Measuring the efficiency of Portuguese and Spanish Airports: A two-stage DEA analysis

Gonçalo Valente Monteiro da Silva
goncalovalentesilva@tecnico.ulisboa.pt

Instituto Superior Técnico, Lisboa, Portugal

October 2025

Abstract

The liberalization of the air transport market in Europe led to unprecedented air traffic growth and the emergence of Low-Cost Carriers (LCCs), which fundamentally transformed the aviation industry. This evolution has intensified the need for airports to operate efficiently and adapt continuously to changing market conditions. Additionally, the growing adoption of concession models in airport management emphasizes the importance of continuous performance evaluation, to provide objective measures of efficiency to public regulators. The present dissertation evaluates the performance of 41 Iberian airports from 2016 to 2023 by combining Data Envelopment Analysis with a two stage truncated regression and applying a bootstrap procedure for bias correction. Additionally, the Malmquist Productivity Index (MPI) is utilized to assess productivity changes over time. The results reveal a low average efficiency across airports of the Iberian Peninsula (0.522, excluding COVID-19 years), especially in the Spanish network, and identify the best and worst performing airports. The truncated regression highlights the importance of rail intermodal terminals on airports, and indicates that airports located on Islands, those with Military operations, or those with a higher cargo orientation tend to be more efficient. The MPI allowed to identify the effects of the COVID-19 pandemic on each component of airport efficiency, while also presented the airports with best and worst efficiency evolution in the studied period.

Keywords: DEA, Truncated Regressions, MPI, Airport Efficiency, Portugal and Spanish Airports

1. Introduction

The air transport market has suffered significant transformations over the last decades, driven by the liberalization of the industry, which started in 1978 when the United States of America (USA) deregulated its domestic airline market, meaning airlines were free to set their own fares and routes, without federal control. This new regulatory framework without market entry barriers and market restrictions, marked the beginning of an era of unprecedented air traffic growth, where the number of passengers in the world increased from 310 million in 1970 to 4.5 billion in 2019 [1][2].

Central to this evolution was the emergence and expansion of Low-Cost Carriers (LCCs). Around 2002, less than 10 years after the implementation of the third package of the EU liberalization process, a steep growth of LCCs started, reaching 30.3% of the market share in 2018, 10 times more than in 2002 [3]. Initially operating mostly from secondary or regional airports, LCCs gradually expanded their operations to larger airports, and are now competing directly with legacy airlines at major airports [4]. This strategic shift of LCCs towards larger airports highlights the dynamic nature of the air transport market and the consequent need of constant benchmarking to evaluate the performance of airports and adapt accordingly to the changing market conditions. This need for performance analysis is further intensified by the increasing trend towards business models such as privatization and the use of concessions for airport management, as regulation by public entities and stakeholders requires transparent and objective performance metrics.

There are two main benchmarking methodologies: Stochastic Frontier Analysis (SFA), a parametric approach, meaning it requires a predefined functional form for the production function, and the Data Envelopment Analysis (DEA), a non-parametric approach. These methods are commonly applied in a two-stage analysis, where in the first stage the efficiency scores are calculated using SFA or DEA, and then a second stage analysis is performed to identify exogenous factors that influence efficiency.

Motivated by the decision of developing a new airport in Lisbon, the present work aims to benchmark the efficiency of 41 Iberian airports (5 Portuguese and 36 Spanish) from 2016 to 2023 and identify exogenous factors that influence airport efficiency, such as rail intermodal terminals.

In the next section, a thorough literature review is presented. Then, the methodology used in this work is described in Section 3, followed by the presentation and discussion of the results in Section 4. Finally, the main conclusions are drawn in Section 5.

2. Literature review

In this section a review of the main methodologies used in airport benchmarking is presented, as well as the most commonly employed variables.

Spain, having one of the largest airport operator (Aena), is one of the most frequently analyzed countries in the literature. Therefore, a special focus is given to works analyzing Spanish airports.

3. Methodology

This section outlines the methodology to be applied throughout this study, namely Data Envelopment Analysis (DEA), Truncated Regression, and the Malmquist Productivity Index (MPI).

3.1. Data Envelopment Analysis (DEA)

DEA is a non-parametric method used to evaluate the efficiency of Decision Making Units (DMUs) that convert inputs into outputs, by comparing each DMU to a best-practice frontier. The calculated efficiency is relative and is measured by the distance to the frontier, meaning a DMU is efficient if it lies on the frontier, and inefficient if it lies below it.

DEA models can be oriented in two ways: input or output oriented. In an input-oriented model the focus is on how much the inputs of a DMU can be proportionally reduced, without affecting the outputs produced. On the other hand, an output-oriented model focuses on increasing output quantities propor- tionally, while maintaining the same level of inputs [5].

Another important aspect of DEA is the assumption on returns to scale. In this regard there are two main formulations, the CCR model (Charnes, Cooper, Rhodes) and the BCC model (Banker, Charnes, Cooper). The first assumes constant returns to scale (CRS), meaning that an increase in inputs will lead to a proportional increase in outputs. The second assumes variable returns to scale (VRS), meaning it separates the inefficiencies due to scale from those due to pure technical inefficiency, and therefore compares DMUs of similar size [6].

Even though the CCR model is a valuable measure of overall efficiency, as airports cannot easily adjust their scale, the BCC model is often more appropriate in this context and will, therefore, be the model applied in this work. Eq.(1) present the formulation for the output-oriented BCC model. Eq.(2) represent the respective constraints . The main difference between the CCR and BCC models is the inclusion of the convexity constraint (i.e., $\sum_j \lambda_j = 1$), which ensures that an inefficient DMU is only benchmarked against similar sized DMUs.

Output-oriented BCC Model

$$max_{\phi,\lambda} \quad \phi \tag{1}$$

subject to

$$\begin{aligned} \sum_j y_{r,j}\lambda_j &\geq \phi y_{r,o} \quad \text{for } r = 1, \ldots, s \\ \sum_j x_{i,j}\lambda_j &\leq x_{i,o} \quad \text{for } i = 1, \ldots, m \\ \sum_j \lambda_j &= 1 \\ \lambda_j &\geq 0 \end{aligned} \tag{2}$$

To obtain the input-oriented version, the function of Eq.(1) is replaced by $min_{\theta,\lambda} \quad \theta$, and the two first inequations are reversed, keeping the rest the same.

Having obtained the efficiency scores using both the CCR and BCC models, it is possible to obtain the scale efficiency (SE) of an airport. SE measures the loss that a DMU suffers for not operating at optimal scale, and it is calculated as the ratio between the efficiency scores obtained using CRS and VRS [7]:

$$SE = \frac{E_{CRS}}{E_{VRS}} \tag{3}$$

The value of SE, is always between 0 and 1, since the efficiency score obtained using the CCR model is always less than or equal to that obtained using the BCC model. An SE value of 1 indicates that the DMU is operating at optimal scale, while a value less than 1 indicates that it is not.

Analyzing the value of SE does not provide information on the type of scale inefficiency, i.e., whether the DMU is operating at increasing or decreasing returns to scale. To identify the nature of the returns to scale, another model as to be used: the non-increasing returns to scale (NIRS) model, which is derived from the BCC model by replacing the $\sum_j \lambda_j = 1$ restriction with $\sum_j \lambda_j \leq 1$ [8]. Eq.(4) summarizes the classification criteria for the different RTS that can be identified by comparing the models explained above [9].

$$RTS = \begin{cases} IRS, & \text{if } E_{NIRS} \neq E_{VRS} \\ CRS, & \text{if } E_{NIRS} = E_{VRS} = E_{CRS} \\ DRS, & \text{if } E_{NIRS} = E_{VRS} \neq E_{CRS} \end{cases} \tag{4}$$

Efficiency scores obtained using DEA can be influenced not only by management decisions and scale operation conditions, but also by different exogenous factors. Second-stage regressions are usually applied to identify the effect of these factors, in which the DEA efficiency values obtained in the first stage are regressed against a set of potential explanatory variables. In this study, a truncated regression is going to be applied.

3.2. Truncated Regression

Following [10], a double bootstrapping procedure is applied in the second-stage truncated regression that is given by:

$$\hat{\theta}_i = \alpha + \beta Z_i + \varepsilon_i, \quad i = 1, \ldots, n \tag{5}$$

where

$$\varepsilon_i \sim N(0, \sigma_\varepsilon^2), \quad \text{such that} \quad \varepsilon_i \geq 1 - \alpha - Z_i\beta \tag{6}$$

which is estimated by maximizing the corresponding likelihood function.

$\hat{\theta}_i$ represents the bias corrected efficiency value of the n DMUs, α a constant term, β the vector of regression coefficients, Z_i a set of explanatory variables used to evaluate the efficiency scores and ε_i a random variable accounting for statistical noise.

In previous efficiency studies employing DEA, a common practice for estimating the model in Eq.(5) had been to employ a censored regression (Tobit). However, [10] demonstrated that this approach is inappropriate because efficiency scores are always higher than 0 and below or equal to 1, meaning the data is truncated at this value rather than censored. Consequently, using a censored regression model would lead to a bias in the estimation.

Since the DEA efficiency scores are relative and not absolute, there is a strong statistical dependency between each observation. Therefore, using them directly in a second-stage regression may violate fundamental assumptions of regression analysis, such as the independence of the dependent variable. To overcome the above problems, the bootstrap technique is applied. The double bootstrap approach proposed by [10] enables consistent inference in the second stage regression, by addressing the dependency problem, while simultaneously correcting for bias and estimating variance and confidence intervals. To facilitate the interpretation of the required steps and their sequential order for the implementation of algorithm 2 of [10], Fig.1 provides a flowchart detailing the 7-step procedure.

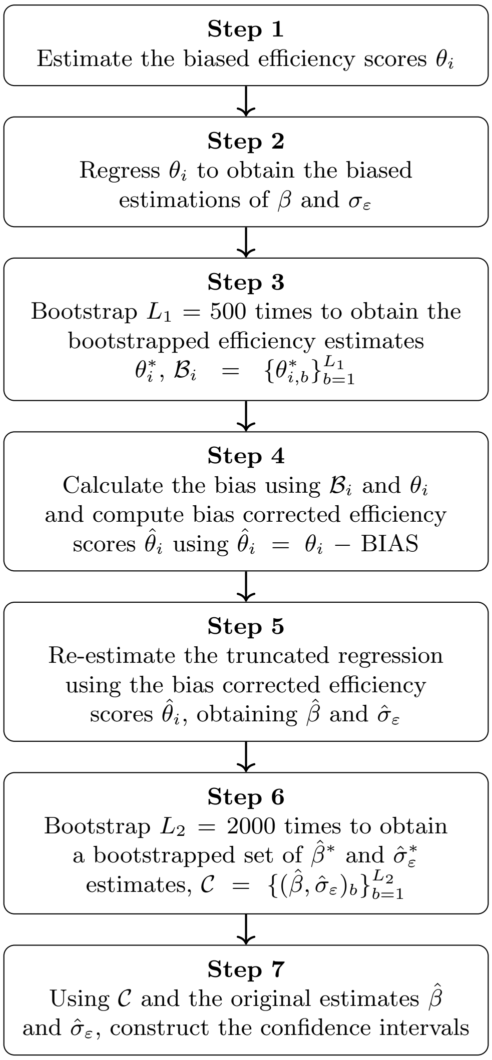

Figure 1: Algorithm 2 flowchart based on [10].

Although the DEA methodology provides an accurate static measure of relative efficiency for each year, it does not fully capture how productivity evolves over time. To address this limitation, the Malmquist Productivity Index (MPI) is also applied, to provide a dynamic perspective on efficiency changes.

3.3. Malmquist Productivity Index (MPI)

MPI evaluates the productivity change of a DMU, in our case an airport, by calculating the ratio of the distance to the frontier in two different time periods, t and t + 1, relative to a common reference technology. Initially, [11] defined the MPI as follows:

$$M_{CCD,\,t} = \frac{D_o^t\,(x_{t+1}, y_{t+1})}{D_o^t\,(x_t, y_t)} \tag{7}$$

where $\left(x^{t+1}, y^{t+1}\right)$ represents the input/output combination for the $t+1$ period, and (x^t, y^t) for the t period. $D_o^t\left(x^{t+1}, y^{t+1}\right)$ and $D_o^t\,(x^t, y^t)$ would then be the distance between the DMU observation in $t+1$ and t periods, respectively, and the best practice frontier in the t period, for airport o.

If one wants to consider the technology from the t + 1 period as the reference, the distance would be measured to the frontier in t + 1 period, meaning D_o^t would be replaced by D_o^{t+1}, in the functions of Eq.(7). To provide a visual illustration of the distance functions defined above, Figure 2 displays the MPI distance functions, for $\mathrm{DMU_X}$, when considering an input orientation.

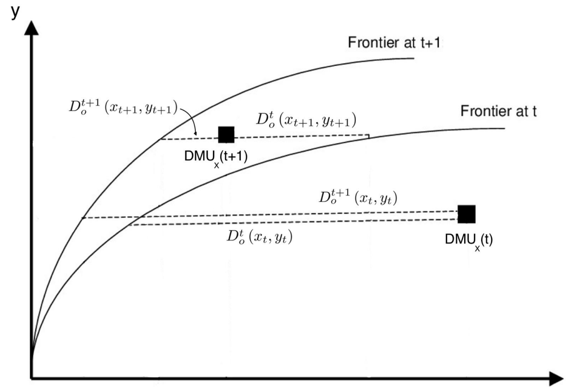

Figure 2: Malmquist Productivity Index distance functions for $\mathrm{DMU_X}$.

In order to avoid the arbitrary selection of a reference technology, [12] specified the output-based MPI as the geometric mean of the index from Eq.(7), using both reference technologies, given by:

$$MPI_o = \left[\left(\frac{D_o^t(x_{t+1}, y_{t+1})}{D_o^t(x_t, y_t)} \right) \left(\frac{D_o^{t+1}(x_{t+1}, y_{t+1})}{D_o^{t+1}(x_t, y_t)} \right) \right]^{1/2} \tag{8}$$

According to [12], an equivalent way of writing the index of Eq.(8) is:

$$MPI_o = \underbrace{\frac{D_o^{t+1}(x_{t+1}, y_{t+1})}{D_o^t(x_t, y_t)}}_{\text{Efficiency Change (EC)}} \times \underbrace{\left[\frac{D_o^t(x_{t+1}, y_{t+1})}{D_o^{t+1}(x_{t+1}, y_{t+1})} \times \frac{D_o^t(x_t, y_t)}{D_o^{t+1}(x_t, y_t)} \right]^{1/2}}_{\text{Technological Change (TC)}} \tag{9}$$

This formulation decomposes Eq.(8) into two different components: Efficiency change (EC) and Technological change (TC). The former evaluates if the airport's efficiency is getting closer or further away from the best practice frontier (catching-up effect). The latter captures shifts in the frontier itself, indicating whether there has been technological progress or regress over time.

So far, the analysis has been conducted under constant returns to scale (CRS). However, the first term (EC) can be further decomposed into Pure Efficiency Change (PEC), associated with VRS, and Scale Efficiency Change (SEC). To obtain this full decomposition, two additional programming problems are required, namely the calculation of Dt+1 o (xt+1, yt+1) and Dt o(xt, yt) under VRS, which provides the value of PEC and allows the calculation of SEC, following the definition of Eq.(3).

A MPI_o greater than one indicates an improvement in efficiency between periods t and t + 1. The same interpretation applies to the other all the other components of the MPI. Conversely, a value less than one indicates a decline in efficiency

4. Results

In this section, the dataset used is described and the results obtained are presented. First, the descriptive statistics are provided, then the DEA scores are obtained, followed by the truncated regression analysis, and finally the Malmquist index results.

4.1. Dataset description

Our dataset includes 41 Iberian airports, including 5 in Portugal and 36 in Spain, over a period of eight years (2016-2023). Following the airport size definition from [13], Fig.3 displays a map with the geographical location of the airports and their respective sizes.

Figure 3: Location and size classification of the 41 Iberian airports

DEA models require the identification of the inputs and outputs of the analysis. As DEA is not a statistical technique, there is no systematic approach for the selection of inputs and outputs, therefore the first practical criterion for selecting these variables is data availability. Tab.1 lists these variables and summarizes their main descriptive statistics, namely the minimum (Min.), maximum (Max.), mean, and standard deviation (St. Dev.) values.

Even though this selection of input variables does not fully represent the most common variables in the literature review conducted in Section 2 due to data availability constraints, it is still in line with the previous literature.

It is important to highlight that only physical measures of capital were considered in this analysis. This approach was necessary since airport-level

Table 1: Summary Statistics for Input and Output Variables (2016–2023)

Variables	**Min.**	**Max.**	**Mean**	**St. Dev.**
Inputs				
Employees	17	42,222	3,409	7,862
Runway Area (m^2)	37,500	910,020	169,293	142,191
Gates	2	238	24.8	42.4
Outputs				
Passengers	2,358	61,652,021	6,437,865	11,112,114
ATM	1,086	426,324	53,780	76,780
Cargo (t)	0	655,586	27,546	89,429

financial data stopped being published, following Aena's partial privatization in 2014.

Regarding the second-stage regression, Tab.2 lists the explanatory variables used in the second-stage regression to explain DEA efficiency scores.

Table 2: Summary Statistics for explanatory variables

Explanatory Variables	**Min.**	**Max.**	**Mean**	**St. Dev.**
Island	0	1	0.32	0.47
Military	0	1	0.27	0.44
Rail existence	0	1	0.10	0.30
Share of cargo (%)	0	89.33	4.68	15.65
Share of LCC passengers (%)	0	96.67	49.62	26.78

Island is a binary variable indicating whether an airport is located on an island (Island=1) or the mainland (Mainland=0). The inclusion of this variable is justified, as 13 out of the 49 airports in the dataset operate on an island. Military is another binary variable indicating whether there are military operations at the airport. In the considered dataset, 11 out of the 41 airports operate as mixed civil-military airports. Share of cargo represents the percentage of cargo in the total WLU and Share of LCC passengers represents the percentage of low-cost carrier (LCC) passengers in the total number of passengers. Due to data constraints from the Portuguese airports, only the passengers from LCCs ranked among the top 10 airlines at each airport (by passenger volume) are considered. Additionally, a novel input in Iberian airport efficiency studies was included: the existence of a railway connection inside the airport. This variable was included to capture the impact of intermodal connectivity on airport efficiency.

4.2. First-stage: Static DEA scores

The first stage of the analysis involved calculating the efficiency scores for each airport across the different years considered. For that, an output oriented DEA model under Variable Returns to Scale

(VRS) was applied.

The choice of output orientation is particularly appropriate in the context of Iberian airports, since most of the Spanish airports operate with overcapacity, meaning the existing infrastructure is underutilized [14]. As some of the airport inputs are considered fixed in the short and medium term, airport managers have limited capacity to adjust input levels, and should, therefore, focus on maximizing their utilization [15]. Regarding the returns to scale, VRS was assumed due to the large size difference between the airports considered, as shown in Fig.3. Nonetheless, the CRS scores were also determined for the calculation of Scale efficiencies.

Tab.3 presents the bootstrapped results obtained for each airport. It includes the average efficiency scores for Constant Returns to Scale (CRS), Variable Returns to Scale (VRS), and Scale efficiency (Scale) for each airport. It should be noted that the biased scores were also calculated for comparison, even though they are not presented here for brevity. Following the definition in Eq.(4), the last column indicates the type of returns to scale (RTS) each airport is operating, which can be either Increasing Returns to Scale (IRS), Decreasing Returns to Scale (DRS), or Constant Returns to Scale (CRS). As this study analyzes a period of 8 years, different classifications can be obtained in different years. In Tab.3, the most common classification will be displayed. In cases where the two most common classifications are observed the same number of times across the eight-year period, both classifications are presented.

Analyzing Tab.3, it is possible to observe that Iberian airports present low values of efficiency, averaging 0.480 for the bootstrapped VRS model, in the years under analysis. When excluding the years 2020 and 2021, due to the COVID-19 pandemic, the average bootstrapped VRS efficiency increases to 0.522, while the CRS model increases to 0.436. It is also possible to note that there is no average efficiency score of 1, with a maximum observed value of 0.823 for Madrid-Barajas airport, meaning none of the considered airports operates in the frontier. Regarding scale efficiency, the average bootstrapped scale efficiency is 0.854, indicating that Iberian airports are not operating at their optimal scale.

4.3. Second-stage: Truncated regression

After computing the DEA efficiency scores in the first stage, a second-stage truncated regression was conducted to address DEA's main limitation, which is its inability to explain the effect of some determinants in the efficiency scores. The regression was applied to the bootstrapped DEA scores, using the explanatory variables described in Tab.2, under the following model:

Table 3: Bootstrapped average CRS, VRS and Scale efficiencies.

Airports	**CRS**	**VRS**	**Scale**	**RTS**
A Coruña	0.323	0.343	0.941	IRS
A S Madrid-Barajas	0.568	0.823	0.693	DRS
Alicante	0.591	0.596	0.988	IRS/DRS
Almeria	0.226	0.232	0.978	IRS/CRS
Asturias	0.188	0.190	0.987	CRS
Badajoz	0.121	0.360	0.335	IRS
Barcelona	0.382	0.741	0.518	DRS
Bilbao	0.436	0.501	0.871	DRS
El Hierro	0.325	0.768	0.425	IRS
Faro	0.514	0.551	0.928	IRS
FGL Granada	0.366	0.414	0.883	IRS
Fuerteventura	0.353	0.370	0.952	DRS
Girona	0.183	0.186	0.982	IRS/CRS
Gran Canaria	0.448	0.552	0.809	IRS
Ibiza	0.694	0.698	0.991	DRS/CRS
Jerez	0.653	0.680	0.961	DRS
La Gomera	0.183	0.516	0.388	IRS
La Palma	0.276	0.288	0.959	IRS
Lanzarote	0.588	0.596	0.985	IRS
Leon	0.124	0.492	0.297	IRS
Lisbon	0.617	0.701	0.880	IRS
Madeira	0.237	0.254	0.933	IRS
Malaga	0.522	0.583	0.883	DRS
Menorca	0.332	0.342	0.970	IRS/DRS
Palma De Mallorca	0.464	0.661	0.701	IRS
Pamplona	0.173	0.224	0.776	IRS
Ponta Delgada	0.417	0.703	0.596	IRS
Porto	0.608	0.650	0.923	IRS
Reus	0.262	0.262	0.999	IRS/CRS
Salamanca	0.645	0.649	0.995	IRS/CRS
San Sebastian	0.128	0.148	0.866	IRS
Santiago	0.234	0.243	0.963	DRS
Santander	0.191	0.193	0.992	CRS
Sevilla	0.534	0.564	0.946	DRS
Tenerife-Norte	0.534	0.580	0.916	IRS
Tenerife-Sur	0.636	0.658	0.966	DRS
Valencia	0.536	0.550	0.971	IRS
Valladolid	0.177	0.178	0.995	CRS
Vigo	0.168	0.168	0.997	CRS
Vitoria	0.563	0.694	0.820	IRS
Zaragoza	0.802	0.822	0.976	IRS
Mean	0.398	0.480	0.854	
Mean excluding COVID	0.436	0.522	0.859	
# of efficient DMUs	0	0	18	

$$\begin{aligned}\theta_{i,t} = \alpha + \beta_1 \mathrm{Island}_i + \beta_2 \mathrm{Military}_i + \beta_3 \mathrm{Rail}_i \\ + \beta_4 \mathrm{ShareCargo}_{i,t} + \beta_5 \mathrm{ShareLCC}_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{10}$$

reports the coefficients and p-values for the variables considered in both the biased and bootstrapped models. For binary variables, the coefficient represents the estimated change in the efficiency score when the specific variable applies, while for continuous variables, the coefficient reflects the marginal effect on the efficiency score of a one-unit increase in the corresponding variable [10].

4.4. Dynamic Evolution: Malmquist index

5. Conclusions

Conclusions, future work and some final remarks...

Acknowledgements

The author would like to thank ...

References

[1] Badi H. Baltagi, James M. Griffin, and Daniel P. Rich. Airline Deregulation: The Cost Pieces of the Puzzle. 36(1):245–258.

[2] World Bank Data. World air passenger traffic evolution, 1970-2020 – Charts – Data & Statistics, 2025.

[3] Eurocontrol. Eurocontrol data snapshot on the rise of low cost carriers in europe, 2025.

[4] Edgar Jimenez and Pere Suau-Sanchez. Reinterpreting the role of primary and secondary airports in low-cost carrier expansion in Europe. 88:102847.

[5] Abraham Charnes, William W. Cooper, Arie Y. Lewin, and Lawrence M. Seiford. *Data Envelopment Analysis: Theory, Methodology, and Applications*. Springer Netherlands.

[6] R. D. Banker, A. Charnes, and W. W. Cooper. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. 30(9):1078–1092.

[7] Peter Bogetoft and Lars Otto. *Benchmarking with DEA, SFA, and R*, volume 157 of *International Series in Operations Research & Management Science*. Springer New York.

[8] Tim Coelli, editor. *An Introduction to Efficiency and Productivity Analysis*. Springer, 2. ed edition.

[9] Jean-Marc Huguenin. *Data Envelopment Analysis (DEA) a Pedagogical Guide for Decision Makers in the Public Sector*. IDHEAP.

[10] Léopold Simar and Paul W. Wilson. Estimation and inference in two-stage, semi-parametric models of production processes. 136(1):31–64.

[11] Douglas W. Caves, Laurits R. Christensen, and W. Erwin Diewert. The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity. 50(6):1393–1414.

[12] Rolf Färe, Shawna Grosskopf, Mary Norris, and Zhongyang Zhang. Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries. 84(1):66–83.

[13] Ane Elixabete Ripoll-Zarraga and Cecilio Mar-Molinero. Exploring the reasons for efficiency in Spanish airports. 99:186–202.

[14] Adrian Nerja. An efficiency analysis of Spanish airports. (1).

[15] Juan Carlos Martín and Concepción Román. An application of DEA to measure the efficiency of Spanish airports prior to privatization. 7(3):149–157.