Measuring Technical Efficiency of Airports in Latin America

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Abstract

This paper studies technical efficiency and its determinants of airports in Latin America (LAC). The evolution of productive efficiency in the LAC Region has seldom been studied, mainly due to lack of publicly available data. Relying on a unique dataset that was obtained through questionnaires distributed to airport operators, we use Data Envelopment Analysis (DEA) methods to compute an efficient production frontier and compare the technical efficiency of LAC airports relative to airports around the world. In a second stage we estimate a truncated regression to study the drivers of observed differences in airport efficiency. According to our results, institutional variables (private/public operation), the socioeconomic environment (GDP level) and airport characteristics (Hub, share of commercial revenues) matter to explain airport productive efficiency. Finally, we also compute total factor productivity changes for LAC airports for the period 1995-2007. LAC is a region that has implemented a wide variety of private sector participation schemes for the operation of airports since the mid 90s. Our results show that private operators have not had higher rates of total factor productivity change.

JEL classification: L25, L33, L90

1. Introduction

During the last two decades there has been a growing interest in measuring the efficiency and performance of airports. On the one hand, the process of introducing private participation in the management and operation of airports and the birth of regulatory agencies in charge of setting tariffs for the sector brought along the need to assess the way in which airports are being operated. On the other hand, with the liberalization of competition among airlines, airports started competing with each other for connecting traffic (to become hub airports) which prompted them to increase their efficiency.

This interest has spurred a growing literature aimed at estimating the efficiency of the airport sector, mainly through the use of data envelopment analysis (DEA) methods. However,

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and mainly due to the lack of available data, to the best extent of our knowledge, there has not been any study that computes the efficiency and performance of airports of a representative sample of airports in Latin America[2].

The main objective of this paper is to fill this gap in the literature. We are able to do so using data collected from a questionnaire that was sent to the major airport operators in LAC (see Table A1 in the Appendix for a list of all LAC airports that responded our questionnaire). It should be noted that the sample assembled for this study is representative of the air transport sector in the LAC region. Indeed, the airports included in the sample account for more than 80% of total passengers and aircraft movements in the region and for 70% of total air cargo.

The paper first computes a data envelopment analysis (DEA) activity frontier for commercial airports around the world, using the data collected through the questionnaire together with information from airports in Europe, North America and Asia-Pacific taken from the Airport Benchmarking Report by the Air Transport Research Society (ATRS)[3]. These estimations allow us to observe where LAC airports are standing relative to the best practice in the sector. The method used also allows us to identify the peers of each airport in Latin America (i.e. airports around the world which are comparable to LAC airports and which operate on the efficiency frontier).

We then proceed to identify factors that drive the observed differences in technical efficiency in the airport sector. In order to do this we estimate a truncated regression model, using the efficiency scores of the first part as dependent variables, and as independent variables different factors that attempt to capture the institutional framework and socioeconomic environment in which airports operate as well as other airport specific characteristics.

Finally, the dataset we use in this paper also allows us to measure Total Factor Productivity Changes (TFPC) for LAC airports over the period 1995-2007. The methodology used to perform these estimations consists on the computation of a Malmquist quantity index of TFPC based on the non-parametric DEA approach.

The rest of the paper is organized as follows. Section 2 presents a brief review of the existing related literature. In Section 3 we present our estimations of a DEA activity frontier for commercial airports around the world and use these results to identify the peers of each of the airports in LAC. Section 4 studies the determinants of airport efficiency by estimating a truncated regression model. Section 5 presents Malmquist quantity indexes of TFPC for LAC airports over the period 1995-2007. Finally, Section 6 presents some concluding remarks.

2. Literature Review

Guillen and Lall (1997) pioneered the use of Data Envelopment Analysis techniques to study efficiency in the airport sector. Their paper uses data from 21 US airports for the period 1989-

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[2] Recent papers have used DEA to assess the technical efficiency of airports in Peru (Flor and de la Torre, 2008) and the airport of Santiago de Chile relative to a set of airports from several regions of the world (Gomez Lobo and Gonzalez, 2008).

[3] We use data for the years 2005 and 2006 from 22 airports in LAC, in addition to 23 airports from Asia-Pacific, 40 from Europe and 63 from Canada and US. See Table A2 for details.

1993. Using this dataset they define airports as producing two different classes of services: terminal services and movements. The authors then compute two different DEA frontiers for US airports, one for each of these two services. Finally, they estimate (using Tobit regressions) the effect that different variables (like whether or not an airport has rotational runways, whether or not it has preferential runway use or whether or not it has limit of operations, etc.) have on the efficiency scores of each airport.

Following Guillen and Lall (1997), a literature flourished using DEA methods to study the technical efficiency of the airport sector.[4] In what follows we do not attempt to provide a complete account of this literature. Instead, we review a small fraction of the existing papers in this area that is the most relevant for our paper. For a more complete and comprehensive account we refer the reader to Pestana Barros and Dieke (2008).

Using a Malmquist total factor productivity index and data envelopment analysis, Abbot and Wu (2002) investigate the efficiency and productivity of Australian airports during the 1990s. Their results show that Australian airports recorded strong growth in technological change and total factor productivity during this period. However, this growth was based almost exclusively on a shift of the production frontier, with growth in technical and scale efficiency lagging behind.

Pestana Barros and Dieke (2008) compute a single DEA frontier for Italian airports using data from the period 2001-2003. However, instead of using a Tobit regression to find determinants of airport efficiency as in Gillen and Lall (1997), following the suggestions made by Simar and Wilson (2007), they estimate a truncated regression. Among many other results, Pestana Barros and Dieke (2008) find that Hub airports tend to be more efficient and that privately operated airports also tend to have higher efficiency scores than their publicly operated counterparts. Following Pestana Barros and Dieke (2008) and Simar and Wilson (2007), in this paper we also rely on truncated regressions in order to study the determinants of the observed differences in airport efficiency.

It is worth highlighting that there are a few papers studying efficiency of airports in Latin America. For example, Flor and de la Torre (2008) use DEA methods to analyze efficiency and total factor productivity of airports in Peru. Similarly, Fernandes and Pacheco (2002) also employ DEA methods to compute a production frontier using data for Brazilian airports. However, these papers focus on the efficiency of the airport sector in one single Latin American country. Indeed, to the best extent of our knowledge our paper is the first one that computes a global efficient frontier for the airport sector including data from a representative set of Latin American countries. In contrast to previous studies, this paper identifies how far away Latin American airports stand from the best practice worldwide.

Given the trend towards the introduction of private sector participation in the airport sector, one of the variables we are interesting in testing is the effect that ownership has on airport efficiency (indeed, in our truncated regressions we include a dummy variable that determines whether airports are privately or publicly operated). There are other papers that study this issue. For example, using DEA methods Parker (1999) analyses the effect that privatization had on the efficiency level of British airports, and finds that privatization had no noticeable impact on technical efficiency. Based on panel data for the major airports in Asia-Pacific, Europe and

[4] Some other examples not mentioned in the main text are Gillen and Lall (2001), Murillo-Melchor (1999) and Fung *et al* (2008).

North America for the years 2001-2003, Oum, Adler and Yu (2006) study the effect that the type of ownership has on productive efficiency and profitability. Their results suggest that airports with government majority ownership and those owned by multi-level government are significantly less efficient than airports with private majority ownership.

Lastly, it should be noted that DEA is not the only methodology available that can be used to study the efficiency of the airport sector.[5] Indeed, some authors have studied productivity in this sector through methods different than DEA. For instance, Hooper and Hensher (1997) use index number methods to study the evolution of total factor productivity of Australian airports for the period 1988-1992. Oum, Yan and Yu (2008) study the effects of ownership forms on airports' cost efficiency by applying stochastic frontier analysis to a panel data of the world's major airports. Pestana Barros (2008) also uses stochastic frontier analysis to study the technical efficiency of airports in the UK. Finally, analyzing the efficiency of European airports, Pels, Nijkamp and Rietveld (2001) compare the results they get from DEA methods to the results obtained using stochastic frontier analysis. Their analysis shows that the stochastic frontier model they consider reproduces the DEA results in a quite reasonable way.

3. DEA Performance Indicators: Cross section for 2005-2006

In this section we compute a DEA activity frontier for commercial airports around the world. We use data for the years 2005 and 2006 from 22 LAC airports, in addition to 23 airports from Asia-Pacific, 40 from Europe and 63 from Canada and US (see Table A2 for details).

DEA is a deterministic non parametric approach used to build a benchmark, best practice frontier, based on available information. The method was first developed by Farrel (1957) and later consolidated by Charnes *et al* (1978). One of the main advantages of this approach is that it takes into account the multi-output multi-input dimensionality of production. Another advantage is that computations are based exclusively on measures of physical outputs and inputs, without the need of using prices, which are neither available nor are comparable, mainly at the international level.

Two models are computed under the competing assumptions of constant returns to scale (CRS) and variable returns to scale (VRS). This allows us to compute scale efficiencies and to identify for each airport the returns to scale region - increasing, constant or decreasing - in which it operates. We assume that airports have as production target the maximization of outputs for a given input combination; therefore we use an output orientated framework for this study.

Frontier models like DEA require the specification of inputs and outputs used in the industry under study. There have been considerable differences in the literature of airport efficiency estimation at the time of defining inputs and outputs. On the output side the more complete and often used model specification includes three output dimensions: passenger, freight and aircraft movements. On the inputs side there is fewer consensuses in the literature, mainly due to data availability problems. In any case, most studies include a bundle of variables representing labor and capital inputs. The most frequently used variables are number of

[5] For a complete and updated presentation of frontier analysis methods proposed in the literature, see Coelli et al. (2005) and Fried, Lovell and Schmit (2008).

employees as proxy for labor input, and capital proxies such as the number or size of runways, terminal size and the number of boarding bridges. When comparable accounting data is available, inputs are represented by operating costs and the monetary value of the capital stock.

In our case, and given the data at our disposal, we chose to specify a three-input three-output production function. The outputs that we use are (i) number of passengers, (ii) tons of freight and (iii) number of aircraft movements. On the other hand, our specification includes the following inputs: (i) number of employees, (ii) number of runways and (iii) number of boarding bridges.

The data, corresponding to the years 2005 and 2006, is well balanced for the 22 LAC airports but unbalanced for the other regions of the world, particularly for European airports. For this reason, we chose to pool the data for the benchmark study. In other words, we computed one single DEA frontier for the period 2005-2006.

Table 1 presents descriptive statistics on outputs and inputs by region. LAC airports are on average smaller than those from the other regions in terms of all three outputs: passenger, tons and aircraft movements. However, in spite of these differences in the scale of production, on average LAC airports employ nearly as much staff as Canadian and US airports. At the same time, in terms of capital investments, the number of runways and boarding bridges is several times lower in LAC airports than in Canadian and US airports.

Table 1: Descriptive statistics by world region (2005-2006)

Stat.	Outputs (x1000)			Inputs		
	Passenger	Tons of freight	Aircraft movements	Employees	Runways	Boarding bridges
LAC (22 airports, 44 observations)						
Mean	6,430.6	117.2	96.1	424.0	1.5	11.3
STD	6,033.6	119.0	82.9	412.0	0.5	9.7
Min.	181.0	0.2	1.9	20.0	1.0	0.0
Max.	24,727.0	470.9	356.0	1,568.0	2.0	38.0
ASIA (23 airports, 39 observations)						
Mean	18,776.7	836.0	148.2	1,044.0	1.7	52.3
STD	12,432.4	970.7	82.7	1,107.3	0.6	35.5
Min.	1,293.3	10.3	10.5	137.0	1.0	0.0
Max.	45,100.0	3,600.0	286.5	4,873.0	3.0	143.0
Europe (40 airports, 66 observations)						
Mean	19,305.0	318.3	211.8	2,029.4	2.3	67.9
STD	15,728.4	515.7	127.8	2,982.6	1.0	58.3
Min.	1,218.9	3.6	29.8	298.0	1.0	6.0
Max.	67,915.0	2,131.0	533.0	17,528.0	6.0	264.0
Canada & US (63 airports, 125 observations)						

Mean	21,318.4	406.5	310.9	549.9	3.4	69.9
STD	17,976.6	641.8	196.7	480.7	1.2	42.6
Min.	2,657.1	3.6	60.5	119.0	1.0	14.0
Max.	85,907.4	3,713.4	980.4	3,000.0	7.0	178.0

The computed Technical Efficiency (TE) scores for airports in the four regions are presented in Table 2.[6] The average TE score of airports in all regions is 0.545 under the constant returns to scale (CRS) assumption. This means that, on average, the airports included in the sample are half technically efficient or, in other words, that they could almost double their outputs using the same quantity of inputs.

However, part of the distance to the best practice CRS frontier is explained by the scale of operation. Under the variable returns to scale (VRS) assumption the average TE is 0.629 and the average scale efficiency is 0.875[7] . Moreover, for each scale inefficient airport we can identify the type of scale inefficiency: either increasing or decreasing returns to scale, denoted in Table 2 as IRS and DRS, respectively. In the last three columns of Table 2 we report the percentage of airports corresponding to this classification. Grouping all regions, 44.5%, 8.4% and 47.1% of the airports in our dataset operate under increasing, constant and decreasing returns to scale, respectively.[8]

LAC airports appear to be the ones that suffer the most from a suboptimal scale operation. Scale inefficiency is close to 20% (SE = 0.801), mainly concentrated in the increasing returns to scale area (70.5% of observations). This means that on average, airports in LAC could improve their efficiency 20% if they were to increase its scale of operation to the optimal scale. On the contrary, nearly 70% of Canadian and US airports operate in the decreasing returns to scale region. The results of return to scale diagnosis coincided with the intuition: airports in LAC are smaller and given that the production technology of airports is characterized by large fixed investments (runways, terminals) it is logical to expect that smaller airports are still in the increasing return to scale zone of the production function. Airports identified as operating at the optimal scale (CRS) in our database handle between 20 to 30 millions of passenger each year.

[6] All DEA computations, including Malmquist indexes presented in Section 5, were performed using the DEAP program developed by Coelli (1996).

[7] It should be noted that by construction, TE under VRS multiplied by SE equals TE under CRS.

[8] Table A2 in the Appendix replicates Table 2 but adds the results of computing average TE scores using a model with two inputs (leaving runways and staff and taking out boarding bridges). Investment in boarding bridges show a significant underinvestment in LAC (569,000 passengers per boarding bridge, compared with 359,000, 284,000 and 305,000 in Asia, Europe and North America respectively) and given that DEA can not measure quality of service, it tends to reward airports that underinvest in capital. When taking out boarding bridges the average TE score for LAC airports fall significantly relative to the average in other regions.

Table 2: Average TE scores and scale efficiency by region (2005-2006 average)

World Region	Technical efficiency			Returns to scale diagnosis (% of observations)		
	CRS	**VRS**	**Scale**	**IRS**	**CRS**	**DRS**
Latin America	0.532	0.690	0.801	70.5	9.1	20.5
Asia	0.670	0.771	0.869	84.6	12.8	2.6
Europe	0.490	0.530	0.927	43.9	6.1	50.0
Canada & US	0.540	0.616	0.875	23.2	8.0	68.8
All	0.545	0.629	0.875	44.5	8.4	47.1

Table 3 presents detailed results for LAC airports. Only two airports in the region are technically efficient under both CRS and VRS: CGH (Congonhas, São Paulo) and VCP (Viracopos, São Paulo). However, it is important to highlight that VCP is a special case: it is an efficient unit in DEA 'by default', which occurs when a production unit has no peers to which it can be compared. VCP is an airport that can be characterized as a dedicated freight airport as it has virtually no passenger movement and no boarding bridges. Other results of Table 3 can be summarized as: (a) TE scores for LAC airports show notable variations: from airports on the frontier (with a value of 1) to airports that have TE scores close to 0; (b) when assuming CRS, only two airports CGH and VCP are on the frontier; and (c) when VRS are assumed and consequently scale efficiency is isolated, the TE of LAC airports improve. Out of 22 airports, 6 are on the frontier. The subsection of sources of technical efficiency tries to identify the variables that explain the observed differences in TE scores across airports.

Table 3: Technical efficiency scores (2005-2006 average)

Country	Airport	CRS	VRS	Scale efficiency
Argentina	**AEP**	0.612	0.998	0.614
	EZE	0.414	0.417	0.993
	FTE	0.115	1.000	0.115
Brasil	**BSB**	0.498	0.536	0.931
	CGH	1.000	1.000	1.000
	GIG	0.318	0.320	0.994
	GRU	0.677	0.678	0.998
	MAO	0.377	0.692	0.544
	VCP	1.000	1.000	1.000
Chile	**SCL**	0.786	1.000	0.786

Colombia	**BAQ**	0.329	0.524	0.628
	CLO	0.496	0.734	0.676
Costa Rica	**SJO**	0.594	0.983	0.605
Ecuador	**GYE**	0.472	0.646	0.739
El Salvador	**SAL**	0.114	0.127	0.900
México	**CUN**	0.860	1.000	0.860
	GDL	0.643	0.649	0.991
	MEX	0.961	0.963	0.998
	MTY	0.403	0.410	0.982
Panamá	**PTY**	0.164	0.178	0.926
Perú	**LIM**	0.621	0.961	0.646
Rep. Dominicana	**SDQ**	0.260	0.372	0.699
ALL		0.532	0.690	0.801

The DEA approach allows the identification of peers for each airport, which are the set of efficient airports that make up the relevant frontier for a given airport. Table 4 presents the peers for LAC airports in 2005 under the VRS DEA model. Observations corresponding to 2006 are in brackets and airport peers from the LAC region appear underlined. It should be noted that, by construction, technically efficient airports do not have other airport as peers. Technical inefficient airports have, on the contrary, a benchmark composed by other units. Given the 3-output 3-inputs dimensionality of the production setting, the maximum number of peers is 6 but an airport can have less than 6 peers.

It is important to remark that some LAC airports are peers for other airports. Not only do they serve as peers (benchmark) for other airports in the LAC region but also for other airports around the world. This is the case mainly of CGH (Congonhas, São Pablo), which is a reference for 28 observations (2005 and 2006 airport observations taken together). Other airports playing the same role of peers are AEP (Aeroparque, Ciudad de Buenos Aires), SCL (Comodoro Merino Benítez, Santiago de Chile), CUN (Cancún) and, to a less extent, FTE (Calafate) and SJO (San José, Costa Rica). An interesting result is that all LAC airports in our sample, with the exception of MAO (Manaos), have as peers at least one Latin American airport. Eight airports from outside the LAC region act as peers for LAC airports: XMN (Xaimen), ICN (Seoul), SDF (Louisville), LAX (Los Angeles), MEM (Memphis), SNA (Costa Mesa, California), ATL (Atlanta) and MFM (Macau).

For illustration purposes, let us look in more detail at one observation, the case of BSB (Juscelino Kubitschek, Brasilia). For this airport we computed a DEA TE score of 0.552, which corresponds to a 45% output inefficiency diagnosis. The airports identified as peers for BSB are CGH (Congonhas, São Pablo) and three US airports: MEM (Memphis), LAX (Los Angeles) and SNA (Costa Mesa, California). If we simply compare BSB against CGH, its only LAC peer, and look at some of their main output-input features (for the year 2005), we get a confirmation of the

DEA result. On the output side BSB handles 9.4 million passengers per year, against the 17.1 million passengers of CGH. Similarly, BSB had 171.6 thousand aircraft movements in 2005, against 282.6 thousand aircraft movements in CGH. Finally, on the input side we see that BSB had 365 employees and 13 boarding bridges, while CGH had 225 employees and 8 boarding bridges.

Table 4: Peer analysis, DEA-VRS 2005

Country	Airport	TE-VRS 2005	As peer for other airports	Peers				
				1	2	3	4	5
Argentina	**AEP**	1.000	9	AEP				
	EZE	0.404	0	CGH	(CGH)	(XMN)	(ICN)	(SDF)
	FTE	1.000	7	FTE				
Brasil	**BSB**	0.552	0	CGH	LAX	MEM	SNA	
	CGH	1.000	28	CGH				
	GIG	0.316	0	(CGH)	(XMN)	(ICN)	ATL	
	GRU	0.680	0	(CGH)	(XMN)	(ICN)	ATL	
	MAO	0.680	0	SJO	(XMN)	MFM	SNA	
	VCP	1.000	0	VCP				
Chile	**SCL**	1.000	10	SCL				
Colombia	**BAQ**	0.507	0	FTE	SJO	(XMN)	SNA	
	CLO	0.747	0	(FTE)	SCL	S NA		
Costa Rica	**SJO**	1.000	6	SJO				
Ecuador	**GYE**	0.814	0	(FTE)	SJO	(XMN)	SNA	
El Salvador	**SAL**	0.131	0	(CGH)	LAX	MEM	SNA	
México	**CUN**	1.000	11	CUN				
	GDL	0.615	0	CGH	FTE	(XMN)	(SDF)	
	MEX	0.947	0	CGH	ICN	(XMN)	ATL	SNA
	MTY	0.424	0	CGH	(FTE)	(ATL)	MEM	SNA
Panamá	**PTY**	0.188	0	CGH	ICN	(XMN)	(SDF)	SNA
Perú	**LIM**	0.922	0	AEP	(LIM)	(SCL)	(XMN)	SNA
Rep. Dominicana	**SDQ**	0.386	0	AEP	(LIM)	(SCL)	SNA	(XMN)

Notes: Underlined peers are LAC airports. Between brackets are 2006 observations. Other airports: ICN (Seoul, Korea); MFM (Macau); XMN (Xiamen, China); ATL (Atlanta International); SDF (Louisville), MEM (Memphis), LAX (Los Angeles); SNA (Costa Mesa, California).

4. Sources of Technical Efficiency

In this section we estimate the effect that institutional factors, socioeconomic conditions, the demographic environment and characteristics particular to each airport have on efficiency. We do this by estimating a truncated regression model, using the airport efficiency scores of the previous section as dependent variables and these factors as explanatory variables. The choice of a truncated model is dictated by the nature of the technical efficiency measure (which is by definition truncated at 1.0) and by the findings of the recent academic literature (Simar and Wilson (2007)).[9]

Before presenting our results we stress that service quality is likely to be another potential factor behind the observed differences in airport efficiency. It is likely that, other things equal, airports operating with a large staff and/or a large number of boarding bridges provide better service quality to passengers. Unfortunately, survey data on users' satisfaction is not yet available at an international scale for us to be able to include quality indicators in our regression analysis.

Table 5 presents average values by region for the candidate variables to account for observed differences in technical efficiency. Starting with the institutional setting, Table 5 shows that on average LAC airports operate under a more liberalized framework. Indeed, more than half of LAC airports (54.5%) in our sample operate as private concessions, and 31.8% are regulated by an independent regulatory agency. In contrast, only 25.6% of Asian airports and 37.9% of European airports are under private management, while 10.3% and 16.7% of Asian and European airports respectively are regulated by an independent regulatory agency. Finally, all airports in Canada and the United States are operated by state-owned enterprises, and regulatory agencies in these two countries still depend directly from a political authority (a ministry).

Another potential factor that could have a role in the explanation of airport performance is the socioeconomic environment in which they operate. We incorporate this effect with two indicators: GDP per capita (measured in current dollars) and tourism expenditures (also measured in current dollars). However, it is worth stressing that these variables are only available at the country level and don't correspond necessarily to the area of influence of the airports.[10]

The demographic environment is represented by the concentration of population in the area served by the airport. On average, LAC airports appear to serve very large urban agglomerations, like their Asian counterparts. Compared to European and North-American airports, which are on average located in cities with 3 to 4 million inhabitants, LAC airports are on average located in cities with 8 million people. In the regression analysis this information will be incorporated with a binary (dummy) variable that takes a value 1 for airports located in cities with more than 5 million people and 0 otherwise[11].

[9] We estimate truncated regressions using the "truncreg" procedure of SATA 9.0.

[10] Given that our dataset contained a lot of airports in the United States and given the availability of data, for these airports we used GDP per capita of the state in which each airport is located, instead of GDP per capita for the country as a whole.

[11] The value of 5 million corresponds to the mean of the population of the cities where airports are located.

Finally, we introduce a set of variables that represent characteristics that are particular to each airport. One of them is their specialization as a hub, represented by the percentage of connecting passengers. LAC airports have the lowest percentage of connecting passengers (and also have the lowest percentage of Hubs), followed by Asian airports. The highest percentage is observed among European airports, where nearly one third of passengers are connecting. Another variable that is particular to each airport is the share of aeronautical revenues in total revenues. In Table 5 below we see that aeronautical revenues are on average rather more important for LAC airports (where they represent almost 60% of total revenues) than for airports in any other region.

Table 5: Potential explanatory factors of technical inefficiency (2005-2006)

Explanatory factors	Latin America	Asia	Europe	Canada & United States
Institutional framework				
Private airport (%)	54.5	25.6	37.9	0
Independent Regulatory Agency (%)	31.8	10.3	16.7	0
Socioeconomic environment				
GDP per capita (U$D)	5,442	17,397	32,598	42,219
Tourism expenditures per capita (U$D)	69	532	943	393
Population concentration				
Population in the area (1,000)	7,719	6,709	3,200	3,984
Population > 5,000,000 (%)	45.5	48.7	22.7	34.4
Airport characteristics				
Hub airport (%)	9.1	17.9	40.9	27.2
Passengers connecting (% of passenger)	7.9	9.5	32.8	23.4
Aeronautical Revenues (% of total revenue)	56.9	53.8	51.6	49.2

Table 6 reports the results -in the form of marginal effects- of estimations for alternative truncated regression models. The first two columns show the estimates of two models with VRS TE scores as dependent variable, with and without dummies for each world region. The third column presents the estimates of a model with CRS TE scores as dependent variable, without regional dummies. The Likelihood Ratio Tests (LT) indicate that in all three cases the variables included in the model, taken together, have a statistically significant effect on the dependent variable.

First, it should be noted that there are two variables that appear as the main drivers of technical efficiency in the airport sector. On the one hand Hub airports are, on average and depending on the specification of the model, 10% to 15% points more efficient than non-Hub airports. On the other hand, the size of the population in the area served by the airport also seems to matter: airports located in cities with more than 5 million inhabitants are 17% to 20% more efficient than airports that serve less populated areas.

Second, our results show that the institutional variables (whether the airport is private or public and whether it is regulated by an independent regulatory agency), are associated with positive marginal effects. However, these variables are not statistically significant, with the exception of the dummy for private airports under the VRS assumption. According to these results, privately operated airports tend to be more efficient, with a TE score that is on average 6% to 8% points higher than publicly operated airports.

Another important feature that distinguishes airports is the importance of aeronautical activities in their operation. As expected, the importance of these activities, summarized by the share of aeronautical revenues in the total airport revenue, plays a negative effect on efficiency (although this effect is statistically significant only when we use VRS TE scores as the dependent variable). In other words, airports in which non-aeronautical (i.e. commercial) activities are more important tend to be more efficient. The estimated marginal effect indicates that, on average and holding the other variables constant, a 10% increase in the share of aeronautical revenues produces a loss in technical efficiency of nearly 2%.

GDP per capita seems to have a positive effect on airport efficiency. However, it estimate is only significant in the VRS model (with regional dummies). In this case, when GDP per capita increases 10,000 USD higher the technical efficiency of airports is expected to increase 6%. Finally, tourism expenditure is not significant in the three specifications..

Table 6: Truncated regressions - Marginal effects

Explanatory factors	**VRS TE With regional dummies**		**VRS TE Without regional dummies**		**CRS TE Without regional dummies**	
	Marginal effect	**(std)**	**Marginal effect**	**(std)**	**Marginal effect**	**(std)**
Institutional framework						
Private airport (dummy)	0.064	(0.036)*	0.082	(0.035)**	0.068	(0.041)
Regulation authority (dummy)	0.048	(0.048)	0.041	(0.050)	0.083	(0.059)
Socioeconomic environment						
GDP per capita	0.006	(0.002)***	0.001	(0.001)	0.001	(0.001)
Tourism expenditures per capita	- 0.033	(0.049)	- 0.005	(0.033)	- 0.045	(0.036)
Population concentration						
Population > 5,000,000 (dummy)	0.169	(0.025)***	0.201	(0.027)***	0.173	(0.031)***
Airport characteristics						
Hub airport (dummy)	0.122	(0.028)***	0.099	(0.031)***	0.153	(0.031)***
Aeronautical Revenues	- 0.150	(0.081)*	- 0.183	(0.085)**	- 0.134	(0.102)
Control variables (dummies)						
Asia	0.059	(0.047)	-	-	-	-
Europe	- 0.200	(0.059)***	-	-	-	-
Canada and US	- 0.201	(0.069)***	-	-	-	-

Year 2006	- 0.023 (0.023)	- 0.107 (0.024)	- 0.210 (0.274)
LR test	$Chi^2(11)$ 110.3***	$Chi^2(8)$ 80.8***	$Chi^2(8)$ 56.7***
Observations	251	251	251

***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

5. Measuring productivity change of LAC airports

The objective of this section is to assess how airport productivity evolved in Latin America. To that end we compute annual total factor productivity change (TFPC) for LAC airports over the period 1995 to 2007. The period covered was determined by the data compiled through the questionnaires distributed for the elaboration of a World Bank report on Airports in Latin America (World Bank, 2009). We rely on the same 3-output 3-input model specification used in the international benchmark study presented above and the methodology consists in the computation of a Malmquist quantity index of TFPC based on the non-parametric DEA approach (the reader is referred to Färe *et al* (1994) for details).

The Malmquist index of TFPC presents two advantages with respect to traditional index numbers. On the one hand prices are not needed to calculate this index. On the other hand, the index can be decomposed into a measure of technical progress (TC) of the activity level taken as a whole, and another measure (TEC) that captures how each unit is catching up with respect to the technological frontier. Its main disadvantage compared with traditional index numbers is that it cannot be computed separately for each unit. Its computation relies on the estimation of sequential frontiers. And for this purpose panel data must be available for representative units operating in the sector.

Table 7 presents descriptive statistics for the three sub periods in which we decomposed the sample: 1995-1999, 2000-2003 and 2004-2007. For each of these three sub periods the number of airports in our sample varies noticeably, from 7 to 22. As a consequence, the benchmark used for TFPC computations varies as well and the results should be interpreted carefully, mainly for the TFPC decomposition into TEC and TC[12].

The average TFPC values reported in Table 8-Table 10 exclude 14 over 154 observations. These observations correspond to airports which introduced major changes in their capital stock in a particular year (given by increases in either the number of runways or boarding bridges). Given that these types of investments are lumpy by nature and that their introduction is followed by an initial period of underutilization, they tend to have a big negative impact on measures of productivity change. Table A3 in the Appendix reports the detailed results for all airports and years. Those cases corresponding to changes in the stock of either the number of runways or boarding bridges are in bold. In most cases the TFPC index corresponding to these observations are, as expected, highly negative.

[12] The only criterion used to split the data was to obtain 3 sub periods with equivalent number of years. The sample covers a large range of airports sizes. Measuring size by the number of passengers per year the sample ranges from 158,000 to 25,800,000 passengers. Zero values are reported for some variables. On the output side, this is the case for freight transportation for at least one airport. And on the input side, at least one airport is not equipped with boarding bridges, still in the year 2007.

Table 7: Descriptive statistics by period

Stat.	Outputs (x1000)			Inputs		
	Passenger	Tons of freight	Aircraft movements	Employees	Runways	Boarding bridges
1996-1999 (7 airports, 26 observations)						
Mean	5,039.7	145.4	119.1	723.5	1.5	9.7
STD	4,586.1	125.7	80.9	690.0	0.5	10.1
Min.	250.6	21.4	30.5	77.0	1.0	0.0
Max.	14,705.1	409.2	293.8	2,056.0	2.0	38.0
2000-2003 (17 airports, 60 observations)						
Mean	6,136.6	132.8	112.4	429.3	1.5	11.8
STD	5,314.4	124.2	88.0	465.8	0.5	10.9
Min.	654.8	10.4	29.5	56.0	1.0	0.0
Max.	21,694.0	418.9	334.5	1,940.0	2.0	38.0
2004-2007 (22 airports, 85 observations)						
Mean	6,579.4	121.1	99.1	433.9	1.5	12.0
STD	5,992.7	120.6	83.6	421.9	0.5	10.7
Min.	157.9	0.0	1.9	20.0	1.0	0.0
Max.	25,882.0	470.9	379.0	1,598.0	2.0	56.0

In Table 8 we present the main results: TFPC by sub period and by airport. In order to avoid potential biases due to unbalanced panel data, Malmquist index computations were performed separately for each two-year sequential period using in each case a balanced panel of airlines.

Average productivity growth oscillated over the three sub periods. Between 1995 and 1999, airports in the region posted an average annual productivity growth of 4.4%. However, it should be noted that this growth corresponds to the average scores of Brazilian airports and the airport in Barranquilla, Colombia, the only airports for which data is available for this period. Average productivity growth during the intermediate period (1999-2003) was negative (-1.2% per year), and was driven mainly by some airports which experimented dramatic losses in productivity, like EZE (Ministro Pistarini, Buenos Aires) which showed an average loss in productivity of -18.1% per year over this period as a direct consequence of the severe economic and financial crisis Argentina suffered during 2001/2002. On the contrary, positive rates of growth appear to be the norm (with only some exceptions) during the last sub period (2003 to 2007). The average TFPC rate was 3.9% during this period, with many airports experimenting annual productivity growth rates close to, or even higher than, 10%.

Table 8: Average TFPC by airport and sub period (Annual %)

Country	Airport	1995-1999	1999-2003	2003-2007
Argentina	AEP	-	-7.0	-3.0
	EZE	-	-18.9	4.0
	FTE	-	-	22.9
Brasil	BSB	12.0	5.4	2.9
	CGH	11.5	2.6	-4.0
	GIG	4.5	-5.5	16.3
	GRU	7.2	-0.9	2.7
	MAO	-3.7	0.3	6.8
	VCP	-0.5	-7.6	-0.8
Chile	SCL	-	1.3	2.0
Colombia	BAQ	-2.2	-8.4	1.5
	CLO	-	-6.2	-5.1
Costa Rica	SJO	-	22.1	0.0
Ecuador	GYE	-	-	8.1
El Salvador	SAL	-	2.7	1.4
México	CUN	-	6.6	-0.3
	GDL	-	-6.1	9.5
	MEX	-	1.1	4.9
	MTY	-	5.8	4.7
Panamá	PTY	-	-	7.4
Perú	LIM	-	-	9.7
Rep. Dominicana	SDQ	-	-	-3.7
ALL		4.4	- 1.2	3.9

A relevant policy question is whether private operated airports in LAC, a region that has experienced with a wide variety of private sector participation schemes for the operation of airports, have higher productivity gains. Table 9 sheds some light to this question. As the exercise of estimation of explanatory variables of TE scores at the international level showed, private operation is a relevant variable to explain differences in productivity. Table 9 also presents changes in productivity dividing airports by size and then uses the Work Load Unit measure to weight airports to avoid reaching a conclusion on public/private operated airports biased by the size of airports.

The results reported in Table 9 show that the largest airports are the ones that registered faster productivity growth. In particular, those airports that handle between 7.5 and 10.0 million passengers per year posted an average annual growth rate of 5.3% for the whole period, and an even higher growth of 7.0% during the last sub period. Interestingly, the category made up by the three biggest airports in the region (CGH, GRU and MEX, which handle more than 10 million passengers per year), grew faster during the first sub period, but at a rather low rate over the two last sub periods.

Public airports appear to have performed better on average over the whole period compared to private airports (annual productivity changes of 2.8% and 1.4%, respectively). Nevertheless, if we focus on their evolution over the last two sub periods, for which the available information is more complete, both groups behaved quite similarly, registering negative productivity growth during the period 1999-2003 and positive growth between 2003 and 2007 (although with a slightly more favorable profile for public airports). These results are confirmed when we weight TFPC averages using work-load unites (WLU) as the weight variable.[13] Weighted averages give a better approximation of the productivity growth for the whole airport activity in the region. Since larger airports performed better than smaller ones, we see that the weighted average TFPC is higher than the non-weighted average (2.8% against 2.2%).

Table 9: Average TFPC by airport categories (Annual %)

Airport categories	**1995-1999**	**1999-2003**	**2003-2007**	**ALL**
Non-weighted				
Size (10^6 passengers)				
< 5.0	- 2.1	- 1.8	3.5	1.0
5.0 to 7.5	-	- 4.3	3.7	0.5
7.5 to 10.0	8.7	1.7	7.0	5.3
> 10.0	9.4	0.9	1.8	3.6
Private-Public				
Private	- 2.2	- 1.6	3.4	1.4
Public	5.0	- 0.8	4.5	2.8
ALL	4.4	- 1.2	3.9	2.2
Weighted *				
Private-Public				
Private	- 1.9	- 0.5	2.7	1.5
Public	7.0	0.2	4.4	3.4
ALL	6.8	0.0	3.7	2.8

[13] One WLU is equivalent to one terminal passenger or 100 kg of freight or mail.

* Weighted by WLU.
Public airports: BSB, CGH, GIG, GRU, MAO and VCP (Brasil); SAL (El Salvador); MEX (México); and PTY (Panamá). Private airports: AEP, EZE, FTE (Argentina); SCL (Chile), BAQ and CLO (Colombia); SJO (Costa Rica); GYE (Ecuador); CUN GDL and MTY (México); and LIM (Perú).
Airport size: < 5.0: BAQ, CLO, FTE, GYE, MAO, PTY, SAL, SDQ and SJO; 5.0-7.5: AEP, EZE, GDL, LIM, MTY and SCL; 7.5-10.0: BSB, CUN and GIG; > 10.0: CGH, GRU and MEX.

Finally, Table 10 presents the decomposition of Malmquist TFPC index into its two main components, technical efficiency change (TEC) and technical change (TC). This table presents weighted (by WLU) average results. They show that the airport industry in Latin America did not experiment any improvement in productivity due to technical change over the period. In other words, there was no significant change in the production frontier of the industry between 1995 and 2007, since the TC index is near zero or even negative, except for the first sub period.

In fact, the table shows that the main source of TFPC corresponds to improvements in technical efficiency (TEC), particularly during the last sub-period. This result should be interpreted in terms of a catching-up phenomenon. LAC airports, certainly many among them, grew during this period mainly by adapting well known technologies and production processes. This process allowed them to stand today closer to the activity frontier than they were at the beginning of the period.

Table 10: Malmquist TFPC index decomposition – Weighted averages by period (Annual %)

Period	TEC	TC	TFPC
1995-1999	0.5	6.3	6.8
1999-2003	1.1	-1.1	0.0
2003-2007	4.3	-0.6	3.7
1995-2007	2.6	0.2	2.8

* Weighted by WLU.

6. Conclusions

To the best extent of our knowledge, this paper is the first to conduct a comprehensive efficiency estimation of Latin American airports. In this sense, the main objective of this study was to fill in this gap of the literature on airport efficiency estimation.

Our results show that Latin American airports are on average less efficient than Asian and North American airports under a CRS model, but more efficient than European airports. If we assume instead a VRS model then LAC appears as the second region in terms of airport efficiency, behind Asia.

Two airports in Latin America are operating on the efficient frontier under both CRS and VRS: Congonhas airport (in São Pablo, Brazil) and VCP (Viracopos, São Paulo). VCP is a special case: it is an efficient unit in DEA 'by default', which occurs when a production unit has no peers to which it can be compared. VCP is an airport that can be characterized as a dedicated freight airport as it has virtually no passenger movement and no boarding bridges.

Using the DEA efficiency scores, we estimated a truncated regression model in order to find factors that might explain the observed differences in airport efficiency. As expected, the regression analysis shows that airports that serve as Hubs tend to be more efficient. Moreover, airports which are located in cities with more than 5 million inhabitants are also more efficient than airports located in smaller cities. The level of income (GDP) also seems to positively influence productive efficiency. Airports that rely more on revenue sources other than aeronautical tariffs also tend to be more efficient, a finding consistent with the recent literature (ATRS, 2008). Finally, airports which are privately operated tend to stand closer to the efficient frontier than their publicly operated counterparts, although this effect is not significant across all the different specifications of the model we tested.

Our estimations of Total Factor Productivity Change show that productivity growth in the airport sector in Latin America has been driven mainly by improvements in technical efficiency, and not by pure technical change. This finding implies that the efficient production frontier of the sector did not experience any major shift between 1995 and 2007, but many airports were able to raise their efficiency level and become more productive, a process by which they were able to come closer to the efficient frontier. Probably the most unexpected result is that privately operated airports in LAC have not outperformed publicly operated airports. Given the wide variety of private participation schemes used by Latin American countries, this result should lead to more detailed and case by case research to assess the effects of private participation on airport performance. In addition, future research should also assess financial efficiency as well as the impact of private participation in the quality of service delivered. Strikingly, no LAC airport operator among the 22 sampled fully answered the questionnaire' section devoted to measuring the quality of service.

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Appendix

Table A1: Airports in Latin American and Caribbean Airports that responded the questionnaire

Country	*Airport Name*	*IATA Code*
Buenos Aires, Argentina	Aeroparque Jorge Newbery	AEP
Buenos Aires, Argentina	Aeropuerto Internacional Ministro Pistarini	EZE
El Calafate, Argentina	Aeropuerto Internacional El Calafate	FTE
Nassau, Bahamas	Lynden Pindling International Airport	NAS
São Paulo, Brazil	Congonhas International	CGH
São Paulo, Brazil	Viracopos-Campinas International	VCP
São Paulo, Brazil	Guarulhos International	GRU
Brasilia, Brazil	Juscelino Kubitschek	BSB
Manaos, Brazil	Eduardo Gomes International	MAO
Rio de Janeiro, Brazil	Galeão International	GIG
Santiago de Chile, Chile	Aeropuerto Int. Comodoro Arturo Merino Benítez	SCL
Bogotá, Colombia	Aeropuerto Internacional El Dorado	BOG
Cali, Colombia	Aeropuerto Alfonso Bonilla Aragón	CLO
Barranquilla, Colombia	Aeropuerto Internacional Ernesto Cortissoz	BAQ
Medellín, Colombia	Aeropuerto Internacional José María Córdova	MDE
San José, Costa Rica	Aeropuerto Internacional Juan Santamaría	SJO
Guayaquil, Ecuador	Aeropuerto Internacional José Joaquín de Olmedo	GYE
San Salvador, El Salvador	Aeropuerto Internacional El Salvador	SAL
Ciudad de Guatemala, Guatemala	Aeropuerto Internacional La Aurora	MGGT
Guadalajara, México	Aeropuerto Internacional De Guadalajara	GDL
Monterrey, México	Aeropuerto Int. General Mariano Escobedo	MTY
Ciudad de México, México	Aeropuerto Internacional Benito Juárez	MEX
Cancún, México	Aeropuerto Internacional de Cancún	CUN
Ciudad de Panamá, Panamá	Aeropuerto Internacional de Tocumen	PTY
Lima, Perú	Aeropuerto Internacional Jorge Chávez	LIM
Sto. Domingo, Rep. Dominicana	Aeropuerto Internacional de Las Américas	SDQ
Port of Spain, Trinidad and Tobago	Piarco International Airport	POS

Table A2: airports included in ATRS Airport Benchmarking Report

North America – United States		
City, State	*Airport Name*	*IATA Code*
Atlanta, Georgia	Albuquerque International Sunport	ABQ
Albany, New York	Albany International Airport	ALB
Atlanta, Georgia	Hartsfield-Jackson Atlanta International Airport	ATL
Austin, Texas	Austin Bergstrom Airport	AUS
Nashville, Tennessee	Nashville International Airport	BNA
Boston, Massachusetts	Boston Logan International Airport	BOS

Baltimore, Maryland	Baltimore Washington International Airport	BWI
Cleveland, Ohio	Cleveland-Hopkins International Airport	CLE
Charlotte, North Carolina	Charlotte Douglas International Airport	CLT
Cincinnati, Ohio	Cincinnati/Northern Kentucky International Airport	CVG
Washington, DC	Ronald Reagan Washington International Airport	DCA
Denver, Colorado	Denver International Airport	DEN
Dallas, Texas	Dallas/Fort Worth International Airport	DFW
Detroit, Michigan	Detroit Metropolitan Wayne County Airport	DTW
Newark, New Jersey	Newark Liberty International Airport	EWR
Ft. Lauderdale, Florida	Fort Lauderdale Hollywood International Airport	FLL
Honolulu, Hawaii	Honolulu International Airport	HNL
Washington, DC	Washington Dulles International Airport	IAD
Houston, Texas	Houston-Bush Intercontinental Airport	IAH
Indianapolis, Indiana	Indianapolis International Airport	IND
Jacksonville, Florida	Jacksonville International Airport	JAX
New York, New York	New York-John F. Kennedy International Airport	JFK
Las Vegas, Nevada	Las Vegas McCarran International Airport	LAS
Los Angeles, California	Los Angeles International Airport	LAX
New York, New York	LaGuardia International Airport	LGA
Kansas City, Missouri	Kansas City International Airport	MCI
Orlando, Florida	Orlando International Airport	MCO
Chicago, Illinois	Chicago Midway Airport	MDW
Memphis, Tennessee	Memphis International Airport	MEM
Miami, Florida	Miami International Airport	MIA
Milwaukee, Wisconsin	General Mitchell International Airport	MKE
Minneapolis, Minnesota	Minneapolis/St. Paul International Airport	MSP
New Orleans, Louisiana	Louis Armstrong New Orleans International Airport	MSY
Oakland, California	Oakland International Airport	OAK
Ontario, California	Ontario International Airport	ONT
Chicago, Illinois	Chicago O'Hare International Airport	ORD
West Palm Beach, Florida	Palm Beach International Airport	PBI
Portland, Oregon	Portland International Airport	PDX
Philadelphia, Pennsylvania	Philadelphia International Airport	PHL
Phoenix, Arizona	Phoenix Sky Harbor International Airport	PHX
Pittsburgh, Pennsylvania	Pittsburgh International Airport	PIT
Raleigh, North Carolina	Raleigh-Durham International Airport	RDU
Richmond, Virginia	Richmond International Airport	RIC
Reno, Nevada	Reno/Tahoe International Airport	RNO
San Diego, California	San Diego International Airport	SAN
San Antonio, Texas	San Antonio International Airport	SAT
Louisville, Kentucky	Louisville International-Standiford Field	SDF
Seattle, Washington	Seattle-Tacoma International Airport	SEA
San Francisco, California	San Francisco International Airport	SFO
San José, California	Norman Y. Mineta San José International Airport	SJC
Salt Lake City, Utah	Salt Lake City International Airport	SLC
Sacramento, California	Sacramento International Airport	SMF
Costa Mesa, California	John Wayne Orange County Airport	SNA
St. Louis, Missouri	St. Louis-Lambert International Airport	STL

Tampa, Florida	Tampa International Airport	TPA

North America – Canada

City, Province	*Airport Name*	*IATA Code*
Edmonton, Alberta	Edmonton International Airport	YEG
Halifax, Nova Scotia	Halifax International Airport	YHZ
Ottawa, Ontario	Ottawa International Airport	YOW
Montréal, Quebec	Montréal-Pierre Elliot Trudeau International Airport	YUL
Vancouver, British Columbia	Vancouver International Airport	YVR
Winnipeg, Manitoba	Winnipeg International Airport	YWG
Calgary, Alberta	Calgary International Airport	YYC
Toronto, Ontario	Toronto Lester B. Pearson International Airport	YYZ

Europe

City, Country	*Airport Name*	*IATA Code*
Amsterdam, Netherlands	Amsterdam Schiphol International Airport	AMS
Stockholm, Sweden	Stockholm Arlanda International Airport	ARN
Athens, Greece	Athens International Airport	ATH
Barcelona, Spain	Barcelona El Prat Airport	BCN
Birmingham, England	Birmingham International Airport	BHX
Brussels, Belgium	Brussels International Airport	BRU
Budapest, Hungary	Budapest Ferihegy International Airport	BUD
Bratislava, Slovak	Bratislava Milan Rastislav Stefanik Airport	BTS
Paris, France	Paris Charles de Gaulle International Airport	CDG
Cologne, Germany	Cologne/Bonn Konrad Adenauer International	CGN
Rome, Italy	Ciampino Airport	CIA
Copenhagen, Denmark	Copenhagen Kastrup International Airport	CPH
Dublin, Ireland	Dublin International Airport	DUB
Dusseldorf, Germany	Flughafen Dusseldorf International Airport	DUS
Edinburgh, Scotland	Edinburgh Airport	EDI
Rome, Italy	Rome Leonardo Da Vinci/Fiumicino Airport	FCO
Frankfurt, Germany	Frankfurt Main International Airport	FRA
Geneva, Switzerland	Geneve Cointrin International Airport	GVA
Hamburg, Germany	Hamburg International Airport	HAM
Helsinki, Finland	Helsinki Vantaa International Airport	HEL
Istanbul, Turkey	Istanbul Ataturk International Airport	IST
Kiev, Ukraine	Boryspil State International Airport	KBP
Reykjavik, Iceland	Keflavik International Airport	KEF
London, England	London Gatwick International Airport	LGW
London, England	London Heathrow International Airport	LHR
Lisbon, Portugal	Lisbon Portela Airport	LIS
Ljubljana, Slovenia	Ljubljana Airport	LJU
Madrid, Spain	Madrid Barajas International Airport	MAD
Manchester, England	Manchester International Airport	MAN
Valleta, Malta	Malta International Airport	MLA
Munich, Germany	Munich International Airport	MUC
Milan, Italy	Milan Malpensa International Airport	MXP
Paris, France	Paris Orly Airport	ORY
Oslo, Norway	Oslo Airport	OSL
Prague, Czech Republic	Prague International Airport	PRG

Riga, Latvia	Riga International Airport	RIX
Sofia, Bulgaria	Sofia International Airport	SOF
London, England	London Stansted Airport	STN
Tallinn, Estonia	Tallinn Airport	TLL
Berlin, Germany	Berlin Tegel Airport	TXL
Vienna, Austria	Vienna International Airport	VIE
Warsaw, Poland	Warsaw Frederic Chopin Airport	WAW
Zurich, Switzerland	Zurich International Airport	ZRH

Asia Pacific

City, Country	*Airport Name*	*IATA Code*
Adelaide, Australia	Adelaide International Airport	ADL
Auckland, New Zealand	Auckland International Airport	AKL
Bangkok, Thailand	Bangkok International Airport	BKK
Brisbane, Australia	Brisbane Airport	BNE
Mumbai, India	Chhatarpati Shivaji International Airport	BOM
Guangzhou, China	Bai Yun Airport	CAN
Jakarta, Indonesia	Jakarta Soekarno-Hatta International Airport	CGK
Christchurch, New Zealand	Christchurch International Airport	CHC
Cairns, Australia	Cairns International Airport	CNS
Chiang Mai, Thailand	Chiang Mai International Airport	CNX
New Delhi, India	Indira Gandhi International Airport	DEL
Dubai, UAE	Dubai International Airport	DXB
Haikou, China	Meilan International Airport	HAK
Hat Yai, Thailand	Hat Yai International Airport	HDY
Hong Kong, Hong Kong	Hong Kong Chek Lap Kok International Airport	HKG
Phuket, Thailand	Phuket International Airport	HKT
Seoul, Korea	Incheon International Airport	ICN
Osaka, Japan	Kansai International Airport	KIX
Kuala Lumpur, Malaysia	Kuala Lumpur International Airport	KUL
Chennai, India	Chennai International Airport	MAA
Melbourne, Australia	Melbourne Tullamarine International Airport	MEL
Macau	Macau International Airport	MFM
Manila, Philippines	Ninoy Aquino International Airport	MNL
Tokyo, Japan	Tokyo Narita International Airport	NRT
Beijing, China	Beijing Capital International Airport	PEK
Penang, Malaysia	Penang International Airport	PEN
Perth, Australia	Perth International Airport	PER
Shanghai, China	Shanghai Pudong International Airport	PVG
Seoul, South Korea	Seoul Gimpo International Airport	SEL
Shanghai, China	Shanghai Hongqiao International Airport	SHA
Singapore, Singapore	Singapore Changi International Airport	SIN
Sydney, Australia	Sydney Kingsford Smith International Airport	SYD
Shenzhen, China	Shenzhen Baoan International Airport	SZX
Taipei, Taiwan	Chiang Kai-Shek International Airport	TPE
Wellington, New Zealand	Wellington International Airport	WLG
Xiamen, China	Xiamen Gaoqi International Airport	XMN

Table A11: Average TE scores and scale efficiency by region (2005-2006 average)
Model with 3 Outputs and 2 Inputs

World Region	Technical efficiency			Returns to scale diagnosis (% of observations)		
	CRS	VRS	Scale	IRS	CRS	DRS
Latin America	0.283	0.399	0.796	63.6	6.8	29.5
Asia	0.477	0.528	0.901	38.5	2.6	59.0
Europe	0.454	0.512	0.886	47.0	7.6	45.5
Canada & US	0.443	0.491	0.911	36.8	5.6	57.6
All	0.425	0.487	0.885	43.8	5.8	50.4

Table A3: LAC airports TFPC (Annual %)

Year	Argentina			Brazil						Chile	Colombia		Costa Rica
	AEP	EZE	FTE	BSB	CGH	GIG	GRU	MAO	VCP	SCL	BAQ	CLO	SJO
1995-1996	-	-	-	9.9	8.4	4.1	11.7	-21.5	-4.4	-	-	-	
1996-1997	-	-	-	23.6	20.3	9.3	5.3	-3.0	9.0	-	-	-	
1997-1998	-	-	-	17.7	8.8	0.2	15.2	8.5	2.6	-	9.6	-	
1998-1999	-	-	-	-1.5	9.1	**-22.7**	-2.5	4.0	-8.4	-	-12.7	-	
1999-2000	-	-	-	8.2	12.9	5.6	1.2	5.9	20.0	11.8	9.2	-	
2000-2001	**-40.1**	-24.8	-	-1.5	13.1	-1.6	-5.7	-7.6	-1.7	**-9.7**	-27.8	-	
2001-2002	-15.8	-41.9	-	10.0	3.7	-8.2	-1.4	6.2	-22.7	-10.4	-0.9	-23.7	57.0
2002-2003	2.8	22.2	-	**-4.4**	-16.3	-16.5	2.3	-2.5	-20.0	3.7	-9.7	15.3	-5.0
2003-2004	5.9	20.0	60.3	12.1	**-84.2**	6.5	2.6	9.6	0.6	2.8	-2.8	-17.2	1.2
2004-2005	-2.5	-9.0	14.6	**-39.0**	9.0	43.7	9.4	2.0	-6.6	5.7	3.0	-5.2	-0.6
2005-2006	-9.3	5.2	3.9	-11.0	-15.4	2.3	-6.7	3.0	-18.6	-2.2	4.5	-2.6	-4.1
2006-2007	-5.5	1.9	19.7	9.2	**-26.5**	16.9	6.0	12.8	26.5	**-15.2**	1.3	5.9	3.6

Note: In bold are indicated the year of changes in capital stock, either in the number of runways or in the number of boarding bridges.

Table A3 (continued): LAC airports TFPC (Annual %)

Year	Ecuador	El Salvador	México				Panamá	Perú	Rép. Dom.
	GYE	SAL	CUN	GDL	MEX	MTY	PTY	LIM	SDQ
1995-1996	-	-	-	-	-	-	-	-	-
1996-1997	-	-	-	-	-	-	-	-	-
1997-1998	-	-	-	-	-	-	-	-	-
1998-1999	-	-	-	-	-	-	-	-	-
1999-2000	-	-	18.5	-	0.8	-1.2	-	-	-
2000-2001	-	-	-3.3	-	**-9.9**	-5.9	-	-	-
2001-2002	-	7.4	1.9	-	0.4	18.0	-	-	-
2002-2003	-	-1.8	10.4	-6.1	2.2	14.1	-	-	-
2003-2004	-	12.4	10.2	5.1	6.0	1.7	9.0	-	-
2004-2005	-	-0.6	-8.2	**-13.9**	3.3	3.8	6.8	-	-9.1
2005-2006	**-28.2**	-0.9	-2.1	12.3	5.5	-0.5	**-20.3**	9.6	**-10.5**
2006-2007	8.1	-4.7	**-1.7**	11.3	**-6.9**	14.2	6.3	9.8	2.0

Note: In bold are indicated the year of changes in capital stock, either in the number of runways or in the number of boarding bridges.