Cost efficiency of Belgian local governments: A comparative analysis of FDH, DEA, and econometric approaches

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Abstract

The purpose of this paper is to analyze the efficiency of local governments in Belgium using a broad variety of non-parametric and parametric reference technologies. Specifically, we calculate indices of cost efficiency for five different reference technologies, two non-parametric ones (Free Disposal Hull (FDH) and variable returns to scale Data Envelopment Analysis (DEA)) and three parametric frontiers (one deterministic and two stochastic). We first compare the various alternatives in terms of the efficiency–inefficiency dichotomy, we look at the distributions of the different measures, and we consider the differences in ranking. In a final stage we examine the degree to which the calculated inefficiencies can be explained by a common set of explanatory variables.

Keywords: Local government performance; Cost efficiency; Non-parametric frontiers

JEL classification: D24; D60; H71; H72

1. Introduction

In this paper we study the cost efficiency of local governments in Belgium. Our purpose is twofold. First, we calculate cost-efficiency measures using a

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variety of parametric and non-parametric methods to evaluate the sensitivity of the rankings of municipalities with respect to the underlying reference technology. Second, we explain each of the calculated efficiency scores in terms of the social, economic, and political characteristics of municipalities. This provides some insight into the determinants of inefficiencies, and it yields information about the degree to which the set of significant explanatory variables is robust across various specifications of the reference technology.

To analyze technologies and cost efficiencies a variety of alternative methods have been developed in the literature. In addition to deterministic and stochastic parametric frontiers, several non-parametric reference technologies have been suggested, including Data Envelopment Analysis (DEA) (see, for example, Charnes et al., 1978) and the non-convex Free Disposal Hull (FDH) reference technology introduced by Deprins et al. (1984). Surveys of the various methods are found in, for example, Førsund et al. (1980), Lovell and Schmidt (1988), and, most recently, Lovell (1993).

Not surprisingly, several recent studies have used these methodologies to analyze the efficiency of municipal governments. However, most of this research has been based on either stochastic frontier approaches (see, for example, Davis and Hayes, 1993; Deller, 1992; Deller and Rudnicki, 1992; Hayes and Chang, 1990), or non-parametric methods (see, for example, De Borger et al., 1994; Vanden Eeckaut et al., 1993). Unfortunately, a large methodological literature suggests that the ranking of production units may be quite sensitive to the reference technology being postulated. For example, comparisons of deterministic and stochastic parametric frontiers have revealed non-negligible differences in rankings (Corbo and de Melo, 1986; Lovell and Schmidt, 1988; Van Den Broeck et al., 1980). More recent comparative analyses of parametric and non-parametric approaches have yielded mixed results. Using a deterministic parametric and a DEA approach Bjurek et al. (1990) found strong similarities between the different efficiency measures, except for the smallest production units. However, Ferrier and Lovell (1990) studied both a DEA model and a stochastic parametric frontier, and found a very weak correlation between the resulting efficiency measures. Finally, comparisons of different non-parametric reference technologies have also been found to substantially affect the resulting efficiency scores (see, for example, Bjurek et al., 1990; Vanden Eeckaut et al., 1993).

In view of the importance of the underlying reference technology, the purpose of this paper is to add to the evolving literature on the performance of local governments by studying the cost efficiency of Belgian municipalities using a large variety of alternative methods. Specifically, we calculate indices of cost efficiency for five different reference technologies, two non-parametric ones (FDH and variable returns to scale DEA) and three

parametric frontiers (one deterministic and two stochastic). Moreover, we study the results not only in terms of differences in distributions and rankings, but also consider the degree to which calculated inefficiencies can be explained by a common set of explanatory variables. This is not unimportant. If the set of significant determinants is robust across various specifications of the reference technology, then the explanatory analysis is not subject to manipulation and provides useful information to policy-makers.

Our focus on cost efficiency (rather than technical efficiency) is closely related to the nature of our data. The empirical analysis is based on information on total current expenditures and various output indicators for a single cross-section of all 589 municipalities in Belgium. A consequence of the Belgian institutional framework is that the sample does not contain input price variability. There is no wage flexibility as salary scales of municipal personnel are completely fixed. Moreover, all municipalities have access to the same capital market, and in fact obtain most of their funds from one and the same specialized financial institution. Therefore, the assumption of identical input prices across municipalities may not be too unreasonable. Consequently, throughout the analysis we focus on the measurement of cost efficiency.[1]

The paper is organized as follows. In Section 2 we review the five reference technologies used. In view of the empirical analysis we define the non-parametric approaches in terms of a cost correspondence; the parametric approaches are based on a cost frontier. In Section 3 we apply each of the five methods. We compare the various alternatives in terms of the efficiency–inefficiency dichotomy, we look at the distributions of the different efficiency measures, and we consider the differences in ranking they imply. In Section 4 we explain the calculated efficiency scores of Belgian municipalities using a number of economic and political variables, and analyze the differences in explanatory patterns across reference technology specifications. Section 5 concludes.

2. DEA, FDH and parametric reference technologies: Some methodological issues

In this section we briefly review the production technologies that will be used in the empirical analysis. To be consistent with the application that follows, it will be instructive to present the various reference technologies

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[1] If, for some reason, the assumption of identical input prices were not valid, Färe and Primont (1988) show within the framework of non-parametric reference technologies that our estimates of cost efficiency would provide a lower bound to the true technical efficiency.

and the corresponding efficiency indices in a dual cost framework. Throughout the analysis we focus on differences in assumptions and interpretation, and refer for the technical details to the relevant literature.

2.1. Deterministic non-parametric frontiers: DEA and FDH

The deterministic non-parametric methods, which originate from the seminal contribution of Farrell (1957), are based on piecewise linear frontiers calculated using mathematical programming techniques. They envelop the data as tightly as possible subject to certain maintained assumptions on the structure of the production technology.

We first consider the DEA model, which constructs a convex hull to envelop the data, subject to some weak economic assumptions. This DEA model was introduced by Charnes et al. (1978) and extended in Färe et al. (1985) and Seiford and Thrall (1990), among others. In this paper we consider a popular DEA model which assumes, in addition to the usual regularity axioms, strong disposability in both inputs and outputs, and allows for variable returns to scale. The disposability assumptions imply that an increase in inputs never results in a decrease in outputs, and that any reduction in outputs remains producible with the same amount of inputs.

Assuming identical input prices, a cost correspondence can be constructed from observed activities in the following way (see, for example, Färe and Grosskopf, 1985; Färe et al., 1988):

$$C(y)^{\text{DEA}} = \left\{ c \mid Y'z \geq y , \; C'z \leq c , \; I_k^t z = 1 , \; z \in \mathbb{R}_+^k \right\} , \tag{1}$$

where Y is the $k \times n$ matrix of observed outputs, C is the $k \times 1$ vector of observed costs, z is a $k \times 1$ vector of intensity or activity variables, I_k is a $k \times 1$ unit vector, y is an $n \times 1$ vector of outputs and c is a scalar representing a cost or budget level.[2] This dual or indirect correspondence denotes the set of budget or cost levels, c, which allow us to produce the output vectors, y.

Cost efficiency, CE_i, is calculated with respect to this DEA dual reference technology by solving the following linear program for each observation (see Färe and Grosskopf, 1985):

$$\min_{\lambda_{\text{DEA}}, \, z} \lambda_{\text{DEA}}$$

$$\text{s.t. } Y'z \geq y^0 , \quad C'z \leq c^0 \lambda_{\text{DEA}} , \quad I_k^t z = 1 , \tag{2}$$

$$\lambda_{\text{DEA}} \geq \qquad z \geq 0,$$

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[2] The following vector inequality conventions are used in the text: $x \geq y$ if and only if $x_i \geq y_i$ for all $i = 1, 2, ..., k$; $x \geqslant y$ if and only if $x_i \geqslant y_i$ and $x \neq y$; and $x > y$ if and only if $x_i > y_i$ for all i.

where y^0 is an $n \times 1$ vector of outputs and c^0 is the cost of the observation being evaluated. Consistent with the idea of variable returns to scale the intensity vector is restricted to sum to one. Solving this linear program generates, for each observation k, the optimal values $(\lambda^*_{DEA}$ and $z^*)$, where λ^*_{DEA} is the measure of cost efficiency and z^* is the optimal activity vector. The optimal value of λ^*_{DEA} is smaller than unity for inefficient observations and equals unity for efficient observations. The optimal activity vector, z^*, indicates the projection point on the boundary of the convex hull relative to which observations are being evaluated.

We next consider the FDH reference technology, proposed by Deprins et al. (1984), which recently gained substantial popularity as an alternative to the DEA model (see, for example, Tulkens, 1993; Lovell and Vanden Eeckaut, 1994). It differs from DEA in that it drops the convexity assumption. In a dual context, the FDH cost correspondence can be defined as

$$C(y)^{FDH} = \{c | Y'z \geqq y , \ C'z \leqq c , \ I^t_k z = 1 , \ z_i \in \{0, 1\}\} . \tag{3}$$

Cost efficiency is computed by solving the same programming problem as for DEA, except that a constraint is added: $z_i \in \{0, 1\}$ for all $i = 1, ..., k$. In other words, consistent with allowing for non-convexity the elements of the activity vector z are constrained to be either zero or one. Fortunately, solving the above mixed-integer programming problem to obtain the cost-efficiency measure for each activity is possible by means of a computationally simple weak vector dominance procedure (this algorithm is outlined in Tulkens, 1993). We observe that the optimal values $(\lambda^*_{FDH}$ and $z^*)$ have an identical interpretation as in DEA, except of course that only one component in z^* can differ from zero.

In Fig. 1 we develop some intuition for the graphical representation of both the DEA and the FDH models for the case of one output. We first consider the FDH cost frontier. Reflecting strong disposal in outputs and cost levels, each observed cost and output combination spans one orthant, positive in the cost level and negative in the output. The FDH cost reference technology is then the boundary to the union of all such orthants. In Fig. 1, observations A, B, C, D and E are FDH efficient. Observation 1 is inefficient. A typical cost frontier is given by the staircase-shaped line $ABCDE$. In contrast, a typical DEA cost frontier is depicted on Fig. 1 using the dashed line $ABCE$. Note the implications of the convexity assumption. Observation D, which is efficient relative to the FDH cost frontier, is inefficient relative to the convex combination of C and E on the DEA model.

An important characteristic of the FDH reference technology has been stressed by, among others, Lovell and Vanden Eeckaut (1994). Using the
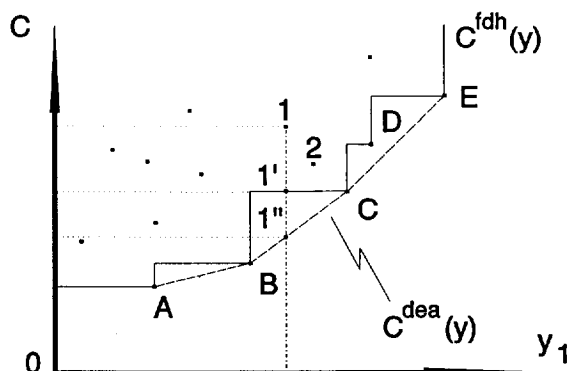
Fig. 1. A cost frontier of a strongly disposable DEA model and the FDH.

cost-efficiency measure, inefficient observations are projected onto an orthant spanned by a single efficient producer which is weakly dominating in both cost and outputs. For example, in Fig. 1 the inefficient observation 1 is dominated by C and D as well as by 2, which is itself inefficient. Observation 1 is projected onto point 1' situated on the orthant spanned by C, which is one of the dominating observations.[3] This single producer can therefore be interpreted to function as a role model for the inefficient unit. In DEA, typically no such unique role model is available. Inefficient observations are projected onto a fictitious linear combination of efficient observations. For example, observation 1 is projected to point 1", which is a linear combination of observations B and C. Moreover, it is clear that cost-efficiency measures based on the suggested DEA model can never exceed those calculated on FDH (Lovell and Vanden Eeckaut, 1994). Finally, the number of efficient observations on FDH is typically larger than on DEA.

2.2. Deterministic and stochastic parametric frontiers

Parametric frontier methods postulate a functional form with a given number of parameters to describe the production technology. As previously indicated, we focus on cost function representations of the technology. For an arbitrary observation i the cost function $C(y_i, w_i; \beta)$ defines a lower

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[3] Note that the traditional radial projections used in the non-parametric approach are more likely to leave slacks (unmeasured inefficiency) on FDH than on DEA. The problem is that the radial efficiency measure always projects onto the isoquant, and not necessarily onto the efficient subset. Lovell (1993) and Lovell and Vanden Eeckaut (1994) review the problem and suggest some solutions, including the use of non-radial efficiency measures. De Borger and Kerstens (1993) explore the use of several non-radial measures in the case of FDH.

bound to the expenditures C_i necessary to produce a given vector of outputs y for given input prices w. The parameter vector β is to be estimated.

In the deterministic case it is assumed that any deviation of observed cost, C_i, from the frontier $C(\cdot)$ can be attributed to technical inefficiency. Assuming a multiplicative disturbance term u, the model can be succinctly written as follows:

$$C_i = C(y_i, w_i; \beta)\exp(u_i) , \quad \text{where } u_i \geq 0 . \tag{4}$$

The error term, u_i, has a one-sided distribution. Although alternative methods are available, a simple methodology is to estimate the deterministic cost frontier using 'corrected' ordinary least squares (COLS) after logarithmic transformation (for details, see Greene, 1993; Lovell, 1993). The procedure is to first estimate β by ordinary least squares (OLS), and then to obtain the frontier by shifting down the constant term so that all residuals are positive and at least one is zero. This amounts to simply adding the minimal residual to the constant term. Finally, cost efficiency, CE_i, is defined as the ratio of observed cost, C_i, to the minimal possible cost, $\hat{C}$. For observation i cost efficiency is given by

$$CE_i = C_i/\hat{C}_i = \exp(u_i) . \tag{5}$$

Stochastic parametric frontiers are based on a composed error model which allows us to differentiate between cost inefficiency and other stochastic influences. A symmetric component, v_i, captures the usual disturbance in econometrics, and a one-sided error component, t_i, represents cost inefficiency. Both error terms are assumed to be independent. Assuming a multiplicative composite error term, the stochastic cost frontier is defined as

$$C_i = C(y_i, w_i, \beta)\exp(v_i + t_i) , \quad \text{where } t_i \geq 0 . \tag{6}$$

Several procedures are available to estimate the frontier, depending on the assumed distribution of the cost-efficiency component (see Greene, 1993, for a careful review). In this paper we assume that the one-sided efficiency component, t_i, is distributed half normally and estimate the frontier using maximum likelihood (ML) techniques. As is common in the literature, the error component, v_i, is taken to be independently and identically distributed as $N(0, \sigma_v^2)$.[4] Two different cost-efficiency measures

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[4] We observe that under our assumptions a 'modified' ordinary least squares method (MOLS) is also available. In this case the estimated OLS intercept is shifted down by minus the estimated mean of the technical inefficiency term, $E(t)$, which is derived from the moments of the residuals. Monte Carlo analysis indicates that the performance of MOLS vs. ML depends on sample size and the relative variation in both error terms t_i and v_i (Olson et al., 1980). For our data, the application of MOLS resulted in qualitatively very similar results as ML. Finally, we note that for a variety of other distributions of the technical efficiency term (e.g. truncated normal, gamma) ML procedures have also been developed.

for individual observations are obtained using the procedure proposed by Jondrow et al. (1982). They suggest constructing point estimates for the individual error component t_i based on either the mean $(CE_i = E(t_i|v_i + t_i))$ or the mode $(CE_i = M(t_i|v_i + t_i))$ of the conditional distribution.[5]

3. Computing cost-efficiency measures for Belgian municipalities

In this section we study the cost efficiency of Belgian municipalities in the provision of local public services using all of the methodologies outlined above. Although a number of recent studies have analyzed the technical efficiency of municipal governments, none of the available analyses has considered the broad variety of reference technologies dealt with in this paper (see, for example, Davis and Hayes, 1993; De Borger et al., 1994; Deller, 1992; Hayes and Chang, 1990; Vanden Eeckaut et al., 1993). We calculate indices of cost efficiency using FDH, DEA, a deterministic parametric frontier (DF), and a stochastic parametric frontier (SF). In the latter case we present point estimates based on both the conditional mean (SF-Mean) and the conditional mode (SF-Mode). As a consequence, five cost-efficiency measures are reported below, denoted FDH, DEA, DF, SF-Mean, and SF-Mode. In each case the reported indices have a straight-forward cost interpretation. For example, a value of 0.80 indicates that a 20% cost reduction is feasible.

A careful comparative analysis of the various methods is not unimportant in view of the substantial differences in the underlying assumptions (see, for example, Lovell, 1993). First, stochastic methods make explicit assumptions concerning the stochastic properties of the data in an effort to distinguish between noise and inefficiency, while deterministic methods lump any potential measurement error with inefficiency. Corbo and de Melo (1986), for instance, provide extensive comparisons between deterministic and stochastic parametric frontiers and conclude that the former often yield implausibly low efficiency measures relative to stochastic frontiers. Second, with respect to the distinction between parametric and non-parametric methods, it is clear that the former are sensitive to the risk of misspecification and are more likely to confound specification error with technical inefficiency. Third, among the non-parametric methods the impact of the choice of reference technology on efficiency measurement is related to

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[5] The formulas given for the case of a production frontier by Jondrow et al. (1982) can easily be adapted for the case of a cost frontier. These authors also point out that the mode of the conditional distribution has an attractive interpretation as a ML estimator. Moreover, because it allows for at least some efficient observations, it offers the possibility of comparison with the non-parametric approaches.

specific maintained assumptions with regard to the set of production possibilities (Grosskopf, 1986). Unfortunately, knowledge of the relative performance of the various available methodologies is still very limited.[6] Therefore, the best strategy for applied research seems to be to utilize several methods and to check for the robustness of the resulting efficiency measures.

The sample consists of observations on total current municipal expenditures and on five output indicators for each of the 589 local governments in 1985.[7] The output indicators are meant to capture important aspects of the most relevant services provided by municipal governments. Belgian municipalities have important responsibilities in the field of education, social and recreational services, and overall administrative services. The following indicators were used:

(i) the number of beneficiaries of minimal subsistence grants (SUB);
(ii) the number of students enlisted in local primary schools (STUD);
(iii) the surface of public recreational facilities (REC);
(iv) the total population (POP); and
(v) the fraction of the population older than 65 (OLD).[8]

Admittedly, many of these 'output' variables should be considered as crude proxies for the services delivered by municipalities. For example, population (POP) is assumed to proxy for the various administrative tasks (e.g. maintaining the register of births, marriages, and deaths; issuing certificates, passports, etc.) performed by municipal governments, but it is

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[6] Recently, Gong and Sickles (1992) analyzed the comparative performance of several stochastic parametric frontier estimators and the DEA model utilizing Monte Carlo techniques. These gave complete control to the underlying technology and the level of technical inefficiencies attributed to the artificially generated data. Their findings indicate that the former methods outperform the latter only when the chosen functional form is close to the underlying technology and when there is little correlation between the regressors and the technical inefficiency term.

[7] The data come from a more elaborate database constructed at the research institute CADEPS (Free University of Brussels) on the basis of information from the Nationaal Instituut voor de Statistiek (NIS) and from the Gemeentekrediet van België (GKB). Note that we used the same database (De Borger et al., 1994) in order to calculate FDH-based technical efficiency measures, using explicit input indicators such as personnel and capital.

[8] Note that Vanden Eeckaut et al. (1993) have also reported cost-efficiency results using the non-parametric approaches only. Our work differs from theirs in three respects. First, their study uses the subsample of Walloon municipalities. Second, to some extent our study uses different output indicators. To be specific, while SUB, STUD, POP and OLD are common to both analyses, we use REC, whereas they use road length and the crime rate. We did not include a road network indicator because it yielded a negative marginal cost in the estimation of the parametric cost frontier. We opted for REC because we think it is a more direct type of output indicator than the crime rate, although that may be open to discussion. Third, most of our data refer to the fiscal year 1985, while Vanden Eeckaut et al. (1993) use—with one exception—1986 figures.

clearly not a direct output of local production. Similarly, the variable *OLD* proxies for the supply of social services to the elderly (retirement homes, medical services in public hospitals, general assistance, etc.). Minimal subsistence grants (*SUB*) are related to services provided to low-income families, where it should be noted that in Belgium local governments cover 50% of the cost of such grants.

Unfortunately, it is clear that the quality of our outputs is less than desirable. To some extent this is a reflection of the general problems inherent in the definition of inputs and outputs for the public sector (see, for example, Bradford et al., 1969; Levitt and Joyce, 1987). More specifically, however, it is simply the result of the lack of better local government data in Belgium. As a consequence, the outputs used are rather loosely related to the services delivered by municipal governments, and it was not possible to correct for unobservable variations in quality. For example, it is clear that it would be preferable to use test scores or, as has recently been argued by Card and Krueger (1992), labor market outcomes as output measures for schooling. However, this information was not available, nor were quality indicators.[9]

The parametric approaches are based on the following cost function specification:

$$\ln C = \alpha + \sum_{i=1}^{5} \beta_i \ln y_i + (1/2) \sum_{i=1}^{5} \sum_{j=1}^{5} \gamma_{ij} \ln y_i \ln y_j \,, \tag{7}$$

where C are total costs and y_j are output indicators, and the local approximation is at the sample means. For reasons previously explained, there is no observable variation in input prices, so that input prices are ignored.

The deterministic and stochastic frontiers were estimated by corrected OLS and ML, respectively. The resulting parameter estimates are reported in Table 1, where standard errors are in parentheses. With the obvious exception of the constant term, the estimates are remarkably similar. The stochastic frontier intercept exceeds the deterministic one, because the former method attributes only part of the error term to cost inefficiency.[10] Using the estimated residuals we finally determined the inefficiency measures DF, SF-Mean and SF-Mode for each individual municipality using the procedures previously outlined.

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[9] More details about the interpretation and the limitations of the data are in De Borger et al. (1994). As noted by a referee, it would be desirable to try to use panel data in future work to test the robustness of the empirical results.

[10] The Cobb–Douglas cost function was rejected in both the corrected OLS and the ML estimation using an *F*-statistic and a likelihood ratio test, respectively.

Table 1
Cost frontier estimates

Independent variables	Parameters	Deterministic frontier	Stochastic frontier
Intercept	α	18.926 (0.019)***	19.263 (0.026)***
ln SUB	β_1	0.187 (0.028)***	0.202 (0.029)***
ln STUD	β_2	0.106 (0.036)***	0.102 (0.035)***
ln REC	β_3	0.063 (0.029)**	0.072 (0.028)**
ln POP	β_4	0.795 (0.053)***	0.788 (0.049)***
ln OLD	β_5	0.306 (0.096)***	0.284 (0.097)***
$(\ln SUB)^2$	γ_{11}	0.060 (0.035)*	0.080 (0.039)**
$(\ln STUD)^2$	γ_{22}	−0.030 (0.074)	−0.015 (0.077)
$(\ln REC)^2$	γ_{22}	0.086 (0.038)**	0.065 (0.038)*
$(\ln POP)^2$	γ_{44}	0.472 (0.168)**	0.482 (0.162)**
$(\ln OLD)^2$	γ_{55}	−0.043 (0.327)	0.097 (0.441)
ln SUB * STUD	γ_{12}	0.087 (0.081)	0.091 (0.081)
ln SUB * REC	γ_{13}	0.066 (0.058)	0.064 (0.060)
ln SUB * POP	γ_{14}	−0.155 (0.121)	−0.215 (0.129)*
ln SUB * OLD	γ_{15}	0.361 (0.190)*	0.330 (0.194)*
ln STUD * REC	γ_{23}	0.074 (0.085)	0.059 (0.078)

Table 1 (continued)

Independent variables	Parameters	Deterministic frontier	Stochastic frontier
ln STUD * POP	γ_{24}	−0.084 (0.183)	−0.090 (0.184)
ln STUD * OLD	γ_{25}	0.213 (0.270)	0.268 (0.231)
ln REC * POP	γ_{34}	−0.487 (0.134)***	−0.454 (0.127)***
ln REC * OLD	γ_{35}	0.149 (0.203)	0.160 (0.216)
ln POP * OLD	γ_{45}	−0.861 (0.445)*	−0.861 (0.397)**
$\gamma = \sigma_y / \sigma_v$		– –	2.358 (0.269)***
		R^2 0.947 SER 0.243	Log likelihood 20.781
Translog vs. Cobb–Douglas:		F 13.185***	LR 167.738***

* Denotes significance of at the 90% level.
** Denotes significance of at the 95% level.
*** Denotes significance of at the 99% level.

To retain consistency we calculated cost-efficiency indices based on the non-parametric FDH and DEA frontiers using exactly the same data, i.e. five outputs (SUB, STUD, REC, POP, OLD) and current municipal expenditures. The DEA-based efficiency indices are obtained using standard linear programming software, whereas the FDH-based efficiency measures are generated by applying the weak vector dominance algorithm described in Tulkens (1993).

We now turn to a brief discussion of the results. An elementary insight is obtained by considering the dichotomous classification of observations as either efficient or inefficient. The number of efficient observations resulting from the use of different reference technologies is shown in the last column of Table 2. Clearly, and consistent with expectations, the FDH method turns out to be very prudent relative to all other reference technologies. It results in 66% efficient observations, compared with 10.8% for DEA, and 12.2% for the estimates based on the conditional mode of the stochastic frontier SF-Mode. By construction, the DF-frontier contains only a single observation, while according to the estimates based on the conditional mean

Table 2
Summary statistics for efficiency measures ($N = 589$)

	Mean	Standard deviation	Skewness	Kurtosis	Minimum	Maximum	No. of efficient observations
FDH	0.937	0.119	−2.005	6.182	0.441	1.000	391 (66.4%)
DEA	0.727	0.174	−0.114	2.232	0.318	1.000	64 (10.8%)
DF	0.570	0.131	0.250	3.010	0.233	1.000	1 (0.2%)
SF-Mean	0.781	0.117	−0.839	3.087	0.347	0.953	0 (0%)
SF-Mode	0.809	0.142	−0.449	2.459	0.347	1.000	72 (12.2%)

(SF-Mean) all observations are inefficient. Obviously, the latter two methods are not useful in performing the efficient–inefficient classification and only yield a relative ordering of performance.

It is interesting to consider the extent to which the different methodologies agree on this basic dichotomous classification. By definition, all DEA efficient observations are FDH efficient too. More informative is the fact that out of 72 efficient observations based on the estimates of the conditional mode (SF-Mode) 70 are shared with FDH. Although FDH leads to a very large number of efficient municipalities, this is nevertheless a remarkable result. Apparently, there is somewhat less similarity between the SF-Mode method and DEA. From the 64 DEA efficient observations, 38 are common to the set of efficient municipalities based on the conditional mode. Furthermore, the single DF efficient observation is common to FDH, DEA and SF-Mode.

The results also clearly illustrate the implications of imposing convexity for non-parametric technical efficiency measurement. From the 391 efficient observations in FDH only 64 (16%) remain so under DEA. The impact of convexity is clearly enormous. This is important from a managerial viewpoint because there is some evidence that economic agents subjected to a DEA-based performance evaluation object precisely to the convexity assumption. The comparison of an inefficient observation to an unobservable and fictitious linear combination of observations on the boundary is deemed uninformative to improve performance (see, for example, Epstein and Henderson, 1989). Clearly, the FDH reference technology is not vulnerable to this critique, because it relates each inefficient observation to an orthant spanned by a single dominating observation.[11] These and similar observations have led Vanden Eeckaut et al. (1993, p. 312) to conclude that in general the close fit of FDH makes its efficiency scores more acceptable

[11] Of the 391 efficient observations in FDH, 85 are identified as role models for the inefficient municipalities. It turns out that these are, on average, among the smaller municipalities with a relatively old population.

relative to those obtained using DEA models. Its extreme prudence, of course, leaves a large number of efficient observations.

In addition, Table 2 contains some descriptive statistics for each of the five cost-efficiency measures. In general, the results are in line with expectations. The mean of the FDH-based index exceeds all others. The FDH and SF-Mean distribution are the least dispersed. The use of the deterministic estimator DF yields extremely low mean efficiencies compared with any of the other frontier methods. As far as the relationship with the stochastic parametric cost frontier is concerned, this confirms the earlier findings of, among others, Corbo and de Melo (1986). Also we observe that mean efficiencies based on DEA and the stochastic frontier are quite similar. The results for the stochastic frontier are in line with the average efficiency scores reported in the literature (see, for example, Grosskopf and Hayes, 1993; Davis and Hayes, 1993). The FDH- and DEA-based scores are, on average, below those summarized in Vanden Eeckaut et al. (1993), which is most probably due to our larger sample.

The distributions of all efficiency measures are presented graphically in Fig. 2, based on the inefficient observations only.[12] In particular, the efficiency distribution computed on the FDH has a long and fat left tail relative to the normal distribution. The distribution of the DF estimator has
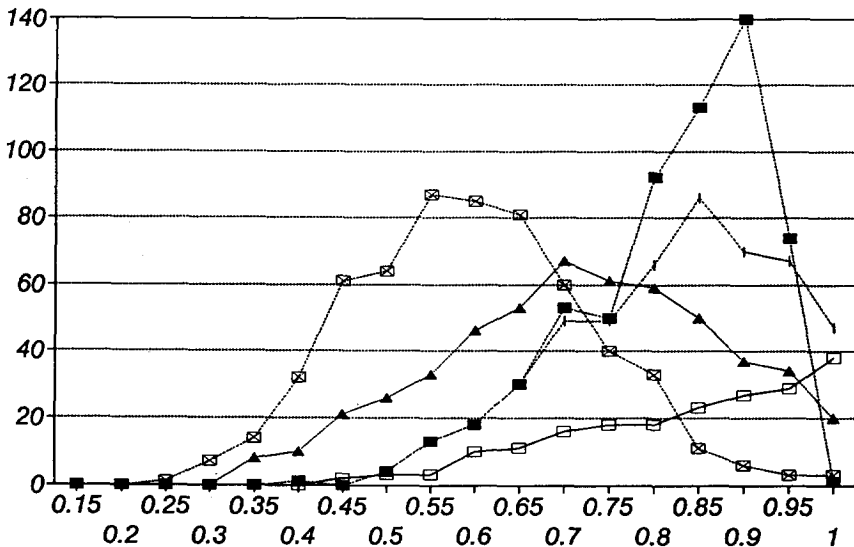

Fig. 2. Histogram of inefficiency for inefficient Belgian municipalities. —☐—FDH; -▲-DEA; –☐– DF; –■– SF-Mean; ■ ■ ■ ■ ■ ■ SF-Mode.

[12] Obviously, this implies that the distributions in Fig. 2 are based on different sample sizes.

the widest range. As stressed by Vanden Eeckaut et al. (1993), it has been repeatedly observed that the complete distribution of the FDH scores has a totally different shape (i.e. exponential) than the normal or truncated normal distributions resulting from other methodologies.

Further insight into the distributions of the different measures is gained by looking at the results for a number of size classes. Therefore we consider, for different expenditure classes, both the percentage of efficient observations and the mean inefficiency scores, the latter calculated on the inefficient observations only. The results are presented in Table 3. The main findings can be summarized as follows. First, with respect to the efficient–inefficient dichotomy, FDH, DEA and SF-Mode yield remarkably similar results in that the highest percentages of efficient observations are mainly concentrated in the extremes of the size distribution. Also we observe the difference between FDH and DEA in the overall dispersion of the efficient observations, which in the non-parametric approach serve as role models. In FDH the number of efficient observations is more evenly spread than in DEA, indicating that in the latter case the potential role models are more similar in size. Second, mean inefficiency scores are almost uniformly distributed for all five measures. Finally, the difference between the non-parametric and the parametric approaches for the highest size class is remarkable. While mean efficiencies are rather low in the latter approach, the former methods obtain their highest scores. This is due to the different ways these methods cope with data sparsity typically observed at the tails of the size distribution. Whereas in the case of data sparsity non-parametric approaches, and especially FDH, tend to increase the probability of efficiency, the parametric methods imply the risk of extreme efficiency scores (see, for example, Lovell, 1993).

Not only the shape of the efficiency distribution may be affected by the use of different reference technologies, but they can also alter the implied rankings of individual observations. The similarities in ranking are assessed by comparing both the Spearman rank correlations and the Pearson product moment correlation coefficients (see Table 4). Several observations stand out from these results. First, the three stochastic approaches are closely related both in their ranking and in their assessment of the relative inefficiencies in the sample, rank correlation coefficients being 0.99 and above.[13] Second, the non-parametric models, FDH and DEA, do not imply similarly close rankings. Third, while FDH correlates substantially better with DEA (rank correlation 0.66) than with the parametric approaches (0.59), DEA has a slightly higher similarity in ranking relative to the latter

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[13] Note that the rank correlation between the deterministic frontier (DF) and the mean of the conditional distribution of the stochastic frontier (SF-Mean) is not unity, because the former is estimated using corrected OLS and the latter with ML.

Table 3
Efficiency measures per cost category

Local government expenses (Mio BF)	No. of observations	FDH		DEA		DF		SF-Mean		SF-Mode	
		%ef. obs.	Mean inef.	%ef. obs.	Mean inef.	%ef. obs.	Mean inef.	%ef. obs.	Mean inef.	%ef. obs.	Mean inef.
<100	168	70	0.80	12	0.67	1	0.61	0	0.80	18	0.80
100–199.9	199	57	0.83	5	0.69	0	0.58	0	0.80	14	0.80
200–299.9	70	63	0.79	9	0.70	0	0.55	0	0.78	10	0.78
300–399.9	42	59	0.77	5	0.65	0	0.49	0	0.71	2	0.71
400–499.9	32	81	0.77	9	0.75	0	0.53	0	0.76	0	0.78
500>	78	82	0.85	28	0.75	0	0.53	0	0.75	9	0.75
Total	589	66	0.81	11	0.69	0	0.57	0	0.78	12	0.78

Table 4
Correlation matrix for efficiency measures ($N = 589$)

	FDH	DEA	DF	SF-Mean	SF-Mode
Spearman rank correlations					
FDH	1.000				
DEA	0.662	1.000			
DF	0.594	0.814	1.000		
SF-Mean	0.590	0.829	0.995	1.000	
SF-Mode	0.590	0.827	0.994	0.999	1.000
Pearson product moment correlations					
FDH	1.000				
DEA	0.653	1.000			
DF	0.583	0.813	1.000		
SF-Mean	0.666	0.821	0.949	1.000	
SF-Mode	0.638	0.828	0.962	0.991	1.000

methods (0.81–0.82) than relative to FDH. Of course, the correlations between FDH and the other models is rather low owing to the large number of efficient observations in the former case.

4. Explaining measures of cost efficiency: Empirical results

In this section we provide an explanatory analysis of the calculated cost-efficiency measures using economic and political indicators as independent variables. However, before we proceed it is worthwhile making two remarks. First, we are clearly using a two-step approach to the explanation of inefficiency. Initially, efficiency indices are calculated, and then they are explained. Although this two-stage approach is typical in the literature (see, for example, Deller, 1992) a crucial underlying assumption is that the explanatory variables only influence technical efficiency and not the transformation process from inputs into outputs (Lovell, 1993). This assumption is especially important for the parametric approach. In the first stage a composed stochastic error cost frontier, $C_i = C(y_i, w_i; \beta)\exp(v_i + t_i)$, was estimated. In the second step the resulting cost-efficiency measure, $CE_i = \exp(t_i)$, was explained by postulating the relation $CE_i = f(z_i; \gamma)\exp(e_i)$, where z_i is a vector of explanatory variables and e_i is $N(0, \sigma_e^2)$ distributed noise. This two-step procedure is only meaningful provided the exogenous variables in the first stage, here y_i and w_i, are uncorrelated with the second-stage exogenous variables, z_i. To the extent that both series of variables are correlated, the parameter estimates may be biased. This should

be kept in mind when interpreting the results.[14] A second remark relates to the selection of an appropriate model for the second stage, taking account of the characteristics of the distribution of the efficiency measures. The Tobit censored regression model was selected to accommodate the efficiency scores at unity in DEA, FDH, and SF-Mode. Since there is no upper censoring in the case of DF and SF-Mean, OLS was used for these two efficiency measures.

We now proceed by reviewing the variables included in the explanatory analysis. First, it is well known that the incomes and wealth of citizens affect the incentives of both politicians and taxpayers to monitor expenditures. At the local level, higher incomes increase the fiscal capacity of municipalities and may foster featherbedding of politicians and public managers, thereby increasing the scope for inefficient operation (see, for example, Spann, 1977; Silkman and Young, 1982). Similar arguments were presented by both Wyckoff (1990), at the national level, and De Groot and Van der Sluis (1987), for the case of university departments. They also report evidence suggesting that bureaucratic slack (technical inefficiency) increases with the organizations' income. Finally, at the local level citizens of high-income municipalities may be less motivated to effectively monitor expenditures owing to high opportunity costs. To proxy for the above effects, per capita personal income (*INCOME*) is included in the specification.

Second, the financing of local public services may be important for several reasons. First, for a given level of service provision, high tax prices may increase the voters' awareness about controlling public expenditures, especially if cost comparisons between municipalities are easy (see, for example, Spann, 1977). Recently, Davis and Hayes (1993) found evidence of a positive relation between tax rates and monitoring effort in the United States. In Belgium the two main municipal taxes are a local income tax and the property tax. The results reported below only include the latter tax rate (*HTAX*), since the former yielded consistently insignificant results. Second, local government operations are partly funded by block grants. These are often believed to induce the well-known 'flypaper' effect (see, for example, Hamilton, 1983). Although this is not directly implied by the flypaper effect, one can hypothesize a negative relationship between grants and technical efficiency. For example, Silkman and Young (1982) argued that such a relationship is to be expected because the cost of inefficient behavior is increasingly shared by a broader constituency (national taxpayers) as the proportion of outside funding increases. Using data on libraries and school bus transportation, they found evidence for this phenomenon in the United

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[14] The relevant correlations were considered carefully. With the exception of one inefficiency determinant (per capita block grants, see below) correlations between the two sets of variables were extremely low.

States. Moreover, the findings of Wyckoff (1990) and De Groot and Van der Sluis (1987) may be interpreted as suggesting a negative relationship between technical inefficiency and the budget derived from grants. We therefore added the size of the per capita block grant (*GRANT*) as an explanatory variable.

Third, both the property rights and principal–agent literature have suggested a number of reasons why politicians and public managers may lack proper incentives to effectively audit and control expenditures. For example, it has been argued that the process of political decision-making itself may impede the effective control of the public sector (Mueller, 1989; Bartel and Schneider, 1991). One suspects that cost efficiency may be affected by the size and composition of political coalitions, as arbitrage in the political bargaining process may require more explicit or implicit side payments (e.g. log-rolling) depending on the number and nature of the coalition partners. Following Vanden Eeckaut et al. (1993), the above ideas were approximated by two types of variables: the number of coalition parties (*CPAR*), and dummies indicating the participation of a particular political family in the ruling coalition (*CLIB* and *CSOC* for the liberal and socialist parties, respectively). The latter variables have often been found to affect government spending in Belgium (see also De Grauwe, 1985).

Fourth, the political participation of the citizens may enhance the performance of a municipality. While this is difficult to quantify directly, there is some evidence that political participation is related to education (see Mueller, 1989). Therefore we included as an explanatory variable the share of the adult population holding a degree in primary education as their final educational achievement (*PEDUC*).[15] Note that this variable may also capture the impact of population characteristics on costs, as emphasized by, for example, Schwab and Oates (1991). Finally, we hypothesized that population density may affect the costs of providing a given bundle of public services. We might expect that cost, and hence measured cost inefficiency, rises with lower population density. We therefore added population density (*DENS*) to the specification.

The regression results are reported in Table 5. Standard errors are in parentheses. Tobit estimates relating to the FDH, DEA and SF-Mode models were obtained by ML; in the case of DF and SF-Mean, OLS estimates are reported. Because of space limitations only one common specification for the different reference technologies is reported. However,

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[15] Three levels of final educational achievement were considered, namely primary, secondary and higher education. The shares of primary and higher education were separately introduced, treating secondary education as the benchmark case. However, the higher education dummy was found to be consistently insignificant.

Table 5
Regression results for the efficiency measures ($N = 589$)

	FDH	DEA	DF	SF-Mean	SF-Mode
CONSTANT	1.491	0.826	0.928	1.027	1.190
	(0.183)***	(0.104)***	(0.673E-01)***	(0.600E-01)***	(0.822E-01)***
HTAX	0.714E-04	0.417E-04	0.132E-04	0.129E-04	0.137E-04
	(0.308E-04)**	(0.178E-04)**	(0.115E-04)	(0.103E-04)	(0.140E-04)
INCOME	-0.200E-02	-0.634E-03	-0.149E-02	-0.950E-03	-0.149E-02
	(0.716E-03)***	(0.405E-03)	(0.261E-03)***	(0.233E-03)***	(0.318E-03)***
GRANTS	-9.277	-6.416	-16.313	-15.165	-20.170
	(5.742)	(3.186)**	(2.020)***	(1.800)***	(2.442)***
CLIB	-0.239E-01	0.334E-01	0.205E-01	0.107E-01	0.195E-01
	(0.311E-01)	(0.185E-01)*	(0.119E-01)*	(0.106E-01)	(0.145E-01)
CSOC	0.628E-01	0.336E-01	0.375E-01	0.107E-01	0.103E-01
	(0.288E-01)**	(0.167E-01)**	(0.108E-01)***	(0.961E-02)	(0.131E-01)
PEDUC	-0.405E-02	-0.149E-02	-0.134E-02	-0.101	-0.131E-02
	(0.150E-02)**	(0.895E-03)	(0.579E-03)**	(0.519E-01)**	(0.709E-03)
DENS	29.883	11.361	2.622	-0.781	0.373
	(15.91)*	(5.074)*	(3.155)	(2.812)	(3.818)
Log likelihood	-215.83	58.946	–	–	179.94
R^2	–	–	0.138	0.134	–

* Denotes significance of at the 90% level.
** Denotes significance of at the 95% level.
*** Denotes significance of at the 99% level.

the results with respect to the most important explanatory variables were quite robust across different specifications.

The results are easily summarized. The income variable (*INCOME*) has a negative and, except for the model based on DEA, significant impact, consistent with the interpretation of this variable as affecting both politicians' and taxpayers' incentives to control local expenditures. The tax price (*HTAX*) contributes positively to efficiency, in line with the interpretation of its relation to monitoring effort postulated above. However, the effect is insignificant for the efficiency scores evaluated relative to the parametric technologies. Importantly, the per capita block grant variable (*GRANT*) yields a negative and, with the exception of FDH (where it is marginally insignificant), significant coefficient. This finding, which is consistent with the results of, for example, Silkman and Young (1982), suggests that grants may not only encourage local service provision, but also stimulate inefficiency. Within the Belgian institutional environment this is not entirely surprising. Quite a lot of the funds municipalities receive from higher-level governments take the form of unconditional block grants, and there exists relatively little ex post control on actual spending.

The primary education proxy (*PEDUC*) consistently has the expected negative sign, although it is not always significant. Population density (*DENS*) yields a positive sign, but the variable is only significantly different from zero in the non-parametric approach. The estimates finally suggest that the presence of the socialist party (*CSOC*) has a positive effect, while the effect of liberals (*CLIB*) in the coalition is unclear because the sign of the coefficient is not robust across specifications of the reference technology.[16] Similar results, which run contrary to popular opinion on the supposedly spendthrift left parties, have been reported by De Grauwe (1985). Note that our results with respect to the impact of the political variables do differ somewhat from those obtained by Vanden Eeckaut et al. (1993). They found that only the FDH results revealed an effect of political factors, whereas no such impact was obtained using the DEA efficiency scores. However, since they did not use formal regression analyses, a comparison between the two studies is difficult.

The standard way to facilitate the interpretation of Tobit coefficients is to compute the partial effects of changes in the explanatory variables for the truncated sample. Adjusting the approach of McDonald and Moffitt (1980) for upper censoring, we calculated for each Tobit equation the multiplicative correction factor which transforms the estimates of Table 5 into partial effects. Computed at the sample means, the correction factors are 0.279,

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[16] As suggested in the text, we also included the number of coalition partners (*CPAR*) in the Tobit analyses. However, it did not always have the expected sign or it was totally insignificant. It is not included in the reported specifications.

0.748 and 0.670 for FDH, DEA, and SF-Mode, respectively. Performing this analysis suggests that the differences between DEA and FDH, and between SF-Mean, SF-Mode and DF, are much less pronounced than those between the non-parametric and parametric approaches. The largest deviations were found for the income and the block grants variables. The differences for the tax variable and the educational indicator were much less important.[17]

However, since the range and distribution of the efficiency measures differ, it remains difficult to interpret these partial effects in a meaningful way. For our purposes a qualitative assessment is therefore more relevant. First, it is interesting to observe that almost all parameters consistently have the same sign across the five equations. Exceptions are the dummy for the liberal coalition member, which is (insignificantly) negative for the FDH reference technology, and, also just in one specific case, the population density variable. The high degree of consistency in terms of the signs of the explanatory variables across specifications is reassuring. Second, it is clear that there are some non-trivial differences in the associated degree of significance, depending on the precise reference technology considered. This seems to suggest that focusing on just one reference technology, as most previous studies of local government efficiency have done, may be misleading. In addition to differences in rankings implied by the various methods, the significance of particular determinants of inefficiencies may depend on the specific reference technology being used. Third, in terms of policy relevance, it is important to note that block grants and income consistently affect efficiency negatively. In particular, the former effect requires further attention, because it could have substantial policy implications for the design of grants between various tiers of government. If these results were corroborated in future studies, it may suggest the need to incorporate proxies for municipal efficiency into the design mechanisms of grants. This is not yet the case in the Belgian context.

Although this paper has provided a detailed comparative analysis of parametric and non-parametric frontiers, it is clear that the problem of choosing the 'best' frontier methodology has not yet been satisfactorily solved (see, for example, Gong and Sickles, 1992). However, our study does add some useful evidence concerning this issue. First, it confirms the unrealistic low efficiency scores typically obtained with deterministic parametric frontiers. Second, the comparative results indicate that the search for an appropriate reference technology should not be limited to choosing between parametric and non-parametric methodologies. For

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[17] We indicated earlier that this may to some extent be a consequence of a bias in the second step of the parametric approach owing to the above-mentioned correlations of the block grant variable with the first-step independent variables.

instance, for our data DEA correlates better with the parametric frontiers than with the non-parametric FDH. Third, since the efficiency results clearly do depend on the specific frontier methodology employed, it seems to be more useful to focus future research on the validity of the assumptions underlying the various reference technologies. For example, in some applications there may be good economic reasons for explicitly imposing convexity; in others the introduction of stochastic components might be thought to be crucial. In those cases, the choice between different reference technologies can be narrowed down on the basis of economic arguments. To the extent that there are no a priori reasons to prefer one methodology over the others, and as long as there is no solution to the problem of choosing the 'best' reference technology (and there simply may be no solution), it seems to be preferable to analyze public sector efficiency questions using a broad spectrum of different methods and to find out just how robust the results are. Finally, in view of the relatively weak assumptions underlying the FDH and its advantages for managerial purposes, this reference technology provides a useful alternative to the more traditional methods. This may be especially true for the analysis of public sector production, since our knowledge of the production process and of behavioural goals in the public sector is surrounded with uncertainties.

5. Conclusions

The purpose of this paper was to compare a broad variety of non-parametric and parametric reference technologies using Belgian municipal data. Cost-efficiency measures were calculated on five different reference technologies: two non-parametric ones (FDH and variable returns to scale DEA) and three parametric frontiers (one deterministic and two variants of the stochastic approach). The analysis proceeded in two steps. We first investigated the efficiency measures in terms of differences in the resulting efficiency–inefficiency classification, and considered their distributions and implied rankings of municipalities. We then examined the degree to which the calculated inefficiencies could be explained by a number of economic and political variables.

The results can be summarized as follows. First, considering the various reference technologies, we found large differences in mean efficiency scores. The estimated means ranged from 0.57 to 0.94. Moreover, rank correlations between the parametric and non-parametric measures were relatively low, ranging between 0.59 and 0.83. As long as the problem of choosing the 'best' reference technology has not satisfactorily been solved, the ability to measure public sector performance accurately remains limited. Therefore, it would seem prudent to analyze efficiency questions using a broad variety of

methods to check the robustness of the results. Second, despite the variability in mean efficiency scores the explanatory analysis of inefficiency yielded, at least qualitatively, reasonably robust results. Although some non-trivial differences were found in terms of significance levels, it was reassuring to observe that with minor exceptions all parameters of the explanatory variables consistently had the same sign across the five specifications. Local tax rates and education were estimated to influence municipal efficiency positively. More importantly, both the per capita block grant and average income affected efficiency in a negative way. This finding certainly deserves further research, because the design of grants might take account of the unintended, negative impact on cost efficiency.

In general, given the data limitations of our study there certainly is a need to replicate this analysis for local governments in other countries. The literature could probably also benefit from more disaggregate studies that focus on particular local government outputs (fire brigade, police, civil registry, etc.).

Acknowledgements

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