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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 nonparametric and parametric reference technologies. 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). 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 implied differences in ranking of municipalities. In a final stage we examine the degree to which the calculated inefficiencies can be explained by a common set of explanatory variables.

JEL-Codes: D24, D60, H71, H72.

Keywords: local government performance, cost efficiency, nonparametric frontiers.

COST EFFICIENCY OF BELGIAN LOCAL GOVERNMENTS: A COMPARATIVE ANALYSIS OF FDH, DEA, AND ECONOMETRIC APPROACHES*

Although other aspects of public sector activities deserve careful attention as well, it is generally agreed that technical efficiency is an important component of the overall performance of the public sector (see, e.g., Rees (1984, p. 14-20)). It has been argued that technical efficiency is compatible with any other goal attributable to the public sector, including allocative efficiency, distributional considerations and macroeconomic objectives (see, e.g., Pestieau and Tulkens (1990, p. 6-7)). Moreover, it is well known that technically efficient production in second-best economies is welfare optimal under relatively weak assumptions (Bös (1986, p. 68)). Therefore, an analysis of technical efficiency provides an important, albeit partial, indicator for performance comparisons both within the public sector and between private and public sectors.

To analyze technical efficiency a variety of alternative methods have been developed. In addition to deterministic and stochastic parametric frontiers, several non-parametric reference technologies have been suggested in the litterature, including Data Envelopment Analysis (DEA) (see, e.g., Charnes, Cooper and Rhodes (1978)) and the nonconvex Free Disposal Hull (FDH) reference technology introduced by Deprins, Simar and Tulkens (1984). Surveys of the various methods are found in, e.g., Førsund, Lovell and Schmidt (1980), Lovell and Schmidt (1988), and, most recently, Lovell (1993).

Unfortunately, it is well known 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 nonnegligible differences in results (Corbo and de Melo (1986), Lovell and Schmidt (1988), Van Den Broeck, Førsund, Hjalmarsson (1980)). More recent comparative analyses of parametric and non-parametric approaches have yielded mixed results. Using a deterministic parametric and a DEA approach Bjurek, Hjalmarsson and Førsund (1990) found strong similarities between the different efficiency measures, except for the smallest production units. Ferrier and Lovell (1990) on

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the other hand 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, e.g., Grosskopf (1986), Bjurek, Hjalmarsson and Førsund (1990), and Vanden Eeckaut, Tulkens and Jamar (1993)).

This paper deals with the efficiency of local governments. Although a number of studies have recently analyzed the efficiency of municipal governments, most of this research has been based on either stochastic frontier approaches (e.g., Davis and Hayes (1993), Deller (1992), Deller and Rudnicki (1992), and Hayes and Chang (1990)), or non-parametric methods (e.g., Vanden Eeckaut, Tulkens and Jamar (1993)). In view of the importance of the underlying reference technology, the purpose of this paper is to add to this litterature by studying the cost efficiency of local governments in Belgium using a large variety of alternative methods. The contribution of the paper is twofold. First, by including the recently popularized FDH approach in the analysis we compare a larger variety of alternative methods than is typically the case in the litterature. 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). Second, 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. If not, then the analysis does not imply a uniform advice.

The data for the empirical analysis consist of information on total current expenditures and various output indicators for a single cross-section of all 589 municipalities in Belgium[1]. Note that there is no input price variation in the data. However, the fixity of salary scales of municipal personnel and the fact that all municipalities have access to the same capital markets imply that the assumption of identical input prices across municipalities may not be

[1] De Borger et al. (1992) use the same data set to analyse technical efficiency relative to the non-parametric FDH reference technology. The present paper largely extends that analysis by calculating cost efficiency indices relative to a broad variety of alternative reference technologies.

unreasonable. We therefore focus on the measurement of cost efficiency throughout the analysis[2].

The structure of the paper is as follows. In Section 1 we review the five reference technologies used in this paper. 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 2 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. The five efficiency indices are subjected to an explanatory analysis in Section 3. We explain the performance of Belgian municipalities using a number of economic and political variables, and analyze the differences in explanatory patterns across reference technology specifications. Section 4 concludes.

1. 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 and the corresponding efficiency indices in a dual cost framework.

Deterministic Non-Parametric Frontiers: DEA and FDH

The deterministic non-parametric methods, originating 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

[2] It is well known that the assumption of identical input prices implies that cost efficiency and technical input efficiency coincide. 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.

maintained assumptions on the structure of the production technology.

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, Cooper and Rhodes (1978) and extended in Färe, Grosskopf and Lovell (1985) and Seiford and Thrall (1990), among others. In this paper we consider a DEA model which assumes, in addition to the usual regularity axioms, strong disposability in costs and outputs, and allows for variable returns to scale.

Assuming identical input prices the DEA-cost correspondence can be constructed from observed activities in the following way (see, e.g., Färe and Grosskopf (1985) and Färe, Grosskopf and Lovell (1988)):

$$C(y)^{DEA} = \{\, c \mid Y^t z \geq y,\ C^t z \leq c,\ I_k^t z = 1,\ z \in \mathbb{R}_+^k \,\}$$

where Y is the kxn matrix of observed outputs, C is the kx1 vector of observed costs, z is a kx1 vector of intensity or activity variables, I_k is a kx1 unity vector, y is a nx1 vector of outputs and c is a scalar representing a cost or budget level. This dual or indirect correspondence denotes the set of budget or cost levels c which allow to produce the output vectors y.

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

$$\begin{aligned} &\min_{\lambda, z} \lambda \\ \text{s.t. } & Y^t z \geq y^\circ \\ & C^t z \leq c^\circ \lambda \\ & I_k^t z = 1 \\ & \lambda \geq 0,\ z \geq 0 \end{aligned}$$

where y° is a nx1 vector of outputs and c° 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 the optimal values (λ^*, z^*) where λ^* is the measure of cost efficiency and z^* is the optimal activity vector. The optimal value of λ^* 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.

Next consider the FDH reference technology, proposed by Deprins, Simar and Tulkens (1984), which recently gained substantial popularity as an alternative to the DEA model (see, e.g., Tulkens (1993), and Lovell and Vanden Eeckaut (1992)). It differs from DEA in that it drops the convexity assumption. In a dual context, the FDH-cost correspondence can be defined as:

$$C(y)^{FDH} = \{c \mid Y^t z \geq y,\ C^t z \leq c,\ I_k^t z = 1,\ z_i \in \{0,1\}\}$$

Cost efficiency is computed by solving the same programming problem as for DEA, except that the constraint

$$z_i \in \{0,1\} \quad for\ i = 1,\ldots,k$$

is added. In other words, consistent with allowing for nonconvexity the elements of the activity vector z are constrained to be either zero or one. Fortunately, while the cost efficiency measure can be calculated for each activity by solving the above mixed integer programming problem, a computationally simpler alternative is available based on weak vector dominance procedures (this algorithm is outlined in Tulkens (1993)). Observe that the optimal values (λ^*,z^*) have an identical interpretation as in DEA, except of course that only one component in z^* can differ from zero.

In Figure 1 we develop some intuition for the graphical representation of both the DEA and the FDH models for the case of one output. 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. On Figure 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 the same Figure 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 (1992). Using the cost efficiency measure inefficient observations are projected on an orthant spanned by a single efficient producer which is weakly dominating in both cost and outputs. For example, in Figure 1 the inefficient observation 1 is dominated by C and D as well as by 2 which is itself inefficient. Observation 1 is projected on 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 on 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 (1992)). Finally, the number of efficient observations on FDH is typically larger than on DEA.

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

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

$$C_i = C(y_i, w_i; \beta) \exp(u_i) \quad where\ u_i \geq 0$$

where u has some 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 (see Greene (1993) and Lovell (1993) for

[3] As noted by a referee, the traditional radial projections used in the nonparametric approach are more likely to leave slacks (unmeasured inefficiency) on FDH than on DEA. The problem is that the radial efficiency measure always projects on the isoquant, not necessarily on the efficient subset. Lovell (1993) and Lovell and Vanden Eeckaut (1992) review the problem and suggests 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. Of course, in the application of the current paper slacks occur only in the output dimensions.

details). The procedure is to first estimate β by OLS, and next 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 it is given by

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

Second, stochastic parametric frontiers are based on a composed error model which allows 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 can be defined as

$$C_i = C(y_i, w_i, \beta)\exp(v_i + t_i) \quad where\ t_i \geq 0$$

Several procedures are available to estimate the stochastic 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 litterature the error component v_i is taken to be independently and identically distributed as $N(0,\sigma_v^2)$. Two different cost efficiency measures for individual observations are obtained by adjusting the procedure proposed by Jondrow et al. (1982) for the case of a cost frontier. They suggest to construct point estimates for the individual error component t_i based on either the mean $E(t_i \mid v_i+t_i)$ or the mode $M(t_i \mid v_i+t_i)$ of the conditional distribution.

2. 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 the methodologies outlined previously. We calculate various indices of cost efficiency on four different reference technologies, viz. 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 straightforward cost interpretation. For example, a value of 0.80 indicates that a 20% cost reduction is feasible.

The sample consists of observations on total current municipal expenditures and on five output indicators for each of the 589 local governments in 1985[4]. The data used in the analysis are described in detail in De Borger et al. (1992). The output indicators intend to capture important aspects of local production in the field of education, social and recreational services, and overall administrative tasks. The following indicators were used:

(i) the number of beneficiaries of minimal subsistence grants (SUB);
(ii) the number of students enrolled in local primary schools (STUD);
(iii) the surface of public recreational facilities (REC);
(iv) the total population (POP);
(v) the fraction of the population aged 65 and above (OLD).

It is obvious from the list of outputs that, at best, they are to be considered proxies for the services delivered by municipalities rather than direct outputs. Moreover, in some cases substantial unobservable quality differences may exist. Unfortunately, direct outputs are not available for Belgian municipalities (De Borger et al. (1992)).

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

$$\ln C = \alpha + \sum_{i=1}^{5} \beta_i \ln y_i + \frac{1}{2} \sum_{i=1}^{5} \sum_{j=1}^{5} \gamma_{ij} \ln y_i \ln y_j$$

where C are total costs and y_j are output indicators, and the local approximation is at the sample means. For reasons previously explained, 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

[4] De Borger et al. (1992) have calculated FDH based efficiency measures for the same sample, but using explicit input indicators such as personnel and capital. They furthermore report a limited sensitivity analysis. Also note that Vanden Eeckaut, Tulkens and Jamar (1993) have reported results for the non-parametric approaches using the subsample of Walloon municipalities.

errors are between brackets. With the obvious exception of the constant term, the estimates are remarkably similar. The stochastic frontier intercept exceeds the deterministic one, as the former method attributes only part of the error term to cost inefficiency[5]. 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.

To retain consistency we calculated cost efficiency indices based on the 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 to 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 (SF-Mean) all observations are inefficient. Obviously, the latter two methods are not useful to perform 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 in common with FDH. Although FDH leads to a very large number of efficient municipalities, this is nevertheless a remarkable result. Apparently, there is somewhat less concordance between the SF-Mode method and DEA. From the 64 DEA efficient observations, 38 are common to the set of efficient

[5] Interestingly, we found that the restriction of a Cobb-Douglas cost function was rejected in both the corrected OLS and the ML estimation using respectively an F-statistic and a likelihood ratio test. This is reassuring because, as pointed out by a referee, the Cobb-Douglas specification implies a non-convex production set. The specification used does not impose, but at least allows for, convexity.

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, e.g., Epstein and Henderson (1989)). Clearly, the FDH reference technology is not vulnerable to this critique, as it relates each inefficient observation to an orthant spanned by a single dominating observation[6]. 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 lower mean efficiencies than measures estimated relative to a stochastic cost frontier. Also observe that mean efficiencies based on DEA and the stochastic frontier are quite similar.

The distributions of all efficiency measures are presented graphically in Figure 2, based on the inefficient observations only[7]. Especially 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 the widest range.

Further insight in 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. Results are in Table 3. The main

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

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

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 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 case of data sparsity nonparametric approaches, and especially FDH, tend to increase the probability of efficiency, the parametric methods imply the risk of extreme efficiency scores (see, e.g., Lovell (1993)).

Not only the shape of the efficiency distribution may be affected by the use of different reference technologies, 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 in Table 4. Several observations stand out from these results. First, the three stochastic approaches are closely related in their ranking of the relative inefficiencies in the sample, rank correlation coefficients being 0.99 and above. 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 methods (0.81-0.82) than relative to FDH. Of course, the correlations between FDH and the other models is rather low due to the large number of efficient observations in the former case.

3. 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. A preliminary explanatory analysis was performed for FDH-based efficiency scores in De Borger et al. (1992). We build upon that paper to investigate the degree to which the set of determinants of inefficiency is robust across various specifications of the reference technology. Robustness is a condition for the explanatory analysis to be useful for public policy.

Before proceeding it is worthwhile to make two remarks. First, we are clearly using a two-step approach to the explanation of inefficiency. Initially efficiency indices have been calculated, next they are explained. Although this two-stage approach is typical in the literature (Martin and Page (1983), Deller (1992)) a crucial underlying assumption is that the explanatory variables only influence technical efficiency but not the transformation process from inputs into outputs (Lovell (1993)). This assumption is especially important for the parametric approach. The two-step procedure is only meaningful as long as the first and second stage exogenous variables are uncorrelated. 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[8]. 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. In line with, e.g., Martin and Page (1983) the Tobit censored regression model was selected to accommodate the efficiency scores at unity in DEA, FDH, and SF-Mode[9]. Of course, there is no upper censoring in the case of DF and SF-Mean. Therefore, for these two efficiency measures OLS was used.

We now proceed by briefly reviewing the variables included in the specification[10]. First, it is well known that the incomes and wealth of citizens affect the incentives of both politicians and taxpayers to monitor expenditures. Higher incomes increase the fiscal capacity of municipalities and may foster featherbedding of politicians and public managers, thereby

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

[9] As stated in footnote 3 the non-parametric approaches may imply important slacks, and non-radial efficiency measures may provide useful alternatives. As far as explanation is concerned, De Borger and Kerstens (1993) found only minor qualitative differences between radial and non-radial measures.

[10] For more detailed justification we refer to De Borger et al. (1992)), where a number of other potential determinants are suggested as well.

increasing the scope for inefficient operation (see, e.g., Spann (1977), and Silkman and Young (1982)). Moreover, citizens of high-income municipalities may be less motivated to effectively monitor expenditures due to the high opportunity costs. To proxy for these 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' attention for controlling public expenditures, especially if cost comparisons between municipalities are easy (see, e.g., Spann (1977)). Recently, Davis and Hayes (1993) found evidence of a positive relation between tax rates and monitoring effort. 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), as 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. Although this is not directly implied by the flypaper effect, one can hypothesize a negative relation between grants and technical efficiency. In the US, Silkman and Young (1982) found evidence for this phenomenon. 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 as to 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 decisionmaking itself may impede the effective control of the public sector (Mueller (1989) and 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., logrolling) depending on the number and nature of the coalition partners. Two sets of variables were constructed to approximate the above ideas, viz. the number of parties in a municipal coalition (CPAR), and dummy variables indicating the presence 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 (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 of primary education as their final educational achievement (PEDUC)[11]. Finally, population density may affect the costs of providing a given bundle of public services. One 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 between brackets. 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, 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 impact, consistent with its interpretation as affecting both politicians' and taxpayers' incentives to control local expenditures. The tax price (HTAX) contributes positively to the explanation, in line with the monitoring effort relation postulated above. But the effect is insignificant for the efficiency scores evaluated relative to parametric technologies. The per capita block grant variable (GRANT) yields a negative coefficient. Thus grants not only encourage local service provision, but may also stimulate inefficiency. Note, however, that GRANT is only highly significant for the non-parametric approaches[12]. The estimates further suggest that the presence of the socialist party (CSOC) has a positive effect, while the effect of liberals (CLIB) in the coalition is unclear as the sign of the coefficient is not robust across specifications of the reference technology[13]. Furthermore, the primary

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

[12] This may be a consequence of a bias in the second step of the parametric approach due to the above mentioned correlations of the block grant variable with the first step independent variables. Alternatively, as emphasized by a referee, it may reflect the fact that the non-parametric approaches' primary objective is to classify municipalities according to whether or not they are efficient.

[13] 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 specification.

education proxy (PEDUC) has consistently the expected negative sign, although it is not always significant. Finally, population density (DENS) yields a positive sign, but the variable is only significantly different from zero in the non-parametric approach.

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 calculate 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, 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 nonparametric 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.

However, although they do provide some information the importance of the above differences should not be overstated. As 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. From this perspective it is interesting to observe that almost all parameters have consistently 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, in one case, the population density variable. Importantly, although there are some remarkable differences in their degree of significance depending on the precise reference technology considered, it turns out that block grants and income consistently affect efficiency negatively. Especially the former effect requires further attention, as it could have important policy implications for the design of grants between various tiers of government.

4. 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 nonparametric 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 nonparametric measures were relatively low, ranging between 0.59 and 0.83. Second, despite the variability in mean efficiency scores the explanatory analysis of inefficiency yielded, at least qualitatively, reasonably robust results. Although some nontrivial 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 deserves further research, as the design of grants might take account of the unintended, negative impact on cost efficiency.

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Figure 1: A cost frontier of a strongly disposable DEA model and the FDH

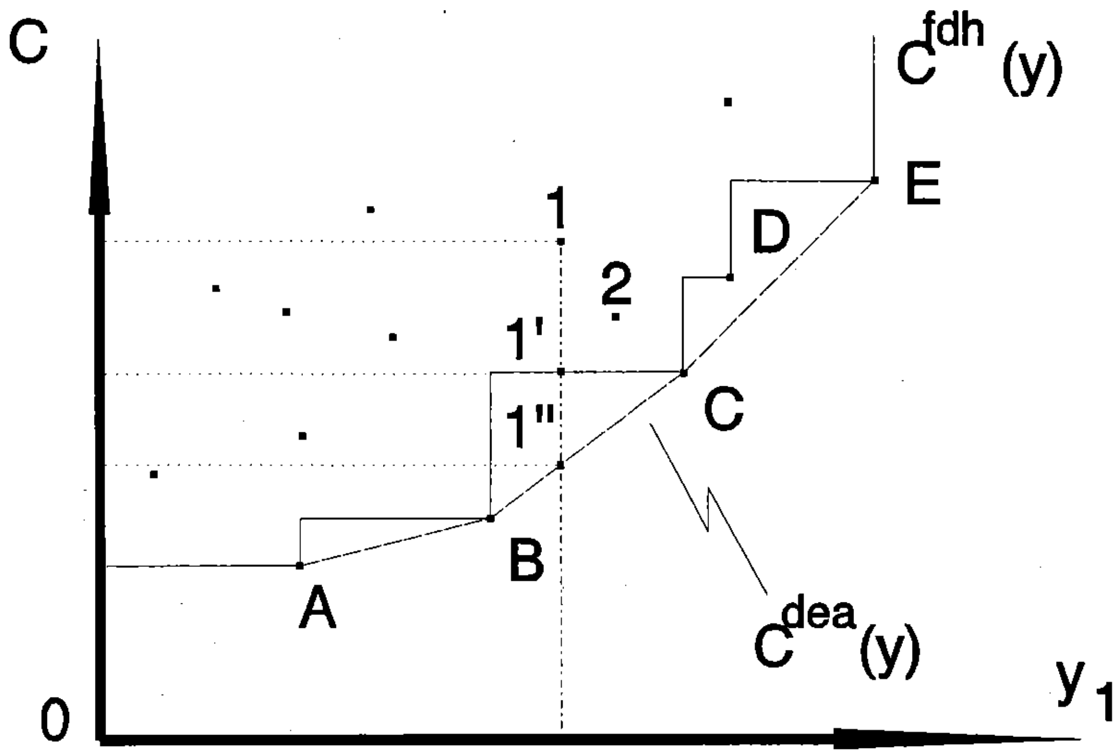

Table 1: Cost Frontier Estimates

Independent Variables	Parameters	Deterministic Frontier	Stochastic Frontier
Intercept	α	18.926	19.263
		(.019)***	(.026)***
ln SUB	β_1	.187	.202
		(.028)***	(.029)***
ln STUD	β_2	.106	.102
		(.036)***	(.035)***
ln REC	β_3	.063	.072
		(.029)**	(.028)**
ln POP	β_4	.795	.788
		(.053)***	(.049)***
ln OLD	β_5	.306	.284
		(.096)***	(.097)***
(ln SUB)^2	γ_{11}	.060	.080
		(.035)*	(.039)**
(ln STUD)^2	γ_{22}	- .030	- .015
		(.074)	(.077)
(ln REC)^2	γ_{33}	.086	.065
		(.038)**	(.038)*
(ln POP)^2	γ_{44}	.472	.482
		(.168)***	(.162)***
(ln OLD)^2	γ_{55}	- .043	.097
		(.327)	(.441)
ln SUB*STUD	γ_{12}	.087	.091
		(.081)	(.081)
ln SUB*REC	γ_{13}	.066	.064
		(.058)	(.060)
ln SUB*POP	γ_{14}	- .155	- .215
		(.121)	(.129)*
ln SUB*OLD	γ_{15}	.361	.330
		(.190)*	(.194)*
ln STUD*REC	γ_{23}	.074	.059
		(.085)	(.078)
ln STUD*POP	γ_{24}	- .084	- .090
		(.183)	(.184)
ln STUD*OLD	γ_{25}	.213	.268
		(.270)	(.231)
ln REC*POP	γ_{34}	- .487	- .454
		(.134)***	(.127)***
ln REC*OLD	γ_{35}	.149	.160
		(.203)	(.216)
ln POP*OLD	γ_{45}	- .861	- .861
		(.445)*	(.397)**
$\lambda=\sigma_\epsilon/\sigma_v$		-	2.358
		-	(.269)***
		R^2 .947	LogL 20.781
		SER .243	
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

Figure 2: Histogram of Inefficiency for Inefficient Belgian Municipalities

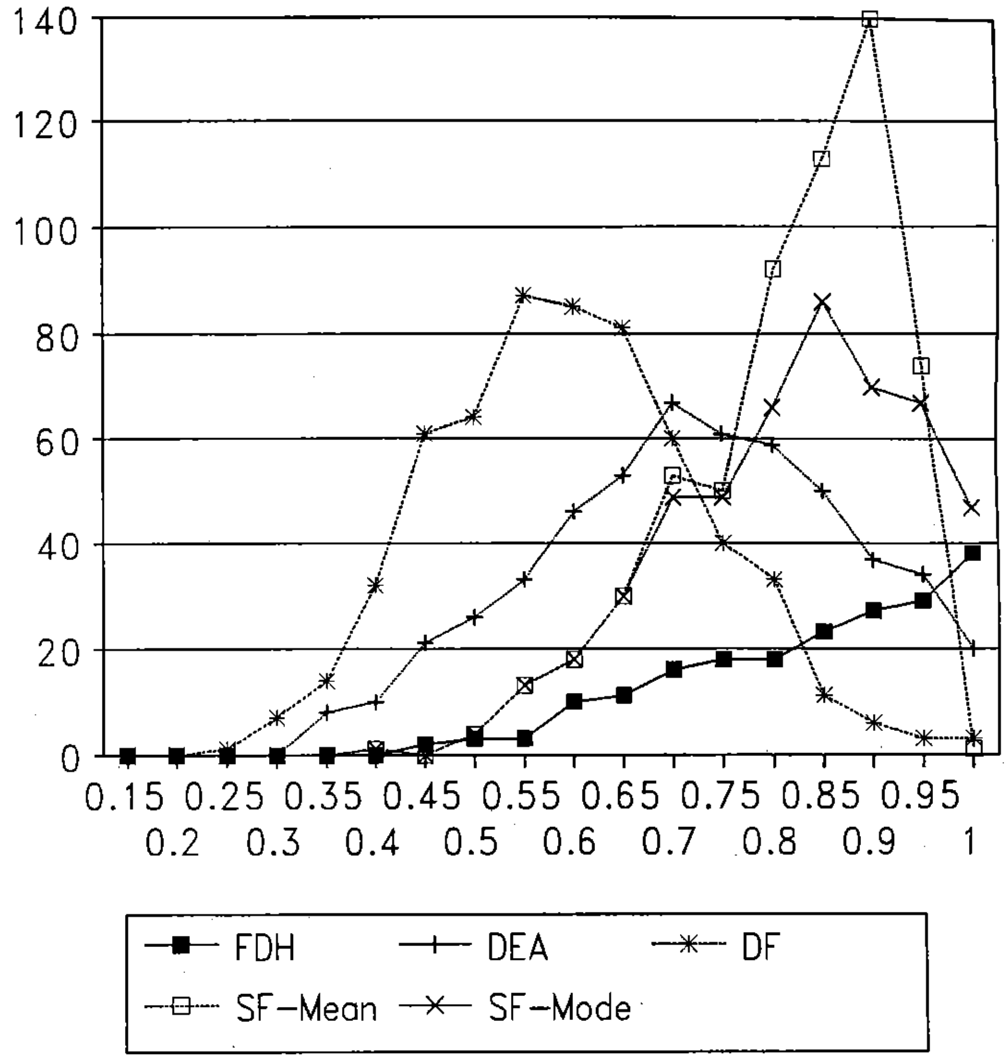

Table 2: Summary Statistics for Efficiency Measures (N=589)

	Mean	Standard Deviation	Skew-ness	Kur-tosis	Mini-mum	Maxi-mum	# Efficient Observations
FDH	.937	.119	-2.005	6.182	.441	1.000	391 (66.4%)
DEA	.727	.174	-.114	2.232	.318	1.000	64 (10.8%)
DF	.570	.131	.250	3.010	.223	1.000	1 (0.2%)
SF-Mean	.781	.117	-.839	3.087	.347	.953	0 (0 %)
SF-Mode	.809	.142	-.449	2.459	.347	1.000	72 (12.2%)

Table 3: Efficiency Measures per Cost Category

Local Government Expenses (Mio BF)	# Obs.	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%	.80	12%	.67	1%	.61	0%	.80	18%	.80
100-199.9	199	57%	.83	5%	.69	0%	.58	0%	.80	14%	.80
200-299.9	70	63%	.79	9%	.70	0%	.55	0%	.78	10%	.78
300-399.9	42	59%	.77	5%	.65	0%	.49	0%	.71	2%	.71
400-499.9	32	81%	.77	9%	.75	0%	.53	0%	.76	0%	.78
500>	78	82%	.85	28%	.75	0%	.53	0%	.75	9%	.75
Total	589	66%	.81	11%	.69	0%	.57	0%	.78	12%	.78

Table 4: Correlation Matrix for Efficiency Measures (N=589)

	FDH	DEA	DF	SF-Mean	SF-Mode
Spearman rank correlations					
FDH	1.000				
DEA	.662	1.000			
DF	.594	.814	1.000		
SF-Mean	.590	.829	.995	1.000	
SF-Mode	.590	.827	.994	.999	1.000
Pearson product moment correlations					
FDH	1.000				
DEA	.653	1.000			
DF	.583	.813	1.000		
SF-Mean	.666	.821	.949	1.000	
SF-Mode	.638	.828	.962	.991	1.000

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)**	(0.519)**	(0.709E-03)
DENS	29.883	11.361	2.622	-0.781	0.373
	(15.91)*	(5.074)**	(3.155)	(2.812)	(3.818)
LogL	-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