The impact of the Economic Crisis on the efficiency of Spanish airports: A DEA Visualisation Analysis

Ane Elixabete Ripoll-Zarraga [a], Fabiola Portillo [b], Cecilio Mar-Molinero [c] *

[a] Business Department, Universitat Autònoma de Barcelona (UAB), 08193 Bellaterra, Spain
[b] Economics and Business Department, Universidad de La Rioja, 26005 Logrono, Spain
[c] Kent Business School, University of Kent, Canterbury CT2 7FS, UK

Abstract

We study DEA efficiencies of 47 Spanish airports over the period 2009-2013. Because the selection of inputs and outputs in the DEA model is problematic, we consider 186 input/output specifications obtained by combining six inputs and five outputs. Given the large differences in size between the airports, we use Variable Returns to Scale. Since it is a characteristic of economic crisis that some capacity remains idle, we use the output-oriented version of DEA. The results are visualised using the tools of multivariate statistical analysis. The analysis reveals six independent aspects of efficiency that can be assessed for an airport, and how their relative importance evolved during the economic crisis. Important changes in efficiency between 2009 and 2010 are revealed. They were followed by a period of slow return to the pre-crisis situation. The methodology presented here makes it possible to assess the strengths and weaknesses of each airport in terms of efficiency.

Keywords: *Data Envelopment Analysis (DEA); Multivariate Statistical Analysis; Airport Efficiency; Spanish Airport-System; Panel-data.*

* Corresponding author.

E-mail addresses:

ane_rz@yahoo.com (A.E. Ripoll-Zarraga),
fabiola.portillo@unirioja.es (F. Portillo),
C.Mar-Molinero@kent.ac.uk (C. Mar-Molinero).

The impact of the Economic Crisis on the efficiency of Spanish airports: A DEA Visualisation Analysis

Ane Elixabete Ripoll-Zarraga [a], Fabiola Portillo [b], Cecilio Mar-Molinero [c] *

[a] Business Department, Universitat Autònoma de Barcelona (UAB), 08193 Bellaterra, Spain
[b] Economics and Business Department, Universidad de La Rioja, 26005 Logrono, Spain
[c] Kent Business School, University of Kent, Canterbury CT2 7FS, UK

Abstract

We study DEA efficiencies of 47 Spanish airports over the period 2009-2013. Because the selection of inputs and outputs in the DEA model is problematic, we consider 186 input/output specifications obtained by combining four inputs and five outputs. Given the large differences in size between the airports, we use Variable Returns to Scale. Since it is a characteristic of economic crisis that some capacity remains idle, we use the output-oriented version of DEA. The results are visualised using the tools of multivariate statistical analysis. The analysis reveals six independent aspects of efficiency that can be assessed for an airport, and how their relative importance evolved during the economic crisis. Important changes in efficiency between 2009 and 2010 are revealed. They were followed by a period of slow return to the pre-crisis situation. The methodology presented here makes it possible to assess the strengths and weaknesses of each airport in terms of efficiency.

Keywords: *Data Envelopment Analysis (DEA); Multivariate Statistical Analysis; Airport Efficiency; Spanish Airport-System; Panel-data.*

* Corresponding author.

E-mail addresses:

ane_rz@yahoo.com (A.E. Ripoll-Zarraga),
fabiola.portillo@unirioja.es (F. Portillo),
C.Mar-Molinero@kent.ac.uk (C. Mar-Molinero).

1. Introduction

Airports are public resources that require large investments, and there has been substantial interest in exploring whether such resources have been effectively and efficiently used. Some of the funds that were spent in Spanish airport infrastructure were provided by the European Union. The European Court of Auditors (2014) investigated if investment expenditure in Spanish airports had been justified.

The study of the efficiency of airports has long been a matter of interest. Bezerra and Gomes (2016) give a literature review of performance measurement in airports. Some relevant studies are Gillen and Lall (1997), Parker (1999), Sarkis (2000), Bazargan and Vasigh (2003), Sarkis and Talluri (2004) , Wang *et al.* (2004), Yu (2004; 2010), Barros *et al.* (2007), Barros (2008a; 2008b; 2009), Pathomsiri *et al.* (2008), Yu *et al.* (2008), Assaf *et al.* (2012), and Pacagnella Junior et al. (2021). This literature has been reviewed by Lieber and Niemeir (2013 and 2010). In Spain we can mention Murillo-Melchor (1999), Salazar de la Cruz (1999), Martin and Roman (2001; 2006), Martin-Cejas (2002), Coto-Millan *et al.* (2007; 2014; 2016), Tapiador *et al.* (2008), Martin *et al.* (2009; 2011), Tovar and Martin-Cejas (2009; 2010), Lozano and Gutierrez (2011), and Lozano *et al.* (2013).

A popular technique for efficiency assessment is Data Envelopment Analysis (DEA). DEA takes a particular airport whose efficiency is to be assessed as the focus of analysis and asks if the inputs used by such airport would have been better employed elsewhere. The question is basically: imagine that we close the airport under observation and distribute its inputs amongst other airports. Having expanded, the airports that have received extra inputs are expected to generate extra outputs. The question is if these extra outputs be at least as large as the outputs that were generated by the airport we consider closing. If the answer to this question is "yes", then the airport under observation is deemed to be inefficient.

This paper reports the result of a study of Spanish airport efficiency over a five-year period that includes an economic crisis. Several issues are addressed using DEA and multivariate statistical methods. Since DEA efficiency scores depend on the outputs and inputs included in the model, we estimate efficiencies under a variety of combinations of inputs and outputs (specifications). This approach has the further advantage of avoiding the zero-weight problem that is common in DEA. It also serves to highlight the strengths and weaknesses of each airport in terms of efficiency. We do this for a five-year period. This results in 43,710 efficiency scores, a large amount of information that can only be fully understood using statistical methods. For this reason, we visualise the efficiency models and results using scaling methods.

We think this is the first time that this methodology has been applied in this context.

DEA efficiency is measured in the form of a score between one (if the airport is fully efficient) and zero (if the airport is fully inefficient). These scores are often multiplied by one hundred and reported in the form of percentages. This way of proceeding is appropriate, but we would like to go beyond a mere score. We would like to know what is special about the airport being assessed, what are its strengths and what are its weaknesses. The methodology presented in this paper addresses this issue from a different perspective from previous studies such as Pacagnella Junior et al. (2021).

A major issue in DEA is the choice of inputs and outputs to be included in the model. DEA is not a statistical technique and there are no tools —such as t-tests in regression— to assess if an input or an output are important or could be deemed to be redundant and removed from the data. It is known that efficiencies depend on the number of inputs and outputs included in the specification. The more inputs or outputs included in the model, the higher the calculated efficiencies will be. For a discussion of the issues related to specification in DEA see, for example, Grosskopft (1986 and 1996), Thrall (1989), Hughes and Yaisawarng (2004), and Pastor et al (2002).

There are many possible input/output combinations (specifications) that can enter into a DEA study, and calculated efficiencies depend on the specification chosen. In fact, two different analysts working on the same data can come up with different results just because they have chosen different specifications. It is difficult to justify how two different results can arise from the same data when the analysis is performed by two perfectly competent people using the same technique. A solution proposed by Serrano-Cinca *et al.* (2016) is to estimate a variety of specifications for each unit under observation and to analyse the results using Factor Analysis. This approach has been revealed to be very effective in various studies: Gutierrez-Nieto *et al*., (2007); Serrano-Cinca *et al.*, (2016); and Sagarra *et al.*, (2017). Ripoll-Zarraga and Mar-Molinero (2020) applied this approach to study the efficiency of Spanish airports.

Extreme values are a problem in DEA since they may have considerable influence on the results. But an extreme efficiency value may just be consequence of the choice of inputs and outputs. Serrano Cinca *et al.* (2016) demonstrated that whether a particular unit of assessment appears to be discordant depends on the particular choice of inputs and outputs incorporated in the specification. Airports that are associated with extreme efficiency values under a particular specification may not appear to present discordant behaviour under other specifications. For this reason, we have decided not to start the modelling by looking for extreme values, as it is common practice. By estimating a variety of specifications, we will be able to reveal the reasons why some airports present extreme behaviour, if any such units exist. This will disclose the strengths and weaknesses in the efficiencies of the various airports.

A standard problem in DEA studies is the treatment of zero weights. The methodology proposed here avoids it. Attaching a zero weight to an input (or to an output) is equivalent to removing this input (or output) from the analysis. Our methodology removes or includes an input (output) in an explicit way. If an input (output) has no impact on the assessment of efficiency, this will be revealed by the data reduction techniques of multivariate analysis that we adopt.

Airport efficiency studies tend to be static, in the sense that data on inputs and outputs are collected for a particular year, and the model is estimated. Here we take the analysis a step further by adding the time dimension to the analysis. Hence, our approach reveals the dynamics of airport efficiency over time.

The standard approaches used to incorporate time changes in DEA are the Malmquist index approach (Thanassoulis, 2001), or the multiperiod network model of Kao and Hwang (2014), Liu (2017), Fragoudaki et al (2016), and Ahn and Min (2014). However, these approaches suffer from the same limitations as the standard DEA approach in that a particular specification has to be selected, and no alternatives are normally considered.

Our data consists in four inputs and five outputs for 47 Spanish airports over a five-year period. DEA efficiency was calculated for each airport under an output-oriented variable returns to scale model (VRS). VRS is justified given the large difference in size between the various airports. Output orientation was selected as an approach because we considered that the 2008 economic crisis had left capacity under-utilised, and we wanted to see how this had impacted on efficiency. As for the specifications, many can be contemplated, but we were selective in the sense that some of them did not make much managerial sense and these were excluded from the analysis. For example, having Commercial Revenues but not Passengers in a specification seems not to make sense unless the commercial income is generated mostly by employees, which is unlikely to happen. But it is possible to have Cargo without Passengers. At the same time, any specification with Passengers, Cargo, or Percentage of Flights on Time will require having aircraft movements. Although some unrealistic specifications may be missed, the DEA-Visualisation approach proposed here will disregard any 'uninteresting' combination of inputs and outputs.

The final data set was a three-way table of airports by specifications by years. The cells in the table contained efficiencies. There is an efficiency score for each airport under each specification for each year. This generates a very large amount of information that may obscure any relevant findings.

To reveal the findings and make them accessible to anybody without a strong technical background we resorted to visualisation techniques. The approach followed to analyse the results was based on the Individual Differences Scaling (INDSCAL) model of Carroll and Chang (1970). This model returns a "common map" that reveals what has remained constant over the time period, and a set of weights that informs about any time effects that may exist.

The common map revealed that there are at least nine ways in which airport efficiency can be described, although only six such approaches to efficiency were explored. These are: a) efficient use of investment in order to generate Air Traffic Movements (ATM); b) cost efficiency with respect to aeronautical activity; c) efficiency in obtaining revenues in relation to Air Traffic Movements (ATM); d) cost efficiency in dealing with passengers; e) efficiency in dealing with cargo; and f) efficiency effects associated with runway length.

The relative importance of these approaches to efficiency changed as result of the 2009 economic crisis. We found that, after 2009, the emphasis appears to have shifted from generating ATM to generating passenger activity given the investment available in each airport. During the worst years of the economic crisis (2010 and 2011) cost efficiency in dealing with passengers appears to have taken great importance. Before the crisis, efficiency effects in dealing with cargo appear to have been prominent over efficiency effects in dealing with passengers. The situation was reversed during the crisis period, something that may just reflect the fall in cargo activity during the crisis.

The approach described in this paper, besides identifying the various efficiency aspects that can be associated with an airport, and the way in which their importance has evolved over time, permits to visualise the strengths and weaknesses of each airport. In the concluding section we show how to do this by concentrating in Vitoria airport.

This introductory section is followed by a discussion of data, particularly in what concerns airport inputs and outputs. The third section of the paper is technical. It describes how the efficiencies were calculated, the statistical model used, and visualises the findings. The paper ends with a discussion and conclusions section.

2. The Data

Spanish airports are government owned and managed by a public company named AENA. AENA manages 49 civilian aviation airports. One of the consequences of this centralised management structure is that airports do not compete. There has been much debate about the adequacy of a centralised system versus a system based on local managerial decision making (Cambra de Comerç de Barcelona, 2010; CNMC-The National Board for Markets and Competition, 2014; and Word Finance, 2016).

Our data set includes 47 airports over a period of five years (2009-2013). 2009 was chosen as starting point because there is no financial data information on individual airports prior to 2009. The list of airports can be seen in Table 4. Two airports were excluded due to lack of data: Son Bonet (in Majorca Island) and Algeciras.

The network contains 14 large airports (i.e. more than 3.5 million of passengers per year). The remaining 33 airports are medium or small sized, with a high variability in terms of passengers and cargo. The data, except for the depreciation of assets, flight delays, and runway surface, have been extracted from the annual reports of AENA from 2009 to 2013.

Despite being government owned, AENA does not receive public subsidies. To obtain extra funds, Spanish airports have engaged in commercial activities alongside their aeronautical mission. Amongst these commercial activities, we can list duty-free shops, car rental, food services, shops, advertising, VIP lounges, banking, travel agencies, and vending machines. Diversification towards commercial activities is normally associated with privatisation processes (Humphreys, 1999). In the Spanish case, commercial revenues are as important as aeronautical revenues (ICAO, 2013). Non-aviation revenues in airports have been studied by Fasone et al. (2016).

Table 1 List of inputs and outputs included in the DEA model.

Inputs		Outputs	
(A)	Labour costs excluding air traffic control services	(1)	Passengers
		(2)	Air traffic movements (ATM)
(B)	Operating costs	(3)	Cargo
(C)	Depreciation of airside assets	(4)	Commercial revenues
(D)	Runway surface	(5)	Percentage flights on time

DEA model requires specifying what are the inputs and the outputs of an airport. The inputs and outputs used in this study are listed in Table 1.

All the inputs are in euros except for runway surface. The letters in brackets indicate the symbols used in the analysis. As for outputs, cargo is measured in tons and commercial revenues are measured in euros. The numbers in brackets indicate the symbols used in the analysis. The choice of inputs and outputs has been guided by a revision of the literature and by data availability as published by AENA. Labour and operating costs; the number of passengers; movements; cargo and commercial revenues have been extracted from AENA's annual reports. Runway surface was calculated from the geographical maps of the airports. These inputs and outputs have been frequently used in airports' efficiency studies; see Tovar and Martin-Cejas (2010).

On the side of outputs, cargo has increased its importance over the years. It requires different handling methods as compared to passengers (Tovar and Martin-Cejas, 2009; Chi-Lok and Zhang, 2009). Air Traffic Movements (ATM) are treated as an output of airside operations. They generate revenues in the form of landing and aircraft parking charges (Coto-Millan *et al.*, 2014). The percentage flights on time has been used as an indicator of good management of traffic flows. The data for percentage flights on time was obtained from CODA (Central Office for Delay Analysis).

Turning our attention to inputs, airport resources are normally related to infrastructure. Infrastructure includes the number of runways, terminal buildings, boarding gates, number of checking desks, terminal size, parking capacity, and number of full-time employees. Nevertheless, infrastructure is difficult to define or quantify. Indeed, one of the main challenges of airport benchmarking analysis is the inclusion of capital measures (Parker, 1999). Various capital proxies have been used in airport industry research: rent expenses (Parker, 1999); depreciation of fixed assets (Murillo and Melchor, 1999; Martin and Roman 2001; Martin *et al.*, 2009; 2011); capital expenses (Martin-Cejas, 2002); book value (Barros and Sampaio, 2004; Coto-Millan *et al.*, 2014; 2016); length of runways (Martin *et al.*, 2011); and airport surface area or number of gates (Tovar *et al*., 2009; 2010). It is also possible to take into account if assets are linked to aircraft movements (boarding gates, apron capacity and runways areas), or to loading processes such as checking counters and baggage belts (Lozano *et al.*, 2013).

In this study we have employed as a proxy for capital usage the depreciation of airside assets. From an accounting perspective, depreciation reflects the consumption of airport assets that takes place in the process of generating revenues. Following Ashford *et al.* (1996) airport infrastructure was classified into airside and landside. In this study, only the depreciation of airside assets is considered. The split between airside and landside assets has been discussed by Gillen and Lall (1997), and Pels *et al.* (2001; 2003). Airside assets are considered to be essential to conduct aeronautical activities. The depreciation of airside assets concerns aviation terminals, aprons, taxiway and air traffic control and visualisation systems (beacon), and excludes runway depreciation.

Depreciation was calculated using established depreciation rules whilst taking into account the historical cost of non-current assets. The calculation required knowing the initial cost of assets and of the subsequent work performed on them. The historical cost of non-current assets was obtained from the construction certifications of works performed in airports. It was not possible to find individual airport infrastructure expenditure information before 2000, and calculations were made as if airports had started their activity in the year 2000. Airports' initial investments for 2000 were estimated from depreciation charges for 2004 (released by the Spanish Government). These depreciation expenses were available per airport within individual income statements. The useful life of the assets conforms to current regulation in the transportation sector for buildings and structures as required by international financial reporting standards (IFRS) for property, plant and equipment (IAS 16).

There was no information regarding the type of labour cost (full or part-time; permanent or fixed term).

In a few instances, there was missing data. We preferred to make a small estimation error rather than removing an airport from the data set because a particular data item was not available, and we inputted an estimate using the nearest neighbour approach. We estimated some items in the cases of Ceuta, Cordoba, Huesca, La Gomera, and Madrid-4Vientos.

Table 2 Descriptive Statistics. Source: AENA 2009-2013 except for depreciation and runway length. Data deflated by the GDP deflator base Spain, 2010.

Variables	Mean	Standard Deviation	Minimum	Maximum
Passengers (number)	4,094,892	8,656,221	0	49,866,113
Air Traffic Movements (number)	42,736.41	72,758.36	476	435,187
Cargo (Tons)	13,472,972	53,369,951	0	394,154,078
Aeronautical Revenues (mill €)	35.45	97.33	0.03	703.93
Commercial Revenues (mill €)	13.40	31.16	0	186.82
Labour Costs (mill €)	8.25	11.36	0.12	81.83
Operating Costs (mill €)	21.75	55.88	0.45	350.82
Depreciation Airside (€)	2,208.97	5,498.38	0	31,100.24
Runway Surface (m^2)	177,574.20	161,175.30	10,626	927,000

Runway surface is a non-discretionary input in the sense that it cannot be changed in the short term in order to improve efficiency. Non-discretionary inputs in DEA have been studied, amongst others, by Banker and Morey (1986), Ruggiero (1998), and Cordero-Ferrara *et al.*, (2008). In our case, the DEA models estimated are output oriented, and the standard model does not need to be modified.

All the data measured in monetary units was deflated by the Spanish gross domestic product deflator (base Spain, 2010).

Descriptive statistics for inputs and outputs are given in Table 2.

3. Analysis and Results

Efficiencies were estimated under 186 DEA specifications for each airport and for each of the five years. Estimations were made using the software EMS (Efficiency Management Software). Each specification containing a subset of the inputs and outputs shown in Table 1. This makes a total of 43,710 estimations. Inputs were identified by means of capital letters, and outputs by means of numbers, in line with the notation introduced in Table 1. For example, model AC32 contains as inputs labour (A) and depreciation (C) and as outputs cargo (3) and ATM (2). The specifications estimated are not all the possible combinations between the five outputs and the four inputs since some were excluded on the grounds that they did not make operational sense.

3.1. Factor analysis of efficiencies for individual years

The data to be analysed is a three-way matrix of 186 specifications, by 47 airports, and by 5 years. The cells in the table contain estimated efficiencies. Although some relevant information can be obtained through visual inspection of the data, it is clearly necessary to use a data reduction technique in order to deal with such a large set of numbers.

The data set was treated, in the first instance, as a set of five matrices of airports by specifications, one such matrix for each year. Specifications were treated as variables, and airports were treated as cases. Each matrix was analysed using Unrotated Orthogonal Factor Analysis. This was done in order to assess the dimensionality of the data. The calculations were performed using the IBM-SPSS computer package.

There was little variation between the five years. In general, either 9 or 8 factors were associated with eigenvalues greater that unity, the standard Kaiser's criterion. The 9 factors always accounting for more than 95% of the variability in the data. The first factor was clearly an overall measure of efficiency and accounted for more than 60% of the variability in the information. Similar patterns were reported by Gutierrez-Nieto *et al.*, (2007), Serrano-Cinca *et al.*, (2016), Sagarra *et al.*, (2017), and Ripoll-Zarraga and Mar-Molinero (2020).

It was also observed that factorial weights associated with dimensions 7, 8, and 9 were low (less than 0.3). Considering that the statistical package employed, IBM-SPSS, orders factors in terms of their eigenvalues, it can be conjectured that factors 7, 8, and 9 are of lesser importance in the analysis.

Following this— matrix by matrix— factor analysis study, it was decided to model the data as nine-dimensional, although we did not explore dimensions higher than six.

3.2. The individual differences scaling model

Given the amount of data we had, we decided to use a statistical technique that reveals its main characteristics in a graphical form. There are several such approaches that can be used to model three-way data. We preferred to employ the Individual Differences Scaling (INDSCAL) model of Carroll and Chang (1970). Estimations were performed with the PROXSCAL routine of the package SPSS.

Scaling models are estimated using numerical hill-climbing methods and can suffer from local minima problems. To be sure that it was not the case in this instance, several approximation methods were used. Another problem with hill-climbing approaches is that iterations can finish before the optimal value is found. To avoid this problem as far as possible, the default level of precision in SPSS was increased by a factor of one thousand. The results reported here were found to be robust to the estimation method used and to the level of precision in the calculations.

The INDSCAL model is proximity based. First, proximities between airports are calculated for every year. There are various ways in which proximities can be calculated. We used Euclidean metric between airports using as variables standardised efficiency values. This method is equivalent to Factor Analysis when certain restrictive conditions apply; Coxon (1982). In other words, each airport is a point in a space of 186 dimensions (one dimension for each specification). The proximity (similarity) between any two airports is taken to be the distance between the points in the 186-dimensional space. Since there are 47 airports in the data set, this results in the calculation of 1081 proximity values for each year. In mathematical terms, the proximity between airport i and airport j in year t is given by:

$$\delta_{ij}^t = \left(\sum_{k=1}^{186} \left(e_{ik}^t - e_{jk}^t\right)^2\right)^{1/2}, \tag{1}$$

where e_{ik}^t is the standardised efficiency of airport i under specification k for year t.

INDSCAL models the airports as a set of points in a d-dimensional space. Following the findings of the year by year factor analysis, d was set to 9. INDSCAL is not rotation invariant, as is the case with factor analysis or with Multidimensional Scaling. It has been found that the dimensions in an INDSCAL study often have a meaning. Attaching a meaning to the dimensions is important in order to interpret the results of the analysis. This is done below.

INDSCAL assumes that the relative position of the airports with respect to each other, in this 9-dimensional space, remains invariable over time, but that the relative importance (salience) of the dimensions in the space changes over time. This assumption is appropriate for the Spanish airport data set since it is reasonable to assume that the airports that are similar in a particular year will continue to be similar over the time period. For example, if Vitoria and Zaragoza airports are similar during the first year, they will continue to be similar during the following four years. This does not mean that things do not change; the relative importance of the dimensions in the space may change over time as a result of, for example, the economic cycle.

INDSCAL returns as output both a common map that represents what has remained invariant over time, and a set of weights that reveals time-related effects. The set of weights, one for each dimension and for each year, are used to "distort" the common map. The distortion is a simple change of scale that is used to emphasise the importance (salience) of each dimension in each particular year.

Mathematically, INDSCAL performs a non-linear regression where the dependent variables are the δ_{ij}^t and the unknowns are of two types: the coordinates of the airports in the common space, c_{id}, and the set of weights w_d^t. Where c_{id} is the coordinate d of airport i in the common space, and w_d^t is the weight attached to dimension d in the specific year t.

We can write:

$$\delta_{ij}^t = \left(\sum_{d=1}^{9} (c_{id} - c_{jd})^2 w_d^t\right)^{\frac{1}{2}} + \varepsilon_{ij}^t = d_{ij}^t + \varepsilon_{ij}^t, \tag{2}$$

where the d_{ij}^t are the distances between airports in the common space taking into account the importance taken by the dimensions in year t.

Being regression based, model fit can be assessed using the correlation between the dissimilarities, δ_{ij}^t, and the distances d_{ij}^t. This is done for each year.

$$R_t = Correlation\left(\delta_{ij}^t, d_{ij}^t\right) \tag{3}$$

The model contains an ambiguity: if we multiply the coordinates of the common space by a constant and divide the weights by the square of this constant, the value under the square root remains unchanged. To avoid this, the weights for each year are normalised so that

$$R_t^2 = \sum_{d=1}^{9} (w_d^t)^2 \tag{4}$$

In other words, the sum of the square of the weights for each year adds up to the square of the correlations between dissimilarities and distances for that particular year.

The weights for each dimension and each year can be seen in Table 3. This table also contains the sum of squares of the weights for each particular year.

Table 3 INSCAL weights (w_t) and Goodness of Fit (R_t^2) measure for each year.

Year	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	R_t^2
2009	0.240	0.589	0.106	0.000	0.137	0.009	0.228	0.022	0.025	0.4877
2010	0.219	0.178	0.165	0.158	0.232	0.095	0.185	0.132	0.491	0.4874
2011	0.260	0.145	0.248	0.502	0.212	0.121	0.146	0.042	0.057	0.4880
2012	0.301	0.171	0.277	0.165	0.163	0.100	0.094	0.467	0.000	0.4873
2013	0.289	0.141	0.247	0.117	0.195	0.506	0.100	0.000	0.075	0.4878

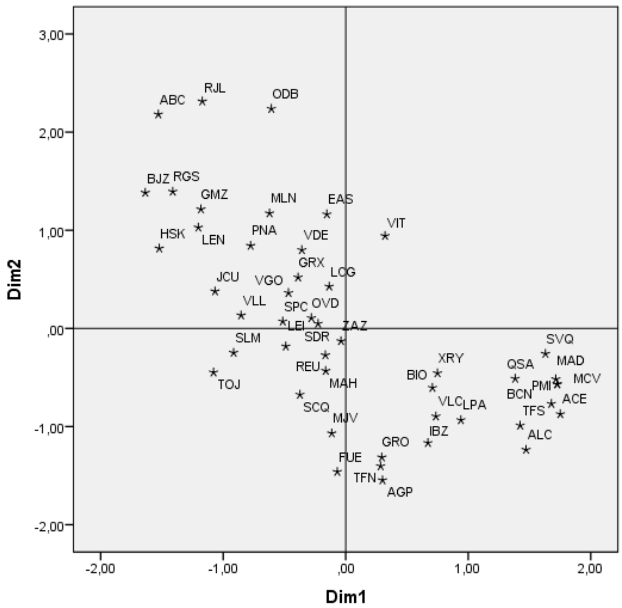
It can be seen in Table 3 that correlations between dissimilarities and distances for each year are in the region of 0.7 (the square root of the figure under the R_t^2 column). It can also be seen that the relative salience of the dimensions, as measured by the weights, changes over time. This is something we will further explore below.

Another way of assessing the goodness of fit of the model is known as "stress". Stress is a measure of lack of fit. As such, we would like stress to be near to zero. There are various measures of stress. The most common measure is known as Stress1; Kruskal (1964). In this case Stress1 was found to be 0.0610, which ranks as "very good" in Kruskal's (1964) verbal classification.

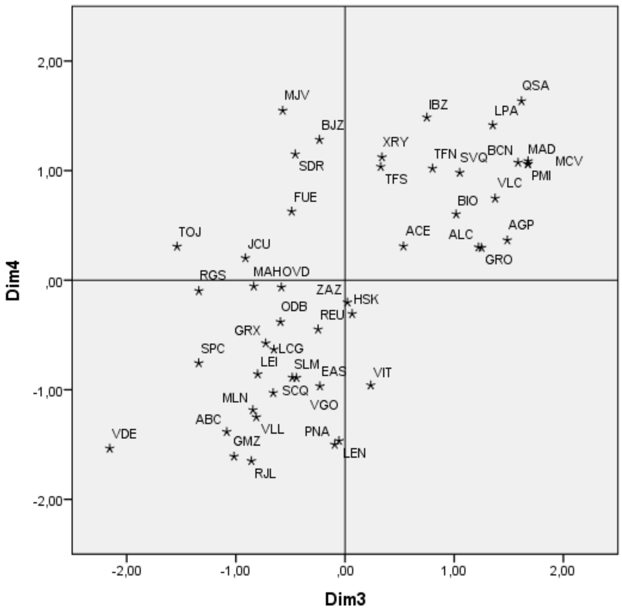
As previously stated, INDSCAL generates a common map. The common map is a consensus map over time, which plots each airport in the 9-dimensional space. Each airport is then, a point in a 9-dimensional space. The coordinates of each airport in the common map are given in Table 4.

A mathematical map in nine dimensions is difficult to comprehend. It needs to be projected into pairs of dimensions. The projection of the common map into dimensions 1 and 2 can be seen in Figure 1(a). The projection of the common map into dimensions 3 and 4 can be seen in Figure 1(b), and the projection of the common map into dimensions 5 and 6 can be seen in Figure 1(c). Airports are identified by means of their IATA codes, as given in Table 4.

a) Dimension 1 (Dim1) vs Dimension 2 (Dim2)



b) Dimension 3 (Dim3) vs Dimension 4 (Dim4)



c) Dimension 5 (Dim5) vs Dimension 6 (Dim6)

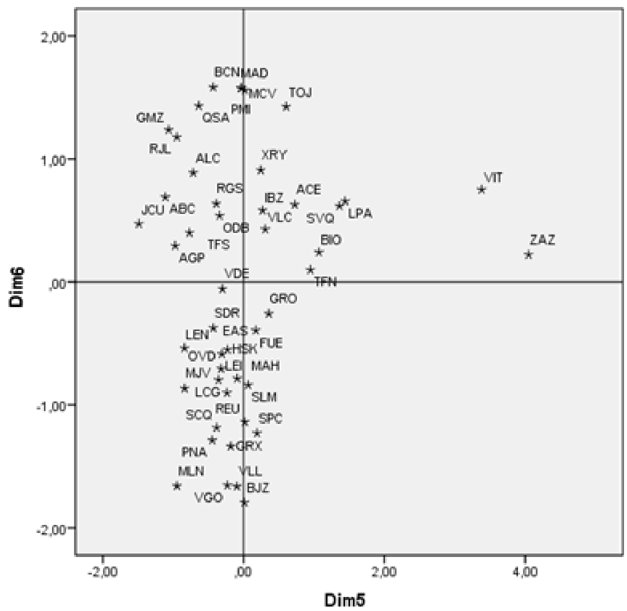


Fig. 1. Common Map. Projection into pairs of dimensions. Airports identified by means of their IATA codes.

3.3. Interpreting the common map. Property Fitting

In order to better understand the results of the analysis, it is important that dimensions in the common map be attached a meaning. This can be done using the Property Fitting approach (ProFit); Schiffman *et al.* (1981). ProFit is a form of biplot; Gower and Hand (1996). ProFit attempts to establish if there are directions in the common space that are related to the way in which efficiency under a particular specification changes. For example, if efficiency in dealing with cargo grows in the direction of Dimension 5, we plot a vector in the direction of Dimension 5 to make this explicit. To draw the vectors, we need to perform a regression in which the independent variables are the coordinates of the airports in the common space, and the dependent variable is the efficiency under the specification of interest. For a mathematical justification of this procedure see Mar-Molinero and Mingers (2006). All calculations were made with the regression routine of the IBM-SPSS package.

ProFit vectors were normalised to unit length,

$$\beta_i^* = \frac{\beta_i}{\sqrt[2]{\sum_{i=1}^{9} \beta_i^2}}\,, \qquad i = 1 \ldots .9\,, \tag{5}$$

where β_i is the i −th regression coefficient. The β_i^* values can be seen in Table 5. Table 5 also shows the R^2, that measures Goodness of Fit in the regression.

Normalisation is important for the interpretation of the dimensions. All ProFit vectors have their origin in the centre of co-ordinates and, after normalization, have unit length. If, in a two-dimensional projection, the end point of the ProFit vector associated with a particular specification is close to the centre of coordinates, it is concluded that the dimensions on which the vector is plotted are unrelated to efficiency under that particular specification. If, on the other hand, the vector appears to have unit length in a particular projection, one can conclude that the dimensions of the figure are the relevant ones for the interpretation.

3.4. Interpreting the common map. Hierarchical Cluster Analysis

Figures 2, 3, and 4 complement Figure 1. Ideally, one would project on the same pair of dimensions both the end points of the profit vectors and the airports, but this would have resulted in too much information within each figure.

Before we proceed to interpretation, we need to realise that the end points of the ProFit vectors are located in a 9-dimensional space, and it is possible for two such end points to appear near to each other in the projection while being far away in the space. In order to address this issue we have conducted a Hierarchical Cluster Analysis of the end points of the ProFit vectors using the IBM-SPSS computer package. The β_i^* values were treated as variables, and the specifications as observations. Ward´s agglomeration method was chosen since it maximises homogeneity within clusters and heterogeneity between clusters. After observing the dendrogram, it was decided that six would be an appropriate number of clusters. The specifications that belong to the same cluster have been identified in Figures 2, 3, and 4.

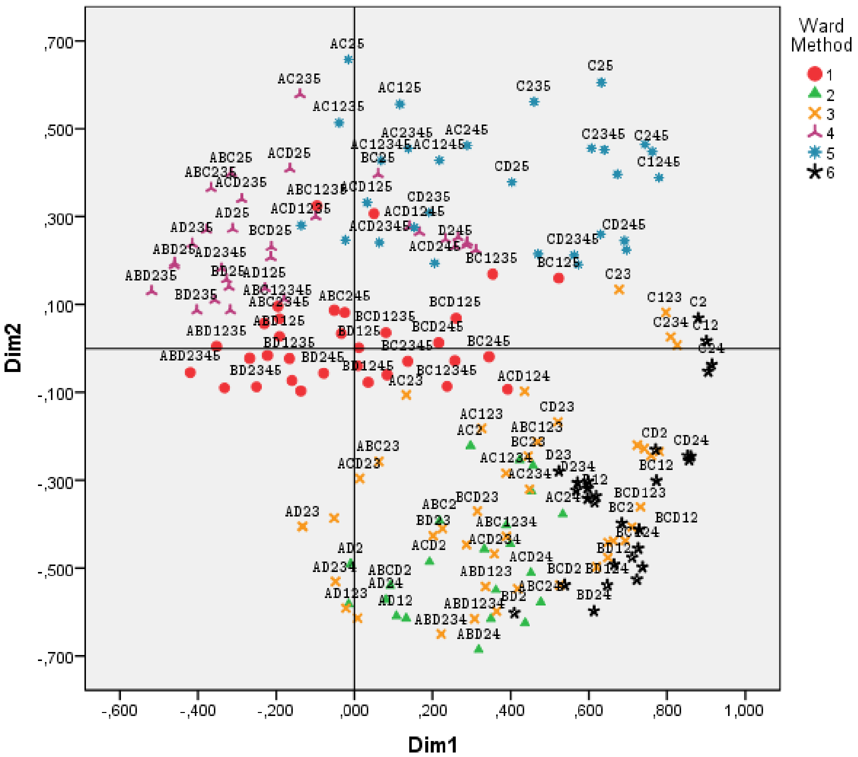


Fig. 2. DEA Specifications projection into Dimension 1 and Dimension 2 with indication of Ward clustering method.

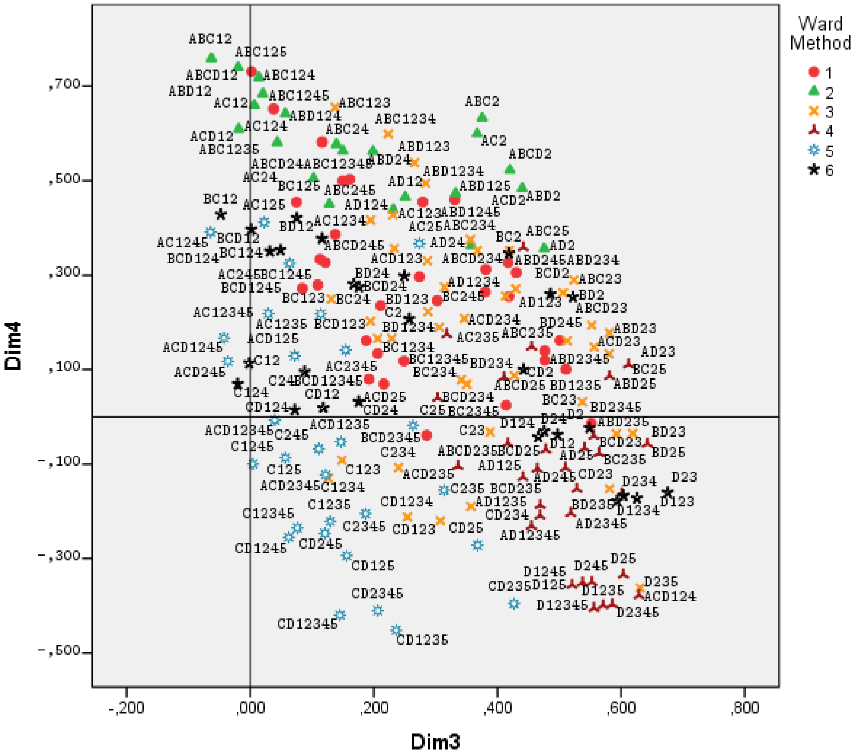


Fig. 3. DEA Specifications projection into Dimension 3 and Dimension 4 with indication of Ward clustering method.

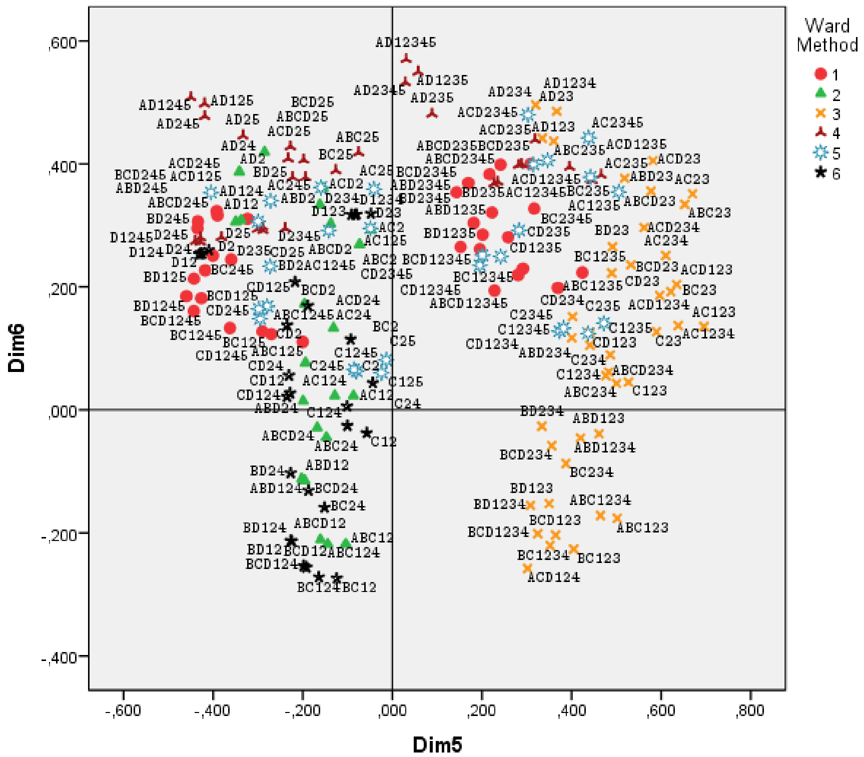


Fig. 4. DEA Specifications projection into Dimension 5 and Dimension 6 with indication of Ward clustering method.

3.5. Interpreting the common map. Exploring the meaning of the dimensions

In this section we interpret the common map, as projected in Figure 1 taking into account the results of ProFit and Cluster analysis.

We observe in Figure 1(a) that airports concentrate in the lower right-hand-side quadrant and in the upper left-hand-side quadrant. Airports located in the lower right-hand side of the figure are, on the whole, large or medium-sized (Madrid Barajas, Barcelona El Prat, Palma, Alicante). Airports located on the top left-hand side quadrant are small airports (Albacete, Logrono, Badajoz). It is clear that the north-west, south-east diagonal is related to the size of the airport. To understand how the efficiency of large airports differs from the efficiency of small airports, we turn our attention to Figure 2.

In Figure 2 we observe that the end points of ProFit vectors that are most distant from the centre of coordinates in the direction south-east belong to Cluster 6 and, to a smaller extent, to cluster 3. Furthermore, the distance from the origin of coordinates to points that belong to Cluster 6 is almost unity, indicating that this cluster is important for interpretation purposes. Members of Cluster 6 contain as inputs Operating Costs (B), Depreciation (C), and Runway Surface (D) and as outputs Passengers (1), ATM (2), and Commercial Revenues (4). This indicates that large airports are efficient at generating aeronautical activity and revenues given the use they make of the infrastructure, while the same cannot be said of small airports.

We now turn our attention to Dimension 1 in Figure 2. ProFit vectors that point towards the right-hand side contain Depreciation (C) and Runway Surface (D) as inputs; as outputs they contain Passengers (1), ATM (2), and Commercial Revenues (4). We can then identify Dimension 1 as the efficient use of investment in order to generate air traffic movements (passengers) and commercial revenues.

If we look at Dimension 2 in Figure 2 we see that the ProFit vectors that point towards the top contain as inputs Labour Cost (A) and Depreciation (C), and as outputs ATM (2), Cargo (3), and Flights on Time (5). We have already observed that the airports that are located towards the top of Figure 1(a) are small ones. This suggests that small airports have high punctuality records, and deal with aircraft traffic in a cheap way, both from the point of view of labour and the point of view of investment in infrastructures. We can label this dimension as cost efficiency with respect to aeronautical activity in terms of punctuality.

Dimension 3 is associated with a variety of specifications combining a variety of inputs and outputs, but all of them include ATM (output 2). This suggests that dimension 3 is related to the efficiency in obtaining financial resources in relation with Air Traffic Movements (airport charges in relation to approach and landing taxes).

It can be seen in Figure 3 that the ProFit vectors most associated with Dimension 4 contain Labour Costs (A) and Operating Costs (B) as inputs, and Passengers (1) and ATM (2) as outputs. This dimension could be interpreted as cost efficiency in dealing with passengers.

Dimension 5 is clearly associated with the efficiency in dealing with cargo (3).

Finally, Dimension 6 captures efficiency effects associated with runway surface (D). Clearly, larger runways make it possible for larger aircraft to land, as well as unfolding runways make it possible for more aircraft to land. This impacts on efficiency, especially in Air Traffic Movements (ATM) (2) and Flights on Time (5).

3.6. Time evolution

Time related effects are captured by the weights in Equation 2. For a given year and a given dimension, the absolute value of the weight is not important, since this depends on the normalisation performed in Equation 4. What is important for a given year, t, is whether the value of the weight associated with a particular dimension is greater or smaller than the value of the weight associated with another dimension. If both weights are of equal value, the common map is a good representation of the efficiency situation for the airports. If the weight for dimension i is higher than the weight for dimension j, the common map has to be elongated along dimension i and shrunk along dimension j. This is to say, if weight, w_i^t, is higher than weight, w_j^t, dimension i takes more importance than dimension j during year t.

This is best explored graphically, but because there are 6 weights, 15 such graphs are necessary to give full details. We have decided to reproduce here only the most informative graphs.

There are various ways in which the relative importance of the weights can be revealed. Here we have opted for Young's plots; Coxon (1982, p.199). Four such plots can be seen in Figure 5.

It can be seen in section (a) of Figure 5 that there was a large change in the relative importance of Dimension 2 with respect to Dimension 1 after 2009. This can be directly attributed to the impact of the economic crisis. In 2009 Dimension 2 was clearly more important than Dimension 1, a situation that was reversed in the following years. Dimension 2 has been interpreted as cost and investment efficiency, and Dimension 1 was interpreted as efficiency in the use of investment in order to generate passenger activity. From this we deduce that in the year 2009, when passenger activity was high, the emphasis was on cost reduction and good use of infrastructures. After 2009 the emphasis appears to have shifted to generating passenger activity given the investment available in each airport.

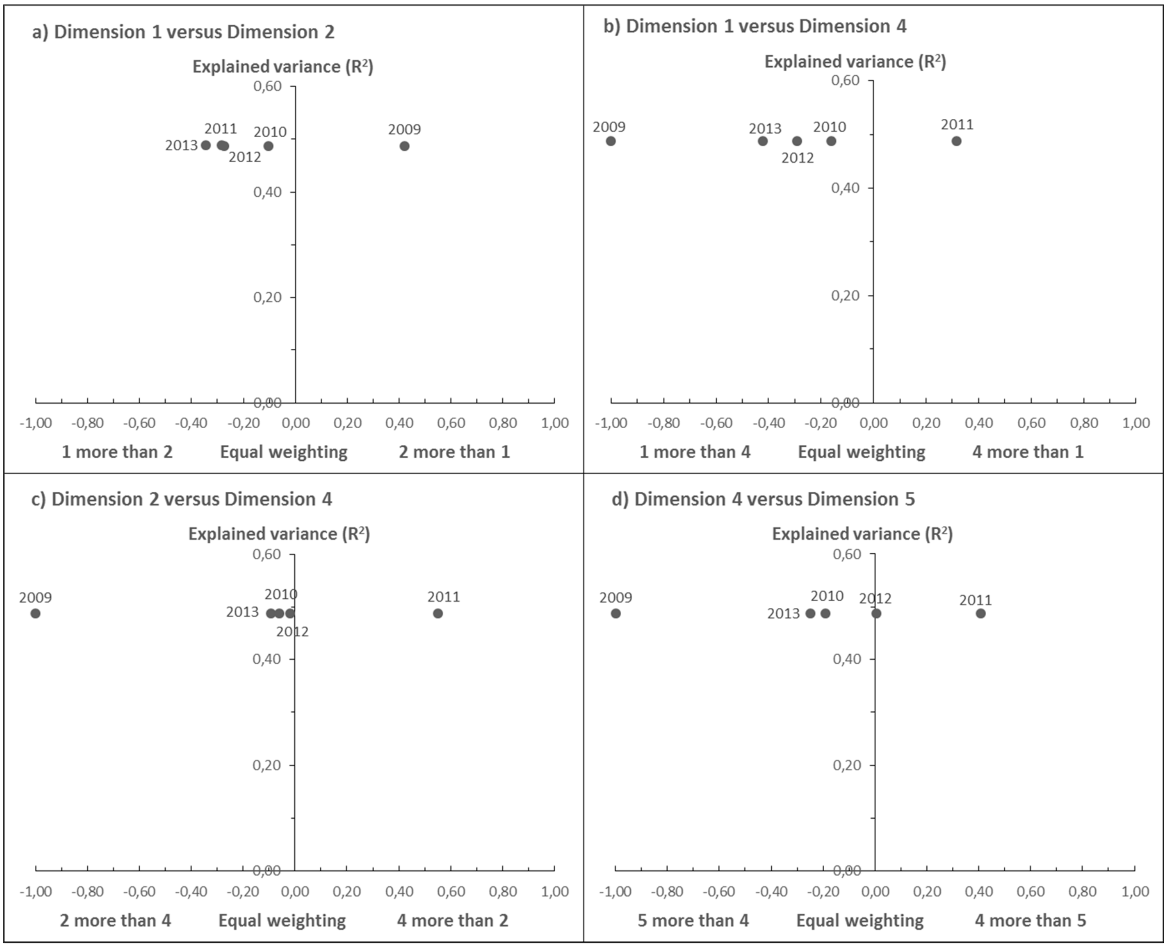


Fig. 5. INDSCAL weights, Young's plots.

The next plot of interest corresponds to section (b) of Figure 5. Here we concentrate on cost efficiency in dealing with passengers, which was associated with Dimension 4. This efficiency appears to have taken more importance during the worst years of the economic crisis (2010 and 2011). In years 2012 and 2013 the relative importance of Dimension 4 with respect to Dimension 1 decreased, indicating a return to the pre-crisis situation.

The relative importance of Dimension 4 with respect to Dimension 2 is explored in section (c) of Figure 5. We see that cost efficiency in relation to passengers appears to have had relatively low emphasis in 2009, before the economic crisis hit Spanish airports, but that the situation was reversed during the crisis.

Finally, the relative salience of efficiency in dealing with passengers or cargo is explored in section (d) of Figure 5. We can see that efficiency in cargo took more importance before the crisis and that, as the crisis developed, efficiency in dealing with passengers took more importance. This can be due to a fall in cargo activity as a consequence of the economic crisis.

4. Discussion and conclusions

Airports are important infrastructures that command many resources. In Spain, airports are nationally owned and managed through a state company: AENA. There has been substantial interest in establishing if the resources have been efficiently managed in the aeronautical industry.

From 2004 to 2007, the vast majority of small and medium sized airports increased their number of passengers. The financial crisis that started in 2008 impacted on small and medium sized airports that suffered a significant reduction in air traffic compared to large airports. In fact, the reduction in traffic that took place between 2007 and 2013 was so drastic that only two airports reported increases in the number of passengers (27.86% Santander and 1.12% Santiago). However, efficiency depends on inputs and on outputs. This begs the question of how the crisis affected the efficiency of the airport system. The research reported in this paper addresses such question using the technique of Data Envelopment Analysis combined with the tools of Multivariate Statistical Analysis.

The first issue explored is: what is airport DEA efficiency? Is there just one form of DEA efficiency or can several efficiencies be identified? In standard studies data is collected on the values of inputs and outputs and calculations take place. But the results of the analysis depend on the choice of inputs and outputs. This is no trivial matter, as inputs (and outputs) tend to be correlated and there are no modelling rules equivalent to the ones that are available in statistical analysis.

Our approach has been to estimate a variety of input/output combinations that we have named specifications. We have used four inputs and five outputs that are standard in the airport efficiency literature.

The treatment of capital assets has been particularly complex since appropriate data could not be had from AENA's financial statements. Capital usage had to be estimated from investment expenditure (tangible assets) whilst taking into account established depreciation rules.

In total, efficiencies were estimated under 186 combinations of inputs and outputs. The calculations were performed for each of the five years for which we had data. Since we had data for 47 airports, this represents the calculation of 43,710 efficiency values.

To analyse such a large number of results we resorted to the tools of multivariate statistical analysis, in particular to scaling techniques because these permit the graphical presentation of the main features of the data.

The particular statistical approach chosen was the Individual Differences Scaling model of Carrol and Chang (INDSCAL). INDSCAL produces a “common map”, that shows what has remained constant over time, and a set of weights that contain information about time-related changes.

The study of the common map revealed that six efficiency definitions can be identified: (a) efficient use of investment in order to generate passenger activity and commercial revenues; (b) cost efficiency in relation to aeronautical activity; (c) efficiency in obtaining revenues in relation to Air Traffic Movements; (d) cost efficiency in dealing with passengers; (e) efficiency in dealing with cargo; and (f) efficiency effects associated with runway surface.

Having interpreted the meaning of the dimensions, it is possible to assess the strengths and weaknesses of each airport in terms of efficiency. To give an example we will discuss the particular case of Vitoria airport. Vitoria airport is located near the centre of the representation in Figure 1(a). This suggests that Vitoria is slightly better than average in terms of efficient use of investment in order to generate passenger activity, and that it is slightly better than average in terms of cost efficiency as related to aeronautical activity. From Figure 1(b) we deduce that Vitoria airport is slightly better than average in terms of cost efficiency in relation to ATM, and that it is below average in cost efficiency when dealing with passengers. However, in Figure 1(c) we see that the real strength of Vitoria is in cargo efficiency. We conclude that in Vitoria airport there is room for improvement in terms of use of investment, cost reduction, and generation of passenger activity, but that it stands as an example of good practice in relation to cargo. Similar analyses can be easily performed for any other airport, since this only requires the observation of the location of the airport in the different dimensions of the common map. In fact, it has been shown that operational knowledge can be derived from appropriate processing of the data and that this knowledge can be represented in a graphical way for easy understanding.

The relative importance of these approaches to efficiency has varied over time, and this is revealed in the weights generated by the INDSCAL model. We see in Figure 5 (a) that in 2009 cost efficiency took priority over efficient use of investment in the generation of passenger activity, but that the situation was reversed as a consequence of the economic crisis. In Figure

5 (b) we see that after 2009, cost efficiency in dealing with passengers was gaining priority over efficient use of investment along 2010 and 2011, turning then toward the pre-crisis situation. From Figure 5 (c) we observe that, before the crisis, cost efficiency in dealing with passengers also took priority over cost efficiency in relation to aeronautical activity. Figure 5 (d) shows how cost efficiency in dealing with cargo lost importance during the period, and this was gained by cost efficiency in relation to passengers. These changes can be related to the loss of outputs as a consequence of the crisis, whilst inputs were slow to adapt to change. What is more, the slow return that is observed to the pre-crisis situation has probably more to do with increases in the outputs than with decreases in the inputs.

We conclude that the combination of multivariate statistical analysis with DEA efficiency evaluation can produce important insights in time related effects in efficiency. However, in this analysis we have not taken into account shifts in the production frontier. This may not be a great loss, since five years is a short period, and, in this case, the situation is dominated by the impact of the economic crisis.

References

Ahn, Y.H,, and Min. H. (2014) Evaluating the multi-period operating efficiency of international airports using data envelopment analysis and the Malmquist productivity index. Journal of Air Transport Management, 39, 12-22.

Ashford, N.; Stanton, H. and Moore, C. (1996): *'Airport Operations'* New York, McGraw-Hill Education (second edition)

Assaf, A.G.; Gillen, D. and Barros, C. (2012): 'Performance assessment of UK airports: evidence from a Bayesian dynamic frontier model'. *Transportation Research Part E* 48, 603–615

Banker, R.D. and Morey, R.C. (1986): 'Efficiency analysis for exogenously fixed inputs and outputs'. *Operations Research* 34 (4), 513-521

Barros, C. and Dieke, P.U.C. (2007): 'Performance evaluation of Italian airports: A data envelopment analysis' *Journal of Air Transport Management* 13, 184–191

Barros, C. (2008a): 'Airports in Argentina: Technical efficiency in the context of an economic crisis' *Journal of Air Transport Management* 14, 315–319

Barros, C. (2008b): 'Technical efficiency of UK airports' *Journal of Air Transport Management* 14, 175–178

Barros, C. (2009): 'The measurement of efficiency of UK airports, using a Stochastic Latent Class Frontier Model'. *Transport Reviews* 29, 479–498

Barros, C. and Sampaio, A. (2004): 'Technical and allocative efficiency in airports' International Journal of Transport Economics 31, 355-377

Bazargan, M. and Vasigh, B. (2003): 'Size versus efficiency: A case study of US commercial airports'. *Journal of Air Transport Management* 9, 187–193.

Bezerra, G.C.L.; and Gomes, C.F. (2016) Performance measurement in airport settings: a systematic literature review. Benchmarking: an International Journal, 23, 1027-1050.

Cambra de Comerç de Barcelona (November 2010): *'El modelo de gestión aeroportuaria en España: marco institucional y jurídico y líneas maestras para una propuesta de cambio'.*

Carroll, J.D. and Chang, J.J. (1970): 'Analysis of individual differences in multidimensional scaling via an N-way generalization of "Eckart-Young" decomposition' *Psychometrika* 35, 283–319

Chi-Lok, A.Y. and Zhang, A. (2009): 'Effects of competition and policy changes on Chinese airport productivity: an empirical investigation' *Journal of Air Transport Management* 15, 166-174.

Comisión Nacional de los Mercados y la Competencia (CNMC, July 2014): *'El Sector Aeorportuario en España: Situación Actual y Recomendaciones de Liberización'*

Cordero-Ferrara, J.M.; Pedraja-Chaparro, F. and Salinas-Jimenez, J. (2008): 'Measuring efficiency in education: an analysis of different approaches for incorporating non-discretionary inputs'. *Applied Economics* 40, 1323-1339

Coto-Millan, P.; Carrera-Gomez, G.; Castanedo-Galan, J.; Inglada, V.; Nuñez-Sanchez, R.; Pesquera, M.A.; Sainz, R. (2007): 'Efficiency Stochastic Frontiers: a Panel Data Analysis for Spanish Airports (1992–1994)' in *Essays on Transport Economics* (chapter 121-126), Physica-Verlag HD

Coto-Millan, P.; Casares-Hontañón, P.; Inglada, V.; Agüeros, M.; Pesquera, M.A.; Badiola, A. (2014): 'Small is beautiful? The impact of economic crisis, low cost carriers, and size on efficiency in Spanish airports (2009–2011)' *Journal of Air Transport Management* 40, 34-41

Coto-Millan, P.; Inglada, V.; Fernandez, X.L.; Inglada-Perez, L. and Pesquera, M.A. (2016): 'The *effect procargo* on technical and scale efficiency at airports: The case of Spanish airports (2009–2011)' U*tilities Policy* 39, 29-35

Coxon, A.P.M. (1982): '*The user's guide to Multidimensional Scaling'* Heinemann Educational Books, London, UK.

EMS available from www.holger-scheel.de/ems/

European Commission European Court of Auditors (2014): *'EU-funded airport infrastructures: poor value for money'* Special Report, 21 (URL: http://www.politico.eu/article/eu-wasted-money-on-new-airports-say-auditors/)

Fasone, V.; Kofler, L.; and Scuderi, R. (2016) Business performance in airports: non-aviation revenues and their determinants. Journal of Air Transport Management, 53, 35-45.

Fragoudaki, A.; Giokas, D.; and Glyptou, K. (2016) Efficiency and productivity changes in Greek airports during the crisis years 2010-2014. Journal of Air Transport Management, 57, 306-315.

Gillen, D., and A. Lall (1997): 'Developing Measures of airport productivity and performance: an application of Data Envelopment Analysis'. *Transportation Research Part B* 33 (4), 261-73

Gower, J. C. and Hand, D. J. (1996): *'Biplots'* Chapman and Hall, London

Gutiérrez-Nieto, B.; Serrano-Cinca, C. and Mar-Molinero, C. (2007): 'Microfinance institutions and efficiency' *Omega, the international journal of Management Science* 35, 131-142.

Grosskopft, S. (1986) The role of reference technology in measuring productive efficiency. The Economic Journal, 96, 499-513.

Grosskopft, S. (1996) Statistical inference and non-parametric inference: a selective survey. Journal of Productivity Analysis, 7, 161-176.

Hughes, A.; and Yaisawarng, S. (2004) "Sensitivity and dimensionality tests of DEA efficiency scores". European Journal of Operational Research, 154(2), 410-422.

Humphreys, I. (1999): 'Privatisation and commercialisation Changes in UK airport ownerships patterns' *Journal of Transport Geography* 7, 121-134.

IBM Corp. (2017) IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp.

International Civil Aviation Organization (ICAO) (March 2013): '*Worldwide Air Transport Conference (ATCONF) Sixth meeting: Airport Competition' https://www.google.com/maps/d/viewer?mid=zylWTnxRlUJE.kU5cVv1m27wk&hl=en_US*

Kao, C.; Hwang, S.N. (2014) Multi-period efficiency and Malmquist productivity index in two-stage production systems. European Journal of Operational Research, 232, 512-521.

Kruskal, J.B. (1964): 'Multidimensional scaling by optimizing goodness of fit to a non-metric hypothesis' *Psychometrika* 29, 1-27.

Lieber, V; and Niemeier, H.M. (2013) A Survey of Empirical Research on the Productivity and Efficiency Measurement of Airports. Journal of Transport Economics and Policy, 47, 157-189.

Liebert, V.; and Niemeier, H. M. (2010, July). Benchmarking of airports-A critical assessment. In Proceedings of the 12th World Conference on Transport Research (pp. 11-15).

Liu, D. (2017) Evaluating the multi-period efficiency of East Asia airport companies. Journal of Air Transport Management, 59, 71-82.

Lozano S. and Gutiérrez, E. (2011): 'Slacks-based measure of efficiency of airports with airplanes delays as undesirable outputs', *Journal Computers and Operations Research* 38(1), 131-139

Lozano S.; Gutierrez, E. and Moreno, P. (2013): 'Network DEA approach to airports performance assessment considering undesirable outputs' *Applied Mathematical Modelling* 37, 1665-1676

Mar-Molinero, C. and Mingers, J. (2006): 'An evaluation of the limitations of, and alternatives to, the Co-Plot Methodology' *Journal of the Operational Research Society* 58, 874-886

Martin J.C. and Roman, C. (2001): 'An application of DEA to measure the efficiency of Spanish airports prior to privatization' *Journal of Air Transport Management* 7(3), 149-157

Martin J.C. and Roman, C. (2006): 'A benchmarking analysis of Spanish commercial airports. A comparison between SMOP and DEA ranking methods' *Networks and Spatial Economics* 6(2), 111-134

Martin J.C.; Roman, C. and Voltes-Dorta, A. (2009): 'A stochastic frontier analysis to estimate the relative efficiency of the Spanish airports' *Journal of Productivity Analysis* 31(3), 163-176

Martin J.C.; Roman, C. and Voltes-Dorta, A. (2011): ‘Scale economies and marginal costs in Spanish airports’ *Transportation Research Part E* 47, 238-248

Martin-Cejas, R.R. (2002): ‘An approximation to the productive efficiency of the Spanish airports network through a deterministic cost frontier’ *Journal of Air Transport Management* 8 (4), 233–238

Murillo-Melchor, C. (1999): ‘An Analysis of technical efficiency and productivity changes in Spanish Airports using the Malmquist Index’ *International Journal of Transport Economics* 26(2), 271-292

Pacagnella Junior, A. C., Hollaender, P. S., Mazzanati, G. V., and Bortoletto, W. W. (2021). Efficiency drivers of international airports: A worldwide benchmarking study. Journal of Air Transport Management, 90(C).

Parker, D. (1999): ‘The Performance of BAA Before and After Privatisation: A DEA Study’ *Journal of Transport Economics and Policy* 33 (2), 133-146.

Pastor, J.T.; Ruiz, J.L.; and Sirvent, I. (2002) A statistical test for nested radial DEA models. Operations Research, 50, 728-735.

Pathomsiri S.; Haghani, A.; Dresner, M. and Windle, R.J. (2008): ‘Impact of undesirable outputs on the productivity of US airports’ *Transportation Research Part E* 44, 235–259

Pels, E.; Nijkamp, P. and Rietveld, P. (2001): ‘Relative Efficiency of European Airports’. *Transport Policy* 8 (3), 183-92

Pels, E.; Nijkamp, P. and Rietveld, P. (2003): ‘Inefficiencies and scale economies of European airport operations’ *Transportation Research Part E* 39, 341-361

Ripoll-Zarraga, A.E. and Mar-Molinero, C. (2020): ‘Exploring the reasons for efficiency in Spanish airports’. In press (December 2020, volume 99, 186-202) *Transport Policy* ISSN 0967070X (URL: http://doi.org/10.1016/j.tranpol.2020.08.021; accessed online 10/09/2020)

Ruggiero, J. (1998): ‘Non-discretionary inputs in Data Envelopment Analysis’. *European Journal of Operational Research* 111, 461-469

Sagarra, M.; Mar-Molinero, C. and Agasisti, T. (2017): ‘Exploring the efficiency of Mexican universities: integrating Data Envelopment Analysis and Multidimensional Scaling’. *Omega, the international journal of Management Science* 67, 123-133

Salazar de la Cruz, F. (1999): ‘Technical, allocative and economic efficiency in transport’ *International Journal of Transport Economics* 26(2), 255-270

Sarkis, J. (2000): ‘An Analysis of the Operational Efficiency of Major Airports in the United States’. *Journal of Operations Management* 18 (3), 335-51

Sarkis, J. and Talluri, S. (2004): ‘Performance based clustering for benchmarking of US airports’ *Transportation Research Part A* 38, 329–346

Schiffman, J.F.; Reynolds, M.L. and Young, F.W. (1981): *‘Introduction to Multidimensional Scaling: Theory, Methods, and Applications’* Academic Press, London.

Serrano-Cinca, C.; Mar-Molinero, C. and Fuertes, Y. (2016): ‘Input and output search in DEA: the case of financial institutions'. Chapter 3 in *'Handbook of operations analytics using Data Envelopment Analysis'* Hwang, S.N.; Lee, H.S. and Zhu, J. Editors, Springer. New York.

Tapiador, F.J.; Mateos, A. and Marti-Henneberg, J. (2008): 'The geographical efficiency of Spain's regional airports: a quantitative analysis' *Journal of Air Transport Management* 14(4), 205-212

Thanassoulis, E. (2001): *'Introduction to the theory and application of Data Envelopment Analysis: a foundation text with integrated software'* Springer, USA.

Thrall, R.M. (1989) Classification transitions under expansion of inputs and outputs in Data Envelopment Analysis. Managerial and Decision Economics, 10, 159-162.

Tovar, B. and Martin-Cejas, R.R. (2009): 'Are outsourcing and non-aeronautical revenues important drivers in the efficiency of Spanish airports?' *Journal of Air Transport Management* 15(5), 217-220

Tovar, B. and Martin-Cejas, R.R. (2010): 'Technical efficiency and productivity changes in Spanish airports: A parametric distance functions approach' *Transportation Research Part E* 46(5), 249-260

Wang R.T.; Ho, C.T.; Feng, C.M. and Yang, Y.K.(2004): 'A comparative analysis of the operational performance of Taiwan's major airports' Journal of Air Transport Management 10, 353–360.

Word Finance (March, 2016): *'Spain's infrastructure woes are more serious than they appear'* (URL: http://www.worldfinance.com/infrastructure-investment/government-policy/spains-infrastructure-woes-are-more-serious-than-they-appear):

Yu, M.M.; Hsu, S.H.; Chang, C.C. and Lee, D.H. (2008): 'Productivity growth of Taiwan's major domestic airports in the presence of aircraft noise' *Transportation Research Part E* 44, 543–554

Yu, M.-M. (2004): "Measuring Physical Efficiency of Domestic Airports in Taiwan with Undesirable Outputs and Environmental Factors." Journal of Air Transport Management 10 (5), 295-303.

Yu, M.-M. (2010): "Assessment of Airport Performance Using the SBM-NDEA model." Omega 38 (6), 440-52.

Acknowledgment

The research reported in this manuscript was supported by the Research and University Secretary, Department of Business and Knowledge of the Generalitat de Catalunya (Industrial Doctorate Grant 2015 DI84).(URL: http://identitatcorporativa.gencat.cat/web/.content/Documentacio/descarregues/dpt/BN/Vice_Economia/scunirec_bn_h3.jpg).

Table 4. Coordinates of Spanish airports in the common space.

Code	Airport	Dim1	Dim2	Dim3	Dim4	Dim5	Dim6	Dim7	Dim8	Dim9
LCG	A Corunna	-0,14	0,43	-0,65	-0,63	-0,24	-0,90	0,71	0,93	-0,57
ABC	Albacete	-1,53	2,18	-1,08	-1,38	-1,11	0,69	0,14	0,64	0,64
ALC	Alicante-Elche	1,47	-1,24	1,22	0,30	-0,72	0,89	-1,02	-0,50	0,67
LEI	Almeria	-0,49	-0,18	-0,80	-0,86	-0,36	-0,80	1,46	0,76	-1,02
OVD	Asturias	-0,28	0,11	-0,58	-0,07	-0,32	-0,71	0,19	0,44	-0,55
BJZ	Badajoz	-1,64	1,38	-0,24	1,28	0,01	-1,79	-0,22	-0,82	0,08
BCN	Barcelona-El Prat	1,68	-0,77	1,59	1,07	-0,43	1,58	-1,31	-1,46	1,41
BIO	Bilbao	0,71	-0,61	1,02	0,60	1,07	0,24	-1,23	-0,74	0,82
RGS	Burgos	-1,41	1,39	-1,34	-0,10	-0,39	0,64	0,45	-0,20	0,34
JCU	Ceuta	-1,07	0,38	-0,91	0,20	-1,49	0,47	1,22	-0,94	0,33
ODB	Cordoba	-0,61	2,24	-0,59	-0,38	-0,34	0,54	0,03	-0,29	0,97
VDE	El Hierro	-0,36	0,80	-2,16	-1,54	-0,30	-0,06	0,47	-0,25	-0,30
FUE	Fuerteventura	-0,07	-1,46	-0,49	0,63	0,17	-0,39	1,04	0,38	0,01
GRO	Girona	0,30	-1,31	1,25	0,30	0,36	-0,26	-0,94	0,64	-0,24
LPA	Las Palmas GC	0,94	-0,93	1,35	1,42	1,44	0,66	-1,19	-1,23	1,25
GRX	Granada-Jaen	-0,39	0,52	-0,73	-0,58	-0,18	-1,34	0,30	1,45	-0,92
HSK	Huesca	-1,52	0,82	0,07	-0,31	-0,23	-0,55	-0,99	-0,45	-1,59
IBZ	Ibiza	0,67	-1,17	0,75	1,49	0,27	0,58	-0,33	-0,35	0,45
XRY	Jerez	0,75	-0,46	0,34	1,12	0,24	0,91	0,79	-0,29	0,23
GMZ	La Gomera	-1,18	1,21	-1,02	-1,61	-1,07	1,24	1,14	2,97	-3,16
SPC	La Palma	-0,51	0,07	-1,34	-0,76	0,19	-1,23	1,59	1,59	-1,27
ACE	Lanzarote	1,75	-0,87	0,54	0,31	0,73	0,63	-0,40	-0,72	0,51
LEN	Leon	-1,20	1,03	-0,06	-1,47	-0,84	-0,54	0,76	1,10	-0,55
RJL	Logrono-Agoncillo	-1,17	2,31	-0,86	-1,65	-0,95	1,18	-0,63	0,49	-0,20
MAD	Madrid-Barajas	1,73	-0,57	1,68	1,06	-0,04	1,58	-1,57	-1,52	1,55
MCV	Madrid-4Vientos	1,72	-0,52	1,68	1,09	0,02	1,56	-1,54	-1,51	1,50
TOJ	Madrid-Torrejon	-1,08	-0,45	-1,54	0,31	0,60	1,43	2,26	0,75	-1,66
AGP	Malaga	0,30	-1,55	1,49	0,36	-0,97	0,29	-1,15	-0,34	1,32
MLN	Melilla	-0,62	1,17	-0,84	-1,19	-0,95	-1,66	-0,03	-1,12	-0,92
MAH	Menorca	-0,16	-0,43	-0,84	-0,06	-0,09	-0,79	1,54	0,72	-1,00
MJV	Murcia	-0,11	-1,07	-0,57	1,55	-0,84	-0,87	1,20	0,88	-0,35
PMI	Palma de Mallorca	1,73	-0,57	1,68	1,06	-0,04	1,58	-1,57	-1,52	1,53
PNA	Pamplona	-0,78	0,84	-0,10	-1,50	-0,45	-1,29	0,72	-0,11	-0,29
REU	Reus	-0,17	-0,27	-0,25	-0,45	0,02	-1,14	0,96	1,72	-0,60
QSA	Sabadell	1,38	-0,51	1,62	1,63	-0,64	1,43	-1,45	-1,20	1,44
SLM	Salamanca	-0,92	-0,25	-0,48	-0,89	0,06	-0,84	-0,97	1,98	-0,83
EAS	San Sebastian	-0,15	1,16	-0,23	-0,97	-0,31	-0,59	-0,66	-1,16	0,41
SDR	Santander	-0,23	0,05	-0,46	1,15	-0,43	-0,38	0,85	0,06	-0,24
SCQ	Santiago Compost	-0,37	-0,68	-0,45	-0,89	-0,39	-1,19	0,55	0,86	-0,83
SVQ	Sevilla	1,63	-0,26	1,05	0,98	1,36	0,62	-1,15	-0,96	0,98
TFN	Tenerife Norte	0,29	-1,40	0,80	1,02	0,95	0,10	-0,21	-0,53	0,56
TFS	Tenerife Sur	1,42	-0,99	0,33	1,04	-0,77	0,40	-0,23	-0,06	0,44
VLC	Valencia	0,74	-0,90	1,38	0,75	0,31	0,43	-1,33	-0,23	0,94
VLL	Valladolid	-0,85	0,13	-0,81	-1,25	-0,10	-1,66	0,55	0,08	-0,97
VGO	Vigo	-0,47	0,36	-0,66	-1,03	-0,23	-1,65	1,03	0,62	-1,28
VIT	Vitoria	0,32	0,94	0,24	-0,96	3,38	0,75	0,07	-0,45	0,80
ZAZ	Zaragoza	-0,04	-0,13	0,02	-0,20	4,05	0,22	0,08	-0,12	0,14

Table 5. End points of normalised ProFit vectors.

Model	β_1^*	β_2^*	β_3^*	β_4^*	β_5^*	β_6^*	β_7^*	β_8^*	β_9^*	R^2
ABCD12345	-0,230	0,057	0,137	0,386	0,228	0,194	-0,301	-0,155	0,756	0,519
ABCD12	0,388	-0,403	-0,020	0,740	-0,161	-0,211	-0,241	-0,070	-0,078	0,820
ABCD2	0,092	-0,540	0,420	0,522	-0,138	0,303	-0,278	-0,223	-0,115	0,800
ABCD2345	-0,222	-0,016	0,206	0,134	0,241	0,399	-0,307	-0,212	0,731	0,544
ABCD234	0,364	-0,598	0,367	0,352	0,483	0,062	0,013	-0,044	0,109	0,863
ABCD235	-0,460	0,195	0,417	-0,056	0,288	0,400	-0,134	-0,329	0,453	0,586
ABCD245	-0,033	0,034	0,113	0,333	-0,391	0,316	-0,447	-0,183	0,623	0,537
ABCD23	-0,052	-0,386	0,552	0,193	0,577	0,356	-0,010	-0,200	0,078	0,856
ABCD24	0,437	-0,625	0,150	0,563	-0,168	-0,029	-0,214	-0,028	-0,061	0,859
ABCD25	-0,378	0,270	0,411	0,083	-0,198	0,407	-0,264	-0,379	0,436	0,539
ABC12345	-0,196	0,096	0,149	0,499	0,280	0,219	-0,321	0,043	0,670	0,548
ABC1234	0,389	-0,428	0,223	0,599	0,464	-0,172	-0,020	-0,064	0,090	0,833
ABC1235	-0,096	0,324	0,116	0,582	0,369	0,198	-0,308	0,007	0,513	0,523
ABC1245	-0,051	0,087	0,038	0,652	-0,290	0,128	-0,441	0,059	0,515	0,545
ABC123	0,468	-0,213	0,137	0,655	0,502	-0,176	-0,039	-0,059	0,001	0,820
ABC124	0,399	-0,445	0,014	0,718	-0,145	-0,218	-0,226	-0,048	-0,069	0,840
ABC125	0,050	0,307	0,002	0,731	-0,201	0,111	-0,426	0,020	0,367	0,498
ABC12	0,457	-0,267	-0,063	0,758	-0,104	-0,218	-0,243	-0,046	-0,146	0,809
ABC2	0,218	-0,393	0,375	0,632	-0,073	0,269	-0,305	-0,199	-0,217	0,786
ABC2345	-0,192	0,068	0,274	0,296	0,308	0,400	-0,328	-0,011	0,658	0,565
ABC234	0,418	-0,547	0,356	0,375	0,500	0,043	-0,012	-0,014	0,077	0,862
ABC235	-0,367	0,365	0,455	0,148	0,395	0,395	-0,146	-0,179	0,371	0,591
ABC245	-0,025	0,082	0,161	0,503	-0,324	0,311	-0,483	0,015	0,529	0,553
ABC23	0,063	-0,258	0,524	0,289	0,652	0,334	-0,030	-0,183	-0,010	0,859
ABC24	0,477	-0,578	0,140	0,577	-0,148	-0,045	-0,235	-0,003	-0,087	0,855
ABC25	-0,315	0,399	0,442	0,358	-0,076	0,418	-0,254	-0,053	0,412	0,523
ABD12345	-0,332	-0,090	0,380	0,264	0,181	0,304	-0,145	-0,091	0,716	0,497
ABD1234	0,308	-0,615	0,284	0,494	0,420	-0,046	0,055	-0,060	0,131	0,828
ABD1235	-0,352	0,004	0,419	0,255	0,222	0,321	-0,134	-0,135	0,669	0,478
ABD1245	-0,160	-0,073	0,279	0,455	-0,418	0,227	-0,283	-0,072	0,611	0,510
ABD123	0,336	-0,542	0,266	0,538	0,461	-0,039	0,045	-0,058	0,118	0,809
ABD124	0,349	-0,615	0,057	0,642	-0,196	-0,115	-0,169	-0,048	-0,040	0,851
ABD125	-0,192	0,028	0,331	0,459	-0,401	0,251	-0,273	-0,125	0,573	0,480
ABD12	0,362	-0,550	0,020	0,684	-0,203	-0,112	-0,195	-0,049	-0,068	0,828
ABD2	-0,014	-0,582	0,440	0,484	-0,162	0,333	-0,223	-0,198	-0,086	0,796
ABD2345	-0,420	-0,055	0,477	0,140	0,169	0,369	-0,120	-0,125	0,616	0,533
ABD234	0,222	-0,650	0,419	0,352	0,441	0,105	0,048	-0,020	0,141	0,842
ABD235	-0,519	0,130	0,556	-0,040	0,235	0,371	-0,019	-0,253	0,382	0,572
ABD245	-0,268	-0,022	0,417	0,326	-0,392	0,323	-0,258	-0,112	0,557	0,542
ABD23	-0,133	-0,406	0,581	0,178	0,518	0,377	0,023	-0,177	0,077	0,830
ABD24	0,318	-0,686	0,198	0,562	-0,199	0,015	-0,180	-0,010	-0,030	0,855
ABD25	-0,461	0,189	0,581	0,086	-0,194	0,378	-0,116	-0,288	0,360	0,534
ACD12345	-0,023	0,247	0,040	-0,007	0,314	0,399	-0,545	-0,398	0,473	0,569
ACD1234	0,287	-0,447	0,233	0,356	0,597	0,186	-0,246	-0,293	-0,002	0,829
ACD1235	-0,136	0,280	0,147	-0,053	0,346	0,406	-0,440	-0,446	0,449	0,571
ACD1245	0,154	0,275	-0,043	0,167	-0,300	0,306	-0,651	-0,371	0,354	0,544
ACD123	0,226	-0,410	0,287	0,330	0,634	0,204	-0,189	-0,331	0,015	0,825
ACD124	0,435	-0,098	0,631	-0,362	0,301	-0,258	0,304	-0,142	0,047	0,053
ACD125	0,033	0,332	0,072	0,129	-0,272	0,340	-0,586	-0,453	0,360	0,534
ACD12	0,333	-0,457	0,043	0,581	-0,194	0,077	-0,426	-0,291	-0,178	0,784
ACD2	0,192	-0,486	0,332	0,473	-0,155	0,360	-0,328	-0,314	-0,182	0,818
ACD2345	0,064	0,241	0,122	-0,122	0,302	0,480	-0,493	-0,373	0,451	0,572
ACD234	0,358	-0,468	0,346	0,208	0,562	0,297	-0,181	-0,226	-0,047	0,872
ACD235	-0,289	0,340	0,336	-0,104	0,318	0,440	-0,237	-0,390	0,419	0,583
ACD245	0,206	0,194	-0,036	0,117	-0,405	0,354	-0,655	-0,336	0,271	0,525
ACD23	0,014	-0,296	0,557	0,147	0,581	0,405	-0,023	-0,278	0,004	0,866
ACD24	0,452	-0,510	0,128	0,450	-0,196	0,172	-0,400	-0,201	-0,219	0,846
ACD25	-0,165	0,409	0,303	0,040	-0,228	0,428	-0,380	-0,438	0,375	0,540
AC12345	0,069	0,428	0,029	0,218	0,442	0,379	-0,548	-0,186	0,300	0,591
AC1234	0,388	-0,284	0,195	0,416	0,638	0,137	-0,254	-0,244	-0,088	0,846
AC1235	-0,039	0,514	0,114	0,218	0,505	0,355	-0,429	-0,225	0,243	0,582
AC1245	0,218	0,428	-0,064	0,391	-0,142	0,292	-0,667	-0,167	0,183	0,537
AC123	0,326	-0,182	0,231	0,427	0,695	0,136	-0,191	-0,274	-0,106	0,837
AC124	0,453	-0,325	-0,019	0,609	-0,129	0,023	-0,446	-0,204	-0,244	0,799

Model	β_1^*	β_2^*	β_3^*	β_4^*	β_5^*	β_6^*	β_7^*	β_8^*	β_9^*	R^2
AC125	0,117	0,556	0,022	0,412	-0,049	0,295	-0,588	-0,226	0,142	0,499
AC12	0,423	-0,254	0,007	0,659	-0,087	0,023	-0,419	-0,245	-0,279	0,762
AC2	0,297	-0,222	0,367	0,600	-0,047	0,292	-0,306	-0,279	-0,330	0,789
AC2345	0,138	0,455	0,154	0,141	0,438	0,443	-0,490	-0,154	0,279	0,594
AC234	0,448	-0,321	0,314	0,275	0,610	0,251	-0,192	-0,187	-0,125	0,887
AC235	-0,139	0,578	0,318	0,175	0,466	0,382	-0,247	-0,180	0,241	0,589
AC245	0,289	0,462	0,064	0,325	-0,160	0,362	-0,625	-0,139	0,166	0,543
AC23	0,133	-0,106	0,506	0,263	0,670	0,351	-0,036	-0,246	-0,110	0,878
AC24	0,533	-0,377	0,102	0,505	-0,132	0,133	-0,405	-0,166	-0,285	0,844
AC25	-0,015	0,658	0,274	0,367	-0,041	0,359	-0,402	-0,196	0,164	0,505
AD12345	-0,317	0,087	0,455	-0,231	0,030	0,570	-0,177	-0,412	0,323	0,450
AD1234	0,008	-0,614	0,413	0,256	0,334	0,442	-0,072	-0,271	-0,033	0,776
AD1235	-0,357	0,110	0,469	-0,209	0,057	0,550	-0,154	-0,402	0,326	0,450
AD1245	-0,179	0,112	0,441	-0,128	-0,450	0,508	-0,221	-0,404	0,267	0,493
AD123	-0,022	-0,591	0,430	0,271	0,360	0,437	-0,049	-0,261	-0,006	0,778
AD124	0,132	-0,615	0,231	0,439	-0,350	0,306	-0,240	-0,240	-0,166	0,819
AD125	-0,228	0,137	0,464	-0,110	-0,420	0,498	-0,201	-0,402	0,275	0,487
AD12	0,108	-0,609	0,251	0,465	-0,338	0,308	-0,226	-0,236	-0,146	0,814
AD2	-0,009	-0,491	0,475	0,356	-0,286	0,419	-0,146	-0,317	-0,165	0,795
AD2345	-0,340	0,182	0,518	-0,204	0,029	0,533	-0,120	-0,393	0,296	0,460
AD234	-0,048	-0,531	0,512	0,161	0,320	0,496	-0,031	-0,276	-0,041	0,788
AD235	-0,414	0,238	0,529	-0,153	0,088	0,481	-0,064	-0,380	0,285	0,464
AD245	-0,214	0,208	0,510	-0,108	-0,419	0,478	-0,160	-0,386	0,246	0,505
AD23	-0,133	-0,405	0,581	0,133	0,367	0,486	0,030	-0,303	-0,024	0,782
AD24	0,081	-0,572	0,358	0,362	-0,342	0,387	-0,202	-0,262	-0,174	0,828
AD25	-0,311	0,272	0,541	-0,066	-0,334	0,446	-0,104	-0,387	0,247	0,493
BCD12345	0,084	-0,060	0,192	0,080	0,195	0,262	-0,173	-0,141	0,889	0,508
BCD1234	0,693	-0,437	0,229	0,166	0,324	-0,201	0,087	0,080	0,298	0,871
BCD1235	0,081	0,036	0,216	0,070	0,258	0,281	-0,184	-0,197	0,850	0,492
BCD1245	0,257	-0,028	0,084	0,272	-0,444	0,161	-0,300	-0,106	0,727	0,514
BCD123	0,732	-0,361	0,195	0,202	0,364	-0,203	0,056	0,078	0,269	0,856
BCD124	0,711	-0,476	0,049	0,353	-0,198	-0,254	-0,113	0,079	0,137	0,885
BCD125	0,260	0,069	0,109	0,279	-0,427	0,182	-0,319	-0,170	0,701	0,486
BCD12	0,729	-0,412	0,002	0,397	-0,192	-0,256	-0,156	0,073	0,096	0,860
BCD2	0,539	-0,539	0,486	0,260	-0,189	0,169	-0,200	-0,043	0,100	0,866
BCD2345	0,009	-0,040	0,285	-0,039	0,217	0,383	-0,200	-0,198	0,802	0,549
BCD234	0,649	-0,476	0,350	0,069	0,356	-0,058	0,087	0,110	0,275	0,909
BCD235	-0,327	0,157	0,469	-0,187	0,282	0,398	-0,065	-0,329	0,513	0,580
BCD245	0,215	0,013	0,187	0,161	-0,436	0,295	-0,341	-0,167	0,687	0,547
BCD23	0,315	-0,371	0,592	-0,036	0,532	0,236	0,061	-0,045	0,258	0,905
BCD24	0,723	-0,526	0,176	0,275	-0,188	-0,131	-0,113	0,116	0,125	0,916
BCD25	-0,213	0,231	0,478	-0,070	-0,233	0,409	-0,189	-0,385	0,512	0,536
BC12345	0,237	-0,086	0,249	0,118	0,291	0,230	-0,144	0,086	0,834	0,524
BC1234	0,710	-0,407	0,206	0,166	0,352	-0,221	0,066	0,103	0,270	0,865
BC1235	0,354	0,169	0,211	0,235	0,424	0,223	-0,151	0,043	0,701	0,493
BC1245	0,392	-0,093	0,121	0,327	-0,363	0,133	-0,302	0,103	0,682	0,520
BC123	0,781	-0,235	0,131	0,249	0,405	-0,226	0,037	0,095	0,176	0,849
BC124	0,726	-0,455	0,032	0,350	-0,164	-0,272	-0,131	0,101	0,116	0,873
BC125	0,523	0,160	0,075	0,454	-0,271	0,123	-0,317	0,059	0,545	0,465
BC12	0,773	-0,301	-0,048	0,428	-0,124	-0,274	-0,165	0,090	0,023	0,839
BC2	0,684	-0,398	0,419	0,346	-0,093	0,115	-0,238	-0,005	-0,007	0,846
BC2345	0,137	-0,029	0,414	0,024	0,316	0,327	-0,166	0,037	0,757	0,553
BC234	0,663	-0,438	0,341	0,078	0,387	-0,087	0,059	0,148	0,252	0,903
BC235	-0,099	0,300	0,564	-0,077	0,446	0,373	-0,035	-0,175	0,454	0,561
BC245	0,344	-0,019	0,303	0,246	-0,360	0,245	-0,343	0,063	0,646	0,542
BC23	0,445	-0,245	0,537	0,032	0,621	0,192	0,034	-0,014	0,168	0,911
BC24	0,737	-0,498	0,167	0,281	-0,152	-0,159	-0,140	0,151	0,105	0,903
BC25	0,061	0,397	0,612	0,110	-0,126	0,389	-0,202	-0,210	0,446	0,486
BD12345	-0,137	-0,097	0,477	0,120	0,152	0,265	-0,024	-0,073	0,795	0,508
BD1234	0,620	-0,497	0,305	0,189	0,308	-0,155	0,125	0,112	0,304	0,864
BD1235	-0,166	-0,023	0,511	0,101	0,201	0,285	-0,024	-0,122	0,751	0,491
BD1245	0,035	-0,077	0,381	0,312	-0,460	0,185	-0,161	-0,049	0,690	0,527
BD123	0,649	-0,442	0,288	0,223	0,350	-0,152	0,106	0,110	0,287	0,845
BD124	0,647	-0,539	0,116	0,377	-0,225	-0,213	-0,081	0,108	0,144	0,894
BD125	0,012	0,001	0,430	0,305	-0,444	0,213	-0,162	-0,112	0,664	0,497

Model	β_1^*	β_2^*	β_3^*	β_4^*	β_5^*	β_6^*	β_7^*	β_8^*	β_9^*	R^2
BD12	0,665	-0,492	0,075	0,421	-0,227	-0,213	-0,119	0,100	0,108	0,871
BD2	0,410	-0,602	0,522	0,254	-0,218	0,208	-0,160	-0,026	0,123	0,861
BD2345	-0,250	-0,087	0,552	-0,014	0,143	0,354	-0,022	-0,105	0,684	0,544
BD234	0,526	-0,539	0,427	0,087	0,333	-0,027	0,121	0,138	0,312	0,883
BD235	-0,403	0,086	0,601	-0,162	0,226	0,368	0,046	-0,249	0,438	0,577
BD245	-0,078	-0,057	0,501	0,162	-0,435	0,306	-0,154	-0,090	0,632	0,559
BD23	0,202	-0,426	0,619	-0,035	0,491	0,265	0,089	-0,030	0,271	0,882
BD24	0,613	-0,598	0,249	0,298	-0,227	-0,103	-0,083	0,144	0,161	0,907
BD25	-0,321	0,140	0,642	-0,057	-0,223	0,378	-0,042	-0,286	0,430	0,544
CD12345	0,573	0,191	0,145	-0,420	0,195	0,235	-0,324	-0,312	0,378	0,613
CD1234	0,759	-0,244	0,254	-0,212	0,401	0,117	-0,196	-0,110	0,171	0,890
CD1235	0,470	0,215	0,236	-0,452	0,242	0,249	-0,279	-0,360	0,381	0,610
CD1245	0,696	0,224	0,062	-0,255	-0,296	0,148	-0,387	-0,269	0,255	0,608
CD123	0,724	-0,220	0,307	-0,220	0,441	0,126	-0,169	-0,139	0,163	0,890
CD124	0,856	-0,254	0,072	0,015	-0,235	0,022	-0,364	-0,092	0,004	0,878
CD125	0,630	0,260	0,156	-0,294	-0,280	0,168	-0,369	-0,328	0,273	0,592
CD12	0,853	-0,244	0,118	0,019	-0,229	0,027	-0,362	-0,120	-0,009	0,865
CD2	0,771	-0,230	0,442	0,100	-0,235	0,138	-0,257	-0,077	0,034	0,906
CD2345	0,562	0,212	0,206	-0,410	0,201	0,251	-0,302	-0,299	0,380	0,618
CD234	0,742	-0,228	0,357	-0,190	0,402	0,152	-0,149	-0,073	0,148	0,925
CD235	0,191	0,309	0,427	-0,396	0,283	0,292	-0,162	-0,365	0,453	0,598
CD245	0,691	0,245	0,121	-0,246	-0,299	0,164	-0,370	-0,258	0,259	0,613
CD23	0,521	-0,167	0,581	-0,152	0,489	0,223	-0,021	-0,080	0,210	0,925
CD24	0,861	-0,246	0,175	0,032	-0,231	0,056	-0,326	-0,060	-0,016	0,919
CD25	0,403	0,378	0,368	-0,272	-0,273	0,234	-0,279	-0,371	0,375	0,573
C12345	0,673	0,397	0,076	-0,235	0,373	0,128	-0,355	-0,115	0,185	0,606
C1234	0,826	0,008	0,126	-0,130	0,477	0,056	-0,211	-0,096	0,024	0,880
C1235	0,606	0,456	0,129	-0,221	0,437	0,125	-0,329	-0,136	0,161	0,594
C1245	0,780	0,389	0,004	-0,100	-0,080	0,063	-0,448	-0,102	0,097	0,552
C123	0,797	0,082	0,148	-0,092	0,527	0,045	-0,189	-0,109	-0,014	0,871
C124	0,905	-0,053	-0,020	0,070	-0,101	-0,026	-0,377	-0,088	-0,110	0,825
C125	0,744	0,464	0,057	-0,086	-0,025	0,060	-0,441	-0,128	0,074	0,518
C12	0,901	0,017	-0,002	0,113	-0,058	-0,037	-0,370	-0,103	-0,153	0,787
C2	0,880	0,069	0,257	0,208	-0,044	0,044	-0,287	-0,055	-0,148	0,846
C2345	0,640	0,452	0,187	-0,205	0,382	0,133	-0,314	-0,092	0,198	0,607
C234	0,809	0,026	0,240	-0,107	0,486	0,090	-0,162	-0,065	0,014	0,922
C235	0,460	0,562	0,313	-0,155	0,472	0,141	-0,228	-0,108	0,211	0,581
C245	0,762	0,448	0,111	-0,067	-0,086	0,066	-0,415	-0,081	0,106	0,556
C23	0,678	0,134	0,388	-0,032	0,589	0,127	-0,066	-0,055	0,017	0,924
C24	0,915	-0,037	0,088	0,095	-0,102	0,006	-0,340	-0,060	-0,125	0,876
C25	0,632	0,605	0,263	-0,018	-0,014	0,081	-0,360	-0,107	0,130	0,498
D12345	0,289	0,242	0,556	-0,405	-0,302	0,294	0,037	-0,328	0,313	0,534
D1234	0,597	-0,318	0,593	-0,178	-0,092	0,317	0,087	-0,181	0,095	0,892
D1235	0,265	0,253	0,571	-0,399	-0,289	0,292	0,045	-0,332	0,316	0,530
D1245	0,311	0,224	0,521	-0,356	-0,440	0,274	-0,007	-0,327	0,281	0,553
D123	0,598	-0,303	0,604	-0,166	-0,080	0,318	0,094	-0,185	0,089	0,892
D124	0,615	-0,350	0,466	-0,043	-0,431	0,253	-0,034	-0,171	0,002	0,923
D125	0,287	0,236	0,538	-0,351	-0,429	0,273	0,001	-0,332	0,284	0,549
D12	0,618	-0,336	0,476	-0,030	-0,425	0,254	-0,029	-0,176	-0,005	0,922
D2	0,567	-0,323	0,549	-0,023	-0,410	0,260	-0,005	-0,190	-0,001	0,910
D2345	0,233	0,248	0,586	-0,397	-0,290	0,298	0,050	-0,324	0,320	0,532
D234	0,571	-0,306	0,626	-0,172	-0,084	0,317	0,099	-0,179	0,099	0,889
D235	0,141	0,278	0,629	-0,378	-0,239	0,295	0,076	-0,338	0,316	0,519
D245	0,258	0,232	0,553	-0,350	-0,429	0,280	0,007	-0,324	0,290	0,551
D23	0,523	-0,280	0,675	-0,160	-0,048	0,319	0,123	-0,195	0,095	0,884
D24	0,597	-0,342	0,497	-0,038	-0,428	0,255	-0,024	-0,172	0,005	0,920
D25	0,167	0,264	0,604	-0,334	-0,382	0,281	0,035	-0,342	0,288	0,534

The impact of the Economic Crisis on the efficiency of Spanish airports: A DEA Visualisation Analysis

Ane Elixabete Ripoll-Zarraga [a] , Fabiola Portillo [b], Cecilio Mar-Molinero [c] *

[a] Business Department, Universitat Autònoma de Barcelona (UAB), 08193 Bellaterra, Spain
[b] Economics and Business Department, Universidad de La Rioja, 26005 Logrono, Spain
[c] Kent Business School, University of Kent, Canterbury CT2 7FS, UK

Author Statement

We have revised the original manuscript considering all the comments of the referees.

Yours sincerely,

Cecilio Mar-Molinero