Cross-country Efficiency of Secondary Education Provision: a Semi-parametric Analysis with Non-discretionary Inputs[1]

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Abstract

We address the efficiency of expenditure in education provision by comparing the output (PISA results) from the educational system of 25, mostly OECD, countries with resources employed (teachers per student, time spent at school). We estimate a semi-parametric model of the education production process using a two-stage procedure. By regressing data envelopment analysis output scores on non-discretionary variables, both using Tobit and a single and double bootstrap procedure, we show that inefficiency is strongly related to GDP per head and adult educational attainment.

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Keywords: education, technical efficiency, DEA, bootstrap, semi-parametric

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Contents

1. Introduction

In this paper we systematically compare the output from the educational system of 25 countries with resources employed (number of teachers per student, time spent at school). Using data envelopment analysis (DEA), we derive a theoretical production frontier for education. In the most favourable case, a country is operating on the frontier, and is considered as efficient. However, most countries are found to perform below the frontier and an estimate of the distance each country is from that border line is provided – the so-called efficiency score. Moreover, estimating a semi-parametric model of the education production process using a two-stage approach, we show that inefficiency in the education sector is strongly related to two variables that are, at least in the short- to medium run, beyond the control of governments. These are the family economic background and the education of parents.

In methodological terms, a two-stage approach has become increasingly popular when DEA is used to assess efficiency of decision-making units (DMUs). In some cases, this approach has been applied to the education sector[4], but rarely in an international framework with whole countries as units of observation. The most usual two-stage approach has been recently criticised in statistical terms.[5] The fact that DEA output scores are likely to be biased, and that the environmental variables are correlated to output and input variables, recommend the use of bootstrapping techniques, which are well suited for the type of modelling we apply here. Therefore, we employ both a more usual DEA/Tobit approach and single and double bootstrap procedures suggested by Simar and Wilson (2004). Our paper is one of the first application examples of this very recent technique. Our results following this technique are compared to the ones arising from the more traditional one.

The paper is organised as follows. In section two we provide motivation and briefly review some of the literature and previous results on education provision efficiency. Section three outlines the methodological approach used in the paper and in section four we present and discuss the results of our efficiency analysis. Section five provides conclusions.

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[4] See Ruggiero (2004) for a survey.
[5] See Simar and Wilson (2000, 2004).

2. Motivation and literature on education efficiency

Education is one of the most important services provided by governments in almost every country. According to OECD (2004a), OECD countries expended an average of 6.2 percent of GDP in 2001 on education institutions, of which 4.8 percent of GDP were from public sources. In a general sense, education provision is efficient if its producers make the best possible use of available inputs, and the sole fact that educational inputs weight heavily on the public purse would call for a careful efficiency analysis. An education system not being efficient would mean either that results (or "outputs") could be increased without spending more, or else that expense could actually be reduced without affecting the outputs, provided that more efficiency is assured. Research results presented here indicate that there are cases where considerable improvements can be made in this respect.

The fact of education spending being predominantly public is particularly true namely in OECD countries, and for all education levels. Table 1 summarises some relevant data for 30, mostly OECD, countries in 2001, concerning pre-primary, primary and secondary and tertiary education. For instance, and in what respects primary and secondary education provision, public expenditure as a share of total spending averaged 92.2%, ranging from 76.2% in Korea to more than 95% in several countries, namely Denmark, Finland, Italy, Portugal and Sweden. On the other hand, the average share of public spending in total spending for pre-primary and for tertiary levels was respectively 78.3% and 79.3%, the diversity among countries being now much higher. All in all, this implies that public resources accounted for some 88% of the total financing of education provision in the surveyed country sample.

Table 1 – Public expenditure on education, 2001
(% of total expenditure in each level)

	Pre-primary education	Primary and secondary education	Tertiary education	All levels of education
Australia	68.9	84.4	51.3	75.6
Austria	79.3	96.3	94.6	94.4
Belgium	96.6	95.0	84.1	93.0
Czech Republic	91.8	92.1	85.3	90.6
Denmark	81.7	98.0	97.8	96.1
Finland	91.0	99.1	96.5	97.8
France	95.9	93.0	85.6	92.0
Germany	62.3	81.1	91.3	81.4
Greece	na	91.4	99.6	94.2
Hungary	90.6	93.1	77.6	89.0
Iceland	na	95.3	95.0	91.7
Indonesia	5.3	76.3	43.8	64.2
Ireland	33.2	95.3	84.7	92.2
Italy	97.0	98.0	77.8	90.7
Japan	50.4	91.5	43.1	75.0
Korea	48.7	76.2	15.9	57.1
Mexico	86.7	87.2	70.4	84.6
Netherlands	98.2	95.1	78.2	90.9
Norway	na	na	96.9	95.9
Portugal	na	99.9	92.3	98.5
Slovak Republic	97.4	98.5	93.3	97.1
Spain	83.4	93.3	75.5	87.8
Sweden	100.0	99.9	87.7	96.8
Switzerland	na	84.8	na	na
Thailand	97.8	na	82.5	95.6
Tunisia	na	100.0	100.0	100.0
Turkey	na	na	95.8	na
United Kingdom	95.7	87.2	71.0	84.7
United States	68.1	93.0	34.0	69.2
Uruguay	81.3	93.5	99.5	93.4
Mean	78.3	92.2	79.3	88.2
Median	86.7	93.3	85.3	91.9
Minimum	5.3	76.2	15.9	57.1
Maximum	100.0	100.0	100.0	100.0
Standard deviation	24.3	6.8	21.8	10.8
Observations	23	27	29	28

Sources: *Education at a Glance 2004*, OECD – Tables B3.2a, B3.2b.
Notes: Public expenditure on education includes public subsidies to households attributable for educational institutions and direct expenditure on educational institutions from international sources. Private expenditure on education is net of public subsidies attributable for educational institutions. na – not available.

Concern with education also comes from the belief that this is an important source of human capital formation and therefore of economic growth, as suggested by economic theory.[6] However, empirical work on this relationship has not been conclusive, and

[6] For recent literature surveys on the influence of human capital formation on growth, see Krueger and Lindahl (2001), Sianesi and Van Reenen (2003) and De la Fuente and Ciccone (2002).

the correlation between education and growth is not statistically significant in some published results.[7] Most empirical work on this field has progressed by means of cross-country regressions where human capital *quantity* measured as the average number of years of schooling is one of the independent variables deemed to explain growth. Some researchers have found that *quality* matters for growth. Namely, Hanushek and Kimko (2000) and Barro (2001) showed that education quality, as measured by international comparative tests of skills, has a strong relationship with economic growth.

Moreover, the relevance of assessing the quality of public spending and redirecting it to more growth enhancing items is stressed in EC (2004) as being an important goal for governments to pursue. Additionally, there is also internationally a shift in the focus of the analysis from the amount of public resources used by a government, to the services delivered, and also to the outcomes achieved and their quality (see namely OECD (2003b)).

In our research, we measure and compare education output across countries using precisely the abovementioned type of quality measures – we resort to the most recent cross-nationally comparable evidence on student performance, the 2003 results from the Programme for International Student Assessment (PISA), launched by the OECD.[8]

Previous research on the international comparative performance of the public sector in general and of education systems in particular, including Afonso, Schuknecht and Tanzi (2003) for public expenditure in the OECD, St. Aubyn (2003) for education spending in the OECD and Gupta and Verhoeven (2001) for education and health in Africa, has already suggested that important inefficiencies are at work. All these studies use free disposable hull analysis (FDH) with inputs measured in monetary terms. Using both FDH and DEA analysis, Afonso and St. Aubyn (2005) studied efficiency in providing health and education in OECD countries using physically measured inputs and concluded that average input inefficiency varies between 0.859

[7] See Benhabib and Spiegel (1994) and Pritchett (2001).
[8] OECD (2004b) presents the first results from PISA 2003.

and 0.886 – if all countries were efficient, input usage could be reduced by about 13 percent without affecting output.

In a related but separate research strand, some authors have studied the determinants of schooling quality across countries using cross-country regressions, by specifying and estimating linear models for the relationship between schooling quality and its determinants. The former is measured by cross-country comparative studies assessing learning achievement. The latter include resources allocated to education (e. g. teachers per pupil or expenditures per student) and other factors that may affect the educational output, such as parents' income or instruction level. Barro and Lee (2001) find that student performance is positively correlated to the level of school resources, such as pupil-teacher ratios, and also to family background (income and education of parents). Hanushek and Kimko (2000) and Hanushek and Luque (2003) find little or no evidence of a positive link from more resources allocated to the education system and test performance. However, they find that adult schooling levels have a positive and significant effect on student performance.

In this paper, we put these two strands of the literature together by estimating a semi-parametric model of the education production process using a two-stage approach. In a first stage, we determine the output efficiency score for each country, using the mathematical programming approach known as DEA, relating education inputs to outputs. In a second stage, these scores are explained using regression analysis. Here, we show that family background variables identified by previous authors are indeed highly correlated to inefficiency, i.e., they are significant "environmental variables", using DEA jargon.[9] They are, however, of a fundamentally different nature from input variables, in so far as their values cannot be changed in a meaningful spell of time by the DMU, here a country.

9 Throughout the paper we use interchangeably the terms "non-discretionary", "exogenous" and "environmental" when qualifying variables or factors not initially considered in the DEA programme.

3. Analytical methodology

3.1. DEA framework

DEA, originating from Farrell (1957) seminal work and popularised by Charnes, Cooper and Rhodes (1978), assumes the existence of a convex production frontier. This frontier in the DEA approach is constructed using linear programming methods, the term "envelopment" stemming from the fact that the production frontier envelops the set of observations.[10]

DEA allows the calculation of technical efficiency measures that can be either input or output oriented. The purpose of an output-oriented study is to evaluate by how much output quantities can be proportionally increased without changing the input quantities used. This is the perspective taken in this paper. Note, however, that one could also try to assess by how much input quantities can be reduced without varying the output. The two measures provide the same results under constant returns to scale but give different values under variable returns to scale. Nevertheless, both output and input-oriented models will identify the same set of efficient/inefficient producers or DMUs.

The analytical description of the linear programming problem to be solved, output oriented and assuming variable returns to scale hypothesis, is sketched below. Suppose there are p inputs and q outputs for n DMUs. For the i-th DMU, y_i is the column vector of the outputs and x_i is the column vector of the inputs. We can also define X as the $(p \times n)$ input matrix and Y as the $(q \times n)$ output matrix. The DEA model is then specified with the following mathematical programming problem, for a given i-th DMU:

[10] Coelli, Rao and Battese (1998) and Thanassoulis (2001) offer good introductions to the DEA methodology.

$$\begin{aligned} & Max_{\lambda,\delta_i} \delta_i \\ & \text{s. to} \quad \delta_i y_i \leq Y\lambda \\ & \qquad x_i \geq X\lambda \\ & \qquad n1'\lambda = 1 \\ & \qquad \lambda \geq 0 \end{aligned} \quad . \qquad (1)$$

In problem (1), δ_i is a scalar satisfying $\delta_i \geq 1$. It is the efficiency score that measures technical efficiency of the i-th unit as the distance to the efficiency frontier, the latter being defined as a linear combination of best practice observations. With $\delta_i > 1$, the decision unit is inside the frontier (i.e. it is inefficient), while $\delta_i = 1$ implies that the decision unit is on the frontier (i.e. it is efficient).

The vector λ is a $(n \times 1)$ vector of constants, which measures the weights used to compute the location of an inefficient DMU if it were to become efficient. The inefficient DMU would be projected on the production frontier as a linear combination of its peers using those weights. The peers are other DMUs that are more efficient and therefore used as references.

$n1$ is a n-dimensional vector of ones. The restriction $n1'\lambda = 1$ imposes convexity of the frontier, accounting for variable returns to scale. Dropping this restriction would amount to admit that returns to scale were constant.

Notice that problem (1) has to be solved for each of the *n* DMUs in order to obtain *n* efficiency scores.

3.2. Non-discretionary inputs and the DEA/Tobit two-steps procedure

The standard DEA models as the one described in (1) incorporate only discretionary inputs, those whose quantities can be changed at the DMU will, and do not take into account the presence of environmental variables or factors, also known as non-discretionary inputs. However, socio-economic differences may play a relevant role in determining heterogeneity across DMUs – either secondary schools, universities or countries' achievements in an international comparison – and influence educational outcomes. These exogenous socio-economic factors can include, for instance, household wealth and parental education.

As non-discretionary and discretionary inputs jointly contribute to each DMU outputs, there are in the literature several proposals on how to deal with this issue, implying usually the use of two-stage and even three-stage models.[11]

Let z_i be a $(1 \times r)$ vector of non-discretionary outputs. In a typical two-stage approach, the following regression is estimated:

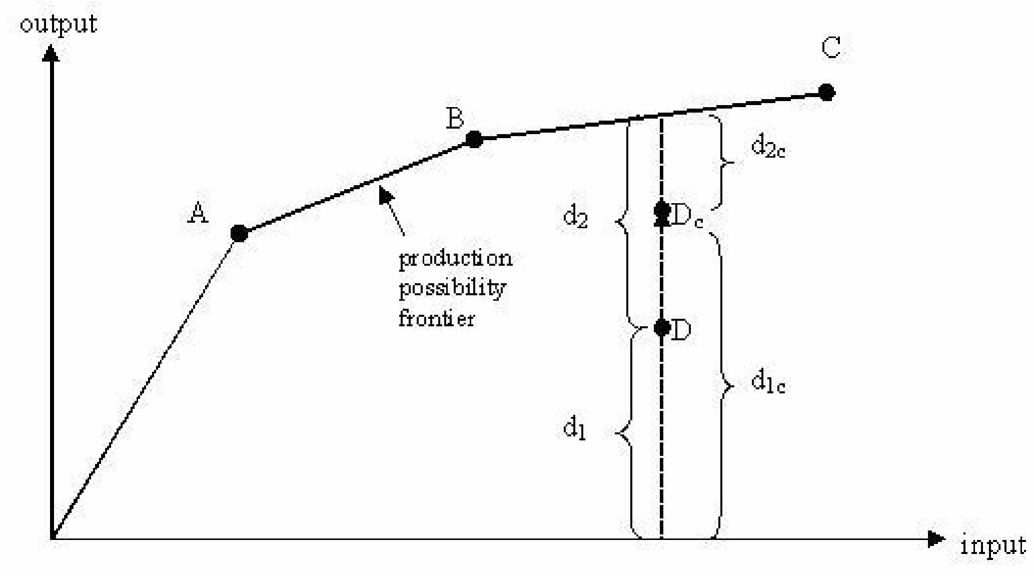
$$\hat{\delta}_i = z_i \beta + \varepsilon_i \,, \tag{2}$$

where $\hat{\delta}_i$ is the efficiency score that resulted from stage one, i.e. from solving (1). β is a $(r \times 1)$ vector of parameters to be estimated in step two associated with each considered non-discretionary input. The fact that $\hat{\delta}_i \geq 1$ has led many researchers to estimate (2) using censored regression techniques (Tobit), although others have used OLS.[12]

Figure 1 illustrates the basic idea behind a two-stage approach. In a simplified one output and one input DEA problem, A, B and C are found to be efficient, while D is an inefficient DMU. The output score for unit D equals $(d_1+d_2)/d_1$, and is higher than one. However, unit D inefficiency may be partly ascribed to a "harsh environment" – a number of perturbing environmental factors may imply that unit D produces less than the theoretical maximum, even if discretionary inputs are efficiently used. In our example, and if the environment for unit D was more favourable (e. g. similar to the sample average), then we would have observed D_c. In other words, unit D would have produced more and would be nearer the production possibility. The environment corrected output score would be $(d_{1c}+d_{2c})/d_{1c}$, lower than $(d_1+d_2)/d_1$, and closer to unity.

[11] See Ruggiero (2004) and Simar and Wilson (2004) for an overview.
[12] See Simar and Wilson (2004) for an extensive list of published examples of the two step approach. In what concerns education, Kirjavainen and Loikkanen (1998) is a good example of the DEA/Tobit approach.

Figure 1 – DEA and non-discretionary outputs



3.3. Non-discretionary inputs and bootstrap

The two-stage method has been criticised in so far as results are likely to be biased in small samples[13]. Note that a perturbation to an observation located on the DEA estimated frontier will shift that very same frontier. As a result, some DMUs will find themselves closer or further to the frontier, and their scores will change accordingly. In terms of equation (2), this means that the error term ε_i is serially correlated in a complicated and unknown way. As the sample increases, this correlation disappears slowly in the DEA context. An additional source of bias comes from the fact that that non-discretionary variables z_i in equation (2), are correlated to the error term ε_i. This correlation derives from the correlation between non-discretionary inputs and the outputs (and most probably the other inputs), which were the ingredients to estimate the scores. Again, this last correlation also disappears asymptotically, but at a slow rate.

[13] This is recognised by Coelli, Rao and Battese (1998), p. 171. We follow Simar and Wilson (2004), who take this point very seriously.

Thus, standard approaches to inference are usually not valid in small samples. To overcome this, Simar and Wilson (2004) propose an alternative estimation and inference procedures based on bootstrap methods.

Assume that the *true* efficiency score depends on the environmental variables, so that

$$\delta_i = \psi(z_i, \beta) + \varepsilon_i \geq 1, \qquad (3)$$

where ψ is a smooth, continuous function and β a vector of parameters. ε_i is a truncated normal random variable, distributed $N(0, \sigma_\varepsilon^2)$ with left-truncation at $1 - \psi(z_i, \beta)$.

The efficiency score that solves problem (1), $\hat{\delta}_i$, is then considered as an estimate for δ_i, and this is the first stage in the procedure. The second stage is designed to assess the influence of non-discretionary inputs on efficiency. Simar and Wilson (2004) propose two algorithms to achieve these two stages, which are presented below[14].

The first algorithm involves the following steps:

[1] The computation of $\hat{\delta}_i$ for all *n* decision units by solving problem (1);

[2] The estimation of equation (2) by maximum likelihood, considering it is a *truncated* regression (and not a censored or Tobit regression).[15] Denote by $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ the maximum likelihood estimates of β and σ_ε.

[3] The computation of *L* bootstrap estimates for β and σ_ε, in the following way:

> For $i = 1, ..., n$ draw ε_i from a normal distribution with variance $\hat{\sigma}_\varepsilon^2$ and left truncation at $1 - z_i\hat{\beta}$ and compute $\delta_i^* = z_i\hat{\beta} + \varepsilon_i$.

[14] We implemented these algorithms in Matlab. Programmes and functions are available on request.

[15] In a censored regression, it is assumed that independent variables are always observed, even if there is some information loss concerning the dependent variable. In a truncated regression, neither independent nor dependent variables are observed in some cases. See Simar and Wilson (2004) for details.

Estimate the truncated regression of δ_i^* on z_i by maximum likelihood, yielding a bootstrap estimate $(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*)$.

With a large number of bootstrap estimates (e.g. $L=2000$), it becomes possible to test hypotheses and to construct confidence intervals for β and σ_ε. For example, suppose that we want to determine the p-value for a given estimate $\hat{\beta}_1 < 0$. This will be given by the relative frequency of nonnegative $\hat{\beta}_1^*$ bootstrap estimates.

It can be shown that the estimate $\hat{\delta}_i$ is biased towards 1 in small samples. Simar and Wilson (2004) second bootstrap procedure, "algorithm 2", includes a parametric bootstrap in the first stage problem, so that bias-corrected estimates for the efficiency scores are produced. The production of these bias-corrected scores is done as follows:

[1] Compute $\hat{\delta}_i$ for all n decision units by solving problem (1);

[2] Estimate equation (2) by maximum likelihood, considering it is a truncated regression. Let $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ be the maximum likelihood estimates of β and σ_ε.

[3] Obtain L_1 bootstrap estimates for each δ_i, the following way:

For $i = 1, ..., n$ draw ε_i from a normal distribution with variance $\hat{\sigma}_\varepsilon^2$ and left truncation at $1 - z_i\hat{\beta}$ and compute $\delta_i^* = z_i\hat{\beta} + \varepsilon_i$.

Let $y_i^* = \dfrac{\hat{\delta}_i}{\delta_i^*} y_i$, be a modified output measure.

Compute $\hat{\delta}_i^*$ by solving problem (1), where Y is replaced by $Y^* = \left[y_1^* \quad ... \quad y_n^*\right]$. (But note that y_i is not replaced by y_i^* in the left-hand side of the first restriction of the problem.)

[4] Compute the bias-corrected output inefficiency estimator as $\hat{\hat{\delta}}_i = 2.\hat{\delta}_i - \bar{\hat{\delta}}_i^*$, where $\bar{\hat{\delta}}_i^*$ is the bootstrap average of $\hat{\delta}_i^*$.

Once these first stage bias-corrected measures are produced, algorithm 2 continues by replacing $\hat{\delta}_i$ with $\hat{\hat{\delta}}_i$ in algorithm 1, from step 2 onwards. Following Simar and Wilson (2004), we set $L_1=100$.

4. Empirical analysis

4.1. Data and indicators[16]

Education achievement, the output, is measured by the performance of 15-year-olds on the PISA reading, mathematics, problem solving, and science literacy scales in 2003. Note that the PISA programme was specially conceived to "monitor the outcomes of education systems in terms of student achievement on a regular basis and within an internationally accepted common framework".[17] Students from 40 countries were therefore evaluated with the same set of questions to be solved, in what constitutes the more recent exercise of this kind. In a parsimonious formulation, we use the four scores country average.[18]

As performance of 15-year olds is likely to depend on resources employed not only in one year, but also in previous years, we have taken time average values. We use two input measures:

- the total intended instruction time in public institutions in hours per year for the 12 to 14-year-olds, average for 2000-2002;
- the number of teachers per student in public and private institutions for secondary education, calculations based on full-time equivalents, average for 2000-2002.[19] Table 2 summarises the key statistics for our selected data sample.

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[16] The data and the sources used in this paper are presented in the Annex.
[17] See OECD (2004b, pp. 3).
[18] The four results in the PISA report are highly correlated, with correlation coeficients ranging from 0.94 and 0.99.
[19] Since with a non-parametric approach, higher performance is directly linked with higher input levels, we constructed the variable "Teachers Per Student," *TPS,* where $TPS = (Students / Teachers)^{-1} \times 100$, using the original information for the students-to-teachers ratio (see Annex). Naturally, one would expect education performance to increase with the number of teachers per student.

Note that the number of observations used in the empirical analysis is lower than the number of countries that participated in the PISA, because some input variables are not available for some units in the sample.

Table 2 – Summary statistics of our data sample
(25 countries)

	Mean	Standard deviation	Minimum	Maximum
PISA (2003)	490.5	41.4	374.6 (IND)	545.9 (FI)
Teachers per 100 students (2000-02)	7.7	1.7	5.1 (KOR)	11.5 (PT)
Hours per year in school (2000-02)	946.5	121.2	740.9 (SW)	1274.0 (IND)
Parent education attainment (2001-02)	65.0	24.4	19.0 (THA)	94.0 (JP)
GDP per capita, PPP USD (2003)	22267.1	9327.9	3364.5 (IND)	37063.4 (NO)

Note: FI – Finland; IND – Indonesia; JP – Japan; KOR – Korea; NO – Norway; PT – Portugal; THA – Thailand.

Input measures such as the ones we are considering here, have been used by several other authors studying the relationship between educational inputs and outputs. Examples are Barro (2001), Hanushek and Kimko (2000), Hanushek and Luque (2003) and Kirjavainen and Loikkanen (1998).

We have considered the option of using education spending per student as an input. However, results would be hardly interpretable, as they would reflect both inefficiency and cost provision differences. For example, countries where teachers are better paid would tend to show up as inefficient, irrespective of the intrinsic performance of the education system. Moreover, results would also depend on the exchange rate used to convert expenses to the same units. Physical inputs and outputs have the important advantage of being comparable across countries without the need of any questionable transformation.

4.2. DEA efficiency results

In Table 3 we report results for the standard DEA variable-returns-to-scale technical efficiency scores and peers of each of the 25 considered countries.

Table 3 – Results for education efficiency (n=25)

2 inputs (teachers-students ratio, hours in school) and 1 output (PISA 2003 indicator)

	DEA Output oriented		Peers
Country	VRS TE	Rank	
Australia	1.038	7	Finland
Austria	1.095	14	Finland
Belgium	1.055	8	Finland
Czech Republic	1.068	9	Finland
Denmark	1.093	13	Finland
Finland	1.000	1	Finland
France	1.072	10	Finland
Germany	1.083	12	Finland, Korea
Greece	1.182	21	Finland
Hungary	1.105	15	Finland
Indonesia	1.447	25	Finland, Korea
Ireland	1.079	11	Finland, Korea
Italy	1.151	19	Finland
Japan	1.024	4	Finland, Korea
Korea	1.000	1	Korea
Netherlands	1.037	6	Finland, Korea
New Zealand	1.036	5	Finland, Korea
Norway	1.109	16	Finland
Portugal	1.161	20	Finland
Slovak Republic	1.118	17	Finland
Spain	1.129	18	Finland
Sweden	1.000	1	Sweden
Thailand	1.283	24	Finland, Korea
Turkey	1.260	22	Finland, Korea, Sweden
Uruguay	1.278	23	Finland, Korea
Average	1.116		

Note: VRS TE – variable returns to scale technical efficiency.

It is possible to observe from Table 3 that three countries would be labelled as the most efficient ones with the standard DEA approach: Finland, Korea, and Sweden. Finland and Korea are located in the efficient frontier because they perform quite well in the PISA survey, getting respectively the first and the second position in the overall education performance index ranking. Sweden is also an above average performer concerning the output measure, using below average inputs. Another set of three countries is located on the opposite end – Thailand, Turkey and Uruguay. DEA analysis indicates that their output could be increased by more than 25 percent if they were to become efficient.[20] On average and as a conservative estimate, countries could have increased their results by 11.6 percent using the same resources.

[20] We also used an extended country sample including Brazil and Mexico. However, these two countries are efficient by default, not showing up as peers to other DMUs, and are quite below average

One can briefly compare this set of results with the ones reported by Afonso and St. Aubyn (2005) that addressed education efficiency using the PISA 2000 performance indicator and a similar set of inputs, even if, as mentioned by OECD (2004b), the PISA 2000 and the PISA 2003 are not fully comparable (the latter included an extra item). Interestingly, the countries located in the efficient frontier were Finland, Korea, Japan, and Sweden, essentially the same results as the ones we report.

4.3. Explaining inefficiency – the role of non-discretionary inputs

Using the DEA efficiency scores computed in the previous subsection, we now evaluate the importance of non-discretionary inputs. We present results both from Tobit regressions and bootstrap algorithms. Even if Tobit results are possibly biased, it is not clear that bootstrap estimates are necessarily more reliable. In fact, the latter are based on a set of assumptions that may be disputed. Equation (3) summarises some of these important assumptions concerning the data generation process and the perturbation term distribution. Taking the pros and cons of both methods into account, it seems sensible to apply both of them. If outcomes are comparable, this adds robustness and confidence to the results we are interested in.

In order to explain the efficiency scores, we regress them on GDP per capita, *Y*, and parents' educational attainment, *E*, as follows[21]

$$\hat{\delta}_i = \beta_0 + \beta_1 Y_i + \beta_2 E_i + \varepsilon_i \,. \tag{4}$$

in one of the inputs (Mexico has the lowest teachers per students ratio) or both of them (Brazil). Given the inputs allocated to education provision by these countries, their performance in the PISA index is not comparable to any other country with similar or inferior outcome and with lower inputs. Moreover, one has to note that Brazil and Mexico are among lowest PISA survey performers. Therefore, we do not consider these efficient by default DMUs in the main text. Their inclusion would not affect further results in any meaninful way. The interested reader may refer to the Appendix, where we present main results for the extended sample.

[21] Parents' educational attainment is given by the percentage of population aged 35–44 that has attained at least upper secondary education in 2001–2002, and GDP per capita refers to 2003 (see the Annex).

We first report in Table 4 results from the censored normal Tobit regressions for several alternative specifications of equation (4), namely including only one of the explanatory variables or taking logs of GDP per head.

Table 4 – Censored normal Tobit results
(25 countries)

	Model 1	Model 2	Model 3	Model 1a	Model 3a
Constant	1.295024	1.342502	1.374361	2.614888	2.237114
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Y	-0.825e-5		-0.427e-5		
	(0.000)		(0.012)		
Log(Y)				-0.152062	-0.101269
				(0.000)	(0.000)
E		-0.003566	-0.002574		-0.001903
		(0.000)	(0.000)		(0.001)
$\hat{\sigma}_{\varepsilon}$	0.081428	0.071752	0.062480	0.063324	0.051811
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: *Y* – GDP per capita; *E* – Parental educational attainment. $\hat{\sigma}_{\varepsilon}$ – Estimated standard deviation of ε. P- values in brackets.

Inefficiency in the education sector is strongly related to two variables that are, at least in the short to medium run, beyond the control of governments: the family economic background, proxied here by the country GDP per capita, and the education of parents. The estimated coefficients of both non-discretionary inputs are statistically significant and negatively related to the efficiency measure. For instance, an increase in parental education achievement reduces the efficiency score, implying that the relevant DMU moves closer to the theoretical production possibility frontier. Therefore, the better the level of parental education attainment, the higher the efficiency of secondary education provision in a given country. The same reasoning applies to the second non-discretionary input, with higher GDP per capita resulting in more efficiency.

Adults' educational attainment tends to be higher in richer countries, the correlation coefficient between *E* and *Y* being equal to 0.59. Even so, adding educational attainment to the right hand side of a regression where income is already there results in a clearly better fit. The estimated standard deviation of ε is substantially smaller for model 3a (where both education and income are present) than for models 1a or 2 (where income or education are not included, respectively). Moreover, this error term variance reduction goes in pair with coefficients for both explanatory variables that are highly significant in statistical terms, with p-values equal or smaller than 0.001. That both factors may act in a separate way is suggested by identifying a group of countries in the sample that display high values for educational attainment in spite of being poorer than average (the Czech and Slovak Republics, Hungary, Korea) contrasting to richer countries with lower levels of adult education (Italy, Spain, Portugal).

Additionally, we also considered the ratio of public-to-total expenditure in secondary education as a non-discretionary input. However, this variable did not prove to be statistically significant, probably because most spending in this level of education is essentially public and high for most countries. We report those results in the Appendix, for a more reduced country sample due to data availability.

Table 5 reports the estimation results from the bootstrap procedures employing algorithms 1 and 2, as described in sub-section 3.3. Estimated coefficients are very similar irrespective of the algorithm used to estimate them. Moreover, they are close to the estimates derived from the more usual Tobit procedure, and, very importantly, they are highly significant.

Table 5 – Bootstrap results
(25 countries)

	Model 1	Model 2	Model 3	Model 1a	Model 3a
			Algorithm 1		
Constant	1.367000	1.395726	1.455587	2.907919	2.347747
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Y	-0.150344e-4		-0.710790e-5		
	(0.000)		(0.001)		
Log(Y)				-0.184488	-0.112575
				(0.000)	(0.000)
E		-0.00523442	-0.00269907		-0.00209274
		(0.000)	(0.000)		(0.001)
$\hat{\sigma}_{\varepsilon}$	0.102022	0.0876502	0.0677879	0.0710499	0.0544861
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			Algorithm 2		
	Model 1	Model 2	Model 3	Model 1a	Model 3a
Constant	1.435993	1.412244	1.455827	3.028311	2.596005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Y	-0.151096e-4		-0.712013e-5		
	(0.000)		(0.001)		
Log(Y)				-0.191403	-0.135911
				(0.000)	(0.000)
E		-0.00482225	-0.00270063		-0.00178054
		(0.000)	(0.001)		(0.0005)
$\hat{\sigma}_{\varepsilon}$	0.0985940	0.0875667	0.0678872	0.0588680	0.0471327
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: *Y* – GDP per capita; *E* – Parental educational attainment. $\hat{\sigma}_{\varepsilon}$ – Estimated standard deviation of ε; P- values in brackets.

In all three methods, it is apparent that Model 3a provides the best fit (as can be seen by the lower estimated standard deviation of ε). This is important and robust empirical evidence that efficiency in education depends both on a country’s wealth and on parents’ education levels. In a nutshell, students coming from poorer countries where adults’ education levels are low tend to under perform, so that results are further away from the efficiency frontier.

Equation (4) can be regarded as a decomposition of the output efficiency score into two distinct parts:

– the one that is the result of a country’s environment, and given by $\beta_0 + \beta_1 Y_i + \beta_2 E_i$;

– the one that includes all other factors that have an influence on efficiency, including therefore inefficiencies associated with the education system itself, and given by ε_t.

The first column in Table 6 includes the bias corrected scores for Model 3a, the one with the best fit.[22] Recall that algorithm 2 implies a bias correction after estimating output efficiency scores by solving program (1) and taking into account the correlation between these scores and the environmental variables. We also present score corrections for the two environmental variables. GDP and education attainment corrections were computed as the changes in scores by artificially considering that Y and E varied to the sample average in each country. Fully corrected scores are estimates of output scores purged from environmental effects and result from the summation of the previous three columns.

Comparing the ranks in the last column of Table 6, resulting from corrections for both bias and environmental variables, with the previously presented ranking from the standard DEA analysis (see Table 3 above), it is apparent that significant changes occurred. For instance, countries previously poorly ranked are now less far away from the production possibility frontier – this is the case of Portugal, Uruguay, Hungary, Turkey and Spain. On the other hand, some countries see a worsening in their relative position after taking into account environmental variables, namely Sweden, Japan, Denmark, Norway, Germany and Austria.

[22] Estimated bias corrected scores were very similar across models. A full set of results is available upon request.

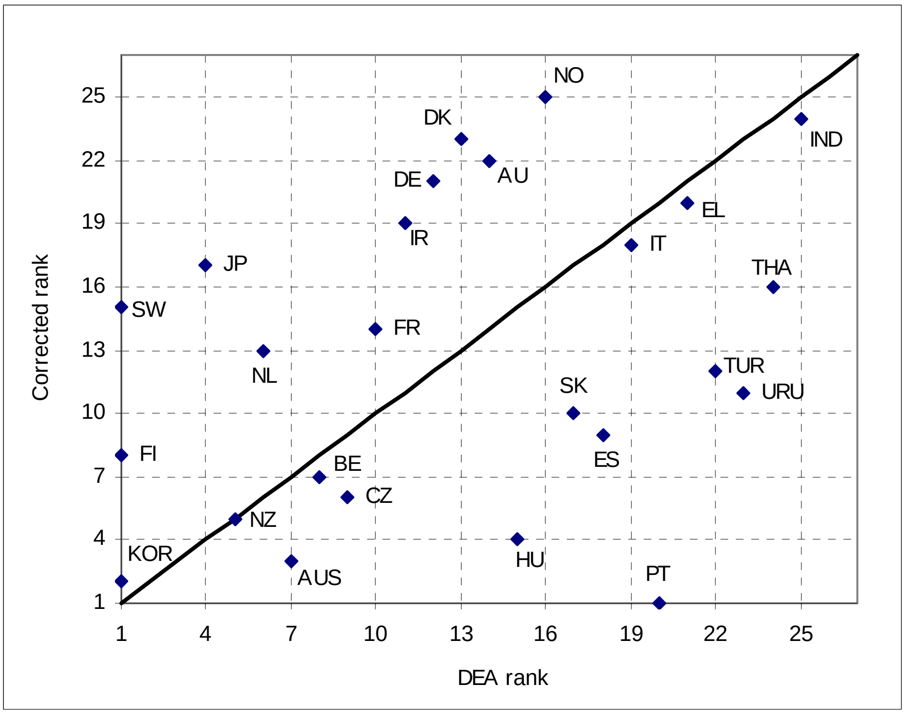
Table 6 – Corrected output efficiency scores (for Model 3a)

	Bias corrected scores (1)	GDP correction (2)	Education attainment correction (3)	Fully corrected scores (4)=(1)+(2)+(3)	Rank
Australia	1.047	0.037	-0.007	1.077	3
Austria	1.104	0.040	0.030	1.174	22
Belgium	1.063	0.033	-0.001	1.095	7
Czech Republic	1.083	-0.041	0.046	1.087	6
Denmark	1.108	0.048	0.028	1.184	23
Finland	1.037	0.027	0.035	1.100	8
France	1.082	0.028	0.005	1.115	14
Germany	1.104	0.029	0.037	1.170	21
Greece	1.191	-0.015	-0.010	1.167	20
Hungary	1.115	-0.058	0.024	1.082	4
Indonesia	1.528	-0.257	-0.075	1.196	24
Ireland	1.094	0.068	-0.002	1.159	19
Italy	1.160	0.026	-0.028	1.159	18
Japan	1.044	0.032	0.052	1.127	17
Korea	1.075	-0.030	0.023	1.068	2
Netherlands	1.066	0.038	0.009	1.112	13
New Zealand	1.068	-0.007	0.026	1.087	5
Norway	1.131	0.069	0.046	1.246	25
Portugal	1.172	-0.026	-0.080	1.067	1
Slovak Republic	1.131	-0.068	0.045	1.108	10
Spain	1.140	0.000	-0.035	1.105	9
Sweden	1.052	0.024	0.039	1.116	15
Thailand	1.348	-0.146	-0.082	1.120	16
Turkey	1.343	-0.162	-0.072	1.109	12
Uruguay	1.296	-0.134	-0.053	1.109	11
Average	1.143	-0.018	0.000	1.126	

Additionally, by looking at GDP and education attainment corrections in Table 6, it is apparent that in some countries, environmental “harshness” essentially results from poor adult education, and less from low GDP per head, as in Spain and Portugal. In Hungary, the Czech Republic and Korea, on the other hand, lower than average GDP is offset by higher educational attainment. Finally, note that Indonesia, Thailand, Turkey and Uruguay are countries where both environmental variables strongly push down performance, as opposed to the Scandinavian countries or Japan.

Figure 2 further illustrates the ranking changes. Countries below and to the right of the diagonal improve their relative position after non-discretionary inputs information have been accounted for. On the other hand, countries above and to the left of the diagonal face a worsening of their relative positions once the efficiency scores have been corrected.

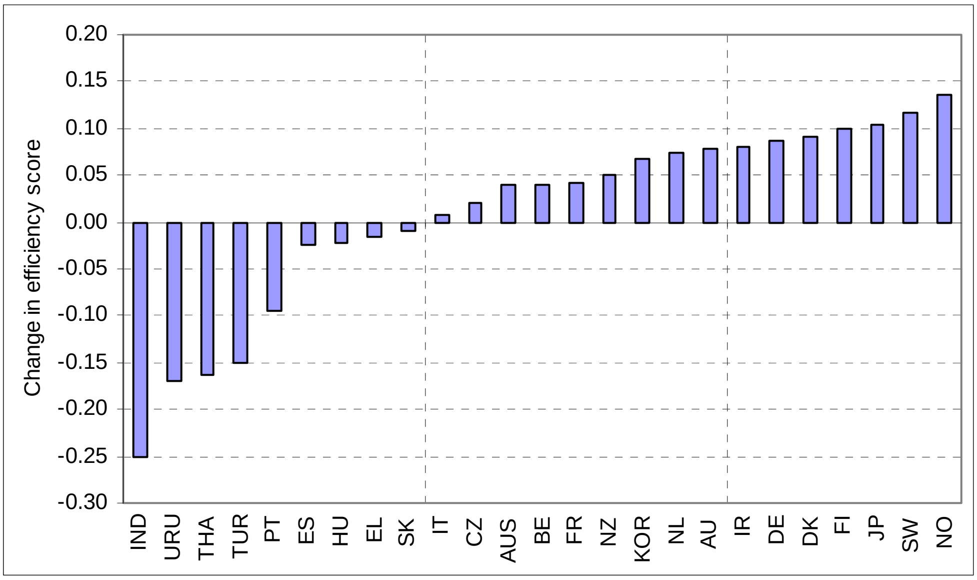
Figure 2 – Relative change in efficiency rankings



Note: AUS – Australia; AU – Austria; BE – Belgium; CZ - Czech Republic; DK – Denmark; FI – Finland; FR – France; DE – Germany; EL – Greece; HU – Hungary; IND – Indonesia; IR – Ireland; IT – Italy; JP – Japan; KOR – Korea; NL – Netherlands; NZ - New Zealand; NO – Norway; PT – Portugal; SK - Slovak Republic; ES – Spain; SW – Sweden; THA – Thailand; TUR – Turkey; URU - Uruguay.

By comparing efficiency scores changes following the bias correction and information about exogenous factors, we can also check which countries actually approached the production possibility frontier, and by how much. These changes are depicted in Figure 3 – negative (positive) changes correspond to countries that move closer (further away) to (from) the production frontier.

Figure 3 – Change in efficiency scores after correction
-/+: DMU moves closer (further away) to (from) the production frontier



Note: see note to Figure 2 for country abbreviations.

Figure 3 essentially derives from the environmental harshness in each considered country. Indonesia, for example, being the poorest country in the sample and the second worst in terms of parents` educational attainment, is the place where environment is less favourable to student achievement. This implies that a bias corrected output score of 1.528 is reduced to 1.196, meaning that about 62.9 percent of measured inefficiency may be ascribed to exogenous factors. Norway is one opposite case – this is the richest country in the sample, and one where adults are more instructed. Taking this into account, leads to the highest fully corrected output score, 1.246. Note that Norwegian PISA average performance (492.23) was below other developed and comparable countries (e.g. Finland or Sweden).

5. Conclusion

In this paper, we have evaluated efficiency in providing secondary education across countries by assessing outputs (student performance) against inputs directly used in the education system (teachers, student time) and environment variables (wealth and parents' education). In methodological terms, we have employed a two-stage semi-parametric procedure. Firstly, output efficiency scores were estimated by solving a standard DEA problem with countries as DMUs. Secondly, these scores were explained in a regression with the environmental variables as independent variables.

Results from the first-stage imply that inefficiencies may be quite high. On average and as a conservative estimate, countries could have increased their results by 11.6 percent using the same resources[23], with a country like Indonesia displaying a waste of 44.7 percent.

The fact that a country is seen as far away from the efficiency frontier is not necessarily a result of inefficiencies engendered within the education system. Our second stage procedures show that GDP per head and parents' educational attainment are highly and significantly correlated to output scores – a wealthier and more cultivated environment are important conditions for a better student performance. Moreover, it becomes possible to correct output scores by considering the harshness of the environment where the education system operates. Country rankings and output scores derived from this correction are substantially different from standard DEA results.

Non-discretionary outputs considered here cannot be changed in the short run. For example, parental educational attainment is essentially given when considering students performance in the coming year. However, contemporaneous educational and social policy will have an impact on future parents' educational attainment. As the children of today are the parents of tomorrow, and considering that parental educational attainment is an important determinant of students' outcomes, it results that policies oriented towards reducing present school dropout rates or increasing youth education length will positively affect the future efficiency of the educational system of given country.

Finally, note that we have applied both the usual DEA/Tobit procedure and two very recently proposed bootstrap algorithms. Results were strikingly similar with these three different estimation processes, which bring increased confidence to obtained conclusions.

[23] This results from the average output score from Table 3. Any bias correction necessarily implies higher average scores, as in Table 6.

Appendix – Additional Tobit and bootstrap results

Table A1 – Censored normal Tobit results
(27 countries, includes Brazil and Mexico)

	Model 1	Model 2	Model 3	Model 1a	Model 3a
Constant	1.213629	1.265284	1.278989	2.178233	1.862711
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Y	-0.548e-5		-0.204e-5		
	(0.012)		(0.412)		
Log(Y)				-0.109971	-0.067701
				(0.000)	(0.081)
E		-0.002674	-0.002192		-0.001580
		(0.000)	(0.022)		(0.095)
$\hat{\sigma}_{\varepsilon}$	0.106527	0.098319	0.096023	0.095875	0.090651
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Y – GDP per capita; E – Parental educational attainment. $\hat{\sigma}_{\varepsilon}$ – Estimated standard deviation of ε; P- values in brackets.

Table A2 – Censored normal Tobit results
(21 countries)

	Model 4	Model 5	Model 6	Model 7	Model 5a	Model 7a
Constant	1.483093	1.360996	1.605412	1.496527	2.626978	2.375158
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pub	-0.417987	-0.068827	-0.286462	-0.090810	0.148174	0.068794
	(0.241)	(0.807)	(0.236)	(0.655)	(0.515)	(0.688)
Y		-0.859e-5		-0.555e-5		
		(0.000)		(0.003)		
Log(Y)					-0.167262	-0.120034
					(0.000)	(0.000)
E			-0.003604	-0.002742		-0.002137
			(0.000)	(0.000)		(0.000)
$\hat{\sigma}_{\varepsilon}$	0.109699	0.082045	0.073550	0.059098	0.063605	0.047561
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Pub – public-to-total expenditure in education ratio. Y – GDP per capita; E – Parental educational attainment. $\hat{\sigma}_{\varepsilon}$ – Estimated standard deviation of ε; P- values in brackets.

Table A3 – Bootstrap results
(27 countries, includes Brazil and Mexico)

	Algorithm 1				
	Model 1	Model 2	Model 3	Model 1a	Model 3a
Constant	1.29834	1.35914	1.49384	3.4082	2.52437
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Y	-0.22800e-4		-0.14238e-4		
	(0.000)		(0.001)		
Log(Y)				-0.25082	-0.13721
				(0.000)	(0.0405)
E		-0.0073074	-0.0040814		-0.00336
		(0.000)	(0.000)		(0.048)
$\hat{\sigma}_{\varepsilon}$	0.17528	0.14757	0.10380	0.13497	0.12369
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

	Algorithm 2				
	Model 1	Model 2	Model 3	Model 1a	Model 3a
Constant	1.35924	1.37764	1.40856	2.85792	2.38279
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Y	-0.12303e-4		-0.060890e-4		
	(0.000)		(0.002)		
Log(Y)				-0.17692	-0.11663
				(0.000)	(0.000)
E		-0.0045012	-0.0026775		-0.0018025
		(0.0)	(0.0005)		(0.0025)
$\hat{\sigma}_{\varepsilon}$	0.09707	0.092488	0.071508	0.07532	0.064324
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Y – GDP per capita; E – Parental educational attainment. $\hat{\sigma}_{\varepsilon}$ – Estimated standard deviation of ε; P- values in brackets.

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Annex – Data and sources

Country	PISA (2003) 1/	Hours per year in school, 2000-2002 2/	Teachers per 100 students, 2000-2002 3/	GDP per capita, 2003 (USD) 4/	Parental education attainment, 2001-2002 5/	Public-to-total expenditure ratio 2001-2002 6/
Australia	526.15	1023.7	8.0	29143. 4	61.1	84.6
Austria	498.35	1072.5	10.0	29972. 5	81.9	96.0
Belgium	517.59	1005.0	10.5	28396. 1	64.6	94.4
Brazil	379.84	800.0	5.5	7767. 2	57.3	
Czech Republic	511.16	867.0	7.5	16448. 2	90.5	91.9
Denmark	499.65	860.0	7.8	31630. 2	80.5	97.9
Finland	545.90	807.0	7.3	27252. 2	84.7	99.3
France	509.34	1037.0	8.1	27327. 2	67.9	93.0
Germany	502.53	886.0	6.6	27608. 8	85.6	80.8
Greece	461.67	1064.0	10.1	19973. 2	59.4	91.6
Hungary	494.06	925.0	8.7	14572. 3	78.6	92.9
Iceland	501.57	821.9	na	30657. 3	61.0	95.2
Indonesia	374.55	1274.0	5.5	3364. 5	22.7	76.4
Ireland	505.54	896.3	7.0	36774. 8	63.7	95.7
Italy	474.31	1020.0	9.8	27049. 9	49.4	97.9
Japan	531.79	875.0	6.7	28162. 2	94.0	91.6
Korea	541.29	867.0	5.1	17908. 4	77.8	78.5
Mexico	393.56	1166.9	3.3	9136. 2	15.6	86.7
Netherlands	523.87	1066.9	6.1	29411. 8	69.9	94.8
New Zealand	524.68	952.6	6.1	21176. 9	79.6	na
Norway	492.23	826.8	9.6	37063. 4	90.8	99.2
Poland	492.81	na	6.8	11622. 9	47.9	na
Portugal	470.29	881.7	11.5	18443. 5	20.0	99.9
Russian Federation	469.61	989.0	8.9	9195. 2	na	na
Slovak Republic	488.49	886.3	7.4	13468. 7	90.3	98.1
Spain	483.75	907.2	8.6	22264.	45.3	93.1
Sweden	509.50	740.9	7.3	26655. 5	86.8	99.9
Switzerland	514.99	887.0	na	30186. 1	87.3	86.9
Thailand	422.73	1167.0	5.6	7580. 3	19.0	97.8
Tunisia	365.70	890.0	4.6	7082. 9	na	100.0
Turkey	426.54	841.3	5.7	6749. 3	24.7	na
United States	486.67	na	6.5	37352. 1	88.5	91.5
Uruguay	426.35	913.0	6.9	8279. 9	35.1	93.5
Mean	480.82	942.5	7.4	21202.3	63.9	92.8
Minimum	365.70	740.9	3.3	3364.5	15.6	76.4
Maximum	545.90	1274.0	11.5	37352.1	94.0	100.0
Standard deviation	48.87	122.0	1.9	10168.7	24.6	6.5
Observations	33	31	31	33	31	28

na – not available.

1/ Average of performance of 15-years-old on the PISA reading, mathematics, problem solving and science literacy scales, 2003. Source: OECD (2004b).

2/ Total intended instruction time in public institutions in hours per year for 12 to 14-years-old, average for 2000-2002. Source: OECD (2002, 2003a, 2004a, Table D1.1).

3/ Students per teaching staff in public and private institutions, secondary education, calculations based on full-time equivalents, average for 2000-2002. Source: OECD (2002, 2003a, 2004a, Table D2.2).

4/ PPP GDP and population in 2003. Source: *World Development Indicators Database*, September 2003.

5/ Population that has attained at least upper secondary education, aged 35-44, average for 2001-2002. OECD(2003a, Table A1.2, 2004a, Table A2.2).

6/ Public-to-total expenditure in upper secondary education ratio, average for 2000-2001. Source: OECD (2003a, 2004a, Table B3.2a).