Pesquisa Operacional (2024) 44: e281311 p.1-46
doi: 10.1590/0101-7438.2023.043.00281311

Printed version ISSN 0101-7438 / Online version ISSN 1678-5142
www.scielo.br/pope
ARTICLES

OPERATIONAL EFFICIENCY IN BRAZILIAN AIRPORTS: AN ANALYSIS THROUGH THE HIERARCHICAL LINEAR MODELING WITH REPEATED MEASURES

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Received December 11, 2023 / Accepted February 12, 2024

ABSTRACT. This study analyzes the operational efficiency of Brazil's 30 largest airports from 2014 to 2018, using a two-stage model. Operational efficiency is defined as an airport's capacity to effectively utilize resources, such as facilities, staff, and technology, to cater to air traffic and passenger needs. The first stage involved measuring operational efficiency through data envelopment analysis. The second stage used a three-level hierarchical linear model to identify influencing variables. Key findings reveal that location significantly impacts airport efficiency, which generally declined during the study period. The interest rate, the only notable economic factor, had a negative effect on efficiency. Factors like the number of aircraft parking positions, years of airport operation, and the number of airlines positively influenced efficiency. Conversely, governance structure, airport size, commercial establishment count, and vehicle parking lot

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JEL: D24; R40; C30

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numbers didn't notably affect efficiency variation. This methodological approach provided more accurate predictions than traditional regression models.

Keywords: data envelopment analysis, performance analysis, three-level hierarchical linear model with repeated measures, efficiency and productivity, airport.

1 INTRODUCTION

Productivity measures, such as effectiveness and efficiency, are used to evaluate organizational performance. An effective organization reaches its objectives, regardless of the amount of resources used. An efficient organization uses the least amount of resources to reach its objectives. In addition to being effective and efficient, some organizations (e.g., airports) operate in competitive markets. These organizations can integrate comparative and targeted effectiveness and efficiency measures into their strategic planning to gain a competitive advantage. Until recently, airport efficiency has been neglected in the study of transport. Tovar and Martín-Cejas (2010) describe an airport as not only an intermediate terminal of transport modals but also a system that serves a wide and complex network related to the movement of people and goods around the world. Therefore, the study of airport efficiency has become crucial to ensure operational improvements, cost-effectiveness, and good customer service.

The deregulation and liberalization of airlines around the world has increased demand for airport services with fast and efficient aircraft, passenger, cargo, and baggage processes (Oum et al. 2003). The result is worldwide growth in the commercialization and privatization of airports, which has increased the need for control and performance improvement from the perspectives of both investors and regulators. Yet, as Oum et al. (2003) point out, quality standards, governance and regulatory structures, services, and operational characteristics in the industry remain inconsistent, and external factors related to location and environment are diverse across airports.

Ahn and Min (2014) show that newly implemented policies and practices for airport management make them more efficient and effective. These practices include airport capacity expansion; promotional incentives for airlines and cargo companies (landing fees, terminal rental rates, airline advertising subsidies etc.); passenger offers and incentives; and airport modernization in terms of facilities, technology, and equipment. According to the authors, airports play a key role in regional economic development, as they facilitate global supply chain operations connecting different modes of transportation. These factors underscore the importance of research in airport management, specifically to evaluate efficiency and productivity.

Measuring and comparing airport performance is a complex and crucial task. Performance measurement research seeks to answer important questions, which guide this research. For example, does airport location play an important role in efficiency (do airports with the same characteristics but from different location have different efficiency)? Are private airports more efficient than public ones? Does outsourcing services improve performance? How do commercial activities affect airport performance? Did airport efficiency increase over the analyzed period?

In this context, Data Envelopment Analysis (DEA), term introduced by Charnes et al. (1978), is an optimization technique based on linear programming and designed to establish a measure of relative efficiency among different decision making units.

In this paper, we conducted a comprehensive analysis of the operational efficiency of the 30 largest Brazilian airports during the period from 2014 to 2018, using a two-stage model approach. This timeframe, preceding the impactful era of the Covid-19 pandemic, offered a unique opportunity to assess the efficiency of airport operations in a pre-pandemic context.

In the first stage, our study utilized DEA methodologies, particularly the Slacks-Based Measure (SBM) model, through a Data Envelopment Window Analysis (DEWA) model. DEWA is a non-parametric method that assesses the performance of entities, like airports, by comparing their efficiency in converting inputs into outputs over time, providing a dynamic perspective on operational efficiency (Peykani et al., 2021). This approach allows for an in-depth analysis of airport efficiency across different time periods.

In the second stage, we explored a novel approach in airport efficiency literature by employing a three-level hierarchical linear model (HLM3) with repeated measures. This is a sophisticated statistical technique that can handle data organized at more than one level, such as airports within regions. HLM3 accounts for the nested structure of data and is particularly useful in examining the influence of both airport-specific factors and broader regional factors on airport efficiency (Subedi et al., 2015). This methodology allowed us to identify and analyze several socio-economic variables that explain airport efficiency, thus providing insights into the impacts of privatization and other external factors on airport management. This approach not only offered a deeper understanding of the variables influencing the productive efficiency of airports but also produced a better fit for the observed efficiency than traditional ordinary least squares regression methods.

Our study's bifurcated model approach, combining DEA and HLM3, reflects the critical importance of operational efficiency in airport management as an indicator of an airport's capability to efficiently manage its resources and services, catering to the needs of air traffic and passenger demands. In this sense, our main objectives is to study the determinants of efficiency of airports operating in different locations in Brazil, as well as the reasons why efficiency variability occurs among airports from the same location and among those from different locations.

2 LITERATURE REVIEW

Gillen and Lall (1997) and Hooper and Hensher (1997) pioneered the study of airport efficiency. Since then, a lot of papers have been published on airport efficiency. As shown by Tovar and Martín-Cejas (2010) and corroborated in our literature review, most studies use either data envelopment analysis (DEA) for non-parametric models or stochastic frontier analysis (SFA) for parametric models. The advantage of DEA is that it does not require specification of the functional form for the frontier nor any form of distribution for the error terms. SFA has those requirements, but it also can manage random shocks and measurement errors, allowing the use of traditional hypothesis tests (Tovar and Martín-Cejas 2010).

Different types of DEA models have evolved over the years (e.g., Assaf 2010; Barros and Dieke 2007, 2008; Bazargan and Vasigh 2003; Chang et al. 2013; Fernandes and Pacheco 2002; Gillen and Lall 1997; Lam et al. 2009; Lozano and Gutiérrez 2011a, b; Martín and Román 2001; Merkert and Assaf 2015; Merkert and Mangia 2014; Pacheco and Fernandes 2003; Sarkis 2000; Tsekeris 2011; Wanke 2012a, b; Yoshida and Fujimoto 2004). The two major DEA models in the literature are the Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) models. The primary difference between these two models is in their assumptions about the returns-to-scale property (Zou et al. 2015). SFA is a parametric modeling tool that accounts for the stochastic random error in the production and cost frontier (Zou et al. 2015). The first SFA studies originated from Pels et al. (2001, 2003). Several other works have applied SFA to measure airport productivity changes (e.g., Assaf et al. 2012; Chow and Fung 2012; Ha et al. 2013; Scotti et al. 2012; Tovar and Martín-Cejas 2009, 2010; Yang 2010). Barros (2008b) implemented the stochastic cost frontier with long-run inefficiency (SCF-LR). Other studies implemented the stochastic cost frontier with short-run inefficiency – SCF-SR (Martín et al. 2013; Oum et al. 2008; Voltes-Dorta and Pagliari 2012).

Other papers have considered undesirable outputs in the study of airport efficiency, using the directional distance function approach (e.g., Lozano and Gutiérrez 2011b; Martini et al. 2013; Pathomsiri et al. 2008; Scotti et al. 2014; Yu et al. 2008). Total factor productivity is a non-parametric approach that has been used to measure airport efficiency (e.g., Hooper and Hensher 1997; Oum et al. 2013; Yoshida and Fujimoto 2014). Similar to total factor productivity, variable factor productivity has been used in Oum and Yu (2004), Oum et al. (2006), and Choo and Oum (2013). Several indices of total factor productivity have been used to estimate productivity levels, such as the Fisher Ideal index (e.g., Ray and Mukherjee 1996), the Malmquist index (e.g., Ahn and Min 2014; Barros and Weber 2009; Chi-Lok and Zhang 2009; Chow and Fung 2012; Coto-Millán et al. 2014; De Nicola et al. 2013; Gitto and Mancuso 2012; Perelman and Serebrisky 2012; Suwanwong and Sopadang 2020; Tovar and Martín-Cejas 2010; Tsui et al. 2014a; Yu et al. 2008), and the Hicks-Moorsteen index (e.g., See and Li, 2015). Other studies have used the slack-based measure model to investigate airport efficiency (e.g., Lam et al. 2009; Lozano and Gutiérrez 2011b; Tsui et al. 2014a).

Early works measuring airport productivity and performance are based on a single-stage model (Martín and Román 2001; Pels et al. 2001, 2003; Sarkis and Talluri 2004; Yoshida and Fujimoto 2004). Two-stage models deepen the analysis by identifying variables that impact airport efficiency and productivity. The second stage typically includes linear regression models estimated using the ordinary least squares (OLS) method (Chi-Lok and Zhang 2009; Nicola et al. 2013), as well as Tobit models estimated by maximum likelihood (Chi-Lok and Zhang 2009; Gillen and Lall 1997; Ha et al. 2013; Scotti et al. 2014; Ülkü 2015; Huynh et al. 2020). Simar and Wilson (2007) propose a bootstrapping truncated regression model as the second stage, known as Simar-Wilson bootstrapping truncated regression. Several subsequent studies applied this approach (e.g., Assaf and Gillet 2012; Barros 2008a; Barros & Dieke 2008; Chang et al. 2013; Chaouk et al. 2020; Martini et al. 2013; Merkert and Assaf 2015; Merkert and Mangia 2014; Örkcü et al. 2016; Tsekeris 2011; Tsui et al. 2014a, b). Finally, regression models that consider fixed effects and random effects have been proposed by Choo and Oum (2013), Adler and Liebert (2014), Zou et al. (2015), and Zuidberg (2017).

Regression models that do not account for temporal evolution and use a cross-sectional approach (i.e., a snapshot of the moment data is collected) are classified as generalized linear models. These models include OLS, log-linear, and Tobit and Simar-Wilson bootstrapping truncated regression models. Regression models that account for temporal evolution (various cross-sections over time) are classified as longitudinal regression models or models with repeated measures for panel data. Because none of these studies consider the grouped, or nested, structure in the data, they do not estimate models considering the hierarchical perspective. In the grouped data structure, certain explanatory variables do not vary between observations (representing one level of analysis) from a given group (representing another level of analysis). In studies on airport efficiency, some variables fit this classification: location, international airport status, airport hub status, and ownership structure. The use of an HLM3 model with repeated measures, as we proposed in this paper, is novel in the airport efficiency literature. The main studies in the airport efficiency literature, including the sample data, inputs, outputs, and explanatory variables for the two-stage models, are summarized in the Appendix.

3 METHODOLOGY

We proposed a two-stage model. The first stage involves data envelopment analysis, and the second stage involves an HLM3 model with repeated measures.

3.1 First Stage: Data Envelopment Analysis

DEA models are based on the analysis of efficiency of decision making units with multiple inputs and outputs, and originate in the idea of creating a frontier of efficiency in which more efficient decision making units are placed on the surface of the frontier. Some recent papers use DEA to evaluate efficiency in the field of operations, logistics and supply chain, such as Hong and Jeong (2019), Vishnu et al. (2020) and Hassan and Oukil (2021).

To assess airport operating efficiency and productivity changes over time, the DEWA model is applied. Efficiency scores of each airport are obtained for each year and for the respective benchmark airports. In the traditional DEA model, each decision-making unit is observed only once. In the DEWA model, each decision-making unit is unique in each period. DEWA models are considered more robust than traditional DEA models in panel data applications. They identify trends and variations in efficiency and technical change over time (Shawtari et al. 2018), as shown in the data behavior of this study.

Additional research emphasizes this robustness. For instance, Astanti et al. (2022) highlight the importance of considering product deterioration and quality issues in supply chain models, which can be integrated into DEWA analyses for a deeper understanding of operational efficiency. Moreover, studies like that of Jin et al. (2023) demonstrate how DEA models, including variations like DEWA, can be adapted for efficiency assessments in uncertain environments, underlining the versatility of these models.

Similarly, works such as that of Qu et al. (2022) employ robust DEA models to measure the operational efficiency of complex systems, like pension insurance systems, effectively addressing uncertainty. This approach is complemented by research like that of Singh et al. (2022), which explores the optimization of DEA models in uncertain environments, showing the adaptability of DEWA models to different operational contexts.

Therefore, the use of DEWA models in this study is in line with recent trends in efficiency analysis literature, leveraging their ability to handle complexities and variations over time and among different decision-making units.

For comparison, we also present the results of the DEA Charnes-Cooper-Rhodes output oriented (CCR-O) model. The CCR model aims to maximize multiple outputs, given a set of multiple inputs, so that the maximum possible score for a decision-making unit is 1 (Charnes et al. 1978). The CCR model can be expressed mathematically as follows:

$$
\begin{aligned}
&\max \frac{\sum_{r=1}^{n}(u_{rb})(y_{rb})}{\sum_{k=1}^{m}(v_{kb})(x_{kj})} \\
&\text{subject to:} \\
&\frac{\sum_{r=1}^{n}(u_{rb})(y_{rj})}{\sum_{k=1}^{m}(v_{kb})(x_{kj})} \leq 1 \text{ for every } j \\
&u_{rb}, v_{kb} \geq \varepsilon \text{ for every } r, k
\end{aligned}
\tag{1}
$$

where

y_{rj} – output vector r produced by unit j

x_{kj} – input vector k used by unit j

u_{rb} – weight given to output r per basic unit b

v_{kb} – weight given to input k per basic unit b

j = 1, 2, 3,..., p; p represents the number of DMUs being evaluated.

r = 1, 2, 3,..., n; n denotes the number of different types of outputs produced by each DMU.

k = 1, 2, 3,..., m; m is the number of different types of inputs utilized by each DMU.

ε = very small positive number

3.2 Second Stage: Three-Level Hierarchical Linear Model with Repeated Measures

In the second stage, we sought to identify the critical success factors that affect airport efficiency through a hierarchical linear model. In this work, we estimated a three-level linear hierarchical model with repeated measures that, as far as we know, has never been used in the airport literature.

In hierarchical models, the key advantage over traditional regression models lies in their consideration of the natural nesting of data. These models stand out in identifying and analyzing individual heterogeneities between groups, allowing the specification of random effects at each level of analysis. This approach is reinforced by recent studies, such as that of Ferreira et al. (2021), which explore fast and scalable calculations for hierarchical Gaussian models with autoregressive conditional intrinsic spatial random effects. Similarly, Diestelkaemper et al. (2021) emphasize the need for holistic approaches to understand and manage missing answers in nested data, further underlining the significance of hierarchical models in handling data complexities. Therefore, these models' ability to manage nested data structures and individual group differences underpins their effectiveness and growing application in various research fields.

For instance, since airports are nested in locations such as states, a hierarchical model will define a random component at the airport level and another at the state level. In a traditional regression model, the effect of the locations on certain units (in this case, airports) would be homogeneous. In this sense, hierarchical models are also called random coefficient models or multilevel models. In a hierarchical model, the explanatory variables can be inserted in both fixed and random effects components, since the estimated parameters of the fixed effects' component indicate the relationship between the explanatory variables and the outcome variable, and the random effects' component can be represented by the combination of the explanatory variables and unobserved random terms (West et al., 2015, Fávero et al. 2018).

These models propose a framework of analysis that recognizes the levels at which data are structured, being each level represented by its own equation (Fávero and Belfiore 2019; Gelman 2006; Raudenbush and Bryk 2002; Rabe-Hesketh and Skrondal 2012; Snijders and Bosker 2011).

Therefore, following Hair Jr. and Fávero (2019), we can define a general model with three analysis levels and nested data. The first level presents explanatory variables Z_1, ..., Z_P, which refer to level-1 units i (i = 1, ..., n). The second level presents explanatory variables X_1, ..., X_Q, which refer to level-2 units j (j = 1, ..., J). The third level presents explanatory variables W_1, ..., W_S, which refer to level-3 units k (k = 1, ..., K), as follows:

$$\textbf{Level 1: } Y_{\mathrm{ijk}} = \pi_{\mathrm{0jk}} + \sum_{p=1}^{P} \pi_{\mathrm{pjk}} \cdot Z_{\mathrm{pjk}} + e_{\mathrm{ijk}} \tag{2}$$

where π_{pjk} (p = 0, 1, ..., P) refers to the level-1 coefficients, Z_{pjk} is the p-th level-1 explanatory variable for observation i in the level-2 unit j and in the level-3 unit k, and e_{ijk} refers to the level-1 error terms that follow a normal distribution, with mean equal to zero and variance equal to σ^2.

$$\textbf{Level 2: } \pi_{\mathrm{pjk}} = b_{p0k} + \sum_{q=1}^{Q_p} b_{\mathrm{pqk}} \cdot X_{\mathrm{qjk}} + r_{\mathrm{pjk}} \tag{3}$$

where b_{pqk} (q = 0, 1, ..., Q_p) refers to the level-2 coefficients, X_{qjk} is the q-th level-2 explanatory variable for unit j in the level-3 unit k, and r_{pjk} are the level-2 random effects, assuming for each unit j that the vector $(r_{0jk}, r_{1jk}, ..., r_{Pjk})'$ follows a multivariate normal distribution, which is a generalization of the one-dimensional normal distribution to higher dimensions. It represents a distribution for a vector of random variables where each element of the vector is normally distributed and there is some correlation between the elements (Karamikabir et al., 2023). Each element has a mean of zero and variance of $\tau_{r\pi pp}$.

$$\textbf{Level 3: } b_{\text{pqk}} = \gamma_{\text{pq0}} + \sum_{s=1}^{S_{\text{pq}}} \gamma_{\text{pqs}} \cdot W_{\text{sk}} + u_{\text{pqk}} \tag{4}$$

where Υ_{pqs} ($s = 0, 1, ..., S_{pq}$) refers to the level-3 coefficients, W_{sk} is the s-th level-3 explanatory variable for unit k, and u_{pqk} are the level-3 random effects, assuming that for each unit k the vector formed by terms u_{pqk} follows a multivariate normal distribution with each element having a mean of zero and variance of $\tau_{u\pi pp}$, which results in a variance-covariance matrix $\mathbf{T_b}$ with a maximum dimension equal to:

$$\text{Dim}_{\text{max}}\mathbf{T_b} = \sum_{p=0}^{P} (Q_p + 1) \cdot \sum_{p=0}^{P} (Q_p + 1) \tag{5}$$

which depends on the number of level-3 coefficients specified with random effects.

In this sense, we assume a single level-1 explanatory variable that corresponds to the periods in which the data of the dependent variable are monitored, and this temporal evolution characterizes the term repeated measures. Thus, we have that:

$$Y_{\text{tjk}} = \pi_{\text{0jk}} + \pi_{\text{1jk}} \cdot \text{period}_{\text{jk}} + e_{\text{tjk}} \tag{6}$$

being π_{0jk} and π_{1jk} the intercept and the slope (evolution across time) of the model, respectively. For a model with only one explanatory variable X representing a level-2 characteristic for a unit j, and also one explanatory variable W representing a level-3 characteristic for a unit k, we can define, from Expression (6), the following model:

$$\textbf{Level 1: } Y_{\text{tjk}} = \pi_{\text{0jk}} + \pi_{\text{1jk}} \cdot \text{period}_{\text{jk}} + e_{\text{tjk}} \tag{7}$$

$$\textbf{Level 2: } \pi_{\text{0jk}} = b_{00k} + b_{01k} \cdot X_{\text{jk}} + r_{\text{0jk}} \tag{8}$$

$$\pi_{1jk} = b_{10k} + b_{11k} \cdot X_{\text{jk}} + r_{\text{1jk}} \tag{9}$$

$$\textbf{Level 3: } b_{00k} = \gamma_{000} + \gamma_{001} \cdot W_k + u_{00k} \tag{10}$$

$$b_{01k} = \gamma_{010} + \gamma_{011} \cdot W_k + u_{01k} \tag{11}$$

$$b_{10k} = \gamma_{100} + \gamma_{101} \cdot W_k + u_{10k} \tag{12}$$

$$b_{11k} = \gamma_{110} + \gamma_{111} \cdot W_k + u_{11k} \tag{13}$$

The result of combining Expressions (7) to (13) is the following equation:

$$
\begin{aligned}
Y_{\text{tjk}} = & \underbrace{\left(\gamma_{000} + \gamma_{001} \cdot W_k + \gamma_{010} \cdot X_{\text{jk}} + \gamma_{011} \cdot W_k \cdot X_{\text{jk}} + u_{00k} + u_{01k} \cdot X_{\text{jk}} + r_{0\text{jk}} \right)}_{\text{random effects intercept}} \\
& + \underbrace{\left(\gamma_{100} + \gamma_{101} \cdot W_k + \gamma_{110} \cdot X_{\text{jk}} + \gamma_{111} \cdot W_k \cdot X_{jk} + u_{10k} + u_{11k} \cdot X_{jk} + r_{1\text{jk}} \right) \cdot \text{period}_{\text{jk}}}_{\text{random effects slope}} \\
& + \text{e}_{\text{tjk}}
\end{aligned} \qquad (14)
$$

According to Tabachnick and Fidell (2019), hierarchical models allow interactions both between error terms and variables in the random effects component, and between variables in the fixed effects component. Additionally, if the variances of the random terms u_{10k}, u_{11k}, r_{0jk}, and r_{1jk} are statistically significant at a specific confidence level, traditional parameter estimations, such as OLS, will not be adequate.

3.3 Methodological Process

Considering the integration of two different methodological processes, we provide a graphical explanation of the process steps to be followed in the evaluation of airport capacities. In this sense, Figure 1 presents the methodological flowchart.

4 VARIABLE SELECTION AND DATA COLLECTION

4.1 Variable Selection

We used a two-stage model. In section 4.1.1 we presented the input and output variables used in the first stage to determine the airports' operational efficiency (first stage of the model). In section 4.1.2 we presented the variables used to explain that efficiency (second stage of the model).

4.2 Selection of the First Stage Variables

Several combinations of inputs and outputs have been considered in the airport literature, as shown in the Appendix. In terms of physical infrastructure efficiency, the main inputs are runway area for the landing and takeoff of aircraft, cargo terminal area, passenger terminal area, number of runways, and runway length. Some papers consider financial factors, such as labor, material, and capital (operating) costs. The most common outputs are number of air passenger movements (number of paying passengers: boarding and disembarking), number of air transport movements (number of landings and takeoffs), and cargo volume. Some studies combine passengers and cargo into one measure, denominated workload units.

We considered the following inputs: (i) passenger terminal total area (square meters), (ii) takeoff and landing total area (square meters), and (iii) aircraft yard area (square meters). We considered the following outputs: (i) number of air passenger movements, (ii) paid cargo and mail (kg) of shipments and receipts, and (iii) number of air transport movements.

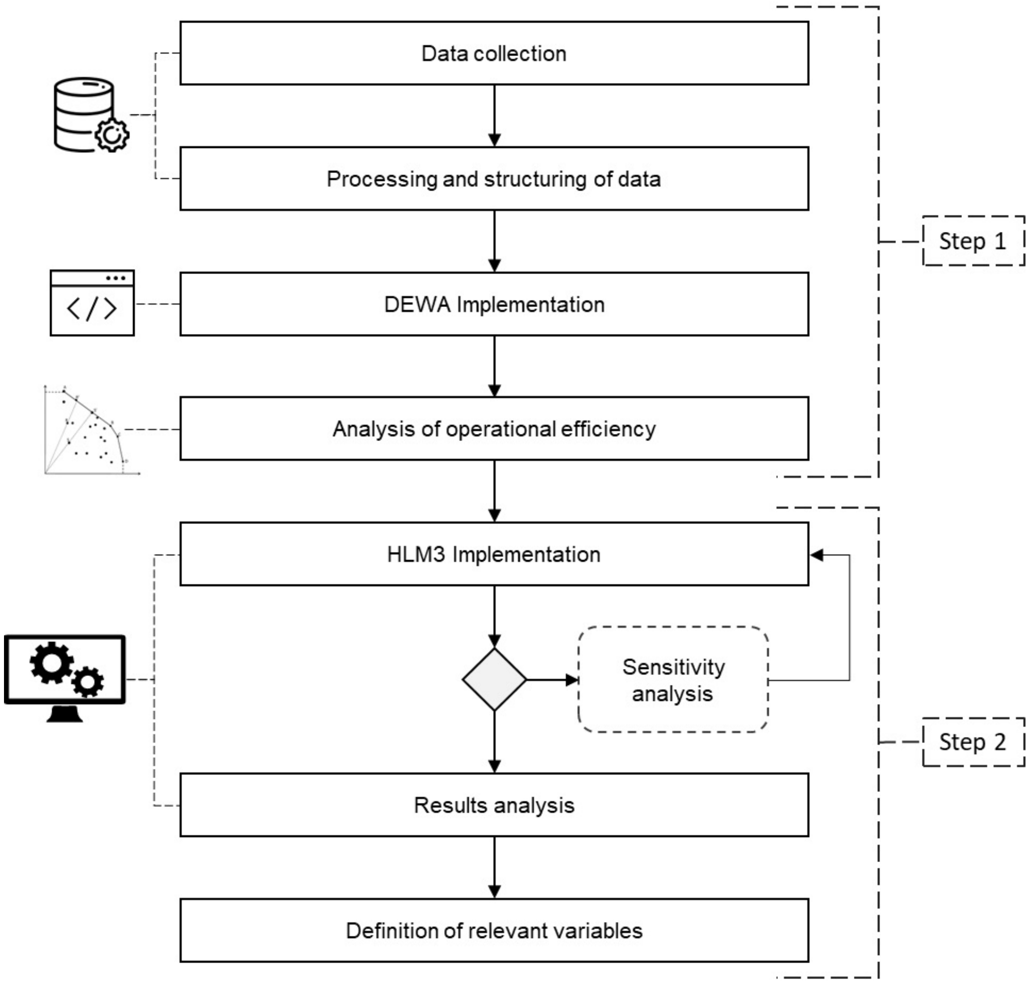

Figure 1 – Methodological process.

4.3 Selection of the Second Stage Variables

The efficiencies calculated in the first stage for each year correspond to the dependent variables of the second-stage HLM3 with repeated measures. To identify the explanatory variables to be considered as determinants of airport efficiency, two points must be considered. First, the input and output variables in the first stage should not be reused as explanatory variables in the second stage (Lin & Hong, 2006). Second, as shown in the Appendix, several studies in the airport literature have defined airport efficiency determinants (e.g., Adler and Liebert 2014; Assaf and Gillen 2012; Choo and Oum 2013; Martín et al. 2013; Martini et al. 2013; Merket and Assaf 2015; Oum et al. 2006; Pathomsiri et al. 2008; Scotti et al. 2012; See and Lin 2015; Ülkü 2015; Voltes-Dorta and Pagliari 2012; Wanke 2012a, b, 2013; Zou et al. 2015). Table 1 details the explanatory variables of the HLM3 model with repeated measures in the present study.

Table 1 – Second-Stage Explanatory Variables.

Determinant Factor	Variable	Unit	Label
Governance Structure	Property	Nominal	Public = 0 Private = 1 Mixed = 2
Airport Operational Characteristics	Size	m2	Size
	Number of commercial establishments		Commerce
	Number of aircraft parking positions		Positions
	Number of vehicle parking lots		Parking lots
	Airport years of experience		Experience
Service Strategy	Number of airlines		Airlines
Economic Factors	Average oil barrel price	US$/bbl[a] FOB[b]	Oil
	Foreign exchange	R$/US$	Exchange
	Interest rate	%	Interest
	GDP[c] growth (t-1)	%	GDP
	Unemployment rate (t-1)	%	Unemployment
Location	Airport location	State	Location

4.4 Main Brazilian Airports

The initial sample comprised 60 Brazilian airports, of which the 30 largest accounted for about 94% of air traffic movements (passengers, cargo, landings, and takeoffs) (ANAC, 2020a, 2020b). Ribeirão Preto and Porto Seguro airports were excluded from the sample due to lack of information. Table 2 shows the study sample.

Table 2 – Study Sample: Top 30 Brazilian Airports for Air Traffic Movements.

Aracaju Airport (SE)	Teresina Airport (PI)	Belo Horizonte International Airport – Cofins (MG)
Brasilia International Airport (DF)	Belém International Airport – Val-de-Cans (PA)	Campo Grande International Airport (MS)
Cuiabá International Airport – Mal. Rondon (MT)	Campinas International Airport – Viracopos (SP)	Florianópolis International Airport – Hercílio Luz (SC)
Fortaleza International Airport – Pinto Martins (CE)	Curitiba International Airport – Afonso Pena (PR)	Goiânia International Airport – Santa Genoveva (GO)
João Pessoa International Airport – Bayeux (PB)	Foz do Iguaçu/Cataratas International Airport (PR)	Maceió International Airport – Zumbi dos Palmares (AL)
Manaus International Airport (AM)	Londrina Airport (PR)	Navegantes International Airport (SC)
Porto Alegre International Airport – Salgado Filho (RS)	Natal International Airport (RN)	Porto Velho International Airport (RO)
Recife International Airport – Guararapes (PE)	Salvador International Airport (BA)	Rio de Janeiro International Airport – Galeão (RJ)
Rio de Janeiro Airport – Santos Dummont (RJ)	São Paulo Airport – Congonhas (SP)	São Paulo International Airport – Guarulhos/Cumbica (SP)
São Luís International Airport – Tirirical (MA)	Uberlândia Airport (MG)	Vitória Airport (ES)

4.5 Data Collection

The input and output variables of the DEA model for each airport, as well as the explanatory variables of the HLM3 model with repeated measures, were collected for 2014–2018. Output data of the first stage were collected from the airport rankings of the Agência Nacional de Aviação Civil (National Civil Aviation Agency)[1]. Other data regarding the input variables of the DEA model and the explanatory variables of the second stage were obtained from the Infraero website[2]. Table 3 summarizes selected information on the sample airports for 2014-2018.

Table 3 – Average Values per Airport, 2014-2018.

Airport (Decision-making Unit)	**Air Transport Movements[a]**	**Paid Cargo and Mail (kg): Shipments and Receipts**	**Air Passenger Movements[b]**
Aracaju	10,511.40	2,893,534.00	1,221,695.80
Belém	33,554.80	29,280,421.00	3,428,490.80
Belo Horizonte - Confins	101,554.80	32,483,399.00	10,205,399.60
Brasília	143,482.00	90,067,094.00	17,817,206.40
Campinas	114,229.40	233,051,174.60	9,217,247.40
Campo Grande	14,625.20	6,505,266.80	1,522,068.80
Cuiabá	30,828.40	11,420,587.60	2,980,598.60
Curitiba	65,415.00	26,904,066.20	6,639,258.20
Florianópolis	32,072.20	9,769,247.80	3,550,457.80
Fortaleza	46,312.20	45,596,343.20	6,087,102.80
Foz do Iguaçu	15,977.00	660,115.40	1,999,410.20
Goiânia	31,441.60	11,898,892.60	3,039,459.20
João Pessoa	10,987.40	4,284,924.20	1,374,182.60
Londrina	10,500.00	1,794,999.00	962,442.40
Maceió	15,133.80	2,965,716.00	1,977,262.40
Manaus	31,000.80	127,774,118.60	2,907,680.40
Natal	17,384.60	9,764,213.80	2,219,867.80
Navegantes	14,505.60	2,470,712.60	1,504,842.00
Porto Alegre	68,519.40	32,369,834.60	7,904,932.60
Porto Velho	9,062.40	5,735,882.80	840,006.60
Recife	61,295.00	55,433,938.80	7,254,243.20
Rio de Janeiro - Galeão	117,770.00	119,819,456.00	15,981,285.40
Rio de Janeiro - Santos Dummont	95,320.20	6,467,327.00	9,214,135.40
Salvador	69,681.40	52,960,646.20	8,201,773.40
São Luís	15,711.20	9,410,590.00	1,635,881.40
São Paulo - Congonhas	170,321.40	47,345,630.60	19,798,121.40
São Paulo - Guarulhos	267,549.40	577,000,267.40	37,984,034.40
Teresina	10,876.20	5,225,293.60	1,088,293.60
Uberlândia	12,474.20	1,811,140.60	1,058,368.40
Vitória	28,757.20	18,602,615.80	3,118,685.20

Obs.: a. Air transport movements (number of landings and takeoffs); b. air passenger movements (number of paying passengers: boarding and disembarking).

[1] https://www.gov.br/anac/pt-br/assuntos/dados-e-estatisticas/mercado-do-transporte-aereo/demanda-e-oferta. Accessed on February 6th, 2024.

[2] http://www4.infraero.gov.br. Accessed on January 28th, 2024.

Table 4 presents a statistical summary for the input and output variables in the model.

Table 4 – Descriptive Statistics for Input and Output Variables in the Data Envelopment Analysis.

	Input			Output		
	Aircraft Yard Area - m^2 (Input)	**Takeoff & Landing Total Area - m^2 (Input)**	**Passenger Terminal Total Area - m^2 (Input)**	**Air Transport Movements (Output)**	**Paid Cargo & Mail (kg): Shipments and Receipts (Output)**	**Air Passenger Movements (Output)**
Average	143,519	145,243.7	63,277.07	55,561.81	52,725,581.66	6,424,481.14
Standard Deviation	208,136.7	63,673.25	87,025.25	58,960.61	111,046,809.40	7,782,323
Minimum	14,633	76,545	4,414	7,728	614,492	767,851
Maximum	975,513	329,460	387,000	283,781	634,000,267.40	41,284,034.40

Note: Air transport movements (number of landings and takeoffs); air passenger movements (number of paying passengers: boarding and disembarking). Total of 150 observations.

5 MODEL IMPLEMENTATION AND ANALYSIS OF RESULTS

5.1 First Stage (Airport Efficiency): CCR-O and Data Envelopment Window Analysis Models

5.1.1 CCR-O Model

The Charnes-Cooper-Rhodes output oriented (CCR-O) model was implemented first to evaluate airport efficiency in each year from 2014 to 2018, using the ISYDS (Integrated System for Decision Support) free software.

The computational tests were carried out on VAIO desktop, Intel Core i5 10210U CPU 8GB 512GB SSD. The average computational time was 5 seconds.

Table 5 presents the results, including the average efficiency during the analyzed period and airport rank according to the average efficiency.

As shown in Table 5, Campinas, Rio de Janeiro (Santos Dummont), São Paulo (Congonhas), and São Paulo (Guarulhos) airports obtained maximum efficiency for all years analyzed. Among the remaining airports, those with the best average performance in the analyzed period were Teresina, Manaus, and Fortaleza, respectively. Natal airport had the worst performance, followed by Maceió, Foz do Iguaçu, Curitiba, and Rio de Janeiro (Galeão), respectively.

Table 5 – CCR-O Model Results for 2014-2018.

Decision-making Unit	2014	2015	2016	2017	2018	Average	Rank
Aracaju	0.4448	0.4234	0.4059	0.3832	0.3739	0.4062	25
Belém	0.7895	0.7451	0.6074	0.6022	0.5574	0.6603	16
Belo Horizonte - Confins	0.6693	0.6483	0.5583	0.5584	0.5683	0.6005	20
Brasília	0.7473	0.7903	0.7358	0.6562	0.6650	0.7189	12
Campinas	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
Campo Grande	0.6989	0.8667	0.8718	0.7948	0.7915	0.8047	10
Cuiabá	0.7521	0.8710	0.7383	0.5826	0.5923	0.7073	13
Curitiba	0.3595	0.3201	0.2740	0.2725	0.2616	0.2975	27
Florianópolis	0.7799	0.8694	0.8911	0.9308	0.9201	0.8783	8
Fortaleza	1.0000	1.0000	0.9605	0.9126	0.9577	0.9662	7
Foz do Iguaçu	0.2296	0.2454	0.2141	0.2415	0.2584	0.2378	28
Goiânia	0.5058	0.4558	0.3905	0.3689	0.3888	0.4220	24
João Pessoa	0.4146	0.4836	0.5236	0.5335	0.5424	0.4995	22
Londrina	0.4296	0.4375	0.4685	0.4599	0.4726	0.4536	23
Maceió	0.2118	0.2249	0.2319	0.2290	0.2415	0.2278	29
Manaus	1.0000	1.0000	1.0000	0.9880	0.8981	0.9772	6
Natal	0.1463	0.2612	0.2489	0.2267	0.2455	0.2257	30
Navegantes	0.6216	0.6977	0.7034	0.7461	0.9635	0.7465	11
Porto Alegre	0.6842	0.6687	0.5849	0.5728	0.5925	0.6206	18
Porto Velho	0.8125	0.7940	0.6336	0.4256	0.4408	0.6213	17
Recife	0.9004	0.9430	0.8287	0.8013	0.8235	0.8594	9
Rio de Janeiro - Galeão	0.3988	0.3757	0.3503	0.3381	0.3179	0.3562	26
Rio de Janeiro - Santos Dummont	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
Salvador	0.7158	0.6763	0.5965	0.5239	0.5220	0.6069	19
São Luís	0.8040	0.8144	0.6441	0.6537	0.5724	0.6977	15
São Paulo - Congonhas	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
São Paulo - Guarulhos	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1
Teresina	1.0000	1.0000	1.0000	0.9877	0.9003	0.9776	5
Uberlândia	0.7507	0.7422	0.6397	0.6505	0.7097	0.6986	14
Vitória	0.4892	0.5202	0.5446	0.5842	0.6005	0.5477	21

5.1.2 Data Envelopment Window Analysis Model

The DEWA model was used to evaluate airport efficiency in each year, in the same conditions of the CCR-O model. Table 6 presents the results, including the average efficiency during the analyzed period and the airport rank according to the average efficiency.

As shown in Table 6, although the DEWA model follows a logic similar to the CCR-O model in determining scores, the DEWA model produced more accurate results. The best ranked airports remain the same as the CCR-O model, but they are no longer tied. According to the DEWA model, the most efficient airports were São Paulo (Congonhas), Rio de Janeiro (Santos Dummont), São Paulo (Guarulhos), and Campinas, respectively, and the least efficient were the same as those in the CCR-O Model. The efficiencies obtained from the DEWA model will correspond to the dependent variables of the second-stage hierarchical model with repeated measures.

Table 6 – Data Envelopment Window Analysis Results, 2014-2018.

Decision-making Unit	2014	2015	2016	2017	2018	Average	Rank
Aracaju	0.4045	0.3590	0.3511	0.3533	0.3541	0.3644	25
Belém	0.7741	0.6476	0.4917	0.5076	0.5139	0.5870	15
Belo Horizonte - Confins	0.5932	0.6284	0.5496	0.5514	0.5683	0.5782	16
Brasília	0.6830	0.6823	0.6286	0.6005	0.6474	0.6484	13
Campinas	1.0000	0.9364	0.8483	0.9074	1.0000	0.9384	4
Campo Grande	0.6989	0.7211	0.6371	0.6146	0.6508	0.6645	11
Cuiabá	0.7305	0.7705	0.6185	0.5087	0.5391	0.6335	14
Curitiba	0.3212	0.3048	0.2647	0.2674	0.2604	0.2837	27
Florianópolis	0.7521	0.7483	0.7109	0.7834	0.8030	0.7595	9
Fortaleza	1.0000	0.9034	0.7917	0.8068	0.9118	0.8827	5
Foz do Iguaçu	0.1990	0.2197	0.1977	0.2324	0.2527	0.2203	28
Goiânia	0.4302	0.4006	0.3513	0.3517	0.3875	0.3843	24
João Pessoa	0.3998	0.4171	0.4135	0.4376	0.4677	0.4271	22
Londrina	0.4296	0.4076	0.3828	0.3658	0.3919	0.3955	23
Maceió	0.1998	0.2021	0.2030	0.2114	0.2304	0.2094	29
Manaus	1.0000	0.8122	0.7536	0.8053	0.8377	0.8418	6
Natal	0.1450	0.2388	0.2105	0.2064	0.2350	0.2071	30
Navegantes	0.6028	0.6602	0.6155	0.6783	0.8790	0.6872	10
Porto Alegre	0.6123	0.5967	0.5360	0.5471	0.5856	0.5756	18
Porto Velho	0.7878	0.6512	0.5060	0.3622	0.3894	0.5393	20
Recife	0.8333	0.8064	0.7127	0.7333	0.8051	0.7782	8
Rio de Janeiro - Galeão	0.3472	0.3295	0.3154	0.3198	0.3174	0.3259	26
Rio de Janeiro - Santos Dummont	1.0000	1.0000	0.9096	0.9335	0.9616	0.9609	2
Salvador	0.7093	0.6085	0.4986	0.4710	0.5020	0.5579	19
São Luís	0.7982	0.6571	0.4703	0.4952	0.4701	0.5782	16
São Paulo - Congonhas	0.8911	0.9776	0.9909	0.9920	1.0000	0.9703	1
São Paulo - Guarulhos	0.9949	0.9526	0.8887	0.9131	1.0000	0.9499	3
Teresina	1.0000	0.8917	0.7538	0.7459	0.7406	0.8264	7
Uberlândia	0.7185	0.7176	0.5834	0.5951	0.6485	0.6526	12
Vitória	0.4460	0.4471	0.4544	0.5109	0.5632	0.4843	21

Obs.: Considering window length of 5 (W=5).

5.2 Second Stage (Efficiency Determinants): Three-level Hierarchical Linear Model with Repeated Measures

In the first stage, we calculated airport efficiency and rank. In the second stage, we identified the explanatory variables that impact airport efficiency. Our objective, however, is wider. In addition to identifying the explanatory variables of the efficiency of Brazilian airports during 2014–2018, we investigated whether variability occurred in efficiency over time among airports from the same location and among airports from different locations. In cases of such variability, we identified the explanatory airport (level 2) and location (level 3) characteristics. Given the hierarchical structure of the data, we used the hierarchical model proposed in section 3.2 to achieve our objectives. In this model, level 1 (repeated measure) represents time, level 2 airport characteristics, and level 3 airport location, as shown in Table 7.

Table 7 – Airport Efficiency Over Time (Level 1, Repeated Measure), Characteristics (Level 2), and Location (Level 3).

Year *t* (Level 1)	**Airport *j* (Level 2)**	**Location *k* (Level 3)**	**Efficiency (Y_{tjk})**
1	1	1	0.4045
2	1	1	0.3590
3	1	1	0.3511
4	1	1	0.3533
5	1	1	0.3541
1	11	10	0.1990
2	11	10	0.2197
3	11	10	0.1977
4	11	10	0.2324
5	11	10	0.2527
1	30	23	0.4460
2	30	23	0.4471
3	30	23	0.4544
4	30	23	0.5109
5	30	23	0.5632

Obs.: Efficiency was determined using the Data Envelopment Window Analysis model (Table 6).

Table 7 samples a stratum of the database used, and aims to show the nested structure and temporal evolution of the data, which characterizes repeated measurements. While time (*year*) is defined as level 1 (periods nested within airports), there are sometimes more than one airport per location and, therefore, airports are also nested within locations. In this sense, airports characterize level 2, while the location characterizes level 3 of the analysis. This is the reason why, in this study, there are 30 airports nested in 23 locations.

To estimate the null model ("Null Model") and the full HLM3 model with repeated measures ("Full Model"), we followed the steps in Fávero and Belfiore (2019, 2024). For the Full Model, we first estimated a preliminary Full Model with all variables and then we estimated a final Full Model with only significant variables. Table 8 presents the results from the Null Model, comparing it with the correspondent OLS estimation.

Our panel was balanced, as each airport had a minimum and maximum number of monitoring periods equal to five, with an average also equal to five. In relation to the fixed effects component, as shown in Table 8, we verified that the estimation of the parameter Υ_{000} equaled 0.5886, which corresponds to the average of the expected annual efficiencies of the airports (horizontal line estimated in the Null Model or general intercept).

Table 8 also presents the estimates of the variances of error terms. They are τ_{u000} = 0,0247316 for the location level; τ_{r000} = 0,0248524 for the airport level; and σ^2 = 0,0055 for the repeated measure level. Therefore, we defined two intraclass correlations, given the existence of two proportions of variance. The first one refers to the correlation between the data of the *efficiency* variable in t and in t' ($t \neq t'$) of a certain airport j belonging to a certain location k (level 2 intraclass correlation). The other one refers to the correlation between the data of the *efficiency* variable in t and in t' ($t \neq t'$) of different airports j and j' ($j \neq j'$) belonging to a certain location k (level 3 intraclass correlation).

Table 8 – Results of the Null OLS and HLM3 Models.

	OLS	HLM3
Fixed Effects	**Coefficient**	**Coefficient**
Υ_{000}	0.5970773 ***	0.5886218 ***
	(0.0196281)	(0.0449662)
Random Effects		
Location (τ_{u000})		0.0247316 *
		(0.0139129)
Airport (τ_{r000})		0.0248524 **
		(0.011066)
Residual (σ^2)		0.0055248 ***
		(0.0007133)
Log restricted-likelihood		119.041
LR test vs. OLS linear regression		chi2 (2) = 241.14
		sig. chi2 = 0.000

Obs.: Std. errors in parenthesis. *, **, *** indicate, respectively, significance levels of 10%, 5%, and 1%.

As demonstrated by Fávero and Belfiore (2024), in relation to the model estimation, while the fixed effects parameters are estimated by maximum likelihood - ML), the variance components of the error terms were estimated in this study by restricted estimation of maximum likelihood – REML).

Regarding the statistical significance of these variances, the fact that the estimated values of τ_{u000}, τ_{r000}, and σ^2 are considerably higher than the respective standard errors indicates significant variation in annual efficiency among airports and among locations. This variation is more significant among airports, with ratios greater than 1.96, which is the critical value of the standardized normal distribution that results in a significance level of 5%. At the very bottom of Table 8, we verified this fact by analyzing the result of the likelihood ratio test (long-run test). As $Sig.\chi_2 = 0,000$, we reject the null hypothesis that the random intercepts equal zero (H_0: u_{00k} = r_{0jk} = 0) and thus discard the estimation of a traditional OLS linear regression model with repeated measures in favor of a hierarchical model for our data.

Although researchers often disregard the estimation of null models, their results may help decide whether to reject some research hypotheses and even provide adjustments in relation to the proposed constructs. In this sense, our findings can independently reject or confirm research hypotheses and help structure research, depending on the researcher's objectives, without needing to estimate additional models. Moreover, they allow researchers to draw important conclusions.

For our data, the results of the Null Model affirm that there is significant variability in airport efficiency (i) over the five-year analysis period, (ii) among airports in the same location over time, and (iii) among airports from different locations over time. Thus far, our results indicate that location plays an important role in airport efficiency.

As an additional objective, we sought to identify airport characteristics that explain the variability in efficiency among airports from the same location and different locations. The variable *property* is qualitative with three categories (public, private, and mixed). Thus, it was transformed into n-1 dummies or a binary (*property_pu* and *property_pr*), as the explanatory variables of the HLM3 model with repeated measurements must be quantitative or binary. The order of insertion of the random effects components is decreasing when there are more than two levels; thus, we started with the higher level of data nesting and proceeded to the lower level (level 2). Table 9 shows the outputs of the preliminary Full OLS and HLM3 Models, considering all variables (even non-significant ones).

The preliminary Full Model (Table 9) presents significant estimates, at a significance level of 5%, of both the fixed effects parameters and the random effect variance terms. At this point in the modeling, we identified that airport efficiency followed a negative linear trend over time, with significant variance of intercepts and slopes among airports from the same location and different locations. In other words, there is variance of Y (efficiency) over time, of Y over time among airports, and of Y over time among airports from different locations.

These statements can be confirmed through the efficiency tables generated by the CCR-O and DEWA models (Tables 5 and 6). First, we verified variation of efficiency over the five-year period, among airports over the five-year period, and among airports from different locations over the five-year period. Based on the results from the DEWA model in Table 6, the analysis can be enhanced to present a more detailed perspective of the performance of Brazilian airports. For example, we found that all airports in the state of São Paulo (Congonhas-SP, Guarulhos-SP, and Viracopos-Campinas) and one airport in the state of Rio de Janeiro (Santos Dummont-RJ) demonstrated superior performance. Each of these airports exhibited consistently high performance throughout the study period.

On the other end, airports like Natal, Maceió, Foz do Iguaçu, Curitiba, and Rio de Janeiro - Galeão were among the least efficient. This comprehensive analysis, highlighting the top and bottom performers, provides a clearer understanding of the relative efficiency of these airports over the years. The results reflect significant variability in efficiency among the airports, with certain locations like São Paulo and Rio de Janeiro showing consistently high performance. This suggests that factors like location, infrastructure, and operational strategies could be influencing airport efficiency significantly.

Table 9 – Results of the Preliminary Full OLS and HLM3 Models.

	OLS	HLM3
Fixed Effects	**Coefficient**	**Coefficient**
year	omitted because of collinearity	-0.0304682 **
		(0.0137552)
property_pu	0.0005183	0.0636678
	(0.0845324)	(0.1958613)
property_pr	0.0253428	0.0403057
	(0.0779822)	(0.1598442)
size	-7.56e-09 *	-5.01e-09
	(4.21e-09)	(9.25e-09)
commerce	-0.002915 ***	-0.0011862
	(0.0004977)	(0.0008209)
positions	-0.003262 ***	-0.0043217 ***
	(0.0007276)	(0.0006438)
parkinglots	0.0000941 ***	0.0000429
	(0.0000178)	(0.0000464)
experience	0.0053331 ***	0.0052709 ***
	(0.0008272)	(0.0015987)
airlines	0.0178514 ***	0.014936 ***
	(0.0036366)	(0.0035717)
oil	0.0003901	-0.0022386
	(0.0017475)	(0.0018278)
exchange	omitted because of collinearity	0.1175076 *
		(0.0650074)
interest	-0.0060879	-0.0114815 ***
	(0.0215517)	(0.0018883)
gdp	2.47e-06	omitted because of collinearity
	(0.0262107)	
unemployment	-0.019004 *	omitted because of collinearity
	(0.0107965)	
constant (Υ_{000})	0.550622 **	0.1969086
	(0.2689884)	(0.3244751)
Random Effects		
Location		
(τ_{u000} - year)		0.0009724 **
		(0.0004136)
(τ_{u000})		0.0564411 ***
		(0.0194064)
Airport		
(τ_{r100} - year)		0.0002049 ***
		(0.0001765)
(τ_{r000})		0.0020173
		(.0037822)
Residual (σ^2)		0.0011933 ***
		(0.0001814)
Log restricted-likelihood		115.081
LR test vs. OLS linear regression		chi2 (4) = 288.65
		sig. chi2 = 0.000

Obs.: Std. errors in parenthesis. *, **, *** indicate, respectively, significance levels of 10%, 5%, and 1%.

We also identified airport characteristics (factors) that explain the variability in efficiency. Table 9 shows that the most significant factors (p-value <0.05) were *positions* (number of aircraft parking positions), *airlines* (number of airlines operating at the same airport), *interest* (interest rate), and *experience* (airport years of experience). We also concluded that among the economic variables analyzed, only *interest* rate was significant. The variables *gdp* and *unemployment* were omitted from the model due to multicollinearity problems, which can affect the quality of the results and make data interpretation difficult. The variables *property* (public, private, or mixed), *size* (airport size), *commerce* (number of commercial establishments), and *parkinglots* (number of vehicle parking lots) were not significant in explaining the variability in airport efficiency. To estimate the final parameters of the HLM3 model with repeated measures, we excluded non-significant variables and those with multicollinearity problems. Table 10 shows the results for the Final Full OLS and HLM3 Models, for comparison purposes.

Table 10 – Results of the Final Full OLS and HLM3 Models.

	OLS	**HLM3**
Fixed Effects	**Coefficient**	**Coefficient**
year	-0.030452 **	-0.0352056 ***
	(0.0162027)	(0.0075832)
positions	-0.0023563 ***	0.0039658 ***
	(0.0007067)	(0.0005659)
experience	0.0039631 ***	0.0036492 ***
	(0.0008674)	(0.0011499)
airlines	0.0185042 ***	0.012948 ***
	(0.0038505)	(0.0029331)
interest	-0.0112002	-0.0112002 ***
	(0.0084779)	(0.001534)
constant	0.5182444 ***	0.623239 ***
	(0.1439958)	(0.0956811)
Random Effects		
Location		
(τ_{u100} - year)		0.0009993 **
		(.000398)
(τ_{u000})		.0529503 ***
		(.0174719)
Airport		
(τ_{r100} - year)		.0001285
		(.0001394)
(τ_{r000})		.0026943
		(.0025413)
Residual (σ^2)		.0015415 ***
		(.0002327)
Log restricted-likelihood		147.297
LR test vs. OLS linear regression		chi2 (4) = 311.96
		sig. chi2 = 0.000

Obs.: Std. errors in parenthesis. *, **, *** indicate, respectively, significance levels of 10%, 5%, and 1%.

As $Sig.\tau^2$ = 0,000 in Table 10, we can reject the null hypothesis that the random intercepts equal zero (H$_0$: $u_{00k} = r_{0jk} = u_{10k} = r_{1jk} = 0$) and thus discard the estimation of the traditional OLS linear regression model with repeated measures in favor of a hierarchical model for our data. One can also observe that the OLS estimation can produce biased parameters, with different statistical significances (as observed for variable *interest*) and even inverted signals (as observed for variable *positions*).

The final Full Model has the following specification:

$$\begin{aligned} \text{efficiency}_{\text{tjk}} = \; & 0,623 - 0,0352.year_{\text{jk}} + 0,00397.positions_{\text{jk}} + 0,00365.experience_{\text{jk}} \\ & - 0,0112.interest_{\text{jk}} + 0,01295.airlines_{\text{jk}} \\ & + u_{00k} + u_{10k}.year_{\text{jk}} + r_{0jk} + r_{1\text{jk}}.year_{\text{jk}} + e_{\text{tjk}} \end{aligned} \tag{15}$$

Compared to the preliminary Full Model, the final Full Model has one important difference, in terms of significant variables: the inversion of the signal of *positions*, corroborating the need for this last step. In Expression (15), the signal of variable *year* is negative in the final Full Model, indicating that efficiency of Brazilian airports decreased from 2014 to 2018. The other negative signal relates to the interest rate, indicating that it negatively affected airport efficiency; that is, the higher the interest rate, the lower the efficiency. All other significant characteristics (e.g., *positions*, *experience*, and *airlines*) had positive signals, indicating that airports with higher scores for these characteristics had higher efficiency scores.

Finally, we estimated an OLS regression model, neglecting the nested structure of the data. The OLS model points at the same significant variables and impact (positive or negative) on airport efficiency. Notwithstanding the fact that the results are similar, the HLM3 model with repeated measurements produced a much better fit to the observed data than the OLS model. Figure 2 compares the predicted efficiency values generated by the HLM3 model with repeated measurements to those generated by OLS estimation, for all airports in each analyzed period, using the explanatory variables of the final Full Model.

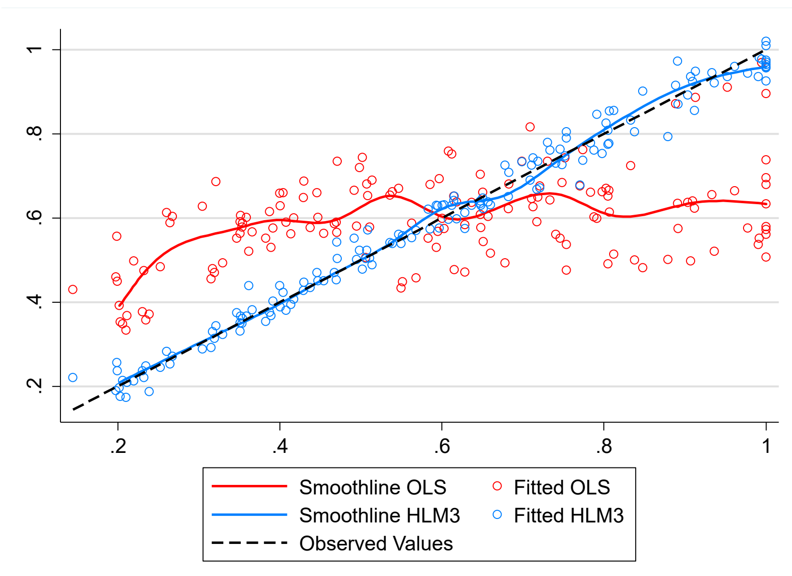

Figure 2 – Three-level Hierarchical Linear Model and Ordinary Least Squares Regression Model Fit.

Obs.: Considered only significant variables.

As Figure 2 shows, both models capture the overall trend of the observed data, but there are differences in how closely they fit the observed values. It seems the HLM3 model, which accounts for the nested data structure, fits the data points more closely than the OLS model. This is particularly noticeable in the middle of the graph, where the HLM3 smoothline follows the cluster of observed values more tightly than the OLS smoothline. The scatterplot supports the claim that the HLM3 model, with repeated measurements, provides a better fit to the observed data compared to the OLS model, which does not account for the nested structure of the data.

In sum, our hierarchical linear model has a better fit, in comparison to the OLS model, since it takes into account the nested structure of the data.

6 FINAL CONSIDERATIONS

The present paper analyzed the efficiency of the 30 largest Brazilian airports (corresponding to 94% of Brazilian traffic) during 2014 to 2018. The analysis consisted of two stages. The first stage assessed the airports' operational efficiency and changes in productivity over time using two techniques, CCR-O and DEWA. The DEWA model offered better results among the best ranked airports. In the second stage, we identified the explanatory variables that impacted airport efficiency, considering the annual efficiencies calculated in the first stage. Given the temporal and nested structure of the data, we applied, in the second stage, an HLM3 model with repeated measures. This is the first time, to our knowledge, that such a model has been used in the airport efficiency literature. In comparing the HLM3 model with an OLS regression model, our tests indicated (i) not only that the hierarchical model performed better in terms of model fit but also (ii) that it was the correct model to be used.

The explanatory variables (critical success factors) analyzed included airport operational characteristics, governance structure, service strategy, economic factors, location, and period. First, we identified variance of Y (efficiency) over time, of Y over time and among airports, and of Y over time among airports from different locations. We concluded that location played an important role in airport efficiency – airports with the same characteristics but from different locations have different operational efficiency. It is thus important to properly model the nested structure, which we did by adopting a hierarchical model. With regard to the efficiency variability among airports from different locations, we concluded that all airports in São Paulo (Congonhas-SP, Guarulhos-SP and Viracopos-Campinas) and one in Rio de Janeiro (Santos Dummont-RJ) performed better than the other airports analyzed. With regard to the efficiency variability over time, we noted a decrease in the average efficiency of airports from 2014 to 2018.

Significant factors with positive influence that explained efficiency included number of aircraft parking positions, airport years of experience, and number of airlines. The only economic factor with significant negative influence was the interest rate. Opposing the expected assumptions and conclusions of several papers (Adler and Liebert 2014; Adler et al. 2013; Hooper and Hensher 1997; Martín and Román 2001; Merkert and Mangia 2014; Perelman and Serebrisck 2012; Tovar and Martín-Cejas 2009), we found that governance structure (public, private, or mixed) did not affect the efficiency of Brazilian airports in the analyzed period. Also in contradiction to several assumptions in the literature (Coto-Millán et al. 2014; Merkert and Mangia 2014; Tovar and Martín-Cejas 2009), the following operational characteristics were not significant to explain variation in the efficiency of Brazilian airports: airport size, number of commercial establishments, and number of vehicle parking lots.

The results of this study can help inform policy and regulatory decision makers by highlighting areas that affect airport efficiency, thereby facilitating targeted developments that will improve service and lower costs.

Researches in Operations and Logistics Management still use hierarchical models with parsimony. Although there has been an increase in the use of such models, there is still considerable room for improvement, given the many opportunities related to interesting themes, such as supply chain management, demand forecasting and service level management, for instance. In fact, even when studying the influence of economic factors over operational efficiency, researchers might benefit from using hierarchical models. While we believe the results presented here provide additional evidence supporting the use of hierarchical models, we emphasize the importance of considering different levels, or contexts, when analyzing certain phenomena that consider heterogeneities over time and among locations. In a broader sense, these results are important for emphasizing potential uses of this class of models in distinct areas of Operations and Logistics Management.

As we considered data from 2014 to 2018, future researches can be carried out considering broader periods and even taking into account the pandemic period of Covid-19, since the use of airports was deeply affected during this crisis.

Abbreviations

Assurance region (AR); clustering analysis (CA); data envelopment analysis (DEA); directional distance function (DDF); endogenous weight (EW); factor analysis (FA); fixed effects (FE) regression; feasible generalized least square (FGLS); free disposal hull (FDH); generalized method of moments (GMM); input distance function (IDF); long-run (LR); maximum likelihood (ML) estimation; restricted estimation of maximum likelihood (REML); Malmquist productivity index (MPI); ordinary least square (OLS) regression; principal component analysis (PCA); random effects (RE) regression; Slacks-based measure (SBM); stochastic cost frontier (SCF); stochastic frontier analysis (SFA); short-run (SR); Simar-Wilson bootstrapping truncated (SWBT) regression; total factor productivity (TFP) index; variable factor productivity (VFP).

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How to cite

BELFIORE P, LUIZ PAULO FÁVERO LP, SERRA RG, TARANTIN JUNIOR W, COSTA IPA, MOREIRA MAL, TERRA AV & SANTOS M. 2024. Operational Efficiency in Brazilian Airports: An Analysis through the Hierarchical Linear Modeling with Repeated Measures. *Pesquisa Operacional*, **44**: e281311. doi: 10.1590/0101-7438.2023.043.00281311.

APPENDIX

Table A1 – Airport Efficiency Studies.

Reference	Sample data	Model	Input	Output	Explanatory variables
Hooper and Hensher (1997)	6 Australian airports, 1988-1993	TFP index and OLS regression	• Labor costs • Capital costs • Other operating costs	• Non-aeronautical revenues • Aeronautical revenues	• Size of operation (output index) • Airport-specific dummy variables
Gillen and Lall (1997)	21 US airports, 1989-1993	Two-stage DEA model: 1) DEA 2) Tobit regression	**(i) Terminal services** • Number of runways • Number of gates • Terminal area • Number of employees • Number of baggage claim belts • Number of vehicle parking lots **(ii) Movements** • Airport area • Number of runways • Runway area • Number of employees	**(i) Terminal services** • Number of passengers • Cargo **(ii) Movements** • Aircraft movements • Number of passengers	**i) Structural variables** • Number of runways • Terminal area • Number of gates • Number of baggage claim belts per gate **ii) Environmental variables** • Annual service volume **iii) Dummy variables for the time period** • Year 1989 • Year 1990 • Year 1991 • year 1992 **iv) Dummy variables for hub airports** • Atlanta • San Francisco • Minnesota and St Paul • Seattle – Tacoma • Phoenix **v) Noise strategy variables** • Preferential flight path • Preferential runway use • Limit on operations • Limit on stage II aircraft • Limit on operating hours • Noise budget **vi) Management operational and investment variables** • Number of airlines hubs • % of gates common use .• % of gates exclusive use • % of international airports • Financing regime • % of general aviation traffic

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Sarkis (2000)	44 major US airports, 1990-1994	DEA, Multi-factor efficiency models and CA	• Operating costs • Number of employees • Number of gates • Number of runways	• Operating revenues • Aircraft movements • General aviation movements • Number of passengers • Cargo	
Martín and Román (2001)	37 Spanish airports, 1997	DEA models	• Labor costs • Capital costs • Material costs	• Number of passengers • Cargo • Aircraft movements	
Pels et al. (2001)	34 European airports, 1995-1997	DEA and SFA	**i – DEA (PAX model)** • Terminal size • Number of aircraft parking positions (terminal) • Number of remote aircraft parking positions • Number of check-in counters • Number of baggage claim belts **ii – DEA (ATM model)** • Airport area • Number of runways • Runway length • Number of aircraft parking positions (terminal) • Number of remote aircraft parking positions **iii – SFA (PAX model)** • Number of baggage claim belts • Number of aircraft parking positions (terminal) • Number of remote aircraft parking positions **iv – SFA (ATM model)** • Number of runways • Number of aircraft parking positions (terminal) • Number of remote aircraft parking positions	**i – DEA (PAX model)** • Number of passengers **ii – DEA (ATM model)** • Aircraft movements **iii – SFA (PAX model)** • Number of passengers **iv – SFA (ATM model)** • Aircraft movements	
Fernandes and Pacheco (2002)	35 Brazilian airports, 1998	DEA	• Apron area • Departure lounge • Number of check-in counters • Curb frontage • Number of vehicle parking lots • Baggage claim area	• Number of passengers	

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Bazargan and Vasigh (2003)	45 US airports, 1996-2000	DEA	• Number of runways • Number of gates • Operating costs • Non-operating costs	• Number of passengers • Aircrafts movements • Other movements • Aeronautical revenues • Non-aeronautical revenues • % of on-time operations	
Oum et al. (2003)	50 worldwide airports, 1999	TFP and log-linear regression	• Number of employees • Number of runways • Terminal area • Number of gates • Soft cost input	• Aircraft movements • Number of passengers • Cargo • Non-aeronautical revenue	**Factors beyond managerial control** • Ownership structure • Airport size • Average aircraft size • % of international passengers **Factors under managerial control** • Business diversification strategy • Outsourcing • Service quality
Pacheco and Fernandes (2003)	35 Brazilian domestic airports, 1998	DEA	• Number of employees • Payroll • Operating costs	• Domestic passengers • Cargo plus mail • Operating revenue • Non-aeronautical revenues • Other revenues	
Pels et al. (2003)	33 European airports, 1995-1997	DEA and SFA	**i - ATM model** • Airport area • Number of runways • Number of terminal aircraft parking positions • Number of remote aircraft parking positions **ii – APM model** • Number of check-in counters • Number of baggage claim belts • Aircraft movements	**i – ATM model** Aircraft movements **ii – APM model** • Number of passengers	
Oum and Yu (2004)	76 worldwide airports, 2000-2001	VFP and log-linear regression	• Number of employees • Soft cost input	• Number of passengers • Cargo • Aircraft movements • Non-aeronautical revenues	**Factors beyond airport control** • Airport size • Average aircraft size • % of international passengers • % of cargo in total traffic • Capacity constraints **Factors within airport control** • Passenger satisfaction • % of non-aeronautical revenue • Terminal operator

Table A1 – Continuation.

Reference	**Sample data**	**Model**	**Input**	**Output**	**Explanatory variables**
Sarkis and Talluri (2004)	44 US airports, 1990-1994	DEA, Multi-factor efficiency models and CA	• Operating costs • Number of employees • Number of gates • Number of runways	• Operating revenues • Aircraft movements • General aviation movements • Number of passengers • Cargo	
Yoshida and Fujimoto (2004)	67 Japanese airports, 2000	Two-stage DEA model: 1) DEA and TFP index; 2) OLS regression	• Runway length • Terminal area • Access cost • Number of employees	• Number of passengers • Cargo • Aircraft movements	• Third-category regional airports • Airports that started their operations in the 1990s
Lin and Hong (2006)	20 major worldwide airports, 2003	DEA models	• Number of employees • Number of check-in counters • Number of runways • Number of parking positions • Number of baggage claim belts • Number of aprons • Number of boarding gates • Terminal area	• Number of passengers • Cargo • Aircraft movements	
Oum et al. (2006)	116 worldwide airports, 2001-2003	VFP and log-linear regression	• Number of employees • Soft cost input	• Number of passengers • Aircraft movements • Non-aeronautical revenues	**Airport characteristics** • Airport size • Runway utilization • Average aircraft size • % of international passengers • % of cargo in total traffic **Other factors** • Ownership structure • Regional business environments • Business diversification (% of non-aeronautical revenue)
Barros and Dieke (2007)	31 Italian airports, 2001-2003	DEA models	• Labor • Capital costs • Other operating costs	• Aircraft movements • Number of passengers • Cargo • Handling receipts • Aeronautical sales • Non-aeronautical sales	
Barros (2008a)	32 Argentine airports, 2003-2007	Two-stage DEA model: 1) DEA 2) SWBT regression	• Number of employees • Runway area • Apron area • Passenger terminal area	• Aircraft movements • Number of passengers • Cargo	• Time trend • Airport hub status • Work load units (WLU)

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Barros (2008b)	27 UK airports, 2000-2005	SCF (LR) estimated using ML	• Operating costs • Labor costs • Capital premises • Capital investments	• Number of passengers • Aircraft movements	• Time trend • Labor costs • Capital premises • Capital investments • Number of passengers • Aircraft movements • Owned by BAA • Owned by Manchester airports • Owned by TBI
Barros and Dieke (2008)	31 Italian airports, 2001-2003	Two-stage DEA model: 1) DEA models 2) SWBT regression	• Labor costs • Capital invested • Operating costs excluding labor costs	• Aircraft movements • Number of passengers • Cargo • Handling receipts • Aeronautical revenues • Non-aeronautical revenues	• Time trend • Airport hub status • Work load units (WLU) • Ownership structure • Location
Oum et al. (2008)	109 Worldwide airports, 2001-2004	SCF (SR) estimated via Bayesian approach	**Variable inputs** • Number of employees • Non-labor variable cost **Fixed inputs** • Number of runways • Passenger terminal area **Variable inputs' prices** • Wage rate • Non-labor input price **Variable inputs' share** • Labor cost share	• Number of passengers • Aircraft movements • Non-aeronautical revenue	**(i) Geographic distribution of airports (%)** **(ii) Ownership structure (%)** **(iii) Airport characteristics** • % of international passengers • % of cargo
Pathomsiri et al. (2008)	56 US airports, 2000-2003	DDF and Luenberger productivity index	• Land area • Number of runways • Runway area	**Desirable outputs** • Non-delayed flights • Number of passengers • Cargo **Undesirable outputs** • Delayed flights • Time delays	
Yu et al. (2008)	4 Taiwan's airports, 1995-1999	• Traditional MPI • Extended MPI • Extended MLPI with DDF	**Inputs** • Operating costs • Labor costs • Capital costs **Environmental factors** • Aircraft movements • Number of passengers	**Desirable output** • Aeronautical revenue • Non-aeronautical revenue **Undesirable output** • Aircraft noise	
Barros and Weber (2009)	27 UK airports, 2000-2005	DEA and MPI	• Labor costs • Capital costs • Other costs	• Number of passengers • Cargo • Aircraft movements	

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Chi-Lok and Zhang (2009)	25 Chinese airport, 1995-2006	Two-stage DEA model: 1) DEA and MPI 2) OLS and Tobit regression	• Runway length • Terminal size	• Number of passengers • Cargo • Aircraft movements	**(i) Airport localization program** **(ii) Competition intensity** **(iii) Public listing** **(iv) Airport characteristics** • Airport hub status • Local economy • Coastal city • Tourist city • Population • Demand and supply shocks **(v) Event variables** • Airline mergers • Open-skies agreements • Guangzhou new airport
Lam et al. (2009)	11 major Asian Pacific airports, 2001-2005	DEA models: a) CCR b) BCC c) SBM d) Cost efficiency model e) Allocative efficiency model	• Labor costs • Capital costs • Soft cost input • Trade value	• Aircraft movements • Number of passengers • Cargo	
Tovar and Martín-Cejas (2009)	26 Spanish airports, 1993-1999	SFA	• Number of employees • Land area • Number of gates	• Aircraft movements • Average aircraft size • % of non-aeronautical revenue	• Outsourcing • Non-aeronautical revenue • Cargo
Assaf (2010)	27 UK airports, 2007	DEA and Bootstrapped DEA	• Number of employees • Airport area • Number of runways	• Number of passengers • Cargo • Aircraft movements	
Yang (2010)	12 international airports in Asia-Pacific region, 1998-2006	DEA and SFA (Cobb-Douglas production function) estimated using ML	• Number of employees • Number of runways • Operating costs	• Operating revenues	• Number of employees • Number of runways • Operating costs • Time trend
Tovar and Martín-Cejas (2010)	26 Spanish airports, 1994-1999	SFA and MPI	• Number of employees • Number of gates • Airport area	• Aircraft movements • Average aircraft size • % of non-aeronautical revenue	

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Lozano and Gutiérrez (2011a)	41 Spanish airports, 2006	Non-radial DEA models: a) RMOTE b) CRS c) SE d) NIRS Target-setting DEA model	• Runway area • Apron capacity • Passenger throughput capacity • Number of baggage claim belts • Number of check-in counters • Number of boarding gates	• Number of passengers • Aircraft movements • Cargo	
Lozano and Gutiérrez (2011b)	39 Spanish airports, 2006-2007	SBM model and DDF	• Runway area • Apron capacity • Number of baggage claim belts • Number of check-in counters • Number of boarding gates	**Desirable outputs** • Aircraft movements • Number of passengers • Cargo **Undesirable outputs** • % of delayed flights • Average delay time	
Tsekeris (2011)	39 Greek airports, 2007	Two-stage DEA model: 1) DEA models; 2) SWBT regression and Bootstrapped censored quantile regression	• Number of runways • Terminal and airplane parking area • Operating hours	• Number of passengers • Cargo • Aircraft movements	• Location (island or mainland) • Size of operations • Operating characteristics
Assaf and Gillet (2012)	73 International airports across Europe, North America and Australia, 2003-2008	Two-stage DEA model: 1) DEA and SFA; 2) SWBT regression	• Number of employees • Other operating costs • Number of runways • Passenger terminal area	• Number of passengers • Aircraft movements • Non-aeronautical revenue	• Ownership structure • Economic regulation
Assaf et al. (2012)	27 UK airports, 1998-2008	SFA	• Labor costs • Capital costs • Materials costs	• Number of passengers • Aircraft movements • Cargo • Non-aeronautical revenues	
Chow and Fung (2012)	30 Chinese airports, 2000-2006	MPI and SFA	• Terminal area • Runway length • Time trend	• Number of passengers • Cargo • Aircraft movements	
Gitto and Mancuso (2012)	28 Italian airports, 2000-2006	Bootstrapped MPI	• Labor costs • Capital costs • Soft cost input	• Aircraft movements • Number of passengers • Cargo • Aeronautical revenues • Non-aeronautical revenues	
Perelman and Serebrisky (2012)	21 Latin America airports, 2000-2007	DEA models and MPI	• Number of employees • Number of runways • Terminal area	• Number of passengers • Cargo • Aircraft movements	

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Scotti et al. (2012)	38 Italian airports, 2005-2008	SFA	• Runway capacity • Number of aircraft parking positions • Terminal area • Number of check-in counters • Number of baggage claim belts • Number of employees	• Aircraft movements • Number of passengers • Cargo	• Airport competition • Ownership structure • Degree of dominance of the main airline in an airport
Voltes-Dorta and Pagliari (2012)	194 Worldwide airports, 2007-2009	SCF (SR)	**(i) Variable costs** • Labor costs • Materials costs **(ii) Fixed factors** • Terminal area • Runway length • Number of boarding gates • Number of check-in counters • Number of baggage claim belts **(iii) Other** • Time trend • Number of employees • % of dominant carrier • % of airline traffic • % of charter traffic • % of low-cost traffic • Ownership structure	• Domestic-Schengen passengers • International passengers • Aircraft movements • Maximum take-off weight • Cargo • Non-aeronautical revenue	
Wanke (2012a)	65 Brazilian airports, 2009	Bootstrapped DEA and FDH model	• Aircraft movements	• Number of passengers • Cargo • Mail	
Wanke (2012b)	63 Brazilian airports, 2009	DEA, Bootstrapped DEA, PCA, and CA	• Airport area • Apron area • Number of runways • Runway length • Number of aircrafts parking positions • Terminal area • Number of vehicles parking lots	• Aircraft movements • Number of passengers • Cargo	(Cluster analysis) • Regular flights • Location • International airport • Airport hub status
Adler et al. (2013)	43 European airports (1998-2007)	Two-stage network DEA model: 1) CA; 2) DEA models and PCA	• Staff costs • Other operating costs • Runway capacity • Terminal capacity	• International passengers • Domestic passengers • Cargo • Aircraft movements	
			• International passengers • Domestic passengers • Cargo • Aircraft movements	• Non-aeronautical revenues • Aeronautical revenues	

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Choo and Oum (2013)	63 US airports, 2007-2010	Two-stage model: 1) VFP and SFA; 2) a) VFP regressions: OLS, RE and FE; b) SFA: Tobit regression	• Number of employees • Soft cost input	• Number of passengers • Aircraft movements • Non-aeronautical revenues	• % of LCC passenger • Airport output scale • % of non-aeronautical revenue • % of international passengers • % of connecting passengers • % of cargo traffic • Runway utilization • Average aircraft size
De Nicola et al. (2013)	20 Italian-airports, 2006-2008	Two-stage model: 1) MPI; 2) FA and Pooled-OLS regression	• Labor costs • Capital costs • Soft cost input	• Work load units (WLU) • Aircraft movements	**Quality indicators** • % of delayed flights • Waiting time in queues at check-in • Baggage reclaim time • Mishandled bags
Martini et al. (2013)	33 Italian-airports, 2005-2008	Two-stage DEA model: 1) DDF and DEA; 2) Adapted SWBT regression	• Terminal area • Runway length • Number of baggage claim belts • Number of aircraft parking positions	**Desirable outputs** • Aircraft movements • Work load units (WLU) **Undesirable outputs** • Total costs of local air pollution • Noise levels	**Aeronautical factors** • Fleet mix • Airport size • Presence of low-cost-carriers • Airline's market power (degree of dominance of the main airline at each airport) **Non-aeronautical factors** • Ownership structure
Chang et al. (2013)	41 Chinese-airports in 2008	Two-stage DEA model: 1) DEA-imposed quasi-fixed input constraints models; 2) SWBT regression	• Business hour • Runway area • Terminal area	• Aircraft movements • Number of passengers • Mail/Cargo	**Airport service strategies** • Number of destinations • Number of airlines served • Number of international routes **Airport geographical characteristics** • City levels • Distance to Central Business District (CBD) • Flight area

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Ha et al. (2013)	11 Northeast Asia airports, 1994-2011	Two-stage DEA model: 1) DEA models and SFA; 2) Tobit regression	• Runway length • Terminal size • Number of employees	• Work load units (WLU)	**Governance structure** • Ownership transition • Corporatization • Localization • State shares **Competition** **User impacts** • Customer power • Dominant airline market share • Airline concentration **Airport characteristics** • Input variable • Output variable • Open sky • New airport • Runway structure **Hinterland characteristics** • Per capita GPD • Population **Traffic composition** • International traffic • Cargo traffic
Martín et al. (2013)	194 Worldwide airports, 2007-2009	Two-stage model: 1) SCF-SR; 2) Linear regression	**(i) Variable costs** • Labor costs • Materials costs **(ii) Fixed factors** • Check-in desks • Number of boarding gates • Warehouse area • Terminal area • Runway length **(iii) Other** • Time trend • Number of employees • Airline traffic shares • Share of charter traffic • Share of low-cost traffic • Ownership structure	• Domestic-Schengen passengers • International passengers • Aircraft movements • Average landed maximum take-off weight • Cargo • Non-aeronautical revenues	**Ownership structure** **Outsourcing** • % of materials costs **Diversification** • % of non-aeronautical revenue **Airline dominance and traffic mix** • Airline traffic shares • Share of charter traffic • Share of low-cost traffic **Other factors** • Airport size • Variation in passenger traffic between 2007 and 2009 • Pre-crisis efficiency level • Localization
Wanke (2013)	63 Brazilian airports, 2009	Two-stage network-DEA model and CA	• Terminal area • Number of aircraft parking positions • Number of runways • Aircraft movements	• Aircraft movements • Number of passengers • Cargo	(Cluster analysis) • Location • International airport • Airport hub status • Regular flights

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Adler and Liebert (2014)	51 European and Australian airports, 1998-2007	Two-stage DEA model: 1) DEA (WA-I); 2) Robust cluster and RE regression	• Staff costs • Other operating costs • Runway capacity	• Number of passengers • Cargo • Aircraft movements • Non-aeronautical revenues	**Airport characteristics and management strategies** • % of non-aeronautical revenue • High levels of delay • Runway capacity utilization • Aircraft movements • Average aircraft size **Ownership, regulation and competition** • Ownership structure • Economic regulation • Regional competition **Time trend** • Year 1999 : : • Year 2009
Ahn and Min (2014)	23 major international airports, 2006-2011	DEA (CCR, BCC, SE, both input and output oriented) and MPI	• Land area • Runway length • Passenger terminal area • Cargo terminal area	• Aircraft movements • Number of passengers • Cargo	
Coto-Millán et al. (2014)	35 Spanish airports, 2009-2011	Two-stage DEA approach: 1) DEA and MPI; 2) Tobit regression	• Labor costs • Capital costs • Other operating costs	• Number of passengers • Cargo • Aircraft movements	• Airport size • Share of LCC (low-cost carriers) passengers
Li (2014)	Magong airport, 1991-2000	Two-stage DEA model: 1) DEA; 2) Regression analysis	• Number of employees • Labor costs • Apron area • Cargo terminal area • Passenger terminal area • Scheduled flight numbers • Number of passengers • Arrival passenger numbers • Departure passenger numbers • Passenger capacity of peak hour • Cargo	• Airport Service Costs	• Number of employees • Labor costs • Apron area • Cargo terminal area • Passenger terminal area • Scheduled flights numbers

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Merkert and Mangia (2014)	35 Italian and 46 Norwegian airports, 2007-2009	Two-stage DEA model: 1) Bootstrapped DEA; 2) Tobit regression	**Technical inputs** • Terminal area • Apron area • Number of runways • Runway length • Runway area • Airport area • Number of employees **Financial inputs** • Operating costs • Staff costs • Material costs	• Aircraft movements • Number of passengers • Cargo	• Classification of the airports • Military aviation • Italy or Norway • Population • Profitability • Competition
Scotti et al. (2014)	44 US airports, 2005-2009	Two-stage model: 1) DDF approach; 2) Tobit Regression	• Land area • Terminal area • Runway length • Number of boarding gates • Operating costs	**Desirable outputs** • Number of passengers • Aircraft movements • Cargo **Undesirable outputs** • Flight delays • Noise • Local air pollution	• Fleet mix • Airport size • Percentage of night flights • Multiple airport system • % of international passengers
Tsui et al. (2014a)	11 New-Zealand airports, 2010-2012	Two-stage model: 1) SBM model and MPI; 2) SWBT regression	• Operating costs • Number of runways	• Operating revenues • Number of passengers • Aircraft movements	• Population around the airport • Airport hub status • Airport operating hours • Airport ownership structure • Christchurch earthquakes • Rugby World Cup 2011
Tsui et al. (2014b)	21 Asia-Pacific airports, 2002-2011	Two-stage DEA approach: 1) DEA; 2) SWBT and RE Tobit regression	• Number of employees • Number of runways • Runway length • Passenger terminal area	• Number of passengers • Cargo • Aircraft movements	• Time trend • GPD per capita • % of international passengers • Airport hub status • Airport ownership structure • Airport operating hours • Airport hinterland population • Alliance membership of dominant airline
Lai et al. (2015)	24 major international airports, 2010	DEA and AHP/DEA-AR	• Number of employees • Number of gates • Number of runways • Terminal area • Runway length • Operating costs	• Number of passengers • Cargo and mail • Aircraft movements • Aeronautical and non-aeronautical revenues	

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Merkert and Assaf (2015)	30 international airports, 2013	Two-stage DEA model: 1) DEA and bootstrapped DEA; 2)SWBT Regression	• Runway length • Terminal size • Number of employees	**Profitability** • Profit margin **Perceived service quality** • Skytrax (ranking determined by industry body) • Pax reviews (ranking determined by costumers) **Other common outputs** • Number of passengers • Cargo • Aircraft movements	• % of non-aeronautical revenue • Ownership structure • % of LCC airlines • Asia-Pacific localization • % of international passengers • Number of gates
Zou et al. (2015)	42 US airports, 2009-2012	Two-stage DEA model: 1) DEA; 2) RE regression	• Labor costs • Capital costs • Material costs	**Desirable outputs** • Number of passengers • Aircraft movements • Cargo • Non-aeronautical revenue **Undesirable output** • Total flight arrival delay	**Funding sources used by US airports** • Passenger facility charges • Airport improvement program grants **Runway utilization factors** • Passengers per runway • Cargoes per runway • Delay per runway **Year** • 2010 • 2011 • 2012 **Hub size** • Medium • Small • Non-hub
See and Li (2015)	45 UK airports, 2001-2009	Two-stage model: 1) Hicks-Moorsteen TFP index; 2) FGLS and continuous updated GMM regression	• Labor costs • Capital costs • Other operating costs	• Aeronautical revenue • Non-aeronautical revenue	• Ownership structure • Airport size (number of passengers) • First lag of TFP level • Economic regulation
Ülkü (2015)	41 Spanish and 32 Turkish airports, 2009-2011	Two-stage DEA model: 1) DEA; 2) OLS and Tobit regression	• Staff costs • Other operating costs • Runway area	• Number of passengers • Aircraft movements • Cargo • Non-aeronautical revenues	• Weekly opening hours • Ownership structure • % of international traffic • Airport size (WLU) • Population density around the airport • Level of seasonality • Joint military-civil airport • Spain or Turkey • Year (2009, 2010 or 2011)

Table A1 – Continuation.

Reference	Sample data	Model	Input	Output	Explanatory variables
Örkcü et al. (2016)	21 Turkey airports, 2009-2014	Two-stage DEA model: 1) DEA and Malmquist productivity index; 2) SWBT Regression	• Number of runways • Runway units • Passenger terminal area	• Aircraft movements • Number of passengers • Cargo	• Population around the airport • Airport hub status • Airport operating hours • Joint military-civil airport • Percentage of international traffic
Chaouk et al. (2020)	59 European and Asia-Pacific airports	Two-stage DEA model: 1) DEA; 2) SWBT Regression	• Number of runways • Number of gates • Terminal area • Number of employees	• Number of passengers • Aircraft movements • Cargo • Non-aeronautical revenues	• Air transport output • Institutions • Infrastructure • Macro-economic environment • Health and primary education • Higher education and training • Goods market efficiency • Labour market efficiency • Financial market development • Technological readiness • Market size • Business sophistication • Innovation • Safety and security • Corruption perception • Human development • Travel and tourism
Huynh et al. (2020)	9 major Southeast Asia airports	Two-stage DEA model: 1) DEA; 2) Tobit Regression	• Runway length • Terminal area • Apron capacity	• Passenger movement • Cargo • Aircraft movements	• Airport characteristics • Governance structure • Competition • User impact