# Efficiency of Brazilian international airports: applying the bootstrap data envelopment analysis

## Eficiência dos aeroportos internacionais brasileiros: uma análise envoltória de dados com bootstrap

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**Abstract:** In the setting of open market organizations, efficiency has gained greater relevance, which in Brazil began around the 1990s. This paper applies the bootstrap data envelopment analysis aiming to study the efficiency of Brazilian airports, using the databases of the Agência Nacional de Aviação Civil (ANAC) and the Empresa Brasileira de Infraestrutura Aeroportuária (INFRAERO), dated of 2010, 2011 and 2012. We used multiple regression to validate the variables of the model. In this model, the measure used to represent the performance of airports was the number of processed passengers (dependent variable); for the variables that determine performance (independent variables) we used: number of runways, number of check-in counters, number of aircraft parking bays and passenger areas. The method was applied to study 16 Brazilian international airports in an operational approach. To correct the efficiency values found, given the inherent random error of the data, a bootstrap technique was applied. The approach showed that an airport's size is not the determining factor to assign their efficiency. The use of resources to achieve the product was the most relevant criterion to investigate the airport's good performance and efficiency in this study. The results obtained indicate that the Curitiba Airport is the most efficient. Moreover, the least efficient airports were the Galeão and Manaus Airports.

**Keywords:** Brazilian International airports; Data envelopment analysis; Operational efficiency.

**Resumo:** *A eficiência adquiriu maior relevância entre as organizações no cenário de mercados abertos, que teve início no Brasil por volta dos anos 1990. O objetivo deste artigo foi analisar, por envoltória de dados com bootstrap, a eficiência dos aeroportos brasileiros, utilizando as bases de dados da Agência Nacional de Aviação Civil (ANAC) e da Empresa Brasileira de Infraestrutura Aeroportuária (INFRAERO) de 2010, 2011 e 2012. Uma regressão múltipla foi utilizada para validar as variáveis do modelo proposto. Nesse modelo, a medida utilizada para representar o desempenho dos aeroportos foi a quantidade de passageiros processados (variável dependente); para as variáveis que determinam o desempenho (variáveis independentes) foram utilizados: número de pistas, número de balcões de check-in, número de estacionamento de aeronaves e área de passageiros. A partir de então, a técnica Análise Envoltória de Dados foi aplicada para os 16 aeroportos internacionais brasileiros, em abordagem operacional Para corrigir os valores de eficiência encontrados, tendo em vista o erro aleatório inerente aos dados, aplicou-se uma abordagem da técnica de bootstrap. Os resultados encontrados apontam que a grandeza de um aeroporto não foi determinante para atribuir eficiência, embora seja critério relevante para impulsionar melhorias no seu desempenho. Convém salientar, também, que a utilização dos recursos (inputs) para o alcance do produto (output) foi o critério mais relevante na busca do bom desempenho e da eficiência aeroportuária no estudo aqui apresentado. Nesse sentido, o aeroporto de Curitiba, na Região Sul do país, foi classificado como o mais eficiente em todos os períodos, e os aeroportos do Galeão (Rio de Janeiro) e Manaus (Amazonas) como os menos eficientes.*

**Palavras-chave:** *Aeroportos brasileiros internacionais; Análise envoltória de dados; Eficiência operacional.*

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# 1 Introduction

It is evident that Brazil has fallen behind in its much-needed infrastructure investments for some time. There are several reasons for this situation, particularly the economic stagnation that has prevailed for years in the country.

Compared to the previous decade, a more significant economic growth was seen from 2000 to 2010, resulting in a higher number of people employed, increased income generation, higher consumption and consequently reduced poverty.

With a more positive scenario in 2007, the Federal Government launched the Growth Acceleration Program (PAC), and its investments were used to finance infrastructure projects. However, despite resuming the investments, still short of the amount needed, major bottlenecks were detected.

The bottle necks that most standout today, evidenced by the average, are those related to airport infrastructure. The sector's deregulation process, although limited and which took place in the 1990s, along with the economic growth of the last decade, resulted in a growing demand for air services. In addition, the two major sporting events held in Brazil, the World Cup 2014 (already held) and the Olympic Games in 2016, reveal the existing infrastructure problems in Brazilian airports.

Within this context and using the bootstrap data envelopment analysis (BDEA) technique, this study investigated the efficiency of 16 Brazilian international airports from 2010 to 2012, applying an operational approach. These results facilitate identifying the better performance airports.

This work is related to studies published in the literature that investigate the importance of transport infrastructure for socio-economic development, as well as the lack of infrastructure as a bottleneck factor in growth and regional development.

Along these lines, Berechman (1994) argues that transportation infrastructures can increase business productivity, impact prices of products and also affect the location of firms, resulting in a net economic growth. In his study of the countries of west and central Africa, Njoh (2009) achieves similar results, but also points out that the relationship between transportation and development infrastructure may be stronger in less developed countries.

Considering a real and positive relationship between transportation and development infrastructure, this work focuses on airport infrastructures.

Graham (2001) mentions the economic and social impacts that arise from the existence and maintenance of airports, such as impacts related to income, employment, investments, tax revenues and fees (related to airport economic activities), developing tourism and remote infrastructure investments (warehouses, branches of companies, improved urban infrastructure) etc.

To promote these impacts, the airport must be efficient and must adequately meet the demands for their services. In this sense, the available literature on airport efficiency has no precise definition on how to measure the efficiency of an airport. It should be noted that creating a standard model of efficiency, which adapts to any situation, is no easy task and will likely result in a relative model of efficiency. Therefore, many authors use different approaches with variables that are sometimes repeated and sometimes not.

Curi et al. (2011) used the data envelopment analysis to estimate the efficiency of 18 Italian airports from 2000 to 2004. According to the authors, the size of airports does not provide advantages in terms of operational efficiency, but rather financial efficiency advantages for hubs and disadvantages for smaller airports.

There are several other studies that have analyzed the efficiency of airports in a number of countries. Lozano & Gutiérrez (2011) analyzed the efficiency of 41 Spanish airports using 2006 data; Yang (2010) estimated the efficiency of 12 airports in the Asia Pacific region from 1998 to 2006; Barros & Dieke (2008) estimated the efficiency of Italian airports for 2003; Martin & Roman (2006) investigated the efficiency of 34 Spanish airports for 1997; Yoshida & Fujimoto (2004) estimated the efficiency of 67 Japanese airports for 2000; and Oum et al. (2008) and Lin & Hong (2006) analyzed the efficiency of the main airports in the world.

For Brazil, the work of Fernandes & Pacheco (2002) examined the efficiency of 35 domestic airports. The DEA technique was used to identify which airports used their resources efficiently and which demonstrated idle operations.

The literature presents a wide range of models using different efficiency approaches, always aiming for a greater role of the decision makers. Therefore, in this work the main motivation is to contribute to this discussion, also taking into account the two major sporting events hosted in Brazil. One is the World Cup, which already took place, and the other event is the Olympic Games in 2016; both of which have demanded and will demand Brazilian airport services.

This paper is structured as follows: section 2 has a brief literature review on data envelopment analysis, with the Bootstrap technique already incorporated. Section 3 describes the work methodology, defines the variables used and the application of the proposed model. Section 4 includes the discussions of the results achieved from the model application; and Section 5 offers the closing remarks.

# 2 Data envelopment analysis

The DEA is a management technique used to assess and compare organizational units. As it encompasses a large number of data (inputs and outputs), transforming

them into a single index of relative overall efficiency, this technique assists decision makers.

The DEA is an operational research technique based on linear programming, with the objective to comparatively analyze independent units in terms of their relative performance. It is classified as non-parametric because it does not use a predefined production function, identical for all organizations in the input-output analysis relationship. Therefore, to use it does not require preparing a fixed weighted formula to measure the efficiency of the analyzed units, because the weights of each variable are determined by the technique.

The DEA can be regarded as a body of concepts and methodologies embedded within collection models with different possible interpretations (Charnes et al., 1994).

## 2.1 Application steps of DEA models

The application of DEA models requires executing a sequence of steps, as follows:

a) Choose the units to be entered into the analysis;

b) Choose the appropriate variables (input and output) to establish the relative efficiency of the units chosen; and

c) Identify the model orientation and returns to scale.

To select the units (a), the specialized literature suggests calling them decision making units (DMUs). According to Lins & Meza (2000), the first observation to be made concerns the homogeneity of the DMUs. Homogeneous DMUs are those that perform the same tasks with the same goals and which are working under the same market conditions, such that the variables used are the same, except for their size. The units evaluated need to be sufficiently similar so that the comparison makes sense, but should also be sufficiently different to perform the discrimination.

Similar units can be understood as those that perform the same functions, or that produce the same type of products and services; that operate under the same conditions and that are subject to the same laws and regulations. The only factors that differentiate these units should be: location (considering a geographic area governed by the same rules), production scale and size.

Location and size will not be the factors that determine the efficiency of the units, provided they operate under the same laws and regulations. What makes these units different in terms of efficiency is how they use their resources to obtain results.

Thus, the imposition of the similarity between units refers to the functions and the products/services

generated. Moreover, in order to perform discrimination these units must be different, considering that the use of resources is different in each of these units, as well as the results achieved.

As for choosing the variables (b), Golany & Roll (1989) structured the procedures in three alternatives: careful judgment, quantitative analysis not based on DEA techniques and selection based on DEA.

As for the first alternative, the big question is with regard to differentiating between the factors that cause the efficiency and the factors that explain it. The authors claim that only an analysis of causality, with the support of experts, can help decide whether a variable is cause or effect in the model being created.

The second alternative is with regard to statistics and regression analyses, to assist in the characterization of an input or output variable, as well as to assess their relevance and/or redundancy. For the authors, the weak relationship of some variables may indicate a need to review them and, if necessary, dismiss them.

And finally, for selecting variables from the DEA technique, Norman & Stoker (1991) proposed a systematic procedure for validating pre-selected variables, inspired by the stepwise method. The method uses an initial input-output pair, calculates the efficiency score of DMUs based on this pair and the correlation coefficients of all the other variables with this score. To select the next variable to enter the model, the list of variables is covered in a descending order of the correlation coefficient module. The goal is to incorporate the variable that allows to better fit the DMUs to the efficiency frontier.

In the third step (c), that identifies the model orientation and returns to scale, the models that best represent production technology are defined, however there some restrictions, especially with respect to the orientation and type of returns to scale.

The efficiency model can answer either of two questions:

a) Do the units produce a certain level of output, or, to what level can the inputs be reduced while maintaining the current output level? This means minimizing inputs; and

b) The units use a certain level of input, then which is the highest output level that can be achieved with this level of input? This means maximizing the outputs.

It is then necessary to choose the direction of minimizing inputs and/or maximizing outputs.

The ratio between inputs and outputs is called returns to scale. There are two returns possibilities in DEA models: constant returns to scale (CRS) and variable returns to scale (VRS).

A technology has constant returns to scale when the inputs increase or decrease in the same proportion as the outputs. A technology has variable returns to scale when the inputs are multiplied by a factor λ and the outputs can follow any behavior regarding this λ factor.

Among these models, the most suitable one can be chosen for the sample used. A mechanism used for this choice is the hypotheses test of returns to scales, presented by Banker (1996), that checks which is the most appropriate returns to scale (constant or variable) for the data set used. Banker (1996) suggests applying the nonparametric two-sample Kolmogorov-Smirnov test, based on the maximum distance of cumulative distribution of efficiency indicators of the CRS and VRS models.

The test evaluates the null hypothesis of constant returns to scale as opposed to the alternative hypothesis of variable returns to scale. The test is based on the maximum vertical distance between $\hat{F}^c\left(\ln\left(\hat{\theta}_j^c\right)\right)$ and $\hat{F}^v\left(\ln\left(\hat{\theta}_j^v\right)\right)$; the empirical distributions of $\ln\left(\hat{\theta}_j^c\right)$ and $\ln\left(\hat{\theta}_j^v\right)$ are used. The values are concentrated between 0 and 1. Values close to 1 tend to reject the null hypothesis and therefore accept the alternative hypothesis (Banker & Natarajan, 2004).

Accordingly, the Kolmogorov-Smirnov test was performed and the VRS model was selected as the most appropriate. This procedure is detailed in section 4.2.

As in this study the proposal was to consider the output increase (processed passengers) in the airports investigated, the output-oriented approach was chosen. The model proposed, known as output-oriented VRS (Banker et al., 1984) is presented as follows (Equation 1):

$$Maximize \sum_{i=1}^{n} v_i x_{ki} + v_k \qquad (1)$$

where as:

$$\sum_{r=1}^{m} u_r y_{rk} = 1$$

$$\sum_{r=1}^{m} u_r y_{jr} - \sum_{i=1}^{n} v_i x_{jr} - v_k \geq 0$$

$$u_r, v_i \geq 0$$

considering:

y = *outputs*; x = *inputs* / u, v = weights / r = 1,..., m.; i = 1,..., n; j=1,...,n.

The goal of the output-oriented VRS is to maximize the production level, using the observed consumption of inputs. The variables $u_k$ and $v_k$ were introduced representing the variable returns to scale. These variables should not meet the limit of positivity and may have negative values.

## 2.2 DEA bootstrap

To correct the efficiency values in view of the random error inherent in the data, Simar & Wilson (1998) propose an approach. The bootstrap method is applied through the DEA technique to proceed with the statistical inference of the efficiency results obtained by the DEA.

Thus, for each unit the efficiency confidence interval was estimated, the bias and the corrected efficiency, to be used for the airport performance assessment. Equation 2 shows the process to generate the confidence interval for the performance indicator.

$$\Pr\left(\hat{\theta} - \delta \leq \theta \leq \hat{\theta} + \delta\right) = 1 - \alpha \qquad (2)$$

where: θ is the 'true' efficiency indicator; $\hat{\theta}$ is an estimate of the efficiency indicator; δ is the margin of error; α is the level of statistical significance. With the confidence interval of the efficiency estimator, obtained via the resampling process, $IC\left[\theta, (1-\alpha)\%\right] = \hat{\theta} \pm \delta$, which is a more robust performance index of the data sensitivity. Also, the size of the bias efficiency estimator can be found $\left(\hat{\theta} - \hat{\theta}boot\right)$.

# 3 Research method

This section presents the procedure steps used in the empirical research.

## 3.1 The database

The data used were the Operational Performance Reports records of Airports, obtained from the National Civil Aviation Agency website (Brasil, 2013) and other airport technical data taken from the website of the Brazilian Airport Infrastructure Enterprise (INFRAERO, 2013).

The analysis period (2010 to 2012) was determined due to the data availability of ANAC and INFRAERO, choosing to use the most recent periods with fully standardized data.

## 3.2 The sample

The sample investigated in this study was composed of 16 Brazilian international airports. The delineation was because the ANAC had disaggregated data only for this category of airports. The idea was to include different sizes of airports so the analysis could also make use of this aspect. The Chart 1 shows the airports that were investigated.

Of these 16 airports, 12 are located in the host cities of the 2014 World Cup games, namely: Guarulhos, Congonhas, Brasília, Galeão, Salvador, Confins, Porto Alegre, Recife, Curitiba, Fortaleza, Manaus and Natal.

## 3.3 Selection of variables and application of the model

The proposal to choose the variables and define a theoretical model was based on two factors: (i) data availability of Brazilian airports; (ii) different models of airport efficiency, defined in major international studies.

As the units analyzed were Brazilian airports, a suitable measure to assess their performance was the Number of Processed Passengers.

Considering the two factors mentioned above, some operational variables that are related to the performance measure proposed were identified (number of passengers processed). Chart 2 shows the variables identified and their classifications.

A multiple linear regression was used to validate the proposed model. Therefore, it was determined whether the proposed variables (inputs) contributed to determine the number of passengers processed in the airports investigated. The analysis was composed of panel data of 16 airports, observed in 3 years (t=3), representing a total of 48 observations.

The model estimated in this work is the log-log type and is presented as follows (Equation 3):

$$PaxProc = \propto_t + \beta_1 NPistas_{it} + \beta_2 Checkin_{it} + \beta_3 EstAero_{it} + \beta_4 AreaPax_{it} + \varepsilon_{it} \qquad (3)$$

The variable $\alpha_t$ of technical progress reflects the model dysfunctions that are common to all airports at each time period, a dummy. In practice, this variable controls the effects of qualitative characteristics, which acts on the number of passengers processed in each airport investigated.

Regarding the error structure, the panel data availability allowed greater flexibility for its specification, which is shown below (Equation 4):

$$\varepsilon_{it} = \eta_i + \mu_{it} \qquad (4)$$

where $\mu_{it}$ is the supposed error and $\eta_i$ concerns the individual characteristics and effects of each airport, which are constant over time and not observed, such as effects of size, location and a mix of other factors that materialize in significant differences between the airports.

Considering that component $\eta_i$ can vary in the cross section, it is the specification of the estimators. The two most common formulations to specify the nature of the individual effects in a panel model are the use of fixed effects (*Least Squares Dummy Variable Model*) or random effects (*Estimated Generalized Least Squares*).

Choosing the treatment of the individual effects (fixed or random) depends on the lack of correlation between the individual effects not observed ($\eta_i$) and the explanatory variables. The choice was made based on the test proposed by Hausman (1978).

## 4 Presentation and analysis of results

This section describes the validation and application of the proposed model, as well as the results and their analysis.

### 4.1 Validation of the variables

From the model proposed earlier (Equation 3), in which the number of passengers processed at an airport is determined by the number of runways, check-in counters, number of aircraft parking bays and passenger terminal areas, the elasticities of each of the explanatory variables in relation to the dependent variable were explored.

After establishing, via the Hausman test, that the explanatory variables are exogenous, it can be stated that they have no correlation with the error term. Estimating the model by applying the individual effects of each airport was also considered. It was presupposed that the unobserved characteristics that

**Chart 1.** Airports investigated.

| Guarulhos International Airport (SP) | Confins International Airport (MG) | Manaus International Airport (AM) |
|---|---|---|
| Congonhas International Airport (SP) | Porto Alegre International Airport (RS) | Florianópolis International Airport (SC) |
| Brasilia International Airport (DF) | Recife International Airport (PE) | Belem International Airport (PA) |
| Galeão International Airport (RJ) | Curitiba International Airport (PR) | Natal International Airport (RN) |
| Maceio International Airport (AL) | Fortaleza International Airport (EC) | |
| Salvador International Airport (BA) | São Luís International Airport (MA) | |

**Chart 2.** Variables proposed for the analysis.

| *Inputs* | *Output* |
|---|---|
| Number of runways (Nrunways) Number of check-in counters (Checkin) Number of aircraft parking bays (EstAero) Passenger terminal area (AreaPax) | Passengers processed (PaxProc) |

may vary from airport to airport should be considered in the model, as they could have an effect on the results of the parameters. Thus, the model was estimated considering the fixed and random effects.

The Hausman test was again performed and the results indicated the rejection of the null hypothesis ($H_0$), therefore, the fixed effects model was considered as consistent and efficient (Table 1).

The Hausman specification test provided evidence that there is a correlation between the unobservable effects and the explanatory variables in the model. Accordingly, Table 2 shows the estimation results considering the fixed effects, using the heteroscedasticity-robust White matrix.

In the fixed effects model, the estimate was made assuming that the heterogeneity of airports is captured in the constants, which is different from airport to airport, capturing invariant differences over time. It was observed that the estimated coefficients are significant, especially for passenger terminal areas (3.94), check-in counters (2.27) and aircraft parking bays (1.36). Thus, the parameters obtained by estimating the fixed effect model can be considered as the best linear estimators and the adjusted high coefficient helps validate the model (Equation 3).

## 4.2 Data envelopment analysis

Table 3 summarizes the distribution of efficiency scores of the airports considering the cumulative period (2010-2012), for the variable returns to scale

(DEA-VRS) model. Considering this specificity, 62.50% of the airports were efficient.

Regarding the definition of the DEA model (constant or variable scale), the literature suggests conducting the Kolmogorov-Smirnov (KS) test, since the technology choice is a key issue, which can produce distorted results if decided arbitrarily.

In the test procedure, the statistics value (0.7911) was obtained ($\alpha = 1\%$) which allowed to accept the hypothesis of variable returns to scale. The result of this test justifies presenting only the results of the variable returns to scale model (Table 3 – cumulative results; Table 4 – non-cumulative results).

The model used in this study did not consider the weight restriction possibility of the variables. The proposed model was validated by multiple linear regression, which showed significant coefficients for independent variables, which means that to some extent they can explain the number of passengers processed in airports.

This procedure does not guarantee that the weights of all model variables in the data envelopment analysis will assume non-zero values. However, considering that in only 6 observations (total of 48) zero weight variables were observed and that there were no major differences in the weights of the variables for the units investigated, it was decided not to impose any weight restrictions or exclude variables, thereby preventing subjectivity in the model.

For the few cases that zero weights were observed for certain variables, we consider that they did not contribute to the efficiency indexes obtained.

**Table 1.** Hausman Test.

| Cross Section and Random Effects Test (Test Summary) | | | |
|---|---|---|---|
| | **Chi-Sq.** Statistic | **Chi-Sq.** d.f. | **Prob.** |
| Random Cross Section | 10.073047 | 6 | 0.1974 |

**Table 2.** Regression – Fixed effects.

| Dependent Variable: LOG(Paxproc) | | | | |
|---|---|---|---|---|
| Method: Panel Least Squares | | | | |
| Periods included: 3        Units: 16 | | | | |
| White diagonal standard errors & covariance | | | | |
| **Variable** | **Coefficient** | **Standard deviation** | **t-Statistic** | **Prob.** |
| LOG(AreaPax) | 3.945909 | 2.113378 | 2.548584 | 0.0000 |
| LOG(Checkin) | 2.277672 | 1.049872 | 2.169476 | 0.0087 |
| LOG(EstAero) | 1.361969 | 0.535090 | 2.545309 | 0.0017 |
| (Nrunways) | 0.005367 | 0.023717 | 0.226308 | 0.0086 |
| R- squared | 0.996860 | | | |
| Adjusted R-squared | 0.994729 | | | |
| SE of regression | 0.063385 | | | |
| Residual sum of squares | 0.112494 | | | |
| F-statistic | 467.8058 | | | |
| Prob(F-statistic) | 0.000000 | | | |

Moreover, in the six situations, the variables were "number of check-in counters" and "number aircraft parking bays", in the three years of investigation, for a major airport in the Southeast region of the country. This airport is known for being very large (large number of check-in counters and aircraft parking bays) and not very busy (low number of processed passengers, considering the installed potential), which partly explains the zero weight for those variables.

In order to correct the efficiency values, considering the random errors inherent in the data, we used the approach proposed by Simar & Wilson (1998). Table 5 shows the original efficiency index (biased), the bias and indices corrected by the bootstrap technique. The bootstrap results were generated by resampling 200 pseudo-samples (B=2000).

We chose to present the average results per airport, which despite the annual bias corrections, the indicators remained relatively stable over the years.

According to the results in Table 5, the significant effect of the efficiency indexes can be seen with respect to the sample variations, reducing the average efficiency by 17.36%. The corrected average efficiency values in most cases are considerably different in magnitude when compared with the original values. An example that confirms this observation is with regard to the airport in Natal (Rio Grande do Norte), which after applying the bootstrap technique, its efficiency index of 100.00% was corrected to 66.67%.

What was in fact found was that through a purely deterministic analysis, without considering the statistical bias influence, the results found are overestimated.

## 4.3 Analysis of results

Table 6 summarizes the descriptive efficiency statistics of 16 airports. The analysis of the non-cumulative periods shows a decrease in the average efficiency of 2.7 percent (2010-2012).

Another analysis concerns the efficiency differences observed at the airports considering their size. Therefore, the average efficiency indicators of the airports were calculated for the three sizes investigated (extra large, large and medium) in 2010, 2011 and 2012. Table 7 shows the results.

We highlight that the size of the airports was set based on the criteria proposed by Burman et al. (2007, apud Brasil, 2012), which classifies airports according to the number of passengers processed per year.

For the sample of 16 airports surveyed, in 2010 four airports were classified as extra large, six airports were classified as large and six as medium-sized. This classification remained unchanged in 2011. However in 2012, six airports were classified as extra

**Table 3.** Distribution of airports according to class.

| Performance Class | Airports | |
|---|---|---|
| 0-20% | 0 | 0% |
| 20-40% | 1 | 6.25% |
| 40-60% | 0 | 0% |
| 60-80% | 2 | 12.5% |
| 80-99% | 3 | 18.75% |
| 100% | 10 | 62.5% |
| Total | 16 | 100% |
| | Score | |
| Minimum | 38.56 | |
| Average | 89.6 | |
| Maximum | 100 | |

**Table 4.** Efficiency indicators of airports.

| Airport | Total | 2010 | 2011 | 2012 | Average |
|---|---|---|---|---|---|
| Belém | 98.77 | 100.00 | 97.5 | 95.97 | 97.82 |
| Brasília | 100.00 | 98.67 | 100.00 | 100.00 | 99.55 |
| Confins | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Congonhas | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Curitiba | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Florianópolis | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Fortaleza | 80.75 | 81.95 | 82.83 | 78.14 | 80.97 |
| Galeão | 63.47 | 67.37 | 58.89 | 64.67 | 63.64 |
| Guarulhos | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Maceió | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Manaus | 38.56 | 41.00 | 39.30 | 36.32 | 38.87 |
| Natal | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Porto Alegre | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Recife | 81.55 | 93.53 | 84.56 | 71.62 | 83.23 |
| Salvador | 70.91 | 72.89 | 69.90 | 70.05 | 70.94 |
| São Luís | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| **Average** | 89.62 | 90.96 | 89.56 | 88.54 | 89.69 |

**Table 5.** Corrected efficiency indicators.

| Airport | Mean efficiency | Bias | Corrected mean efficiency |
|---|---|---|---|
| Belém | 97.82 | 22.61 | 75.21 |
| Brasília | 99.55 | 23.18 | 76.37 |
| Confins | 100.00 | 8.56 | 91.44 |
| Congonhas | 100.00 | 23.33 | 76.67 |
| Curitiba | 100.00 | 1.79 | 98.21 |
| Florianópolis | 100.00 | 21.24 | 78.76 |
| Fortaleza | 80.97 | 14.75 | 66.22 |
| Galeão | 63.64 | 21.21 | 42.43 |
| Guarulhos | 100.00 | 17.33 | 82.67 |
| Maceió | 100.00 | 27.33 | 72.67 |
| Manaus | 38.87 | 1.09 | 37.78 |
| Natal | 100.00 | 33.33 | 66.67 |
| Porto Alegre | 100.00 | 5.23 | 94.77 |
| Recife | 83.23 | 13.86 | 69.37 |
| Salvador | 70.94 | 23.64 | 47.30 |
| São Luís | 100.00 | 19.33 | 80.67 |
| **Average** | 89.69 | 17.36 | 72.33 |

**Table 6.** Descriptive statistics of the efficiency indicators of 16 airports.

| Measures | 2010 | 2011 | 2012 |
|---|---|---|---|
| Average | 73.19 | 72.58 | 71.23 |
| Median | 76.66 | 75.83 | 75.32 |
| Standard deviation | 16.45 | 17.44 | 18.15 |
| Maximum | 98.21 | 97.73 | 98.70 |
| Minimum | 42.18 | 39.26 | 36.41 |

**Table 7.** Average efficiency by size.

| | 2010 | 2011 | 2012 |
|---|---|---|---|
| Total sample | 73.19 | 72.58 | 71.23 |
| Extra large | 70.00 | 68.81 | 69.63 |
| Large | 79.25 | 78.75 | 71.73 |
| Mid-size | 69.60 | 69.17 | 73.49 |

large, six airports were classified as large and only four were classified as medium-sized.

Table 7 shows that the average efficiency of the total sample decreased by 2.7%. For airports classified as extra large, between 2010 and 2012 there was a small decrease in the average efficiency of about 0.5 percent.

With regard to the extra large airports, despite the change in the number of airports over the years within this group, there are some peculiarities. The first concerns the inclusion of two other airports in this group (Galeão and Salvador) in 2012, which show the efficiency indicators as only "reasonable". Accordingly, the group (2010 and 2011) that was earlier composed of well-qualified airports in terms of operational efficiency (Guarulhos, Congonhas, Brasília and Confins), increased in size and showed a slightly reduced average efficiency.

Moreover, it is seen that most of the airports in that group operated with an overload in 2012.

The Galeão Airport is admittedly underutilized. In this airport all resources are quite substantial. This is a very large airport. However, it has an average number of processed passengers, which results in an inefficient use of its resources.

The Salvador Airport also deserves attention when analyzed. This airport and the Confins airport share some similarities concerning their available resources. The Confins airport was a benchmark for the Salvador airport in all the years investigated. Considering this aspect, the data envelopment analysis suggests that the Salvador airport under-utilized its resources (considering the performance achieved by Confins) and was considered inefficient. Consequently, the Salvador airport would have the potential to increase the number of passengers processed.

As for the large airports, the average efficiency decrease was of 9.5%. This is a major downturn. In 2010 and 2011 this group was composed of the airports of Salvador, Confins, Porto Alegre, Recife, Curitiba and Fortaleza. In 2012 the airports of Salvador and Confins became extra large. Additionally, also in 2012, two other airports were included in the large category, the airports of Manaus and Florianopolis.

Therefore, as seen in Table 4 (even without disregarding the bias), the only airport in the large category that over the years did not remain stable in the efficiency indicators is Recife. There is also a significant decrease between 2011 and 2012.

In all the years investigated, the benchmark for the Recife airport was the Porto Alegre airport. We see that these airports were close with regard to some variable inputs, however the Porto Alegre airport transported more passengers than the Recife airport, and this difference intensified even more between 2011 and 2012.

Moreover, in 2012 the Manaus airport was classified as large; and this airport showed the lowest efficiency indicators in all the investigated years. Thus, these two airports (Recife and Manaus) became the ones responsible for the large efficiency decrease in the group as a whole.

The benchmark criterion of the Manaus airport was the Curitiba airport. This is a peculiar case. In all years investigated, the Manaus airport had a higher number of passenger terminal areas, check-in counters and aircraft parking bays. Only the number of runways in the airports was similar. However, the Curitiba airport carried more passengers than the Manaus airport. Accordingly, the resources of the Manaus airport were underutilized (compared with the use of resources of the Curitiba Airport) and the data envelopment analysis classified it as an inefficient airport.

And finally, the mid-sized airports increased their average yield by 5.5%. This development was mainly due to the new classification of the Manaus airport, which in 2010 and 2011 was a medium sized airport. However in 2012 it was classified as large. We emphasize that the efficiency indicators of this airport were the lowest in the three years investigated. For this reason, its new category (large-sized) had a decrease in average efficiency and the old category absorbed an increase (medium-sized).

The DEA method does not consider the airport size to classify it as efficient, but rather the relationship between the use of resources (inputs) to obtain the product (outputs). Therefore, the efficiency addressed here refers to the relationship between the results obtained and the resources used. The managerial aspects (resource allocation decisions) are more important than the size of the investigated airport.

For example, the Guarulhos International Airport classified as the largest airport in the country according to the ranking of Burman et al. (2007 apud Brasil, 2012), obtained an average efficiency score of 82.67% in the data envelopment analysis (Table 5). This means that the Guarulhos airport did not optimize the use of its resources (passenger terminal areas, number of check-in counters, number of aircraft parking bays and number of runways) taking into account the total number of passengers processed. In terms of efficiency and considering the variables used, the Guarulhos airport could improve the use of its resources and has the potential to significantly increase the number of passengers processed, while maintaining the input levels observed.

As for the Curitiba airport, the data envelopment analysis determined that this is the most efficient airport with regard to using its resources. However, according to the classification of Burman et al. (2007 apud Brasil, 2012), this airport ranked as the ninth largest airport.

Table 5 also shows the two least efficient airports in the period investigated: the Manaus (AM) and Galeão (RJ) airports. Using the data envelopment analysis the potential increase of passengers processed (output) was estimated considering the resources used (inputs) by these two airports.

The Galeão airport in Rio de Janeiro, which in the overall period and also annually was less efficient, could increase its production (processed passengers) by 57.5% in the total period; 48.4% in 2010; 69.8% in 2011; and 54.6% in 2012.

The Manaus Airport, taking into account the resources used (inputs), had the potential to increase the passengers processed by 159.3% in the overall period; 143.9% in 2010; 154.5% in 2011; and 175.3% in 2012.

According to the results of the data envelopment analysis (Table 5), the efficiency ranking of Brazilian airports was as follows: Curitiba, Porto Alegre, Confins, Guarulhos, São Luís, Florianópolis, Congonhas, Brasília, Belém, Maceió, Recife, Natal, Fortaleza, Salvador, Galeão and Manaus.

We highlight that by the end of 2012, 9 of the 16 surveyed airports had an occupancy level greater than its capacity, namely: Guarulhos, Congonhas, Brasília, Maceió, Confins, Porto Alegre, Fortaleza, Florianópolis and Natal (Brasil, 2013).

However, there is an exception that should be considered. It is important to use caution when estimating the potential increase of inefficient airports, determined by the performance of overloaded airports.

It is also observed that neither of the two airports identified as the least efficient – Galeão and Manaus – operated above the maximum capacity of passengers processed in all periods investigated. At the end of 2012, the Galeão Airport was operating at a capacity

**Table 8.** Airports/Data.

| Airports | Passengers processed /Passenger terminal area | Passengers processed /Check-in counters |
|---|---|---|
| Belém | 78.30 | 86,727 |
| Brasília | 155.23 | 191,596 |
| Confins | 138.48 | 177,883 |
| Congonhas | 237.20 | 189,118 |
| Curitiba | 130.35 | 195,531 |
| Florianópolis | 209.35 | 87,807 |
| Fortaleza | 139.57 | 160,554 |
| Galeão | 46.45 | 78,083 |
| Guarulhos | 145.61 | 100,744 |
| Maceió | 62.09 | 56,920 |
| Manaus | 57.69 | 74,149 |
| Natal | 198.85 | 88,412 |
| Porto Alegre | 129.29 | 209,565 |
| Recife | 112.77 | 94,586 |
| Salvador | 110.60 | 116,889 |
| São Luís | 173.14 | 63,747 |
| Average | 132.62 | 123,269 |

of 86% and the Manaus airport was operating at 90% (Brasil, 2013).

Table 8 identifies the productivity of the two main explanatory variables of the model and verifies some of the reasons why some airports are considered more efficient than others. For example, if an airport's efficiency depended exclusively on the ratio between the passenger terminal areas and the total processed passengers, the Congonhas airport (São Paulo) would be the most efficient, since each square meter processed up to 237 passengers. Therefore, the least efficient would be the Galeão Airport in Rio de Janeiro (46.45 passengers/m$^2$).

In the "passengers processed/check-in counters" ratio, the most efficient airport was Porto Alegre (Rio Grande do Sul) since each check-in counter processed 209,565 passengers. The less efficient airport in this respect was the Maceio airport (Fortaleza), with 56,920 passengers processed/check-in counter.

## 5 Final remarks

This work evaluated the efficiency of 16 airports, using the bootstrap data envelopment analysis. The technique was applied to a set of airports using data for 2010, 2011 and 2012.

The data envelopment analysis considered the best combination of inputs in order to generate better results, respecting the different production scales. Therefore, for each period investigated, an ideal combination was found, which served as a reference for the less efficient airports. An ideal combination means that the resources (inputs) were optimized, which means they were better used for the findings, which does not necessarily represent the absolute best

use. We underscore that the results do not refer to an absolute efficiency, that is, the airports considered efficient are only classified like this in the group in question. Therefore, the ideal combinations (of inputs to generate results) represent the most efficient of this group.

The results achieved indicate the Curitiba airport as the most efficient. Moreover, the least efficient ones were the Galeão and Manaus airports.

Accordingly, the Airports Operational Performance Report (Brasil, 2013) designated the Brasilia airport as the most efficient, followed by the Curitiba airport. The Galeão and Manaus Airports were ranked second to last and last, respectively. We emphasize that this indicator, developed and used by the ANAC, uses operating and financial variables.

The differences in results between the DEA efficiency indexes and the rankings of the best airports of ANAC do not subtract values from any of the results. Each one is suited to its proposed objective. It should be noted that although the results of both analyses are different, they can be used together to better understand the factors that may affect the performance of airports.

The analyses did not indicate the predominance of greater efficiency among the extra large airports. It was concluded that the medium- and large-sized airports were considered to be more efficient in the period investigated, with the variables used. Therefore, to achieve the results found, the question of the best use of inputs is more relevant than the size of the airport.

It is also important to consider the performance of airports, particularly taking into account the two sporting events (World Cup and Olympic Games)

hosted in Brazil. The World Cup has already taken place and although there were improvements made in the host city airports, potential problems are not ruled out.

Changes are needed. Of the airports in the Southern region, considered the most efficient, until the end of 2011 only the Curitiba airport was not operating with overloads. The airports of Porto Alegre and Florianópolis were operating well above their capabilities. These changes are already in operation, although at a slower pace than needed to properly meet, with quality, the increased demand observed.

The results presented here are relevant for two major reasons. The first one concerns the crucial relevance of airports for the dynamics of passenger transport in Brazil. Since 2006, when the tariff liberalization of the sector took place, Brazilians started to travel more by plane. Prior to this period, the infrastructure bottlenecks of the airport system were not in evidence. It was only after 2006 that the existing flaws were identified. Accordingly, the results presented here highlight how the Brazilian airports are classified through different criteria used by the Regulatory Agency of the Sector and particularly point out aspects that can be improved.

Furthermore, added to the condensed number of studies on airport performance in Brazil, the bootstrapped data envelopment analysis technique is not often disseminated in the national literature. The use of bootstrapping as a method to correct the random error inherent in the data is a common practice in the international literature, and it produces robust and consistent results.

Therefore, the results presented here meet the proposed objectives and are in line with the methodological rigor of important research in the area of infrastructures, and also with the data envelopment analysis.

For future studies we suggest using the bootstrapping data envelopment analysis in other sectors, as well as incorporating other techniques for selecting variables.

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