Public sector efficiency: Leveling the playing field between OECD countries

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Public spending efficiency: Leveling the playing field between OECD countries

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Abstract: In this paper we seek a robust methodology to measure the relative public spending efficiency of 19 OECD countries over the period 1980-2000. Based on the functional classification of government expenditure, we decompose total public spending into its separate accounts and we employ a semi-parametric method to obtain relative efficiency scores (for the separate accounts as well as for aggregate public spending). The econometric method isolates the impact of government inefficiency from the inefficiency arising from the socioeconomic environment or luck, thus leveling the playing field between the examined countries. The results suggest that the quality of governance is more important than the socioeconomic environment or luck. Finally, we propose a technique to measure the allocative efficiency of public spending, in an effort to proxy the optimal allocation of public funds when the governments set specific targets.

JEL classification: C14; H11; H50
Keywords: Public spending; Technical and allocative efficiency; Stochastic DEA

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1. Introduction

It has long been recognized that the efficient function of the public sector is a requisite for a country's economic success. Yet, the measurement of government efficiency and the resulting comparison of individual countries' public sectors present a number of difficulties related to the scarcity of publicly available data and the complicated problems that may emerge in the estimation procedure. Only recently a small number of studies cultivated an effort towards the computation of relative public sector efficiency indicators.[1] Concerning OECD economies, Afonso et al. (2005) employed a nonparametric method to estimate relative efficiency scores for several parts of the public sector in 23 OECD countries during the 1980s and the 1990s.[2] Using similar techniques, Afonso and St. Aubyn (2005) estimated the efficiency of government spending on education and health using a sample of 30 OECD countries.

The basic shortcoming of the simple nonparametric approaches to efficiency measurement has been their inability to distinguish the inefficiency attributable to bad governmental managerial practices from the inefficiency arising from differences in socioeconomic environments or factors attributable to mere luck.[3] In light of this shortcoming, some recent studies involved two- and three-stage analyses that purge the

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[1] There is an abundant literature measuring the productive efficiency of various types of decision making units at the micro level, using either parametric or nonparametric techniques (which are discussed in some detail in the following section). For an introduction to the parametric methods see Kumbhakar and Lovell (2000) and for the nonparametric methods see Charnes et al. (2004). However, only a few papers used these techniques (primarily the nonparametric ones) on cross-country data to measure public sector efficiency. Gupta and Verhoeven (2001) assessed the efficiency of government spending on education and health for 37 African countries, while Herrera and Pang (2005) estimated several health and education efficiency indicators for a sample of 140 countries from 1996 to 2002. Sijpe and Rayp (2007) estimated government inefficiency for 52 developing countries over the 1990's. Afonso et al. (2006) estimated the public sector efficiency of the new EU member states and emerging economies. Using a parametric methodology, Angelopoulos et al. (2007) obtained relative public sector efficiency scores for a world sample of 64 countries over the period 1980-2000.

[2] More precisely Afonso et al. (2005) estimate 4 public sector "opportunity" indicators that take into account administrative, education, health and the quality of infrastructure outcomes, and three other indicators that reflect the so-called "Musgravian" tasks of the government (i.e. distribution, stabilization and economic performance).

[3] A large branch of literature emphasizes the importance of exogenous socio-economic factors on the translation of government activities into services of interest to citizens (see e.g. Duncombe et al., 1997; Bradford et al., 1969). In the same spirit, Tanzi and Schuknecht (2000, pp.76) note that "Governments cannot be assumed to be responsible for all the differences in the countries' performance as represented by these indicators. In fact, differences between countries and changes over time often have a lot to do with technical progress or cultural differences between countries".

effect of the so-called environmental and noise factors (Fried et al., 2002; Glass et al., 2006; Simar and Wilson, 2007; Balaguer-Coll et al., 2007).

Therefore, a first central element of this paper is that it accounts for this problem. In terms of a three-stage analysis (similar to that of Fried et al., 2002) we construct public spending efficiency (PSE hereafter) indexes that do not misleadingly count institutional superiority or luck as governmental efficiency. As our measure is able to distinguish between these effects, we argue (in contrast to Duncombe et al., 1997; Bradford, et. al., 1969) that exogenous socioeconomic factors generally have less of an influence (compared to sound policies) on the efficient translation of government spending into services of interest to citizens.

Moreover, based on the "Classification of expenditure according to purpose" (i.e. the functional classification of public spending), we decompose total public spending into its sub-components, and we estimate relative efficiency scores for each separate public spending account. In this way, we obtain relative efficiency indicators for public spending on (i) education, (ii) health, (iii) social security and welfare, (iv) general public services and (v) economic affairs.[4] The decomposition of public spending allows us to derive allocative efficiency scores of public spending; that is we examine the governments' ability to distribute their accounts optimally in order to achieve specific targets (e.g. better economic performance or economic stability). Using nonparametric techniques once again, and employing spending on the five public accounts as inputs, we proxy the optimal inputs (as a share of GDP) for each country and for each separate spending category.

The structure of the rest of the paper emerges along the following lines: Section 2 presents the methodology employed. In Section 3 we describe the data used in our empirical analysis. In Section 4 we present the empirical results and finally Section 6 concludes.

[4] Decomposing public spending is essential since OECD economies differ in the composition of their government expenditures, and thus we may lose valuable information by solely examining the efficiency of the overall public spending. For example, it has been pointed out (see e.g. Tanzi and Schuknecht, 2000) that the main difference between big-government and small-government OECD countries lies in the spending for social security and welfare. In the 1990s, social security related expenditure in big-government countries was two and one-half times higher than in small-government countries (that is an average of 0.20 as a share of GDP versus 0.08 as a share of GDP).

2. Methodology

Our focus in this article is on frontier efficiency (also called x-efficiency), in other words in the distance (in terms of production) of a decision making unit (DMU) from the best-practice equivalent. This is given by a scalar measure ranging between zero (the lowest efficiency measure) and one (corresponding to the optimum DMU). Farrell (1957) suggested that the efficiency of a DMU consists of two components: technical efficiency (TE), which reflects the ability of a DMU to maximize output given a set of inputs, and allocative efficiency (AE), which reflects the ability of a DMU to use the given set of inputs in optimal proportions, assuming input prices and technology are known. Subsequently, the product of technical and allocative efficiency provides a measure of overall economic efficiency (EE). The literature on the measurement of efficiency is divided into two major approaches that use either parametric or nonparametric frontiers. For our purpose we refer to the various techniques used to measure efficiency by indicating only the main lines of methodology.

In the parametric frontier analysis the technology of a DMU is specified by a particular functional form for the cost, profit or production relationship that links the DMU's output to input factors, and as the term "parametric" implies it includes a stochastic term. The literature includes various parametric frontier approaches that differ in the assumptions made on the stochastic error term, the most widely used being the stochastic frontier approach (SFA).[5]

Among the nonparametric approaches to efficiency measurement the most commonly employed is Data Envelopment Analysis (DEA). DEA is a programming technique that provides a linear piecewise frontier by enveloping the observed data points, yielding a convex production possibilities set. As such, it does not require the explicit specification of a functional form of the underlying production relationship.[6] Even though they account for the main problem of the stochastic frontier methods, namely the arbitrary imposition of a specific functional form, the nonparametric methods have some pitfalls of

[5] Other approaches include the distribution-free approach and the thick-frontier approach. For more technical definitions of these concepts see Kumbhakar and Lovell (2000).

[6] The Free Disposal Hull (FDH) is a special case of DEA, where instead of convexity free disposability of inputs and outputs is assumed. Because the FDH frontier is either congruent with or interior to the DEA frontier, FDH will typically generate larger estimates of average efficiency compared to DEA (Tulkens, 1993). Both approaches permit efficiency to vary over time and make no prior assumptions regarding the form of the distribution of inefficiencies (except that the best-practice firms are 100% efficient).

their own. Most notably they do not permit for random error and, as such, noise can cause severe problems in misleadingly shaping and positioning the frontier. Furthermore, tests of hypotheses regarding the existence of inefficiency and also regarding the structure of the production technology cannot be performed with DEA.[7]

In the nonprofit sector, like the public sector, where prices of inputs and – most importantly – outputs are difficult to define, PSE measurement is reasonable over longer time periods relative to micro-level applications. Hence, the researcher is likely to be faced with comparatively small samples, in which DEA's relative performance vis-à-vis stochastic methods may improve (Resti, 2000). Yet, if noise is created from computational inaccuracies of the accounting rules used by the international organizations (that provide the relevant data), then DEA will generally overestimate efficiency. At the same time, simple DEA techniques are unable to account for the effect of the macroeconomic or institutional environment on PSE. Furthermore, in the one input-one output case,[8] stochastic frontiers are not so computationally expensive in terms of degrees of freedom. Certainly, the parametric methods still require the specification of a functional form for the frontier of each country under consideration, as well as distributional assumptions regarding the error term and the residual inefficiency component. Since neither approach strictly predominates over the other, we consider an advanced procedure that (*i*) accounts for the effect of environmental variables on the estimated efficiency scores and (*ii*) incorporates statistical noise into DEA.

This leads to a three-stage DEA model, which may be described as follows:[9] In the first stage we apply simple input-oriented, variable returns to scale (VRS) DEA[10] to

[7] For a detailed discussion of the pros and cons of each methodology see Coelli et al. (2005).
[8] This is the case a researcher is probably to be faced with when examining the efficiency of various segments of the public sector (i.e. educational system, health system etc.). Given the single input, estimation of allocative efficiency is not possible.
[9] This model is a variant of the one developed by Fried et al. (2002), also used by Glass et al. (2006), to produced a "technically-level playing field" among DMUs operating in different macroeconomic environments and subject to different levels of exposition to luck.
[10] DEA may be computed either as input or output oriented. Input-oriented DEA shows by how much input quantities can be reduced without varying the output quantities produced. Output-oriented DEA assesses by how much output quantities can be proportionally increased without changing the input quantities used. The two measures provide the same results under constant returns to scale but give slightly different values under VRS. Nevertheless, both output and input oriented models will identify the same set of efficient/inefficient DMUs (see Coelli et al., 2005). Also, a constant returns to scale assumption is only appropriate when all DMUs are operating in an optimal scale (imperfections, asymmetries, etc. are not present).

obtain an initial evaluation of DMU – in our case government – performance. In the second stage we use the SFA to separate Stage 1 inefficiency into inefficiency attributable to government managerial practices and inefficiency that is due to the macroeconomic environment and statistical noise. Finally, in the third stage the original dataset of inputs is adjusted to account for the effects uncovered in the second stage, and DEA is used to re-evaluate government performance under a new "technically-level playing field". In the rest of the present section we describe each of the three stages in more detail.

2.1. Stage 1

To introduce some notation, let us assume that for *N* observations there exist *M* inputs producing *S* outputs. Hence, each observation *n* uses a nonnegative vector of inputs denoted $x^n = (x_1^n, x_2^n, ..., x_m^n) \in R_+^M$ to produce a nonnegative vector of outputs, denoted $y^n = (y_1^n, y_2^n, ..., y_S^n) \in R_+^S$. Production technology, $F = \{(y, x): x \text{ can produce y}\}$, describes the set of feasible input-output vectors, and the input sets of production technology, $L(y) = \{x : (y, x) \in F\}$ describe the sets of input vectors that are feasible for each output vector (Kumbhakar and Lovell, 2000).

To measure productive efficiency we use the following input-oriented DEA model, where the inputs are minimized and the outputs are held at their current levels:

$$
\begin{aligned}
&\theta^* = \min \theta, \text{ s.t.} \\
&\sum_{j=1}^{n} \lambda_j x_{ji} \leq \theta x_{i0} \quad i = 1, 2, ..., m; \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} \quad r = 1, 2, ..., s; \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0 \qquad j = 1, 2, ..., n;
\end{aligned}
\tag{1}
$$

where DMU_0 represents one of the *N* DMUs under evaluation, and x_{i0} and y_{r0} are the *i*th input and *r*th output for DMU_0, respectively. If $\theta^* = 1$, then the current input levels cannot be proportionally reduced, indicating that DMU_0 is on the frontier. Otherwise, if $\theta^* < 1$, then DMU_0 represents an inefficient public sector and θ^* represents its input-oriented efficiency score. Finally, λ is the activity vector denoting the intensity levels at which the S observations are conducted. Note that this approach, through the convexity constraint $\vec{1}\lambda = 1$ (which accounts for VRS) forms a convex hull of intersecting planes, since the frontier production plane is defined by combining some actual production planes.

In measuring PSE, both desirable and undesirable outputs may be present. For example, infant mortality, serving as an output of a country's health system is an undesirable output that a country would want to reduce. Therefore, if we treat infant mortality as a conventional output, then we also assume that it should be increasing with performance, which is of course invalid. In such cases, we opt for transforming Program (1) as follows. First, we multiply each undesirable output by "-1" and then we find a proper value v_r (in our case we use 100) to let all negative undesirable outputs be positive (Zhu, 2003).

As discussed above, even though the single procedure of Program (1) is widely employed to measure efficiency in the empirical literature, it integrates the effect of environmental variables and luck, thus it gives an unfair initial advantage to those public sectors that face e.g. favorable regulatory and macroeconomic environments or are just lucky (a factor captured in parametric methods by the stochastic error term). Giving this unfair initial advantage is avoided by carrying out the two subsequent stages of the empirical methodology.

2.2. Stage 2

In this stage we use the SFA to decompose Stage 1 efficiency scores into their environmental, inefficiency and statistical noise components. To perform this task we apply the methodology of Fried et al. (2002) with slight modifications. The focus here is on efficiency estimates, not total input or output slacks, as the majority of these slacks tend to be zero after Stage 1 estimation. The virtue of using SFA, as opposed to a limited dependent variable approach, is that its error term is asymmetric, with the error term that corresponds to inefficiency following either a fixed or a random effects model. Furthermore, we stack the N separate equations and estimate a single SFA regression model, one for each country (instead of estimating N separate regressions as in Fried et al., 2002). The advantage of this approach, besides its relative simplicity, is that it provides for greater degrees of freedom and thus greater statistical efficiency, given that our sub-sector datasets at each point in time are small.[11]

To further improve on statistical efficiency we choose to stack observations from different time periods and estimate a single equation panel data time-varying model (see Kumbhakar and Lovell, 2000). A panel (repeated observations on each DMU) enables some of the strong distributional assumptions used with cross-sectional data to be relaxed. In particular, as Simar and Wilson (2007) note, DEA efficiency estimates are serially correlated. This implies that the error components under an SFA regression are not iid, since the efficiency scores are derived from the first stage model. A solution to this problem arises if we allow the inefficiency error terms to be correlated amongst themselves and across inputs.[12] The only assumption needed here is that the remainder disturbance is iid and uncorrelated with the regressors. This leads to the estimation of a fixed effects model. In the present context, such a model has the additional virtue (which is a flaw when one is interested merely in efficiency estimation) that the fixed effects, which coincide with inefficiency estimates, capture the effects of all phenomena (such as the institutional environment and other macroeconomic factors; see Kumbhakar and Lovell, 2000). This allows for a direct leveling of the playing field for all DMUs; that is we need not use a large total (and thus and ad hoc mixture) of environmental variables to test out what really explains inefficiency in the second stage regressions. In fact, this suggests that we may not need data on any environmental variables. We just need some control variables to obtain fixed effects that are to be used in the third stage. Consequently, we may also avoid the potential disagreement on which environmental variables actually affect the PSE of each sub-sector (health, education etc.), in which direction and in what magnitude.

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[11] Note that Program 1 is used repeatedly at each point in time. If a multiple period DEA model was specified, it would identify efficient DMUs subject e.g. to different technology conditions, and since technology (among other things) changes rapidly the results would be biased.

[12] Simar and Wilson (2007) propose a double bootstrap procedure, which is computationally more difficult and - more importantly - is better suited for models that seek to examine the relationship between technical efficiency and environmental variables. With similar intentions, Balaguer-Coll et al. (2007) suggest examining the effect of environmental variables on local government performance using nonparametric bivariate kernel regressions in the second stage. Examination of the effect of exogenous determinants on PSE is somewhat beyond the scope of the present study (as we focus on providing efficiency scores when the playing field is leveled for all governments).

Given the above, the Stage 2 model with time-varying efficiency is of the following linear form:[13]

$$Eff_{it} = f(z_i;\beta) + v_{it} + u_{it}$$
$$u_{it} = \beta(t)u_i \qquad (2)$$

where z_i are control country-specific variables with a time dimension only, β are parameter vectors to be estimated, v_{it} represents random statistical noise, u_{it} represents technical inefficiency, and the function $\beta(t)$ is specified as a set of time dummy variables β_t. This model, based on Lee and Schmidt (1993), is more appropriate for short panels than the Cornwell et al. (1990) model, which is generally used to estimate a time-varying fixed effects frontier, since it just requires estimation of T-1 additional parameters. The β_ts are treated as the coefficients of the fixed effects u_{it}, and once both are estimated, u_{it} is obtained as $u_{it} = \max_i\{\hat{\beta}_t\hat{u}_i\} - (\hat{\beta}_t\hat{u}_i)$, from which $TE_{it} = \exp\{-\hat{u}_{it}\}$ can be calculated. As discussed above, we assume that $v_{it} \sim N(0,\sigma^2)$, but no distributional assumption is made on u_{it}, which is allowed to be correlated with the control variables or with the remainder disturbance.

The SFA regression models are interpreted very similar to the analysis of Fried et al. (2002). The impact of both the environment and noise on Stage 1 efficiency scores is captured by the deterministic feasible frontier $f(z_i;\beta) + v_{it}$. Since $u_{it} \geq 0$, the single stochastic feasible frontier represents the efficiency level that can be achieved in any noisy environment characterized by the control variables, technical inefficiency and estimated parameters. Any inefficiency in excess of the stochastic feasible frontier is attributable to government managerial inefficiency, because the effects of both the environment and statistical noise have been netted out, having been captured by the fixed effects.

The results derived from the above analysis are then used to penalize public sectors that have been advantaged by their relatively favorable economic environment and/or their relatively good luck. Thus, this involves the objective of leveling the playing field for all governments before repeating the exercise of Stage 1. To do so we adjust upwards the inputs used by governments relative to the least favorable environment and most

[13] Here we replicate the discussion in Kumbhakar and Lovell (2000, pp. 108-110), which is based on Lee and Schmidt (1993).

unlucky government, given by the highest inefficiency score u_{it}. Thus, governments' adjusted inputs are constructed from the results of Stage 2 SFA regressions by means of

$$x_{it}^{A} = x_{it} + [\max_{it}\{\hat{v}_{it}\} - \hat{v}_{it}] \quad (3)$$

where x_{it}^{A} and x_{it} are adjusted and observed inputs, respectively. As outlined in Fried et al. (2002), the conditional estimators for managerial inefficiency, given by $\hat{E}[u_{it} \mid v_{it} + u_{it}]$, enable estimators for statistical noise to be derived residually via

$$\hat{E}[v_{it} \mid v_{it} + u_{it}] = Eff_{it} - z_i\hat{\beta} - \hat{E}[u_{it} \mid v_{it} + u_{it}] \quad (4)$$

which provide conditional on $v_{it} + u_{it}$ estimators for the v_{it} in Eq. (3).[14]

2.3. Stage 3

In Stage 3 we repeat the exercise of Stage 1, this time using the adjusted input data that resulted from the analysis of Stage 2. Thus, through this procedure we are able to obtain inefficiency scores solely attributable to government managerial practices, which may be directly compared between countries.

2.4. Allocation and targeting

Besides the efficiency concepts highlighted above there may be additional institutional and political decisions that restrict the goals of the government towards improved PSE. For example, it is important to recognize the distinction between allocating the budget to the wrong activities (i.e. producing the wrong output) while being technically efficient. To this end, government decisions regarding inputs (i.e. the expenditure on the various sub-components of the public sector) are made not on how much to spend for, but also on what to spend for. To phrase this differently, budget allocation becomes an extremely important decision that if not done optimally it may lead to additional inefficiency, termed allocative inefficiency. Stricto sensu, AE reflects the DMUs ability to use the inputs in optimal proportions, given their respective prices. As such, and since the

[14] To obtain estimates for v_{it}, we follow the procedure given by Fried et al. (2002), with the modifications discussed above and repeated here for convenience. Their model is altered to use the efficiency Stage 1 scores instead of the slacks, as well as to use a fixed effects model, under which the fixed effects estimates incorporate the effect of the environment (instead of carrying out the double adjustment of initial inputs to capture the separate effect of the environment and luck under a random effects model, as is the one employed by Fried et al., 2002, and Glass et al., 2006).

product of TE and AE provides a measure of overall EE, it is obvious that the AE component cannot be ignored.

Even though estimation of AE requires data on input prices, when governments are viewed as DMUs the inputs employed are spending accounts as a share of GDP, and therefore prices are uniformly set equal to one.[15] This suggests that for general PSE indicators (to be extensively described below) governments may employ the separate public spending accounts as inputs. The Program (1) can be modified to obtain cost efficiency (CE) scores, which include both TE and AE. If we let p_i^0 denote the *i*th input price for DMU_0 and $\tilde{x}_{i0}$ represent the *i*th input that minimizes the cost, then x_{i0} represents the observed cost and CE is given by $(\sum_{i=1}^{m} p_i^0 \tilde{x}_{i0})/(\sum_{i=1}^{m} p_i^0 x_{i0})$. Because the actual cost is a constant for a specific DMU, CE can be directly calculated from the following DEA program:

$$\begin{aligned}
&\min \quad (\sum_{i=1}^{m} p_i^0 \tilde{x}_{i0})/(\sum_{i=1}^{m} p_i^0 x_{i0}) \text{ s.t.} \\
&\sum_{j=1}^{n} \lambda_j x_{ji} \le \tilde{x}_{i0} \quad i = 1,2,...,m; \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0} \quad r = 1,2,...,s; \qquad (5) \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \ge 0 \qquad j = 1,2,...,n;
\end{aligned}$$

Based on the estimates derived from the above model, AE is calculated residually by AE=CE/TE. This procedure has the additional virtue that optimal inputs (the optimal budget proportion allocated to each public spending account) may be derived at some chosen weight (price) imposed by the government.[16] Let us now comment on how the

[15] In the micro literature prices are an important factor affecting optimal allocation because the inputs employed are heterogeneous factors of production, and thus they are differently priced. In our case no such heterogeneity exists, since our inputs are always public spending accounts. Differently phrased, we have equally priced factors of production characterized by different productivity compared to a target. In a similar spirit, Zhu (2003) suggests that if different targets along the frontier are considered optimal for different DMUs, then construction of preference structures over the proportions by which input levels can be changed is appropriate. In other words, DMU-specified input weights serve as input prices, if inputs are given by the budget proportions allocated to the various segments of the sector.

[16] Note that Program (5) is run on the inputs derived from the three-stage procedure described above.

inputs and outputs discussed so far at a methodological level may be observed empirically.

3. Data

To measure PSE we employ as inputs five public spending accounts. More precisely, based on the functional classification of government spending, we use as inputs the public spending on (i) education (denoted as *EducSp*), (ii) health (*HealthSp*), (iii) economic affairs (*EcaffSp*), (iv) general public services (*GPSSp*), and (v) social security and welfare (*WelfSp*), all of them as a share of GDP.[17]

Data for *EducSp* are obtained from the World Bank's "World Development Indicators" (WDI). *EducSp* includes government expenditures on education provided either on individual or on a collective basis. Data for *HealthSp* and *WelfSp* are taken from the OECD's "Health Statistics Database" (2006) and the OECD's "Social Spending Database" (2000), respectively, whereas data for *GPSSp* and *EcaffSp* are obtained from IMF's "Government Financial Statistics" (GFS).

The respective outputs of the public spending accounts given above are described as "performance measures" in the relevant literature (e.g. Afonso et al., 2005; Angelopoulos and Philippopoulos, 2005). Following the rationale of this literature we employ as output of *EducSp* the secondary school enrollment (as a share of gross enrollment) taken from the WDI. Moreover, in order to capture any qualitative differences among the educational systems, we additionally employ as output the quality indicator constructed by Hanushek and Kimko (2000). The infant mortality rate and life expectancy at birth (both obtained from the WDI) are employed as outputs of *HealthSp*, whereas income inequality captured by the GINI coefficient is assumed to be the output of *WelfSp*.

Based on the "Classification of expenditure according to purpose" the Economic Affairs spending account (*EcaffSp*) includes as major sub-components (i) the "spending on construction and operation of electricity supply systems", and (ii) the "spending on construction, improvement, operation and maintenance of communication systems".

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[17] These correspond to the five out of six largest public spending categories. The only financially important spending category that we have not included in this study is public spending on defence. This is because it was fairly difficult to substantiate the output of this spending category. See below for more details on this. Also, for more details on the classification of the functions of government see Classification of Expenditure According to purpose (United Nations, 2000).

Thus, as outputs of *EcaffSp* we use quality measures of the electricity and telecommunications infrastructure, namely the electric power transmission and distribution losses (taken from the WDI), and the standard telephone access lines per 100 inhabitants (taken from the OECD's Telecommunication Database). Finally, we employ as outputs of *GPSSp* (i) the corruption in government, and (ii) the bureaucratic quality measures, both obtained from the IRIS-3 database.[18]

In order to examine the AE of public spending, we need more general indicators that could be interpreted as the output of the overall public spending, and must reflect the objectives (or alternatively the tasks) of government.[19] Again following the rationale of the relevant literature we utilize two well-established indicators that reflect the "Musgravian" tasks of government. These are (i) the general economic performance indicator (*EcPerf*) and (ii) the economic stability indicator (*EcStab*). If we consider these indicators as government targets, we may well estimate AE using the five spending accounts as inputs and the methodology described in Section 2.4. That is we may evaluate how different allocation of public spending among the separate accounts produces different outcomes, and subsequently what is the optimal allocation of public spending.

The outputs of *EcPerf* are assumed to be the unemployment rate, GDP per capita and the annual GDP growth rate. Lower scores in the unemployment rate and higher scores in GDP per capita and GDP growth reflect better economic performance. Data for these variables are obtained from the WDI. Finally, the outputs of *EcStab* are assumed to be the standard deviation of the GDP growth rate, which is interpreted as a measure of economic fluctuations, and the inflation rate. Lower scores in both measures denote improved economic stability.

Apart from the variables described so far, in the second stage of the estimation procedure we additionally use a set of control variables (specific to each sub-component

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[18] The "corruption in government" and "bureaucratic quality" variables are used by Angelopoulos and Philippopoulos (2005) and Afonso et al. (2005) as proxies of public administration performance. Since *GPSSp* is a public expenditure account mainly financing public administration, we employ these measures as outputs of the *GPSSp*.

[19] As Tanzi and Schuknecht (2000, pp. 75) state: "It is difficult or even impossible to consider all the social and economic objectives (and thus all the socioeconomic indicators) that the governments might want to influence with this spending. By necessity, the analysis will include fewer indicators than might have been desirable to include".

of public spending), to carry out the SFA regressions. These are the GDP per capita, the urbanization rate, the population density, the proportion of population above 65 years of age and the international market openness, all obtained from the WDI. Moreover, we use the government stability measure, the investment profile variable and the general proxy of the socioeconomic conditions, obtained from the IRIS-3 database. Finally, we use the Quinn (1997) indicator of capital market international integration.[20]

Table 1 reports the inputs and outputs used, along with some descriptive statistics. Even though the sample of countries considered is rather homogeneous consisting of top income countries, the size and the pattern of government spending in these countries are quite different. Thus, there are countries characterized by relatively large public sectors, whose government spending exceeds 40 percent as a share of GDP (e.g. the Netherlands, Sweden and Denmark), and countries with a public sector size that does not exceed 25 percent as a share of GDP (e.g. Austria, Switzerland and USA). Moreover, as regards the composition of government expenditures, there are countries that present a clear-cut priority towards social security and welfare spending (e.g. the Nordic countries), and others characterized by heavy spending on public infrastructure (such as Ireland, Norway and Finland, whose public spending on economic affairs exceeds 5 percent as a share of GDP). These differences may have appealing implications for the results of the empirical analysis that follows.

4. Estimation results

Space constraints prevent reporting the results of all three stages of analysis, as this would triple the number of tables. Thus, only limited information is provided for the Stage 1 and Stage 2 results in the text to allow comparison with the Stage 3 results. The

[20] More precisely, the efficiency scores of general public services obtained from Stage 1 are regressed on government stability, GDP per capita and the urbanization rate; the efficiency scores of education spending on GDP per capita, the IRIS socioeconomic condition indicator and the population density; the efficiency score of public health on GDP per capita, population density and the proportion of population above 65 years old; the efficiency scores of economic affairs on IRIS-3 investment profile, the socioeconomic conditions indicator and on the capital market international integration proxy constructed by Quinn (1997); the efficiency scores of social spending on government stability, the socioeconomic conditions and the urbanization rate; and finally in the cases of the efficiency scores of economic performance and stability we employ government stability, the socioeconomic conditions and international market integration as control variables. In any case we avoid using in the Stage 2 analysis any of the variables employed as outputs in the production process.

full set of Stage 3 relative PSE scores is reported in Tables 2a and 2b for the 1980s and the 1990s, correspondingly.[21] The results are reported for each of the 19 countries of our sample and for each separate account of public spending, while in the last two columns of Table 2 we present the relative efficiency scores of total spending when the government target is economic performance and economic stability, correspondingly. Sensitivity analysis performed on the Stage 3 results showed that efficient public sectors remained efficient to any simultaneous data changes in the respective inputs (for a detailed discussion of the sensitivity analysis on DEA estimates see Zhu, 2003).

Let us first turn to the discussion of the ranking of countries as derived from the Stage 3 results. Concerning the PSE of education, the frontier is shaped by a number of countries (Denmark, Finland, Norway, Greece, Norway and USA) in the 1980s, and the general ranking remains practically the same in the 1990s. Switzerland, UK and Spain attain relatively high efficiency scores, while Luxembourg and Germany are the last countries in the ranking. Since the educational systems of the OECD countries examined are far from being homogeneous in the sources of spending (private or public), it is important to account for the different ratios of private to public spending on education.[22] As such, we weight the outputs of *Educsp* (i.e. the secondary school enrollment and the quality of education) with the public to total spending ratio. By doing so we isolate the impact of private expenditure on output, and consequently we don't give countries characterized by heavy private funding on education an unfair advantage.

The frontier of the efficiency of public spending on health is shaped by Luxembourg, Portugal and Sweden in the 1980s, and Greece, Ireland, Luxembourg and Sweden in the 1990s. Switzerland, Australia and Spain are ranked among the good performers, whereas France, Germany and Sweden are last in the countries' ranking. As with the case of education, we account for the differences in the ratios of private to public spending on

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[21] The full set of Stage 1 and Stage 2 results is available upon request. The estimations were also carried out for 5-year time periods, the results being similar. Since the outputs used to estimate efficiency do not vary substantially over time we preferred to report the 10-year period results. The 5-year period results are also available upon request.

[22] In our sample there are countries characterized by heavy private funding on education (such as Australia or USA) and countries that base the financing of their educational systems on public funds (such as Finland and Denmark).

health by weighting the outputs of *HealthSp* with the ratio of public to total spending on health.[23]

Turning to the spending on economic affairs we note that even though a number of countries shape the frontier both in the 1980s and in the 1990s, the average efficiency score is only larger than the average efficiency score for general public services. It is not surprising that countries belonging to the efficient group (e.g. Finland, Germany, Sweden and Switzerland) are characterized by citizen-friendly regulatory environments and have been pioneers in ensuring their regulations are clear, cost-effective and directly linked to their policy goals. In contrast and with reference to the bad performers, apart from Luxembourg that represents a unique case (as it almost never implemented a cost-benefit analysis in its public sector), Norway was characterized by a relatively inflexible wage setting in the public sector, and Portugal suffered from weak human resource management and labor market inflexibility (see OECD, various issues).

As regards the efficiency scores of general public services, the frontier in the 1980s is shaped by Switzerland, with Germany, USA and Spain presenting sound performance. In contrast, Luxembourg and Greece appear to be the most inefficient countries. In the 1990s Canada accompanies Switzerland in shaping the frontier, with the general ranking changing only in few cases. Note that since most of the OECD countries examined present satisfactory scores in the outputs of this public sector category, differences in the efficiency scores are mainly driven by differences in spending. Thus, Luxembourg is the last country in the general ranking not because it is characterized by high corruption in government or unsatisfactory bureaucratic quality, but because it spends relatively more in order to achieve these goals.

Social security and welfare is the largest public spending account. According to Tanzi and Schuknecht (1998) this spending account increased the most in the last 35 years, from an average of less than 10 percent of GDP in 1960 to 23 percent of GDP in 1995, which corresponds to about three quarters of the total public expenditure increase since 1960. Thus, if one wants to examine the evolution of total spending and to explain its increasing trend during the last four decades it is crucial to focus on this account. In this

[23] The ratio of public to total spending on health is only 41.6% in USA and 51.9 % in Greece, while it reaches 88.42% and 87.32% in Sweden and Norway, correspondingly.

spending category the frontier is shaped by Australia and Finland in the 1980s, and Australia, Belgium, Denmark and USA in the 1990s. Moreover, the countries' ranking does not seem to change substantially through time.[24] Australia, Canada, Finland, Norway and USA present relatively high efficiency scores in both periods, whereas the scores of France, Ireland and the Netherlands reflect poor performance. Moreover, the results imply that PSE on social security can be achieved through either large or small social security spending accounts. In particular, there are countries characterized by small social security spending accounts that appear to be highly efficient (e.g. USA and Australia), and countries with large social security spending accounts that also present high efficiency scores (e.g. Finland and Norway). Quite a reverse case is presented by the Netherlands and Ireland, both indicating poor performance, although the former spends substantially on welfare policies and the latter much less.[25]

The second to last columns of Tables 2a and 2b report the relative efficiency scores of total spending when the government target is economic performance. Under this government target the frontier is shaped by Australia, Switzerland, Luxembourg and USA in the 1980s, and Switzerland, Ireland, Portugal and USA in the 1990s. Although the ranking of countries appears to change through time, we note that Australia, Canada, and Spain represent relatively efficient countries, whereas France, Denmark, Sweden and the Netherlands are characterized by poor performance. Yet, these results should be interpreted with caution since the countries examined present small differences in GDP per capita, as well as in their GDP growth and unemployment rates (assumed to be the outputs). As such, countries with relatively large public sectors may have a disadvantage under this specification of outputs.

The last column reports the relative efficiency scores of total spending when the government target is economic stability. In this case Australia, Switzerland, France, the Netherlands, Spain and USA in the 1980s, and Australia, Belgium, France, the

[24] The only exception worth noting is Denmark, which appears to be one of the worst performers in the 1980s and one of the best in the 1990s.

[25] One very important issue related with the efficiency of spending on social security and welfare is the design and the targeting of transfers. According to Tanzi and Schuknecht (1998), in France or Sweden more than 20 percent of transfers are redistributed to the richest 20 percent of households. Such a targeting generates a situation that has been described by Palda (1997) as "fiscal churning". The targeting of transfers, and consequently the ability of a system to redistribute towards the deprived, are key determinants of the efficiency of spending on social security and welfare.

Netherlands and USA in the 1990s shape the frontier. Although the countries ranking appear to change substantially through time, note that Canada, Switzerland and Germany perform well, whereas Norway and Sweden present low efficiency scores. Again these results should be interpreted with caution since most OECD economies are characterized by low inflation and stable growth rates during the period examined. Thus, countries with relatively large public sectors may present worse efficiency scores, if they achieve similar economic targets by "paying" relatively more.[26]

Comparing the Stage 1 with the Stage 3 results we note that levelling the playing field between OECD countries does not affect significantly the country ranking. The Spearman correlation of the rankings formed by the first and the third stage efficiency scores in both the 1980s and the 1990s (see last rows of Tables 2a and 2b) is quite high, and never becomes significant at the 5 per cent level.[27] This result has clear implications regarding the forces that shape PSE, since luck and superior institutional environment appear to be less important than sound governance. In turn, this reflects the idea that governments have much to gain by observing and implementing the strategies followed by the efficient governments, in an attempt to improve their own PSE levels.

Tables 3a and 3b report the optimal allocation of inputs when governments set as specific targets economic performance and economic stability, correspondingly. Given the relative homogeneity of the group of countries examined, we should not expect great differences between the optimal levels of inputs across countries, within the same public spending accounts. This is indeed the case. For example, optimal public spending on education ranges between 5.3% for Sweden and 6.2% for Luxembourg as a share of GDP (if the government target is economic performance). The same is true for the rest of the public spending accounts, with the notable exception of public spending on social security and welfare, where the variability of optimal inputs between countries is larger.

[26] However, we should note that our results do not suggest any relationship between government size and greater economic stability (through the function of automatic stabilizers etc). In our set of efficient countries there are some characterized by high public spending (such as the Netherlands, France and Germany), and others characterized by small public sectors (e.g. USA and Switzerland). Moreover, some countries are characterized by large public sectors, while they present poor efficiency scores (e.g. Norway and Sweden).

[27] A point worth noting is that the Spearman correlation of the ranking of countries produced by our Stage 1 results (when the target is economic performance) with the public sector performance indicator ranking reported in Afonso et al. (2005) is 0.846.

Also, the results when economic stability represents the goal of the government are quantitatively similar. Certainly, these optimal inputs may better be viewed as approximations of the true optimal inputs, with the averages presented in the last rows of Tables 3a and 3b being representative of these approximations. At a broader level of analysis and in light of the OECD policy recommendations (see OECD policy briefs, various issues), we contend that the optimal inputs derived seem to be quite reasonable.

6. Conclusions

Recent developments in data envelopment analysis allow the disentangling of efficiency scores that are due to managerial practices form those that are due to the macroeconomic environment or luck. In such a fashion we obtained relative PSE scores for five major public spending accounts across 19 developed OECD countries. The evidence we presented adds credence to the proposition that individual countries have much to gain by looking at the relative efficiency in the provision of public services of other countries. Yet, the exploration of the forces that shape PSE showed that individual country characteristics and the effect of mere luck are less important than governance in determining PSE. By additionally looking at general performance indicators we also proposed a method to estimate the optimal allocation of public funds among the different accounts. The results provide a rigorous consensus that a best practice is quantifiable and that the optimal allocation of funds, perhaps with the exception of spending on social security and welfare, should be fairly uniform between the 19 OECD countries examined.

These results point to a new agenda for research on how government efficiency affects economic performance. This agenda may simply examine the interrelationship between the efficiency of public spending, growth and economic volatility, but may well have other repercussions as well. The implications of the estimated scores for bureaucratic efficiency and capacity, the heavily debated link between democratic institutions and the public sector and the potential benefits of political reform, are only few key extensions to the present analysis. The further progress of such theoretical and empirical studies may significantly improve our understanding of the challenges faced in governing the public sectors as well as the monitoring of economic development. Yet, before moving on to another issue we had better bring this entry to a close.

Table 1
Summary statistics for outputs and inputs

Outputs	Mean	Std.Dev.	Min	Max
Secondary school enrolment	102.46	15.87	72.9	136.5
Quality of education	55.71	5.65	44.5	64.6
Life expectancy at birth	75.94	1.44	73.31	78.56
Infant mortality rate	8.44	2.12	5.00	12.00
Electric power transmission and distribution losses (% of total electric power output)	7.25	3.14	3.85	22.5
Standard access lines per 100 inhabitants	45.86	10.56	19.58	67.98
Corruption in government	5.42	0.605	4.25	6.00
Bureaucratic quality	3.89	0.246	3.00	4.00
GINI coefficient	29.33	4.74	21.5	38.97
Unemployment rate	7.30	3.67	0.59	15.15
GDP growth rate (annual %)	2.72	1.16	0.93	7.1
GDP per capita (constant 1995 US$)	25331.79	8036.63	11611	45210
Std. dev. of the annual GDP growth rate	1.65	0.544	0.89	2.98
Inflation rate (consumer prices annual %)	4.45	2.52	1.89	10.25
Inputs				
Public spending on education (% of GDP)	5.60	1.10	3.1	7.8
Public spending on health (% of GDP)	5.83	1.03	4.08	7.94
Public spending on economic affairs (% of GDP)	3.99	1.91	1.45	8.00
Public spending on general public services (% of GDP)	2.07	0.83	0.92	3.9
Public spending on social security and welfare (% of GDP)	16.95	4.78	7.76	26.28

Table 2a
Stage 3 efficiency scores by public spending account for 19 OECD countries, 1980-1990

	Education		Health		Economic Affairs		General Public Services		Social Security and Welfare		Performance		Stability	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Australia	0.579	12	0.779	7	0.933	2	0.409	7	1.000	1	1.000	1	1.000	1
Austria	0.762	8	0.750	9	0.432	8	0.371	9	0.822	6	0.615	11	0.841	2
Belgium	0.795	5			0.324	10	0.333	12	0.688	10	0.621	10	0.701	9
Canada	0.787	6	0.630	14	0.501	7	0.378	8	0.823	5	0.753	6	0.755	6
Denmark	1.000	1	0.580	16	0.660	4	0.249	15	0.586	14	0.536	14	0.523	13
Finland	1.000	1	0.761	8	0.356	9	0.346	11	1.000	1	0.784	4	0.825	3
France	0.644	9	0.687	13	0.724	3	0.285	14	0.421	17	0.612	12	1.000	1
Germany	0.409	14	0.580	15	1.000	1	0.775	2	0.679	12	0.729	7	1.000	1
Greece	1.000	1	0.834	4	0.282	11	0.211	18	0.639	13	0.762	5	0.756	5
Ireland	0.593	11	0.697	12	0.227	15	0.212	17	0.559	16	0.574	13	0.574	11
Luxembourg	0.348	15	1.000	1	0.227	14	0.196	19	0.708	9	1.000	1	0.546	12
Norway	1.000	1	0.730	11	0.271	12	0.417	6	0.961	2	0.722	8	0.606	10
Portugal	0.523	13	1.000	1	0.269	13	0.311	13	0.885	3	0.822	3	0.822	4
Spain	0.826	4	0.908	2	0.512	6	0.670	4	0.576	15	0.852	2	1.000	1
Sweden	0.618	10	1.000	1	1.000	1	0.359	10	0.724	8	0.524	15	0.732	8
Switzerland	0.947	2	0.804	5	1.000	1	1.000	1	0.681	11	1.000	1	1.000	1
The Netherlands	0.770	7	0.749	10	1.000	1	0.239	16	0.343	18	0.509	16	1.000	1
United Kingdom	0.835	3	0.872	3	0.562	5	0.510	5	0.735	7	0.721	9	0.749	7
USA	1.000	1	0.789	6	1.000	1	0.689	3	0.837	4	1.000	1	1.000	1
Average	0.760		0.786		0.594		0.419		0.719		0.744		0.812	
Spearman correlation with Stage 1 results		0.852		0.925		0.942		0.896		0.866		0.913		0.902

Table 2b
Stage 3 efficiency scores by public spending account for 19 OECD countries, 1990-2000

	Education		**Health**		**Economic Affairs**		**General Public Services**		**Social Security and Welfare**		**Performance**		**Stability**	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Australia	0.843	5	0.865	4	0.836	3	0.390	12	1.000	1	0.942	2	1.000	1
Austria	0.780	8	0.758	10	0.470	8	0.287	14	0.502	16	0.636	10	0.702	10
Belgium	1.000	1	0.717	11			1.000	1	1.000	1	0.798	3	1.000	1
Canada	1.000	1	0.675	14	0.858	2	1.000	1	0.843	5	0.786	4	0.985	2
Denmark	0.795	7	0.682	13	0.798	4	0.419	9	1.000	1	0.597	12	0.767	7
Finland	1.000	1	0.771	9	1.000	1	0.683	4	0.867	4	0.515	14	0.656	12
France	0.651	12	0.664	15	0.619	5	0.239	16	0.504	15	0.571	13	1.000	1
Germany	0.564	15	0.582	16	1.000	1	0.771	2	0.970	2	0.696	7	0.775	6
Greece	1.000	1	1.000	1	0.347	9	0.393	10	0.577	11	0.731	6	0.759	8
Ireland	0.661	11	1.000	1	0.233	11	0.156	17	0.686	10	1.000	1	0.805	4
Luxembourg	0.695	9	1.000	1	0.221	12	0.251	15	0.839	6	1.000	1	0.757	9
Norway	1.000	1	0.689	12	0.235	10	0.442	8	0.878	3	0.639	9	0.606	13
Portugal	0.636	13	0.947	2			0.764	3	0.772	7	1.000	1	1.000	1
Spain	0.690	10	0.864	5	0.499	7	0.669	5	0.687	9	0.769	5	0.782	5
Sweden	1.000	1	1.000	1	1.000	1	0.584	6	0.691	8	0.495	15	0.487	14
Switzerland	0.952	3	0.910	3	1.000	1	1.000	1	0.562	12	1.000	1	0.819	3
The Netherlands	0.816	6	0.859	6	1.000	1	0.390	11	0.516	13	0.629	11	1.000	1
United Kingdom	0.941	4	0.853	7	0.511	6	0.492	7	0.514	14	0.656	8	0.664	11
USA	0.970	2	0.819	8	1.000	1	0.336	13	1.000	1	1.000	1	1.000	1
Average	0.842		0.824		0.684		0.540		0.758		0.761		0.819	
Spearman correlation with stage 1 results		0.925		0.896		0.873		0.913		0.798		0.902		0.902

Table 3a

Optimal inputs: Performance

	1980					**1990**				
	EducSp	*HealthSp*	*EcaffSp*	*GPSSp*	*WelfSp*	*EducSp*	*HealthSp*	*EcaffSp*	*GPSSp*	*WelfSp*
Australia	5.637	4.956	2.283	2.262	7.773	5.355	5.481	1.526	1.554	10.838
Austria	5.324	4.530	2.600	1.457	9.967	5.333	5.684	1.756	1.768	11.549
Belgium	5.920	4.365	2.144	1.435	9.138	5.218	5.866	1.552	2.156	9.220
Canada	5.666	4.897	2.269	2.179	7.910	5.366	5.513	0.842	1.170	10.637
Denmark	5.661	4.283	2.365	1.199	10.026	5.371	5.667	2.166	1.812	12.873
Finland	5.749	4.828	4.500	2.879	11.279	5.237	5.820	1.460	2.029	9.402
France	5.947	4.310	2.131	1.357	9.266	5.224	5.852	1.523	2.116	9.277
Germany	5.823	4.387	2.219	1.431	9.290	5.261	5.817	1.791	2.090	10.367
Greece	5.578	4.875	2.343	2.109	8.189	5.532	5.119	0.049	0.068	12.220
Ireland	5.637	4.956	2.283	2.262	7.773	5.408	4.825	6.880	3.940	14.119
Luxembourg	6.174	4.770	9.396	4.729	18.095	4.150	5.070	7.244	4.792	17.129
Norway	5.459	4.552	3.812	1.994	11.505	4.894	5.623	3.377	2.986	11.849
Portugal	5.637	4.956	2.283	2.262	7.773	5.542	5.095			12.317
Spain	5.637	4.956	2.283	2.262	7.773	5.461	5.288	0.388	0.539	11.543
Sweden	5.263	4.446	2.662	1.298	10.400	5.220	5.874	1.649	2.195	9.420
Switzerland	5.118	4.249	2.808	0.926	11.413	5.639	5.301	3.082	1.133	18.997
The Netherlands	5.891	4.425	2.158	1.519	9.000	5.230	5.773	1.620	2.026	9.948
United Kingdom	5.637	4.956	2.283	2.262	7.773	5.375	5.492	0.799	1.110	10.723
USA	5.951	4.301	2.129	1.345	9.287	5.207	5.892	1.604	2.229	9.116
Average	5.669	4.631	2.892	1.956	9.665	5.264	5.529	2.184	1.984	11.660

Table 3b
Optimal inputs: Stability

	1980					1990				
	EducSp	*HealthSp*	*EcaffSp*	*GPSSp*	*WelfSp*	*EducSp*	*HealthSp*	*EcaffSp*	*GPSSp*	*WelfSp*
Australia	5.637	4.956	2.283	2.262	7.773	5.290	5.580	2.021	2.237	11.142
Austria	5.385	7.108	2.894	1.547	15.708	4.821	6.455	0.625	0.838	16.030
Belgium	4.703	4.703	3.131	1.068	12.356	4.616	6.766			18.703
Canada	5.846	4.521	2.181	1.652	8.779	4.717	6.587	0.305	0.338	17.562
Denmark	5.802	4.612	2.202	1.780	8.567	5.298	6.760	1.678	1.807	20.323
Finland	4.507	5.817	3.516	1.737	15.205	4.671	6.786	0.108	0.109	18.819
France	5.921	6.251	3.184	3.244	18.971	6.228	7.341	3.160	3.209	22.098
Germany	5.333	7.361	2.796	1.195	15.086	4.948	6.182	0.996	1.103	14.976
Greece	5.637	4.956	2.283	2.262	7.773	5.261	5.762	1.343	1.866	9.636
Ireland	5.637	4.956	2.283	2.262	7.773	4.928	6.216	0.938	1.038	15.193
Luxembourg	5.646	4.282	2.378	1.192	10.064	4.795	6.450	0.538	0.596	16.690
Norway	5.645	4.940	2.279	2.239	7.810	5.055	6.012	1.299	1.492	13.413
Portugal	5.637	4.956	2.283	2.262	7.773	5.542	5.095			12.317
Spain	3.280	4.575	4.157	1.382	13.491	5.346	5.561	0.938	1.304	10.444
Sweden	5.006	5.797	3.470	2.460	16.846	5.240	5.813	1.446	2.010	9.430
Switzerland	5.118	4.249	2.808	0.926	11.413	4.987	6.113	1.114	1.232	14.537
The Netherlands	6.819	5.264	5.915	3.873	23.313	5.289	5.614	3.219	3.848	21.143
United Kingdom	5.413	4.356	2.538	1.352	10.134	5.287	5.701	1.219	1.694	9.883
USA	5.951	4.301	2.129	1.345	9.287	5.207	5.892	1.604	2.229	9.116
Average	5.417	5.156	2.879	1.897	12.006	5.133	6.141	1.327	1.585	14.813

References

Afonso, A., St. Aubyn, M., 2005. Non-parametric approaches to education and health: Expenditure efficiency in OECD countries. Journal of Applied Economics 8, 227-246.

Afonso, A., Schuknecht, L., Tanzi, V., 2005. Public sector efficiency: An international comparison. Public Choice 123, 321-347.

Afonso, A., Schuknecht, L., Tanzi, V., 2006. Public sector efficiency: Evidence for new EU member states and emerging markets. ECB Working Paper, no. 581.

Angelopoulos, K., Philippopoulos, A., 2005. The role of government in anti-social redistributive activities. CESifo Working Paper no. 1427.

Angelopoulos, K., Philippopoulos, A., Tsionas, E., 2007. Does public sector efficiency matter? Revisiting the relation between fiscal size and economic growth in a world sample. Mimeo.

Balaguer-Coll, M.T., Prior, D., Tortosa-Ausina, E., 2007. On the determinants of local government performance: A two-stage nonparametric approach. European Economic Review 51, 425-451.

Bradford, D., Malt, R., Oates, W., 1969. The rising cost of local public services, some evidence and reflections. National Tax Journal 22, 185-202.

Charnes, C., Cooper, W.W., Lewin, A.Y., Seiford, L.M., 2004. Data Envelopment Analysis: Theory, Methodology and Applications. Springer, New York.

Coelli, T., Rao, D.S.P., O'Donnell, C.C., Battese, G.E., 2005. An Introduction to Efficiency and Productivity Analysis. Springer, New York.

Cornwell, C., Schmidt, P, Sickles, R.C., 1990. Production frontiers with cross-sectional and time-series variation in efficiency levels. Journal of Econometrics 46, 185-200.

Duncombe, W., Miner, J., Ruggiero, J. 1997. Empirical evaluation of bureaucratic models of inefficiency. Public Choice 93, 1-18.

Farrell, M.J., 1957. The measurement of productive efficiency. Journal of the Royal Statistical Society 120, 253-281.

Fried, H.O., Lovell, C.A.K., Schmidt, S.S., Yaisawarng, S., 2002. Accounting for environmental effects and statistical noise in data envelopment analysis. Journal of Productivity Analysis 17, 157-174.

Hanushek, E.A., Kimko, D.D., 2000. Schooling, labor-force quality, and the growth of nations. American Economic Review 90, 1184-1208.

Herrera, S., Pang, G., 2005. Efficiency of public spending in developing countries: an efficiency frontier approach. Policy Research Working Paper Series 3645, The World Bank.

Glass, J.C., McCallion, G., McKillop, D.G., Stringer, K., 2006. A 'technically level playing-field' profit efficiency analysis of enforced competition between publicly funded institutions. European Economic Review 50, 1601-1626.

Gupta, S., Verhoeven, M., 2001. The efficiency of government expenditure, experiences from Africa. Journal of Policy Modelling 23, 433-467.

Kumbhakar, S.C., Lovell, C.A.K., 2000. Stochastic Frontier Analysis. Cambridge University Press, Cambridge.

Lee, Y.H., Schmidt, P., 1993. A production frontier model with flexible temporal variation in technical inefficiency. In: Fried, H.O., Lovell, C.A.K., Schmidt, S.S. (Eds.), The Measurement of Productive Efficiency: Techniques and Applications. Oxford University Press, New York.

OECD Policy Briefs (various issues).

Palda, F., 1997. Fiscal churning and political efficiency. Kyklos 50, 189-206.

Quinn, D., 1997. The correlates of change in international financial regulation. American Political Science Review 91, 531-551.

Resti, A., 2000. Efficiency measurement of multi-product industries: A comparison of classic and recent techniques based on simulated data. European Journal of Operational Research 121, 559-578.

Sijpe, N., Rayp, G., 2007. Measuring and explaining government efficiency in developing countries. Journal of Development Studies 43, 360-381.

Tanzi, V., Schuknecht, L., 1998. Can small governments secure economic and social well-being? In: Grubel, H. (Ed.), How to Spend the Fiscal Dividend: What is the Optimal Size of Government? Fraser Institute, Vancouver.

Tanzi, V., Schuknecht, L., 2000. Public Spending in the 20th Century: A Global Perspective. Cambridge University Press, Cambridge.

Tulkens, H., 1993. On FDH efficiency analysis: Some methodological issues and applications to retail banking, courts, and urban transit. Journal of Productivity Analysis 4, 183-210.

United Nations, 2000. Department of Economic and Social Affairs, Statistics Division, Statistical Papers, Series M, No.84, New York.

Zhu, J., 2003. Quantitative Models for Performance Evaluation and Benchmarking. Springer, New York.