

**ASSESSING THE EFFICIENCY OF SPANISH LOCAL ENTITIES IN THE PROVISION OF
PUBLIC SPORTS FACILITIES**

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Abstract

In this paper a two-stage double bootstrap procedure is used to estimate the efficiency determinants of local entities in the provision of public sports facilities. In the first stage, robust efficiency estimates are obtained with Data Envelopment Analysis (DEA). We apply the non-parametric double bootstrap (Simar and Wilson, 2007) model based on a truncated-regression, to estimate the effect of a group of environmental factors on robust DEA estimates. The results show the existence of a significant relation between efficiency and all the variables analyzed. We have also considered the influence of the political sign of the governing party.

Keywords: Data Envelopment Analysis (DEA); Performance; Public Sports Facilities

JEL Classification: H71, H83

1. INTRODUCTION

Practice of sport in recent years has become widespread in developed countries and is now considered a public good to be financed by public administrations. Public funds for financing all types of sports facilities and sporting events, be they professional or amateur, have also increased, on account of the growing demand by citizens and the important socio-economic benefits they can generate. Numerous studies have sought to analyse the possible socio-economic benefits of public actions both in funding sports facilities (Santo, 2007; Zimbalist and Siegfried, 2002; Siegfried and Zimbalist, 2000 and Alexander *et al.*, 2000) and in all types of sporting events (Barget and Gouguet, 2007 and Baade *et al.*, 2008). Results show that these benefits are not sufficient to compensate the volume of resources invested.

Our study aims to address an aspect that has not been sufficiently dealt with in the literature – the analysis of public entity efficiency in the provision of sports facilities. Of all the public administrations that provide services for citizens, the local administrations merit special attention. These devote an important part of their resources to financing the development of sports among their citizens so as to improve the quality of their lives, and also to organizing large sporting events, so improving their infrastructures and boosting economic activity in the area. Noteworthy among measures aimed at increasing the practice of sports is the creation of the necessary sports facilities.

Along with the above we would highlight the scarcity of resources available to practically all public administrations on account of the crisis of recent years. This has meant that the few resources administrations have needed to be managed even more efficiently, and this has supposed an opportunity for this piece of research.

Given the volume of resources that local governments devote to financing sports facilities, we believe it is necessary to determine if these resources are being managed efficiently and, if possible, improve the service using the resources available.

Thus, the aim of this paper is to determine how efficient local governments are in providing sports facilities, given the limited resources they have available.

Research efforts into measuring public sector efficiency have focused on the development of methodologies which empirically evaluate the efficiency of the productive units. However, it was at the end of the 1970s that the method proposed by Charnes *et al.* (1978) - *Data Envelopment Analysis (DEA)* – offered new possibilities that went far beyond all initial expectations. The public sector turned out to be the driving force of this limitless growth: it became a focus of interest and thrust methodological development forward. The possibility of empirically analysing efficiency in the public sphere and the extent to which inefficiencies could be detected and corrected supposed a highly attractive alternative to cuts in spending - a widely adopted approach.

The main problem in operative measuring of efficiency lies in the knowledge of the production function. The most common scenario, at least in the public sector, is to be faced with a set observations corresponding to the output levels achieved by a series of productive units when starting from a set of inputs. The attraction of non parametric approximation comes, in the main, from its success in constructing an empirical production function based on observed data, from its capacity to measure in relation to this and, especially, in the way it avoids impositions of restrictive hypotheses on the underlying technology.

The methodology has been widely applied in the assessment of the efficiency of productive units. A collection of these applications can be found in Seiford (1996), Tavares (2002), Emrouznejad *et al.* (2008), and Cook and

Seiford (2009). Following earlier studies by Nyhan and Martín (1999), Bosh *et al.* (2000), Ancarani and Capaldo (2001), Worthington and Dollery (2001), Díez-Ticio and Mancebón (2003), Drake and Simper (2003), Jenkins and Anderson (2003), Karlaftis (2004) and Thanassoulis (2002) in determining how efficient local governments are in providing a public service, we use DEA. We also apply the non-parametric double bootstrap Simar and Wilson (2007) model based on a truncated-regression, to estimate the effect of a group of environmental factors on robust DEA estimates.

The motivation for the study lies in the important increase in recent years of resources that local governments use for sports facilities because of the great importance citizens give to practising sport and to the organization of large sporting events in their area.

The paper is organized as follows. In the next section we provide a brief description of the aims and the methodology employed. In section 3 we describe the sample, the inputs/outputs and the variables used to explain the level of efficiency. Section 4 analyses the results and the last section, 5, offers the main conclusions.

2. METHODOLOGY AND AIMS OF THE ANALYSIS

In this paper we explore the use of DEA as an instrument for assessing the efficiency of local entities in the provision of public sports facilities. The research adopted derives from two sources: estimation of efficiency scores and regression analysis of efficiency determinants. We will analyse the causes of the inefficiency by considering a group of external and continuous factors, $z \in \mathbb{R}^f$, as well as a dummy categorical one so as to better characterize the operational environment - the political sign of the municipalities studied.

Analysis of productive efficiency has been approached from both a parametric and a non parametric perspective. The initial attraction of the non parametric approach enjoyed a large impact because it avoided the imposition of restrictive hypotheses on the data generating process. Since the basic definitions in the original works by Debreu (1951), Shephard (1953), Farrell (1957) and Shephard (1970), a good deal of the literature has used linear programming techniques to obtain envelopment estimators by one of the pathways proposed: Free Disposal Hull (FDH), in the paper by Deprins *et al.* (1984); DEA, from the convex envelopment of the FDH frontier, in Charnes *et al.* (1978), and with less initial impact, Färe *et al.* (1985) proposed measuring efficiency along the hyperbolic path, starting from a set of combinations and going to the frontier of production possibilities. The DEA/FDH methods are popular and widely used due to their nonparametric nature, which requires very few assumptions about the technology. Although labelled deterministic, statistical properties of DEA/FDH estimators are now available using asymptotic results (see Kneip *et al.*, 1998; Park *et al.*, 2000 and Kneip *et al.*, 2008), or using bootstrap (see Simar and Wilson, 1998, 1999, 2000a, 2000b, 2001, 2002 and 2007). To summarize, as pointed out by Simar (2007, p. 185), these nonparametric estimators suffer from the curse of dimensionality, which means that the rate of convergence decreases when the dimension of the attainable set increases¹.

Assessment of the effect of environmental factors on the efficiency of a group of producers has recently aroused a lot of scientific interest. Knowledge of the real operating efficiency of each unit, identification of the economic conditions that generate inefficiency, or the need to improve the management of public services are in part responsible. Methodologically, the presence of such exogenous factors supposes, in Data Generating Process terms, that, together with the conventional inputs, it is necessary to consider other variables over which the

¹ The rate of convergence of the FDH estimator is $n^{1/p+q}$ whereas for the DEA with the additional assumption of convexity, the achieved rate is $n^{2/p+q+1}$. See Simar and Zelenyuk (2010).

decision unit has no control. Thus it responds to the fact that there are specific circumstances that lead to the production possibilities frontier not being common to all the units. To ignore their presence would be to suppose that the productive units that do not reach the frontier for environmental reasons are classified as inefficient. The first mention of the specific character of the type of variables cited (environmental variables) is found in the paper by Charnes *et al.* (1981), which has given rise to the frequent use of the concepts of non discretionary, non controllable or environmental variables. However, as Muñiz (2002) indicates, inclusion in one category or another should be a first step, given the different characteristics and the treatment received in the analysis.

There are three main proposals in the literature to account for the impact of environmental variables on efficiency: the one-stage, two-stage and probability approach². The shortcomings of earlier developments are dealt with and solutions are given in the form of algorithms in Simar and Wilson (2007), a paper which supposed a turning point in the treatment of exogenous factors and which opened up new channels in analysis with the result of the incorporation of the so called two-stage models. Their semi-parametric proposal constitutes the pillar on which our empirical application rests. The estimated efficiency scores are regressed, in an appropriate limited dependent variable parametric regression model, like truncated normal regression models, on the environmental factors. According to these authors (p.32) up to the time of publication, none of the applications using the two-stage approach had taken into account the data generating process. So, there is a series of doubts about what is being estimated in the second stage of the model. Later on (p. 40), they point out that in all the applications they found that the inherent bias in the efficiency coefficients estimated in the first stage had been ignored. A secondary aim of our application will be to overcome this type of defects by checking our results against those most usually reported in the literature.

It is assumed that environmental factors only affect the production process through the probability of their being more or less efficient: the attainable set, and its frontier, is not affected by these environmental factors. Simar and Wilson (2007, p. 36) have stressed the fact that two-stage approaches rely on this restrictive separability condition. One approach, Coelli *et al.*(1998), is to augment the model by treating the environmental factors z as free disposal inputs or outputs, although, in this case we need assumptions both for the functional form and inefficiency distribution. While the stochastic frontier model allows one to include z variables either as a part of production technology or as part of inefficiency term, the challenge is to decide how to model z variables correctly. Moreover, it is based on strong parametric assumptions, which can bias the results even if z variables have been modelled properly.

The third, and prominent, method in this respect, the probabilistic approach, is the conditional efficiency method first suggested by Cazals *et al.*(2002), and Daraio and Simar (2005, 2007, 2007). This fully nonparametric approach provides useful qualities. It avoids the separability assumption³, so overcoming the drawbacks of the two-stage-type approaches. The objective is to analyze the behaviour of the ratio of the conditional efficiency scores over the unconditional scores as a function of the conditioning factor, and it is shown that the shape of a nonparametric regression of these ratios over the conditioning factor allows positive, negative or even variable effects of the environmental factor on the production process to be detected. The asymptotics of the conditional order- m estimator was analyzed in Cazals *et al.* (2002) and recently in Jeong *et al.*(2010).

² An extended and up-to-date review can be found in Simar and Wilson (2007), Cordero-Ferrera *et al.* (2008), or Badin *et al.* (2010).

³ The z -variables are directly included in the nonparametric model. See Badin *et al.* (2010).

Below we use two-stage Simar and Wilson (2007) modelling to analyse the causes of inefficiency from a sample of municipalities. Our initial sample comprises data from 1,984 municipalities of between 1,000 and 50,000 inhabitants. As recommended, we carried out an initial data cleansing in order to eliminate measurement errors or other possible types of errors. Following the recommendations cited above, we also used techniques to detect outliers. The possibilities of these being detected are many according to Wilson (1993), Wilson (1995), Simar (2003), or Porembski *et al.*(2005). As Simar (2003) indicates, the analysis of outliers “*should be used in a first step, before performing any frontier estimation. This is true for DEA, FDH techniques, but also for any parametric techniques using the deterministic approach*”. Similarly, Simar and Zelenyuk (2010, p.3) point out that “*deterministic frontier models have the drawbacks of not allowing random noise in the DGP and, as a result, being very sensitive to extreme data points and outliers*”⁴. Despite the size of the data filter, our final sample size remains relatively large.

We present the results of the initial DEA model when only considering the amount of controllable inputs. The observations at the DEA frontier are efficient, but apparently, i.e. they are low-biased or “*the DEA frontier estimate is nothing more than a biased estimate of the true, but unobserved, frontier*” (Wheelock and Wilson, 2008, p. 125). Using bootstrap techniques in the spirit of Simar and Wilson (2000a) we will correct the bias and also obtain confidence intervals for the estimations obtained. Later we follow the Simar and Wilson (2007) procedure to select an appropriate model to examine the effect of non controllable factors, and to ascertain the significance and sign of the effects of each of them.

Some key aspects will be referred to in the course of this paper, in particular separability and independence conditions that must hold for meaningful first-stage efficiency estimates and second-stage regression, as well as the problem as to what is the most suitable regression type to be used in the second stage. Regarding the categorical variable, an alternative approach, known as Program Analysis, was put forward in Charnes *et al.* (1981). A pioneer study was that by Banker and Morey (1986), who adapted their one-stage model to the case of a category variable. The possible approaches are statistical hypothesis testing for the existence of significant differences in efficiency among the groups considered, following Daraio and Simar (2005) in their comparison of sub-samples using bootstrap techniques, in the style of Simar and Wilson (2002). A further possibility is the use of a three-stage model like that developed by Dios *et al.*(2006), who propose correction of data during the second stage, followed by a third stage that would give rise to efficiency coefficients corrected by the effect of the environmental category variable.

3. SAMPLE AND VARIABLES: CLEANSING AND DETECTION OF OUTLIERS

Our sample is composed of all the Spanish municipalities with more than 1,000 inhabitants (3,179 local governments). The reason for eliminating the local governments with fewer than 1,000 inhabitants is twofold: the reliability of the financial data is doubtful for small local governments, and some variables were only available for local governments with more than 1,000 inhabitants.

For the selection of outputs we have used the studies by de Bosch *et al.* (2000), Worthington and Dollery (2001), Bel (2006), Carr-Hill and Stern (1979), Darrough and Heineke (1979), Gyimah-Brempong (1987, 1989), Cameron (1989), Stevens (1978), Dubin and Navarro (1988) and Callan and Thomas (2001) and we have opted for two outputs: SUCASPC and QUALITY. The first (SUCASPC) is the surface area in square metres per capita

⁴ In their simulated examples, they illustrate how the standard DEA is very sensitive to outliers. Moreover, once the size of the noise increases, the DEA estimator behaves badly.

of all the sports installations owned by each municipality, and has been obtained from the Encuesta de Infraestructuras y Equipamientos Locales (EIEL) (Survey on Local Infrastructures and Equipment) for 2005. The second (QUALITY) is an index built from the survey on the suitability of the service, similarly included in the 2005 EIEL, and according to the expression defined as unity plus a weighted mean of the frequency of the response of each four categories, i , from good to bad appropriateness, with n_j as the total number of responses observed at municipality j .

For inputs of discretionary character we use SPORTSPC, which is the per capita cost according to cost subfunction 452 "Educación física, deportes y esparcimiento" (physical education, sports and recreation), as envisaged by the Order of September, 20, 1989 which stipulates the structure of local entities' budget. Data were provided by the Ministerio de Economía y Hacienda (Ministry of the Treasury) and refer to 2005.

The works of Pommerehne (1978), Abizadeh and Gray (1993), Hetherington (1993), Giménez and Prior (2003), Hagen and Vabo (2005), Hautbois *et al.* (2003), Siegfried and Zimbalist (2000, 2006), Benito *et al.* (2010) and Gammon and Fear (2010) show the relation between certain variables and the management and provision of different public services, among which are sports facilities. Using these studies as reference, we have included the following variables as exogenous factors in the second stage of our model:

- **INCPC**: per capita income; data provided by the L.R. Klein Institute, which depends on the Universidad Autónoma de Madrid, and corresponding to 2005.
- **TRIND**: comparative index of the tourist importance of each municipality in 2005. It is obtained according to the number of rooms and yearly occupation. It serves as an indication of the tourist offer. The value of the index indicates the participation over 10,000, corresponding to each municipality on a regional base of 10,000 units. Data are available in the Anuario Económico de La Caixa (2005).
- **ECACIN**: a comparative index for the whole of the municipal economic activity in 2005. It is obtained from the tax corresponding to all the business (industrial, commercial and services) and professional activities. The value of the index expresses the share of the economic activity in ten thousandths of each municipality on a regional basis of 10,000 units equivalent to the tax revenue from business and professional economic activities. Data can be found in the Anuario Económico de La Caixa (2005).
- **DENPSU**: Population density by urban area (measured as the quotient between the total population and the built up area in square kilometres). Data were obtained from the Instituto Nacional de Estadística (National Bureau of Statistics) and the Dirección General del Catastro (Head Property Registry Office) and corresponding to 2005.
- Finally, we use **DPOLIT** as a dummy category exogenous factor. Its values 0 and 1 represent the political sign, conservative or progressive, respectively, of the party in power in the municipalities. The data were provided by the Ministerio del Interior (Spanish Home Office) and the Ministerio de Política Territorial (Ministry of Territorial Policy and Public Administration) and are based on the 2003 municipal election results.

An initial inspection of the data reveals hundreds of erroneous values, with null values in the SPORTSPC variable and missing values for the SUCASPC, INCPC, TRIND and ECACIN variables. Data cleansing was carried out and the sample was reduced to 1,007 municipalities. The next, logical, step is to detect and control

outliers, which are a source of concern in both parametric and non parametric approaches. From the regression perspective, these atypical observations, whose variable values are unusual, given the values of the regressors, may indicate a mere peculiarity or an error in the data. They produce biases in the predictions and distort parameter estimation. Even when dealing with large samples, the effect of outliers can increase the noise and, hence, affect the accuracy and efficiency of the estimations. There are various ways of treating these, as we have indicated earlier. Two recommended methods of detection found in the literature on efficiency are those proposed by Wilson (1993) and Simar (2003). The first has the advantage that it does not require any priori specific direction to be established for the model and so we will apply this one to our sample of data⁵:

Graph 1 shows the value of the ratios⁶:

$$\log \left[\frac{R_L^{(i)}}{R_{Min}^{(i)}} \right] \quad (1)$$

A straight line connects the second lowest values for each i , thus illustrating the separation between the lowest ratios for each value of i . For $i=1,2,3,4,5,6$ the separation is relatively large; as i is increased from 7 to 8, the separation becomes smaller but then increases for $i = 9$ and 11.

(Insert Graph 1)

Table 1 shows the values of $R_{Min}^{(i)}$ on extending the spectrum from $i=1$ to $i=14$. For $i=6$, the row of the table shows those municipalities that were chosen as being outliers; for $i = 9$ and 11, a second group of outliers is identified, consisting of observations 29, 266, 273, 307 and 674. As Wheelock and Wilson (2008) point out, it is always complicated in empirical applications to ascertain why an observation is atypical. If it is due to a low likelihood of its occurring, the unit may be of interest for analysis. If it is the result of noise in the coding, then this should be repaired or removed. When detected though, the analysis must be repeated without those units so as to avoid any masking effect, as discussed in Wilson (1993), Wilson (1995), and Simar (2003) - one outlier might hide another or others nearby.

(Insert Table 1)

After the removal of the 11 municipalities initially detected and following the sequential repetition of the analysis, the candidate group increased. Following an analysis of the characteristics of the municipalities identified, we opted to eliminate the initial 11 and a further 12⁷.

⁵ We use the software library FEAR, Wilson (2008), which can be linked to the general-purpose statistical package R. The current version is 1.13 (6 March 2010).

⁶ See Wilson (1993).

⁷ We performed an additional test for outlier detection based on order- m frontiers (Cazals *et al.*, 2002). Highly super-efficient should be scrutinized. Order- m efficiency score can be viewed as the expectation of the minimal input efficiency score of the unit i , when compared to m units randomly drawn from the population of units producing at least the output level produced by i , therefore the score is not bounded at unity. Alternative to order- m partial frontiers are quantile based partial frontiers proposed by Aragon *et al.* (2005), extended to multivariate

After all the above, the final sample comprised 984 municipalities. Table 2 summarizes the main descriptors of the final sample.

(Insert Table 2)

4. EFFICIENCY EVALUATION IN THE PROVISION OF PUBLIC SPORTS FACILITIES

4.1. Framework for the analysis

According to the two-stage model, the efficiency coefficients for each municipality are obtained in the first stage in the assessment that exclusively considers variables of a discretionary nature. The DEA model to be solved in our case will have variable returns to scale⁸ and an input orientation that seems to be the most appropriate given that there is a demand minimization policy.

One crucial point in this stage and in the next one lies in the non parametric nature of the estimated frontier. Since the observations are taken from a population or from an unknown generating process, the statistical properties of the estimated coefficients are essential to avoid erroneous conclusions. As Simar and Wilson (2000b, p. 795) point out “*most researchers have used these methods while ignoring the sampling noise in the resulting efficiency estimators, and continue to do so*”. Simar and Wilson (2007, p. 38), also noted that the estimator of the efficiency measure is consistent although two important drawbacks are observed: on the one hand, the rate of convergence is slow and decelerates as $p+q$, the sum of inputs and outputs, increases, i.e. we are dealing with the dimensionality problem mentioned above; on the other hand, and more seriously, estimator $\hat{\theta}_0$ is in its low biased construction, i.e. the real inefficiency is underestimated by the usual DEA coefficients. Simar and Wilson (1998) propose a bootstrap procedure as a means of inferring the statistical properties of the estimated coefficients, which gives an estimated bias and the variance, which in turn provides confidence intervals. The procedure was later made more flexible in Simar and Wilson (2000b), and the algorithm was computationally implemented in statistical software FEAR by Wilson (2008).

Previous conditions must hold for a meaningful first stage efficiency estimates and second-stage regression. First, using the Simar and Wilson (2007) method for first stage without first testing the independence assumption incurs the risk of invalid inference. This can be done using the methods surveyed by Wilson (2003), where, first, the author forms the basis for a number of tests of independence. For its motivation, examination of the mean, median, and coefficients of skewness and kurtosis of our data, reveals that they are non-normal, as is typical of data used in productivity studies. For the test based on smoothing, starting from the work of Ahmad and Li (1997), the statistic result at significant p-value leads to the rejection of the null hypothesis of independence⁹.

Second, the separability assumption means that z-variables are allowed to affect only efficiency scores, not the frontier or efficient levels of inputs and outputs. If z-variables are also important explanatory factors for production technology (or should be included in the first stage), the results given by two-stage approach are

setting by Daouia and Simar (2007). The idea is to replace this concept of “discrete” order-m partial frontier by a “continuous” order-partial frontier, where $\alpha \in [0, 1]$.

⁸ The BCC model was first formulated in the study by Banker *et al.* (1984). Scales of returns to scale were also tested but rejected in favour of the VRS. For more details on the returns to scale test, refer to Simar and Wilson (2002).

⁹ The bootstrap procedure can be solved with the help of FEAR 1.13 Wilson (2008). The statistic $\hat{T}_{s,n}$ results in significant p-value of 0.0354, leading to rejection of the null hypothesis of independence.

biased. Following Simar and Wilson (2007, p. 36), the implicit separability condition can be tested with the methods described by Simar and Wilson (2001)¹⁰. In that paper, the authors define tests to check whether a subset of size r , $0 < r < p$, of the p inputs under consideration may be aggregated, and likewise for outputs. In their Monte Carlo experiments (pp.174-181) they conclude the need to avoid small samples when estimating in high dimensions, and that for $n=400$ the estimated sizes are quite close to the nominal sizes. This implies that for our data and dimension, we should expect reliable results. Their bootstrap procedure to implement the tests, for which we have used 2,000 iterations, was used to determine the significance by p-values that, given the sample variation, let us accept the separability condition¹¹.

4.2. Efficiency measurement: stage I

For the DEA estimations we use the software FEAR 1.13. Efficiency is measured in terms of Shephard's input distance function, which is the reciprocal of Farrell's measure. Shephard's measure is hence one or larger. The DEA model returns a group of 8 efficient municipalities.

However, the situation outlined may be quite different when considering the real underlying process, where it is not certain that there exists a probability mass in the unitary value. It is more a case of an artifice of the finite samples. In order to consider the stochastic nature of the estimation problem we will use Simar and Wilson (2007) double bootstrap procedure, with an initial first bootstrapping to correct for bias in the estimates of the efficiency scores, estimating at the same time the confidence intervals for a Shephard distance input function corresponding to the municipalities of our sample¹².

Table 3 shows the information of bootstrapped DEA results estimated for a selection of municipalities. The third column provides the estimated coefficients in the initial DEA, $\hat{\theta}$. The column $\hat{bias}_B(\hat{\theta})$, gives the estimation of the bias of the initial coefficients obtained with the bootstrap, for which we have used $B=2,000$ bootstrap replications. Column r_i contains the statistical test value; its values may be used to assess whether the bias correction might increase the mean squared error¹³. Column $\hat{\hat{\theta}}$ gives the corrected or unbiased estimated coefficients. Municipalities are classified from lowest to highest values of $\hat{\hat{\theta}}$, i.e. from greatest to lowest efficiency according to the type of distance function employed. Finally, the last three columns show the data for the statistical inference, i.e. the variance estimates and the lower limits (LL) and upper limits (UL) of the confidence intervals at the 95% level.

The bootstrap estimation was solved for all the observations, which points to a correct data cleansing and detection and removal of outliers. The sign of the bias is, obviously, negative in all cases. A main consequence of considering the uncertainty of the data generating process, and one which will affect the regression carried out

¹⁰ At the time of writing, we know of a work in progress by these two authors and Daraio, entitled "Testing separability in a two-stage production process".

¹¹ Environmental variables selection is based on previous literature, what guarantees its correctness to some extent. We have used the multivariate framework as described in Simar and Wilson (2000a) and computed the estimated δ and ρ to obtain the statistics. The p-values are never under below 9% but, given the sample variation, we consider it good enough to accept the condition.

¹² The coefficients are estimated using the routines in the DEA programming and the intervals are built on the method based on differences originally proposed in Hall (1992).

¹³ Simar and Wilson (2000a, p.790) advise that bias-correction should only be used when the ratio is well above unity, something which we will consider.

in the second stage, is that the accumulation of coefficients in the unit disappears. For example, municipality 843, Alcúdia de Crespins, which is efficient when considering the estimation based on the initial distance function, $\hat{\theta}=1$, has a corrected coefficient of 1.776, indicating that to obtain the same level of output it could reduce its input by about 75%. Specifically, the confidence interval at 95% for this unit indicates that it could reduce its inputs by between 43% and 93%.

(Insert Table 3)

4.3. Analysis of the causes of efficiency: stage II

In conventional two-stage analysis, the second stage uses regression techniques to relate the efficiency coefficients to a series of influencing factors. The most frequent aim of this stage is not the goodness of the fit, nor prediction, but to discover the factors that significantly affect the efficiency and the size of the marginal effects of each factor. It is without doubt the most controversial part of the study and many econometric techniques have been tried out. Neither can it be said that the literature has come to any real consensus.

There does seem to be agreement at least in warning against using some regression techniques, for example the inappropriateness of using censored models (tobit) in the second stage, which is usually specified in the literature as:

$$\hat{\theta}_i = z_i \cdot \beta + \xi_i \quad (2)$$

where z_i represents the exogenous factors and the dependent variable, θ_i , the non observed real efficiency coefficients that are substituted by the estimated coefficients in the first stage, $\hat{\theta}_i$. Simar and Wilson (2007) recognize that some applications have used both censored models and ordinary least square ones and then insist none of them take into account how the phenomenon occurs. According to the aforementioned, the consideration of the inherent bias in the estimated coefficients in the first stage leads to¹⁴ :

$$\underbrace{\hat{\theta}_i - \hat{\text{bias}}_B(\hat{\theta}_i)}_{\hat{\theta}_i} + v_i - u_i = z_i \cdot \beta + \varepsilon_i \quad (3)$$

which can be used to give the maximum likelihood that leads to consistent estimations through:

$$\hat{\theta}_i \approx z_i \cdot \beta + \varepsilon_i \quad (4)$$

Most researchers have estimated (2) assuming a tobit specification for the error term caused by some of the efficiency coefficients being equal to the unity, which has nothing to do with the real underlying model nor with the separability condition. Indeed, the authors are saying that the linear version of the real underlying model in (2) is given by:

¹⁴ Simar and Wilson (2007, pp.39-40)

$$\theta_i = z_i \cdot \beta + \varepsilon_i \quad (5)$$

In order to overcome the problems of correlation and bias of the endogenous variable in (2), and the correlation between the error terms and the exogenous factors vector, z , Simar and Wilson (2007) propose two algorithms based on normal truncated regression whose functioning they examine by implementing various Monte Carlo experiments¹⁵. Number 1 is based on a simple bootstrap in which the biased coefficients are regressed; number 2, on a double bootstrap, in which the corrected efficiency coefficients are regressed according to our description of the estimated model in stage I.

In overall terms, number 2 shows a better functioning, although some key aspects have to be taken into account. In general, it is preferable to have a large sample size. As the sum of inputs and outputs used in stage I increases, so the accuracy of the estimations in stage II decreases. The estimations based on the corrected coefficients are more accurate than those based on non corrected ones. On the other hand, when the number of units is low, the use of algorithm 2 worsens the estimation error compared to algorithm 1. Furthermore, although the correlation problems tend to disappear asymptotically, the size of the sample we have used is not sufficient for it to operate satisfactorily and, hence, the need to implement some of the models.

Given the above, we propose that it is convenient in the application to apply algorithm 2, for which, moreover, a relatively optimal behaviour can be expected. Table 4 shows the results¹⁶.

(Insert Table 4)

The truncated regression with a bootstrap model appears to fit the data well, with estimates which are statistically significant for all parameters. The estimations conform to a priori expectations. Therefore, if we take the results returned by algorithm 2, the effect of the per capita income (INCPC) is positive, while the indices for tourist activity (TRIND), population density by urban area (DENPSU) and economic activity (ECACIN) are negative.

In line with literature, we have considered a dummy categorical variable – the political sign of the governing party – on the efficient provision of the facilities under study. The estimated sign for this variable is negative.

In previous studies positive but non significant correlations are observed for the efficiency in the provision of public services and the level of economic activity. However, these studies (Giménez and Prior, 2003; Silkman and Young, 1982 and De Borger and Kerstens, 1996) are of a global nature while the results we report here show a negative and significant correlation when we just consider sports. Hone and Silvers (2006) claim that citizens with higher incomes make stronger demands for these infrastructures, which is in line with our results.

The classical public finance theory shows that income explains the growth of the state sector, especially at local government level. Using this theory, known as the Wagner Law, we can maintain that increase in income will lead to increases in public spending on sports facilities and, elsewhere.

¹⁵ The latest version of FEAR 1.13 (March 2010) includes two, `morm.trunc` and `treg`, among its routines, which facilitate estimations.

¹⁶ As Simar and Wilson (2007) recommend, we use a total of 2,000 iterations, and the values of the variables are scaled appropriately; signs of estimated coefficients can be interpreted in a Farrell – Debreu direction.

Nevertheless, increased density of population decreases efficiency in the provision of sporting facilities. It is to be supposed that the concentration of users complicates management and affects the population's opportunities of being able to practise sports. These results coincide with those reported by Gallardo *et al.*(2009).

The tourist index variable has been little used in studies on efficiency and authors like Bosch *et al.* (2000) find no relevant results, while Bel (2006) reports that the correlation is positive but not significant. There are, however, studies that have sought to establish a relation between a municipality's economic activity and sports tourism (Hetherington, 1993; Turco *et al.*, 2003; Hautbois *et al.*, 2003; Davies and Williment, 2008 and Fyfe, 2008). Our study reveals a significant and negative relation with this variable, which could lead to the conclusion that while sports tourism has increased in recent years with local governments making efforts to improve sports facilities, this has not been accompanied by increased efficiency. It is likely that huge investments have been made in these facilities but these have not been met by efficient use of the same. The use made of the facilities is very often seasonal and maintenance costs become correspondingly excessive. Our findings are in line with those of Gallardo *et al.*(2009) for some of the regional governments the latter analyses.

Regarding the political sign (DPOLIT) the results reported by several authors when analysing this variable have been contradictory. Some, such as De Borger and Kerstens (1996) and Benito *et al.* (2010), in their global study, do not coincide with the results we report, while others (Pommerehne, 1978; Abizadeh and Gray, 1993 and Hagen and Vabo, 2005) find no conclusive results for the variable. The estimated sign for this variable is negative which, on the basis of the assignation of values established a priori (0 conservative and 1 progressive), implies that municipalities governed by conservative parties are more efficient. Our findings would support the thesis that 'partisan politics matters', i.e., that ideology matters in public sector management and performance (Cusack, 1997).

5. CONCLUSIONS

We have analysed the efficiency in the provision of public sports facilities of 984 Spanish municipalities with more than 1,000 inhabitants. We use a non parametric DEA method and have carried out a two-stage study using the methodology developed by Simar and Wilson (2007). The results indicate that there is a relatively low percentage of efficiency in the provision of these infrastructures.

The results from the first stage are the starting point. The proposal by Simar and Wilson (2007), one of the most influential studies of the last decade, was specifically designed to treat the second stage. The effect of certain exogenous variables on the level of efficiency can only be determined during the second stage. One essential aspect that distinguishes our proposal and which is a contribution of value to the area of public services management is the type of regression that we use in the second stage. Simar and Wilson (2007) present Monte Carlo estimations in which they confirm the catastrophic results deriving from the use of other alternatives, especially Tobit regression. Yet it is quite common to find studies that continue to use the Tobit regression in the second stage. At the beginning of 2010, Wilson remarked to the authors of this paper that: "I do not know of any statistical model where second-stage Tobit makes any sense". Secondly, a two-stage approach relies on previous conditions being satisfied for the first-stage estimates to have any meaningful economic interpretation, as well as for making a second-stage regression meaningful. Thus, the supposed independence between the exogenous factors vector, z , and the set of inputs and outputs (x,y) has to be checked. As Simar and Wilson (2010, p. 34) point out, in any case of interest, z is not independent of (x,y) . Hence, the regression to be solved in the second stage rests on the fulfilment of the separability condition, a critical constraint which unavoidably needs to be

statistically tested. None of the works that we have had occasion to consult do this. At most, some comment on the existence of such a condition but take its fulfilment for granted. Such an assumption is considerably serious since its non fulfilment would completely invalidate the results and would advise following other routes. Given all the above, we believe that the paper represents a considerable advance or, at least, it offers highly reliable results.

The results show the existence of a significant relation between efficiency and all the variables analysed (per capita income, population density by urban area, the comparative index of the importance of tourism and that of the whole economic activity). This relation is negative for the tourism index, population density and economic activity.

Few works focus on the impact of political factors on local governments' efficiency and the findings of several researchers of this variable have been contradictory. In this sense, we think it is interesting to know if incumbents' political sign influences efficiency, as the 'partisan politics matters' thesis assumes. In our research municipalities governed by conservative parties are more efficient.

Finally, it should be mentioned that it would be useful to repeat the study in a few years' time in order to ascertain any evolution in efficiency levels of the service under analysis, given the efforts being undertaken by these entities to adapt to the various norms and stipulations and to the scarce financial resources available.

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Graph 1. Log-Ratio. Analysis of Outliers

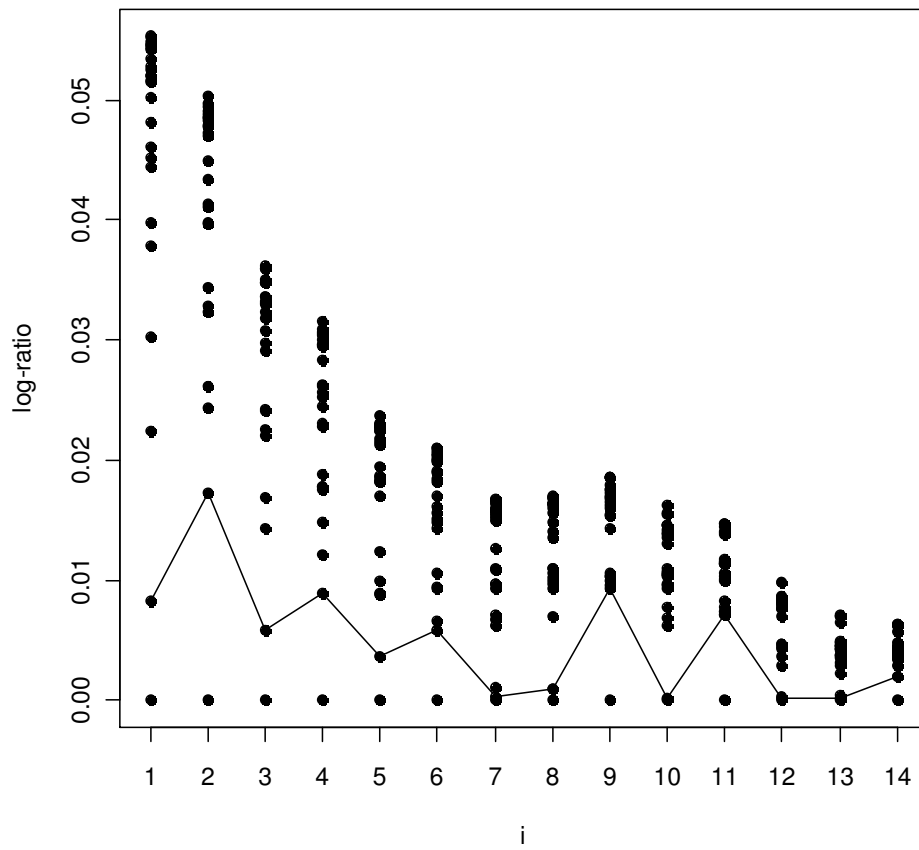


Table 1. Outliers in Data. Values of $R_{Min}^{(i)}$

| i | Municipalities | $R_{Min}^{(i)}$ |
|----|--|-----------------|
| 1 | 325 | 0.9253987 |
| 2 | 736 325 | 0.8588826 |
| 3 | 856 736 325 | 0.809543 |
| 4 | 794 856 736 325 | 0.7656743 |
| 5 | 816 794 856 736 325 | 0.7292074 |
| 6 | 653 816 794 856 736 325 | 0.6956181 |
| 7 | 674 653 816 794 856 736 325 | 0.6662982 |
| 8 | 674 273 653 816 794 856 736 325 | 0.637466 |
| 9 | 266 674 273 653 816 794 856 736 325 | 0.6093701 |
| 10 | 29 266 674 273 653 816 794 856 736 325 | 0.5872218 |
| 11 | 307 29 266 674 273 653 816 794 856 736 325 | 0.5653978 |
| 12 | 725 307 29 266 674 273 653 816 794 856 736 325 | 0.5480757 |
| 13 | 427 725 307 29 266 674 273 653 816 794 856 736 325 | 0.5313115 |
| 14 | 427 725 307 29 529 266 674 273 653 816 794 856 736 325 | 0.5151157 |

$R_{Min}^{(i)}$. i=1 a i=14

Table 2. Summary statistics for inputs and outputs

| Variable | Mean | Standard deviation | Min. | Max. |
|----------|-----------|--------------------|-----------|-----------|
| SPORTSPC | 45.41 | 35.83 | 0.20 | 177.03 |
| SUCASPC | 8.37 | 6.06 | 0.16 | 35.92 |
| QUALITY | 1.80 | 0.28 | 0.38 | 2 |
| TRIND | 4.04 | 4.74 | 1 | 30 |
| ECACIN | 11.73 | 12.12 | 1 | 67 |
| INCPC | 12,506.96 | 2,179.86 | 10,249.43 | 28,764.04 |
| DENPSU | 6,077.67 | 4,005.62 | 145.88 | 25,799.78 |

Table 3. Unbiased estimated coefficients and confidence intervals

| Municipality | Id. Mun. | $\hat{\theta}$ | $\hat{\hat{\theta}}$ | r_i | $\hat{\text{bias}}_B(\hat{\theta})$ | $\hat{\sigma}^2$ | L.L. | U.L. |
|--------------------------------|----------|----------------|----------------------|--------|-------------------------------------|------------------|-------|-------|
| Cantimpalos | 746 | 1.013 | 1.688 | 5.800 | -0.675 | 0.026 | 1.243 | 1.903 |
| Riosa | 628 | 1.497 | 1.749 | 0.649 | -0.252 | 0.033 | 1.509 | 2.148 |
| Alcúdia de Crespins | 843 | 1 | 1.776 | 11.802 | -0.776 | 0.017 | 1.432 | 1.926 |
| Santovenia de la Valdoncina | 384 | 1 | 1.801 | 14.214 | -0.801 | 0.015 | 1.517 | 1.941 |
| Granja de Rocamora | 30 | 1 | 1.835 | 9.615 | -0.835 | 0.024 | 1.367 | 1.974 |
| Torre del Bierzo | 388 | 1.121 | 1.878 | 4.659 | -0.758 | 0.041 | 1.389 | 2.141 |
| Atzeneta d'Albaida | 835 | 1 | 1.902 | 19.611 | -0.902 | 0.014 | 1.547 | 1.989 |
| Valderas | 390 | 1.195 | 1.914 | 3.263 | -0.718 | 0.053 | 1.392 | 2.248 |
| Viana de Cega | 947 | 1 | 1.956 | 47.522 | -0.956 | 0.006 | 1.714 | 1.997 |
| Bruc (El) | 109 | 1 | 1.963 | 50.120 | -0.963 | 0.006 | 1.747 | 1.998 |
| Simancas | 944 | 1 | 1.970 | 53.814 | -0.970 | 0.006 | 1.791 | 1.998 |
| Pinseque | 980 | 1 | 1.971 | 52.461 | -0.971 | 0.006 | 1.784 | 1.999 |
| Villalonga | 919 | 1.192 | 2.053 | 5.314 | -0.861 | 0.046 | 1.470 | 2.303 |
| Villasabariego | 399 | 1.433 | 2.415 | 5.817 | -0.982 | 0.055 | 1.779 | 2.717 |
| Santa Cristina de la Polvorosa | 958 | 1.624 | 2.498 | 2.255 | -0.874 | 0.113 | 1.729 | 2.970 |
| Soto de la Vega | 386 | 1.560 | 2.648 | 7.698 | -1.088 | 0.051 | 2.070 | 2.950 |
| Coca | 748 | 1.893 | 2.928 | 2.979 | -1.035 | 0.120 | 2.145 | 3.435 |
| Castrelo de Miño | 563 | 1.567 | 2.954 | 14.714 | -1.387 | 0.044 | 2.316 | 3.113 |
| Begonte | 456 | 1.886 | 3.258 | 5.367 | -1.372 | 0.117 | 2.333 | 3.647 |
| Pastoriza (A) | 476 | 1.864 | 3.390 | 7.973 | -1.526 | 0.097 | 2.457 | 3.672 |
| Villoria | 691 | 1.972 | 3.549 | 6.815 | -1.577 | 0.122 | 2.490 | 3.877 |
| Hinojos | 346 | 1.831 | 3.549 | 29.389 | -1.718 | 0.033 | 3.039 | 3.653 |
| Portillo | 938 | 2.017 | 3.550 | 5.371 | -1.533 | 0.146 | 2.461 | 3.936 |
| Villalpando | 959 | 2.054 | 3.742 | 8.242 | -1.687 | 0.115 | 2.723 | 4.050 |
| Albalate de Cinca | 353 | 2.187 | 3.796 | 4.847 | -1.609 | 0.178 | 2.630 | 4.247 |
| Gomesende | 572 | 2.169 | 3.830 | 6.605 | -1.662 | 0.139 | 2.749 | 4.223 |
| Valdeganga | 14 | 2.111 | 3.883 | 10.455 | -1.773 | 0.100 | 2.950 | 4.167 |
| Pereiro de Aguiar (O) | 587 | 2.432 | 4.144 | 4.938 | -1.712 | 0.198 | 2.981 | 4.678 |
| Forcarei | 658 | 2.485 | 4.217 | 8.448 | -1.732 | 0.118 | 3.331 | 4.689 |
| Loriguilla | 883 | 2.613 | 4.289 | 3.142 | -1.676 | 0.298 | 2.990 | 4.997 |

Table 4. Stage II results. Simar y Wilson (2007) algorithm II

| Variables | Simar y Wilson (2007) Algorithm II | |
|---------------|------------------------------------|----------------|
| | Score | s.e.boot |
| INCPC | 0.0004700610 (*) | (0.0000506048) |
| TRIND | -0.0077680303 (**) | (0.0019515110) |
| ECACIN | -0.0168233157 (*) | (0.0007333564) |
| DPOLIT | -0.0808179852 (**) | (0.0256332500) |
| DENPSU | -0.0005721429 (*) | (0.0000429282) |

(s.e.boot) The SEs of the estimated parameters are shown in brackets.

(*) Indicate that the parameter estimated is significant at 0.5% level.

(**) Indicate that the parameter estimated is significant at 5% level.