is computed assuming constant returns to scale as discussed previously. The second stage analysis controls for variable returns to scale by including an output scale variable in the regression.

The DEA method distinguishes between input-oriented and output-oriented models. This study uses the input-oriented model because most previous studies, including Abbott and Wu (2002) and Pels et al. (2001, 2003), use it, and it is a plausible assumption that airports have more control over their inputs than outputs. Since air travel demand is derived demand depending directly on economic activities, airports have less control in generating aeronautical outputs (ATMs, air passenger, and air cargo volumes) than adjusting for variable inputs.[8]

Stochastic Frontier Analysis (SFA)

Different from the productivity index number and DEA, SFA specifies the form of a production or cost function and identifies the inefficiency as a stochastic disturbance. Originally introduced by Aigner et al. (1976), the general form of stochastic frontier production function can be specified as follows:[9]

$$(4)\ \ Yi = f(xi;\beta)\ \exp(Vi - Ui)$$

Where, Y_i represents the output of the *i*th firm; $f(x_i;\beta)$ is the deterministic core function of an input vector x_i, and an unknown parametric vector β; V_i is a normally distributed random variable that represents the effects of unobservable explanatory variables and random shocks. U_i is a non-negative random variable representing inefficiency, and it is assumed to follow either half-normal, exponential, or gamma distribution.

As implied from equation (4), SFA explains output by a vector of inputs and a stochastic disturbance, which consists of two parts: a stochastic inefficiency, U_i and a traditional 'noise' term, V_i. While V_i could be either positive or negative, U_i is always positive.

For the deterministic part of efficiency, this study uses a translog specification, and as such, our SFA-production function can be written as follows:

$$(5)\quad \ln Yi = \beta_0 + \sum_{j=1}^{n} \beta_j \ln X_j + \sum_{j=1}^{n}\sum_{k=1}^{n} \beta_{jk} \ln X_j \ln X_k + (V_i - U_i)$$

Where, Y_i is aggregate output index for airport i; X_j is the *jth* input; V_i is assumed to follow the distribution $N(0, \sigma^2 V)$; U_i is assumed to follow $N(\mu, \sigma^2 U)$ where $\mu \geq 0$. The technical efficiency of airport i is then calculated as the ratio of its mean output to the input if it uses inputs most efficiently.

$$(6)\quad TE_i = \frac{E(Y_i \mid \hat{U}_i, X_i)}{E(Y_i \mid U_i = 0, X_i)} = \exp(-U_i)$$

The SFA production function is estimated by using the input quantity indices (labor input and soft cost input) and the output quantity index (aggregated using the multilateral index procedure discussed in the Index Number Method section).

Comparison of Methodologies

Table 1 summarizes and compares key features of the three alternative methods. The index number method assumes that firms are allocatively efficient and under constant returns to scale.[10] In contrast, DEA and SFA assume the continuity and convexity of the production set. SFA further assumes a particular form of inefficiency distribution: usually one of half-normal, exponential, and gamma distribution. As for data requirement, the productivity index number method demands the highest level of data in general.

All three methods have difficulty in precisely measuring capital costs, the DEA method allows for using physical measures of capital inputs such as terminal size, number and/or length of runway as approximation of capital inputs. The DEA method is thus easy to use with less demanding data. However, DEA efficiency index lacks "transitivity," as DEA airport efficiency rankings can change substantially as one adds or drops one or more airports from the sample.[11] In comparison, index number methods preserve the relative index values and rankings, even when one adds or drops one or more airports from the sample.

As the only parametric method, SFA involves a specification of frontier function, which enables it to conduct hypotheses tests and distinguish the sources of efficiency growth. Furthermore, as SFA does not assume that all firms are efficient, it allows the existence of systemic inefficiency in the error terms, and does not restrict the combined error term (which includes inefficiency distribution) to be assumed independently and identically distributed (i.i.d.). However, because use of SFA requires rigorous theoretical concept and complex computation, it is difficult to communicate the method to industry executives and practitioners.

Table 1: Comparison of Index Number Method, DEA and SFA

	Index Number Method	DEA	SFA
Assumption	• CRS • Allocative efficiency	• Continuous and convex production set	• Inefficiency distribution • Continuous and convex production set
Minimum Data Requirement	• Quantity of outputs and inputs • Revenue/cost shares (or prices of outputs and inputs)	• Quantity of outputs and inputs	• Quantity of outputs and inputs • Revenue shares of outputs (when using production function)
Strength	• Specification of functional form is not required • Easy to communicate	• Low data requirement (only output and inputs quantities are required) • Specification of functional form is not required • Can use physical measures of capital as proxy for capital input	• Accounts for statistical noise • Able to conduct hypotheses test • Firms on the frontier are not assumed to be 100% efficient.
Weakness	• High data requirement • Do not account for statistical noise	• Results are sensitive to outliers and to the set of DMUs included in the study • Does not account for statistical noise • Inability to distinguish among 100% efficiency DMUs	• High computational requirements • requires the specification of functional form

DATA CONSTRUCTION

Airports typically charge separately for handling aircrafts and passengers. Therefore, the numbers of aircraft movements (ATMs) and passenger volume are two major aeronautical outputs of an airport. Some argue that ATMs and passenger volume may be correlated and thus ATMs are not independent. In practice, airlines could change the number of flights by adjusting load factors, seating arrangements, and the sizes of aircraft, making ATMs unnecessarily endogenous. As another airport output, air cargo services are handled directly by airlines or third-party logistics companies. In addition, airports only receive small amounts of usage fees for leasing space and terminals, cargo revenue covers only a small percentage of the total airport revenue, and it is thus not reported separately by most airports. As such, air cargo is not included as an individual output when measuring the gross efficiency index, but it is included as an explanatory variable in the second stage regression analysis.

Airports further rely on a number of non-aeronautical activities to generate additional revenues, such as duty-free shops, beverages, car parking and concessions. Such leasing and outsourcing activities offer flexibility to airport managers by allowing them to respond efficiently to market forces. Although non-aeronautical activities are different from traditional aeronautical services, their revenues have become increasingly important and account for somewhere between 30% and 70% of total revenues of most of our sampled airports in 2006. As discussed in Oum et al. (2006)

and Zhang et al. (2010), aeronautical and non-aeronautical activities are not separable, and their demands are closely related to each other. Any efficiency measure computed without including non-aeronautical service output would lead to serious bias against the airports that focus on increasing non-aeronautical revenue in order to reduce airport charges to airlines and passengers. Therefore, this study includes non-aeronautical revenue as the third airport output.[12]

Regarding airports, certain resources are used to provide the services stated above. First, labor is one of the most important inputs. In 2006, personnel expenses accounted for somewhere between 15% and 70% of total operating cost of the sampled airports. As most airports contract out part of their services, some employees are hired by outsourcing companies rather than airport operators. To avoid double counting, this study defines labor input as the full-time equivalent number of employees directly paid for by airport operators. Due to lack of consistent separate data on the outsourced services for the goods, services, and materials purchased directly by an airport, this study defines "soft cost input" to be other variable inputs other than labor input. The concept of soft cost input has been used in previous airport benchmarking studies including ATRS (2001-2011).

In reality, there may be hundreds (if not thousands) of items included in our soft cost inputs that an airport uses during a year. Unless quantities and cost shares of all of these items for all of the airports in the sample are available to the analysts, it is impossible to create an aggregate quantity index for soft cost inputs. Therefore, the method of deflating aggregate soft cost input dollar values by purchasing power parity (PPP) of the year is used. Further, this is divided by the cost of living index of the city in which the airport is located. This is the next best feasible method for creating an approximate quantity index of the soft cost input for the airports in the sample.

Due to various geographic locations, airports in northern regions may incur additional snow removal costs. These airports have extra expenses in hiring additional staff and purchasing snow-removal equipment and supplies. For some airports, snow removal costs could be significant, e.g., in 2006 snow removal cost was estimated to be $9.8 million for the New York JFK airport and over $10 million for the Denver airport. In order to create a fairer comparison, this study deducts snow removal costs from airport expenses.[13]

To address the price differences between the U.S. and Canada, this study uses PPP[14] to deflate non-aeronautical revenues. In order to deal with the price differentials of non-aeronautical revenue items across different cities within a country, the paper further applies the city-based Cost of Living Index (COLI)[15] to deflate non-aeronautical revenue to compute the quantity index of non-aeronautical revenue output.[16] Table 2 provides descriptive statistics for the airport inputs and outputs used in this study.

Table 2: Summary Statistics for Output and Input Variables

	Mean	Median	Maximum	Minimum	Std. Dev
No. Of Passenger	21,462,585	15,730,771	84,846,639	2,899,460	2,328,169
ATM (Air Transport Movements)	293,672	236,723	965,496	60,518	25,236
Non-Aeronautical Revenue Output[1]	88,944,551	63,268,716	288,188,161	13,237,866	8,131,930
No. of Employee	554	407	3,000	123	62
Soft-Cost Input[2]	71,637,907	50,521,745	249,734,305	9,708,149	8,061,183

[1] Deflated by cost of living index.

[2] Snow removal cost is deducted and deflated by cost of living index.

ESTIMATION RESULTS

Based on an identical airport sample, efficiency scores and airport rankings are estimated and compared across the three methods. In addition, as gross efficiency measurement is affected by a number of airport characteristics and may not reflect airports' managerial efficiencies, the paper estimates and compares airport residual efficiencies after removing factors beyond managerial controls.

Comparison of "Gross" Efficiency Results Across the Alternative Methods

Since it is not meaningful to compare actual values of the gross efficiency scores generated by each of the three methods, the efficiency scores generated by each method are normalized around the most efficient airport by setting the value for the most efficient airport at one. After that, airport rankings obtained from these three methods are compared based on their gross efficiency scores. Table 3 reports these efficiency rankings obtained from the gross efficiency scores calculated by each method, together with the mean ranking, mean efficiency, and standard deviations. Some airports have consistent gross rankings regardless of methodologies used, for example, ATL, CLT, RDU, STL, MIA, and MSY. It is found that the rankings in the top and bottom ranges of the gross efficiency scores are quite robust with respect to methodology. Meanwhile, the rankings of some other airports, especially the mid-ranked ones, are more sensitive to the methodology used. For instance, SAT and RNO are ranked between 20 and 30 places in gross VFP and SFA, while these airports are estimated to have 100% gross efficiency by the DEA method. These considerable differences might be explained by the impossibility of the DEA method to distinguish among a large number of 100% efficient firms.

Table 4 reports the Spearman's rank order correlation coefficients of gross efficiency estimates by the three methods. In general, the three sets of efficiency scores are highly correlated with each other. The correlation between VFP and SFA is the highest, implying that both methods yield rather similar (gross) efficiency rankings. Further, the sample is divided into three groups based on average efficiency scores: the top 15 airports (25% of the top-ranked airports), mid-ranked airports, and the bottom 15 airports (25% of the bottom-ranked airports), and their correlations compared again. The results reveal that the correlations for the mid-ranked airports are the lowest, especially between the DEA and SFA models, where it is 0.29 and not statistically significant.

Impact of Airport Specific Characteristics on Gross Efficiency Result

The gross efficiency scores derived in the previous section are affected by a number of airport characteristics, for example, airport output size, capacity constraint, level of commercial services, etc. As some of these factors are beyond an airport manager's control, the gross measure of efficiency scores are not necessarily good estimators for airports' managerial performances. Therefore, this section applies regression analysis to decompose gross efficiency scores estimating the impacts of airport characteristics on measured efficiency.

A log-linear OLS (Ordinal Least Squares) model is used to decompose gross VFPs. However, as gross DEA and SFA efficiency scores have an upper bound of 1.0, there might be a truncation bias if the OLS model is used. Thus, as has been done in many previous studies, a Tobit regression model (Tobin 1958) on DEA scores is used.

Based on previous airport efficiency studies, including the ATRS Global Airport Performance benchmarking report, the following variables are incorporated in the regression function as these may affect the gross efficiency scores.

Table 3: Comparative Gross Efficiency Rankings by the Alternative Methods

Airport Code	Airport Name	VFP	DEA	SFA	Mean Ranking	Std. Dev. (Ranking)	Mean Efficiency Score	Std. Dev. (Score)
ATL	Hartsfield-Jackson Atlanta International Airport	1	1	1	1	0	0.978	0.039
CLT	Charlotte Douglas International Airport	2	1	3	2	1	0.974	0.041
MSP	Minneapolis/St. Paul International Airport	3	1	2	2	1	0.953	0.041
RDU	Raleigh-Durham International Airport	4	1	4	3	1.7	0.945	0.047
YVR	Vancouver International Airport	5	1	5	3.7	2.3	0.926	0.07
YYC	Calgary International Airport	6	1	6	4.3	2.9	0.904	0.096
RIC	Richmond International Airport	7	1	9	5.7	4.2	0.897	0.102
ABQ	Albuquerque International Sunport	9	1	13	7.7	6.1	0.863	0.149
LGA	LaGuardia International Airport	15	1	11	9	7.2	0.845	0.182
TPA	Tampa International Airport	10	18	8	12	5.3	0.807	0.106
SDF	Louisville International-Standiford Field	8	14	17	13	4.6	0.848	0.106
MCO	Orlando International Airport	20	13	10	14.3	5.1	0.818	0.182
RNO	Reno/Tahoe International Airport	23	1	24	16	13	0.823	0.206
LAS	Las Vegas McCarran International Airport	16	26	7	16.3	9.5	0.759	0.133
MEM	Memphis International Airport	12	22	21	18.3	5.5	0.77	0.11
MKE	General Mitchell International Airport	11	19	25	18.3	7	0.781	0.104
SLC	Salt Lake City International Airport	17	23	16	18.7	3.8	0.764	0.126
BNA	Nashville International Airport	14	21	22	19	4.4	0.767	0.113
SAT	San Antonio International Airport	31	1	26	19.3	16.1	0.804	0.236
EWR	Newark Liberty International Airport	39	1	19	19.7	19	0.796	0.257
CVG	Cincinnati/Northern Kentucky International Airport	13	29	18	20	8.2	0.752	0.117
SNA	John Wayne Orange County Airport	21	15	28	21.3	6.5	0.798	0.172
YWG	Winnipeg International Airport	19	16	35	23.3	10.2	0.794	0.149
DEN	Denver International Airport	29	27	15	23.7	7.6	0.729	0.156
PHX	Phoenix Sky Harbor International Airport	27	31	14	24	8.9	0.728	0.152
PDX	Portland International Airport	18	32	23	24.3	7.1	0.738	0.125
IAH	Houston-Bush Intercontinental Airport	22	40	12	24.7	14.2	0.698	0.163
IND	Indianapolis International Airport	26	28	27	27	1	0.728	0.139
SEA	Seattle-Tacoma International Airport	24	38	20	27.3	9.5	0.698	0.158
JAX	Jacksonville International Airport	25	25	34	28	5.2	0.733	0.132
FLL	Fort Lauderdale Hollywood International Airport	34	24	31	29.7	5.1	0.717	0.17
IAD	Washington Dulles International Airport	32	33	32	32.3	0.6	0.704	0.163
YUL	Montréal-Pierre Elliott Trudeau International Airport	33	34	33	33.3	0.6	0.696	0.16
PBI	Palm Beach International Airport	37	20	44	33.7	12.3	0.717	0.171
YEG	Edmonton International Airport	30	30	43	34.3	7.5	0.704	0.134
DTW	Detroit Metropolitan Wayne County Airport	35	42	30	35.7	6	0.665	0.177
YOW	Ottawa International Airport	28	41	45	38	8.9	0.673	0.135
BOS	Boston Logan International Airport	42	36	38	38.7	3.1	0.653	0.186
DCA	Ronald Reagan Washington National Airport	36	45	36	39	5.2	0.639	0.184
SAN	San Diego International Airport	40	37	40	39	1.7	0.655	0.171
JFK	New York-John F. Kennedy International Airport	56	17	49	40.7	20.8	0.675	0.269
ORD	Chicago O'Hare International Airport	43	52	29	41.3	11.6	0.615	0.217
HNL	Honolulu International Airport	38	48	39	41.7	5.5	0.628	0.186
DFW	Dallas Fort Worth International Airport	49	44	37	43.3	6	0.622	0.208
OAK	Oakland International Airport	46	35	50	43.7	7.8	0.639	0.187
MDW	Chicago Midway Airport	48	39	48	45	5.2	0.628	0.188
CLE	Cleveland-Hopkins International Airport	41	49	47	45.7	4.2	0.612	0.186
SFO	San Francisco International Airport	51	47	41	46.3	5	0.599	0.211
MCI	Kansas City International Airport	47	43	51	47	4	0.614	0.183
YHZ	Halifax International Airport	44	46	56	48.7	6.4	0.592	0.163
LAX	Los Angeles International Airport	55	50	42	49	6.6	0.579	0.23
AUS	Austin Bergstrom Airport	45	51	52	49.3	3.8	0.589	0.185

(continued)

Table 3 continued

Airport Code	Airport Name	VFP	DEA	SFA	Mean Ranking	Std. Dev. (Ranking)	Mean Efficiency Score	Std. Dev. (Score)
PHL	Philadelphia International Airport	50	60	46	52	7.2	0.561	0.231
PIT	Pittsburgh International Airport	53	54	54	53.7	0.6	0.545	0.204
STL	St. Louis-Lambert International Airport	52	56	53	53.7	2.1	0.541	0.217
SMF	Sacramento International Airport	54	53	55	54	1	0.548	0.203
ONT	Ontario International Airport	57	58	58	57.7	0.6	0.509	0.209
ALB	Albany International Airport	58	55	61	58	3	0.506	0.188
SJC	Norman Y. Mineta San José International Airport	59	57	59	58.3	1.2	0.508	0.208
BWI	Baltimore Washington International Airport	60	59	57	58.7	1.5	0.51	0.223
MIA	Miami International Aiport	62	61	60	61	1	0.446	0.244
MSY	Louis Armstrong New Orleans International Airport	61	62	62	61.7	0.6	0.427	0.208

Table 4: Spearman's Rank Order Correlation Coefficients Among Airport Gross Efficiency Estimates

	All Sample		Top 15 airports		Mid-ranked airports		Bottom 15 airports	
	VFP	DEA	VFP	DEA	VFP	DEA	VFP	DEA
DEA	0.8338**	1	0.5145**	1	0.4154**	1	0.725**	1
SFA	0.9116**	0.8113**	0.8107**	0.3615	0.6727**	0.2913	0.7071**	0.6**

**correlation is statistically significantly different from zero at the 5% level, two-sided.

*correlation is statistically significantly different from zero at the 10% level, two-sided.

Variables Beyond Airports' Managerial Control

Congestion Delay. Many of the sampled airports suffer from runway and terminal congestion. Pathomsiri et al. (2008) found that the performance ranking of airports would be distorted in favor of congested airports because they have higher utilization of all inputs, while delayed flights are costly to airlines and passengers. In order to control the former effect, the study incorporates the percentage of non-weather delays as an indicator for congestion delay.

Airport Output Scale. Airports handling more outputs are expected to achieve higher operating efficiency, because the continuous flow of outputs helps airports to better utilize their employees and other inputs.

Average Aircraft Size. Large aircrafts carry more passengers and cargo at one time, which requires a larger number of operators and other facilities to provide land services. Thus, airports have to provide sufficient landside capacity for "peak" hours; however, this leads to a lower utilization and productivity in "off-peak" hours. On the other hand, airports that mostly handle large aircraft tend to have higher utilization of airside facilities.

Percentage of International Traffic. International traffic requires more airport services than domestic traffic. On the other hand, airports collect more revenues from international passengers. As a result, the impact of international traffic on airport efficiency depends on the counter-balancing effects of these two factors.

Percentage of Air Cargo. Providing cargo service may have a mixed impact on airport efficiency. While costs are lower to serve cargo traffic, airports may also lose a portion of non-aeronautical revenues that come with passenger traffic. Since the output index used to calculate gross productivity does not include cargo as a separate output, the study incorporates the percentage of cargo as a variable in the regression models in order to control for the effect of cargo on airport efficiency.

Percentage of Connecting Passengers. Hub airports usually have a significant number of connecting passengers. Connecting passengers require less service than do passengers on direct flights. Therefore, airports with a high proportion of connecting passengers are expected to have high productivity.

Hub Carrier Market Share. The dominance of a hub carrier at an airport may allow better coordination and cooperation between the carrier and the airport. Therefore, airports that are dominated by a hub carrier are expected to have higher efficiencies than airports with a large number of competing airlines.

Variable Within Airport's Managerial Control

Percentage of Non-Aeronautical Revenue. This indicator is used to present the business strategy of an airport. Commercial activities expand airport revenue; however, they also require additional resources. Therefore, it is necessary to examine the impact of non-aeronautical activities on airport efficiency.

Table 5 reports the second stage regression results for the three models.[17] All three results show consistently that airport congestion delay, percentage of cargo services, or hub carrier's market share does not have statistically significant impacts on an airport's operating efficiency.

Table 5: Regression Results on the Gross Efficiency Scores

	VFP OLS (log-log)		DEA Tobit (log-log)		SFA Tobit (log-log)	
	Coefficient	**t-Stat**	**Coefficient**	**t-Stat**	**Coefficient**	**t-Stat**
Congestion Delay	0.012	0.07	0.128	0.5	-0.005	-0.14
Output Size	0.231**	3.46	0.207**	2.26	0.086**	5.94
Ave. Aircraft Size	-0.39**	-3.23	-0.197	-1.18	-0.080**	-3.08
% International	-0.021*	-1.71	-0.037**	-2.08	-0.006**	-2.22
% Cargo	-0.037	-1.19	-0.01	-0.23	-0.006	-0.93
% Non-Aeronautical Revenue	0.572**	4.22	0.615**	3.23	0.114**	3.91
% Connecting Passenger	0.027**	2.01	0.033*	1.72	0.005*	1.68
% Hub Carrier	0.003	0.05	-0.026	-0.29	-0.009	-0.65
Intercept	1.283	2.07	0.972	1.12	0.189	1.41
R^2	*0.55*		-		-	
Log-likelihood value	-		*-19.15*		*87.12*	

*The coefficient is significant at the 90% level.

**The coefficient is significant at the 95% level.

The output size variable has significant positive coefficients in all of the three regressions (VFA, DEA, and SFA). This means that the larger the output size, the higher the operating efficiency the airport is expected to achieve. This evidence does not translate into scale economies because the dependent variable in these regressions is only operating efficiency, not total efficiency. Given the quasi-fixed nature of airport capacity in the short run, this evidence may be interpreted as economies of utilization of the given capacity.

Average aircraft size has a statistically significant negative coefficient in the VFP and SFA regressions while not being significant in the DEA regression. This negative coefficient is surprising, and could be the result of more inputs required to service large aircraft.[18]

The statistically significant negative coefficient for the percentage of international (passenger) variables in all of the three models indicates that international traffic requires more resources to deal with customs, immigrations, and more stringent security.

The significant positive coefficient for the percentage of connecting passengers indicates that airports with high proportions of connecting passengers (hub airports) are expected to have high operating efficiency. This is probably because a connecting passenger at an airport is counted twice (deplanement and enplanement), and thus, requires fewer airport resources (not requiring check-in facilities, baggage areas, etc.).

As described above, the percentage of non-aeronautical revenue in total airport revenue is the only variable that can be largely chosen (controllable) by airport managers among the variables included in the second stage regression analysis. Consistent with many previous studies, including Oum et al. (2006, 2008) and Tovar and Martin-Cejas (2009), the percentage of non-aeronautical revenue has significant positive effects on operating efficiency of airports in all three regressions. Thus, an airport that derives a high percentage of its total revenue from non-aeronautical activities is expected to fare well in all three measures of operating efficiency.[19] This result implies that making more effort to increase non-aeronautical revenue beyond the current level of average efforts being expended by the North American airports would increase an airport's operating efficiency, and thus, should be encouraged.

Managerial Efficiency Results Based on the Alternative Methods

After removing the effects of airport characteristics beyond managerial control, residual (managerial) efficiencies[20] are estimated and airports are ranked by their managerial efficiencies. Similar to the gross efficiency estimates, the sample is divided into three groups: the top 15 airports, the bottom 15 airports, and the mid-ranked airports. The comparative residual efficiency rankings between the three alternative methodologies are reported in Table 6. To provide a clear picture of the residual efficiency rankings, Figures 1, 2, and 3 plot the results of the three alternative methods for the top 15, the bottom 15, and the mid-ranked airports. For the top 15 airports, except for BNA (Nashville), airport rankings are largely consistent across the three alternative methods. Most airports in this group have similar efficiency rankings regardless of the method of measurement used. The rankings for the bottom 15 airports are also similar across the three methods except for BOS (Boston) and PHL (Philadelphia). In contrast, significant variations exist in the rankings of mid-ranked airports, notably SEA (Seattle), EWR (Newark), and JFK (New York). Based on the average residual efficiency scores, Atlanta (ATL), Raleigh-Durham (RDU), Charlotte (CLT), Minneapolis-St. Paul (MSP), and Reno (RNO) are the top five most efficient airports in the sample of U.S. airports studied.

In general, the three sets of airport managerial/operational efficiencies are highly correlated with each other as indicated in the Spearman's rank order correlation coefficient reported in Table 7. Similar to the results in gross efficiency estimates, the ranking results between VFP and SFA are more consistent with each other. Because of many corner solutions in DEA measurement and the consequent existence of a large number of efficient DMUs (airports in this case), the managerial efficiency rankings based on DEA method are considerably different from those of the other two methods. The correlation between VFP and DEA for the mid-ranked airports is not even statistically significant.

Table 6: Comparative Airport Rankings by Residual (Managerial) Efficiency Scores

Airport	VFP	DEA	SFA	Mean Ranking	St. Dev. (Ranking)	Mean Efficiency Score	Std Dev (Score)
			Top 15 Ranked Airports				
ATL	3	1	3	2.3	1.2	1.146	0.109
RDU	2	5	4	3.7	1.5	1.101	0.122
RNO	9	2	1	4.0	4.4	1.030	0.134
CLT	1	7	6	4.7	3.2	1.081	0.819
PBI	7	3	5	5.0	2.0	1.029	0.109
BNA	5	12	2	6.3	5.1	1.013	0.102
MSP	4	9	7	6.7	2.5	1.035	0.853
JAX	6	13	8	9.0	3.6	0.966	2.082
LGA	11	4	13	9.3	4.7	0.973	0.106
SAT	12	10	9	10.3	1.5	0.928	0.111
TPA	8	14	10	10.7	3.1	0.945	0.111
SNA	10	16	11	12.3	3.2	0.905	1.701
MCO	13	8	18	13.0	5.0	0.927	0.117
MKE	15	17	12	14.7	2.5	0.871	0.118
FLL	16	15	15	15.3	0.6	0.880	2.531
			Middle Ranked Airports				
PDX	14	21	14	16.3	4.0	0.853	0.124
SAN	19	24	16	19.7	4.0	0.819	0.131
SLC	22	20	20	20.7	1.2	0.814	0.130
OAK	25	19	19	21.0	3.5	0.820	0.137
RIC	18	25	21	21.3	3.5	0.821	0.142
ABQ	23	18	23	21.3	2.9	0.828	3.377
SEA	17	35	17	23.0	10.4	0.802	2.565
HNL	20	27	22	23.0	3.6	0.811	0.151
EWR	38	6	28	24.0	16.4	0.868	0.150
IAD	27	22	26	25.0	2.6	0.794	0.152
LAS	21	30	25	25.3	4.5	0.791	0.152
MEM	30	23	29	27.3	3.8	0.781	0.154
MDW	32	28	27	29.0	2.6	0.765	0.157
DCA	26	38	24	29.3	7.6	0.751	0.161
IAH	24	37	30	30.3	6.5	0.760	0.162
JFK	45	11	36	30.7	17.6	0.794	0.164
IND	33	29	31	31.0	2.0	0.756	0.165
PHX	29	33	33	31.7	2.3	0.753	0.166
SMF	31	26	38	31.7	6.0	0.765	0.167
AUS	28	40	32	33.3	6.1	0.735	0.171

(continued)

Table 6 continued

Airport	VFP	DEA	SFA	Mean Ranking	St. Dev. (Ranking)	Mean Efficiency Score	Std Dev (Score)
				Middle Ranked Airports (continued)			
SDF	34	31	37	34.0	3.0	0.743	5.457
DEN	37	34	39	36.7	2.5	0.729	0.173
DTW	36	41	35	37.3	3.2	0.712	0.178
SFO	40	39	34	37.7	3.2	0.709	0.178
MCI	39	36	41	38.7	2.5	0.715	7.506
				Bottom 15 Ranked Airports			
BOS	41	32	43	38.7	5.9	0.721	0.181
CVG	35	43	40	39.3	4.0	0.702	0.187
CLE	43	44	42	43.0	1.0	0.678	0.188
SJC	42	45	45	44.0	1.7	0.671	0.183
ALB	44	42	50	45.3	4.2	0.669	0.185
PHL	46	54	44	48.0	5.3	0.618	3.856
DFW	53	46	47	48.7	3.8	0.630	0.196
STL	49	52	46	49.0	3.0	0.614	0.200
ONT	48	48	51	49.0	1.7	0.623	0.200
LAX	54	47	48	49.7	3.8	0.617	0.203
ORD	50	51	49	50.0	1.0	0.612	0.206
BWI	51	49	53	51.0	2.0	0.616	0.209
PIT	52	50	52	51.3	1.2	0.609	5.103
MSY	47	53	54	51.3	3.	0.594	3.070
MIA	55	55	55	55.0	0.0	0.506	0.625

Figure 1: Residual Ranking Comparison of Top 15 Airports

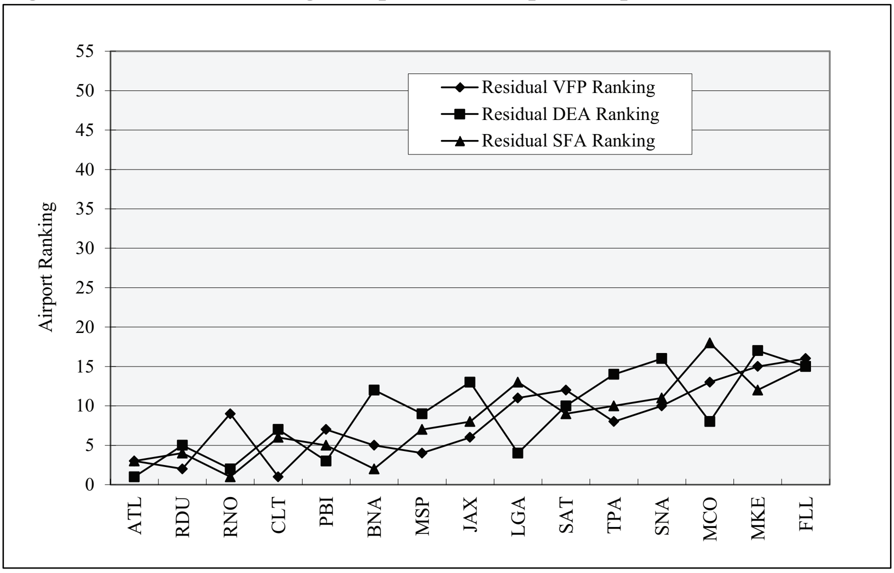

Figure 2: Residual Ranking Comparison of Bottom 15 Airports

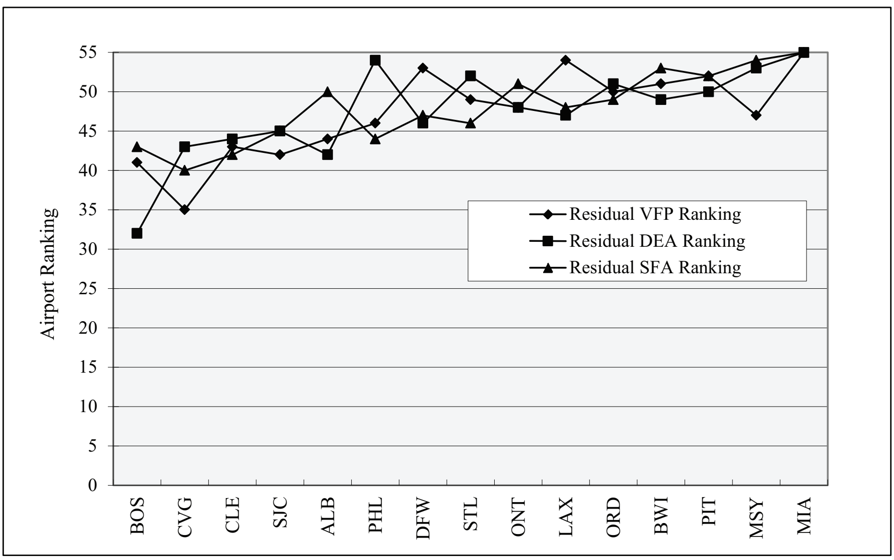

Figure 3: Residual Ranking Comparison of Mid-Ranked Airports

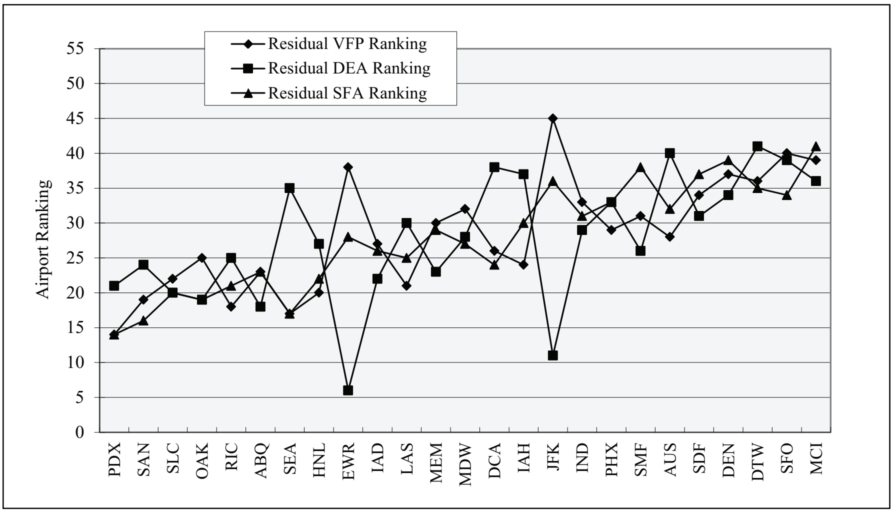

Table 7: Spearman's Rank Order Correlation Coefficients Among Residual Efficiency Estimates

	All sample		Top 15 airports		Mid-ranked airports		Bottom 15 airports	
	VFP	DEA	VFP	DEA	VFP	DEA	VFP	DEA
DEA	0.8468**	1	0.4643*	1	0.18	1	0.5821**	1
SFA	0.969**	0.8899**	0.7393**	0.55**	0.8577**	0.4154**	0.675**	0.5571**

*correlation is statistically significantly different from zero at the 10% level, two-sided.

**correlation is statistically significantly different from zero at the 5% level, two-sided.

CONCLUSION AND FURTHER RESEARCH NEED

This study reviews and compares airport operating efficiency indices measured by VFP (Variable Factor Productivity), DEA (Data Envelopment Analysis), and SFA (Stochastic (Production Frontier Analysis) methods, which have been used widely in past studies. Based on a sample of 62 major Canadian and US airports, this paper has compared the "gross" and managerial ("residual") operating efficiency scores and airport rankings estimated by each of these three alternative methods.

Both the gross efficiency and residual efficiency estimates by these three alternative methods are highly correlated. The airport efficiency rankings for both the top 15 and the bottom 15 airports are largely consistent across these three alternative methods, while significant differences exist in the mid-ranked airports. However, because of many corner solutions in DEA measurement and the consequent existence of a large number of efficient airports, the efficiency rankings based on the DEA method are considerably more different from those of the other two methods.

Given that the DEA application to the data has identified 12 efficient airports, each with gross DEA score of one (Table 3), it begs an important question whether or not there are truly significant differences in operating efficiencies among the top 10-15 airports, and if there are, how deep are the differences. This begs for further research of the top 10-15 airports (especially those 12 airports with gross DEA value of 1.0) based on micro-data.

Based on the average residual efficiency scores, Atlanta (ATL), Raleigh-Durham (RDU), Charlotte (CLT), Minneapolis-St. Paul (MSP), and Reno (RNO) show up as the top five most efficient airports in the U.S.

Endnotes

1. In the short run, airlines wishing to serve certain markets do not have much choice of airports, but in the end, airlines will consider efficient versus inefficient airports when they restructure their route networks.

2. The direct and/or indirect regulators such as aviation departments of cities and the FAA have various means to exert pressure on inefficient airports. Therefore, benchmarking of efficiency among peer airports provides at least indirect pressure on airport management to pay attention on efficiency.

3. To save space, this paper will not review the literature on airport productivity and efficiency in detail, please refer to Liebert and Niemeier (2010).

4. One should note that by excluding capital inputs and costs in the short-to-medium term efficiency analysis, this study aims to compare operating efficiencies that could be affected by airport managers in the short to medium term.

5. Since the CRS assumption may be violated for the airport industry, this problem is dealt with by including an output scale variable in the second stage regression analysis, which is discussed later.

6. Battese and Coelli (1992) define the concept of technical efficiency of a given firm as the ratio of its mean production to the corresponding production if the firm utilized its levels of inputs most efficiently.

7. This additional constraint represents a convexity constraint that ensures that an inefficient firm is only benchmarked against firms of a similar size.

8. On the other hand, one could argue that airport managers have more control over non-aeronautical activity volumes such as parking revenues, revenues from shops and restaurants, rental spaces, hotels, etc. This may be true only in the long run when capital investments on buildings and spaces can be adjusted, not necessarily so in the short to medium term for which the operating efficiency measures are based. Related to non-aeronautical revenue output, recent studies including Zhang et al. (2010), have discovered the increasing importance of external effects of increased aeronautical outputs airlines bring to an airport on the amount of non-aeronautical revenues the airport can generate. This implies that the aviation activity volumes are an increasing cause of the non-aeronautical revenue outputs.

9. The primary reason for using the SFA-production function instead of a cost function is the seemingly direct comparability of the three methodologies. Variable Factor Productivity (VFP) index is based on essentially the ratio of the output index and input index, and the DEA index directly relates outputs to inputs. Therefore, using a production function, which relates the output index directly to input quantities, serves the purpose of the study better. This also reduces our computational work.

10. The constant RTS allows cost shares to be used as aggregating weights for the inputs. Although the use of revenue shares of outputs as aggregating weights for outputs needs further assumptions, since the paper uses a single aggregate output index in all of the three methods, they are even on this dimension.

11. As pointed out by a referee, it is possible to detect outliers using methodologies such as Mahalanobis D2. There are two issues to confront. First of all, within the two-stage framework of analysis, without seeing results of the second stage analysis, it probably is hard to know what observations will be the outliers even if such methodologies as Mahalanobis D^2 are employed. Another issue is that it is expensive to researchers to lose several outlier airports' data points even if we are able to identify true outliers since it is expensive and time consuming to collect even one airport's data.

12. As a referee pointed out to us, airport revenue can be influenced by monopoly power. For example, an airport charging higher rates for parking may be influenced by the unavailability of close off-site parking options. Therefore, the airports with monopoly power may appear to be more productive than in reality.

13. The main reason why snow removal costs are removed from the total soft cost rather than including it in the second stage regression analysis is that for many airports, snow removal costs are zero. As such, this poses a problem in logarithmic transformation of the data unless some sort of transformation function such as Box-Cox form is used, which tends to complicate the analysis unnecessarily.

14. The Purchasing Power Parity (PPP) uses the long-term equilibrium exchange rate of two currencies to equalize their purchasing power. PPP equalizes the purchasing power of different currencies in their home countries for a given basket of goods.

15. The Cost of Living Index (COLI) is a composition index to measure the relative price level for consumer goods and services in areas for a mid-management standard of living. The overall index (100%) is composed of grocery items (13%), housing (29%), utilities (10%), transportation (10%), health care (4%), and miscellaneous goods and services (35%).

16. In the absence of COLI, city-based CPI is used to adjust Canadian airports. The COLI and CPI indices are linked with the US-Canada PPP exchange rate in 2006: 1US$=1.245CA$.

17. A variance inflation factor (*VIF*) diagnostic test was conducted after the OLS regression in order to see if there are significant multicollinearity problems among our explanatory variables. The test reveals there is no concern of multicollinearity problem. *Output size* and *percentage of International Traffic* have the highest *VIF* value of 2.18 and 2.04, respectively. As a rule of thumb, *VIF* values of considerably less than 10 do not raise concern in multicollinearity.

18. This negative coefficient for "aircraft size" in the second stage regression on the Canada/US airport data has been a bother for the last 10 years of the ATRS benchmarking work, especially because similar second stage regressions on European and Asian airport data show positive signs. However, this has been a consistent result over the last 10 years or so (even if each year's cross sectional data or a panel data of cross-section and time-series data are used). Some senior airport managers argue that the coefficient could be positive or negative. The authors would welcome further comments and/or research results on this issue.

19. A referee posed an interesting question on non-aeronautical revenue in the context of this paper's model, which excludes capital input (due to measurement problems) and focuses on operating efficiency measurement. The referee's point is that airport (a) with a lot of parking would be favored in our study as compared with airport (b) without any parking lots. While

this is a good counter example, the results on non-aeronautical revenue show that airport (a) should, in fact, be rated higher than airport (b). Airport (b) is not making a reasonable effort to increase non-aeronautical revenue, a part of which is parking revenue.

20. Since non-aeronautical revenue is controlled by airport managers, its effect is not deducted from "gross" scores when the residual efficiency scores are computed using the second stage regression results.

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