ON THE DETERMINANTS OF LOCAL GOVERNMENT PERFORMANCE: A TWO-STAGENONPARAMETRIC APPROACH*

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ON THE DETERMINANTS OF LOCAL GOVERNMENT PERFORMANCE: A TWO-STAGE NONPARAMETRIC APPROACH

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ABSTRACT

This article analyzes the efficiency of Comunitat Valenciana (Spain) local governments and their main explanatory variables. The analysis is performed in two stages. Firstly, efficiency is measured via (nonparametric) activity analysis techniques. The measurement techniques also enable the sources of inefficiency to be identified, i.e., whether inefficiencies are primarily overall cost, technical, or allocative. The second stage identifies some critical determinants of efficiency, focusing both on political and fiscal policy variables. In contrast to previous two-stage research studies, our approach performs the latter attempt via nonparametric smoothing techniques, rather that econometric methods –such as OLS or Tobit related. Results show that inefficiencies are largely attributable to allocative factors, resulting in a notable gap between cost and technical efficiency. Inefficiencies are also larger for small municipalities. However, they are not exclusively attributable to poor management, as second-stage analysis reveals both fiscal and policy variables, either within or outside local governments control, to be explicably related to municipalities' performance.

KEYWORDS: efficiency, kernel smoothing, local government, nonparametric regression.

JEL classification: D24, D60, H71, H72.

RESUMEN

Este trabajo analiza la eficiencia de las corporaciones locales de la Comunidad Valenciana y sus factores determinantes. El análisis se lleva a cabo en dos etapas. En primer lugar, la eficiencia es medida a través de técnicas (no paramétricas) de análisis de la actividad. El empleo de este tipo de técnicas permite también identificar las fuentes de ineficiencia, esto es, si esta es básicamente en costes, técnica o de carácter asignativo. La segunda etapa identifica algunos determinantes clave de la eficiencia, centrándose tanto en variables políticas, así como de política fiscal. Frente a estudios previos en dos etapas, nuestro enfoque lleva a cabo este último objetivo a través de técnicas no paramétricas de suavizado, en lugar de métodos econométricos (tales como MCO o modelos Tobit). Los resultados indican que las ineficiencias son atribuibles en gran parte a factores asignativos, dando lugar a un margen considerable entre eficiencia en costes y eficiencia técnica. La ineficiencia también es mayor para las corporaciones locales más pequeñas. Sin embargo, no es atribuible exclusivamente a una gestión deficiente, pues el análisis de segunda etapa muestra que tanto las variables políticas como las de política fiscal, independientemente de si están o no bajo el control de las corporaciones locales, se hayan relacionadas con su nivel de eficiencia.

PALABRAS CLAVE: eficiencia, suavizado kernel, corporación local, no paramétrica.

1. Introduction

All individuals, government, and firms have an interest, one way or another, in the achievement of efficiency and productivity improvements in public sector activities. The study of public sector efficiency (or, perhaps more appropriately, its inefficiency) is of paramount importance if we consider that bureaucrats may have an incentive to waste resources, not to use inputs optimally and to produce too much, as claimed by Niskanen (1975) or Breton and Wintrobe (1975), amongst others. This ability shown by bureaucrats in pursuing objectives that are not in the interest of the citizen-voters may not be unlimited (Grosskopf and Hayes, 1993). For these and related, reasons, many research studies have analyzed different aspects of efficiency and productivity in various public sector areas as important as health, education, taxation or, in the case we are dealing with, different government departments such as municipalities.[1] In many cases these attempts have been pursued using frontier techniques, both parametric and nonparametric.

Previous literature on the efficiency and productivity of municipalities all over the world consists of research studies which vary widely in many aspects, ranging from their aims to their conclusions. This literature is not abundant, although some relevant contributions have lately been published. Studies which are closer to both our attempts and techniques are, amongst others, De Borger and Kerstens (1996), De Borger *et al.* (1994), Hayes and Chang (1990), Deller (1992), Deller and Rudnicki (1992) or, more recently, Worthington and Dollery (2002). For an excellent survey of frontier efficiency measurement techniques in local government see Worthington and Dollery (2000). Other related studies are those by Davis and Hayes (1993) or Grosskopf and Hayes (1993) and, in general, the literature on local government efficiency and property values. We should also note that some studies focus on the efficiency of a single service rendered by local authorities, although this depends critically on the services and competencies of local authorities, which differ widely from country to country.

The translation of the production process at municipal level in terms of the standard notion of transforming inputs into outputs very often presents a huge problem. In the case of municipalities it is quite common to distinguish three stages in this production process (Bradford *et al.*, 1969). First, there is the transformation of primary inputs (labor, equipment and external services) into intermediate outputs (e.g., hours of traffic control or the extension of police services). Second, these intermediate outputs are transformed into direct outputs (*D-outputs* as termed by Bradford *et al.*, 1969) ready for "consumption" (e.g., the number of urban streets controlled or the number of cases treated). Third, these direct outputs ultimately have welfare effects on consumers (e.g., increasing perceptions and feelings of safety and welfare). This final process is captured by outcome indicators (labeled *C-outputs* by Bradford *et al.*, 1969) that reflect the degree to which the direct outputs of municipal activities translate into welfare improvements as perceived by consumers. Theoretically, efficiency can be measured at each stage of this production process. Yet in practice, data availability problems typically do not allow us to distinguish between primary inputs, intermediate outputs, direct outputs, and final welfare effects. For this reason the analysis is very often limited to the study of the first and second phases of this process: relations between primary inputs or activities and direct outputs.

In this article we focus on the efficiency of Comunitat Valenciana, or Valencian region (Spain) local governments. In this case the literature is much scarcer. However, the study of Spanish local government efficiency is

relevant for several reasons. Amongst them, we find that the decentralization of public responsibilities to lower levels of government has been growing at a fast rate in Spain over the last few years,[2] fueling the debate on operational efficiency in local governments. During the last twenty-five years, both regional and local administrations in Spain have gained competencies at the expense of central administration, especially since the late seventies, following the establishment of democracy.[3] Specifically, the Spanish Constitution granted higher independence to state and local governments, *Comunidades Autónomas*—states or regions, NUTS2 in European terminology—, *Provincias*—provinces, or NUTS3—, and *Municipios*—municipalities, or NUTS5 (Prieto and Zofío, 2001). Proponents of decentralization of public functions to lower levels of government may argue that local responsibility contributes not only to a better match between public services and the needs or preferences of a diverse citizenry, but also as an effective way to control the overall growth of government (Deller, 1992; Marlow, 1988). Indeed, if effective policy is to be formulated, it becomes necessary to improve our understanding of managerial capacity in local governments, due to the increase in functions deriving from decentralization. However, the literature on the relative superiority of a city manager form of government is inconclusive (Hayes and Chang, 1990) as, on the other hand, some authors argue that the small size of operation for many local governments in inherently inefficient in economic terms, and hence costly.

Other papers dealing with the analysis of efficiency in Spanish municipalities are those by Prieto and Zofío (2001) and Giménez and Prior (2001), and differ from ours in several aspects, including the regions studied. Our study focuses on the Valencian region,[4] whereas theirs considered Castilla-León and Catalonia, respectively. Unfortunately, the type of information provided for Spanish municipalities is often different for each region, and very difficult to homogenize, which confines us to the analysis of a single region. There are other works that evaluate Spanish local services, but all of them concentrate on the evaluation of specific services: garbage collection, urban public transport, water supply, local police, fire service, etc. An alternative perspective is presented here, with a focus on the evaluation of local organizations as a whole, such as decision-making units that organize the production process of multiple services (although in some cases only through finance and control but not management). There is, therefore, a risk of classifying a council as inefficient in spite of the fact that some of its services may be well managed. This gives rise to the typical discussion on whether the evaluation should concentrate on basic production plants (understanding "efficiency" as it is applied to fields such as engineering) or, on the contrary, whether it is reasonable to analyze the efficiency of more complex organizations that share common strategic objectives. As mentioned above, this study has opted to carry out a global analysis, relating research to that of Vanden Eeckaut *et al.* (1993) and De Borger and Kerstens (1996) although with significant and specific methodological contributions.

This decision has both positive and negative aspects. On the positive side it should be stressed that each council receives a global efficiency score representing the weighted average efficiency of the different services provided. Furthermore, although it may appear paradoxical, by opting for the evaluation of more disaggregated decision-making units, the analysis of the results obtained could be extremely controversial. For instance, if the information required is not directly available, the application of ungranted cost-accounting imputation criteria is needed to estimate the inputs consumed. This fact is especially important in the sector analyzed, given that, to date, the spillover of cost-accounting practices in Spanish municipalities is very limited. The negative aspect of

the decision lies in the selection of representative variables for the output, as our choice must be representative of the global level of services. This fact hinders further diagnosis of precisely those services which require better management. To summarize, the analysis of specific services provides an acceptable evaluation of production, although all the factors that are actually consumed cannot be analyzed. The choice of the alternative option, however, presents weaknesses on the production side, although the determination of the inputs is more exact.

We focus not only on efficiency but, more importantly, on its determinants. In this case, as suggested by De Borger *et al.* (1994), we find that many studies dealing with estimating inefficiencies in the public sector "simply do not attempt to explain the estimated inefficiencies in a systematic way". In other words, it may also be of interest to determine whether some factors, either discretionary or beyond the control of local managers, may affect the performance of municipalities. This is the spirit of the so-called two-stage, or two-step analyses.

On this point, previous literature has focused less thoroughly on the determinants of inefficiency. However, our study differs substantially from previous contributions[5] in the techniques we employ. Those considered to measure efficiency are fairly standard. Specifically, we use the nonparametric DEA (Data Envelopment Analysis) technique, which is quite often employed in public sector studies. However, we also use a set of nonparametric techniques to analyze the determinants of efficiency, based on previous work by Deaton (1989), DiNardo *et al.* (1996), or Marron and Schmitz (1992), amongst others, in contrast to the more common set of parametric techniques—such as OLS, or Tobit censored regression model—used in the two-stage analyses. These techniques focus on graphical aspects of efficiency results, which provide a great deal of meaningful information, and which may be particularly relevant in our setting, given the peculiar distributions of DEA efficiency scores, which are bounded at unity.

The study is organized as follows. After this introductory section, section 2 introduces the model for measuring efficiency. Section 3 presents the data, inputs and outputs definition, and results. Section 4 sets out both the different explanatory variables for efficiency and the techniques to be employed in the second-stage analysis, together with some results. Finally, section 5 outlines the most relevant conclusions.

2.   Overall cost, technical, and allocative inefficiencies

In principle, measurement of efficiency notions is easy if reliable data are available on both quantities and prices of all inputs and outputs. When some necessary information is unavailable, then we are restricted in the type of efficiency that can be measured. For instance, technical efficiency solely requires data on inputs and outputs, while allocative efficiency requires additional information on input prices. If data on costs are available, but data on prices and physical units are not, cost efficiency can be evaluated, but its decomposition into allocative and technical dimensions cannot. However, if we assume that all Decision Making Units (DMUs) face the same input prices, this decomposition can take place. Consequently, the type of information available determines the flexibility of performance measurement.

To introduce some notations, let us assume that for S observations there are J inputs producing I outputs. Hence, each s observation uses an input vector $\mathbf{x}^s = (x_1^s, \ldots, x_j^s, \ldots, x_J^s) \in \mathbb{R}_+^J$ to produce an output vector

$\mathbf{y}^s = (y_1^s, \ldots, y_i^s, \ldots, y_I^s) \in \mathbb{R}_+^I$. Production technology is defined by the set of feasible input and output vectors:

$$F = \{(\mathbf{x}, \mathbf{y}) | \mathbf{x} \text{ can produce } \mathbf{y}\}. \tag{1}$$

It is also useful to consider the output and input sets associated with this technology. For a given input vector $\mathbf{x}^s$, the output set denotes all output vectors ($\mathbf{y}$) that can be produced from the given input vector $\mathbf{x}^s$:

$$P(\mathbf{x}^s) = \{\mathbf{y} | (\mathbf{x}^s, \mathbf{y}) \in F\}. \tag{2}$$

Also, for a given output vector $\mathbf{y}^s$, the input set denotes all input vectors $\mathbf{x}$ capable of producing the output vector:

$$L(\mathbf{y}^s) = \{\mathbf{x} | (\mathbf{x}, \mathbf{y}^s) \in F\}. \tag{3}$$

The next theoretical building block is the cost efficiency measurement. Treating outputs $\mathbf{y}^s$ as given, we can compute for each observation s the minimum expenditure ($\mathbf{p}^s\mathbf{x}$) to produce observed output vector ($\mathbf{y}^s$):

$$TC^*(\mathbf{y}^s, \mathbf{p}^s) = min\{\mathbf{p}^s\mathbf{x} | \mathbf{x} \in L(\mathbf{y}^s)\}. \tag{4}$$

According to Färe *et al.* (1995), the minimal cost may be calculated as the solution to the linear programming problem:

$$
\begin{aligned}
TC^*(\mathbf{y}^s, \mathbf{p}^s) &= min \ \mathbf{p}^s\mathbf{x} \\
s.t. \quad & \mathbf{x} - \lambda\mathbf{N} \geq \mathbf{0}, \\
& -\mathbf{y}^s + \lambda\mathbf{M} \geq \mathbf{0}, \\
& \overrightarrow{\mathbf{1}}\lambda = 1,
\end{aligned}
\tag{5}
$$

where $\mathbf{N}$ is a matrix containing the observed S input vectors, $\mathbf{M}$ is a matrix containing the observed S output vectors and λ is the activity vector denoting the intensity levels at which the S observations are conducted.[6] As previously mentioned, when information on input prices and input quantities is not available, all units are assumed to face the same input prices, and we operate with input costs variables.

With $TC^*(\mathbf{y}^s, \mathbf{p}^s)$, the overall cost efficiency measure OE^s can easily be defined as the ratio of minimum cost ($\mathbf{p}^s\mathbf{x}$) to observed cost ($\mathbf{p}^s\mathbf{x}^s$), i.e., $OE^s = \mathbf{p}^s\mathbf{x}/\mathbf{p}^s\mathbf{x}^s$. Computing the individual cost efficiency scores requires program (5) to be solved for each s observation, or DMU, in the sample. The value of OE^s is smaller than unity for inefficient observations, and equals unity for efficient observations.

Overall cost efficiency is the multiplicative result of technical efficiency (TE) and allocative efficiency (AE):

$$OE^s = TE^s \cdot AE^s \tag{6}$$

Allocative efficiency requires there to be no divergence between observed and optimal input mix. A municipality is allocatively inefficient otherwise. Overall and allocative efficiency imply price-dependent characterizations of efficiency, while technical efficiency is an entirely price-independent notion.

A more informal definition of the decomposition first requires the specification of the nonparametric tech-

nology with variable returns to scale technological assumption:

$$F = \{(\mathbf{x}, \mathbf{y}) | \mathbf{x} \text{ can produce } \mathbf{y}\} = \{(\mathbf{x}, \mathbf{y}) | \lambda \mathbf{N} = \mathbf{x} \leq \mathbf{x}^s, \lambda \mathbf{M} = \mathbf{y} \geq \mathbf{y}^s, \overrightarrow{\mathbf{1}}\lambda = 1\}. \tag{7}$$

Using this technology, the decomposition is implemented as follows. Technical efficiency is evaluated relative to this technology and allocative efficiency is derived from dividing overall efficiency by technical efficiency. In order to quantify this decomposition we must solve a new linear program that quantifies the technical inefficiency coefficient:

$$
\begin{aligned}
TE^s(\mathbf{y}^s, \mathbf{x}^s) &= min \ \rho^s \\
s.t. \quad &\rho^s \mathbf{x}^s - \lambda \mathbf{N} \geq \mathbf{0}, \\
&-\mathbf{y}^s + \lambda \mathbf{M} \geq \mathbf{0}, \\
&\overrightarrow{\mathbf{1}}\lambda = 1.
\end{aligned}
\tag{8}
$$

Like the OE^s coefficient, the value of TE^s is smaller than unity for technically inefficient observations, and equals unity for technically efficient DMUs. Finally, the allocative inefficiency, due to problems with the observed input mix, is calculated residually from overall cost and technical efficiency coefficients, i.e., $AE^s = OE^s/TE^s$.

So far we have introduced the so-called Farrell-Debreu's idea of efficiency (Farrell, 1957). Yet there exists a more urgent concept based upon the Pareto-Koopmans' idea,[7] which makes allowances for the possible input *excesses*, or output *shortfalls*, represented by $\mathbf{s}^- \in \mathbb{R}^J$ and $\mathbf{s}^+ \in \mathbb{R}^I$, respectively. If these components are to be computed, program (5) becomes:

$$
\begin{aligned}
TC^*(\mathbf{y}^s, \mathbf{p}^s) &= min \ \mathbf{p}^s \mathbf{x} - \epsilon \overrightarrow{\mathbf{1}} \mathbf{s}^+ \\
s.t. \quad &\mathbf{x} - \lambda \mathbf{N} = \mathbf{0}, \\
&-\mathbf{y}^s + \lambda \mathbf{M} - \mathbf{s}^+ = \mathbf{0}, \\
&\overrightarrow{\mathbf{1}}\lambda = 1,
\end{aligned}
\tag{9}
$$

whereas program (8) becomes:

$$
\begin{aligned}
TE^s(y^s, x^s) &= min \ \rho^s - \epsilon \overrightarrow{\mathbf{1}} \mathbf{s}^+ - \epsilon \overrightarrow{\mathbf{1}} \mathbf{s}^- \\
s.t. \quad &\rho^s \mathbf{x}^s - \lambda \mathbf{N} - \mathbf{s}^- = \mathbf{0}, \\
&-\mathbf{y}^s + \lambda \mathbf{M} - \mathbf{s}^+ = \mathbf{0}, \\
&\overrightarrow{\mathbf{1}}\lambda = 1.
\end{aligned}
\tag{10}
$$

where ϵ is an infinitesimal constant introduced so as to provoke a second stage movement via the slack variables, $\mathbf{s}^+$ and $\mathbf{s}^-$ (see Cooper *et al.*, 1999).

3.   Computing efficiency measures for Spanish municipalities

3.1.   Data, inputs, and outputs

The different types of data we will deal with throughout the paper were provided by different institutions. Inputs came from the budget data of local authorities in the Valencian region, which presented information to the Valencian Audit Institution in the year of study (1995). On the other hand, the outputs were obtained

from information gathered in a survey of local infrastructure and equipment devised by the Spanish Ministry for Public Administration. Due to data unavailability, our focus is entirely confined to the year 1995, since output values are only available for that year.

As stated by Fox (2001), it is difficult to measure the inputs and, more especially, the outputs of a hospital, a police force, or a government department. This was also reflected long ago in, for instance, the studies by Bradford *et al.* (1969), or Levitt and Joyce (1987). It also often constitutes a serious source of controversy. Fletcher and Snee (1985) have ranked what hinders output measurement in the public sector, by considering firstly problems in setting the objectives, and secondly problems in measuring the outputs themselves. Given our aims, and considering we are dealing with municipalities, we are not free from criticism. However, in many cases this criticism is leveled as a result of limitations in the database, or simply because of variables which can hardly be justifiable as outputs. On this point, we must acknowledge the virtues of our database, which provides not only quantities for each output but also includes an indicator of quality (good, average, or bad), which turns out to be crucial for assessing local government performance.

Our selection of inputs is based on budgetary variables that reflect municipalities' costs. These are implemented rather than forecasted expenditures, given the usual discrepancies amongst these figures. It is often the case that forecasts underestimate expenditure and overestimate revenues. In contrast to many other studies, we included capital measures—capital expenditures and capital transfers. Descriptive statistics for the year 1995 are provided in Table 1. This choice implies certain problems, as in many instances costs are shared by several government departments.

The selection of outputs is based on the minimum services provided by each municipality. Specifically, all local authorities must provide public street lighting, cemeteries, waste collection and street cleaning services, drinking water to households, access to population centres, surfacing of public roads, and regulation of food and drink. In some cases we have to select proxies for these services. For instance, as pointed out by De Borger and Kerstens (1996), population is assumed to proxy for the various administrative tasks undertaken by municipalities, but it is clearly not a direct output of local production. Other important outputs, such as provision of primary and secondary education, do not come within the responsibilities of municipalities. The list of outputs for 1995, along with summary statistics, is displayed in Table 1. Table 2 also enumerates what service attempts to measure, or to proxy, each output indicator.

We also include an interesting variable aimed at measuring not only the quantity but also the *quality* of the services provided. This unusual type of data turns out to be very informative for municipality output. It is often the case that each local government cannot directly affect, at least in the short-run, the quantity of outputs such as street infrastructure surface area or the registered surface area of public parks. However, it may have a decisive impact on their quality. The information available on this variable is of a categorical nature—the quality of the services offered is arranged in three classifications: good, average or bad. It is quantified using the proposal set out by Banker and Morey (1986b), which involves breaking down the quality variable into two categorical variables, d_1 and d_2. Thus, for unit s, the values taken by d_1 and d_2 are $d_{s1} = d_{s2} = 0$, if the quality is bad, $d_{s1} = 1$ and $d_{s2} = 0$, if the quality is average, and $d_{s1} = d_{s2} = 1$, if the quality is good, weighting for each output's share. Hence, our model includes both production and quality variables, enabling a joint assessment

Table 1: Descriptive statistics for the relevant variables (1995)

Inputs[a]	Mean	Std.dev.
Wages and salaries (X_1)	117335.95	198594.00
Expenditure on goods and services (X_2)	94683.56	153212.62
Current transfers (X_3)	17492.75	35637.52
Capital transfers (X_4)	1587.99	7005.55
Capital expenditure (X_5)	74603.31	115218.63
Outputs	Mean	Std.dev.
Population (Y_1)	4730.18	7607.53
Number of lighting points (Y_2)	594.52	1038.66
Tons of waste (Y_3)	13093.19	75751.95
Street infrastructure surface area[b](Y_4)	126010.25	196552.32
Registered surface area of public parks[b](Y_5)	15957.28	32503.52
Quality (Y_6)	2.632	0.308

[a] In thousands of 1995 pesetas.

[b] In square metres.

Table 2: Output indicators based on the minimum services provided

Minimum services provided	Output indicators
Public street lighting	Number of lighting points
Cemetery	Total population
Waste collection	Waste collected
Street cleaning	Street infrastructure surface area
Supply of drinking water to households	Population, street infrastructure surface area
Access to population centres	Street infrastructure surface area
Surfacing of public roads	Street infrastructure surface area
Regulation of food and drink	Total population

of both efficiency and quality to be made.

3.2. Results

We estimate a common frontier for the year 1995. Results are presented in Table 3. It shows not only simple summary statistics such as mean and standard deviation but also additional statistics which provide further insights into the distribution of efficiency scores. Since the distribution of efficiency measures is skewed, it is of interest using other statistics, such as the median, for a better understanding of what efficiency indices reveal. We also considered that providing results for the different size classes was of interest.

Out of 414 observations, only 32 (7.73%) were found to be cost efficient—i.e., had an efficiency score of 1. Efficiency is enhanced when costs are handled separately and, consequently, technical efficiency is evaluated, for which we find 144 efficient municipalities (34.78%). There are exactly the same number of allocative inefficient units, since allocative inefficiency is computed residually. Therefore, there is a notable gap between overall cost and technical inefficiency attributable to allocative reasons. Specifically, average cost efficiency is 53.1%, whilst average technical inefficiency is 80.1%. Hence, each municipality's specific input mix has quite an effect on its level of cost inefficiency. A sound reallocation of resources would probably lead to a substantial increase in the cost efficiency of many municipalities.

Table 3 also shows that the highest levels of efficiency are found amongst the most highly populated municipalities. Of special note is the technical efficiency for cities with more than 20,000 inhabitants, whose average efficiency is 96.8%. On the other hand, overall cost efficiency is quite low for the smallest group of municipalities (on average, 42.8%). This is also the group of municipalities that shows the greatest disparities amongst DMUs in the group. In addition, small municipalities are those with higher allocative inefficiency, probably stemming from the fact that this is the group of municipalities facing greater difficulties in reallocating inputs in order to achieve cost reductions, given their lower negotiation power. In fact, differences between the most populated and the least populated municipalities are much higher for allocative efficiency (0.887 vs. 0.554), than for technical efficiency (0.968 vs. 0.792, respectively). Furthermore, we should also bear in mind that municipalities with populations of under 5,000 do not have to disclose as much accounting information as those over 5,000, which could lead to less effort being made to monitor expenditures.

We also provide Tukey's box plots to attain a more in-depth interpretation of results. They are particularly informative in the case of efficiency scores obtained via linear programming techniques, which are bounded by zero and unity, and for which a mass of observations achieves the upper bound, typically yielding skewed distributions. Yet as suggested by Lovell *et al.* (1994), skewness of DEA scores is rarely reported, "and even more rarely put to any good use". We report box plots since they disclose a more scrupulous illustration of the distributions, consequently encoding further information on the features possibly hidden by data, such as multi-modality or the existence of outliers, which may have quite an impact on mean efficiency—along with the aforementioned mass of scores at unity.

Box plots are shown in Figure 1 for each size class and the interpretation is straightforward. For each size class, the box represents the 50% mid-range values of the efficiency scores. The length of each box represents the interquartile range (IQR). The line breaking down each box represents the median. The whiskers define the

Table 3: Summary statistics for efficiency measures by population sizes ($N = 414$)

Inefficiency	Size class	Mean	Standard deviation	Skewness	Kurtosis	Minimum	Maximum	% of efficient observations
	All sizes	0.531	0.246	0.373	−0.746	0.014	1.000	32/414(7.73%)
Overall cost	$POP < 1,000$	0.428	0.232	1.016	0.456	0.014	1.000	9/161(5.59%)
	$1,000 \leq POP < 5,000$	0.495	0.202	0.409	−0.091	0.080	1.000	4/144(2.78%)
	$5,000 \leq POP < 20,000$	0.688	0.191	0.042	−0.790	0.260	1.000	8/82(9.76%)
	$POP \geq 20,000$	0.861	0.159	−0.942	−0.084	0.470	1.000	11/27(40.74%)
	All sizes	0.801	0.210	−0.800	−0.377	0.149	1.000	144/414(34.78%)
Technical	$POP < 1,000$	0.792	0.225	−0.641	−0.957	0.232	1.000	66/161(40.99%)
	$1,000 \leq POP < 5,000$	0.749	0.209	−0.607	−0.240	0.149	1.000	30/144(20.83%)
	$5,000 \leq POP < 20,000$	0.855	0.170	−1.153	0.561	0.371	1.000	30/82(36.59%)
	$POP \geq 20,000$	0.968	0.064	−2.003	3.079	0.773	1.000	18/27(66.67%)
	All sizes	0.658	0.219	−0.286	−0.697	0.014	1.000	32/414(7.73%)
Allocative	$POP < 1,000$	0.544	0.225	0.280	−0.543	0.014	1.000	9/161(5.59%)
	$1,000 \leq POP < 5,000$	0.658	0.175	−0.242	−0.556	0.243	1.000	4/144(2.78%)
	$5,000 \leq POP < 20,000$	0.805	0.141	−0.574	−0.307	0.441	1.000	8/82(9.76%)
	$POP \geq 20,000$	0.887	0.138	−1.182	0.427	0.537	1.000	11/27(40.74%)

Figure 1: Tukey's box plots of efficiency scores (overall cost, technical, and allocative) by size classes

a) **Overall cost**

b) **Technical**

c) **Allocative**
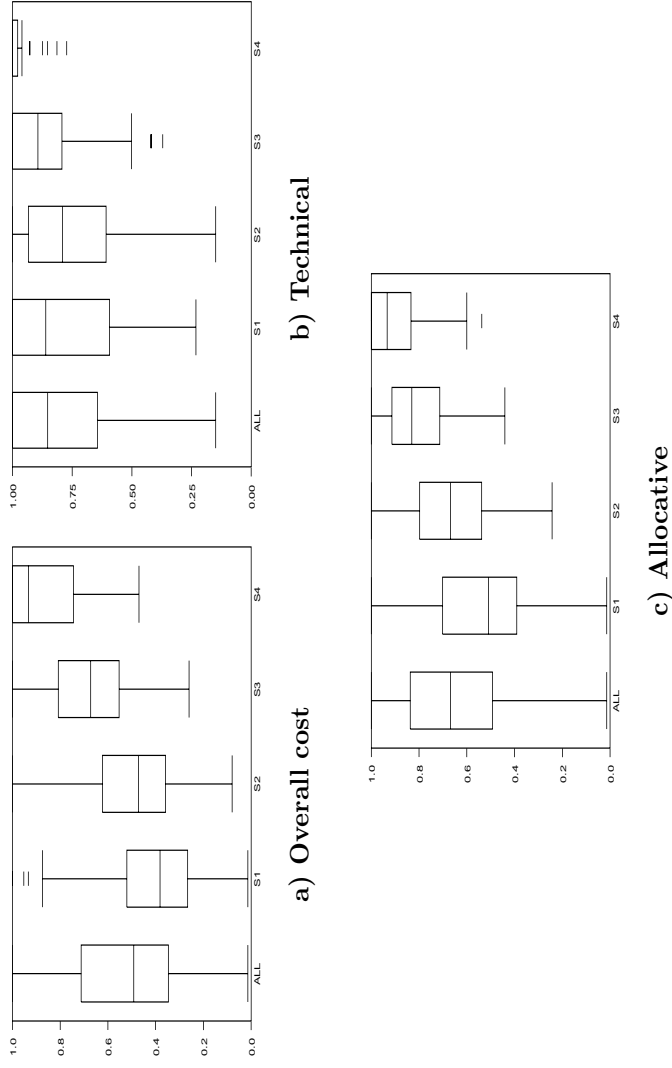
All sizes: all municipalities.
S1: municipalities with $POP < 1,000$.
S2: municipalities with $1,000 \leq POP < 5,000$.
S3: municipalities with $5,000 \leq POP < 20,000$.
S4: municipalities with $POP \geq 20,000$.

natural bounds of the distributions, i.e., the mean$\pm IQR$, while the short lines represent outliers lying outside the natural bounds.

It can be observed from the IQRs that the distribution of efficiency scores steadily shrinks with size. The most inefficient observations are found amongst the smallest size classes, especially amongst those municipalities with fewer than 1,000 inhabitants. On the other hand, most of the largest municipalities are efficient. Indeed, all inefficient municipalities in this size class are classified as outliers. However, given our variable returns to scale assumption, this inefficiency does not take problems of scale into account, and only compares entities with those of similar sizes. Therefore, although it seems that larger municipalities are closer to the frontier due to their greater resources (qualified staff, better information technology resources, etc.), we must bear in mind the scale effect, i.e., we are comparing equals.

Technical inefficiency is generated due to a failure in the use of the different inputs required in the production process. Yet the efficiency measures we have computed so far do not inform on what the greatest sources of input waste are. We already know there is a notable disparity between cost and technical inefficiencies due to allocative reasons, but nothing is known about exactly which inputs are those inputs whose use might be optimized to a greatest extent. This type of information is summarized by the input and output specific inefficiencies, representing input excesses and output shortfalls, respectively. Indeed, some authors argue that any non-zero input or output specific inefficiencies should be reported so as to provide an accurate indication of a municipality's technical efficiency.

Table 4 reports summary statistics for input specific inefficiencies, or input excess, indicating whether excessive use of specific resources exists. Figures closer to zero indicate optimal behavior (no waste of inputs), whereas figures closer to one indicate greater input waste. For all input variables, we find similar average values, ranging from 21.2% to 24.7%—except for capital transfers (X_4), whose average input excess is only 11.7%. A meticulous scrutiny of each figure displayed in Table 4 reveals that, once more, large cities (in terms of population) show the leading performance. Yet we can also observe that the two least populated categories show a similar behavior.

The lower value of X_4 with respect to X_5 could give a misleading impression, given that both variables are related to capital expenditures. A deeper scrutiny of both variables suggests X_4 refers to external transfers (to firms, etc.), whereas X_5 is related to direct transfers to the council. The emerging picture seems to suggest that the expenditures which are not to be invested in the municipality itself are managed more diligently, so as to minimize this type of expenditures.

Of special note is also the high value found for X_3, encoding current transfers, which could stem from the tendency of some municipalities to confer public services to other firms and organizations, either public or private. An input excess could therefore imply that some public contracts are awarded inefficiently. Yet for large municipalities X_3 holds the lowest value, suggesting either that external firms are not contracted, or that these firms and/or organizations perform their tasks much more efficiently, given the tough competition they face from other possible firms being contracted.

Table 5 discloses results for output shortfalls, or underprovision of outputs. Optimal behavior must be interpreted the other way round, as figures closer to zero indicate stronger underprovision of outputs. In

Table 4: Summary statistics for specific input inefficiency[a]

Variable	Size class	Mean	Standard deviation	Median	Kurtosis	Skewness	Minimum	Maximum
X_1	All sizes	0.212	0.219	0.164	−0.418	0.762	0.000	0.881
	$POP < 1,000$	0.227	0.236	0.167	−0.897	0.596	0.000	0.881
	$1,000 \leq POP < 5,000$	0.257	0.214	0.211	−0.208	0.629	0.000	0.851
	$5,000 \leq POP < 20,000$	0.155	0.183	0.114	0.068	1.067	0.000	0.629
	$POP \geq 20,000$	0.062	0.125	0.000	7.178	2.586	0.000	0.527
X_2	All sizes	0.221	0.226	0.170	−0.497	0.720	0.000	0.922
	$POP < 1,000$	0.237	0.245	0.220	−1.009	0.528	0.000	0.922
	$1,000 \leq POP < 5,000$	0.274	0.224	0.246	−0.438	0.529	0.000	0.900
	$5,000 \leq POP < 20,000$	0.155	0.177	0.121	0.649	1.123	0.000	0.698
	$POP \geq 20,000$	0.049	0.102	0.000	6.090	2.454	0.000	0.415
X_3	All sizes	0.247	0.261	0.176	−0.450	0.804	0.000	0.972
	$POP < 1,000$	0.266	0.285	0.181	−0.773	0.689	0.000	0.972
	$1,000 \leq POP < 5,000$	0.308	0.257	0.312	−0.670	0.513	0.000	0.908
	$5,000 \leq POP < 20,000$	0.171	0.207	0.114	0.385	1.181	0.000	0.732
	$POP \geq 20,000$	0.044	0.093	0.000	8.920	2.797	0.000	0.412
X_4	All sizes	0.117	0.267	0.000	3.561	2.217	0.000	1.000
	$POP < 1,000$	0.142	0.302	0.000	1.850	1.866	0.000	1.000
	$1,000 \leq POP < 5,000$	0.120	0.262	0.000	3.254	2.110	0.000	1.000
	$5,000 \leq POP < 20,000$	0.085	0.217	0.000	9.798	3.139	0.000	1.000
	$POP \geq 20,000$	0.049	0.196	0.000	20.902	4.486	0.000	0.975
X_5	All sizes	0.246	0.248	0.184	−0.886	0.601	0.000	0.851
	$POP < 1,000$	0.264	0.267	0.229	−1.311	0.424	0.000	0.842
	$1,000 \leq POP < 5,000$	0.287	0.239	0.246	−0.680	0.514	0.000	0.851
	$5,000 \leq POP < 20,000$	0.195	0.225	0.116	−0.354	0.890	0.000	0.781
	$POP \geq 20,000$	0.081	0.149	0.000	2.555	1.825	0.000	0.535

[a] Specific input inefficiency includes both the radial reduction of inputs plus the input slack, and refers to the magnitude of inputs "to gain".

Table 5: Summary statistics for specific output inefficiency[a]

Variable	Size class	Mean	Standard deviation	Median	Kurtosis	Skewness	Minimum	Maximum
Y_1	All sizes	0.933	0.157	1.000	11.984	−3.214	0.010	1.000
	$POP < 1,000$	0.968	0.111	1.000	30.931	−5.100	0.089	1.000
	$1,000 \leq POP < 5,000$	0.912	0.179	1.000	9.127	−2.799	0.010	1.000
	$5,000 \leq POP < 20,000$	0.899	0.190	1.000	6.307	−2.403	0.040	1.000
	$POP \geq 20,000$	0.941	0.119	1.000	4.359	−2.182	0.545	1.000
Y_2	All sizes	0.818	0.280	1.000	1.209	−1.488	0.000	1.000
	$POP < 1,000$	0.844	0.281	1.000	2.344	−1.856	0.000	1.000
	$1,000 \leq POP < 5,000$	0.735	0.292	0.809	−0.485	−0.758	0.000	1.000
	$5,000 \leq POP < 20,000$	0.867	0.256	1.000	4.519	−2.218	0.000	1.000
	$POP \geq 20,000$	0.965	0.107	1.000	19.547	−4.240	0.465	1.000
Y_3	All sizes	0.914	0.173	1.000	6.672	−2.431	0.007	1.000
	$POP < 1,000$	0.947	0.134	1.000	12.156	−3.162	0.086	1.000
	$1,000 \leq POP < 5,000$	0.891	0.195	1.000	5.510	−2.248	0.007	1.000
	$5,000 \leq POP < 20,000$	0.882	0.199	1.000	3.740	−1.852	0.009	1.000
	$POP \geq 20,000$	0.934	0.143	1.000	2.250	−1.922	0.522	1.000
Y_4	All sizes	0.719	0.388	1.000	−0.920	−0.896	0.000	1.000
	$POP < 1,000$	0.679	0.430	1.000	−1.290	−0.760	0.000	1.000
	$1,000 \leq POP < 5,000$	0.721	0.366	1.000	−1.034	−0.806	0.000	1.000
	$5,000 \leq POP < 20,000$	0.736	0.357	1.000	−0.619	−0.955	0.000	1.000
	$POP \geq 20,000$	0.887	0.283	1.000	4.700	−2.451	0.025	1.000
Y_5	All sizes	0.969	0.100	1.000	60.096	−6.936	0.001	1.000
	$POP < 1,000$	0.973	0.071	1.000	10.924	−3.188	0.566	1.000
	$1,000 \leq POP < 5,000$	0.961	0.124	1.000	45.446	−6.340	0.001	1.000
	$5,000 \leq POP < 20,000$	0.969	0.114	1.000	64.870	−7.681	0.006	1.000
	$POP \geq 20,000$	0.992	0.036	1.000	24.130	−4.845	0.818	1.000
Y_6	All sizes	0.984	0.107	1.000	63.420	−7.804	0.013	1.000
	$POP < 1,000$	0.982	0.102	1.000	57.503	−7.241	0.039	1.000
	$1,000 \leq POP < 5,000$	0.980	0.123	1.000	52.757	−7.157	0.013	1.000
	$5,000 \leq POP < 20,000$	0.989	0.102	1.000	81.999	−9.055	0.075	1.000
	$POP \geq 20,000$	1.000	0.001	1.000	27.000	−5.196	0.993	1.000

[a] Specific output inefficiency, includes both the radial expansion of outputs plus the output slack, and refers to the magnitude of outputs "achieved". Consequently, figures closer to 1 suggest absence of output shortfall.

some cases, the interpretation of certain results is slightly critical. For instance, a DMU for which variable Y_1 shows an indicator below unity would indicate that this municipality is "underproviding" population. In the case of Y_3, the output not provided in sufficient amount is "tones of waste". Yet both Y_1 and Y_3 show the lowest shortfalls—the indicator is close to unity. This would imply that for the amount of services provided, population could be higher. On the other hand, both Y_2 and Y_4 exhibit the highest shortfalls—as shown by lower indicators, i.e., closer to zero. This means that the most underprovided outputs are the number of lighting points and street infrastructure surface area, respectively, which particularly holds for small municipalities. This explanation coincides with that for input excesses, as small municipalities do not manage variable X_5, i.e., capital expenditure as efficiently. However, this also occurs because small municipalities require higher capital expenditures per capita.

4. Efficiency explanatory variables

DEA computations yield only a first-stage, first-order, or first-step measure of relative efficiency. What is not known is the reason for variations in such efficiency patterns, and it is clear that computing individual efficiency scores may not be enough for either consulting purposes or for policy analysis. Accordingly, a second-stage analysis is called for, as efficiency may be affected not only by inadequate management but also by exogenous factors beyond the control of each local government. As Lovell *et al.* (1994) pointed out, such ideas had been already considered by Lewin and Minton (1986) in their research agenda, calling for studies aimed at illustrating the "feasibility of using DEA (perhaps in combination with other analytical methods) as a mathematic for relating effectiveness outcomes to features of organization design".

In our search for explanatory variables we considered the information provided by the Valencian Audit Institution on different financial and budgetary, fiscal policy, variables, such as tax revenue, grants, or financial liabilities. We also considered a political variable which is the percentage of votes of the governing party from the total votes in each municipality. This is a group of factors over which a local government may exert certain managerial control. However, others may be thought of as nondiscretionary, or exogenous.[8] The expected impact of each factor on the efficiency scores is commented on below.

Of the fiscal policy variables the first one to be considered is tax revenue per capita ($TAXES$). We may hypothesize a negative impact on efficiency, as it seems reasonable that a local government that is highly capable of generating revenues would be less motivated to manage them efficiently. This idea also comes from the property rights and principal-agent literature, which outlines several reasons why politicians and public managers may lack proper incentives to effectively audit and control expenditures (De Borger and Kerstens, 1996). On the other hand, high taxes may increase voters' awareness of control of public expenditure (Davis and Hayes, 1993). Yet such an awareness might, instead, worsen efficiency, and the situation could occur that bureaucrats had a preference for more visible inputs rather than those which are less tangible, since they are easier to justify in the appropriation process (Lindsay, 1976). For instance, police cars may be more visible than training.[9]

The second fiscal policy variable to be considered is transfers, or grants, divided by population ($GRANTS$),

representing transfers received from higher layers of government, which depend on variables such as number of inhabitants, number of schools, etc. More than 70% of these grants are unconditional grants for current spending. They also account for nearly 40% of total non-financial revenues of Spanish municipalities. Following Silkman and Young (1982), this variable may be regarded as having a negative association with efficiency, as the cost of inefficient behavior is increasingly shared by a broader constituency.[10]

Thirdly, self-generated revenues (divided by population) ($SELFG$), which include not only general taxes but also other revenues such as those from taxes on personal wealth or fortune and local government property transfers, which share the common feature of being self-generated by each municipality. Therefore, this variable partially overlaps with $TAXES$, and the likely impact is expected to be similar, although in this case the intensity of monitoring by the citizens' effect (Davis and Hayes, 1993) is partially lessened.

Local governments with lower fiscal revenue capacity will probably be impelled to follow alternative paths to raise revenues, such as issuing securities or making loans. To proxy for these effects, we include the variable $SECLOAN$, which measures income generated by issuing debt and making loans, divided by population. Its impact on efficiency is not a priori obvious. We may hypothesize that the municipalities that issue bonds and securities are those unable to raise revenues via taxes. In such a case, the taxpayers' incentives to effectively control expenditures may be low and, consequently, we might expect a negative relationship with efficiency. On the other hand, this variable is assumed to be inversely related to $TAXES$ and $SELFG$, as the municipalities with higher levels of issued securities are possibly those unable to generate revenues in more traditional ways— i.e., taxes. In such a case, the impact over efficiency would be positive.

Another variable to be included is total expenses divided by total revenues ($DEFICIT$), which proxies the idea of deficit—although defined in a different way—and is expected to be negatively associated with efficiency. As deficit increases, we may face a higher social awareness to encourage its reduction; in such a case, local governments may adopt strategies to enhance efficiency. Municipalities carry on activities within the framework of a financial contingency which requires a balance between their receipts and their expenditures, the rupture of which can put them in a situation of financial vulnerability. This may be due to inefficient management, or simply to structural insufficiency of resources. Thus, one may hypothesize an inverse relationship between efficiency and financial vulnerability. If we define financial vulnerability as the inability of a municipality to face its present and future financial commitments as they fall due, we may consider deficit a good proxy for it.

Apart from these fiscal policy variables, we have included a political variable representing the relative importance of votes held by the governing party divided by population ($VOTES$). If the governing party has an absolute majority, other parties or coalitions will possibly face greater difficulties in effectively controlling expenditures. Efficiency might not be the criterion used when awarding contracts for public works or building permission, hiring new workers, or setting local managers wages, with the possible result that court orders are the only way to control this expenditure. In such a case the expected association between $VOTES$ and efficiency would be negative. However, one might alternatively hypothesize a positive association since city managers would have an incentive to lower costs and increase efficiency in order to ensure their job security.[11]

4.1. Kernel contributions: nonparametric kernel regression and bivariate density functions

As shown in section 3 in the Tukey's box plots, it may easily be inferred that the distributions of efficiency scores differ substantially from the symmetric Gaussian bell-shape distribution. In such a case, it may be potentially erroneous to consider OLS, given the assumptions inherent in this technique. Accordingly, previous research studies performing this type of two-stage analysis consider alternative estimation techniques, such as the Tobit censored regression model so as to accommodate the efficiency scores at unity. Unfortunately, this alternative method may have further disadvantages as to the (likely) correlation between the efficiency scores and the explanatory variables (see De Borger and Kerstens, 1996). Some other authors (see Charnes *et al.*, 1988) have addressed the violation of normality assumption by employing the L_1-metric regression. Alternatively, Lovell *et al.* (1994) construct modified DEA efficiency scores (MDEA efficiency scores) which are only bounded by zero, following Andersen and Petersen (1993), whereas Ray (1991) considers a variant of corrected least squares in the second stage.

Furthermore, the efficiency scores generated by DEA, in the same manner as other nonparametric techniques for efficiency measurement, are clearly dependent on each other in the statistical sense. The calculation of each DEA efficiency score for one municipality involves all the other municipalities in the observation set. This circumstance indicates that the potential regression analysis results, as one of its basic model assumptions is not met. Whether we consider OLS or Tobit models, in both cases disturbances are assumed to be *i.i.d* drawings from a normal distribution. Since the distributions of both the dependent variable and the disturbances are the same (only their means are different), we are assuming that the efficiency scores are independent, which is not true. In addition, as outlined by De Borger *et al.* (1994), it is well-known that the Tobit estimates are sensitive to any violation in the underlying assumptions. These ideas have been forcefully made by Harker and Xue (1999), who suggest a bootstrap methodology so as to address the problem.[12]

These somewhat troublesome issues have led us to consider an alternative set of techniques for disentangling the variables representing the factors likely to impact on efficiency performance of local governments. Specifically, we consider both nonparametric regression and nonparametric density estimation, which are less powerful in terms of prediction yet extremely informative for explanatory purposes. They are particularly useful in the case of local government studies where the number of observations is usually large. They build on previous work from authors such as, for instance, Deaton (1989), DiNardo *et al.* (1996) or Marron and Schmitz (1992). Their main advantage is their nonparametric nature, conferring them an ability to provide easily comprehended graphical descriptions of the data that are directly informative about the problem in hand. In addition, this methodology is relatively robust to outlying observations.

4.1.1. Nonparametric kernel regression

In econometrics, the assumption of statistical adequacy or correct specification has been a constant concern for some time now. This concern is present in our setting, for the reasons set out above. In fact, as Haavelmo (1944) asks, "what is the use of testing, say, the significance of regression coefficients when maybe the whole assumption of the linear regression equation is wrong?" (Haavelmo, 1944, p. 66). The peculiar structure of our

data, made explicit in Figure 1, puts forward the employment of nonparametric techniques, which allow us not only to relax the assumptions of the underlying model, but also help in corroborating the goodness (or lack) of fit of parametric specifications.

The basic purpose of a regression analysis is to study how a variable Y, in our case efficiency estimates, responds to changes in another variable X. So as to prevent convoluting notation, these two variables will be labeled EFF and z, respectively, where EFF may refer to either overall cost, technical, or allocative efficiency. If we have data on these variables, then smoothing of a data set $\{(Z_s, EFF_s)\}_{s=1}^{S}$ involves the approximation of the mean response curve m in the regression relationship:

$$EFF_s = m(z_s) + \varepsilon_s, \ s = 1, \ldots, S. \tag{11}$$

where ε_s represents the error term. The less we know about the nature of m, the more desirable a nonparametric estimation approach is. These methods impose a minimum of structure on the regression function. Therefore, the main advantage of this technique is that the data are allowed to choose the shape of the function, and there is nothing that forces the points to lie along a straight line, or along a low-order polynomial (Deaton, 1989). Nonparametric methods are also known as *smoothing* methods, i.e., methods aimed at sanding away the rough edges from a set of data or, in other words, to remove data variability that has no assignable cause and to thereby make systematic features of the data more apparent (Hart, 1997).

The basic idea of smoothing lies in a *local averaging procedure*, which is constructed in such a way that it is defined only from observations in a small neighborhood around z, since EFF-observations from points far away from z will have, in general, very different mean values.[13]

More formally, the procedure can be defined as:

$$\hat{m}(z) = S^{-1} \sum_{s=1}^{S} W_{S,s}(z) EFF_s \tag{12}$$

where $\{W_{S,s}(z)\}_{s=1}^{S}$ denotes a sequence of weights which may depend on the whole vector $\{z_s\}_{s=1}^{S}$.

An alternative way of looking at the local averaging formula (12) is to suppose that the weights $\{W_{S,s}\}$ are positive and sum to one for all z, i.e., $S^{-1} \sum_{s=1}^{S} W_{S,s}(z) = 1$. Then $\hat{m}(z)$ is a *least squares estimate* at point z since we can write $\hat{m}(z)$ as a solution to the following minimization problem:

$$\min_{\theta} \ S^{-1} \sum_{s=1}^{S} W_{S,s}(z)(EFF_s - \theta)^2 = S^{-1} \sum_{s=1}^{S} W_{S,s}(z)(EFF_s - \hat{m}(z))^2. \tag{13}$$

According to formula (13), we realize that the basic idea of local averaging is equivalent to the procedure of finding a local weighted least squares estimate.

Nadaraya (1964) and Watson (1964) proposed the estimator of $m(z)$ as a local average of EFF_s, and can be written as:

$$\hat{m}(z) = \frac{\sum_{s=1}^{S} EFF_s K_h(z - z_s)}{\sum_{s=1}^{S} K_h(z - z_s)} \tag{14}$$

which may be decomposed as

$$\hat{m}(z) = \sum_{s=1}^{S} EFF_s W_s(z) \tag{15}$$

and

$$W_s(z) = \frac{K_h(z - z_s)}{\sum_{s=1}^{S} K_h(z - z_s)} \tag{16}$$

where $K_h(\cdot)$ is a kernel function satisfying different properties.

The choice of kernel, $K_h(\cdot)$, may consist of several alternatives. For reasons of simplicity, we used a Gaussian kernel, whose formula is based on the Gaussian density function:

$$K_h(z - z_s) = \frac{1}{(2\pi)^{1/2}} exp\left[-\frac{1}{2} \left(\frac{z - z_s}{h} \right)^2 \right] \tag{17}$$

where the quantity h is the bandwidth or smoothing parameter and controls the smoothness of $\hat{m}$—likewise the window width controls the smoothness of a moving average. Indeed, our choice of kernel is related to the right amount of smoothing, i.e., the choice of bandwidth. This is the most crucial decision in nonparametric regression. Every smoothing method has to be tuned by some smoothing parameter which balances the degree of fidelity to data against the smoothness of the estimated curve. Although more popular techniques are available, such as cross-validation, our focus will be on the more up-to-date approaches. Specifically, we follow the contribution by Ruppert *et al.* (1995), who suggest plug-in rules. As stated by DiNardo *et al.* (1996), plug-in methods do not exhibit the discretization problems associated with cross-validation. Obviously, if we want a smooth to be merely a descriptive device, the "by eye" technique may be satisfactory. However, this approach is unsatisfactory in many circumstances. Thus, the practical implementation of any scatterplot, or nonparametric regression smoother is greatly enhanced by the availability of a reliable rule for automatic selection of the smoothing parameter.

Graphs 2.a–2.f are nonparametric regressions of the efficiency scores on each of the explanatory variables estimated by kernel smoothing, using the Nadaraya-Watson estimator. They generally support the hypothesized signs of the regressions, although to varying extents. Regarding fiscal policy variables, we observe that efficiency decreases with tax revenues, $(TAXES)$, self-generated revenues $(SELFG)$, and deficit $(DEFICIT)$, as expected. However, grants $(GRANTS)$ do not offer a clear pattern either towards increase or decrease. Yet this occurs only for technical efficiency, whilst both cost and allocative efficiency do show a clear negative slope. A plausible explanation, which we defer to the following paragraphs, could come from the existence of extreme observations. In the case of loans and issued securities $(SECLOAN)$, where the sign was hypothesized to be positive, the pattern is less clear, although the visual snapshot partly suggests a negative relationship.

If we examine the particular details, we observe that the explanatory power of the grants variable $(GRANTS)$ exhibits a negative relationship for both allocative and, especially, cost efficiency. In addition, the relationship does not exhibit remarkable ups and downs, rather it is linear. Our finding coincides with those of Silkman and Young (1982), or De Borger and Kerstens (1996), who suggest that grants may not only encourage local service provision, but also stimulate inefficiency, as the cost of inefficient behavior is increasingly shared by national, or

regional, taxpayers. In the case of self-generated revenues ($SELFG$), the association is also negative, although it exhibits some non-linearities: efficiency decreases steadily in the middle range, but the situation is less clear at boundaries. This variable is highly related to tax revenues ($TAXES$). In fact, they only differ because $TAXES$ only accounts for revenues entirely generated via taxes.

In contrast, our variable with the strongest political content, i.e., the governing party share of votes ($VOTES$) does exhibit a fuzzy pattern (Figure 2.f), and no conclusion may be drawn—in principle. Accordingly, we cannot state that there is sufficient empirical evidence to corroborate the hypothesis that municipalities managed by governments with a higher percentage of votes, more unlikely to face monitoring by other parties, have fewer incentives to manage their resources efficiently.

4.2. Nonparametric bivariate density estimation

Unfortunately, the information provided by nonparametric regression is slightly skeletal. To fill out this information, we provide nonparametric estimation of the joint density functions of efficiency and each of the explanatory variables. Its basic ideas closely resemble those underlying scatterplot smoothing (or nonparametric regression), and therefore details have been deferred to appendix A. The main difference is that now observations are counted and weighted, not in an interval band around each point, but in a two dimensional elliptical band. For clearer interpretation, we also provide contour maps, where points linked by a contour have the same density, and the contours are equally spaced.

This complementary approach is extremely informative, as it provides clear awareness of what exactly underlies each regression line. Hence, we know exactly the probability mass or, put it another way, the empirical evidence supporting each claimed sign for the differing associations.

The precise interpretation would suggest that when a negatively sloped regression line is observed, supporting an inverse association between certain variable and efficiency, its corresponding bivariate density function should exhibit probability mass also concentrated along a "hypothetical" negative slope in each contour map. In other words, we would observe a collection of (possibly) consecutive bumps, possibly with high peaks, with probability vanishing at other locations of the figure. In the likely event that these bumps were firmly concentrated along the negative slope, it would indicate empirical evidence to support our prediction. This outcome would constitute a parallelism with the case of (parametric) linear regression when a high value for the t-statistic is achieved. On the other hand, if probability mass in the bivariate figure does not follow the path determined by the nonparametric regression line, the scenario would mirror the case of linear regression when a poorer value for the t-statistic is obtained.

Joint density functions are shown in Figures 3, 4 and 5 for all overall cost, technical and allocative efficiency, respectively. Their respective contour maps are displayed in Figures 7, 6, and 8. Regarding technical efficiency, a paradigm is constituted by Figure 4.b. Its nonparametric regression counterpart, i.e., Figure 2.b, shows an unstable pattern, as the relationship between efficiency and transfers is negative except for those municipalities with higher transfers, or grants, for which the relationship is positive. But Figure 4.b, together with its contour plot in Figure 7.b, reveals that the units driving the regression line to shift upwards are very few, as probability mass in the 3-d plot is scarce at its top-right end.

Figure 2: Efficiency determinants, Nadaraya–Watson nonparametric regression (overall cost, technical, and allocative efficiency)

a) *TAXES*

b) *GRANTS*

c) *SELFG*

d) *SECLOAN*

e) *DEFICIT*

f) *VOTES*

Overall cost ----- Technical —— Allocative ......
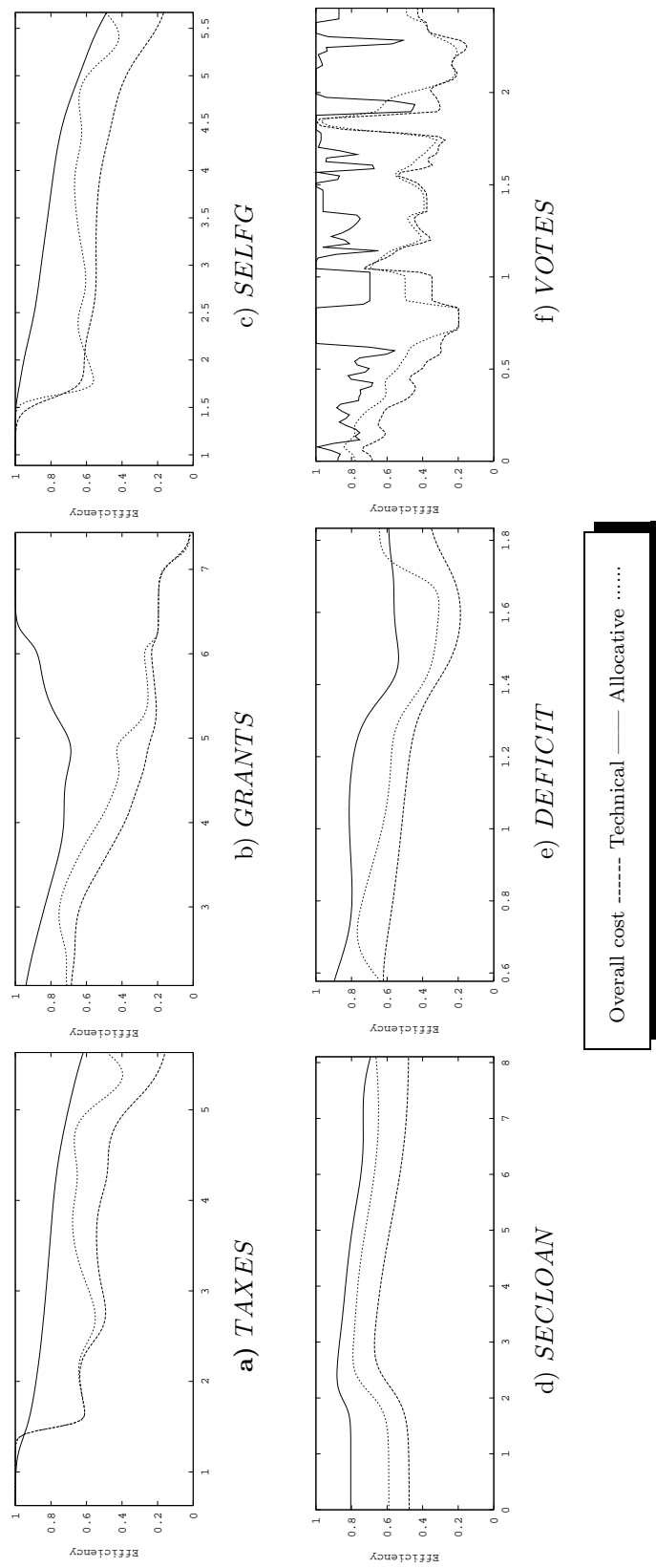
Nonparametric kernel regression, Gaussian kernel, bandwidths chosen according to the plug-in rules in Ruppert, *et al.* (1995) ($h_{TAXES} = 0.1926$, $h_{GRANTS} = 0.3762$, $h_{SELFG} = 0.0808$, $h_{SECLOAN} = 0.4089$, $h_{DEFICIT} = 0.0886$).
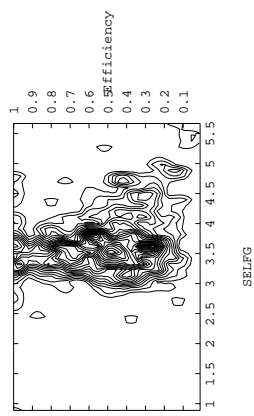
Figure 3: Efficiency determinants, joint densities, overall cost efficiency
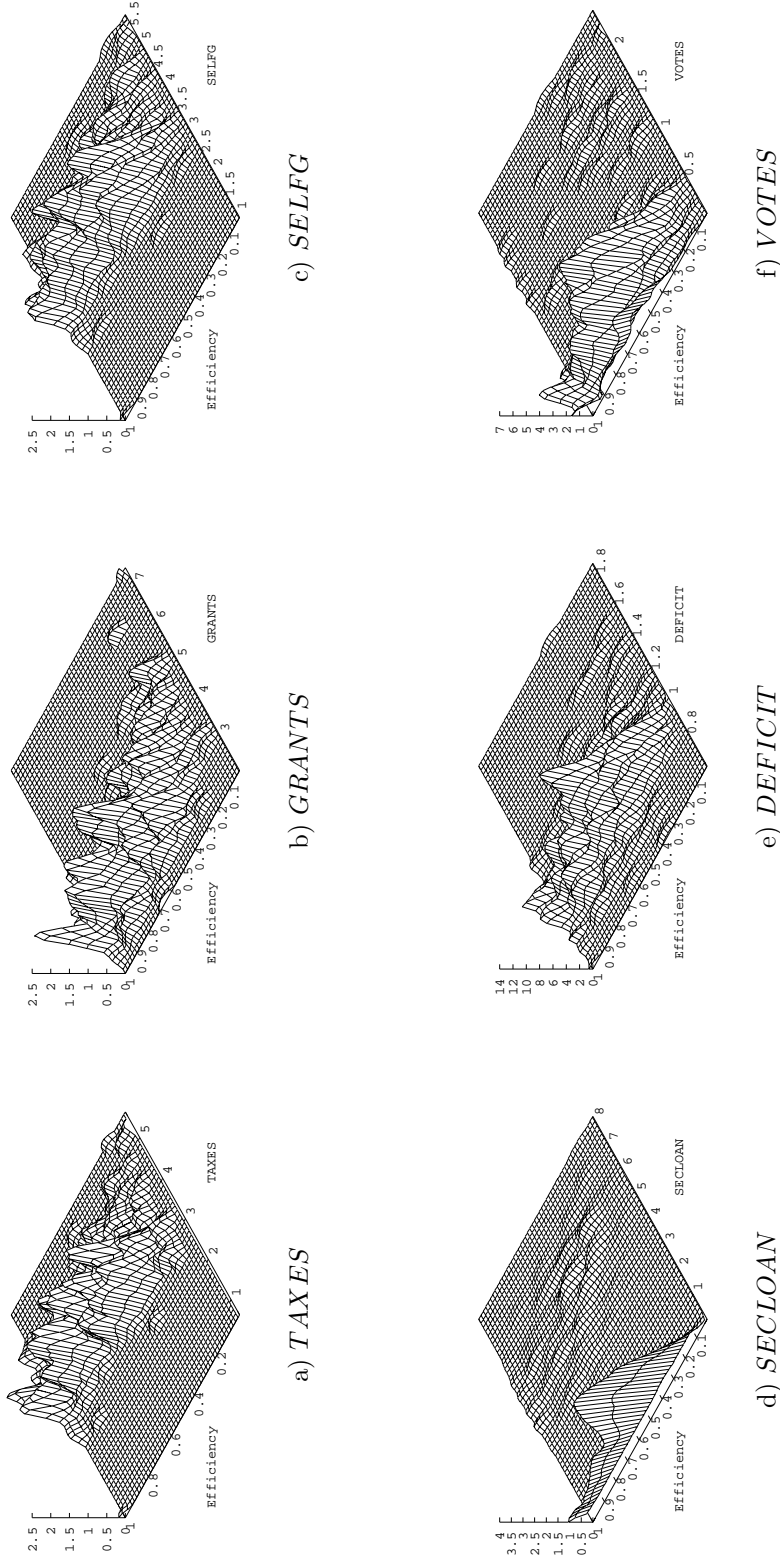
a) *TAXES*

b) *GRANTS*

c) *SELFG*

d) *SECLOAN*

e) *DEFICIT*

f) *VOTES*

Densities estimated nonparametrically by means of Epanechnikov kernel, bandwidths chosen according to Wand and Jones (1994). Different bandwidths are estimated for each co-ordinate direction. $h(TAXES)_{TAXES} = 0.1727$, $h(TAXES)_{\text{Efficiency}} = 0.0513$, $h(GRANTS)_{GRANTS} = 0.1482$, $h(GRANTS)_{\text{Efficiency}} = 0.0653$, $h(SELFG)_{SELFG} = 0.1329$, $h(SELFG)_{\text{Efficiency}} = 0.0849$, $h(SECLOAN)_{SECLOAN} = 0.2768$, $h(SECLOAN)_{\text{Efficiency}} = 0.0884$, $h(DEFICIT)_{DEFICIT} = 0.0325$, $h(DEFICIT)_{\text{Efficiency}} = 0.0808$, $h(VOTES)_{VOTES} = 0.0641$, $h(VOTES)_{\text{Efficiency}} = 0.0815$.

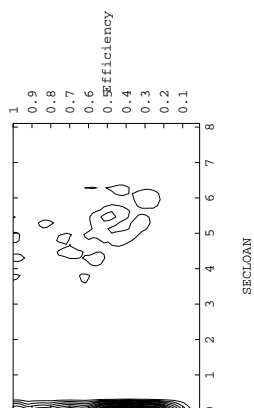**Figure 4:** Efficiency determinants, joint densities, technical efficiency
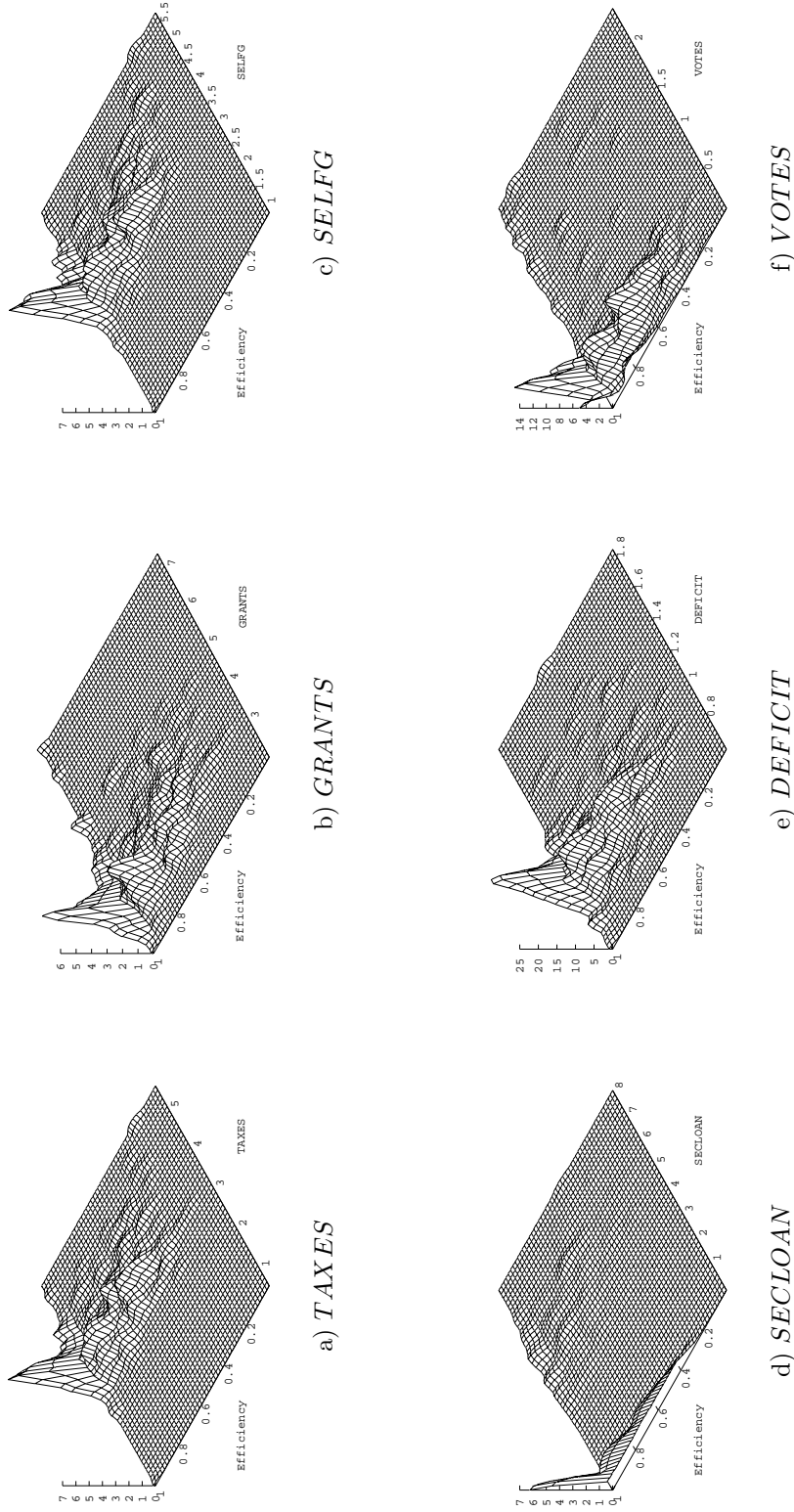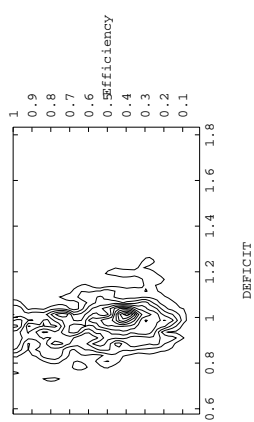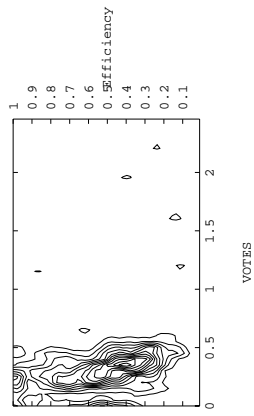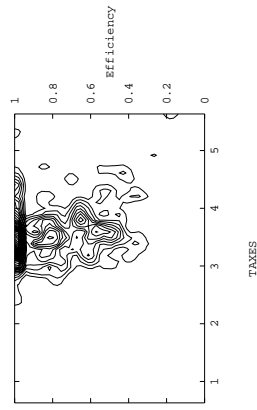

a) *TAXES*

b) *GRANTS*

c) *SELFG*

d) *SECLOAN*

e) *DEFICIT*

f) *VOTES*

Densities estimated nonparametrically by means of Epanechnikov kernel, bandwidths chosen according to Wand and Jones (1994). Different bandwidths are estimated for each co-ordinate direction. $h(TAXES)_{TAXES} = 0.1473$, $h(TAXES)_{\text{Efficiency}} = 0.0631$, $h(GRANTS)_{GRANTS} = 0.1718$, $h(GRANTS)_{\text{Efficiency}} = 0.0606$, $h(SELFG)_{SELFG} = 0.1380$, $h(SELFG)_{\text{Efficiency}} = 0.0618$, $h(SECLOAN)_{SECLOAN} = 0.3115$, $h(SECLOAN)_{\text{Efficiency}} = 0.0801$, $h(DEFICIT)_{DEFICIT} = 0.0350$, $h(DEFICIT)_{\text{Efficiency}} = 0.0690$, $h(VOTES)_{VOTES} = 0.0747$, $h(VOTES)_{\text{Efficiency}} = 0.0656$.

Figure 5: Efficiency determinants, joint densities, allocative efficiency
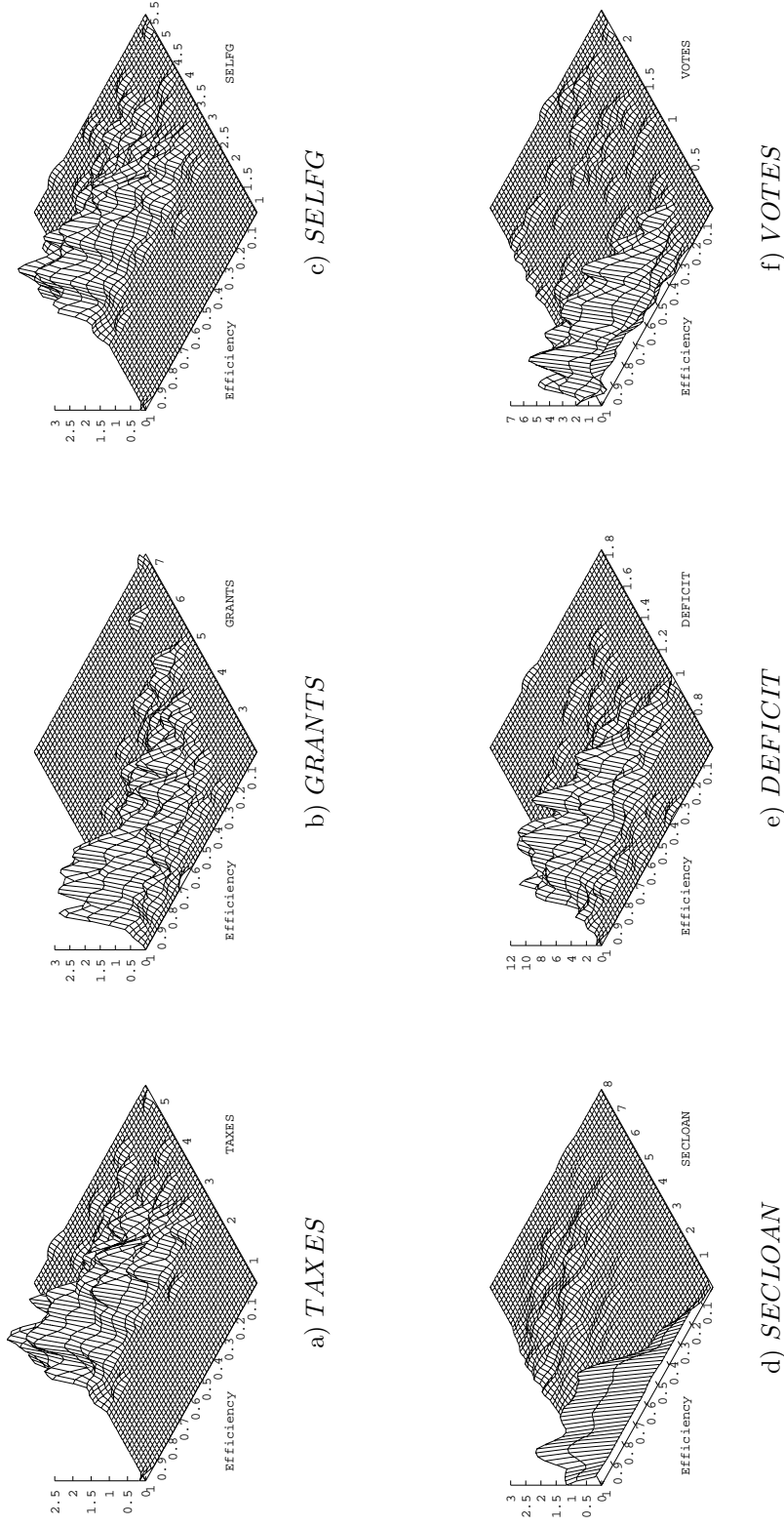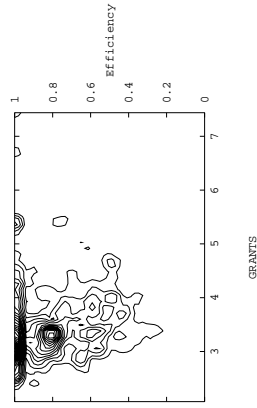

a) *TAXES*

b) *GRANTS*
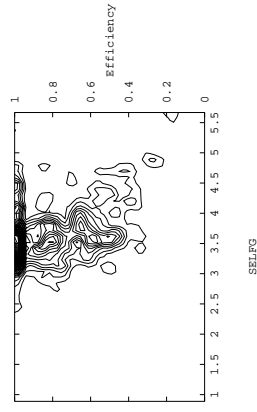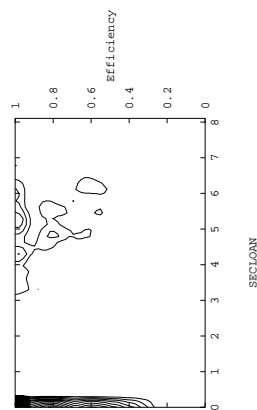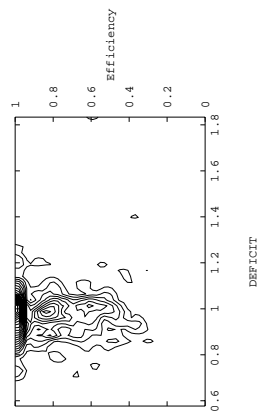
c) *SELFG*

d) *SECLOAN*

e) *DEFICIT*

f) *VOTES*

Densities estimated nonparametrically by means of Epanechnikov kernel, bandwidths chosen according to Wand and Jones (1994). Different bandwidths are estimated for each co-ordinate direction. $h(TAXES)_{TAXES} = 0.1339$, $h(TAXES)_{Efficiency} = 0.0686$, $h(GRANTS)_{GRANTS} = 0.1449$, $h(GRANTS)_{Efficiency} = 0.0562$, $h(SELFG)_{SELFG} = 0.1341$, $h(SELFG)_{Efficiency} = 0.0676$, $h(SECLOAN)_{SECLOAN} = 0.2877$, $h(SECLOAN)_{Efficiency} = 0.0819$, $h(DEFICIT)_{DEFICIT} = 0.0339$, $h(DEFICIT)_{Efficiency} = 0.0675$, $h(VOTES)_{VOTES} = 0.0656$, $h(VOTES)_{Efficiency} = 0.0662$.

Figure 6: Efficiency determinants, joint densities, overall cost efficiency (contour plots)
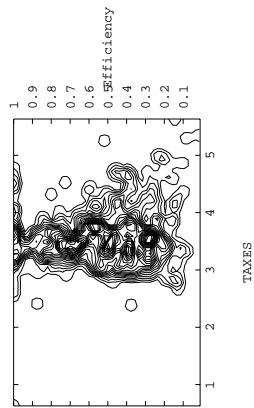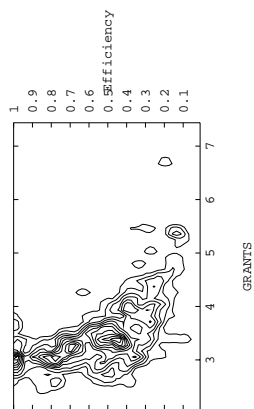
a) *TAXES*

b) *GRANTS*

c) *SELFG*

d) *SECLOAN*

e) *DEFICIT*

f) *VOTES*

Figure 7: Efficiency determinants, joint densities, technical efficiency (contour plots)
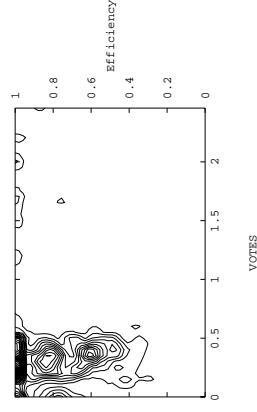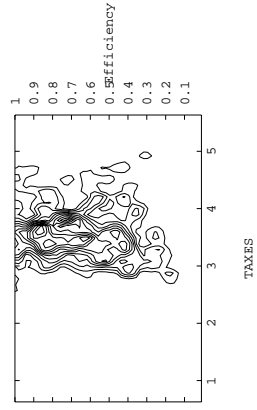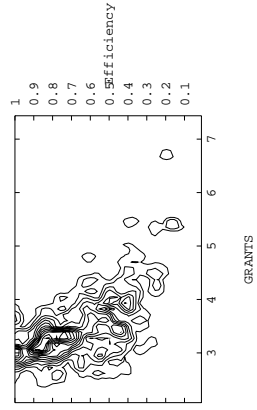

a) *TAXES*

b) *GRANTS*

c) *SELFG*

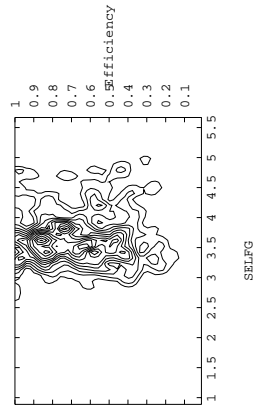d) *SECLOAN*

e) *DEFICIT*

f) *VOTES*

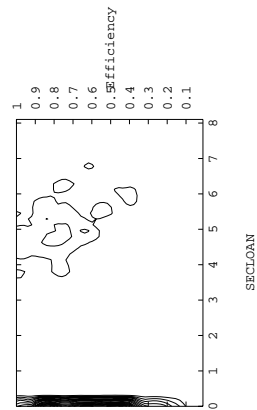**Figure 8:** Efficiency determinants, joint densities, allocative efficiency (contour plots)
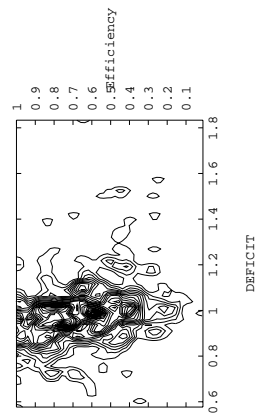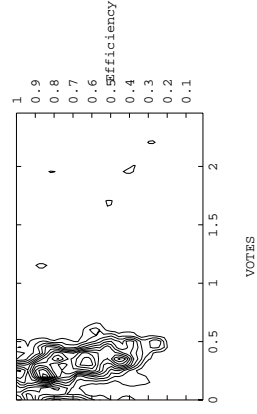

a) *TAXES*

b) *GRANTS*

c) *SELFG*

d) *SECLOAN*

e) *DEFICIT*

f) *VOTES*

A similar pattern is revealed for securities and loans issued by municipalities, whose nonparametric regression exhibits no clear pattern (see Figure 2.d). Yet its 3-d plots counterparts (Figures 4.d and 7.d) unmask what determines this: for most municipalities we cannot infer any link, as they simply do not issue securities. For others, a negative association is observed. But the probability mass supporting the latter assertion is quite scarce, as revealed by a low number of contours (see Figure 7.d).

The remaining fiscal policy variables—$TAXES$ (Figures 4.a and 7.a), $SELFG$ (Figures 4.c and 7.c), and $DEFICIT$ (Figures 4.e and 7.e)—widely confirm what was revealed by regression, as probability mass has a tendency to concentrate along the hypothetical negative slope diagonal. However, in all cases we notice a remarkable amount of multi-modality. Related to this, we face the issue of bandwidth choice, which is critical in nonparametric kernel density estimation, and has not yet been fully addressed in the bivariate case.[14]

Furthermore, we notice the difficulty in fitting a regression line of Y (or EFF, i.e., efficiency) on X (or z, i.e., explanatory variables), given that all cases show substantial probability mass concentrations at boundaries. Yet when analyzing cost (Figures 3 and 6) and allocative efficiencies (Figures 5 and 8) the observed patterns are not exactly coincidental. In these cases the number of efficient municipalities is ostensibly lower, preventing probability mass concentrations at the top—either left or right—of each sub-figure. This feature makes the association between variables clearer in some instances. This is the case of grants and cost efficiency (Figures 3.b and 6.b), for which the negative relationship is apparent. In the case of allocative efficiency (Figures 5.b and 8.b) the negative relationship is also ostensible, yet probability mass does not concentrate so markedly along the "hypothetical" negative slope.

In the other cases where a negative relationship was found between technical efficiency and the explanatory variables, the outcome for the other types of efficiency is different, due to those technical efficient firms which are cost and/or allocative inefficient. Hence, although both taxes and self-generated revenues exhibit a negative association for some municipalities, this does not hold for all of them, for both cost (Figures 3.a, 3.c, 6.a and 6.c) and allocative (Figures 5.a, 3.c, 6.a and 6.c) efficiency.

Of special note is the case of $VOTES$, whose fuzzy nonparametric regression line (Figure 2.f) does not allow us to infer any clear association between the votes of the governing party divided by population and efficiency. Yet the nonparametric bivariate density estimation reveals that the number of observations with $VOTES > 1$ is very low. If we disregard these municipalities, and consider only those with $VOTES < 1$, which are those with the overwhelming majority, the apparent relationship is negative for all types of inefficiency. Thus, it seems that our "preferred" hypothesis is accepted, as governing parties with percentage of votes might be facing strong monitoring from other parties and coalitions, which contributes to enhancing efficiency.

5. Concluding remarks

This article has analyzed the efficiency of Valencian (Spain) local governments, with an explicit attempt at measuring not only economic (cost) efficiency but also its decomposition into its allocative and technical components. Such a decomposition turns out to be of paramount importance, since most inefficiencies are attributable to a non-optimal choice of input mix. Put another way, a reallocation of inputs could lead to a substantial cost

reduction, given their relative prices.

Our linear programming techniques also allow specific input and output inefficiencies to be detected, i.e., input excesses and output underprovisions (or shortfalls). Except for current transfers, all input variables show similar excesses. Disparities are more marked on the output side, for which both number of lighting points and street infrastructure surface area, essentially related to capital expenditure, face the greatest underprovisions. Indeed, street infrastructure surface area is more important than what one might *a priori* expect, provided it also proxies for accesses to population centres, street cleaning, or supply of drinking water to households. It is also important to bear in mind that our output indicators include a *quality* variable, of paramount significance in our setting.

Results do also vary according to local governments' size, as large municipalities generally perform better. Yet this result is not entirely attributable to a more proficient management. Although our findings indicate that there is a wide margin available to public managers for optimization in the use of public resources, some of these inefficiencies might be caused by variables disregarded when measuring efficiency; some partly lie within local governments' control, yet others remain outside it. Specifically, we considered a set of both fiscal policy and political variables out of which self-generated revenues, grants, deficit, and votes of the governing party over total population were found to have a negative impact on efficiency, although they varied with the type of efficiency considered. More precisely, the empirical evidence was quite relevant in the case of overall cost efficiency for unconditional grants received from higher layers of government, and votes of the governing party over total population.

The latter results were obtained via nonparametric smoothing techniques, instead of either OLS or Tobit models. This is important due to the special distributional features of DEA efficiency scores which, by construction, are bounded by zero and unity. As we use linear programming techniques, a mass of efficiency scores achieves the upper bound. Although some authors have attempted to address this issue, they did not consider the statistical dependency of efficiency scores, which leads to the violation of important hypotheses. Alternatively, as our techniques are fully nonparametric, we neither face the skewness nor the statistical dependency problem.

A.   Nonparametric estimation of bivariate density functions

To estimate joint density functions, in which the OX axis represents the explanatory variable and the OY axis represents the dependent variable, i.e., efficiency, we also chose nonparametric techniques. Again, one of the most popular alternatives is kernel smoothing. The basics are quite similar to scatterplot smoothing—or nonparametric regression.

While the approach to smooth data is exactly the same (kernel smoothing), the other two decisions are not exactly coincidental. Regarding the choice of kernel, we consider here, following Wand and Jones (1995) and, in his applied work, Deaton (1989), the Epanechnikov kernel. We proceed with this for efficiency considerations. Its expression is as follows:

$$\widehat{f}(\mathbf{x};\mathbf{H}) = S^{-1}\sum_{s=1}^{S}K_{\mathbf{H}}(\mathbf{x}-\mathbf{v}_s)\tag{18}$$

where $\mathbf{v}_s = (z_s, EFF_s)$, $\mathbf{x} = (x_1, x_2)$ is the point of evaluation, $\mathbf{H}$ is a $d \times d$ (in our case, 2×2) bandwidth matrix, and $K_{\mathbf{H}}$ is a kernel function:

$$K_{\mathbf{H}}(\mathbf{x}) = |\mathbf{H}|^{-1/2} K(\mathbf{H}^{-1/2}\mathbf{x}) \tag{19}$$

We consider $\mathbf{H} \in \mathcal{D}$, where $\mathcal{D} \subseteq \mathcal{F}$ defines the subclass of diagonal positive definite matrices 2×2 ($\mathcal{D} = \{\mathrm{diag}(h_1^2, h_2^2) : h_1, h_2 > 0\}$). Hence, for $\mathbf{H} \in \mathcal{D}$, we have $\mathbf{H} = \mathrm{diag}(h_1^2, h_2^2)$.

According to the above statements, provided $\mathbf{h} = (h_1, h_2)$, the <u>bivariate</u> density function to be estimated is:

$$\widehat{f}(\mathbf{x}; \mathbf{h}) = (nh_1h_2)^{-1} \sum_{s=1}^{S} K\left(\frac{x_1 - z_s}{h_1}, \frac{x_2 - EFF_s}{h_2}\right) \tag{20}$$

Finally, we have chosen the Epanechnikov kernel, whose expression for the bivariate case is as follows:

$$K_e(\mathbf{x}) = \begin{cases} \frac{1}{2}c_d^{-1}(d+2)(1 - \mathbf{x}^T\mathbf{x}) & \text{if } \mathbf{x}^T\mathbf{x} < 1 \\ 0 & \text{otherwise.} \end{cases} \tag{21}$$

where c_d is the volume of the d-dimensional unit sphere: $c_1 = 2$, $c_2 = \pi$, $c_3 = 4\pi/3$, etc.

Unfortunately, we have to deal with a problem that has still not been satisfactorily addressed in the literature—namely, the choice of bandwidth. In this case, the state of the art is in a much more preliminary state than either in the univariate case or that of nonparametric regression. One of the most up-to-date contributions is the work by Wand and Jones (1994), also based on plug-in methods, which is precisely our choice. Although previous research considers by-eye criteria (Deaton, 1989), we do not completely agree with this view, as it partly undermines the impartiality of the analysis. When possible, data-driven methods are preferable.

Notes

[1] An excellent introduction to these topics is provided by Fox (2001).

[2] Similarly to what occurred in the U.S., where one of the legacies of the Reagan Administrations was the decentralization of public functions to lower levels of government.

[3] Yet the decentralization at the *first* level, i.e., regional, has surpassed largely that occurred at the *second* level, i.e., local, which actually has taken place to a short extent—at least when juxtaposed. However, there are frequent debates on whether it should finally come off.

[4] Located along the Spanish east coast, with a very dynamic economy. In terms of other Western European countries, it has a population roughly comparable to that of Ireland or Norway, and it accounts for approximately 10% of total population in Spain.

[5] Such as, for instance, the application of De Borger and Kerstens (1996) for Belgian municipalities.

[6] The constraint $\overrightarrow{\mathbf{1}}\lambda = 1$ accounts for the assumption of variable returns to scale (VRS). By removing such a constraint we would assume constant returns to scale (CRS) technology. The CRS technological assumption is only appropriate when all firms are operating at an optimal scale. Such an assumption does not hold for Spanish municipalities, as shown by Balaguer-Coll *et al.* (2002).

[7] "Pareto-Koopmans efficiency" is the production economics analogous to the more widely known concept of "welfare efficiency" used in economics.

[8] However, the term nondiscretionary is usually employed only when referring to inputs used in the production process. Specifically, nondiscretionary inputs are those beyond the control of a DMU's management. For example, Banker and Morey (1986a) illustrate the impact of exogenously determined inputs that are not controllable in an analysis of a network of fast food restaurants, where four out of six inputs were not controllable by each unit's management: age of store, advertising level, urban/rural location, and drive-in capability.

[9] One must bear in mind, though, that tax income partly measures too the ability of a local government to generate this type of income.

[10] This variable does also partly depend on the tax revenue of each municipality, an effect which might lessen its impact on efficiency.

[11] Obviously, the most desirable variable would be a dichotomous variable, taking values one or zero depending on whether an absolute majority governs the council. Unfortunately, that type of information is unavailable to date.

[12] The fragility of regression estimates has been reported not only in the efficiency literature but also, for instance, in Leamer and Leonard (1983).

[13] We have skipped most details regarding nonparametric regression. See, for instance Härdle (1990), for a good exposition.

[14] The best performers—in terms of balance between bias and variance—are those relying on plug-in methods, such as the ones put forward by Wand and Jones (1994).

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