Efficiency in the Provision of Public Municipal Cultural Facilities

BERNARDINO BENITO, JOSÉ SOLANA & MARÍA-ROCÍO MORENO

ABSTRACT Recent years have seen a wealth of studies on Cultural Economics, in line with the importance of the economic performance of the public sector. In this context, the two-stage double bootstrap procedure of Simar and Wilson (2007) has been used to estimate the efficiency determinants of Spanish local entities in the management of culture oriented public infrastructures, given the limited financial resources available to these entities. The final sample comprises 1,159 municipalities. In the first stage, technical efficiency is estimated by Data Envelopment Analysis (DEA) and, based on a truncated-regression, the resulting efficiency estimates are regressed on a group of 10 selected environmental variables in a second stage. We have also considered the influence of a dummy categorical variable –the political sign of the governing party– on the efficient provision of the facilities under study. The results show the existence of a significant relation between efficiency and all the variables except two: unemployment rate and political strength. Our results also show that municipalities governed by conservative parties are more efficient.

KEYWORDS: • cultural economics • local governments • public infrastructures • efficiency • Spain

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1 Introduction

There have been numerous studies in recent years on Cultural Economics: Throsby (1994, 2001); Hutter and Rizzo (1997); Towse (1997, 2003); Blaug (2001); Herrero-Prieto (2001); Herrero-Prieto et al. (2006); Benhamou (2011), among others. These have highlighted the importance of cultural activity, the culture industry and the historical heritage in fostering economic growth, increasing public revenue and creating employment, especially at regional and local levels: Bianchini and Parkinson (1993); Hall (2000); Markusen and Schrock (2006); Bille-Hansen and Schulze (2006); Markusen and Gadwa (2010). This situation has contributed to Local Entities to devote an important part of their resources to financing cultural events, keeping historical heritage and investing in infrastructures of a cultural nature as a way of increasing economic activity in the area: Evans (2001); McCann (2002); Gibson and Klocker (2004). Moreover, recent decades have seen a significant increase at local level in public restoration and recuperation of heritage objects, because of the evolution of cultural tourism: Caserta and Russo (2002); Sager (2003); Sigala and Leslie (2005); Richards (2007); Richards and Wilson (2008); Pulido-Fernández and Sánchez-Rivero (2010). All these actions have supposed an improvement on the quality of life of the citizens, and they require large amounts of public resources.

Among the various cultural activities carried out by local entities, we would underline those relating to the building and maintenance of culture related infrastructures. These are services that require financing and support from public institutions to ensure their functioning and accessibility to all citizens and, given the increasing cost-pressure on public budgets, it is paramount that the funds be managed efficiently. Considering the volume of resources that local entities devote to financing these actions, it is of interest to analyse the efficiency in the management of these resources in order to improve the service. Still more important, as De Witte and Kortelainen (2009, p. 2) point out, is that efficiency estimations which do not account for the operational environment may have only a limited value. Indeed, there is no justification in comparing productive units that have a favourable level in a specific exogenous factor with that others show a less favourable level. Since, in general, productive units are affected by external variables of an exogenous nature, any analysis evaluating their running and management needs to consider the heterogeneity introduced. Hence, the aim of this study is to analyse the determinants of efficiency of Spanish local entities in the provision of cultural infrastructures, taking into account their limited resources. The motivation for the study lies in the important increase in recent years of resources that local councils use for this kind of facilities.

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 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 offers a critical, up-to-date analysis of the theoretical framework. In Section 5 we present the results of the first and second stage, and these are analysed in Section 6. Section 7 offers the main conclusions.

2 Methodological background

In this paper we explore the use of the two-stage estimation procedure to assess the efficiency of Spanish local entities in the provision of cultural facilities. In the first stage, technical efficiency is estimated by DEA and the resulting efficiency estimates are regressed on some environmental variables in a second stage. Then, we analyse the determinants of the efficiency by considering a group of external and continuous factors, \( z \in \mathbb{R}^r \), as well as a dummy categorical one so as to better characterize the operational environment - the political sign of the municipalities studied.
A large part of the literature on efficiency focuses on estimating the production frontier, which provides the benchmark for the evaluation of the productive units analysed. Nevertheless, our attention here is on a transcendental aspect – the explanation of the differences in efficiency through the inclusion of a series of exogenous or environmental factors that may affect the production process. 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 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.

It is clearly of great interest and importance to identify the particularities of a production process or the economic conditions that may be responsible for the inefficiencies detected. On the other hand, the choice of exogenous variables is linked to the economic field in which the units considered operate and must be based on the knowledge of the characteristics of the specific production process in each case.

The DEA approach constructs the nonparametric frontier as the piecewise linear combination of all efficient Decision Making Units (DMUs). The DEA model proposed by Charnes et al. (1978) assumed constant returns to scale (CRS); Banker et al. (1984) extended this to variable returns to scale (VRS) with a convexity constraint ensuring that DMUs are only compared with similar DMUs. 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).

Non-parametric models suffer from inconveniences and some of these are dealt with in this article. We would make special reference to two problems: first, the models, as developed by Charnes et al. (1978) and Banker et al. (1984), were labelled deterministic, since they did not allow for statistical inference. Statistical properties of DEA/Free Disposal Hull (FDH) estimators are now available using asymptotic results: see Kneip et al. (1998), Park et al. (2000), Kneip et al. (2008),
or by using bootstrap: Simar and Wilson (1998, 1999, 2000). 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 increases. Second, the deterministic frontier models are sensitive to outlying and atypical observations; in this sense, Simar (2003, p. 420) indicates that 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”.

In the second stage, first stage estimates of the efficiency of the DMUs are regressed on the exogenous factors to investigate their effect on efficiency. It generated a wide and varied list of empirical applications which did not take into proper consideration the testing of basic hypotheses for the correct application of the model or the type of regression to be used in the second stage. The situation is quite serious because, as pointed out by Simar and Wilson (2007), the non-fulfilment of suppositions like separability would completely invalidate the results. In Simar and Wilson (2011b) the authors attempt to clear up some of the confusion that has developed, to state what the main points of Simar and Wilson (2007) were, and to dispel “some myths” that have arisen.

In this sense, the correct practical application of the Simar and Wilson (2007) model that we propose will suppose in itself a contribution of value, or even a significant advance. At the very least, we will offer reliable results on an issue of considerable importance for both the economic and the socio-political spheres – the provision of public cultural infrastructures.

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 approach. The shortcomings of earlier one-stage 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. 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. 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 separability condition.

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). This fully nonparametric approach provides useful qualities. It avoids the separability assumption, so overcoming the drawbacks of
the two-stage-type approaches. The objective is to analyse 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 analysed in Cazals et al. (2002) and recently in Jeong et al. (2010). Nevertheless, as the conditional efficiency approach relies on the estimation of nonparametric kernel functions to select the appropriate reference partners, it is based on the choice of bandwidth parameters: although the estimates avoid the separability condition, their bandwidths relied on it.

Below we use two-stage Simar and Wilson (2007) modelling to analyse the causes of inefficiency from a sample of municipalities for the year 2010. Our initial sample comprises data from 1,725 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 and also used techniques to detect outliers. Then, 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 apparent, i.e. they are low-biased or, Wheelock and Wilson (2008, p. 125): “the DEA frontier estimate is nothing more than a biased estimate of the true, but unobserved, frontier”. Using bootstrap techniques, in the spirit of Simar and Wilson (2000) 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. We use the library FEAR 1.15 (9 November 2010), developed by Wilson (2008), linked to the statistical package R.

Some key aspects will be referred to in the course of this paper, in particular the separability condition 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) and, more recently, Simar and Wilson (2011a).
3 Sample and variables

For the selection of outputs we have used the studies by Stevens (1978), Carr-Hill and Stern (1979), Darrough and Heineke (1979), Gyimah-Brempong (1987, 1989), Dubin and Navarro (1988), Cameron (1989) Bosch et al. (2000), Worthington and Dollery (2001), Callan and Thomas (2001) and Bel (2006), and we have opted for two outputs: SURCULPC and QUALITY. The first (SURCULPC) is the surface area in square metres of all the cultural installations per capita owned by each municipality, and has been obtained from the EIEL (Survey on Local Infrastructures and Equipment) for 2010 (this survey is updated every 5 years). The second (QUALITY) is an index built from the survey on the suitability of the service, similarly included in the 2010 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 discrentional character we used CULTUREPC which is the per capita cost according to Spending Policy “Culture”, as envisaged by the Order EHA/3565/2008, of December, 3, which stipulates the structure of local entities’ budget. This category of spending includes creation, maintenance and operation costs of buildings intended for libraries, museums, archives, cultural centres, cultural activities, leisure and free time activities as senior citizens day centres or youth centres; exhibition halls, conference centres, zoos, music bands and musical groups, popular local festivals, recreational activities on beaches, actions in order to preserve the historical and artistic heritage and other cultural and recreational expenditures; as well as transfers to entities or families that collaborate in promoting these activities. Data were provided by the Ministry of the Treasury and refer to 2010.

The works of Hibbs (1977), Pommerehne (1978), Throsby (1994), Abizadeh and Gray (1993), Hetherington (1993), Krebs and Pommerehne (1995), Schulze and Ursprung (2000), Giménez and Prior (2003), Getzner (2004), J. Tavares (2004), Hagen and Vabo (2005), Gammon and Fear (2005), Werck et al. (2008), Benito-López et al. (2010), Pulido-Fernández and Sánchez-Rivero (2010) and Diniz and Machado (2011), show the relation between certain variables and the management and provision of different public services, among which are culture facilities. Using these studies as reference, we have included the following variables as exogenous factors in the second stage of our model:

- POPDSURB: 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 Spanish National Statistics Institute and the Head Property Registry Office, and correspond to 2010.
TRIND: Comparative index of the tourist importance of each municipality in 2010. This is obtained from the quota or Tax on Economic Activities for the tourist activity in question. It takes into account the type of tourist establishment (hotels and motels, hotel-apartments, hostels and pensions, inns and guesthouses, camp sites and apartments offered by firms), the number of rooms and annual occupation (all or part of the year). The value of the index indicates the share, per 100,000, corresponding to each municipality, province or autonomous community, over a national base of 100,000 units (total euros raised under IAE = 100,000). Thus, it is a simple index obtained as the quotient between the quota corresponding to one municipality divided by the total of quotas at national level multiplied by 100,000. Data are available in the Economic Yearbook of “La Caixa” (2010).

ECACIN: a comparative index for the whole of the municipal economic activity in 2010. 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 Economic Yearbook of “La Caixa” (2010).

INCPC: per capita income; data provided by the L.R. Klein Institute, which depends on the Autonomous University of Madrid and for the year 2009, the last available.

UNEM: rate of unemployment of the municipality in 2010. Taken from the Spanish National Statistics Institute.

INMIG: share of immigrants in 2010. Data were obtained from the Spanish National Statistics Institute.

POP65: share of population aged over 65 in 2010. Data were obtained from the Spanish National Statistics Institute.

POP15: share of population aged under 15 in 2010. Taken from the Spanish National Statistics Institute.

POPSEC: share of population with at least second-degree studies in 2010. Taken from the Spanish National Statistics Institute.

FORTAL: to measure the strength of the local government, in line with authors such as Rattsø and Tovmo (2002), Borge (2005), Hagen and Vabo (2005) and Benito-López and Bastida-Albaladejo (2008), we use the Herfindahl Index, which ranges between 0 (maximum fragmentation) and 1 (maximum strength). Maximum fragmentation implies the existence of just one town councilor per party, whereas maximum strength would indicate that all the town councilors belong to the same party.
Where $n$ is the number of parties in the local government, and $p_i$ the number of councilors of party $i$ in the local government.

- **DPOLIT**: 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, as in FORTAL, were provided by the Spanish Home Office and the Ministry for Territorial Policy, and are based on the 2007 municipal election results.

From the above papers cited, it is not possible to establish a priori an expected sign for the relation between efficiency and the variables considered, since there is no unanimous consensus thereon. We therefore believe that our contribution sheds light on the state of the art.

An initial inspection of the data reveals hundreds of erroneous values, with null values in the variables, so the sample was reduced to 1,189 municipalities. The next, logical, step is to detect and control outliers, which are a source of concern in both parametric and non-parametric approaches. By construction, nonparametric deterministic frontier models are quite sensitive to extreme values and to outliers. As Simar (2003, p. 393) points out, “detecting outliers is of primary importance and it is not an easy task in a multivariate setup”. Besides, “no optimal procedure nor miracle procedure can be defined to detect outliers in this difficult context”. So it is important to develop exploratory data analysis tools which allow detection of extreme values. Once a potential outlier is detected, careful consideration must be given to determine why it is an outlier. Outliers 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. Simar and Zelenyuk (2010, p. 3) point out that “deterministic frontier models have the drawbacks of not allowing random noise in the DGP (Data Generating Process) and, as a result, being very sensitive to extreme data points and outliers”. Despite the size of the data filter, our final sample size remains relatively large.

Wilson (1993, 1995) proposes making use of influence functions to detect outliers in this framework. In Wilson (1993), the author extends the Andrews and Pregibon (1978) statistic to the case of multiple outputs. Taking as its base the geometric influence function $R_L(XY)$ of these authors, the method constructs and analyses the graph of the log ratios: 

$$\sum_{i=1}^{n} p_i^2 \left( \sum_{i=1}^{n} p_i \right)^{-2}$$
Examination of the separation between the smallest ratios indicates possible outliers. This ratio is computed for each of the possible subsets \( L \) of size \( i \), where the choice of the stopping point of the analysis, \( i \), is arbitrary and involves increasing computational burden. As discussed in Wilson (1993) and Simar (2003), one outlier might hide another or others nearby. To avoid this masking effect, it should be large enough. When detected though, the analysis must be repeated without those units. The Wilson (1993) procedure has the advantage that it does not require any a priori specific direction to be established for the model. We will apply this procedure to our sample of data.

We will use too the Simar (2003) procedure, that uses the robust order-\( m \) efficiencies of Cazals et al. (2002). The expected frontier function of order-\( m \) is the expected minimal input achieved by any \( m \) firms drawn from the population of firms which produce at least \( y \) outputs, whereas a full frontier indicates for all firms which produce at least level \( y \) of outputs the minimum achievable lower boundary of inputs. The value \( m \) can be viewed as a trimming parameter of the frontier. For large values of \( m \), the two frontiers coincide. A nonparametric estimator of the order-\( m \) frontier is easy to compute with FEAR 1.15, and has remarkable statistical properties: no dimensionality curse and asymptotic normality. Due to the trimming nature of the order-\( m \) frontier, the estimator does not envelop all the observed data points, even for large \( m \), and so it is more robust to outliers. The Simar (2003) method to detect outliers is based on a sensitivity analysis relative to several values of \( m \). With an order-\( m \) input oriented frontier, an observation which lies far above the frontier (i.e., a value considerably larger than 1) will be determined as an outlier.

Due to the specific characteristics of non-parametric deterministic frontier models, several techniques to identify outliers have to be evaluated. As we have indicated, we employ the methods of detection proposed by Wilson (1993) and Simar (2003). Starting with Wilson (1993), we use FEAR 1.15 to obtain Graph 1 and Table 1. The graph shows the smallest values of the log ratios. A straight line connects the second lowest values for each \( i \), thus illustrating the separation between the lowest ratios for each value of \( i \).
Graph 1. Log-Ratio. Analysis of Outliers

For i=1,2,3 the separation is relatively large. Hence observations listed for i=3 in Table 1 are regarded as outliers. As i is increased from 4 to 9, the separation becomes smaller but then increases for i = 10, 11. Hence a second group of outliers is identified, consisting of observations 896, 20, 877, 668, 165, 849, 537 and 533. As Wheelock and Wilson (2008, p. 212) point out: “it is always complicated in empirical applications to ascertain why an observation is atypical and some subjective interpretation is required. 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, measurement errors or other mistakes then this should be repaired or removed”.

<table>
<thead>
<tr>
<th>i</th>
<th>Municipalities</th>
<th>$R_{\text{Min}}^{(i)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>895</td>
<td>0.95098</td>
</tr>
<tr>
<td>2</td>
<td>4 895</td>
<td>0.9085</td>
</tr>
<tr>
<td>3</td>
<td>618 4 895</td>
<td>0.87024</td>
</tr>
<tr>
<td>4</td>
<td>537 618 4 895</td>
<td>0.84069</td>
</tr>
<tr>
<td>5</td>
<td>849 537 618 4 895</td>
<td>0.81287</td>
</tr>
<tr>
<td>6</td>
<td>165 849 537 618 4 895</td>
<td>0.787</td>
</tr>
<tr>
<td>7</td>
<td>668 165 849 537 618 4 895</td>
<td>0.76175</td>
</tr>
<tr>
<td>8</td>
<td>896 668 165 849 537 618 4 895</td>
<td>0.73799</td>
</tr>
</tbody>
</table>
Given the above comments on the masking effect, the process was repeated 5 times, without including the municipalities detected in each phase, in order to obtain the final proposal of outlier candidates. Below, we apply the Simar (2003) detection method. We have:

\[
\hat{\theta}_{m,n}(x_0, y_0) = \hat{E}\left[ \tilde{\theta}_m(x_0, y_0) \mid Y \geq y_0 \right]
\]

(3)

Nonparametric estimators of the order-m frontiers are obtained by using empirical distribution functions in place of the unknown population distributions: the expectation is made with respect to the empirical conditional distribution of \( X \), given \( Y \geq y_0 \). For a given \( y_0 \), draw a random sample of size \( m \) with replacement among those \( x_i \) where \( y_i \geq y_0 \), and denote this sample by \( (X_1, X_2, \ldots, X_m) \). Then compute the values of \( \tilde{\theta}_m(x_0, y_0) \) and repeat this for \( b=1,2,\ldots,B \), where \( B \) is the number of Monte-Carlo replications (for more details refer to Simar, 2003). We have then:

\[
\hat{\theta}_{m,n}(x_0, y_0) = \frac{1}{B} \sum_{b=1}^{B} \tilde{\theta}_m(x_0, y_0) \xrightarrow{B \to \infty} \hat{E}\left[ \tilde{\theta}_m(x_0, y_0) \mid Y \geq y_0 \right]
\]

(4)

We also compute the Monte-Carlo standard deviation of the approximation, i.e.:

\[
SD_{MTC}\left[ \hat{\theta}_{m,n}(x_0, y_0) \right] = \frac{1}{\sqrt{B}} \sqrt{\frac{\sum_{b=1}^{B} \left( \tilde{\theta}_m(x_0, y_0) - \hat{\theta}_{m,n}(x_0, y_0) \right)^2}{B-1}}
\]

(5)

As the order-m results are influenced by the value of \( m \), we compute the order-m efficiency score for different values of \( m \) (25, 50, 75, 100, 150), and we use 200 Monte-Carlo replications in computing the estimates. Although the Simar (2003) procedure is supposed to be more robust with respect to the masking effect (see footnote on Simar, 2003, p. 401), it is convenient to repeat the process here, too. Table 2 shows the results of the candidate outliers obtained after the first application of the Simar (2003) method to the data sample.
Table 2: Outliers in Data. Simar (2003)

<table>
<thead>
<tr>
<th>Municipality</th>
<th>Montecarlo Monte-Carlo Standard Deviation (B=200)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>m = 25</td>
</tr>
<tr>
<td>4</td>
<td>1.555</td>
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<tr>
<td>11</td>
<td>1.284</td>
</tr>
<tr>
<td>14</td>
<td>2.371</td>
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<tr>
<td>17</td>
<td>-</td>
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<tr>
<td>20</td>
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<td>21</td>
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<td>1.948</td>
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<tr>
<td>62</td>
<td>-</td>
</tr>
<tr>
<td>148</td>
<td>-</td>
</tr>
<tr>
<td>165</td>
<td>-</td>
</tr>
<tr>
<td>229</td>
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<tr>
<td>258</td>
<td>0.653</td>
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<tr>
<td>335</td>
<td>0.098</td>
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<tr>
<td>353</td>
<td>0.106</td>
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<tr>
<td>463</td>
<td>-</td>
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<tr>
<td>507</td>
<td>1.745</td>
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<tr>
<td>526</td>
<td>5.455</td>
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<tr>
<td>537</td>
<td>0.679</td>
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<td>561</td>
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<td>1.984</td>
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<tr>
<td>618</td>
<td>3.416</td>
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<tr>
<td>656</td>
<td>-</td>
</tr>
<tr>
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</tr>
<tr>
<td>849</td>
<td>2.369</td>
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<tr>
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<td>2.874</td>
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<td>896</td>
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<td>898</td>
<td>1.485</td>
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<td>899</td>
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<tr>
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<td>3.213</td>
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<tr>
<td>939</td>
<td>1.051</td>
</tr>
</tbody>
</table>
Table 2: Outliers in Data. Simar (2003)

<table>
<thead>
<tr>
<th>Municipality</th>
<th>Montecarlo Monte-Carlo Standard Deviation (B=200)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>m = 25</td>
</tr>
<tr>
<td>1019</td>
<td>0.567</td>
</tr>
<tr>
<td>1125</td>
<td>0.253</td>
</tr>
<tr>
<td>1143</td>
<td>4.230</td>
</tr>
<tr>
<td>1170</td>
<td>6.422</td>
</tr>
<tr>
<td>1174</td>
<td>0.555</td>
</tr>
</tbody>
</table>

Following a rigorous scrutiny of the municipalities detected by both methods, the final sample comprised 1,159 municipalities. All the information available on the municipalities, which goes beyond the mere detection made with the methods employed, has been taken into consideration. As it is difficult to decide on an appropriate value as of which an observation should be determined as an outlier, we consider the most outlying observations as outliers. As pointed out by Simar (2003, p. 417), the points flagged by Wilson’s procedure are expected to be different, except for units which are really extreme. The comparison is difficult because Wilson’s method is based on influence function arguments; it incorporates a convexity assumption and is not direction-specific, as is the Simar method. Table 3 summarizes the main descriptors of the final sample.

Table 3. Summary statistics for inputs and outputs

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>CULTUREPC</td>
<td>51.80</td>
<td>36.38</td>
<td>0.31</td>
<td>178.54</td>
</tr>
<tr>
<td>SURCULPC</td>
<td>0.90</td>
<td>0.78</td>
<td>0.02</td>
<td>4.01</td>
</tr>
<tr>
<td>QUALITY</td>
<td>1.83</td>
<td>0.24</td>
<td>0.61</td>
<td>2</td>
</tr>
<tr>
<td>POPDSURB</td>
<td>6171.80</td>
<td>3715.59</td>
<td>145.88</td>
<td>19482.16</td>
</tr>
<tr>
<td>TRIND</td>
<td>1.83</td>
<td>1.62</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>ECACIN</td>
<td>6.18</td>
<td>6.20</td>
<td>1</td>
<td>30</td>
</tr>
<tr>
<td>INCPC</td>
<td>11267.27</td>
<td>2100.99</td>
<td>1</td>
<td>20555.08</td>
</tr>
<tr>
<td>UNEM</td>
<td>4.29</td>
<td>1.88</td>
<td>0.8</td>
<td>11.20</td>
</tr>
<tr>
<td>INMIG</td>
<td>0.04</td>
<td>0.04</td>
<td>0.001</td>
<td>0.21</td>
</tr>
<tr>
<td>POP65</td>
<td>0.22</td>
<td>0.07</td>
<td>0.05</td>
<td>0.46</td>
</tr>
<tr>
<td>POP15</td>
<td>0.14</td>
<td>0.04</td>
<td>0.002</td>
<td>0.26</td>
</tr>
<tr>
<td>POPSEC</td>
<td>0.33</td>
<td>0.07</td>
<td>0.11</td>
<td>0.56</td>
</tr>
<tr>
<td>FORTAL</td>
<td>0.11</td>
<td>0.04</td>
<td>0.01</td>
<td>0.26</td>
</tr>
<tr>
<td>DPOLIT</td>
<td>0.59</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
4 First and second stage analysis

According to the two-stage procedure, the efficiency coefficients for each municipality are obtained in the first stage in the assessment, which exclusively considers discretion variables. This study investigates efficiency determinants of Spanish local entities: we are interested in second stage results. The initial DEA model returns a group of 8 municipalities with unitary score. 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 sample. Table 4 shows the information of bootstrapped first stage DEA results estimated for a selection of municipalities.

Table 4. First Stage Results

<table>
<thead>
<tr>
<th>Municipality</th>
<th>Id. Mun</th>
<th>$\hat{\delta}$</th>
<th>$\hat{\delta}$</th>
<th>$\hat{r}_i$</th>
<th>$\hat{\text{bias}}_B(\hat{\delta})$</th>
<th>$\hat{\sigma}^2$</th>
<th>L.L.</th>
<th>U.L.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cantimpalos</td>
<td>746</td>
<td>1.013</td>
<td>1.688</td>
<td>5.800</td>
<td>-0.675</td>
<td>0.026</td>
<td>1.243</td>
<td>1.903</td>
</tr>
<tr>
<td>Riosa</td>
<td>628</td>
<td>1.497</td>
<td>1.749</td>
<td>0.649</td>
<td>-0.252</td>
<td>0.033</td>
<td>1.509</td>
<td>2.148</td>
</tr>
<tr>
<td>Alcúdia de Crespíns</td>
<td>843</td>
<td>1</td>
<td>1.776</td>
<td>11.802</td>
<td>-0.776</td>
<td>0.017</td>
<td>1.432</td>
<td>1.926</td>
</tr>
<tr>
<td>Santovenia de la Valdónsina</td>
<td>384</td>
<td>1</td>
<td>1.801</td>
<td>14.214</td>
<td>-0.801</td>
<td>0.015</td>
<td>1.517</td>
<td>1.941</td>
</tr>
<tr>
<td>Granja de Rocamora</td>
<td>30</td>
<td>1</td>
<td>1.835</td>
<td>9.615</td>
<td>-0.835</td>
<td>0.024</td>
<td>1.367</td>
<td>1.974</td>
</tr>
<tr>
<td>Torre del Bierzo</td>
<td>388</td>
<td>1.121</td>
<td>1.878</td>
<td>4.659</td>
<td>-0.758</td>
<td>0.041</td>
<td>1.389</td>
<td>2.141</td>
</tr>
<tr>
<td>Atzeneta d’Albaida</td>
<td>835</td>
<td>1</td>
<td>1.902</td>
<td>19.611</td>
<td>-0.902</td>
<td>0.014</td>
<td>1.547</td>
<td>1.989</td>
</tr>
<tr>
<td>Valderas</td>
<td>390</td>
<td>1.195</td>
<td>1.914</td>
<td>3.263</td>
<td>-0.718</td>
<td>0.053</td>
<td>1.392</td>
<td>2.248</td>
</tr>
<tr>
<td>Viana de Cega</td>
<td>947</td>
<td>1</td>
<td>1.956</td>
<td>47.522</td>
<td>-0.956</td>
<td>0.006</td>
<td>1.714</td>
<td>1.997</td>
</tr>
<tr>
<td>Bruc (El)</td>
<td>109</td>
<td>1</td>
<td>1.963</td>
<td>50.120</td>
<td>-0.963</td>
<td>0.006</td>
<td>1.747</td>
<td>1.998</td>
</tr>
<tr>
<td>Simancas</td>
<td>944</td>
<td>1</td>
<td>1.970</td>
<td>53.814</td>
<td>-0.970</td>
<td>0.006</td>
<td>1.791</td>
<td>1.998</td>
</tr>
<tr>
<td>Pinseque</td>
<td>980</td>
<td>1</td>
<td>1.971</td>
<td>52.461</td>
<td>-0.971</td>
<td>0.006</td>
<td>1.784</td>
<td>1.999</td>
</tr>
<tr>
<td>Villalonga</td>
<td>919</td>
<td>1.192</td>
<td>2.053</td>
<td>5.314</td>
<td>-0.861</td>
<td>0.046</td>
<td>1.470</td>
<td>2.303</td>
</tr>
<tr>
<td>Villasabariego</td>
<td>399</td>
<td>1.433</td>
<td>2.415</td>
<td>5.817</td>
<td>-0.982</td>
<td>0.055</td>
<td>1.779</td>
<td>2.717</td>
</tr>
<tr>
<td>Sta. Cristina Polvorosa</td>
<td>958</td>
<td>1.624</td>
<td>2.498</td>
<td>2.255</td>
<td>-0.874</td>
<td>0.113</td>
<td>1.729</td>
<td>2.970</td>
</tr>
<tr>
<td>Soto de la Vega</td>
<td>386</td>
<td>1.560</td>
<td>2.648</td>
<td>7.698</td>
<td>-1.088</td>
<td>0.051</td>
<td>2.070</td>
<td>2.950</td>
</tr>
<tr>
<td>Coca</td>
<td>748</td>
<td>1.893</td>
<td>2.928</td>
<td>2.979</td>
<td>-1.035</td>
<td>0.120</td>
<td>2.145</td>
<td>3.435</td>
</tr>
<tr>
<td>Castrelo de Miño</td>
<td>563</td>
<td>1.567</td>
<td>2.954</td>
<td>14.714</td>
<td>-1.387</td>
<td>0.044</td>
<td>2.316</td>
<td>3.113</td>
</tr>
<tr>
<td>Begonte</td>
<td>456</td>
<td>1.886</td>
<td>3.258</td>
<td>5.367</td>
<td>-1.372</td>
<td>0.117</td>
<td>2.333</td>
<td>3.647</td>
</tr>
</tbody>
</table>
Table 4. First Stage Results

<table>
<thead>
<tr>
<th>Municipality</th>
<th>Id. Mun</th>
<th>(\hat{\delta})</th>
<th>(\hat{\delta})</th>
<th>(r_i)</th>
<th>(\hat{\text{bias}}_n(\hat{\delta}))</th>
<th>(\hat{\sigma}^2)</th>
<th>L.L.</th>
<th>U.L.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pastoriza (A)</td>
<td>476</td>
<td>1.864</td>
<td>3.390</td>
<td>7.973</td>
<td>-1.526</td>
<td>0.097</td>
<td>2.457</td>
<td>3.672</td>
</tr>
<tr>
<td>Villoria</td>
<td>691</td>
<td>1.972</td>
<td>3.549</td>
<td>6.815</td>
<td>-1.577</td>
<td>0.122</td>
<td>2.490</td>
<td>3.877</td>
</tr>
<tr>
<td>Hinojos</td>
<td>346</td>
<td>1.831</td>
<td>3.549</td>
<td>29.389</td>
<td>-1.718</td>
<td>0.033</td>
<td>3.039</td>
<td>3.653</td>
</tr>
<tr>
<td>Portillo</td>
<td>938</td>
<td>2.017</td>
<td>3.550</td>
<td>5.371</td>
<td>-1.533</td>
<td>0.146</td>
<td>2.461</td>
<td>3.936</td>
</tr>
<tr>
<td>Villalpando</td>
<td>959</td>
<td>2.054</td>
<td>3.742</td>
<td>8.242</td>
<td>-1.687</td>
<td>0.115</td>
<td>2.723</td>
<td>4.050</td>
</tr>
<tr>
<td>Albalate de Cinca</td>
<td>353</td>
<td>2.187</td>
<td>3.796</td>
<td>4.847</td>
<td>-1.609</td>
<td>0.178</td>
<td>2.630</td>
<td>4.247</td>
</tr>
<tr>
<td>Gomesende</td>
<td>572</td>
<td>2.169</td>
<td>3.830</td>
<td>6.605</td>
<td>-1.662</td>
<td>0.139</td>
<td>2.749</td>
<td>4.223</td>
</tr>
<tr>
<td>Valdeganga</td>
<td>14</td>
<td>2.111</td>
<td>3.883</td>
<td>10.455</td>
<td>-1.773</td>
<td>0.100</td>
<td>2.950</td>
<td>4.167</td>
</tr>
<tr>
<td>Pereiro de Aguiar</td>
<td>587</td>
<td>2.432</td>
<td>4.144</td>
<td>4.938</td>
<td>-1.712</td>
<td>0.198</td>
<td>2.981</td>
<td>4.678</td>
</tr>
<tr>
<td>Forcarei</td>
<td>658</td>
<td>2.485</td>
<td>4.217</td>
<td>8.448</td>
<td>-1.732</td>
<td>0.118</td>
<td>3.331</td>
<td>4.689</td>
</tr>
</tbody>
</table>

The column \(\hat{\delta}\) provides the original distance function estimates. The column \(\hat{\text{bias}}_n(\hat{\delta})\), gives the bias estimates obtained with the bootstrap, for which we have used \(B=2,000\) bootstrap replications. Column \(r_i\) contains the statistical test value, where\(^6\):

\[
r_i = \frac{1}{3} \cdot \frac{\hat{\text{bias}}_n(\hat{\delta})}{\hat{\sigma}^2}
\]

Its values may be used to assess whether the bias correction might increase the mean squared error. Column \(\hat{\delta}\) gives the bias-corrected distance function estimates. Municipalities are classified from lowest to highest values of \(\hat{\delta}\), 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. Municipality 30, Granja de Rocamora, which is efficient when considering the estimation based on the initial distance function, has a corrected coefficient of 1.835, indicating that to obtain the same level of output it could reduce its input by about 83%. Specifically, the confidence interval at 95% for this unit indicates that it could reduce its inputs by between 36% and 97%. 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 in the second stage, is that the accumulation of coefficients in the unit disappears.
For the second stage regression, we used the Simar and Wilson (2007) double bootstrap procedure discussed to overcome the serial correlation problem of the DEA efficiency estimates. The model at this stage can be expressed as follows:

$$\hat{\delta}_i = \alpha_1 \text{POPDSURB} + \alpha_2 \text{TRIND} + \alpha_3 \text{ECACIN} + \alpha_4 \text{INCPC} + \alpha_5 \text{UNEM} + \alpha_6 \text{INMIG} + \alpha_7 \text{POP65} + \alpha_8 \text{POP16} + \alpha_9 \text{POPSEC} + \alpha_{10} \text{FORTAL} + \alpha_{11} \text{DPOLIT} + \xi_i$$

(7)

Table 5 shows the results:

Table 5. Stage II results. Simar and Wilson (2007) algorithm II

<table>
<thead>
<tr>
<th>Variables</th>
<th>Simar and Wilson (2007) Algorithm II Score</th>
<th>95% Bootstrap Confidence Intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>POPDSURB</td>
<td>-0.0001332519 (s)</td>
<td>(-0.004680; 0.004414)</td>
</tr>
<tr>
<td>TRIND</td>
<td>0.0034398725 (s)</td>
<td>(-0.001107; 0.007987)</td>
</tr>
<tr>
<td>ECACIN</td>
<td>-0.0335653143 (s)</td>
<td>(-0.038113; -0.029018)</td>
</tr>
<tr>
<td>INCPC</td>
<td>0.0002259341 (s)</td>
<td>(-0.004321; 0.004773)</td>
</tr>
<tr>
<td>UNEM</td>
<td>-0.0094894436 (ns)</td>
<td>(-0.014037; -0.012422)</td>
</tr>
<tr>
<td>INMIG</td>
<td>-4.8775264179 (s)</td>
<td>(-4.882074; -4.872979)</td>
</tr>
<tr>
<td>POP65</td>
<td>-0.8680406922 (s)</td>
<td>(-0.872588; -0.863493)</td>
</tr>
<tr>
<td>POP15</td>
<td>-3.1073853026 (s)</td>
<td>(-3.111933; -3.102838)</td>
</tr>
<tr>
<td>POPSEC</td>
<td>0.7422433147 (s)</td>
<td>(0.737696; 0.746791)</td>
</tr>
<tr>
<td>FORTAL</td>
<td>-0.0989984081 (ns)</td>
<td>(-0.113546; -0.104451)</td>
</tr>
<tr>
<td>DPOLIT</td>
<td>-0.1777530038 (s)</td>
<td>(-0.182300; -0.173206)</td>
</tr>
</tbody>
</table>

(s) Indicate that the parameter estimated is significant (5% level).
(ns) Indicate that the parameter estimated is no significant.

The truncated regression with a bootstrap model appears to fit the data well, with estimates which are statistically significant for all parameters except UNEM and FORTAL. 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),
the indices for tourist activity (TRIND) and the municipal population with higher than second degree studies (POPSEC) are positive, while, population density by urban area (POPDSURB), proportion of immigrants (INMIG), proportion of population aged over 65 years (POP65), proportion of population aged under 15 years (POP15) and economic activity (ECACIN) are negative. In line with previous 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.

5 Discussion

According to Wagner (1958), the increase in the public sector size is a consequence of a rise in income, provided that income elasticity of demand for public goods is greater than unity. This elasticity is supposed to be higher than unity. Following Wagner’s Law, Getzner (2002) posits that income increases will lead to an increase in public spending in culture. Another approach is adopted by Schulze and Rose (1998) to assert that income has a positive effect on public investment in culture. According to the idea that political parties determine their policies taking into account the preferences of the voters, they based their assumption on the fact that high-income people appreciate culture activities to a higher extent: Throsby and Withers (1986), Bille-Hansen (1997). This theoretical statement has been empirically confirmed by Getzner (2002), Wert (2006), Hone and Silvers (2006) and Lewis and Rushton (2007).

Although the majority of the empirical literature supports the theoretical assumptions, Schulze and Rose (1998) show a negative impact of income on culture spending, while Werck et al. (2008) do not find it significant.

Our results confirm what is indicated by the majority of the doctrine, in that citizens with higher incomes will demand an increasing offer of cultural products, accompanied by a greater provision of infrastructures and suitable management of them.

In terms of the economic activity of the municipal as a whole, the results we report here show a negative and significant correlation when we consider cultural facilities. Some authors show that the greater the economic level of municipality and therefore the greater the income local government collects, the less pressure exists on Local Government’s politicians and managers in order to reach efficiency in the provision of municipal services: Spann (1977), Silkman and Young (1982). In a similar way, De Borger and Kerstens (1996) find that greater economic level is linked to more inefficiency. However, Giménez and Prior (2003) analyse the impact of municipal economic level on efficiency and conclude that differences in economic level are not significant when evaluating efficiency.
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 cultural tourism: Greffe (1990); Richards (1996); De Rus and León (1997); Boyle (1997); Herrero-Prieto (2000); Richards (2002); Caserta and Russo (2002); Russo and Van Der Borg (2002); Gibson and Klocker (2004, 2005); Gibson and Kong (2005); Herrero-Prieto et al. (2006); Miles (2008); Gibson et al. (2010). Our study reveals a significant and positive relation with this variable, which could lead to the conclusion that local governments are investing large amounts of resources in the appropriate upkeep of their infrastructures and historical heritage. This, coupled with suitable and efficient management will favour an increase in culture oriented tourism, given the economic benefits to be made, especially in terms of employment, for the municipalities in question.

The effect of population density is ambiguous since it may be related to public expenditure on culture in two ways. On the one hand, in municipalities with higher population density, the distances that people need to travel within them to attend cultural events are lower. Since this distance discourages attendance at cultural events it is likely to decrease demand and spending in municipalities with lower population density: Withers (1979); Schulze and Ursprung (2000); Getzner (2004). This relationship has been found by Borge (1995), Aaberge and Langørgen (2003) and Stastna (2009). On the other hand, higher population density may lead to economies of scale in the provision of cultural services. In this case, public cultural spending per capita will be lower in more densely populated areas. The existence of economies of scale could well explain the significant negative relationship obtained by Werck et al. (2008) between population density and municipal spending on culture in Flanders. As regards efficiency, our results also show that the greater the population density, the less efficient is the management of the cultural infrastructures. It is to be supposed that the concentration of users complicates management and affects the population’s opportunities of being able to visit or participate in cultural events: Withers (1979) and Werck et al. (2008).

The issues of immigration and unemployment seem to lead to governors taking less care in the management of other public services, which has repercussions on efficiency, or so one would deduce from the results of our study. However, the variable unemployment (UNEM) is not significant.

The literature on cultural economics argues that people might support public funding of culture in order to preserve cultural heritage for future generations: Bille-Hansen (1997); Schulze and Ursprung (2000); Frey (2003). Schulze and Ursprung (2000) argue that it is more likely that people with minors exhibit this intergenerational altruism because they are more interested in taking into account future generations. Therefore, increased support for public funding of culture in
populations with a high proportion of young people might be expected. Thus, the 
opportunity cost of parental time might counteract the effect of bequest value, 
thereby reducing overall support for government intervention and spending on 
culture in populations with a high percentage of young people. The influence of 
the proportion of young people on cultural spending has not been clearly 
determined in the literature. There are studies that show a positive relationship: 
Stastna (2009); others that do not find significant results: Kushner et al. (1996); 
Werck et al. (2008); and others that find that their impact on spending is negative: 

Regarding the effect of the share of elderly population on public cultural spending, 
some authors have shown a positive relationship. For example, Stastna (2009) 
indicates that the higher the percentage of elderly inhabitants, the greater the 
expenditure on culture, sport and leisure. Werck et al. (2008) reach the same 
conclusion for the case of municipal spending on culture. In both studies the 
authors attribute their results to the low opportunity cost of time of elderly people. 
This is why, according to Schulze and Ursprung (2000), they will be willing to 
support public financing of cultural activities.

From the results we present here, the deduction is that municipalities with larger 
proportions of either young or elderly members are less efficient in providing 
public facilities for culture, perhaps because the greater demand for these 
infrastructures by citizens with more free time leads to higher costs, which are not 
managed efficiently.

Theoretical arguments suggest that the level of education increases the enjoyment 
of culture and art. First, people understand and enjoy culture to a greater extent the 
more they consume it, and the process of accumulation of capital consumption for 
individuals with higher educational levels is more rewarding, since they obtain 
and decode information more easily: Schulze and Rose (1998); Schulze and 
Ursprung (2000).

Second, highly educated individuals can appreciate art more because they have 
been exposed to an environment in which it is valued. For example, a university 
graduate has experienced peer pressure to attend arts events: Dimaggio and Useem 
(1978).

Finally, better-educated people also often have parents with high educational 
attainments. It is likely that better-educated children have been exposed to art in 
their childhood, and that early socialization influences the assessment of this in 

Schulze and Ursprung (2000), Getzner (2004) and Rushton (2005) show that 
education is one of the main factors affecting support for public funding of culture 
in different referendums on this issue. DiMaggio and Pettit (1999) and Brooks
(2001) obtain similar results analyzing public preferences through surveys. Finally, contingent valuation studies have also confirmed that willingness to pay for culture is higher among people with higher education: Throsby and Withers (1986); Bille-Hansen (1997).

Although all these studies show that people with higher educational levels have a more favourable attitude toward culture and its public funding, most authors who have investigated the influence of education on cultural public expenditure have found no significant results, like Schulze and Rose (1998), Lewis and Rushton (2007), Noonan (2007) or Stastna (2009), except Werck et al. (2008), who show that educational level has a positive and significant impact on municipal cultural spending.

Furthermore, the effect of education on support for public provision of cultural services and spending on culture may depend on the level of government that makes such spending. Brooks (2001) shows level of education is positively correlated with support for local financing of culture, but not when higher-level governments do it. The fact that local public funding has a particularly visible presence in the cultural events contributes to increased support from highly educated individuals, who mostly attend these events.

The result of our study underlines that a more educated population demands efficiently managed quality culture, like Stigler and Becker (1977) and Diniz and Machado (2011).

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-López et al. (2010), in their global study, do not coincide with the results we report, while others like 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).

The political strength of the government has no influence on the management of cultural infrastructures, returning similar results for this variable to those reported by Getzner (2002), Werck et al. (2008) and Stastna (2009), for whom government fragmentation is not significant in culture expense.
6 Conclusions

We have analysed the efficiency in the provision of public cultural facilities of 1,159 Spanish municipalities with populations of between 1,000 and 50,000 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 services.

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, is 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”. Second, 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 (2007, 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 almost all the variables analysed. This relation is negative for population density, proportion of immigrants, proportion of the population aged over 65 years, proportion of the population aged under 15 years and economic activity. The results reveal the difficulties the Spanish municipalities analysed have in managing these infrastructures efficiently. They are characterised by an ageing population, high numbers of immigrants who have increased population density and citizens with low levels of studies and education.
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 the 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.

Notes

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).

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

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

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. See Section 1 in Wilson (1993, pp. 320-321). The numerator is the Andrews and Pregibon (1978) statistic, which Wilson (1993) extends to the case of more than one output. The denominator expresses the minimum value for a certain number of subsets of size $i$ observations. As Wilson (1993) indicates, for large data sets Andrews and Pregibon suggested the graphic representation of the log ratios. Examination of the separation between the smallest ratios indicates possible outliers.

5 We follow Simar and Wilson (2007); the choice of the number of replications $L_1$ in Algorithm #2, determines the number of bootstrap replications used to compute the bias-corrected estimates, $\hat{\delta}$. They found that 100 replications are sufficient for this purpose. For $L_2$ they use 2000 replications. The values of the variables are scaled appropriately; signs of estimated coefficients can be interpreted in a Farrell–Debreu direction. We use the parametric regression bootstrap in order to construct bootstrap-based 95% confidence intervals for each parameter estimate.

References


