Local Government Efficiency: Evidence from the Czech Municipalities*

Lenka Šťastná† Martin Gregor‡

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Abstract

We measure cost efficiency of 202 Czech municipalities of extended scope in period 2003–2008. The study is the first application of overall efficiency measurement of the local governments in the new EU member states, and the second in post-communist countries. We measure government efficiency through established quantitative and qualitative indicators of the provision of education, cultural facilities, infrastructure and other local services. First, we employ non-parametric approach of the data envelopment analysis and adjust the efficiency scores by bootstrapping. Second, we employ the stochastic frontier analysis and control for effects of various demographic, economic, and political variables. We compare scores under our preferred specification, i.e. pseudo-translog time-variant stochastic-frontier analysis with determinants, with alternative scores. The determinants that robustly increase inefficiency are population size, distance to the regional center, share of university-educated citizens, capital expenditures, subsidies per capita, and the share of self-generated revenues. Concerning political variables, increase in party concentration and the voters' involvement increases efficiency, and local council with a lower share of left-wing representatives also tend to be more efficient. We interpret determinants both as indicators of slack, non-discretionary inputs, and unobservable outputs. The analysis is conducted also for the period 1994–1996, where political variables appear to influence inefficiency in a structurally different way. From comparison of the two periods, we obtain that small municipalities improve efficiency significantly more that large municipalities.

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†Corresponding author. Ph.D. candidate. Institute of Economic Studies, Faculty of Social Sciences, Charles University, Opletalova 26, Prague, CZ-110 00; E-mail: stastna@fsv.cuni.cz.

‡Institute of Economic Studies, Faculty of Social Sciences, Charles University, Opletalova 26, Prague, CZ-110 00; E-mail: gregor@fsv.cuni.cz.

1 Introduction

Efficiency of local public spending is a topic of recent interest in public and urban economics. For practitioners, robust efficiency measures serve as performance benchmarks that help to discipline and improve local public management; for academic economists, the production function approach embedded in the efficiency measures allows to measure and explain the government's bias to the production of publicly irrelevant outputs, and separate between competing explanations why the local governments increase public spending.

In the last two decades, measuring efficiency in local governments became widespread particularly within individual European countries. Recent evidence is available from Belgium (Vanden Eeckaut et al. 1993; De Borger, Kerstens 1996; De Borger et al. 1994; for Flanders, see Geys and Moesen 2009a, 2009b), Finland (Loikkanen, Susiluoto 2005), Germany (Geys et al. 2010; Kalb 2010), Italy (Boetti et al. 2010), Norway (Borge et al. 2008), Portugal (Afonso, Fernandes 2006, 2008), and Spain (Arcelus et al. 2007, Balaguer-Coll et al. 2007; Gimenez, Prior 2007). Out of Europe, recent studies cover, inter alia, the large U.S. cities (Grossman et al. 1999; Moore et al. 2005), Canadian municipalities (Pollanen 2005) as well as Australian municipalities (Worthington, Dollery 2002).

There are three reasons to measure efficiency of local governments rather than central governments: (i) Unlike cross-country comparisons of public sector efficiency, single-country studies feature relatively consistent statistics and suffer less from unobserved heterogeneity, hence more likely comply with the restrictive assumption of a homogenous production function. (ii) Municipalities implement many "state-delegated" powers assigned by the central government, where the only room for manoeuvre is on the cost side. (iii) At the local level, policies are more means-focused than ends-focused also because of the absence of many instruments that address the main socio-economic (distributive) conflicts, such as income taxation, and therefore are more related to the provision of (local) public goods.

We empirically asses cost efficiency of 202 municipalities of extended scope in the Czech Republic over the period 2003–2008. This period features institutional and territorial stability, unlike the reform years 2000–2002. By measuring efficiency comprehensively instead by sector-specific scores, we avoid an issue of fungibility of spending and misclassification into spending categories that is quite frequent at the local level. To our knowledge, our study is a first comprehensive local government efficiency exercise in the new EU members states, and the second in the post-communist region (cf. Hauner 2008). The analysis of determinants allows us to assess whether patterns of efficiency in municipalities of a post-communist country differ from those in the culturally and institutionally not so distant Western European countries (e.g., Belgium, Finland, or Germany); it also permits to briefly observe the evolution in performance and efficiency from 1990s to 2000s.

We apply both parametric and non-parametric efficiency measurement methods, and also explain why the most refined parametric method (stochastic frontier analysis with a time-variant Pseudo-Translog specification and determinants) is, at least in our setting, preferred to the best non-parametric method (data envelopment analysis with variable returns to scale and bias corrected by bootstrapping). We end up with efficiency scores and compare with alternative methodologies. For each individual municipality, our procedure allows to isolate away separately (i) the effect of including determinants and (ii) the effect of assuming stochastic parametric versus deterministic non-parametric methodology, which is crucial for the interpretation of individual scores and benchmarking.

This analysis of the slack is conditional on the proper definition of the relevant set of outputs; we focus on basic services and maintenance of infrastructure, including also selected quality indicators. As is typical in the literature, the efficiency scores thus have to be interpreted as the provision of observable core services. In the parametric approach, we employ and control for effects of various demographic, economic, and political variables. Important ones are population size, distance to the regional center, education, fiscal capacity, and local political competition. We interpret determinants both as effects upon the slack and the presence of non-discretionary inputs and unobservable outputs.

With a preferred method, we replicate the analysis also for the period 1994–1996, with a few changes. The effect of determinants is quite similar, with exception of political variables that appear to influence inefficiency in a structurally different way. From comparison of the two periods, we also obtain that small municipalities improve efficiency significantly more that large municipalities. As a result, initially low differences between efficiency scores, especially between medium-size and large municipalities, have magnified over time.

The paper proceeds as follows. Section 2 briefly outlines the methodology on estimation of efficiency scores, and Section 3 presents the dataset. Section 4 gives the non-parametric results with year-specific scores and their averages. The key Section 5 delivers the parametric results for panel data with determinants, evaluates the role of determinants, and compares the available methods. Section 6 analyzes efficiency in 1990s. Section 7 concludes.

2 Methodology

Although discretion exists in many variables in the researcher's menu of choices, a key decision in an efficiency estimation is always whether cost efficiency of decision-making units will be measured in the class of non-parametric or parametric methods. A non-parametric approach generates the best practice frontier by tightly enveloping the data, where this envelopment is achieved by solving a sequence of linear programs. The main advantage of the non-parametric approach is the absence of the apriori specification of the functional form of the frontier. Two main techniques stand out within the non-parametric approach, Data Envelopment Analysis (DEA) and Free Disposal Hull Analysis (FDH). DEA, initiated by Farrel (1957) and made widespread by Charnes et al. (1978), assumes that the production frontier is convex, while FDH, suggested by Deprins et al. (1984), drops the convexity assumption. These methods are fully deterministic, and the entire deviation from the frontier is interpreted as inefficiency.

The parametric approaches establish the best practice frontier on the basis of a specific functional form applied in an econometric estimation. Moreover, the deviations from the best practice frontier derived from parametric methods can be interpreted in two different ways. While deterministic approaches interpret the whole deviation from the best practice frontier as inefficiency (corrected OLS method), stochastic frontier models proposed by Aigner et al. (1977) and Meeusen and van den Brock (1977) decompose the deviation from the frontier into an inefficiency part and a stochastic term. In addition, environmental variables can be easily treated with a stochastic frontier, whereas two-stage DEA models (e.g., OLS and Tobit censored regression) ignore serial correlation of efficiency scores(Simar, Wilson 2007).

We can examine efficiency from an input or an output perspective. Input-oriented efficiency measures how inputs can be contracted given output levels, while output-oriented efficiency keeps input fixed and explores a possible output expansion. The choice of the orientation is not entirely arbitrary; the orientation is better put on the side that is more subject to a discretionary choice. In the case of Czech municipalities, the policy-makers municipalities more likely influence spending levels (inputs) than the size of infrastructure, number of public facilities and amount of population (outputs), hence input-oriented efficiency is more appropriate.

2.1 Data Envelopment Analysis

Data Envelopment Analysis (DEA) determines the most efficient municipalities in the sample. These form the "best practice frontier" in a multi-dimensional space defined by inputs and outputs. The relative efficiency of municipalities lying under this best practice frontier is computed by their deviations from the frontier. The exact procedure is described in Section A.1 in Appendix.

Either of three restrictions on the returns to scales applies: Constant returns to scale (CRS) are reasonable if a proportional increase in inputs is expected to result in a proportional increase in outputs. With sufficiently high fixed costs of operation, smaller municipalities will tend to have higher average costs for outputs and larger municipalities exploiting scale economies will tend to have lower average costs. Hence, it can be more appropriate in our case to select variable returns to scale (VRS) or non-increasing returns to scale (NIRS). We compute efficiency estimates under all three returns-to-scale assumptions to illustrate differences and potential drawbacks of each particular assumption (see also Banker et al. 1996; Simar, Wilson 2002).

Given that DEA is by definition a deterministic method, the efficiency estimates are subject to uncertainty due to sampling variation. To allow for statistical inference, we apply homogenous bootstrap by Simar and Wilson (2000). The technique is described in Section A.3 in Appendix.

2.2 Stochastic Frontier Analysis

Stochastic frontier analysis (SFA) estimates the frontier parametrically, allowing for the error term, and possibly introducing also environmental variables in the estimation. As it represents our preferred method, we introduce the analysis in more details (see also Aigner et al. 1977). We consider input-oriented efficiency where the dependent variable is the level of spending, and independent variables are output levels. The method assumes a given functional form for the relationship between costs y and outputs $\mathbf{x}$, usually Cobb-Douglas or Translog. For a municipality i, a stochastic frontier production function model is given as

$$y_i = f(\mathbf{x}_i) + \epsilon_i, \quad \epsilon_i = v_i + u_i. \tag{1}$$

In contrast to DEA, a deviation from the frontier is not interpreted entirely as an inefficiency. The statistical error ϵ_i is rather decomposed into noise v_i which is assumed to be i.i.d., $v_i \sim N(0, \sigma_v^2)$, and a non-negative inefficiency term u_i having usually half-normal or truncated normal distribution.[1] It is also assumed that $\mathrm{cov}(u_i, v_i) = 0$ and u_i and v_i are independent of the regressors.

The Cobb-Douglas functional form for the costs writes

$$\ln y = \beta_0 + \sum_{p=1}^{P} \beta_p \ln x_p, \tag{2}$$

while Translog generalizes Cobb-Douglas form by adding cross-products,

$$\ln y = \beta_0 + \sum_{p=1}^{P} \beta_p \ln x_p + \frac{1}{2} \sum_{p=1}^{P} \sum_{q=1}^{P} \beta_{pq} \ln x_p \ln x_q. \tag{3}$$

Battese and Coeli (1992) extend the original cross-sectional version of SFA in Eq. (1) to panel data. The model is expressed as

$$y_{i,t} = f(\mathbf{x}_{i,t}) + \epsilon_{i,t} \quad \epsilon_{i,t} = v_{i,t} + u_{i,t}, \tag{4}$$

where $y_{i,t}$ denotes costs of municipality i in time $t = T, T+1, \dots$ and $\mathbf{x}_{i,t}$ is vector of outputs of municipality i in time t. Statistical noise is assumed to be i.i.d., $v_{i,t} \sim N(0, \sigma_v^2)$, and independent of $u_{i,t}$. Technical efficiency $u_{i,t}$ may vary over time

$$u_{i,t} = u_i \exp[\eta(t - T)], \tag{5}$$

where η is parameter to be estimated, and $u_{i,t}$ is assumed to be i.i.d. as truncations of zero of $N(\mu, \sigma_u^2)$. The model is estimated by maximum likelihood.[2] Like Battese and Corra (1977), we introduce parameter $\gamma := \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$ that conveniently represents the magnitude of technical efficiency in the error term; if $\gamma = 0$, then all deviations from the frontier are due to noise, while $\gamma = 1$ represents the opposite case when all deviations are attributed to technical inefficiency.

[1] Exponential or gamma distributions are chosen less commonly, and the resulting ranking is moreover argued to be quite robust to the choice of the distribution (Coelli et al. 2005).

[2] SFA estimation relies on decomposing observable $\epsilon_{i,t}$ into its two components which is based on considering the expected value of $u_{i,t}$ conditional upon $\epsilon_{i,t}$. Jondrow et al. (1992) derive the conditional distribution (half-normal) and under this formulation, the expected mean value of inefficiency is:

$$E[u_i|\epsilon_i] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(\epsilon_i\lambda/\sigma)}{\Phi(-\epsilon_i\lambda/\sigma)} - \frac{\epsilon_i\lambda}{\sigma}\right],$$

where $\lambda = \sigma_u/\sigma_v$, $\phi(\cdot)$ and $\Phi(\cdot)$ are, respectively, the probability density function and cumulative distribution function of the standard normal distribution, $f(u|\epsilon)$ is distributed as $N^+\left(-\epsilon\gamma, \gamma\sigma_v^2\right)$. If $\lambda \to +\infty$, the deterministic frontier results (i.e., one-sided error component dominates the symmetric error component in the determination of ϵ). If $\lambda \to 0$, there is no inefficiency in the disturbance, and the model can be efficiently estimated by OLS.

In Stochastic Frontier Analysis, environmental or background variables may be included by computing the efficiency scores in the first step and then regressing them on environmental variables in the second step. The second-stage efficiency model is expressed as

$$u_{i,t} = \delta \mathbf{z}_{i,t} + w_{i,t}, \tag{6}$$

where $\mathbf{z}_{i,t}$ is a vector of environmental variables of municipality i in time t, δ is a vector of parameters to be estimated, and $w_{i,t}$ is random noise. A shortcoming is inconsistency of assumptions in the two stages that leads to biased results: In the first stage, inefficiencies are assumed to be identically distributed, while in the second-stage, the predicted efficiencies to have a functional relationship with the environmental variables. Therefore, we estimate efficiency and its determinants in a single-stage (Kumbhakar et al. 1991; Reifschneider, Stevenson 1991; Huang, Liu 1994; Battese, Coelli 1995). We follow simultaneous estimation technique by Battese and Coelli (1995) who expand Huang and Liu's (1994) model for panel data context. Eqs. (4) and (6) are estimated simultaneously, and additionally, it is assumed that $v_{i,t} \sim N(0, \sigma_v^2)$, $v_{i,t}$ is i.i.d. and independently distributed of $u_{i,t}$, $u_{i,t}$ is obtained by truncation at zero of $N(\delta \mathbf{z}_{i,t}, \sigma_u^2)$, $u_{i,t} \geq 0$. Hence, environmental variables influence the mean of the truncated normal distribution of $u_{i,t}$.

3 Data

3.1 Municipalities

This section covers the institutional context for the municipalities analyzed, describes inputs and outputs, and provides descriptive statistics. To begin with, notice that time span in our sample, 2003–2008, corresponds to an exceptionally stable period, both from the economic and institutional point of view. In contrast, the preceding years 2000–2002 marked a major reform of the territorial public administration. The tax-allocation formula affecting the sources of municipalities was virtually unchanged in the period analyzed, with a minor parametric reform implemented as late as in the year 2008.

By international comparison, the Czech Republic is characterized by extreme territorial fragmentation (Hemmings 2006). Each municipality exercises both independent competencies and specific delegated powers, and the scale of operation is increased for delegated powers. The reason is that the extent of delegated powers differs with municipality administrative type. Out of 6243 municipalities, 1226 run population registration, 617 provide building permits, 388 are municipalities of the "second type", and 205 are municipalities of extended scope or "third type".

Our subject of analysis are municipalities of extended scope. These third-type municipalities constitute a specific administrative tier in the Czech government. Their origin goes back to a reform initiated in 2000 whose primary aim was to delegate a wide range of responsibilities to 14 new regional governments (NUTS 3 level) from the national level. In the second stage of the reform, 76 territorial districts were dissolved, and major part (approx. 80%) of their agenda passed to the 205 municipalities of extended scope; the minor part of former district services rests now with the 14 regions.[3]

Each municipality of extended scope administers a district comprising, on average, 30 other municipalities. Nevertheless, the third-type municipality always consists of the central town in the district,[4] so population of municipality of extended scope constitutes a relatively large share of total population in the district; mean size of population in the municipality of extended scope is 19,497 and mean population size of the district is 40,712.

Independent competencies of a municipality include provision of primary schools and kindergartens, primary health care, local police, fire brigade, public utilities, territorial planning, maintenance of local roads, and garbage collection. Delegated responsibilities of the municipalities of extended scope encompass mainly administration of population register, issuance of identity cards, travel documents, driving licenses, water and waste management, environmental protection, management of forestry, local transportation provision, roads maintenance, social benefits payments, and social care services. The large extent of delegated responsibilities is one of the motives for input-oriented analysis. However, in some fields, the room for discretion is negligible not only on the output side, but also on the input side. Especially for mandatory social transfers, the municipality is only an administrative intermediary disbursing funds allocated by the central government to beneficiaries. In the subsequent subsection, we attempt to isolate away non-discretionary inputs and outputs.

The revenues of municipalities consist of tax revenues (in 2008, 44%), non-tax revenues (11%), capital incomes (7%) and subsidies/grants (38%). Most of the tax revenue is via a formula-based allocation of personal income tax, corporate income tax and value-added tax. The allocation is a per-capita payment based on population size with 17 brackets (until 2008). In municipalities, a small share of the total tax allocation is based on local incomes of the self employed and the employed. In addition, there is some leeway for local revenue through real-estate taxes (though within statutory limits) and fees. Grants are generally earmarked, and a non-earmarked grant is also provided to cover the cost of providing central-government services. There is regulation on debt, and revenues are also raised through sales of assets and flows from off-budget accounts (Hemmings 2006).

Homogeneity is definitely key in efficiency estimation. In some within-country studies (Afonso, Fernandez 2008), concern for homogeneity motivated even clustering district into subsamples. Even though we can identify and isolate away outliers and also control for determinants, a sufficiently homogeneous sample of municipalities is still necessary to eliminate the risk of omitted variable bias and the resulting misspecification. Therefore, we opt for municipalities with the extended powers: the range of responsibilities is similar, the districts administered are of a similar size, the municipalities constitute regional centers, and the sample is large enough even for single-year cross-sectional analysis. In addition, the municipalities of extended scope have much more discretion over spending than regions. Untied municipal revenue in the form of tax and capital revenue accounts for over 70% of revenue, with earmarked grants accounting for the remainder. In contrast, a little under 40% of revenues of

[3]The transfer of agenda from the former districts also explains why some statistics are still being collected and provided only at the level of the non-existent administrative districts.

[4]Figure A1 in Appendix shows geographical division of the Czech Republic into the districts administered by the municipalities of extended scope.

the regional governments are untied (Hemmings 2006).

For the purpose of homogeneity, we exclude the capital city of Prague, which is not only extremely large (with 1.2 milion inhabitants, four times the second largest city), but also constitutes one of the 14 regions of the Czech Republic, hence exercises an idiosyncratic mix of public services. From the sample, we eliminate also three other largest cities in the Czech Republic, i.e., Brno (371,000), Ostrava (308,000) and Plzen (170,000). They substantially exceed levels of population in the rest of the sample, where median is 12,212, mean is 19,497, and maximal size is 101,268. The analysis is thus employed for 202 municipalities of extended scope with population ranging from around 3,000 up to 101,000. The full list of municipalities is provided in Table A1 in the Appendix.

3.2 Inputs

The crucial task in the computation of efficiency is to properly define outputs and inputs. Following the majority of the literature (see six of out eight recent studies in Table A2), we approximate inputs by *Total current spending*. This is even more appropriate given that capital spending is highly volatile and subject to co-financing with EU Structural Funds. Our source is the complete database of municipality budgets ARIS provided by the Ministry of Finance.[5] In the year 2008, the current expenditures represented 78% of total expenditures (if mandatory expenditures were included) and 72% of total in the absence of mandatory expenditures.

To provide a look into the budget composition, we aggregated data on current expenditures into 10 groups: Administration; Agriculture; Culture and sports; Education; Environment protection; Health; Housing and regional development; Industry and infrastructure; Public safety; Social and labor market policy. Table 1 provides summary statistics of individual expenditure groups. We excluded two groups of large mandatory payments: social transfers payments and subsidies on education. The former are purely non-discretionary formula-allocated grants that are earmarked and monitored in use, and the latter are temporary transfers to municipalities in years 2003 and 2004 associated with financing of the primary schools.[6] The last column in Table 1 shows the share of each expenditure group in the average budget after the exclusion. Prices are adjusted by CPI inflation and expressed in base year 2003.

[5] Available at: http://www.mfcr.cz/cps/rde/xchg/mfcr/hs.xsl/aris.html

[6] Since the year 2005, the state subsidies to primary schools are directly transferred to schools without involvement of the municipality budgets.

Table 1. Expenditures: summary statistics

	Mean	Min	Max	Share (%)
Administration	73,782	18,608	413,069	32.06
Agriculture	1,604	0	34,134	0.7
Culture and sports	29,433	0	282,169	12.79
Education: discretionary	24,410	2,802	156,127	10.61
Environmental protection	20,246	0	175,700	8.80
Health	2,663	0	62,300	1.16
Housing and regional development	31,320	722	219,797	13.61
Industry and infrastructure	27,177	0	385,696	11.81
Public safety	9,719	0	122,909	4.22
Social care: discretionary	9,860	0	107,973	4.29
Total after exclusion	230,163	36,451	1,498,326	100.00

Source: ARIS database, Ministry of Finance; own calculations.
Note: Thousands (Czech koruna), N=1212.

To account for diverse cost conditions in municipalities, we alternatively work with the *wage-adjusted inputs*. Thereby, we assume that the labor cost difference across regions may serve as a good proxy for the overall cost difference. Wage adjustment input is particularly useful in DEA where alternative ways to include wage in the production process are less convenient. The wage variable nevertheless contains sizeable imperfections: since data on gross wages are unavailable on the municipal level, we first collect wages for the 76 territorial districts for the period 2003–2005, and in 2006–2008 use wage growth in 14 regions to approximate for the district wages.

3.3 Outputs

Our preference for a comprehensive approach to efficiency is motivated by issues of fungibility of spending and misclassifications into expenditure categories. Moreover, we can swiftly disregard that some expenditure items may relate to various classes of outputs. At the same time, a single output variable may be relevant for different classes of outputs. Our variable selection is driven primarily by literature in the field (see Table A2 in the Appendix), by the country specifics of the local public sector in the Czech Republic, data availability, and by the attempt to match each specific expenditure group with a group-specific set of output variables. As agriculture and health spending is negligible in municipalities budgets, we do not seek outputs specific to these expenditure groups. In the end, we select the following 19 output variables, listed also in Table 2.

Administration Administration expenditures are related to size of *Population of the district* administered by the municipality. This reflects that a municipality with extended powers carries out many administrative services for the district as the whole. Social care expenditures reflect support for retirements homes and homes for disabled, hence we include *Old population* (population above 65 years of age) and the number of *Homes for disabled* among outputs.

Cultural facilities Expenditures on culture and sports comprise subsidies for theaters, municipal museums and galleries, libraries, sport clubs, sport events and costs on monuments preservation. The numbers of theaters, cinemas, children's centers and libraries are all summed into a variable of *Cultural facilities*; the facilities may be both private and public. Additionally, we include the number of *Municipal museums and galleries* (hence, in public ownership only), the number of *Objects in municipal monuments reserve* and the size of *Sporting and recreational area.*

Education Municipalities finance mostly primary schools and kindergartens, while grammar schools are financed mostly by the regional government. As a quantitative output, we include the number of *Pupils in primary schools and kindergartens* in a municipality. To evaluate the quality of education, we include the percentage of *Pupils who enter the upper secondary schools* at the age of 11 or 13. Thereby, we exploit that children with higher skills and better education have an option to enrol for a six-year or eight-year program in the upper secondary schools with more demanding classwork.

Environment Environmental protection primarily deals with waste collection, air, soil and ground water protection, and nature preservation. *Municipal waste* corresponds to expenditures on waste collection. *Pollution area* is a variable that includes environmentally harming areas such as built-up area and arable land, *Nature reserves* is linked to spending on nature preservations, and the size of *Urban green areas* reflects spending on parks maintenance.

Housing and industry For housing and regional development we selected *Built-up area* and the number of *New dwellings* completed. The built-up area corresponds to the extra provision of services of municipal utilities and the new dwellings represent the effect of municipal financial support for housing construction. Industry and infrastructure spending contains support of businesses, costs on municipal roads maintenance, support of public transportation and costs of water resources management. As corresponding outputs we use the number of *Businesses*, the size of *Municipal roads* (close to traditionally measured surface of roads) and the number of *Bus stations.*

Public safety Expenditures on public safety involve municipal police and fire brigade services which we proxy by *Built-up area* served and *Municipal police* dummy.

Table 2. Outputs: summary statistics

	Mean	Min	Max	Source
Pupils in primary schools and kindergartens	2,154	81.96	11,944	IIE
Pupils entering secondary schools (%)	11.31	0	33.70	IIE
Cultural facilities	11.43	1	69	CZSO
Municipal museums and galleries	0.41	0	3	MGA
Objects in monuments reserve	25.83	0	254	NIM
Sporting and recreational area (ha)	35.12	2.35	273.6	CZSO
Municipal waste (tons)	14,942	16.19	124,836	ME
Nature reserves	10.67	0	48	ANCLP
Pollution area (ha)	2281	14.75	8,746	CZSO
Urban green area (ha)	51.37	3.09	351.7	CZSO
Built-up area (ha)	156.9	17.57	726.0	CZSO
New dwellings	39.47	0	600	CZSO
Businesses	4,440	521	33,084	CZSO
Municipal roads (ha)	52.85	6.62	202.6	CZSO
Bus stations	30.71	4	112	IDOS
Population in district	40,712	9,175	160,720	CZSO
Old population	2,744	380	17,297	CZSO
Homes for disabled	0.41	0	4	CZSO
Municipal police	0.87	0	1	CZSO

Sources: ANCLP = Agency for Nature Conservation and Landscape Protection, MGA = Museums and Galleries Association, CZSO = Czech Statistical Office, IDOS = Transportation timetables, IIE = Institute for Information on Education, ME = Ministry of Environment, NIM= National Institute of Monuments.
Note: $N = 1212$.

As a very preliminary analysis, we carry out individual pre-analyses for each expenditure group, shown in Table 3. In simple pooled OLS, we regress the group-relevant outputs on group expenditures and realize that R^2 falls within the range 0.70–0.90 in all but two cases; for *Housing* and *Social care*, we cannot find better outputs to increase R^2 above 0.45. Although the variable of municipal museums and galleries has negative significant coefficient, we keep it among outputs. Small municipalities, i.e. those having lower spending, are more likely to have municipal museums than big municipalities, where many private museums and galleries operate and survive more easily. Similarly, we observe negative coefficient for new dwellings which may reflect some specific characteristic of a municipality where housing construction is more developed, hence we also keep it among outputs.

When selecting outputs, we also consider tradeoff between relevance and dimensionality. Irrelevant outputs can bias efficiency scores but a high number of (especially highly correlated) outputs artificially makes many municipalities fully efficient. In addition, efficiency analysis suffers from misspecification if the model omits relevant variables or if it includes irrelevant variables. Omission of relevant variables leads to underestimation of the mean efficiency,

Table 3. Outputs relevant for the individual expenditure groups (pooled OLS)

Education			*Housing*		
Constant	−582.7		Constant	−688.2	
Pupils in primary schools and kindergartens	11.36	***	Built-up area	218.6	***
Pupils entering secondary schools	94.84	*	New dwellings	−39.6	***
R^2	0.902		R^2	0.438	
Culture			*Environment*		
Constant	−3,446	***	Constant	−8,820	***
Cultural facilities	2,587	***	Municipal waste	0.727	***
Municipal museums and galleries	−7,334	***	Nature reserves	275.5	***
Objects in monuments reserve	66.24	***	Pollution area	3.617	***
Sporting and recreational area	162.8	***	Urban green area	149.3	***
R^2	0.731		R^2	0.785	
Industry and infrastructure			*Public safety*		
Constant	−16,088	***	Constant	−6,693	***
Businesses	8.962	***	Built-up area	87.29	***
Municipal roads	33.62	*	Municipal police	3,372	***
Bus stations	77.52	**			
R^2	0.880		R^2	0.700	
Administration			*Social care*		
Constant	1,120		Constant	1,665	***
Population in district	1.807	***	Old population	2.507	***
			Homes for disabled	2,496	***
R^2	0.818		R^2	0.402	

while the inclusion of irrelevant variables leads to overestimation, and the effect of omission of relevant inputs on efficiency is more adverse compared to the inclusion of irrelevant ones (Galagedera, Silvapulle 2003).

If we err on the side of caution and include a larger set of outputs, the problem of dimensionality emerges. As a given set of observations is projected in an increasing number of orthogonal directions, the Euclidean distance between the observations necessarily must increase. Moreover, for a given sample size, increasing the number of dimensions results in more observations lying on the boundaries of the estimated production set (Simar, Wilson 2008). When dimensionality is large, unless a very large quantity of data is available, the results will have a large bias, large variance and very wide confidence intervals.

Banker et al. (1989) argues that the total number of observations should be at least three times as much as the total number of inputs and outputs. Additional tests show that the ratio of observations and dimensionality should be even higher (Pedraja-Chaparro et al. 1999). On the basis of convergence rates for DEA estimators, Simar and Wilson (2008) also conclude that a much larger sample size is needed. In our case, we would have 202 (or 1212) observations and 20 inputs and outputs in total, therefore some reduction is reasonable.

The recent literature offers several methods how to decrease dimensionality. Geys and Moesen (2009a) seek the most representative output per each expenditure group and construct the set of outputs from a few pre-selected variables. Borge et al. (2008) apply fixed national cost weights upon 20 indicators; Afonso and Fernandez (2008) normalize to averages. Most often, however, discrimination among outputs tends to diminish importance of outputs that are largely correlated with others. Two procedures stand out in the literature. Jenkins and Anderson (2003) propose a variable-reduction procedure that decides which of the original correlated variables can be entirely omitted with the least loss of information. In contrast, principal component analysis decreases dimensionality by produces uncorrelated linear combinations of the original outputs. Adler and Yazhemsky (2010) apply Monte Carlo simulation to generalize that principal components analysis provides a more powerful tool with consistently more accurate results. Adler and Yazhemsky (2010) also suggest that the most cautious approach would be to drop PCs one-by-one until a reasonable level of discrimination is achieved or until you have reached the rule-of-thumb of at least 80% (or 76% under VRS) of the variance of the original data.

If we included all output variables as outputs, the model would have 20 (19+1) dimensions. This dimensionality would not only bring wide confidence intervals, but is also unnecessary, as many variables contain largely identical information related to the municipality size. Table A4 shows the correlation matrix of output variables, where population of a municipality is very highly correlated with the number of pupils (0.993), the number of old people (0.988), the number of businesses (0.967), built-up area (0.935), the length of municipal roads (0.916), district population (0.898), municipal waste (0.846), cultural facilities (0.831), and urban green area (0.827).

Therefore, we follow principal components analysis and use the 80-percent rule. Table 4 shows weights of the output variables that are aggregated into the first six principal components. Six components suffice to explain 80.28% of the variance in the original outputs. The first component PC1 explains more than 51.6% of the variance and represents the size effect of a municipality, as it mainly contains information of variables which are highly correlated with population; note that correlation between population in the municipality and PC1 is 0.976. PC2 represents mostly cultural outputs, PC3 is for environmental amenities, PC4 is quality of educating and raising children, and PC5 is safety. For some observations, the values of components can be negative.

To get positive output data, we apply an affine transformation which does not affect results either for SFA or DEA (Ali, Seiford 1990; Pastor 1996). Specifically, for each municipality i, we transform the original value of a component k, $Y_{k,i}$, $\forall k \in \{1, \ldots, 6\}$. We obtain the transformed value $Y'_{k,i} = Y_{k,i} + B_k$, where $B_k = |\min\{Y_{k,i}\}_{i=1}^{N}| + 1$ which will ensure strictly positive output data.

In the next step, we try to identify atypical observations which can be outliers and therefore distort our efficiency estimates. Outliers play a relatively important role in determining efficiency scores of other observations in the sample. By distorting efficiency frontier, some virtually efficient observations may be regarded as inefficient. To obtain robust scores, it is thus necessary to identify and potentially remove the outliers. Out of several ways how to

Table 4. Principal component analysis

	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalue	9.799	1.385	1.280	1.089	0.906	0.795
Proportion	0.516	0.073	0.067	0.057	0.048	0.042
Cumulative	0.516	0.589	0.656	0.713	0.761	0.803
Pupils in primary schools and kindergartens	0.308	-0.126	-0.040	0.041	-0.004	0.021
Pupils entering the upper secondary schools	-0.041	0.292	0.149	0.615	-0.559	-0.297
Cultural facilities	0.272	0.076	-0.130	0.033	-0.034	0.093
Municipal museums and galleries	-0.070	0.339	-0.471	0.332	0.227	0.579
Objects in monuments reserve	0.132	0.546	0.253	-0.076	-0.028	0.135
Sport in and recreational area	0.203	0.283	-0.024	-0.133	0.210	-0.407
Municipal waste	0.269	-0.171	-0.045	0.088	-0.100	0.084
Nature reserves	0.079	0.141	0.648	-0.212	0.166	0.292
Pollute area	0.219	0.361	-0.237	-0.184	0.097	-0.158
Urban green area	0.256	-0.169	-0.111	0.012	0.077	-0.232
Built-up area	0.305	0.002	-0.036	0.014	-0.042	0.041
New dwellings	0.217	0.139	0.140	-0.052	-0.346	0.179
Businesses	0.308	-0.064	0.015	0.037	-0.083	0.047
Municipal roads	0.251	0.218	-0.209	-0.110	0.111	-0.219
Bus stations	0.241	-0.151	-0.025	0.159	-0.071	0.296
Population in district	0.288	-0.107	0.171	0.002	0.007	0.125
Old population	0.311	-0.079	-0.024	0.029	-0.072	0.021
Homes for disabled	0.179	-0.286	0.015	0.136	0.061	-0.015
Municipal police	0.079	0.003	0.296	0.581	0.619	-0.158

deal with outliers, we apply both Wilson's method (Wilson 1993) and order-m frontiers by Cazals et al. (2002). A full description of the methods follows in Section A.2 in Appendix.

Firstly, we estimate Wilson statistics (Wilson 1993) to observe maximally 10 potential outliers for each year. We construct log-ratio plot of the statistics and define from 5 to 10 potential outliers with only small variance across years. When closely scrutinized, we find out that all of them are bigger cities representing regional centers with atypically high outputs. We decide to keep these data in the sample, as there are no errors in the data and these observations are atypical only because of size. We also perform an additional test for outlier detection based on order-m frontiers (Czasals et al. 2002) that scrutinizes super-efficient observations. We construct order-m efficiency scores for $m = 25, 50, 100, 150$, and find no super-efficient observation with a low DEA score, hence our super-efficient values do not distort efficiency rankings.

3.4 Determinants

The idea to test for effects of various demographic, economic and political variables upon efficiency scores. The determinants may represent either (i) a direct effect of operational environment on pure inefficiency (either technical or allocative), or the presence of (ii) non-discretionary inputs and (iii) unobservable outputs. Non-discretionary inputs represent production in a more or less favorable environment, e.g., stocks of human capital and other competitiveness indicators. Unobservable outputs are typically associated with service quality; given that we focus on core services with largely quantitative characteristics, extra value added of services may be produced based on the characteristics of the municipalities, such as the municipality size and the level of income. We cannot neglect the hidden inputs or outputs; once the selection of inputs and outputs is imperfect, missing inputs and extra outputs may be misinterpreted as budgetary slack in terms of low effort, over-employment and large private rents.

Unfortunately, a single determinant may theoretically bring in several effects, and extra analysis is required to discriminate between the effects. Moreover, there is vague boundary between the very definition of the effects. For instance, explaining inefficiency by slack stemming from less effort can be alternatively interpreted as lower amount of human capital, which is not slack, but lacking input. Sometimes, like in the case of education variable, we can suspect the presence of hidden inputs and hidden outputs at the same time, where each predicts the opposite sign of the education variable. Thus, our interest is restricted mainly to finding if the overall effect is robust across specifications, and based on the sign we may conclude which of the effects dominates.

In line with the literature, and based on the data available, we control for the following determinants:

Population Economies of scale and agglomeration externalities typically make the larger municipalities more efficient; moreover, small governments are less efficient than the central government due to fiscal vulnerability, or the absence of sufficient experience among local staff (Prud'homme 1995). Small governments may also be captured by local interest groups

(Bardhan, Mookherjee 2000), or prone to moral hazard if dependent on transfers from the central government (Rodden 2003). On the other hand, higher electoral control typical at the local level reduces incentives for incumbents for rent-seeking (Seabright 1996) and yardstick competition disciplines local representatives not to waste resources. In addition, the scale economies and agglomeration externalities may be larger in the private than public sector, hence the relative cost of public sector (e.g., reservation wage) increases in a large municipality. We introduce dummies for population sizes of the municipalities around three thresholds: 10,000; 20,000 and 50,000. This construction reflects that population variable as such is highly correlated with the first component. Another point is that the three thresholds are also used in tax-revenue sharing schemes, consisting of 17 population thresholds in total.

Geography The smaller is geographical distance between the municipality and the regional center, the higher is (yardstick) competition between municipalities, and also more direct access to local public goods provided by the region. Both yardstick competition and the level of consumption spillovers suggest that distance increases costs hence reduces input-oriented efficiency; evidence for the effect is, inter alia, in Loikkanen and Susiluoto (2005). We measure distance in time to reach the regional center; for municipalities located in the center, we measure distance to the closest neighboring regional center. The spatial interdependence between efficiency scores can also be analyzed in the direct way, but based on the preliminary spatial analysis of groups of expenditures (Šťastná 2009), we leave this topic to future research.

Education Municipalities with a higher share of *University graduates* may be more efficient either by disposing with more qualified labor, or through voters' higher and more competent control (De Borger, Kerstens 1996). Yet, university graduates may also raise productivity in the private sector, and raise reservation wage for the public sector. In addition, wealth or income effect cannot be identified directly, and education thus may involve also the income effect that leads to demand for (unobservable) high-quality services. The effect of education is thus ambiguous. We are also aware of reverse causality; the characteristics that make a municipality cost-efficient may also attract the mobile (high-skilled) citizens. A good message is at least that correlation of the variable with the output variable *Pupils entering secondary schools* is only 0.027, hence the effect of graduate education is not captured in the output variable. This point is particularly relevant in the Czech context where the parent's education is the strongest determinant of a pupil's achievement.

Fiscal capacity Low fiscal capacity may serve as a hard-budget constraint that reduces public sector wages, lowers operating surpluses and induces fiscal stress, in which case efficiency goes up. This finding is in line with earlier analyses of overall efficiency in Belgium (De Borger et al. 1994; De Borger and Kerstens 1996), and Spain (Balaguer-Coll et al. 2007).

We introduce three dimensions of fiscal capacity. The extent how municipality is dependent on *Self-generated revenues* is the direct measure of hard-budget constraint. Balaguer-Coll et al. (2007) speak in this case of "patrimonial revenues" and relate them to lower willingness to save. Next, we study whether the past *Government debt* implying larger interest and amortization payments serve as fiscal hardship that improves efficiency. Geys and Moesen (2009a) find that high debt repayments rather impinges on municipal efficiency; the idea is that past fiscal mismanagement persists over time. The last fiscal variable is *Capital spending*. A hypothesis is that fiscal vulnerability, in this case high capital investment in a given year, pushes for cost savings on the current expenditures (Athanassopoulos, Triantis 1998).

By including *Subsidies from the upper levels of government* among determinants, we answer the question whether the grants fully translate into a larger provision of public goods or if municipalities receiving higher grants tend to be less efficient (Hines, Thaler 1995). Empirical evidence supports that the option of sharing expenditures in a broader constituency induces slack, hence the "flypaper effect" is rather significant (e.g. Kalb 2010; De Borger et al. 1994; De Borger, Kerstens 1996; Loikkanen, Susiluoto 2005).

Politics Political characteristics of a municipality may largely influence its efficiency. By weak-government hypothesis, high *Political concentration* reflecting low party fragmentation should decrease narrowly focused spending, hence should improve efficiency. Some evidence nevertheless suggests that single-party municipal governments in particular are inefficient (Geys et al. 2010; Borge et al. 2008). In Czech municipalities, concentration could be measured either in the council or in the executive board led by the mayor. The members of the executive board, including the mayor and the deputy mayor, are elected from the members of the local council and represent the majority coalition. We dispose only with data on seats in the municipality council, hence our concentration index (i.e., Laakso-Taagepera or Hirschmann-Herfindahl index) exhibits downward bias relative to concentration of the executive power in the coalition.

Electoral year may be related to larger spending into additional (unobservable) outputs, hence to inefficiency. At the same time, local elections take place in the same year like national election, hence effects are confounded with the national political business cycle. Wage growth in the electoral year is nevertheless average, namely third largest in the sample out of six years.

Additionally, we consider political ideology, albeit it is not easy to identify ideology on the local level. We prefer to measure the share of municipal-council representatives from *Left-wing* parliamentary parties (Social Democrats and Communists) out of representatives from all parliamentary parties. Geys et al. (2010) find that the high share of left-wing parties is associated with higher efficiency. We expect the opposite; the left-wing parties in the Czech Republic have an older and less educated electorate, and this should represent less monitoring and higher level of the social services, which are in our dataset unobservable output variables. Moreover, ideological variable may also represent (un)willingness to introduce high-powered incentives in the public sector.

Finally, we include two variables that are related to the interest in monitoring and shaping local politics. The first is the share of seats of *Parliamentary parties* in the municipality council. The second is voters' involvement measured by *Turnout* in municipal elections (see Geys et al. 2010; Borge et al. 2008). While the former is expected to increase costs, the latter should improve efficiency.

Table 5 presents statistics of potential determinants; more information about the data follows in Table A5 in the Appendix. Correlation matrix of the determinants in Table A6 features generally very low degrees of correlation. Only two patterns stand out. In small municipalities (below 10,000 inhabitants), we find less university-educated people (−0.378), less votes for parliamentary hence more votes for local parties (−0.331) and bigger voters' turnout (0.661). In contrast, large municipalities (above 50,000 inhabitants) attract better educated citizens (0.385), lead to more concentrated political competition (0.233) of parliamentary rather then local parties (0.197), and local elections have lower turnout (−0.395).

Table 5. Determinants: descriptive statistics

	Mean	Std. Dev.	Min	Max
Pop < 10,000	0.398	0.490	0	1
Pop 10,000–20,000	0.315	0.465	0	1
Pop > 50,000	0.086	0.280	0	1
University graduates (%)	6.154	1.589	2.540	12.20
Subsidies per capita	3,856.3	3,451.8	73	25,511
Capital expenditures per capita	5,473.2	3,293.6	481	37,567
Lagged debt dummy	0.446	0.497	0	1
Self-generated revenues (%)	18.06	5.534	6.39	43.77
Distance from regional center	37.84	16.40	11	101
Voters' turnout	42.38	7.413	21.69	60.55
Political concentration	0.218	0.053	0.107	0.539
Left-wing share	0.447	0.127	0	1
Parliamentary parties (%)	0.721	0.156	0.220	1
Electoral year dummy	0.167	0.373	0	1

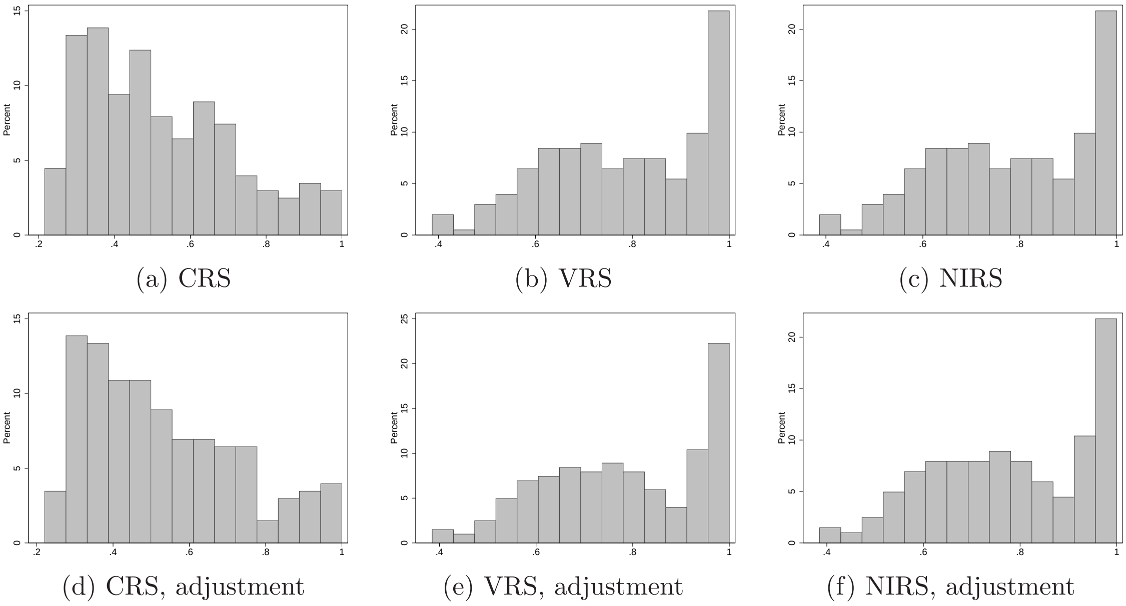
Source: Czech Statistical Office, Ministry of Finance.
Note: $N = 1212$. Nominal data adjusted for inflation, base year 2003.

4 Non-parametric efficiency

4.1 General results

This section presents cross-sectional results computed by Data Envelopment Analysis in the years 2003–2008. We allow for constant (CRS), variable (VRS) and non-increasing returns to scale (NIRS). Figure 1 presents the distributions of efficiency scores where we average year-specific municipality scores over the 2003–2008 period. As outputs do not vary too much over time, averaging scores computed for each year can smooth errors on the input side. Unlike the upper three panels, the bottom three panels in Figure 1 adjust for wage differences.

The distribution of CRS scores substantially differs from that of VRS and NIRS. On the other hand, distributions of VRS and NIRS scores are very similar, hence municipalities very rarely operate on the part of production function with increasing returns to scale. Wage adjustment does not introduce major differences in either case; the distributions with adjust-



(a) CRS (b) VRS (c) NIRS

(d) CRS, adjustment (e) VRS, adjustment (f) NIRS, adjustment

Figure 1. Distributions of DEA efficiency scores: 2003–2008 averages

ment are only a bit smoother suggesting that some extreme efficiency scores can be attributed to relatively (un)favorable wage conditions in the municipality.

Concerning the case without adjustment, the mean value of CRS score is 0.52 and minimum is 0.22. There is only single observation which is fully efficient under CRS for the whole period. For VRS, both mean value ($0.79 > 0.52$) and minimum ($0.39 > 0.22$) increase, as by construction of the VRS frontier, the observations are closer to the VRS frontier. The amount of fully efficient municipalities under VRS varies from 52 in 2005 to 61 in 2007 and there are 30 municipalities which stay fully efficient over the whole period. The Appendix offers descriptive statistics for individual years (Table A7), individual CRS and VRS averaged scores in the case without adjustment (Table A8) and with adjustment for wage differences (Table A9).

4.2 Population subgroups

To obtain a further insight into the differences of efficiency scores under different scale assumptions, it may be useful to explore how these differences vary across subgroups of municipalities defined by population size. Table 6 presents summary statistics and correlations for scores of municipalities if divided into four groups. We use again 2003–2008 averages and the results presented are without wage adjustment. The pattern of correlations is similar for the case with wage adjustment.

CRS scores are highly correlated with the size of population levels if measured in the full sample (-0.869). This only confirms the finding of VRS that large municipalities operate on the part of production function with decreasing returns to scale. However, size is not very indicative of efficiency if we look at within-group differences. For the two groups of

Table 6. Correlations of DEA efficiency scores in subgroups of municipalities

	Obs.	Mean	Min	Max	Correlation			
					Population	CRS	NIRS	VRS
Below 10,000								
CRS	482	0.712	0.235	1	-0.556^{***}	1		
NIRS	482	0.815	0.279	1	-0.299^{***}	0.688^{***}	1	
VRS	482	0.816	0.279	1	-0.304^{***}	0.690^{***}	0.999^{***}	1
10–20,000								
CRS	382	0.452	0.223	0.780	-0.508^{***}	1		
NIRS	382	0.727	0.283	1	-0.149^{***}	0.457^{***}	1	
VRS	382	0.727	0.290	1	-0.149^{***}	0.457^{***}	1	1
20–50,000								
CRS	244	0.338	0.145	0.612	-0.244^{***}	1		
NIRS	244	0.755	0.336	1	0.155^{**}	0.522^{***}	1	
VRS	244	0.755	0.336	1	0.155^{**}	0.522^{***}	1	1
Above 50,000								
CRS	104	0.293	0.167	0.446	-0.220^{**}	1		
NIRS	104	0.934	0.524	1	0.527^{***}	0.216^{**}	1	
VRS	104	0.934	0.524	1	0.527^{***}	0.216^{**}	1	1
Full sample								
CRS	1212	0.519	0.145	1	-0.869^{***}	1		
NIRS	1212	0.785	0.279	1	-0.048^{*}	0.294^{***}	1	
VRS	1212	0.786	0.279	1	-0.050^{*}	0.296^{***}	0.999^{***}	1

above-average-sized municipalities, the correlations are −0.244 and −0.220. In other words, these municipalities form a cloud of observations far from the CRS frontier where the position of each municipality within this cloud is almost unaffected by its population. These results suggest to use variable returns to scale assumption. However, in the presence of variable returns, a municipality is assessed only to peers that have comparable mix of outputs. If an output mix is unique to the municipality, there are no comparable peers, and the municipality is automatically assigned full efficiency. In particular for a small group of large municipalities, their efficiency is driven up by the lack of appropriate benchmark. Indeed, within the group of large municipalities, the correlation between size and VRS score is 0.527.

When correlations between VRS (or NIRS) scores and population are further scrutinized, we can see that in the full sample and within the groups of below-average-sized municipalities, the correlation is low or even absent, as VRS scores manage to correct for the size effects. Thus, the lack of appropriate benchmark presents a problem only for the large municipalities.

Finally, to discriminate between CRS and VRS, we analyze correlations of the efficiency scores. In groups of municipalities with population below 50,000, the two methods produce similar results, but differ significantly for large municipalities. In other words, the scale assumption really matters for large municipalities which are biased downward by the CRS but potentially biased upward by VRS. The next subsection however shows that the lack of comparable peers may be to some extent addressed in VRS by bootstrapping.

4.3 Bias-corrected scores

Our next step is to bootstrap VRS efficiency scores to allow for statistical inference. The original DEA scores are biased by construction (see Section A.3) and bootstrapping helps us to correct for the bias and construct confidence intervals for each efficiency score. To apply homogenous bootstrap as developed by Simar and Wilson (1998), the independence assumption has to hold. For this purpose, we employ graphical test of independence developed by Fisher and Switzer (1985) and described in Wilson (2003). The χ-plot for the VRS efficiency scores in 2008 reveals that all observations are inside the required interval, hence the independence assumption holds.[7]

We apply homogeneous bootstrap by an algorithm described in Simar and Wilson (1998) with $2,000$ bootstrap replications. Figure 2 shows the distribution of bias-corrected efficiency scores averaged over the period 2003–2008 compared to the original VRS estimates and Table 7 offers summary statistics.[8] The distribution of bias-corrected scores is denser but otherwise has a very similar pattern as the original distribution. An expected change is that the originally fully efficient municipalities are shifted to lower percentiles. Generally, municipalities with the lack of comparable observations, i.e. large municipalities in our context, have larger bias and wider confidence intervals. Hence, correction for bias does not help us to deal effectively with the large municipalities. The decrease in efficiency scores of large municipalities also explains why bias-corrected VRS scores correlate with CRS scores more than the original VRS scores (cf. Table 8).

Table 7. VRS and bias-corrected VRS efficiency scores (2003–2008 averages): summary statistics

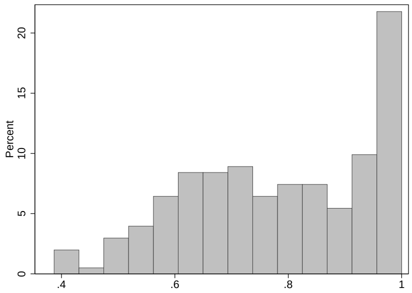
		Mean	Min	Max
(a)	VRS	0.786	0.387	1
(b)	VRS, adjustment	0.784	0.385	1
(c)	VRS, bias-corrected	0.694	0.364	0.879
(d)	VRS, adjustment, bias-corrected	0.692	0.362	0.892

Figure 3 illustrates the size of confidence intervals of the bias-corrected VRS efficiency scores averaged over 2003–2008 in the case without adjustment. (These correspond to Panel (c) in Fig. 2.) The municipalities are ordered by their original VRS efficiency scores. Apparently, the originally fully efficient observations have large confidence intervals. Yet, the ranking of municipalities does not change substantially, as is expressed by the Spearman's correlation coefficients of 0.954 (no adjustment) and 0.949 (wage adjustment). Figure 3 also helps to identify municipalities with atypical values of input-output combinations which have wide intervals even for relatively small scores.

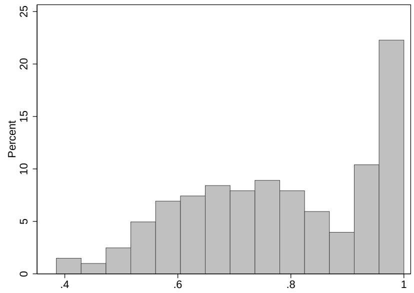
Table 8 summarizes the correlations between six alternative specifications for non-parametric efficiency. We prefer the bias-corrected VRS specification with wage adjustment (denoted

[7]Results of the test are available per request.

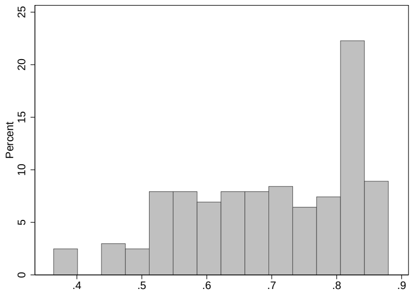
[8]The analysis runs in R software with FEAR package (Wilson 2008). The detailed data on bias-corrected efficiency scores are available in Table A10 in Appendix, and individual data on confidence intervals can be provided upon request.



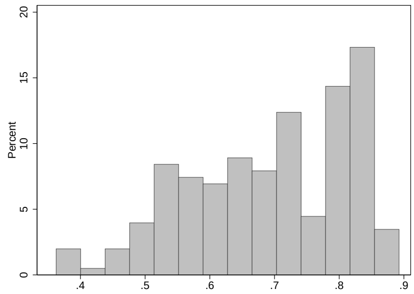
(a) VRS



(b) VRS, adjustment



(c) VRS, bias corrected



(d) VRS, adjustment, bias corrected

Figure 2. Distributions of the original VRS and the bias-corrected VRS efficiency scores: 2003–2008 averages

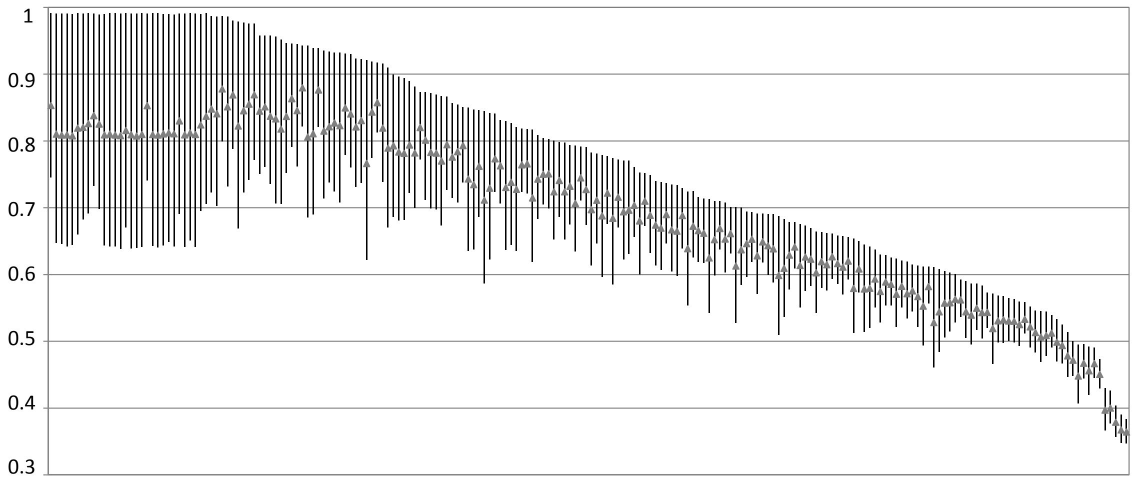


Figure 3. Bias-corrected scores and their confidence intervals: 2003–2008 averages

VRS BC). For robustness check, it is nevertheless illustrative to observe two facts. First, the presence or absence of wage adjustment does not change rankings substantially (correlations 0.98, 0.964, 0.93). Second, correlations between methods differing only in returns to scale assumption are larger in the case with wage adjustment (0.345, 0.408, 0.95) than without adjustment (0.296, 0.359, 0.949). This is another reason for incorporating relative wages in the analysis.

Table 8. Spearman rank correlations of DEA efficiency scores

		No adjustment			*Wage adjustment*		
		CRS	VRS	VRS BC	CRS	VRS	VRS BC
No adjustment	CRS	1					
	VRS	0.296	1				
	VRS, bias-corr. (BC)	0.359	0.949	1			
Wage adjustment	CRS	0.980	0.300	0.362	1		
	VRS	0.313	0.964	0.910	0.345	1	
	VRS, bias-corr. (BC)	0.374	0.910	0.930	0.408	0.950	1

5 Parametric efficiency

5.1 Results without determinants

This section computes efficiency scores using Stochastic Frontier Analysis.[9] Unlike DEA, where year-specific scores are obtained only as cross-sectional estimates, SFA estimates the time-profile of the scores endogenously in a single panel. In addition, determinants can be conveniently included. We consider various specifications: Cobb-Douglas or a more flexible Translog cost function, time-variant or time-invariant efficiency, and efficiency with determinants and without determinants. Furthermore, we treat wage differentials in three ways: (i) no adjustment, (ii) spending adjusted by wage differences exactly as in DEA, and (iii) wages included directly into the cost function. Since wage differentials influence costs directly, we disregard the option when the wage is a part of the vector of determinants. In total, we cope with four dimensions of modeling. We first assess time variance, the inclusion of wage differences, and then discuss the appropriate functional form. Finally, we examine the effect of determinants.

Our baseline estimates for Cobb-Douglas production are in Table 9. First and foremost, coefficients of principal components suggest that the components may be irrelevant explanatory variables. Albeit PC1 is always significant and positively affects total costs, most of the other components have insignificant positive or even negative effect on costs. Our reading is that either we have constructed irrelevant outputs or another functional specification (Translog) is required. As expected, the wage positively affects costs. Concerning other parameters, the variance of the inefficiency in total error variance is relatively large, and statistical noise accounts only for $1 - \gamma \approx 15\%$ of the total variance. Significance of parameter μ confirms that assumption of truncated-normal distribution is more appropriate than half-normal distribution.

[9]We use software *Frontier 4.1* developed by Coelli (1996) for parametric estimation.

Importantly, the parameter η is significant, so efficiency does change over time. In the case without any wage variable, the parameter is negative and significant, which suggests that efficiency decreases over time. Once we control for wages, the sign is exactly opposite, i.e. the efficiency increases over time. Inclusion of wages in the panel data estimation is thus crucial as the real wages increase over time and this effect translates into an increase in spending. As a result, we abandon all time-invariant models that abstract away from wage differences.

Table 9. Baseline SFA results: Cobb-Douglas function, no determinants

	No adjustment		Wage in outputs		Wage adjustment	
	TI	TV	TI	TV	TI	TV
β_0	10.391 ***	10.408 ***	8.045 ***	5.600 ***	8.200 ***	7.510 ***
PC1	1.164 ***	1.161 ***	1.144 ***	1.135 ***	1.042 ***	1.061 ***
PC2	−0.169 ***	−0.160 ***	−0.151 ***	−0.133 ***	−0.163 ***	−0.071 †
PC3	0.000	0.013	0.008	−0.058	−0.112 *	−0.074
PC4	0.049 †	0.038	0.048 †	0.040	−0.020	0.036
PC5	−0.045 †	−0.037	0.000	−0.042 †	−0.026	−0.017
PC6	−0.124 *	−0.149 **	−0.171	−0.140 *	−0.286 ***	−0.061
Wage			0.247 ***	0.504 ***		
σ^2	0.077 ***	0.079 ***	0.064 ***	0.074 ***	0.096 ***	0.081 ***
γ	0.858 ***	0.858 ***	0.834 ***	0.855 ***	0.875 ***	0.861 ***
μ	0.515 ***	0.520 ***	0.462 ***	0.504 ***	0.579 ***	0.529 ***
η		−0.007 *		0.016 ***		0.038 ***
Log likelihood	648.8	652.7	655.0	667.2	560.4	656.7
LR one-sided error	1136 ***	1144 ***	1137 ***	1161 ***	1045 ***	1237 ***

Note: ***, **, * denote statistical significance at 1%, 5% and 10% level, respectively. † denotes statistical significance at 10% level on one-tail.

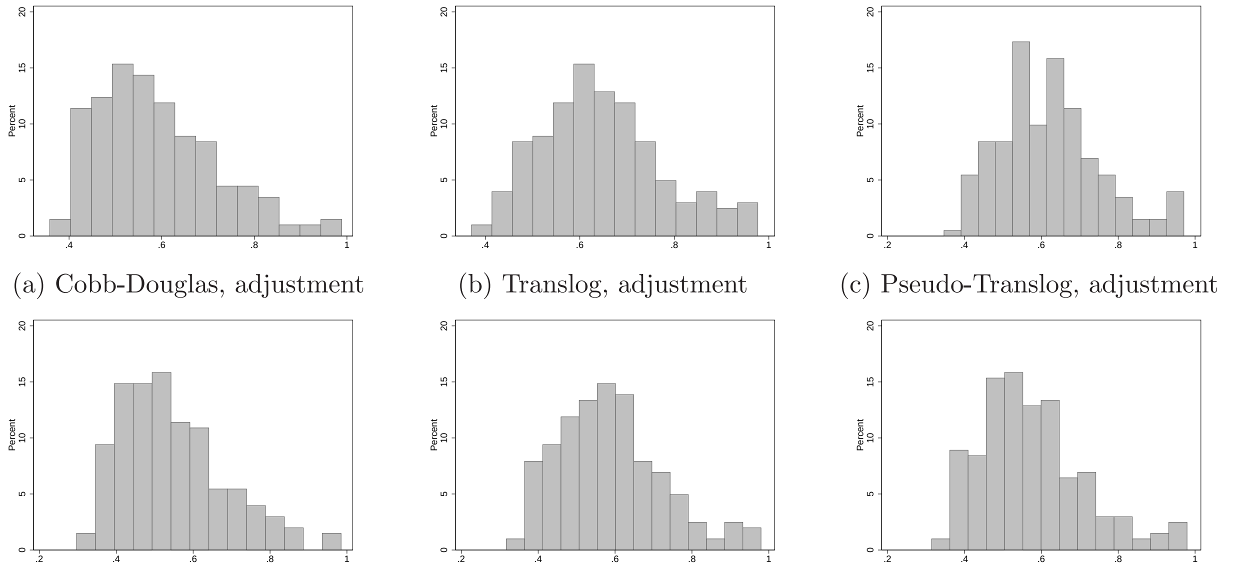
In the next step, we estimate efficiency by means of Translog production with time-variant efficiency and wage differences included. Table 10 reports the results. The first and the third column include all cross-product terms of principal components, i.e. the number of explanatory variables increases from 6 (7) to 27 (28). Some of the basic principal components are still negative and their significance does not change much in comparison with the baseline case. Most of the cross-product terms (16 out of 21) are not significant either. Hence, we drop explanatory variables with high p-value and after a few iterations end up with a new production function encompassing only four significant components and seven significant cross-product terms. This Pseudo-Translog function is captured in the second and fourth column of Table 10. Log-likelihood decreases only slightly when insignificant variables are dropped out. Interestingly, *all* principal components are part of the new production function, although some of them enter the production only in an interaction with another component. Thus, we may conclude that components computed from our output variables are indeed relevant for this analysis. Finally, the estimated parameters γ, μ and η are similar to those obtained in baseline Cobb-Douglas specification with time-variance and wage differences. Table A11 in the Appendix offers individual scores for the Pseudo-Translog, both with costs adjusted by wage differences and wages in outputs.

Table 10. Modified SFA results: Translog and Pseudo-Translog production functions, time-variant efficiency, no determinants

	Wage in outputs		*Wage adjustment*	
	Translog	Pseudo-Translog	Translog	Pseudo-Translog
β_0	8.802 ***	5.816 ***	11.709 ***	10.587 ***
PC1	0.507		0.265	
PC2	−2.031 **	−0.903 ***	−2.145 ***	−1.808 ***
PC3	−0.936 †	−0.215 †	−0.977	−0.390 ***
PC4	−0.245	−0.199 †	−0.062	
PC5	−1.087 †	−0.323 ***	−1.151 †	−0.215 ***
PC6	−1.208 †		−1.000 †	−0.992 **
Wage	0.584 ***	0.614 ***		
PC11	0.439 ***	0.471 ***	0.553 ***	0.555 ***
PC21	0.208	0.466 ***	0.136	
PC31	−0.072		0.042	
PC41	0.049		−0.004	
PC51	0.390 **	0.526 ***	0.397 **	0.453 ***
PC61	−0.448 †	−0.319 **	−0.412	
PC22	−0.037		0.002	
PC32	0.028		0.112	
PC42	0.508		0.465	0.519 **
PC52	0.134		0.182	
PC62	1.507 *	0.465 ***	1.617 **	1.577 ***
PC33	0.262		0.121	
PC43	0.714 †	0.480 **	0.720 †	0.622 ***
PC53	0.292		0.437	
PC63	0.052		−0.046	
PC44	−0.243		−0.268 *	−0.345 ***
PC54	0.251		0.263	
PC64	−0.502		−0.664	−0.425 **
PC55	0.123		0.162	
PC65	0.241		0.091	
PC66	0.330		0.284	
σ^2	0.051 ***	0.058 ***	0.065 ***	0.071 ***
γ	0.791 ***	0.828 ***	0.848 ***	0.866 ***
μ	0.403 ***	0.439 ***	0.469 ***	0.497 ***
η	0.029 ***	0.027 ***	0.043 ***	0.040 ***
Log likelihood	706.2	700.2	698.1	692.9
LR test one-sided error	944.8 ***	1022 ***	1091 ***	1289 ***

Note: ***, **, * denote statistical significance at 1%, 5% and 10% level, respectively. † denotes statistical significance at 10% level on one-tail.

Figure 4 shows distributions of the efficiency scores obtained from different specifications. Again, scores are averaged over the entire period, but now the year-specific scores are achieved simultaneously, and satisfy time profile in Eq. (5). The three upper panels are for wage-adjusted inputs, and the bottom three panels are for wage being included directly among



(a) Cobb-Douglas, adjustment (b) Translog, adjustment (c) Pseudo-Translog, adjustment

(d) Cobb-Douglas, wage in outputs (e) Translog, wage in outputs (f) Pseudo-Translog, wage in outputs

Figure 4. Distributions of the SFA efficiency scores: 2003–2008 averages

outputs. Efficiency scores are on average lower with Cobb-Douglas production function, and density is higher for lower scores. Nevertheless, we tend to prefer Pseudo-Translog specification. A more flexible production function (Translog or Pseudo-Translog) improves scores of some municipalities which suggests that neglecting some outputs in a narrower specification incorrectly shifts a municipality among those with lower efficiency. Comparing densities of Pseudo-Translog case relative to Translog case, we can see that municipalities with extremely below-average scores and extremely above-average scores move closer to the average. That is, removing insignificant outputs increases density around the mean. Table 11 further reveals that correlation among scores is large and significant across different specification and also across different cases of wage inclusion.

Table 11. Spearman correlations of SFA efficiency scores: 2003–2008 averages

				Wage adjustment			*Wage in outputs*		
	Mean	Min	Max	C-D	T	P-T	C-D	T	P-T
Wage adjustment									
Cobb-Douglas (C-D)	0.547	0.297	0.985	1					
Translog (T)	0.587	0.317	0.980	0.857	1				
Pseudo-Translog (P-T)	0.574	0.315	0.979	0.863	0.986	1			
Wage in outputs									
Cobb-Douglas (C-D)	0.590	0.358	0.989	0.925	0.808	0.819	1		
Translog (T)	0.644	0.371	0.977	0.841	0.977	0.957	0.847	1	
Pseudo-Translog (P-T)	0.624	0.347	0.971	0.861	0.975	0.959	0.832	0.964	1

5.2 Results with determinants

This section aims to explore whether extra characteristics significantly affect the efficiency score, which may be attributed either to effect on technical or allocation efficiency, the existence of non-discretionary inputs, or production of additional (directly unobservable) output. We consider both production function specifications, Cobb-Douglas and Pseudo-Translog, and adjust costs for wages or include wage among outputs. This yields four specifications in Table 12. To construct each specification, we run several regressions and based on the log-likelihood ratio test we delete (one by one) insignificant determinants to improve the fit of the model. The four different specifications allow us to see how robust are the effects of determinants upon inefficiency. Note that the inclusion of determinants in a single stage not only explains the inefficiency term, but also affects its level, unlike two-stage estimation.

Table 12 reports the results. By comparing the results with baseline estimates in Table 9 and modified estimates in Table 10, we realize that inclusion of determinants improves the explanatory power of principal components. Most of the components become positive and significant, and for Translog specification, additional cross-product terms are significant. What is also specific for Translog is that we can reject null hypothesis $\gamma = 0$ irrespective how wages are treated. For Cobb-Douglas, in contrast, if wage is included among outputs, the hypothesis that inefficiencies are entirely given by determinants cannot be rejected, and the original cost function model simplifies to $y_{i,t} = f(\mathbf{x}_{i,t}) + \delta \mathbf{z}_{i,t} + v_{i,t}$ that can be estimated by OLS.

The effects of determinants are as follows:

Population size The negative effect of small population dummies upon costs, as well as the positive effect of large population dummy, are robust across all specifications. In absolute terms, coefficients are lower for Pseudo-Translog specification than for Cobb-Douglas specification, especially for big municipalities. The explanation is that output PC11 (the square of PC1) is highly correlated to population. In this way, Pseudo-Translog specification may reflects that population-related outputs increase exponentially with municipality size. Loikkanen and Susiluoto (2005) found the similar relation for Finnish municipalities, whereas Geys and Moesen (2009a) and De Borger et al. (1994) discovered that the marginal diseconomy for Flemish municipalities is positive, but tends to decrease in size. We attribute the effect of size mostly to legacy of the 2002 reform which put enormous fiscal stress especially upon the emerging small municipalities (c.f. Hemmings 2006). The small municipalities had to arrange the agenda for the very first time; in contrast, larger municipalities transferred districts' powers relatively easily, given that the location of the agenda within the town or city remained unchanged. An alternative explanation is through unobservable quality outputs such as the quality of pathways, parks maintenance etc.

Geography The distance from the regional center has a predictable sign, conforming to the literature (Loikkanen, Susiluoto 2005). Citizens in peripheral municipalities have worse access to goods and services provided in the regional center, and their municipalities accordingly produce extra unobservable outputs. Alternatively, the municipalities on the periphery are less subject to yardstick competition.

Education Concerning university-educated population, we find robustly positive effect upon inefficiency, contrary to Afonso and Fernandes (2008), and De Borger and Kerstens (1996). This makes our country-specific study an exception to the literature covering mainly the Western European countries. The effects of higher reservation wage plus extra demand for high-quality (non-core) services are likely behind. What must be absent or offset must be the hypothetically increased monitoring resulting in improved accountability. A topic for future research is if this difference is specific for post-communist countries or not, and also to what extent public sector services drive mobility of the university graduates at the local level.

Fiscal capacity First, we confirm the predicted sign of the share of self-generated revenues; the higher fiscal capacity, the softer budget constraint and the higher is inefficiency (c.f. Balaguer-Coll et al. 2007). In contrast, capital expenditures per capita have positive effect upon inefficiency in all but one case where it is insignificant. Increase in capital expenditures in our context does not introduce fiscal strain that must be compensated but rather need motivates (perhaps complementary) current expenditures.

Then, we have two results which call for a cautious interpretation. The level of debt is significant in only one case; there seems to be only weak, if any, persistence from past overspending decisions. We cannot argue that debt motivates savings. The effect of subsidies per capita is conditional on how wages are incorporated. The positive effect validating the fly-paper hypothesis, as observed elsewhere (Kalb 2010; De Borger et al. 1994; De Borger, Kerstens 1996; Loikkanen, Susiluoto 2005), is only for wage included among outputs. We keep the other specification mainly because it allows for better comparison with DEA scores.

Politics Out of political variables, voters' involvement in terms of turnout in local elections is the best predictor of low costs and high efficiency, quite as, inter alia, Geys et al. (2010) found in German municipalities. The share of left-wing municipal-council representatives (Communists and Social Democrats) among representatives from all parliamentary parties makes the municipality less efficient. Thus, local politics is not entirely devoid of value choices. The result may be driven either by lower competence of Left-wing representatives, or by the production of extra unobservable outputs, typically extra social services. The negative effect of left-wing parties upon efficiency was obtained also in German municipalities (Kalb 2010).

With two remaining political variables, the results are weaker. Political concentration index confirms the well established weak-government hypothesis (low concentration increases costs), but is significant only for wage-adjusted spending. Electoral year dummy is effectively a dummy for single year 2006; costs increase, exactly as predicted, but also if wage is included among outputs.

Table 12. Final SFA results: time-variant efficiency, determinants

	Cobb-Douglas		Pseudo-Translog	
	Adjustment	*Wage in outputs*	*Adjustment*	*Wage in outputs*
β_0	6.878 ***	9.360 ***	6.086 ***	6.697 ***
PC1	0.621 ***	0.649 ***	1.015 ***	0.686 ***
PC2	−0.075 ***	−0.086 ***		
PC3	0.051 **	0.044 **	−0.260 †	0.566 ***
PC4	0.041 **	0.043 **		0.460 ***
PC5	0.049 *	0.008	−0.182 ***	0.526 **
PC6	0.094 ***	0.080 ***	1.549 ***	1.101 ***
Wage		0.171 ***		0.115 *
PC11			0.213 ***	0.154 ***
PC21			0.318 ***	0.367 ***
PC31			−0.316 ***	−0.425 ***
PC51				0.308 ***
PC61			−0.736 ***	−0.480 ***
PC32				−0.181 *
PC42				−0.431 ***
PC62			−0.498 ***	
PC33			0.427 ***	
PC54			0.212 ***	
PC55				−0.252 **
PC65				−0.515 *
PC66			−0.250 **	
δ_0	1.553 **	0.325 ***	0.970 ***	1.167 ***
Pop < 10,000	−0.576 ***	−0.529 ***	−0.514 ***	−0.435 ***
Pop 10,000–20,000	−0.304 ***	−0.276 ***	−0.261 ***	−0.206 ***
Pop > 50,000	0.287 ***	0.296 ***	0.104 **	0.109 ***
University graduates (%)	0.041 ***	0.046 ***	0.028 ***	0.031 ***
Subsidies per capita	−3.93E-06 **	6.76E-06 ***	−5.71E-06 ***	4.21E-06 **
Capital expenditures per capita	6.49E-06 ***		7.34E-06 ***	4.34E-07 ***
Lagged debt dummy	0.020 *			
Self-generate revenues (%)	0.009 ***	0.010 ***	0.009 ***	0.011 ***
Distance from regional center (min)	0.001 ***	0.001 ***	0.002 ***	0.001 ***
Voters' turnout (%)	−0.011 ***	−0.014 ***	−0.011 ***	−0.014 ***
Political concentration	−0.227 **		−0.360 ***	
Left-wing share (%)	0.164 ***		0.257 ***	0.104 **
Parliamentary parties share (%)			0.074 *	
Electoral year dummy		0.038 ***		0.031 **
σ^2	0.034 ***	0.031 ***	0.030 ***	0.026 ***
γ	0.940 **	4.08E-06	0.464 *	0.313
Log likelihood	336.863	397.576	405.856	496.347
LR test one-sided error	597.871 ***	622.042 ***	602.788 ***	606.587 ***
LR test $\gamma = 0$		0.34		20.72 ***

Note: ***, **, * denote statistical significance at 1%, 5% and 10% level, respectively. † denotes statistical significance at 10% level on one-tail.

Table 13 presents descriptive statistics and correlations for efficiency scores obtained in the three specifications where stochastic inefficiency cannot be rejected. Figure 5 plots the distributions. By comparing with Figure 4, the scores under determinants are denser for the bottom part of the distribution. The scores obtained from the Cobb-Douglas specification are again substantially lower. Correlation of all pairs of these three efficiency rankings is nevertheless very high, even higher than in case when determinants are not considered (see Table 11). Although we obtained three very similar efficiency rankings, we prefer the one estimated from the last specification, i.e. Pseudo-Translog and wage among outputs. Including only relevant outputs and their cross-product terms improve the flexibility of the production function in comparison to Cobb-Douglas. Therefore, Table A12 in the Appendix presents only individual scores of the Pseudo-Translog models with wage adjustment and wages in outputs. In addition, adjustment of expenditures for wage is arguably very strict, when wage differentials do not fully translate to differences in costs, so including wage as an output seems to be more appropriate.

Table 13. Spearman correlations of SFA efficiency scores with determinants: 2003–2008 averages

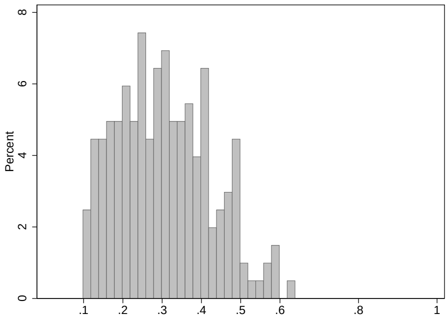
				Wage adjustment		*Wage in outputs*
	Mean	Min	Max	Cobb-Douglas	Pseudo-Translog	Pseudo-Translog
Wage adjustment						
Cobb-Douglas	0.305	0.087	0.863	1		
Pseudo-Translog	0.508	0.221	0.914	0.974	1	
Wage in outputs						
Pseudo-Translog	0.438	0.163	0.790	0.950	0.982	1

5.3 Overall assessment of multiple rankings

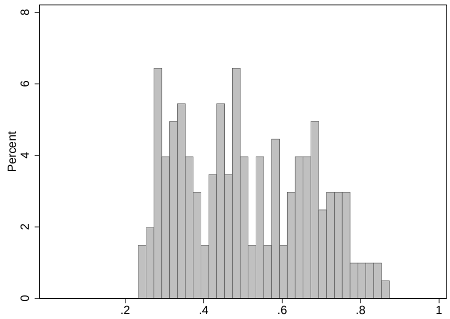
In the final step, we look into similarities and dissimilarities of efficiency scores computed by different approaches, i.e. DEA and SFA. The efficiency ranks from various approaches have been compared both in global efficiency and for specific outputs (Balcombe et al., 2006; De Borger, Kerstens, 1996; Geys, Moesen (2009b); von Hirschhausen et al., 2006). In our perspective, one way to deal with multiple rankings is to correctly identify the causes for differences in the individual efficiency scores. Therefore, although we offer one preferred specification (Pseudo-Translog SFA with determinants), we also present how modifying assumptions shapes the other outcomes.

In specific, by eliminating determinants from Pseudo-Translog SFA specification, and looking at the individual score differences, we can isolate the pure effect of including determinants. Their influence upon a score of an individual municipality is further decomposed by looking into a difference between an individual vector of the determinants and the vector of average values. As a result, policy makers in each municipality can understand which dimension affects their particular score the most.

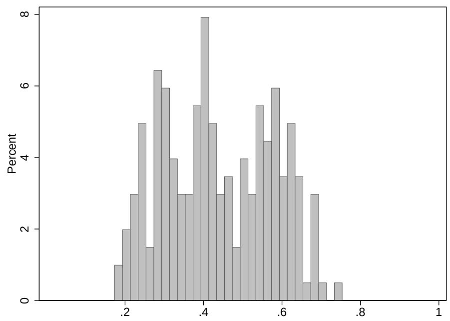
Similarly, by comparing bias-corrected VRS scores with Pseudo-Translog specification without determinants, the pure effect of a deterministic non-parametric frontier is isolated;



(a) Cobb-Douglas, adjustment



(b) Pseudo-Translog, adjustment



(c) Pseudo-Translog, wage in outputs

Figure 5. Distribution of SFA efficiency scores: 2003–2008 average, determinants

the municipality may infer especially if the shift of the score is more due to size (channeled through the scales assumption in VRS) or due to the error expressed by the size of the confidence interval (generated by bootstrapping).

For the purpose of comparability, we select only methods with inputs adjusted by wage. From non-parametric methods, we have CRS, VRS and bias-corrected VRS. From parametric methods, we present both Cobb-Douglas and Pseudo-Translog specifications, both with and without determinants. Table 14 reports the rank correlations.

Table 14. Spearman correlations of DEA and SFA efficiency scores: wage adjustment

	CRS	VRS	VRS BC
No determinants			
Cobb-Douglas	0.791	0.362	0.431
Pseudo-Translog	0.711	0.500	0.560
Determinants			
Cobb-Douglas	0.944	0.230	0.304
Pseudo-Translog	0.928	0.212	0.278

The first interesting observation is two methodologically largely inconsistent methods, DEA CRS and Pseudo-Translog SFA *with* determinants, are in fact highly correlated. Unlike that, bias-corrected VRS that represents the best out of non-parametric methods is only weakly related to the best out of parametric methods, namely Pseudo-Translog with determinants. Finally, by introducing Cobb-Douglas instead of Pseudo-Translog or by estimating without determinants, SFA results tend to be more correlated with the bias-corrected VRS.

Next, we identify robustly strong and robustly weak performers. Table 15 examines if different methods identify the same subsets of municipalities in the top and the bottom deciles. For each pair, the table presents the share of common observations in the respective decile out of total observations in the decile. We confirm the previous observations: Pseudo-Translog SFA with determinants behaves completely differently than bias-corrected DEA VRS, with shares of common observations only 10% and 25%; and again, DEA CRS is surprisingly close to Pseudo-Translog SFA with determinants.

Table 15. The shares of common observations in top/bottom deciles (in %)

	CRS	VRS BC	P-T det.	C-D	P-T
DEA, CRS	.				
DEA, bias-corrected VRS	30/30	.			
Pseudo-Translog, determinants	45/75	10/25	.		
Cobb-Douglas, no determinants	50/40	35/40	10/10	.	
Pseudo-Translog, no determinants	55/60	55/60	55/60	10/10	.

We proceed by identifying those observations which remain highly efficient or highly inefficient across different methods. Table 16 presents observations that occur consistently either at the top or at the bottom. The selection criterion is to appear in the top (or bottom) decile at least for three methods out the five pre-selected. We group the municipalities into population subgroups to demonstrate that size indeed matters.

Table 16. Size of municipalities located in the top and bottom deciles

0–5,000	5,000–10,000	10,000–20,000	20,000–30,000	30,000–50,000	above 50,000
Bottom decile					
		Bílina Mariánské Lázně Roudnice n. L.	Bohumín Český Těšín Kolín Litoměřice Strakonice Šumperk Žďár n. Sáz.	Orlová	České Budějovice Ústí n. L.
Top decile					
Bílovice Konice Králíky Kralovice Pohořelice Stod Vizovice	Bučovice Český Brod Dačice Horažďovice Chotěboř Ivančice Mnichovo Hradiště Moravský Krumlov	Velké Meziříčí			

6 Efficiency in 1990s

The last step of our analysis is to conduct a comparative exercise of efficiency scores in 1990s and 2000s. We compare two distant periods, 1994–1996 and 2004–2006. Scores of municipalities in 2004–2006 are taken from the analysis above. In 1990s, we have to exclude 3 more cities for which some data are missing (Rokycany, Turnov a Havířov), and work with 199 observations per year, i.e. 597 observations in total.

6.1 Data

As inputs, we keep using *Total current spending*, but are aware of possible errors stemming from misclassifications of spending into capital and current expenditures. In terms of outputs, we are fairly limited by data availability. For the purpose of comparability, we replicate as many output variables from the previous analysis as possible. This seems reasonable even if the municipalities in 1990s did not dispose with extended powers delegated by the state, hence were only indirectly responsible for some of the selected outputs. Note that the levels of some outputs are constant for the entire period.

Since pupils in primary schools are available only for small sample of municipalities, we use *Pupils in kindergartens* only. Nevertheless, the correlation 0.99 in the subsample where both variables are present indicates that the distortion is a minor one. The statistics of students entering upper secondary schools, and municipal museums and galleries are not available, hence we introduce just the number of *Museums*. *Cultural facilities* (libraries, cinemas, theaters, galleries, other cultural facilities and children's centers) are summed after Lora normalization. We use *Sport facilities* (swimming pools, playgrounds, stadiums) instead of the recreational area which is unavailable, and again sum after Lora normalization. Instead of waste collected, we introduce dummy for *Landfills*. We do not have *Dwellings completed* or any substitute; for administration, we include *Population of municipality* instead of population of districts, as the municipalities were not vested with administrative powers serving the entire district population. Table 17 gives descriptive statistics of the outputs in 1994–1996. As in previous analysis, we aggregate output variables into six principal components that together explain 80.95 % of the variance in the data and transform them to obtain strictly positive output data (see Table A13).

Table 17. Outputs 1994–1996: summary statistics

	Mean	Min	Max
Pupils in kindergartens	667.0	83	3,485
Museums	1.050	0	6
Cultural facilities	12.37	1	73
Objects in monuments reserve	25.66	0	254
Sports	15.69	1	165
Nature reserves	8.444	0	40
Pollution area (ha)	2,337	216.6	8,664
Urban green area (ha)	75.32	0.001	4,500
Landfill	0.449	0	1
Built-up area (ha)	157.2	36.70	708.5
Businesses	2472	4	17,385
Municipal roads (km)	81.08	2	490
Bus stations	41.85	2	229
Homes for disabled	0.498	0	7
Old population	3,826	519	22,110
Municipal police	0.845	0	1
Population	20,263	3,087	104,380

Sources: Czech Statistical Office with the exception of *Objects in monuments reserves* (National Institute of Monuments), and *Nature reserves* (Agency for Nature Conservation and Landscape Protection).
Note: $N = 597$.

While the construction of demographic and geographic determinants applied in the main analysis of 2003–2008 remains unchanged, we have to reshape fiscal and political variables. First, we split grants into those stemming from 76 administrative districts (to be dissolved in 2002) and those from the central government. The new variables are now denoted *District subsidies* and *State subsidies*, and we expect the same sign, but theoretically a different level. *Self-generated revenues* are inflation-adjusted non-tax revenues plus other revenues (mainly fees), defined as a share of non-tax revenues, tax revenues, other revenues and total subsidies. Interestingly, the size of subsidies and capital expenditures per capita relative to the average budget per capita was higher in 1990s than in 2000s (43.9% versus 30.8% for subsidies, 62.6% versus 43.7 % for capital expenditures). The share of self-generated revenues was also on average higher by 10 percentage points.

Political landscape in the early 1990s was markedly different from that in the post-transition period 2000s. Turnout was at historically high levels, scoring extra 20 percentage points in 1994 elections than in 2006 elections. The main national parties constituted in 1991, and there was still a legacy of a large civic movement called Civic Forum. The left-wing parties represented mainly unreformed Communist Party and a group of relatively small left-wing "reform communists" (Levý Blok, Strana Demokratické Levice, including at that time relatively small Social Democrats). The parties typically built pre-electoral coalitions in 1990s, which turned out to be exceptional after the year 2000. One consequence is that we have to redefine the share of *Parliamentary parties* into the share of those coalitions which involve some parliamentary parties, including independent candidates. For the *Left-wing parties*, we also have to think broadly of coalitions involving left-wing parties (Communist and Social Democrats) and independent candidates, instead of single parties. Summary statistics of the determinants are presented in Table 18, and can be compared to statistics from 2003–2008 available in Table 5.

Table 18. Determinants in 1994–1996: summary statistics

	Mean	Std. Dev.	Min	Max
Pop $<$ 10,000	0.397	0.490	0	1
Pop 10,000–20,000	0.296	0.457	0	1
Pop $>$ 50,000	0.075	0.264	0	1
State subsidies per capita	2,403	1,873	299	17,547
District subsidies per capita	243.61	402.2	0	4,125
Total subsidies per capita	2,647	1,968	361	17,633
Capital expenditures per capita	3,773	2,840	0	24,512
Self-generated revenues (%)	28.98	13.15	2.94	72.65
Distance from regional center	38.15	16.34	11	101
University graduates (%)	6.140	1.597	2.54	12.2
Voters' turnout	60.16	7.987	37.98	77.31
Parliamentary parties (%)	0.812	0.149	0.364	1
Left-wing share in parliamentary parties (%)	0.342	0.195	0	1
Electoral year dummy	0.333	0.472	0	1

Source: Czech Statistical Office, Ministry of Finance.
Note: $N = 597$. Nominal data adjusted for inflation, base year 1994.

6.2 Results

To attain maximal comparability, we directly use Pseudo-Translog SFA specification with time-variant scores, determinants, and wage in outputs. The model estimated is presented in Table 19. We present several specifications. The principal components constructed out of output variables are significant, but some only in the interactions. The first specification includes also electoral year dummy, distance from the regional center and university graduates that however appear to be insignificant. The first two specifications include dummy for the large municipalities, which also proves to be insignificant, hence we exclude it in the last specification. Moreover, in the third specification, instead of total subsidies we use state and district subsidies. Although inclusion of these two variables increase log-likelihood, significance of some other variables improved, hence we prefer the last third specification.

Table 19. Results for 1994–1996: SFA, Pseudo-Translog, time-variant efficiency, determinants

β_0	9.386 ***	9.349 ***	8.563 ***
PC1	1.089 ***	1.152 ***	0.967 ***
PC4	−1.453 ***	−1.456 ***	−1.235 ***
PC5	−4.878 ***	−4.800 ***	−4.642 ***
Wage	0.529 ***	0.525 ***	0.600 ***
PC11	0.274 ***	0.246 ***	0.280 ***
PC31	−0.376 **	−0.431 **	−0.396 **
PC41	0.240 *	0.226 *	0.210 *
PC51	0.329 **	0.396 **	0.306 **
PC61	−0.556 ***	−0.595 ***	−0.412 ***
PC22	−0.397 ***	−0.363 **	−0.366 ***
PC32	−1.106 ***	−1.097 ***	−1.101 ***
PC52	1.652 ***	1.526 ***	1.582 ***
PC62	0.446 *	0.449 †	0.425 **
PC53	1.832 ***	1.868 ***	1.839 ***
PC44	0.509 ***	0.592 ***	0.418 **
PC54	1.427 ***	1.350 ***	1.295 ***
PC65	0.877 ***	0.903 **	0.792 ***
PC66	−0.523 **	−0.512 **	−0.571 ***
δ_0	1.094 ***	1.024 ***	1.187 ***
Pop < 10,000	−0.317 ***	−0.286 ***	−0.334 ***
Pop 10,000–20,000	−0.085 †	−0.077 †	−0.108 ***
Pop > 50,000	0.043	0.051	
Total subsidies per capita	9.60E-05 ***	8.83E-05 ***	
State subsidies per capita			7.09E-05 ***
District subsidies per capita			1.35E-04 ***
Capital expenditures per capita	−4.15E-05 ***	−3.70E-05 **	−2.77E-05 ***
Self-generated revenues (%)	0.015 ***	0.015 ***	0.014 ***
Voters' turnout	−0.013 ***	−0.014 ***	−0.015 ***
Parliamentary parties (%)	−0.313 **	−0.278 *	−0.236 ***
Left-wing share in parliamentary parties (%)	−0.179 *	−0.179 †	−0.150 ***
Electoral year dummy	−0.014		
Distance from regional center	0.000		
University graduates (%)	−0.010		
σ^2	0.050 ***	0.052 ***	0.049 ***
γ	0.048	0.035 **	0.012 ***
Log likelihood	47.159	44.587	53.824
LR test one-sided error	380.387 ***	375.243 ***	393.717 ***

Note: ***, **, * denote statistical significance at 1%, 5% and 10% level, respectively. † denotes statistical significance at 10% level on one-tail.

The effects of determinants are of our main interest. *Population size* increases inefficiency, but the effect is present only for small municipalities. The dummy for the largest municipalities is insignificant. In other words, the scope for improvements in the operation in largest municipalities appeared to not to be significantly different from the medium size municipalities. *Distance* to the regional center is insignificant as well; insignificance of both largest population dummy and distance may be attributed to a very low intensity of interregional competition in the early transition period.

Fiscal capacity in the form of *Self-generated revenues* relaxes the budget constraint, and increases inefficiency, exactly as predicted and seen also in the 2000s. *Subsidies* show an expected positive effect on inefficiency, where the magnitude of the effect of *District subsidies* exceeds the magnitude of *State subsidies*. We may hypothesize that district subsidies, albeit lower in absolute size, less likely bring in additional output that could shift the municipality closer to the best-practice frontier. These local-type subsidies more likely crowd-out other type of productive spending which consequently increases slack. Alternatively, direction of these subsidies is to marginal improvements that are not captured by our rough measure of outputs.

Political variables in 1990s are the least consistent with observations in the next decade. The effect of *Voters' turnout* is unchanged, in a sense that larger participation decreases inefficiency. In contrast, the *Electoral year* is insignificant. Note that in both subsamples, we have just a single electoral year (1994 and 2006), hence implications based on the electoral year have to be stated with utmost care. Interestingly, the share of *Parliamentary parties* decreases costs. We may think of close alignment of political and social elites at that time; managerial expertise in the public sector that was just being developed, and political parties attracted those who looked for a career in the public service. The reason that coalitions with *Left-wing* parties spent significantly less is difficult to identify without extra evidence. We suggest that the effect may go through unobservable outputs; the anti-regime or opposition status of the left-wing parties led these coalitions to focus more on protecting the status quo rather than developing the municipalities. Also, the scope for redistributive policies at the local level was even more limited in 1990s than in the subsequent decade.

As a final step, we compare the individual scores in the two periods. Average individual scores in 1994–1996 period are presented in Table A14. Figure 6 shows the changes for subsamples differentiated by size. Clearly, the large municipalities suffered from a dramatic drop (located in the SE corner) and mainly small and medium municipalities improved significantly (located in the SE corner). Nevertheless, we interpret the individual results with caution: With unobserved differences in sectoral efficiencies, a sufficiently large change in the output mix may affect the comprehensive score even without any change in sectoral efficiencies or any change of the relevant environmental variable. Thus, the scores must be carefully applied in the comparison of two periods that involve substantial difference of the structures of outputs.

The relative improvement is mainly conditional on size. Table 20 reports the average rank improvements for subgroups defined by population level thresholds, and Spearman rank correlations between efficiency scores in periods 1994–1996 and 2004–2006. Apparently, small municipalities tend to outperform large municipalities over time. The relative position within a subgroup is the most stable for medium-size municipalities; in contrast, both small and large municipalities are subject to substantial changes in their relative standing.

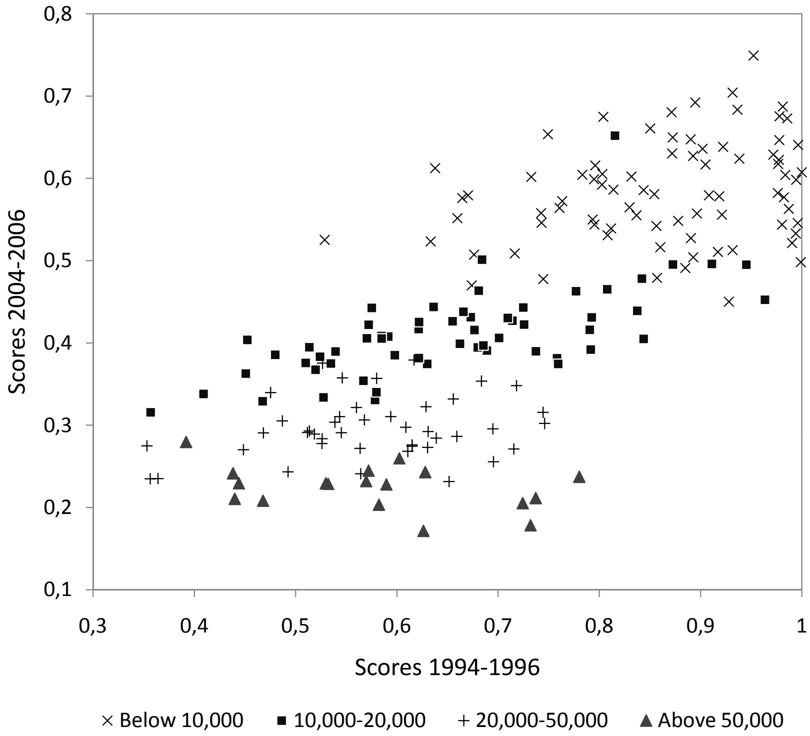


Figure 6. The evolution of the efficiency scores from 1994–1996 to 2003–2008

Table 20. Rank improvement from 1994–96 to 2003–2008 and rank correlation between the scores in 1994–96 and 2003–2008

Municipalities	Average	Max	Min	Correlation
Below 10 000	8.26	103	−74	0.232
10,000–20,000	11.7	76	−68	0.687
20,000–50,000	−15.6	29	−77	0.317
Above 50,000	−45.9	28	−108	−0.203
Full sample	0	103	−74	0.765

7 Conclusion

This article examines the extent of cost inefficiency of local governments in a sample of 202 municipalities of extended scope in the Czech Republic in the period 2003–2008. The input side is defined by current spending of the municipalities, and the outputs are core services provided. We apply both parametric and non-parametric efficiency measurement methods. Given the possibility to treat time variance endogenously and include determinants, we prefer stochastic frontier analysis with a time-variant Pseudo-Translog specification and determinants, estimated in a single stage.

Interestingly, our preferred specification is dissimilar to the best non-parametric method of data envelopment analysis with variable returns to scale and bias corrected by bootstrapping. We discuss how to attribute the differences to the (i) the effect of excluding determinants and (ii) the effect of assuming deterministic non-parametric versus stochastic parametric methodology.

The exogenous variables that robustly increase inefficiency are population size, distance to the regional center, share of university-educated citizens, capital expenditures, subsidies per capita, and the share of self-generated revenues. These are attributed to well-known effects of decreasing yardstick competition, flypaper effect, and softer budget constraint. Concerning political variables, increase in party concentration and the voters' involvement increases efficiency, and local council with a lower share of left-wing representatives also tend to be more efficient. We interpret determinants not only as indicators of slack, but also as indicators of non-discretionary inputs, and unobservable outputs, especially if increased cost (inefficiency) is present in municipalities with a high share of mobile (educated) citizens.

A comparative analysis is conducted also for the period 1994–1996, where a few determinants lose significance, and political variables appear to influence inefficiency in a structurally different way. From comparison of the two periods, we also obtain that small municipalities improve efficiency significantly more than large municipalities. As a result, initially low differences between efficiency scores, especially between medium-size and large municipalities, have magnified over time.

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A Methodology

A.1 Data Envelopment Analysis

Let $\mathbf{X}$ denote the input matrix of dimension $N \times p$, where p denotes the total number of inputs, and $\mathbf{Y}$ denotes the output-matrix of dimension $N \times q$, where q is the number of outputs. Municipality $i \in \{1, \ldots, N\}$ uses inputs $\mathbf{x_i}$ to produce outputs $\mathbf{y_i}$. The objective is to find $\theta_i \in [0, 1]$, representing the maximal possible proportion by which original inputs used by municipality i can be contracted such that given level of outputs remains feasible. Efficiency score of municipality i, θ_i, is obtained by solving the following problem:

$$\begin{aligned} \min_{\theta_i, \lambda_i} \quad \theta_i \quad \text{s.t.} \quad & -\mathbf{y}_i + \mathbf{Y}\lambda_i \geq 0 \\ & \theta_i \mathbf{x}_i - \mathbf{X}\lambda_i \geq 0 \\ & \lambda \geq 0 \end{aligned} \tag{7}$$

Here θ_i is scalar and λ_i is vector of N constants. Inputs $\mathbf{x}_i$ can be radially contracted to $\theta_i \mathbf{x_i}$ such that $\mathbf{y_i}$ is feasible under given technology. This radial contraction of the input vector produces a projected point $(\mathbf{X}\lambda_i, \mathbf{Y}\lambda_i)$, which is a linear combination of the observed data weighted by vector λ_i and lies on the surface of the technology.

This optimization problem is solved separately for each of the N municipalities, therefore each municipality i is assigned its specific set of weights λ_i. The vector λ_i reflects which municipalities form the efficient benchmark for the municipality i. Municipality j affects θ_i if $\lambda_{ij} > 0$. We call these influential observations as peers.

Efficiency computed from the model in (7) is based on underlying assumption of constant returns to scale (CRS) technology, as in the original paper by Charnes et al. (1978). Banker et al. (1984) extend the analysis to account for variable returns to scale (VRS) technology by adding additional convexity constraint

$$\sum_{j=1}^{N} \lambda_{ij} = 1. \tag{8}$$

This constraint ensures that an inefficient municipality is only benchmarked against peers of a similar size. We can easily adjust the model to non-increasing returns to scale (NIRS) (Färe et al. 1985). Under this restriction, the municipality i is not benchmarked against substantially larger municipalities, but may be compared with smaller municipalities. NIRS technology is generated by substituting the restriction (8) by

$$\sum_{j=1}^{N} \lambda_{ij} \leq 1. \tag{9}$$

A.2 Outliers

Wilson (1993) provides a diagnostic statistics which may help to identify outliers, but this approach is computationally infeasible for large data sets. Nevertheless, for our case the statistic is computable. The statistic represents the proportion of the geometric volume in input $\times$ output space spanned by a subset of the data obtained by deleting given number of observations relative to the volume spanned by the entire data set. Those sets of observations deleted from the sample that produce small values of the statistic are considered to be outliers. As noticed in Wilson (1993), the statistics may fail to identify outliers if the effect of one outlier is masked by one or more other outliers. Therefore, it is reasonable to combine this detection method with alternative methods.

Cazals et al. (2002) have introduced the concept of partial frontiers (order-m frontiers) with a nonparametric estimator which does not envelop all the data points. Order-m efficiency score can be viewed as the expectation of the minimal input efficiency score of the unit i, when compared to m units randomly drawn from the population of units producing at least the output level produced by i, therefore the score is not bounded at unity. An alternative to order-m partial frontiers are quantile based partial frontiers proposed by Aragon et al. (2005), extended to multivariate setting by Daouia and Simar (2007). The idea is to replace this concept of "discrete" order-m partial frontier by a "continuous" order-α partial frontier, where $\alpha \in [0, 1]$. Simar (2007) proposed an outlier detection strategy based on order-m frontiers. If an observation remains outside the order-m frontier as m increases, then this observation may be an outlier.

In our case, we construct order-m efficiency scores for $m = 25, 50, 100, 150$. The number of super-efficient observations decreases in m. For $m = 100$ we have 3–6 (depending on the year) observations with $\theta^m > 1$ and 1–3 observations with $\theta^m > 1.01$. To find if these outliers influence efficiency of other observations, i.e. if they constitute peers, we compute basic DEA efficiency scores and explore super-efficient observations serving as peers. In the next step, we scrutinize observations having our potential outliers as peers. We compare their efficiency scores θ^{DEA} and θ^m. If an observation is super-efficient ($\theta^m > 1$ for relatively large m) and if it has low θ^{DEA} score, then it may be distorted by the presence of the outliers. We find no super-efficient observation with a low DEA score, hence our super-efficient values do not distort efficiency rankings.

A.3 Bootstrap in DEA

DEA efficiency estimates are subject to uncertainty due to sampling variation. To allow for statistical inference, we need to know statistical properties of the nonparametric estimators, therefore to define a statistical model that describes the data generating process (Simar 1996), i.e. the process yielding the data observed in the sample $(\mathbf{X}, \mathbf{Y})$.

Once we define a statistical model (see for example Kneip et al. 1998), we can apply bootstrap technique to provide approximations of the sampling distributions of $\hat{\theta}(\mathbf{X}, \mathbf{Y}) - \theta(\mathbf{X}, \mathbf{Y})$, where $\hat{\theta}(\mathbf{X}, \mathbf{Y})$ is the DEA estimator and $\theta(X, Y)$ is the true value of efficiency.

Knowledge of the sampling distribution allows us to evaluate the bias, the standard deviation of $\hat{\theta}(\mathbf{X}, \mathbf{Y})$, and to derive bounds of confidence intervals for $\theta(\mathbf{X}, \mathbf{Y})$. Simar and Wilson (2000) describe the methodology for bootstrapping in non-parametric models.

The bootstrap bias estimate $\hat{\delta}$ can be obtained from:

$$\hat{\delta}(\hat{\theta}(\mathbf{X}, \mathbf{Y})) \approx \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_b^*(\mathbf{X}, \mathbf{Y}) - \hat{\theta}(\mathbf{X}, \mathbf{Y}), \tag{10}$$

where the bias estimate $\hat{\delta}$ is the difference between mean of the Monte-Carlo realizations of $\{\hat{\theta}_b^*(\mathbf{X}, \mathbf{Y})\}_{b=1}^{B}$ and DEA efficiency estimator. Hence, the original DEA efficiency estimator may be corrected for the bias.

$$\tilde{\theta}(\mathbf{X}, \mathbf{Y}) = \hat{\theta}(\mathbf{X}, \mathbf{Y}) - \hat{\delta}(\hat{\theta}(\mathbf{X}, \mathbf{Y}) \tag{11}$$

However, Efron and Tibshirani (1993), recommend not to correct for the bias unless $|\hat{\delta}(\hat{\theta}(\mathbf{X}, \mathbf{Y}))| > \hat{\sigma}(\hat{\theta}(\mathbf{X}, \mathbf{Y}))/4$, where $\hat{\sigma}(\hat{\theta}(\mathbf{X}, \mathbf{Y}))$ is a standard deviation, i.e. a square-root of the variance of the bootstrap distribution:

$$\hat{\sigma}^2(\hat{\theta}(\mathbf{X}, \mathbf{Y})) \approx \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_b^*(\mathbf{X}, \mathbf{Y}) - \Big(\frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_b^*(\mathbf{X}, \mathbf{Y})\Big)^2 \tag{12}$$

The bootstrap is consistent if the available bootstrap distribution mimics the original unknown sampling distribution. The *naive* bootstrap procedure, however, does not satisfy this condition because of the boundary estimation framework (Efron and Tibshirani 1993). Simar and Wilson (1998) propose the homogenous smooth bootstrap which can be applied to overcome this problem. This procedure can be used only if independence assumption holds, i.e. under independence between technical inefficiency and output levels as well as the mix of inputs. Wilson (2003) provides a survey of tests for independence. We employ the graphical method developed by Fisher and Switzer (1985).

B Data and results

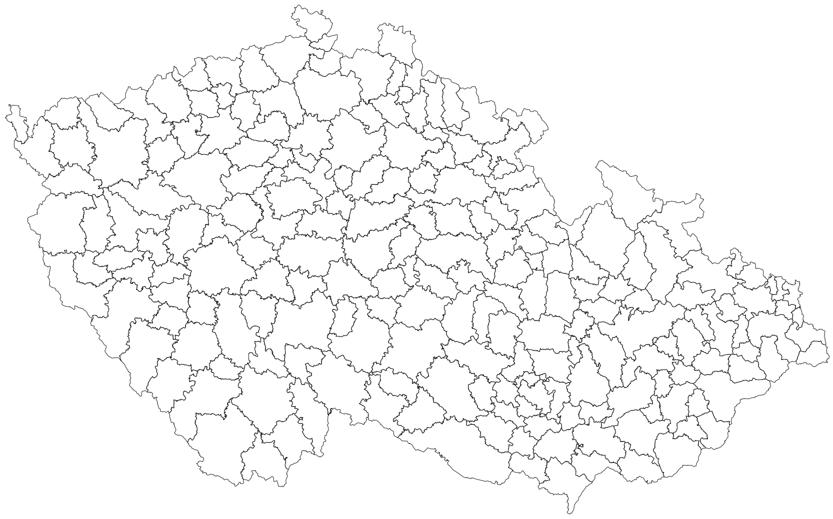

Figure A1. Districts administered by municipalities of extended scope in the Czech Republic

Table A1. List of municipalities

1	Benešov	69	Litoměřice	137	Boskovice
2	Beroun	70	Litvínov	138	Břeclav
3	Brandýs nad Labem-Stará Boleslav	71	Louny	139	Bučovice
4	Čáslav	72	Lovosice	140	Hodonín
5	Černošice	73	Most	141	Hustopeče
6	Český Brod	74	Podbořany	142	Ivančice
7	Dobříš	75	Roudnice nad Labem	143	Kuřim
8	Hořovice	76	Rumburk	144	Kyjov
9	Kladno	77	Teplice	145	Mikulov
10	Kolín	78	Ústí nad Labem	146	Moravský Krumlov
11	Kralupy nad Vltavou	79	Varnsdorf	147	Pohořelice
12	Kutná Hora	80	Žatec	148	Rosice
13	Lysá nad Labem	81	Česká Lípa	149	Slavkov u Brna
14	Mělník	82	Frýdlant	150	Šlapanice
15	Mladá Boleslav	83	Jablonec nad Nisou	151	Tišnov
16	Mnichovo Hradiště	84	Jilemnice	152	Veselí nad Moravou
17	Neratovice	85	Liberec	153	Vyškov
18	Nymburk	86	Nový Bor	154	Znojmo
19	Poděbrady	87	Semily	155	Židlochovice
20	Příbram	88	Tanvald	156	Hranice
21	Rakovník	89	Turnov	157	Jeseník
22	Říčany	90	Železný Brod	158	Konice
23	Sedlčany	91	Broumov	159	Lipník nad Bečvou
24	Slaný	92	Dobruška	160	Litovel
25	Vlašim	93	Dvůr Králové nad Labem	161	Mohelnice
26	Votice	94	Hořice	162	Olomouc
27	Blatná	95	Hradec Králové	163	Prostějov
28	České Budějovice	96	Jaroměř	164	Přerov
29	Český Krumlov	97	Jičín	165	Šternberk
30	Dačice	98	Kostelec nad Orlicí	166	Šumperk
31	Jindřichův Hradec	99	Náchod	167	Uničov
32	Kaplice	100	Nová Paka	168	Zábřeh
33	Milevsko	101	Nové Město nad Metují	169	Bystřice pod Hostýnem
34	Písek	102	Nový Bydžov	170	Holešov
35	Prachatice	103	Rychnov nad Kněznou	171	Kroměříž
36	Soběslav	104	Trutnov	172	Luhačovice
37	Strakonice	105	Vrchlabí	173	Otrokovice
38	Tábor	106	Česká Třebová	174	Rožnov pod Radhoštěm
39	Trhové Sviny	107	Hlinsko	175	Uherské Hradiště
40	Třeboň	108	Holice	176	Uherský Brod
41	Týn nad Vltavou	109	Chrudim	177	Valašské Klobouky
42	Vimperk	110	Králíky	178	Valašské Meziříčí
43	Vodňany	111	Lanškroun	179	Vizovice
44	Blovice	112	Litomyšl	180	Vsetín
45	Domažlice	113	Moravská Třebová	181	Zlín
46	Horažďovice	114	Pardubice	182	Bílovec
47	Horšovský Týn	115	Polička	183	Bohumín
48	Klatovy	116	Přelouč	184	Bruntál
49	Kralovice	117	Svitavy	185	Český Těšín
50	Nepomuk	1185	Ústí nad Orlicí	186	Frenštát pod Radhoštěm
51	Nýřany	119	Vysoké Mýto	187	Frýdek-Místek
52	Přeštice	120	Žamberk	188	Frýdlant nad Ostravicí
53	Rokycany	121	Bystřice nad Pernštejnem	189	Havířov
54	Stod	122	Havlíčkův Brod	190	Hlučín
55	Stříbro	123	Humpolec	191	Jablunkov
56	Sušice	124	Chotěboř	192	Karviná
57	Tachov	125	Jihlava	193	Kopřivnice
58	Aš	126	Moravské Budějovice	194	Kravaře
59	Cheb	127	Náměšť nad Oslavou	195	Krnov
60	Karlovy Vary	128	Nové Město na Moravě	196	Nový Jičín
61	Kraslice	129	Pacov	197	Odry
62	Mariánské Lázně	130	Pelhřimov	198	Opava
63	Ostrov	131	Světlá nad Sázavou	199	Orlová
64	Sokolov	132	Telč	200	Rýmařov
65	Bílina	133	Třebíč	201	Třinec
66	Děčín	134	Velké Meziříčí	202	Vítkov
67	Chomutov	135	Žďár nad Sázavou		
68	Kadaň	136	Blansko		

Table A2. Selected studies on comprehensive efficiency of local governments

Authors	Country	N	Period	Method(s)	Inputs	Outputs
Afonso and Fernandes (2008)	Portugal	278	2001	DEA	Total expenditures per capita	Old people, no. of schools, school enrolment, share of library users in population, water supply, solid waste, licenses for building construction, length of roads per population
Arcelus et al. (2007)	Spain: Navarre region	263	1998–2001	SFA BC	Total current expenditures	Area, total population, share of old people, dwellings, index measuring the scarcity in the provision of municipal services, time trend
Balaguer-Coll et al. (2007)	Spain: Valencian region	414	1995	DEA, FDH	Wages and salaries, expenditure on goods and services, current transfers, capital transfers, capital expenditures	Population, no. of lighting points, tons of waste, street infrastructure area, public parks area, quality services (good, average, bad)
De Borger and Kerstens (1996)	Belgium	589	1985	DEA, FDH, SFA, COLS	Total current expenditures	No. of beneficiaries of minimal subsistence grants, students in local primary schools, surface of public recreational facilities, population, share of old people
Geys et al. (2010)	Germany: Baden-Wurtenberg	1021	2001	SFA BC	Total current expenditures	Students in local public schools, kindergartens, surface of public recreational facilities, population, old people, no. of employees paying social security contributions
Geys and Moesen (2009)	Belgium: Flanders	300	2000	SFA BC	Current expenditures on those issues for which we observe government outputs	Number of subsistence grant beneficiaries, number of students in local primary schools, size of public recreational facilities, length of municipal roads, share of municipal waste collected through door-to-door collections
Kalb (2010)	Germany: Baden-Wurtenberg	245	1990–2004	SFA BC	Total current expenditures	Students in public schools, population, share of old people, number of employees covered by social security, surface of public recovery areas
Vanden Eeckaut et al. (1993)	Belgium: Wallone region	235	1986	DEA, FDH	Total current expenditures	Population, length of roads, old people, no. of beneficiaries of minimal subsistence grants, no. of crimes

Note: We denote the method developed by Battese and Coelli (1995) as SFA BC, and corrected ordinary least squares as COLS.

Table A3. Output variables

	Source	Database	Web page	Available	Note
Pupils in primary schools and kindergartens	IIE	Aggregated data	http://stistko.uiv.cz/vo/	2003–2008	
Pupils entering secondary schools (%)	IIE	Aggregated data	http://stistko.uiv.cz/vo/	2005–2008	2005–2008 average for 2003–2004
Cultural facilities	CZSO	City and municipal statistics (MOS)		2003–2006	2006 data for 2007–2008
Municipal museums and galleries	MGA, municipal websites	Catalog of museums and galleries	http://www.cz-museums.cz/amg/faces/adresar/	Retrieved in 2009	Same for 2003–2008
Objects in monuments reserve	NIM	Monumnet	http://monumnet.npu.cz/monumnet.php	2003–2008	Objects in municipal monuments reserves and zones
Sporting and recreational area (ha)	CZSO	MOS		2006–2008	2006 data for 2003–2005
Municipal waste (tons)	ME	ISOH	http://isoh.cenia.cz/groupisoh	2003–2008	Data for ORP districts adjusted for population share of a municipality in whole district population
Nature reserves	ANCLP	USOP	http://drusop.nature.cz/	2003–2008	Sum of national nature reserves, nature reserves, national nature monuments and nature monuments
Pollute area (ha)	CZSO	MOS		2003–2008	Sum of arable land, built-up and other area
Urban green area (ha)	CZSO	MOS		2006–2008	2006 data for 2003–2005
Built-up area (ha)	CZSO	MOS		2003–2008	
New dwellings	CZSO	MOS		2003–2008	
Businesses	CZSO	MOS		2003–2008	
Municipal roads (ha)	CZSO	MOS		2006–2008	2006 data for 2003–2005
Bus stations	IDOS		http://jizdnirady.idnes.cz/	Retrieved in 2009	Same for 2003–2008
Population in district	CZSO	Regional Yearbooks	http://www.czso.cz/csu/redakce.nsf/i/krajske_rocenky	2003–2008	
Old population	CZSO	MOS		2003–2008	
Homes for disabled	CZSO	MOS		2003–2006	2006 data for 2007–2008
Municipal police	MOS, municipal websites		2003–2008		

Sources: ANCLP = Agency for Nature Conservation and Landscape Protection, MGA = Museums and Galleries Association, CZSO = Czech Statistical Office, IDOS = Transportation timetables, IIE = Institute for Information on Education, ME = Ministry of Environment, NIM= National Institute of Monuments.

Table A4. Correlation matrix of output variables

		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
Pupils in prim. schools and kindergart.	A	1																		
Pupils entering secondary schools (%)	B	−0.150	1																	
Cultural facilities	C	0.820	−0.080	1																
Municipal museums and galleries	D	−0.220	0.082	−0.063	1															
Objects in monuments reserve	E	0.305	0.070	0.353	−0.028	1														
Sporting and recreational area (ha)	F	0.554	−0.066	0.472	−0.099	0.362	1													
Municipal waste (tons)	G	0.839	−0.110	0.642	−0.179	0.228	0.459	1												
Nature reserves	H	0.180	−0.026	0.146	−0.208	0.278	0.176	0.104	1											
Pollute area (ha)	I	0.588	−0.086	0.644	−0.001	0.419	0.537	0.456	0.117	1										
Urban green area (ha)	J	0.819	−0.146	0.657	−0.218	0.155	0.518	0.651	0.088	0.480	1									
Built-up area (ha)	K	0.922	−0.122	0.829	−0.185	0.388	0.579	0.797	0.178	0.672	0.702	1								
New dwellings	L	0.587	−0.006	0.545	−0.166	0.398	0.395	0.555	0.204	0.414	0.435	0.664	1							
Businesses	M	0.949	−0.104	0.817	−0.221	0.351	0.577	0.835	0.214	0.560	0.764	0.934	0.685	1						
Municipal roads (ha)	N	0.706	−0.090	0.681	−0.068	0.351	0.600	0.578	0.140	0.801	0.637	0.710	0.451	0.702	1					
Bus stations	O	0.767	−0.067	0.615	−0.096	0.221	0.325	0.677	0.175	0.408	0.573	0.700	0.432	0.730	0.524	1				
Population in district	P	0.884	−0.151	0.721	−0.274	0.338	0.511	0.791	0.355	0.503	0.689	0.855	0.619	0.886	0.582	0.692	1			
Old population	Q	0.968	−0.124	0.852	−0.226	0.339	0.571	0.840	0.175	0.585	0.803	0.945	0.667	0.971	0.702	0.725	0.888	1		
Homes for disabled	R	0.559	−0.075	0.413	−0.180	0.110	0.199	0.482	0.123	0.299	0.455	0.533	0.235	0.512	0.406	0.443	0.496	0.511	1	
Municipal police	S	0.230	0.074	0.166	−0.017	0.135	0.175	0.187	0.131	0.053	0.200	0.220	0.094	0.222	0.121	0.176	0.270	0.217	0.162	1

Note: N=1212.

Table A5. Determinants and price level normalizations

	Source	Database	Web page	Available	Note
Population	CZSO	Regional Yearbooks	http://www.czso.cz/csu/redakce.nsf/i/krajske_rocenky	2003–2008	
University graduates	CZSO	Census		2001	2001 for 2003–2008
Subsidies	MF	ARIS	http://wwwinfo.mfcr.cz/aris/	2003–2008	Total state subsidies
Self-generated revenues	MF	ARIS	http://wwwinfo.mfcr.cz/aris/	2003–2008	Charges and fees, real estate tax and non-tax revenues / Total revenues (own transfers excluded)
Lagged debt dummy	MF	ARIS	http://wwwinfo.mfcr.cz/aris/	2003–2008	Deficit after consolidation
Distance	Map server	Mapy.cz	http://www.mapy.cz	2010	The shortest distance in minutes
Political concentration	CZSO	Election server	http://volby.cz/	2002, 2006	2002 results for 2003–2006, 2006 results for 2007–2008, Hirschmann-Herfindahl index
Left-wing parties	CZSO	Election server	http://volby.cz/	2002, 2006	2002 results for 2003–2006, 2006 results for 2007–2008, the share of seats of KSČM and ČSSD
Parliamentary parties	CZSO	Election server	http://volby.cz/	2002, 2006	2002 results for 2003–2006, 2006 results for 2007–2008, the share of seats of ČSSD, KDU-ČSL, KSČM, ODS, US-DEU
Turnout	CZSO	Election server	http://volby.cz/	2002, 2006	2002 elections for 2003–2006, 2006 elections for 2007–2008
Wage	CZSO	KROK		2003–2005	2005 data for districts (okresy), 2006–2008 data based on 2005 but adjusted for growths of regional gross wages (13 regions)
Inflation	CZSO		http://www.czso.cz/	2003–2008	CPI, 2003 base year

Sources: CZSO = Czech Statistical Office, MF = Ministry of Finance of the Czech Republic.

Table A6. Correlation matrix of determinants

		A	B	C	D	E	F	G	H	I	J	K	L	M	N
Pop < 10,000	A	1													
Pop 10,000–20,000	B	−0.551	1												
Pop > 50,000	C	−0.249	−0.208	1											
University graduates (%)	D	−0.378	−0.020	0.385	1										
Subsidies per capita	E	0.208	−0.045	−0.162	−0.114	1									
Capital expenditures per capita	F	0.059	−0.024	−0.051	0.019	0.383	1								
Lagged debt dummy	G	0.014	0.027	−0.021	−0.046	−0.044	−0.094	1							
Self-generated revenues (%)	H	−0.044	0.028	−0.088	0.026	−0.110	−0.076	0.048	1						
Distance from regional center	I	−0.075	0.080	0.071	−0.033	−0.001	0.070	0.008	−0.052	1					
Voters' turnout	J	0.616	−0.088	−0.395	−0.104	0.267	0.147	−0.028	0.051	−0.043	1				
Political concentration	K	−0.060	−0.086	0.233	0.047	0.004	−0.039	−0.022	0.177	−0.108	−0.116	1			
Left-wing share	L	−0.212	−0.001	0.148	−0.110	−0.169	−0.054	0.015	0.039	0.011	−0.450	0.073	1		
Parliamentary parties share	M	−0.331	0.050	0.197	0.079	−0.171	−0.013	0.015	0.063	−0.011	−0.314	0.234	0.075	1	
Electoral year	N	−0.002	0.002	−0.003	0.000	−0.214	0.097	0.077	0.107	0.000	−0.006	−0.047	0.032	0.035	1

Note: N=1212.

Table A7. Year-specific DEA efficiency scores

		No adjustment			Wage adjustment		
		Mean	Min	# Fully eff.	Mean	Min	# Fully eff.
2003	CRS	0.545	0.213	9	0.540	0.207	9
	NIRS	0.780	0.320	60	0.785	0.333	55
	VRS	0.781	0.320	60	0.787	0.333	55
2004	CRS	0.442	0.145	4	0.457	0.151	4
	NIRS	0.782	0.279	56	0.787	0.284	56
	VRS	0.782	0.279	56	0.788	0.284	56
2005	CRS	0.548	0.239	9	0.552	0.246	7
	NIRS	0.788	0.342	52	0.787	0.351	48
	VRS	0.788	0.342	52	0.788	0.351	48
2006	CRS	0.540	0.247	5	0.550	0.246	8
	NIRS	0.776	0.383	52	0.771	0.371	53
	VRS	0.776	0.383	53	0.772	0.371	54
2007	CRS	0.519	0.226	6	0.536	0.227	7
	NIRS	0.798	0.376	61	0.781	0.365	53
	VRS	0.798	0.376	61	0.782	0.365	53
2008	CRS	0.519	0.226	6	0.530	0.235	10
	NIRS	0.788	0.380	52	0.786	0.395	52
	VRS	0.788	0.380	52	0.786	0.395	52
Average	CRS	0.519	0.145	1	0.528	0.151	1
	NIRS	0.785	0.279	30	0.783	0.284	31
	VRS	0.786	0.279	30	0.784	0.284	31

Table A8. DEA efficiency scores: 2003–2008 averages, no adjustment

	CRS		VRS			CRS		VRS			CRS		VRS	
ID	Score	Rank	Score	Rank	ID	Score	Rank	Score	Rank	ID	Score	Rank	Score	Rank
1	0.395	133	0.786	104	69	0.299	180	0.551	185	137	0.477	104	1.000	1
2	0.311	176	0.573	179	70	0.320	171	0.568	181	138	0.327	168	0.630	159
3	0.435	120	0.849	84	71	0.368	145	0.617	165	139	0.771	26	0.875	75
4	0.473	107	0.635	157	72	0.384	139	0.430	199	140	0.379	141	0.746	115
5	0.400	130	0.693	137	73	0.289	183	1.000	1	141	0.593	68	0.824	91
6	0.798	22	0.826	89	74	0.772	25	0.788	103	142	0.708	36	0.812	93
7	0.582	71	0.611	168	75	0.361	147	0.435	198	143	0.521	88	0.539	189
8	0.579	72	0.592	174	76	0.462	111	0.505	192	144	0.489	98	0.698	135
9	0.271	194	0.918	64	77	0.348	154	0.940	56	145	0.613	63	1.000	1
10	0.283	188	0.648	154	78	0.230	201	1.000	1	146	0.962	4	1.000	1
11	0.333	164	0.497	195	79	0.403	129	0.614	167	147	0.924	8	0.956	45
12	0.336	161	0.948	50	80	0.533	85	1.000	1	148	0.720	32	0.736	119
13	0.625	61	0.664	149	81	0.368	144	1.000	1	149	0.717	33	0.759	111
14	0.322	170	0.564	182	82	0.709	35	0.904	66	150	0.626	60	0.987	37
15	0.314	172	0.951	49	83	0.284	187	0.876	74	151	0.616	62	0.985	38
16	0.798	23	1.000	1	84	0.652	52	0.680	142	152	0.525	86	0.707	130
17	0.394	134	0.620	163	85	0.285	186	0.989	36	153	0.349	153	0.578	176
18	0.429	121	0.598	171	86	0.515	91	0.690	138	154	0.360	149	0.995	34
19	0.538	83	0.698	134	87	0.603	66	0.790	102	155	0.847	18	0.881	71
20	0.277	192	0.631	158	88	0.650	53	0.698	133	156	0.404	128	0.748	114
21	0.488	99	1.000	14	89	0.407	126	0.662	150	157	0.449	116	0.933	58
22	0.423	122	0.716	125	90	0.866	15	0.863	77	158	1.000	1	1.000	1
23	0.628	59	0.643	155	91	0.556	78	0.576	177	159	0.588	69	0.854	81
24	0.469	108	0.801	98	92	0.663	48	0.743	116	160	0.571	73	0.898	68
25	0.515	90	0.667	147	93	0.398	131	0.519	191	161	0.560	76	0.669	145
26	0.870	14	0.882	70	94	0.649	55	0.930	60	162	0.279	191	1.000	1
27	0.852	16	1.000	1	95	0.283	189	1.000	1	163	0.343	156	0.984	39
28	0.253	199	1.000	1	96	0.485	101	0.889	69	164	0.275	193	0.676	143
29	0.462	112	1.000	1	97	0.446	117	0.806	97	165	0.464	109	0.716	126
30	0.849	17	0.990	35	98	0.758	27	0.811	94	166	0.305	178	0.558	184
31	0.490	96	0.996	33	99	0.383	140	0.709	128	167	0.559	77	0.758	112
32	0.678	43	0.768	110	100	0.676	45	0.778	108	168	0.499	94	0.665	148
33	0.545	81	0.660	151	101	0.609	65	0.715	127	169	0.647	57	0.839	86
34	0.294	181	0.621	162	102	0.690	38	0.701	131	170	0.490	97	0.595	172
35	0.496	95	1.000	1	103	0.443	119	0.756	113	171	0.340	157	0.866	76
36	0.666	47	0.808	95	104	0.362	146	1.000	1	172	0.655	50	0.685	139
37	0.285	185	0.495	196	105	0.506	92	0.858	79	173	0.376	143	0.564	183
38	0.330	166	0.839	85	106	0.411	124	0.618	164	174	0.389	135	0.544	188
39	0.901	12	0.967	40	107	0.482	103	0.651	153	175	0.356	150	0.722	122
40	0.585	70	0.967	41	108	0.716	34	0.741	118	176	0.486	100	0.938	57
41	0.687	41	0.779	107	109	0.455	114	1.000	1	177	0.921	10	1.000	1
42	0.728	31	1.000	1	110	0.960	5	0.960	44	178	0.386	136	0.684	140
43	0.674	46	0.742	117	111	0.546	80	0.589	175	179	0.895	13	0.952	48
44	0.926	7	0.941	55	112	0.405	127	0.908	65	180	0.305	177	0.853	82
45	0.463	110	0.682	141	113	0.534	84	1.000	1	181	0.313	173	0.941	54
46	0.998	2	1.000	1	114	0.338	160	1.000	1	182	0.550	79	0.574	178
47	0.560	75	0.616	166	115	0.601	67	0.800	99	183	0.271	195	0.530	190
48	0.524	87	1.000	1	116	0.653	51	0.799	100	184	0.335	162	0.719	124
49	0.913	11	0.926	62	117	0.338	159	0.550	187	185	0.289	184	0.478	197
50	0.980	3	1.000	1	118	0.385	137	0.592	173	186	0.385	138	0.407	200
51	0.689	39	0.806	96	119	0.503	93	0.668	146	187	0.282	190	0.850	83
52	0.567	74	0.570	180	120	0.686	42	0.903	67	188	0.475	105	0.609	169
53	0.445	118	0.732	121	121	0.688	40	0.732	120	189	0.346	155	0.997	31
54	0.924	9	0.948	51	122	0.396	132	0.826	90	190	0.460	113	0.777	109
55	0.647	56	0.943	52	123	0.516	89	0.636	156	191	0.819	20	0.967	42
56	0.484	102	0.697	136	124	0.737	29	0.955	46	192	0.262	197	0.829	88
57	0.474	106	0.671	144	125	0.311	175	0.996	32	193	0.326	169	0.551	186
58	0.540	82	0.965	43	126	0.655	49	0.657	152	194	0.944	6	0.931	59
59	0.338	158	1.000	1	127	0.782	24	0.798	101	195	0.378	142	0.835	87
60	0.313	174	0.816	92	128	0.650	54	0.943	53	196	0.330	165	0.607	170
61	0.676	44	0.700	132	129	0.749	28	0.878	73	197	0.707	37	0.720	123
62	0.327	167	0.500	193	130	0.455	115	1.000	1	198	0.334	163	1.000	1
63	0.408	125	0.627	160	131	0.817	21	0.928	61	199	0.216	202	0.387	202
64	0.293	182	0.500	194	132	0.733	30	0.925	63	200	0.612	64	0.855	80
65	0.303	179	0.394	201	133	0.353	152	0.785	105	201	0.355	151	0.859	78
66	0.251	200	0.781	106	134	0.645	58	0.954	47	202	0.819	19	0.880	72
67	0.259	198	0.625	161	135	0.268	196	0.707	129					
68	0.361	148	1.000	1	136	0.420	123	1.000	1					

Table A9. DEA efficiency scores: 2003–2008 averages, wage adjustment

	CRS		VRS			CRS		VRS			CRS		VRS	
ID	Score	Rank	Score	Rank	ID	Score	Rank	Score	Rank	ID	Score	Rank	Score	Rank
1	0.402	130	0.808	91	69	0.300	185	0.555	184	137	0.470	112	1.000	1
2	0.376	146	0.686	139	70	0.367	151	0.660	149	138	0.318	177	0.614	168
3	0.525	82	0.977	36	71	0.358	158	0.600	170	139	0.767	26	0.858	76
4	0.524	83	0.687	138	72	0.396	134	0.429	199	140	0.366	152	0.721	125
5	0.503	96	0.813	90	73	0.333	167	1.000	1	141	0.567	73	0.819	88
6	0.860	18	0.893	68	74	0.723	37	0.742	119	142	0.763	30	0.879	69
7	0.574	72	0.596	171	75	0.368	150	0.444	198	143	0.545	80	0.565	181
8	0.698	43	0.712	129	76	0.477	104	0.515	193	144	0.470	113	0.675	144
9	0.306	183	0.930	56	77	0.373	148	0.923	58	145	0.609	65	1.000	1
10	0.304	184	0.699	135	78	0.262	200	1.000	1	146	0.900	14	1.000	1
11	0.381	144	0.576	178	79	0.399	133	0.594	172	147	0.929	11	0.949	49
12	0.387	141	0.975	37	80	0.515	87	1.000	1	148	0.765	28	0.772	109
13	0.646	55	0.675	146	81	0.403	129	1.000	1	149	0.724	36	0.743	118
14	0.372	149	0.649	153	82	0.772	25	0.946	51	150	0.684	47	0.996	32
15	0.412	125	1.000	1	83	0.287	191	0.800	94	151	0.667	50	1.000	1
16	0.991	3	1.000	1	84	0.641	58	0.650	152	152	0.512	90	0.694	136
17	0.447	118	0.675	145	85	0.318	176	0.996	33	153	0.331	168	0.553	185
18	0.419	123	0.577	177	86	0.575	71	0.769	110	154	0.334	166	0.916	64
19	0.509	93	0.700	134	87	0.589	69	0.782	102	155	0.910	12	0.917	63
20	0.280	193	0.590	175	88	0.659	52	0.684	140	156	0.417	124	0.742	120
21	0.519	85	1.000	1	89	0.406	128	0.643	156	157	0.410	126	0.857	78
22	0.506	95	0.832	83	90	0.846	20	0.872	73	158	1.000	1	1.000	1
23	0.623	61	0.637	157	91	0.511	91	0.536	189	159	0.597	66	0.826	86
24	0.539	81	0.919	59	92	0.648	54	0.718	127	160	0.612	64	0.928	57
25	0.515	88	0.677	142	93	0.390	140	0.518	192	161	0.547	79	0.662	148
26	0.872	16	0.875	72	94	0.637	59	0.942	53	162	0.289	190	1.000	1
27	0.870	17	1.000	1	95	0.317	179	1.000	1	163	0.340	164	0.918	61
28	0.293	188	1.000	1	96	0.462	115	0.840	82	164	0.277	195	0.629	160
29	0.472	109	1.000	1	97	0.438	122	0.799	95	165	0.480	103	0.704	130
30	0.767	27	0.948	50	98	0.752	33	0.788	99	166	0.297	186	0.546	187
31	0.456	116	0.958	45	99	0.362	156	0.653	151	167	0.589	68	0.778	104
32	0.694	44	0.793	98	100	0.668	49	0.752	115	168	0.488	101	0.634	159
33	0.513	89	0.623	162	101	0.560	77	0.643	155	169	0.632	60	0.816	89
34	0.277	194	0.560	183	102	0.759	31	0.777	106	170	0.471	111	0.568	180
35	0.476	105	0.994	34	103	0.449	117	0.761	112	171	0.337	165	0.808	92
36	0.673	48	0.803	93	104	0.362	157	1.000	1	172	0.709	38	0.723	124
37	0.286	192	0.500	194	105	0.493	99	0.852	79	173	0.401	132	0.602	169
38	0.330	169	0.784	100	106	0.392	139	0.592	174	174	0.396	135	0.561	182
39	0.996	2	1.000	1	107	0.471	110	0.627	161	175	0.351	161	0.717	128
40	0.564	76	0.938	55	108	0.794	24	0.822	87	176	0.474	106	0.915	65
41	0.747	34	0.793	97	109	0.443	119	0.972	40	177	0.976	5	1.000	1
42	0.699	42	1.000	1	110	0.959	8	0.960	43	178	0.392	138	0.704	131
43	0.666	51	0.704	132	111	0.524	84	0.540	188	179	0.963	7	0.971	41
44	0.932	10	0.956	46	112	0.393	136	0.877	71	180	0.323	174	0.850	80
45	0.472	108	0.704	133	113	0.510	92	1.000	1	181	0.327	171	0.939	54
46	0.976	6	1.000	1	114	0.376	147	1.000	1	182	0.595	67	0.617	166
47	0.564	75	0.618	164	115	0.558	78	0.736	121	183	0.273	197	0.494	195
48	0.509	94	1.000	1	116	0.729	35	0.869	74	184	0.314	180	0.674	147
49	0.905	13	0.917	62	117	0.325	173	0.520	191	185	0.290	189	0.474	197
50	0.986	4	1.000	1	118	0.364	153	0.552	186	186	0.401	131	0.425	200
51	0.684	46	0.784	101	119	0.490	100	0.647	154	187	0.296	187	0.847	81
52	0.564	74	0.575	179	120	0.658	53	0.879	70	188	0.515	86	0.615	167
53	0.484	102	0.777	105	121	0.686	45	0.749	116	189	0.346	162	0.955	47
54	0.936	9	0.959	44	122	0.387	142	0.774	108	190	0.440	120	0.754	114
55	0.622	62	0.914	66	123	0.495	98	0.634	158	191	0.836	21	0.967	42
56	0.473	107	0.690	137	124	0.705	41	0.945	52	192	0.263	199	0.754	113
57	0.467	114	0.680	141	125	0.364	155	1.000	1	193	0.352	160	0.592	173
58	0.497	97	0.903	67	126	0.614	63	0.622	163	194	0.894	15	0.919	60
59	0.326	172	1.000	1	127	0.755	32	0.761	111	195	0.364	154	0.779	103
60	0.309	182	0.748	117	128	0.644	57	0.953	48	196	0.357	159	0.655	150
61	0.709	39	0.720	126	129	0.706	40	0.798	96	197	0.765	29	0.775	107
62	0.317	178	0.494	196	130	0.439	121	1.000	1	198	0.330	170	0.981	35
63	0.392	137	0.585	176	131	0.808	22	0.858	77	199	0.221	202	0.385	202
64	0.311	181	0.529	190	132	0.848	19	0.975	38	200	0.577	70	0.828	85
65	0.321	175	0.403	201	133	0.340	163	0.730	122	201	0.379	145	0.830	84
66	0.257	201	0.727	123	134	0.646	56	0.974	39	202	0.806	23	0.864	75
67	0.273	196	0.618	165	135	0.272	198	0.676	143					
68	0.385	143	1.000	1	136	0.408	127	1.000	1					

Table A10. VRS bias-corrected efficiency scores: 2003–2008 averages

	No adjustment		Adjustment			No adjustment		Adjustment			No adjustment		Adjustment	
ID	Score	Rank	Score	Rank	ID	Score	Rank	Score	Rank	ID	Score	Rank	Score	Rank
1	0.688	113	0.711	99	69	0.513	185	0.516	185	137	0.811	46	0.807	63
2	0.532	177	0.637	132	70	0.530	180	0.619	143	138	0.571	163	0.556	168
3	0.773	77	0.880	3	71	0.582	156	0.566	164	139	0.794	65	0.781	71
4	0.589	153	0.632	137	72	0.400	198	0.398	199	140	0.669	118	0.654	128
5	0.599	151	0.700	106	73	0.809	57	0.809	56	141	0.715	101	0.709	103
6	0.764	81	0.829	25	74	0.711	103	0.673	116	142	0.750	85	0.814	43
7	0.557	168	0.542	172	75	0.397	199	0.408	198	143	0.499	189	0.521	183
8	0.549	170	0.665	122	76	0.472	192	0.483	191	144	0.643	130	0.625	141
9	0.789	69	0.797	67	77	0.849	13	0.836	20	145	0.830	27	0.837	18
10	0.579	157	0.631	138	78	0.808	60	0.808	60	146	0.809	54	0.809	54
11	0.456	195	0.528	178	79	0.544	172	0.522	182	147	0.837	24	0.834	22
12	0.811	45	0.828	29	80	0.816	41	0.819	37	148	0.688	112	0.720	90
13	0.611	147	0.624	142	81	0.809	53	0.807	64	149	0.680	115	0.666	121
14	0.525	182	0.604	150	82	0.783	71	0.810	48	150	0.845	16	0.839	15
15	0.806	63	0.831	23	83	0.770	78	0.696	108	151	0.855	8	0.853	8
16	0.853	9	0.818	42	84	0.626	138	0.594	152	152	0.637	134	0.629	139
17	0.567	164	0.611	148	85	0.822	33	0.828	26	153	0.543	173	0.523	180
18	0.562	166	0.539	175	86	0.609	148	0.678	113	154	0.851	11	0.791	68
19	0.649	128	0.651	130	87	0.697	107	0.688	111	155	0.801	64	0.826	32
20	0.585	154	0.547	169	88	0.628	136	0.612	146	156	0.674	116	0.668	120
21	0.810	49	0.810	49	89	0.620	141	0.601	151	157	0.821	35	0.764	78
22	0.652	127	0.746	80	90	0.784	70	0.789	69	158	0.812	44	0.811	46
23	0.593	152	0.587	154	91	0.519	184	0.483	190	159	0.762	83	0.730	85
24	0.732	92	0.841	14	92	0.690	110	0.664	123	160	0.794	66	0.813	45
25	0.627	137	0.634	135	93	0.478	191	0.479	193	161	0.619	142	0.615	144
26	0.820	37	0.809	51	94	0.766	79	0.776	72	162	0.810	50	0.810	50
27	0.809	58	0.809	57	95	0.807	62	0.809	55	163	0.869	4	0.818	38
28	0.809	56	0.809	52	96	0.782	73	0.739	81	164	0.623	140	0.578	160
29	0.808	61	0.811	47	97	0.724	98	0.720	92	165	0.669	119	0.651	129
30	0.869	5	0.845	11	98	0.751	84	0.725	89	166	0.522	183	0.510	186
31	0.878	2	0.866	4	99	0.661	124	0.612	147	167	0.710	104	0.726	88
32	0.704	106	0.728	87	100	0.694	109	0.669	118	168	0.616	143	0.584	156
33	0.579	158	0.545	171	101	0.653	125	0.582	158	169	0.730	93	0.710	101
34	0.576	160	0.522	181	102	0.646	129	0.719	93	170	0.544	171	0.518	184
35	0.819	39	0.818	40	103	0.689	111	0.692	109	171	0.776	76	0.732	84
36	0.724	97	0.718	96	104	0.810	51	0.807	65	172	0.629	135	0.661	126
37	0.467	194	0.471	194	105	0.743	87	0.739	82	173	0.533	176	0.569	163
38	0.763	82	0.709	104	106	0.553	169	0.529	177	174	0.512	186	0.529	176
39	0.845	17	0.848	10	107	0.578	159	0.558	167	175	0.666	121	0.670	117
40	0.851	12	0.837	19	108	0.665	122	0.736	83	176	0.840	20	0.821	35
41	0.716	100	0.715	98	109	0.853	10	0.837	17	177	0.824	31	0.818	41
42	0.820	36	0.827	30	110	0.818	40	0.820	36	178	0.641	131	0.663	124
43	0.667	120	0.627	140	111	0.543	174	0.491	189	179	0.879	1	0.884	2
44	0.823	32	0.843	13	112	0.793	68	0.767	77	180	0.711	102	0.709	102
45	0.613	145	0.636	134	113	0.809	52	0.809	58	181	0.827	28	0.828	28
46	0.826	29	0.827	31	114	0.809	59	0.807	62	182	0.531	178	0.573	162
47	0.528	181	0.527	179	115	0.706	105	0.642	131	183	0.494	190	0.459	195
48	0.838	21	0.850	9	116	0.745	86	0.805	66	184	0.625	139	0.585	155
49	0.857	7	0.855	7	117	0.509	187	0.479	192	185	0.450	196	0.447	196
50	0.825	30	0.822	34	118	0.539	175	0.499	187	186	0.379	200	0.394	200
51	0.741	89	0.720	91	119	0.615	144	0.592	153	187	0.729	94	0.730	86
52	0.530	179	0.539	174	120	0.781	75	0.757	79	188	0.558	167	0.562	166
53	0.672	117	0.718	95	121	0.639	132	0.655	127	189	0.848	14	0.823	33
54	0.876	3	0.892	1	122	0.766	80	0.719	94	190	0.696	108	0.676	114
55	0.815	42	0.785	70	123	0.575	161	0.577	161	191	0.837	22	0.828	27
56	0.638	133	0.633	136	124	0.863	6	0.856	6	192	0.727	95	0.662	125
57	0.603	150	0.612	145	125	0.841	19	0.834	21	193	0.506	188	0.546	170
58	0.833	25	0.771	73	126	0.608	149	0.579	159	194	0.830	26	0.818	39
59	0.809	55	0.809	53	127	0.727	96	0.699	107	195	0.738	90	0.691	110
60	0.743	88	0.680	112	128	0.821	34	0.831	24	196	0.563	165	0.610	149
61	0.653	126	0.668	119	129	0.782	74	0.708	105	197	0.662	123	0.718	97
62	0.448	197	0.444	197	130	0.811	47	0.808	59	198	0.837	23	0.839	16
63	0.582	155	0.541	173	131	0.843	18	0.771	75	199	0.364	202	0.362	202
64	0.467	193	0.496	188	132	0.819	38	0.843	12	200	0.734	91	0.710	100
65	0.367	201	0.373	201	133	0.722	99	0.675	115	201	0.793	67	0.767	76
66	0.684	114	0.636	133	134	0.845	15	0.866	5	202	0.783	72	0.771	74
67	0.571	162	0.566	165	135	0.613	146	0.584	157					
68	0.810	48	0.808	61	136	0.812	43	0.813	44					

Table A11. Pseudo-Translog efficiency scores: 2003–2008 averages, no determinants

	Wage in outputs		Adjustment			Wage in outputs		Adjustment			Wage in outputs		Adjustment	
ID	Score	Rank	Score	Rank	ID	Score	Rank	Score	Rank	ID	Score	Rank	Score	Rank
1	0.529	155	0.500	139	69	0.418	196	0.372	199	137	0.607	106	0.514	126
2	0.482	173	0.444	167	70	0.520	159	0.534	114	138	0.449	189	0.413	181
3	0.690	58	0.668	42	71	0.537	150	0.469	162	139	0.816	17	0.773	18
4	0.622	97	0.573	90	72	0.495	170	0.443	168	140	0.566	126	0.563	95
5	0.533	153	0.484	149	73	0.704	44	0.509	130	141	0.562	131	0.509	129
6	0.942	6	0.934	5	74	0.774	29	0.740	24	142	0.815	18	0.794	16
7	0.544	144	0.483	151	75	0.409	199	0.373	198	143	0.619	100	0.566	93
8	0.692	55	0.678	40	76	0.551	140	0.504	136	144	0.634	87	0.553	101
9	0.532	154	0.469	161	77	0.645	79	0.566	92	145	0.618	101	0.581	86
10	0.447	190	0.411	182	78	0.542	146	0.527	120	146	0.829	15	0.734	26
11	0.458	185	0.407	183	79	0.498	167	0.445	166	147	0.969	3	0.971	2
12	0.558	134	0.505	133	80	0.694	52	0.621	67	148	0.668	67	0.654	49
13	0.691	57	0.681	39	81	0.679	61	0.585	84	149	0.612	103	0.581	87
14	0.479	175	0.439	172	82	0.709	42	0.658	46	150	0.674	65	0.606	75
15	0.637	83	0.575	88	83	0.493	172	0.390	189	151	0.558	135	0.483	150
16	0.970	2	0.979	1	84	0.586	116	0.550	103	152	0.635	85	0.583	85
17	0.551	139	0.517	125	85	0.610	104	0.642	51	153	0.479	176	0.423	178
18	0.562	130	0.522	124	86	0.588	113	0.525	121	154	0.585	117	0.485	148
19	0.656	72	0.616	71	87	0.666	68	0.541	108	155	0.793	21	0.769	19
20	0.454	187	0.385	191	88	0.628	93	0.571	91	156	0.543	145	0.502	137
21	0.696	49	0.637	56	89	0.562	129	0.489	144	157	0.621	98	0.574	89
22	0.598	110	0.553	100	90	0.698	48	0.627	63	158	0.954	5	0.954	3
23	0.614	102	0.557	98	91	0.495	169	0.441	170	159	0.645	80	0.629	59
24	0.671	66	0.656	47	92	0.704	45	0.636	58	160	0.744	33	0.697	33
25	0.650	75	0.627	62	93	0.480	174	0.435	173	161	0.640	82	0.600	76
26	0.789	22	0.775	17	94	0.629	92	0.540	109	162	0.731	37	0.638	55
27	0.789	23	0.734	27	95	0.780	27	0.629	60	163	0.625	95	0.541	107
28	0.597	111	0.540	110	96	0.608	105	0.539	111	164	0.463	184	0.422	180
29	0.529	156	0.470	160	97	0.564	128	0.507	132	165	0.619	99	0.587	82
30	0.876	12	0.812	12	98	0.695	50	0.655	48	166	0.434	191	0.381	194
31	0.714	40	0.625	65	99	0.570	122	0.465	163	167	0.695	51	0.671	41
32	0.716	38	0.690	38	100	0.691	56	0.626	64	168	0.646	78	0.593	80
33	0.540	148	0.475	154	101	0.634	86	0.560	97	169	0.634	88	0.557	99
34	0.452	188	0.396	185	102	0.709	43	0.690	37	170	0.552	138	0.508	131
35	0.504	165	0.441	169	103	0.644	81	0.563	96	171	0.548	141	0.471	159
36	0.627	94	0.608	73	104	0.557	136	0.502	138	172	0.740	36	0.710	31
37	0.425	194	0.381	193	105	0.633	89	0.532	117	173	0.569	123	0.533	116
38	0.580	119	0.511	128	106	0.476	177	0.395	186	174	0.546	142	0.493	141
39	0.921	9	0.904	7	107	0.494	171	0.428	175	175	0.535	151	0.474	155
40	0.699	47	0.621	68	108	0.681	60	0.664	43	176	0.675	64	0.592	81
41	0.785	25	0.805	13	109	0.693	54	0.608	74	177	0.749	32	0.695	36
42	0.767	30	0.696	34	110	0.895	10	0.871	9	178	0.578	120	0.546	105
43	0.683	59	0.637	57	111	0.545	143	0.485	147	179	0.815	20	0.804	14
44	0.886	11	0.887	8	112	0.456	186	0.426	176	180	0.499	166	0.423	179
45	0.533	152	0.487	145	113	0.539	149	0.485	146	181	0.704	46	0.758	21
46	0.971	1	0.945	4	114	0.927	8	0.799	15	182	0.646	76	0.629	61
47	0.524	157	0.514	127	115	0.659	70	0.595	79	183	0.416	197	0.378	195
48	0.765	31	0.663	44	116	0.860	14	0.824	11	184	0.432	193	0.375	196
49	0.960	4	0.926	6	117	0.434	192	0.373	197	185	0.420	195	0.391	188
50	0.694	53	0.661	45	118	0.467	183	0.384	192	186	0.470	179	0.431	174
51	0.676	63	0.622	66	119	0.598	109	0.546	106	187	0.559	133	0.525	123
52	0.566	127	0.534	115	120	0.554	137	0.479	153	188	0.515	161	0.465	164
53	0.589	112	0.531	118	121	0.741	35	0.696	35	189	0.631	91	0.613	72
54	0.929	7	0.868	10	122	0.588	114	0.525	122	190	0.586	115	0.492	142
55	0.650	74	0.642	52	123	0.572	121	0.527	119	191	0.658	71	0.597	77
56	0.567	124	0.505	134	124	0.815	19	0.732	28	192	0.522	158	0.639	54
57	0.540	147	0.498	140	125	0.637	84	0.565	94	193	0.469	182	0.403	184
58	0.633	90	0.537	112	126	0.663	69	0.618	69	194	0.715	39	0.642	53
59	0.512	162	0.386	190	127	0.646	77	0.586	83	195	0.509	163	0.473	157
60	0.584	118	0.536	113	128	0.777	28	0.720	29	196	0.506	164	0.473	156
61	0.655	73	0.597	78	129	0.677	62	0.644	50	197	0.784	26	0.742	23
62	0.410	198	0.365	200	130	0.567	125	0.618	70	198	0.711	41	0.710	32
63	0.497	168	0.472	158	131	0.862	13	0.761	20	199	0.347	202	0.315	202
64	0.469	181	0.440	171	132	0.741	34	0.736	25	200	0.625	96	0.553	102
65	0.392	201	0.393	187	133	0.561	132	0.504	135	201	0.600	108	0.548	104
66	0.470	180	0.425	177	134	0.819	16	0.716	30	202	0.787	24	0.753	22
67	0.472	178	0.460	165	135	0.395	200	0.330	201					
68	0.519	160	0.490	143	136	0.605	107	0.482	152					

Table A12. Pseudo-Translog efficiency scores: 2003–2008 averages, determinants

	Wage in outputs		Adjustment			Wage in outputs		Adjustment			Wage in outputs		Adjustment	
ID	Score	Rank	Score	Rank	ID	Score	Rank	Score	Rank	ID	Score	Rank	Score	Rank
1	0.330	146	0.387	141	69	0.305	155	0.334	163	137	0.429	97	0.487	100
2	0.356	137	0.434	129	70	0.283	168	0.334	164	138	0.297	160	0.318	173
3	0.383	128	0.502	94	71	0.381	129	0.428	132	139	0.626	18	0.715	27
4	0.409	108	0.501	96	72	0.485	82	0.542	86	140	0.294	163	0.324	167
5	0.501	77	0.627	60	73	0.236	190	0.287	187	141	0.545	57	0.617	62
6	0.585	38	0.741	19	74	0.563	50	0.619	61	142	0.642	13	0.740	20
7	0.528	66	0.590	69	75	0.398	118	0.437	128	143	0.463	86	0.548	81
8	0.560	52	0.678	36	76	0.408	110	0.473	111	144	0.472	84	0.525	89
9	0.229	195	0.295	182	77	0.281	169	0.341	159	145	0.513	72	0.579	72
10	0.233	192	0.303	179	78	0.214	196	0.275	194	146	0.677	5	0.769	12
11	0.368	134	0.432	130	79	0.381	130	0.427	134	147	0.626	19	0.728	22
12	0.295	161	0.340	160	80	0.383	127	0.431	131	148	0.603	30	0.696	31
13	0.549	55	0.628	59	81	0.293	165	0.362	152	149	0.595	33	0.660	48
14	0.371	133	0.438	127	82	0.564	49	0.698	30	150	0.626	17	0.766	13
15	0.280	171	0.356	153	83	0.273	178	0.318	172	151	0.542	61	0.638	57
16	0.622	21	0.829	4	84	0.570	46	0.649	52	152	0.443	91	0.497	98
17	0.389	124	0.464	116	85	0.205	200	0.275	193	153	0.314	152	0.342	158
18	0.387	125	0.441	125	86	0.448	90	0.548	83	154	0.280	172	0.297	181
19	0.442	92	0.510	91	87	0.601	32	0.676	38	155	0.678	4	0.803	7
20	0.280	173	0.304	178	88	0.568	48	0.672	43	156	0.360	135	0.407	137
21	0.398	117	0.486	102	89	0.423	101	0.486	101	157	0.389	122	0.428	133
22	0.428	98	0.541	87	90	0.620	24	0.753	15	158	0.742	1	0.852	2
23	0.537	65	0.640	55	91	0.515	70	0.548	82	159	0.473	83	0.557	78
24	0.438	94	0.523	90	92	0.558	53	0.645	54	160	0.467	85	0.558	77
25	0.413	106	0.479	106	93	0.396	119	0.450	123	161	0.575	45	0.614	63
26	0.645	12	0.750	16	94	0.586	37	0.659	49	162	0.178	201	0.242	201
27	0.593	34	0.703	29	95	0.206	199	0.266	198	163	0.277	175	0.323	168
28	0.173	202	0.233	202	96	0.401	115	0.452	119	164	0.250	181	0.280	191
29	0.381	132	0.451	121	97	0.409	109	0.460	117	165	0.404	114	0.474	110
30	0.637	14	0.717	26	98	0.613	26	0.719	24	166	0.299	158	0.328	166
31	0.322	149	0.364	150	99	0.358	136	0.393	140	167	0.453	89	0.529	88
32	0.591	35	0.675	39	100	0.604	29	0.670	44	168	0.455	88	0.507	92
33	0.545	59	0.574	76	101	0.515	71	0.574	73	169	0.543	60	0.639	56
34	0.259	180	0.288	183	102	0.541	62	0.667	45	170	0.423	100	0.478	108
35	0.423	103	0.481	105	103	0.410	107	0.483	103	171	0.298	159	0.331	165
36	0.561	51	0.649	51	104	0.311	154	0.344	157	172	0.557	54	0.682	35
37	0.277	176	0.311	175	105	0.493	80	0.551	80	173	0.349	139	0.415	135
38	0.243	186	0.283	188	106	0.437	95	0.468	113	174	0.389	123	0.448	124
39	0.676	6	0.857	1	107	0.456	87	0.504	93	175	0.291	166	0.338	162
40	0.513	73	0.579	71	108	0.578	44	0.677	37	176	0.427	99	0.490	99
41	0.578	43	0.687	33	109	0.356	138	0.405	138	177	0.703	2	0.839	3
42	0.538	64	0.634	58	110	0.675	7	0.769	11	178	0.305	156	0.352	154
43	0.569	47	0.664	46	111	0.490	81	0.546	84	179	0.647	10	0.817	5
44	0.686	3	0.777	9	112	0.381	131	0.414	136	180	0.322	150	0.369	147
45	0.421	104	0.473	112	113	0.423	102	0.466	114	181	0.211	197	0.272	196
46	0.674	8	0.788	8	114	0.239	189	0.316	174	182	0.515	69	0.612	65
47	0.505	75	0.543	85	115	0.547	56	0.608	66	183	0.247	183	0.288	184
48	0.332	145	0.385	143	116	0.582	41	0.718	25	184	0.336	143	0.367	148
49	0.658	9	0.772	10	117	0.344	141	0.382	145	185	0.280	174	0.306	176
50	0.625	20	0.738	21	118	0.405	113	0.439	126	186	0.395	121	0.451	120
51	0.545	58	0.675	42	119	0.442	93	0.497	97	187	0.231	193	0.274	195
52	0.540	63	0.601	67	120	0.602	31	0.685	34	188	0.520	68	0.585	70
53	0.399	116	0.482	104	121	0.617	25	0.675	41	189	0.246	184	0.300	180
54	0.646	11	0.813	6	122	0.312	153	0.347	155	190	0.433	96	0.501	95
55	0.511	74	0.574	74	123	0.418	105	0.476	109	191	0.608	28	0.743	18
56	0.406	111	0.465	115	124	0.637	15	0.708	28	192	0.211	198	0.251	200
57	0.395	120	0.450	122	125	0.233	191	0.279	192	193	0.328	148	0.371	146
58	0.405	112	0.479	107	126	0.609	27	0.661	47	194	0.637	16	0.756	14
59	0.245	185	0.287	185	127	0.584	39	0.655	50	195	0.294	164	0.319	170
60	0.229	194	0.269	197	128	0.503	76	0.574	75	196	0.295	162	0.340	161
61	0.522	67	0.614	64	129	0.583	40	0.646	53	197	0.578	42	0.675	40
62	0.329	147	0.367	149	130	0.386	126	0.459	118	198	0.243	187	0.282	189
63	0.341	142	0.396	139	131	0.622	22	0.724	23	199	0.240	188	0.263	199
64	0.281	170	0.323	169	132	0.621	23	0.747	17	200	0.496	79	0.557	79
65	0.318	151	0.362	151	133	0.300	157	0.319	171	201	0.290	167	0.345	156
66	0.260	179	0.287	186	134	0.497	78	0.591	68	202	0.586	36	0.693	32
67	0.247	182	0.281	190	135	0.275	177	0.305	177					
68	0.335	144	0.384	144	136	0.348	140	0.385	142					

Table A13. Principal component analysis: 1994–1996

	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalue	8.468	1.317	1.226	0.988	0.909	0.852
Proportion	0.498	0.078	0.072	0.058	0.054	0.050
Cumulative	0.498	0.576	0.648	0.706	0.759	0.810
Pupils in kindergartens	0.334	−0.059	−0.014	−0.024	0.039	0.045
Museums	0.114	0.268	0.090	0.439	−0.634	−0.379
Cultural facilities	0.307	0.031	0.024	0.057	−0.015	−0.004
Objects in monuments reserve	0.141	0.504	0.168	−0.147	0.117	−0.329
Sports	0.299	0.003	−0.058	0.011	−0.043	0.008
Nature reserves	0.086	0.377	0.363	0.171	0.631	−0.080
Pollution area (ha)	0.223	0.224	0.016	−0.166	−0.119	−0.002
Urban green area (ha)	0.101	−0.442	0.266	0.289	0.202	−0.027
Landfill dummy	−0.028	0.173	0.602	0.133	−0.262	0.691
Built-up area (ha)	0.323	−0.013	−0.048	−0.039	−0.009	0.043
Businesses	0.328	−0.052	−0.012	0.002	0.076	0.003
Municipal roads	0.282	−0.199	−0.041	−0.009	−0.061	0.173
Bus stations	0.295	−0.035	−0.023	0.023	−0.081	−0.007
Homes for disabled	−0.019	0.141	−0.425	0.763	0.198	0.184
Old population	0.335	−0.067	−0.032	−0.024	0.045	0.042
Municipal police	0.030	0.422	−0.455	−0.195	0.008	0.438
Population	0.337	−0.074	−0.032	−0.028	0.036	0.055

Table A14. Pseudo-Translog efficiency scores: 1994–1996 averages, determinants

ID	Score	Rank	ID	Score	Rank	ID	Score	Rank
1	0.578	150	70	0.526	173	139	0.938	23
2	0.451	189	71	0.617	135	140	0.539	165
3	0.758	81	72	0.857	49	141	0.856	50
4	0.572	152	73	0.444	191	142	0.890	41
5	0.999	2	74	0.660	117	143	0.745	84
6	0.854	51	75	0.792	73	144	0.842	55
7	0.990	7	76	0.514	177	145	0.676	110
8	0.896	36	77	0.392	195	146	0.937	24
9	0.532	167	78	0.468	186	147	0.922	28
10	0.651	121	79	0.535	166	148	0.638	123
11	0.759	80	80	0.527	171	149	0.908	33
12	0.468	185	81	0.512	179	150	0.893	39
13	0.812	62	82	0.761	79	151	0.795	69
14	0.520	175	83	0.448	190	152	0.666	114
15	0.611	138	84	0.763	78	153	0.594	142
16	0.977	17	85	0.582	147	154	0.630	127
17	0.737	88	86	0.725	93	155	0.871	47
18	0.680	108	87	0.733	90	156	0.546	161
19	0.790	74	88	0.665	115	157	0.480	183
20	0.353	199	90	0.977	16	158	0.952	21
21	0.685	104	91	0.633	125	159	0.674	111
22	0.838	56	92	0.981	13	160	0.808	64
23	0.994	6	93	0.844	53	161	0.918	30
24	0.575	151	94	0.844	54	162	0.732	91
25	0.570	154	95	0.724	94	163	0.615	137
26	0.749	82	96	0.524	174	164	0.572	153
27	0.984	10	97	0.585	145	165	0.689	103
28	0.626	131	98	1.000	1	166	0.695	102
29	0.510	180	99	0.684	106	167	0.964	20
30	0.996	3	100	0.803	66	168	0.777	77
31	0.744	85	101	0.945	22	169	0.793	71
32	0.796	68	102	0.878	43	170	0.621	134
33	0.996	4	103	0.585	146	171	0.639	122
34	0.695	101	104	0.543	163	172	0.743	87
35	0.673	112	105	0.684	105	173	0.475	184
36	0.987	8	106	0.792	72	174	0.622	133
37	0.715	97	107	0.681	107	175	0.545	162
38	0.492	181	108	0.982	11	176	0.710	99
39	0.981	12	109	0.580	148	177	0.932	26
40	0.885	42	110	0.804	65	178	0.746	83
41	0.670	113	111	0.860	48	179	0.902	35
42	0.808	63	112	0.630	128	180	0.560	160
43	0.837	57	113	0.677	109	181	0.737	89
44	0.895	37	114	0.780	76	182	0.917	31
45	0.726	92	115	0.890	40	183	0.564	158
46	0.978	14	116	0.803	67	184	0.567	157
47	0.928	27	117	0.580	149	185	0.615	136
48	0.656	119	118	0.701	100	186	0.592	143
49	0.850	52	119	0.636	124	187	0.530	168
50	0.872	46	120	0.832	58	188	0.893	38
51	0.921	29	121	0.978	15	190	0.622	132
52	0.743	86	122	0.568	156	191	0.783	75
54	0.873	45	123	0.714	98	192	0.440	192
55	0.716	96	124	0.815	60	193	0.629	129
56	0.662	116	125	0.570	155	194	0.986	9
57	0.539	164	126	0.994	5	195	0.519	176
58	0.452	188	127	0.976	18	196	0.514	178
59	0.356	198	128	0.911	32	197	0.814	61
60	0.590	144	129	0.830	59	198	0.628	130
61	0.529	169	130	0.598	141	199	0.364	196
62	0.467	187	131	0.972	19	200	0.932	25
63	0.409	194	132	0.905	34	201	0.659	118
64	0.526	172	133	0.609	139	202	0.795	70
65	0.357	197	134	0.873	44			
66	0.603	140	135	0.564	159			
67	0.438	193	136	0.718	95			
68	0.527	170	137	0.655	120			
69	0.487	182	138	0.631	126			